Livelihood Sustainability in the Age of Digital Platforms: Insights from Online Freelancing in Kenya

by

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Author's Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners. I understand that my thesis may be made electronically available to the public.

Statement of Contributions

Farhan Latif was the sole author for all chapters, which were written under the supervision of Dr. Larry Swatuk and Dr. Juan Moreno-Cruz.

This thesis includes one published manuscript presented in Chapter 2. Short-Term Digital Platform Work's Long-Term Impact on Livelihoods: A Global South Literature Review and an Analysis Framework has been published in the Journal of Community Informatics doi.org/10.15353/joci.v20i1.5546. Authors retain copyright on their work in this journal, and the article is published under a Creative Commons Attribution-NonCommercial-ShareAlike 2.5 licence.

Chapters 3, 4, and 5 are article-style manuscripts based on original research. These manuscripts are currently unpublished, and the author retains full copyright over these chapters.

Abstract

Digital platforms are reshaping how online freelance work is organized and experienced in the Global South, but their implications for sustaining a meaningful and decent livelihood remain inadequately understood. While platforms offer new ways of making a living, particularly in labour markets characterized by informality and limited work opportunities, they often fail to meet the normative benchmarks typically associated with good-quality employment. These tensions raise questions about what constitutes a sustainable livelihood in the context of rapidly changing platform work, where conventional markers of decent work are increasingly difficult to apply to fragmented digital labour. My PhD research focuses on the intersection of platform work quality and development in the Global South. At its core, it explores the complexity of sustaining a fulfilling and good-quality livelihood through digital platforms, with particular attention to asymmetries in experienced work quality, local development realities, and the diverse, subjective aspirations of platform workers. Building on this foundation, my research bridges the knowledge gap by analyzing both workers' subjective experiences of work quality, framed in relation to decent and meaningful work, and the resilience of their livelihoods to labour market disruptions, such as those driven by artificial intelligence (AI). Grounded in a mixed-methods case study of 52 Kenyan platform workers, this dissertation is structured as a collection of four interrelated research papers. The first paper is a systematic literature review that consolidates the fragmented empirical literature on platform work in the Global South, examining the quality of work, the complexities of skills development, and future career prospects. It then distills the insights into an analytical framework, offering a tool for analyzing how local contextual factors shape platform-labour outcomes. The second paper examines workers' perceptions of work quality in relation to decent work standards, using a development lens. The findings of this paper situate platform work outcomes along a continuum from opportunity to precarity. The third paper focuses on how experiencing meaningful work evolves within the platform work economy. It discusses why many platform workers in the Global South perceive seemingly menial platform tasks as meaningful and analyzes the socioeconomic dynamics that shape this perception. The fourth paper examines the impact of generative AI on platform work. The paper introduces a task-based model to assess the impact of AI on work, offering an evaluation of four freelance occupations and an early-stage empirical validation of the model. Overall, this research advances theoretical debates on labour informality, decent and meaningful work, and automation risks to sustainable livelihoods by framing

platform work as a complex livelihood strategy that simultaneously extends and disrupts traditional pathways of work. Empirically, the dissertation documents persistent inequalities and precarious conditions while highlighting developmentally important forms of opportunity access, worker autonomy, and worker resilience in Kenya's platform economy. The dissertation offers policy-relevant insights, underscoring the need for adaptive labour regulation to extend protections to freelance platform workers, reorienting social safety nets to meet evolving demands, and inclusive digital economy governance so that platform-based work contributes to equitable and sustainable development.

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List of Abbreviations

AI	Artificial Intelligence
AHP	Analytic Hierarchy Process
AIOE	AI Occupational Exposure
AM	Automation Impact
AMT	Amazon Mechanical Turk
API	Application Programming Interface
BPO	Business Process Outsourcing
BPOAK	Business Process Outsourcing Association of Kenya
CA	Capability Approach
CD	Context Dependence
CI	Consistency Index (in AHP)
CMS	Content Management System
CR	Consistency Ratio
CSDDD	Corporate Sustainability Due Diligence Directive
DAQ	Data Availability and Quality
DTDA	Danish Trade Union Development Agency
DCU	Decision Complexity under Uncertainty
DW	Decent Work
DWA	Decent Work Agenda
EF	Education First (English-Proficiency Index)
EFA	Exploratory Factor Analysis
EI	Enhancement Impact

ESG	Environmental, Social, and Governance
FDR	False Discovery Rate (multiplicity adjustment)
FGD	Focus Group Discussion
GRI	Global Reporting Initiative
ICT	Information and Communication Technology
IFRS	International Financial Reporting Standards
ILO	International Labour Organization
ISSB	International Sustainability Standards Board
ITU	International Telecommunication Union
KMO	Kaiser-Meyer-Olkin (measure of sampling adequacy)
NHIF	National Health Insurance Fund (Kenya)
NSSF	National Social Security Fund
OLI	Online Labour Index
OLS	Ordinary Least Squares (regression)
P2B	Platform-to-Business
SACCO	Savings and Credit Co-operative Organization
SASB	Sustainability Accounting Standards Board
SDGs	Sustainable Development Goals
SDPLF	Sustainable Digital Platform Livelihoods Framework
SDT	Self-Determination Theory
SHIF	Social Health Insurance Fund
SEs	Substantive Element(s) of the Decent Work Agenda
SIC	Social and Interactive Complexity (task characteristic)
SI	Substitution Impact

SLF	Sustainable Livelihoods Framework
SMEs	Small and Medium-sized Enterprises
TAM	Technology Acceptance Model
TCD	Task Context Dependence
TCE	Transaction Cost Economics
TMG	Task Modularity and Granularity
UI	User Interface
UN	United Nations
URL	Uniform Resource Locator
VIF	Variance Inflation Factor
ZBJ	Zhu Ba Jie (Chinese freelance-platform marketplace)

List of Symbols

α	Alpha symbol used to show automation-weighting multiplier in the vulnerability formula
β	Beta symbol is used in two different senses: first, it denotes a scaling factor that moderates how unpaid tasks temper vulnerability in the AI impact on work modelling. Second, it is the standardized regression coefficient in statistical tables reporting group effects
σ	Sigma parameter that controls the width of the Gaussian "sweet spot" transformation applied to raw criterion scores in the platform work and AI paper
Σ	Summation operator in occupation-level aggregations
r_{opt}	Optimal reference value used in the AI impact modelling to denote a criterion depending on whether conditions ideally favour Automation, Substitution or Enhancement
d_i	Task-level disruption score combining SI, AM and EI multiplicatively
D_o	Occupation-level disruption score = Σ (Wi · di)
v_i	Task-level vulnerability score after scaling AM by α and offsetting EI by β, then adjusting for role factor R
V_o	Occupation-level vulnerability score = Σ (Wi · vi)
R	Role factor to denote the ratio of core income-generating tasks and unpaid tasks that down-weights vulnerability based on earnings exposure
M	Arithmetic mean of a scale or item, reported in descriptive figures

Chapter 1
Introduction

The world of work is undergoing significant changes, reshaped by accelerating technological advancements, evolving organizational structures, and shifting socio-economic outlooks. Rapid advancements and adoption of digitization, the diffusion of information and communication technologies (ICTs), and the rise of data-intensive business models are reconfiguring how work is organized, valued, and governed (Castells, 2009; Gray & Siddharth, 2019). Recent advances in connecting the digitally disconnected half of the world, and the commercialization of automation and artificial intelligence (AI) tools, further amplify this complexity, reshaping work, the skills demand landscape, and the economic value of skills (Acemoglu, 2021; Latif & Swatuk, 2021).

A significant proportion of today's work is now digital, and organizational structures have adapted accordingly to accommodate and leverage this shift. Today's organizations, whether large firms or small start-ups, are no longer constrained by physical geography in how they conceptualize, organize, and optimize productivity. Contemporary firms have increasingly transitioned away from vertically integrated hierarchies toward modular, digitally networked ecosystems, in which productivity is secured through interdependent yet often geographically dispersed actors and processes (Lee & Wellman, 2012). Now, digitalization allows firms to remain highly fluid and tap seamlessly into dispersed pools of skill and expertise, making remote and transnational work a defining feature of contemporary capitalism (Brynjolfsson & McAfee, 2014; Castells, 2009).

It is not simply that organizations have become more fluid, digital, and geographically dispersed; this dispersion is accompanied by the fragmentation and reorganization of labour itself. Traditional employment relationships, once defined by stability and life-long employment tied to a single firm, are no longer a dominant norm, giving rise to non-standard forms of work that is based on projects and short-term value creation (Castells, 2009; Jessop, 2010; Standing, 2014). In this contemporary work environment, many workers no longer have the choice to or expect to stay in one job or even one occupation for their entire careers. Instead, they are increasingly required to navigate fragmented career paths, shoulder economic risks once absorbed by employers, and adapt continuously to shifting labour market demands (Beck, 2000; Cappelli, 2012).

This convergence of digitalization and the fragmentation of work has facilitated the emergence of a particular form of labour economy, one characterized by just-in-time, readily accessible online labour for short-term, on-demand engagements (De Stefano, 2015; Silva Neto, 2019; Standing, 2016). Digital labour platforms act as intermediaries in this process, matching clients with workers across geographic boundaries, enabling the outsourcing of tasks to a global pool of freelancers. These platforms, such as Upwork, Freelancer, and Fiverr, structure economic activity through algorithmic management, standardized interfaces, and rating systems that govern access to work, remuneration, and reputational capital (Silva Neto, 2019; Wood et al., 2019).

At its core, platform-mediated digital labour represents a radical intensification and acceleration of pre-existing patterns of flexibilization, fragmentation, and individualization (De Stefano, 2015; Wood et al., 2019). Even prior to the rise of platforms, work had been increasingly organized around short-term projects, globalized outsourced contracts, and geographically dispersed teams enabled by digital tools (Kenney & Zysman, 2016). Platforms scale these developments. By leveraging a multi-sided market of work seekers and work providers, digital labour platforms make it technically and economically feasible to decompose work into much smaller tasks and contract labour on a shorter-term basis. For workers, this work model offers flexibility and access to multiple types of work opportunities, but simultaneously imposes precarity and a loss of institutional safeguards tied to traditional employment (Stanford, 2017; Wood, Lehdonvirta, et al., 2018). The platform economy, therefore, embodies the logical extension of neoliberal labour restructuring, where workers are simultaneously dislocated from stable organizational contexts and re-embedded within a system of intense competition and precarity (Vallas & Schor, 2020; Van Doorn, 2017).

Despite the efficiency gains that digital labour platforms deliver to clients and intermediaries, this labour model intensifies informational, managerial, and economic asymmetries that disadvantage workers, creating a cluster of issues now at the center of platform labour studies and policy debates. For instance, employment protection challenges arise as platform workers are typically labelled as independent contractors with no guaranteed base pay and a price-rate incentive system shifting social benefits and income consistency burdens onto the workers (Eurofound, 2018; Gray & Siddharth, 2019).

There is also a noticeable institutional mismatch, where existing labour, social-security, and tax regimes in many countries were built for standard employment and struggle to accommodate multi-country, task-based digital work. To ensure access to work, platform workers must also invest substantial unpaid work in profile curation, bidding, uncompensated revisions and dispute resolution, an overlooked cost of platform participation (De Stefano et al., 2021; Pulignano, Grimshaw, et al., 2024). A decent level of minimum wage protections in this globalized labour ecosystem is challenging to enforce, as average hourly pay continues to decline once unpaid work is factored in. Collective bargaining is hampered by workforce atomization and unclear legal standing (Wood, Lehdonvirta, et al., 2018). These issues suggest that platform-mediated labour faces substantial barriers to achieving a decent work standard for workers (Ayentimi et al., 2022; Standing, 2019).

Despite the prevalence of these significant issues, the online platform work economy is rapidly growing. Across multiple data sources and methodologies, the literature converges on double-digit annual growth rates, whether measured by the count of active platforms, posted tasks, registered workers, or market revenues (Kässi et al., 2021; Stephany et al., 2021). The trends show a widening global client base, but also a much larger acceleration in workers, underscoring intense competition and latent labour oversupply in online markets (Kässi et al., 2021). Most importantly, this labour ecosystem shows a significant North–South divide in the platform economy, with a large proportion of workers located in developing countries (Standing, 2017).

For many workers in the Global South, these platforms provide entry points into the global economy, but they also present a range of additional challenges. For instance, cross-border platforms intensify a race to the bottom in terms of price, pitting workers in low-wage regions against one another and automation, effectively reducing their income potential and income security (S. Ahmed et al., 2021). Payment holds, high remittance fees, and volatile exchange rates further erode take-home pay, making nominal rates misleading (Brooke & Rao, 2024; Pulignano, Grimshaw, et al., 2024). Platform reputation systems amplify client power, embed geographical, gender, and racial biases, and create a tiered work ecosystem where some workers are better positioned to leverage the platform economy than others. For instance, search-ranking and rating systems systematically favour Global North locations, male names, and lighter-skinned profile photos, entrenching a two-tier market of highly successful and peripheral workers (Brooke & Rao, 2024; Demirel et al., 2020; Malik et al., 2021a). Workers in the Global South perform more unpaid work, work in unsocial hours, and operate

within a system where the framing of entrepreneurship masks neo-colonial power asymmetries in platform discourse and design, that is, forms of indirect control and extraction whereby Global North actors disproportionately shape the rules, infrastructure, and rewards of platform labour without formal governance rights (Howson et al., 2023; Wood, Graham, et al., 2018).

This South-North disproportionality further complicates the pursuit of fair and decent quality work standards in the platform work economy at a global scale, as it intersects with and reshapes broader development challenges and structural conditions of underdevelopment in the Global South. My PhD research focuses on this intersection of platform work quality and development in the Global South. It examines the complexity of sustaining a fulfilling and good quality livelihood through digital platforms, with particular attention to the asymmetries in experienced work quality, local development realities, and the diverse and subjective aspirations of platform workers in the Global South. This research uses the terms platform work, digital labour, gig work, and online freelancing interchangeably to refer to short- and medium-term tasks typically performed online. These include, but are not limited to, software and web development, freelance writing, transcription, customer service, and virtual assistance.

1.1 Theoretical Foundations

While the structural issues of inequality associated with the design of the platform economy demand careful attention for a just development agenda, it is hard to ignore the ground realities faced by Global South platform workers who must choose between a limited range of livelihood opportunities to make ends meet. The phenomenon of permanent work never matured for many of these historically disadvantaged social groups and regions, who now have access to these alternative employment opportunities (Scully, 2016). How the combination of existing development inequalities and the ever-changing shape of the platform labour environment produces distinctive platform labour outcomes remains understudied (Huws, 2017; Scully, 2016). In response to this gap in development research, and informed by broader considerations of development conditions in the Global South, my work focuses on the developmental potential and limitations of platform work.

In this research, I adopt a sustainable livelihoods approach to contextualize the evaluation of platform work through the lenses of decent work and meaningful work, guided by the view that such evaluation should ultimately support the expansion of individuals' freedoms to pursue life goals they have reason to value (Chambers & Conway, 1992; Duncombe, 2007; Sen, 2001). A structured

discussion of these theoretical concepts and their relationship to platform work is presented in Chapters 2, 3, and 4.

The primary reason for focusing on the concept of livelihoods is to explain why the same work can translate into security for some groups yet reinforce precarity for others, providing insights that a narrow, work-oriented approach would miss. A livelihood perspective looks beyond wages or work quality and expands the informational basis for judgment by incorporating a broad range of individual capabilities, assets and social relations people mobilize to make a living in specific contexts (Chambers, 1995; Chambers & Conway, 1992; Duncombe, 2007; Latif, 2024; Sen, 2001).

Accordingly, the livelihood approach defines a sustainable livelihood as one that can cope with and recover from stresses and shocks, maintain or enhance workers' capabilities and assets, and provide adequate livelihood opportunities for future generations (Chambers & Conway, 1992; Natarajan et al., 2022). From this perspective, platform work is just one component of a worker's livelihood, highlighting how broader factors, such as gendered care roles, skill capital, or local economic context, influence what platform work outcomes actually mean for the well-being of workers. Throughout this research, I have particularly focused on well-being as the ultimate goal of platform work and a worker's livelihood. The third chapter in this dissertation provides a detailed theoretical overview of how a focus on human capabilities as a measure of well-being helps overcome some of the gaps between objective achievements, such as stable employment, and subjective well-being, such as the capability to make ends meet without compromising one's health.

While a livelihood perspective provides a solid foundation for understanding the development context in which work materializes and workers exist, it does not directly address specific rights and entitlements at work. To focus on specific indicators of a good quality work life, other strands of labour research, such as decent work and meaningful work, offer a valuable perspective for expanding a development agenda that focuses on understanding the broader sustainability of platform workers' livelihoods. More specifically, the concept of decent work, introduced by the International Labour Organization (ILO), entails a thorough evaluation of opportunities for work that is productive, offers a fair income, ensures workplace safety, and provides social protection for workers and their families. It also includes better prospects for personal growth and social inclusion, along with freedom for individuals to voice their concerns, organize, and take part in decisions that affect their

lives, as well as equality of opportunity and treatment for all workers (I. Ahmed, 2003; Ferraro et al., 2016; ILO, 2008, 2013).

Lastly, the focus on the subjective and experiential aspects of work, whether workers find their jobs psychologically fulfilling or meaningfully rewarding, is seen in this research as an intrinsic part of a sustainable livelihood. While decent work tells us whether a job meets basic social and economic standards, it does not tell us whether workers find their jobs psychologically fulfilling or existentially rewarding. The notion of meaningful work addresses this gap by focusing on the lived experience of work, especially how people derive purpose, identity, and dignity from their occupations, even in informal or precarious settings (Bailey et al., 2017; Blustein et al., 2023; Rosso et al., 2010). Accordingly, livelihood sustainability as a metric in this research is understood as a sufficient and fair work that provides meaning to workers life and meets individual development needs without causing excessive hardship, restores rather than depletes the resources that enable it, adapts to inevitable shocks, and preserves or expands the worker's future livelihood options.

1.2 Core Research Questions

My research is grounded in the thesis that platform-mediated digital labour, whether intermittent or full-time, carries significant long-term implications for livelihood sustainability in developing regions. Whether platform work expands or restricts individual aspirations depends not only on the fast-moving dynamics of the global digital labour market but mainly on the local socio-economic inequalities and development conditions that shape workers' everyday choices and realities. A worker-centred, development-oriented perspective that foregrounds subjective well-being and the lived experience of workers is therefore essential for evaluating platform work outcomes and their potential to contribute towards a sustainable livelihood. Guided by this lens, my research uses Kenya as a case study and examines how competing development priorities and rapidly changing labour markets interact over time, shaping workers' livelihoods. The following core questions guide this research:

Question 1: To what extent do digital platform workers in the Global South attain decent work, and how do these outcomes influence workers' well-being and vary across workers?

Question 2: To what extent is platform work in the Global South experienced as meaningful, and what factors explain the variation in these perceptions?

Question 3: How and to what extent does generative-AI–driven labour market disruption reshape the livelihood of platform workers in the Global South?

These questions aim to uncover not only the conditions under which platform work sustains livelihoods but also the depth and quality of that sustainability in light of workers' aspirations, well-being, and capacity to navigate technological and structural change. Question 1 establishes a baseline by evaluating the extent to which digital platform workers attain decent work and how job quality varies across different worker groups, influencing their capabilities and well-being. Question 2 shifts focus to the subjective dimension of work by exploring how meaningfulness of work evolves within the platform work economy, and what factors shape this variation. Lastly, Question 3 examines the impact of generative AI on the sustainability of platform livelihoods, investigating how new technological disruptions are altering the long-term viability of work, particularly in contexts characterized by short-term work and rapid change.

1.3 Research Design

I begin the research design by outlining the epistemological orientation underpinning the study, which is informed by pragmatism. A case study approach is employed to explore the evolving dynamics of digital freelancing in Kenya. While my initial research plan envisioned a multi-country study involving Kenya, South Africa, and Tanzania, carried out in partnership with a regional research institute, this collaboration did not materialize. As a result, the empirical focus was refined to Kenya, allowing for a more in-depth and context-specific examination. The research adopts a multi-methods strategy, combining qualitative and quantitative approaches across multiple data sources. Given the article-based structure of the dissertation, each paper contributes to a distinct aspect of the case while collectively supporting a coherent analysis of livelihood sustainability.

1.3.1 Philosophical Paradigm

I adopted pragmatism as its guiding philosophical stance. Pragmatism foregrounds the practical consequences of ideas, treating knowledge as inseparable from the social, political, and historical contexts in which it is produced (Morgan, 2016; Thayer, 1982). Because this research project is transdisciplinary and examines fluid human–digital interactions, it requires theoretical flexibility; a single, rigid ontology would be ill-suited to such complexity. Pragmatic thinking, therefore, brackets

essentialist claims about a universal reality unless they yield demonstrable, real-world value (Deforge & Shaw, 2012).

In this study, pragmatic thinking shifts attention away from grand narratives of digital transformation toward the practical impacts of platform work on diverse local realities. By privileging actionable insights, a pragmatic lens keeps the focus on how platforms and policy environments shape workers' day-to-day prospects in the Global South (Deforge & Shaw, 2012; Morgan, 2016). Such a way of understanding and valuing knowledge helps me retreat from an excessive focus on the macro-level digital technology discourse that often comes at the expense of diverse local realities, and it keeps the research emphasis on the practical consequences of platforms and relevant policy environments.

1.3.2 Kenya Case Study

In this research, the emphasis is on understanding not only the direct impact of digital platforms but also the intertwined socio-economic, technological, and individual dynamics that shape workers' experiences. Hence, I employed case study approach in this research to emphasize real-life experiences of workers. Case studies are instrumental when the research focuses on contemporary phenomena within real-life contexts, especially where the boundaries between phenomena and contexts are blurred (Thomas, 2021). A case study approach is particularly suitable for examining the implications of digital platform labour on livelihood sustainability as it allows for an in-depth, holistic exploration of the subjective experiences of platform workers through qualitative narratives while also enabling quantitative analyses to identify broader patterns and relationships (Creswell, 2021).

Kenya, as a case study for this research, provides an invaluable backdrop. Kenya's labour market has undergone a pronounced structural transformation over the past two decades, moving away from traditional agriculture toward service-oriented and digital work (Munga et al., 2021). Although agriculture still employs a significant number of people informally, its share of wage-based employment has declined, while vocational sectors such as construction, education, and business process outsourcing (BPO) have expanded, attracting considerable interest from development actors (DTDA, 2025; Munga et al., 2021).

The emergence of tech outsourcing in Kenya, particularly within the BPO sector, shows the changing employment landscape. Just south of Nairobi, known as Silicon Savannah, the development

of an ambitious large-scale tech hub shows the state and private sector interest in harnessing Kenyan technical skills and creating a service sector focused on digital outsourcing work. However, the expansion of Kenya's BPO sector has also been uneven, with some tech hubs experiencing stagnation or decline and the industry overall showing inconsistent growth across regions (Larsen et al., 2023). Informal employment continues to comprise nearly 80 percent of all Kenyan jobs, underscoring a labour market that shifts the responsibility for employment security onto individual workers (Sitati & Onsomu, 2023).

These employment trends are complemented by enabling infrastructure developments. Internet access and speed in Kenya have significantly improved over the last decade. While earlier statistics placed internet penetration at approximately 32 to 41 percent in the early 2020s, an estimated 27 million Kenyans, about 48 percent of the population, are now online (ITU, 2024). Another key aspect of Kenyan workers' interest in online work through platforms is their higher proficiency in the English language, which enables them to work more easily with international clients. Due to the legacy of British colonialism, English is deeply embedded in education, government and media alongside Swahili. Not surprisingly, Kenya ranks high in global English proficiency. Statistics show Kenya is 2nd in Africa and 19th globally in English Proficiency (EF, 2024).

Although Kenya accounts for less than 2 percent of the global freelance digital workforce, according to Online Labour Index (OLI) estimates, Kenya's online gig economy has experienced substantial growth in recent years (Kässi et al., 2021). A 2024 ILO report estimated that the number of Kenyan online platform workers was approximately 36,573 as of 2019, with the sector projected to expand significantly thereafter (ILO, 2024). It is worth noting that most of the new jobs created in Kenya are still in the informal economy, and youth unemployment remains stubbornly high, estimated at 66–67 percent under broader definitions of joblessness. (DTDA, 2025). These development challenges show why working online through platforms has gained significant interest in Kenya.

This growth is not occurring in an institutional vacuum. Kenya's platform economy is being shaped by a set of evolving governance arrangements involving state institutions, regulatory agencies, and policy frameworks that have sought to formalize and support digital labour markets. Key

government actors such as the Ministry of ICT and Digital Economy and the Ministry of Labour and Social Protection have integrated digital work and skills development into the broader Kenya Digital Economy Blueprint and the National Employment Authority's strategies. However, these policy frameworks primarily emphasize job creation and digital inclusion rather than establishing robust labour protections, leaving critical gaps in regulation, taxation, and social security coverage for platform workers.

The Kenyan government, alongside non-governmental and international actors, has increasingly positioned online gig work as a solution to youth unemployment and gaps in the formal labour market. The Kenyan government and non-governmental agencies are increasingly promoting online gig work programmes, such as Ajira Digital[1] spearheaded by the Ministry of ICT and Digital Economy in collaboration with the Kenya Private Sector Alliance and supported by the Mastercard Foundation, to fill gaps in the traditional labour market and curb persistent unemployment. These programmes are complemented by initiatives from the Kenya National Innovation Agency and county-level governments, reflecting a multi-level governance architecture that seeks to align youth training, entrepreneurship, and digital work placement. These interventions are also supported by a growing ecosystem of stakeholders, including international development agencies, the local non-profit sector, and private training institutions, that provide technical training, mentorship, and infrastructural support.

These efforts demonstrate a structured push to equip young people with digital skills and connect them to global online work opportunities. However, this governance ecosystem remains characterized by uneven coordination and limited accountability, as no single institution has a mandate to regulate platform labour conditions, monitor compliance, or enforce worker protections. This governance gap contributes to the precarious and informal character of much platform work despite the state's promotional stance. This convergence of state and non-state initiatives makes

[1] Ajira Digital is a Kenyan government initiative that was launched in 2016 through the Ministry of Information, Communications, and the Digital Economy, with support from development partners such as the Mastercard Foundation. The program promotes youth employment by training young Kenyans in digital skills and connecting them to online freelancing opportunities across different sectors, including transcription, writing, virtual assistance, and software development. For more, see, ajiradigital.go.ke

Kenya a compelling site for development research on the promises and contradictions of digital gig work in the Global South.

1.3.2.1 Case Study Ethics and Research Participants

Because this case study involved collecting sensitive labour-related data from a dispersed and largely informal workforce, I incorporated strict ethical safeguards throughout the process to uphold participants' autonomy, confidentiality, and well-being. I conducted this research in accordance with the ethical standards and policies of the University of Waterloo and the Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans (TCPS 2). Ethics clearance was obtained from the University of Waterloo Research Ethics Board (REB 45638), and I began fieldwork only after receiving formal approval.

The selection of research participants was a crucial aspect of this study, particularly given the unique characteristics of the digital platform work landscape in Kenya. As noted earlier, platform work in many developing contexts features low entry barriers and an oversupply of labour. This means that individuals with very different skills, experiences, and motivations may all be involved in the same broad category of online freelancing. Therefore, identifying experienced participants who could provide meaningful insights into the research questions, especially regarding livelihoods, skill development, and technological change, required a careful and purposeful approach.

Early in the research design process, I recognized the limitations of conventional recruitment strategies commonly used in platform research. One prevalent approach in similar studies involves posting research tasks directly on platforms, where workers are invited to complete surveys or participate in interviews. Although this approach may appear efficient, in my opinion, it introduces several challenges. Platform workers often perceive such studies as just another gig, rather than a space for meaningful engagement. Furthermore, survey participation has become an established subfield of platform work, leading to repetitive and sometimes disingenuous responses driven by incentives rather than authentic interest or experience. Some research studies have also noted that the quality of research data collected through platforms has deteriorated over time (Kurian & Bindu Madhavi, 2024).

This concern was reinforced during the field-testing phase of my survey, when I posted a task on Upwork asking freelancers to complete the questionnaire and provide feedback. Most of the

applicants had little verifiable experience on the platform and appeared to be newer freelancers seeking any available work. More experienced freelancers were largely uninterested. These early experiences prompted a shift in my recruitment strategy. Instead of relying solely on online labour platforms for recruitment, I aimed to create a more targeted and thorough participant selection process that entailed considerable in-person fieldwork in Kenya.

To ensure the relevance and reliability of participant insights, I developed a baseline criterion. Participants must have at least one year of experience working as online freelancers, a threshold I verified through publicly visible platform profiles or portfolio evidence. More importantly, I adopted a more organic, multi-pronged approach. This included in-person visits to co-working spaces in Nairobi known to be frequented by remote and platform-based workers, engagement with training institutions focused on digital work, attendance at local freelancing events, analysis of social media activity related to digital freelancing, and referrals from experienced Kenyan freelancers, who often recommended others in their professional networks. I also recruited participants through curated online freelancing communities on platforms such as TikTok, Facebook, and WhatsApp, which often served as informal hubs of knowledge exchange among more established freelancers.

This combination of purposive and snowball sampling strategy resulted in the successful inclusion of 52 participants, many of whom would likely have been inaccessible through more superficial recruitment strategies, such as posting an open call on freelancing sites. All participants were compensated for their time and effort, in recognition of the value of their contributions and in line with ethical research practices. Survey participants received a flat rate of 500 Kenyan Shillings for completing the online survey questionnaire. From this group, I randomly selected 20 individuals for in-depth interviews, ensuring gender balance to capture a range of perspectives and experiences. Those who participated in the interviews received an additional 1,500 Kenyan Shillings. Interviews were conducted in public locations such as cafes or co-working spaces, at a time and place chosen by the interviewee. This approach was particularly important for addressing potential power imbalances and ensuring participants felt safe, respected, and in control of the interaction. Conducting interviews in neutral and accessible public settings also contributed to a more open and candid conversational dynamic, fostering trust and minimizing any sense of coercion or institutional formality (Creswell, 2014).

To ensure confidentiality, I used pseudonyms in all transcripts, notes, and publications, and removed any identifying information from the data. All data were securely stored on encrypted drives with restricted access, and only aggregated or anonymized results are reported. Throughout the project, I prioritized voluntary participation, transparency about the research purpose and potential risks, and respect for the diversity of participants' professional identities, many of whom combined platform work with other forms of employment or entrepreneurial activities.

This participant selection approach was especially effective given the often hidden and informal nature of online freelancing, where workers may not be concentrated in one physical location or captured in institutional databases. Another notable outcome of this strategy was the marked difference in participant engagement. By recruiting participants outside formal platform channels, conversations were more candid, relaxed, and nuanced. Participants were likely less concerned about how their responses might affect their platform reputations, and the dynamic felt less transactional and more human. This experience underscored the limitations of treating research participation as a gig and highlighted how digital platforms, while central to the nature of the work, can also obstruct the depth and authenticity of research engagement when used uncritically as recruitment tools.

Furthermore, it is important to recognize that freelancing was not the sole professional identity of participants. While all were engaged in platform-based work, several also held paid roles training others in employability skills, maintained long-term remote employment, or operated other entrepreneurial ventures. Acknowledging this diversity of professional commitments and identities within and outside the platform work ecosystem is essential to understanding how platform work fits into broader livelihood strategies and how participants perceive its value and limitations.

Lastly, despite these ethical precautions, it should be noted that the sample size is relatively small and geographically concentrated, with 39 of the 52 participants based in the Nairobi Metropolitan Area. Due to the limited scope and participation, the study does not provide a representative account of platform workers across all parts of Kenya, particularly those from often marginalized groups. Groups such as ethnic minorities, people with disabilities, and workers in rural areas, who may experience distinct forms of exclusion, infrastructural constraints, and digital divide

challenges, are underrepresented. This limitation constrains the generalizability of the findings and highlights the need for future research to more deliberately engage with these voices.

1.3.3 Research Methods

My dissertation uses a mixed-methods design centred on Kenya's online platform work economy, using a survey and worker interviews (Creswell & Plano Clark, 2011). The compatibility of mixed-method inquiry and pragmatic epistemology is well established in the literature, e.g., (Creswell & Plano Clark, 2011; Mingers, 2003). This methodological pluralism allows this research to capture both the subjective experiences of platform workers and the broader patterns that condition their livelihood trajectories, providing a comprehensive yet practically oriented account of digital platform labour in Kenya.

The literature review presented in Chapter 2 follows a systematic approach, involving structured database searches, clear inclusion criteria, and iterative screening of studies, but in the article presented in Chapter, which was submitted to a journal, it is not classified as a full systematic literature review. This is because it was conducted by a single researcher and standard guidelines for systematic reviews emphasize the need for multiple independent reviewers to minimize selection bias (Xiao & Watson, 2019).

Quantitative methods used across the three empirical papers include factor analysis, bivariate analyses, and regression modelling (Long & Freese, 2014; Osborne, 2015). These methods were applied in an exploratory capacity to examine how demographic characteristics and labour inputs relate to livelihood quality outcomes, rather than to test predetermined causal hypotheses. The final article also incorporates a task-level Analytic Hierarchy Process to model the impact of AI on platform work (Brunelli, 2014; Vargas, 1990).

In the original research design, quantitative regression analyses were not intended to be exploratory; the plan anticipated a larger dataset from a multi-country study involving over 500 participants across Kenya, South Africa, and Tanzania. However, when the regional partnership did not materialize and the empirical focus was narrowed to Kenya, the quantitative component was reframed as exploratory. Accordingly, all regression and bivariate analyses in this research are employed in an exploratory capacity. This shift allowed the analysis to identify emerging quantitative

patterns and relationships while placing greater emphasis on qualitative data to capture the complex, context-specific dynamics of digital freelancing.

The qualitative part of this research is based on interviews with 20 Kenyan platform workers and employs thematic and narrative analysis methods (Clarke & Braun, 2017; Riessman, 2008). Twelve interviews are conducted in public locations across Nairobi to ensure accessibility and create a neutral, comfortable setting for participants. For those unavailable for in-person meetings, audio interviews are conducted via Microsoft Teams. All interviews are audio recorded and transcribed verbatim for analysis. To preserve the nuance and authenticity of participants' responses, quotes are presented with minimal editing. This thesis uses block formatting for all quoted material to maintain consistency and enhance the visibility of participants' voices.

In mixed-methods and qualitative research, a key challenge lies in doing justice to the richness of qualitative data, particularly when presenting participant narratives. Qualitative accounts often carry emotional and contextual meaning that can be diluted if reduced to decontextualized codes or brief excerpts (Denzin & Yvonna, 2017). This challenge is heightened in narrative analysis, where meaning depends on the sequence, framing, and subjectivity of participants' stories. To reflect this epistemological issue, I embedded qualitative quotes and their interpretation directly within the discussion sections of Chapters 3, 4, and 5, rather than isolating them in separate results sections. The quantitative findings directly compliment this qualitative data but are presented following conventional reporting norms, where results are shown descriptively in a separate section and without interpretation to provide an impartial account of observed patterns (Creswell, 2021).

1.3.4 Structure of The Dissertation

The study is structured into four manuscripts, each comprising a standalone but interrelated article prepared in a publishable format. Each article employs distinct research methods tailored to its specific sub-questions, with the methods section of each article providing detailed justification of the chosen approach, including its rationale, implementation, and analytical utility within the broader goals of the dissertation. The first article, "Short-Term Digital Platform Work's Long-Term Impact on Livelihoods: A Global South Literature Review and an Analysis Framework", was peer-reviewed and published in the Journal of Community Informatics https://doi.org/10.15353/joci.v20i1.5546. The

remaining three articles have been submitted to peer-reviewed journals and are now under consideration.

1.3.4.1 Short-Term Digital Platform Work's Long-Term Impact on Livelihoods: A Global South Literature Review and an Analysis Framework

Following this introduction (Chapter 1), a review article presented in Chapter 2 undertakes an interpretative literature review of empirical studies on platform labour to consolidate what is currently known about online freelancing in the Global South. Specifically, the paper asks how short-term, task-based digital work affects workers' livelihood quality, skill formation, and whether these outcomes vary systematically across different socio-economic settings.

Building on this synthesis, the article's main contribution is the proposal of a Sustainable Digital Platform Livelihoods Framework that emphasizes a greater focus on understanding local livelihood contexts and social power relations within the platform economy, as features of both local and global layers. This framing provides a tool that explains why seemingly identical platform opportunities could result in different livelihood outcomes. Although the subsequent empirical papers do not formally build on this framework, it acts as an implicit analytical guide and underpins the conceptual and analytical basis of my research.

1.3.4.2 Between Opportunity and Precarity: Decent Work and Capability Formation in Kenya's Online Freelance Platform Work Economy

This second article in Chapter 3 presents an empirical study that focuses on core research question 1, positioning Kenya's growing platform work sector as a critical test case for the ILO's Decent Work Agenda (DWA). Grounded simultaneously in the Decent Work Substantive Elements (SEs) and Sen's Capability Approach (CA), the paper interrogates how platform-mediated gigs expand or constrain freelancers' genuine opportunities to secure sustainable livelihoods and pursue valued life goals among different groups of workers. To capture both structural conditions and lived experiences, it adopts a convergent mixed-methods design that combines a platform worker-centred adaptation of the Decent Work Questionnaire (N = 52) with narrative-rich interviews (N = 20). This article focuses on the following specific questions.

RQ1 To what extent do digital platform-work conditions in Kenya reflect decent work, and where do they diverge?

RQ2: How do interactions between platform workers' demographics (age, education, gender, platform experience) and labour-input intensity (weekly paid hours, unpaid platform hours, time devoted to skill development) shape variations in decent work outcomes?

RQ3: How do the observed alignments or divergences intersect with freelancers' subjective well-being and capability expansion?

1.3.4.3 Social Capital, Job Quality, and the Making of Meaning in Platform Work: A Mixed-Methods Case Study of Nairobi's Online Freelancing Market

Chapter 4 examines how Kenyan gig workers construct a sense of meaning around precarious, algorithmically mediated platform labour. This article is anchored in the literature on meaningful work, job quality and social capital. The paper advances the following two guiding questions and contributes towards core research question 2.

RQ1: To what extent does the perceived meaningfulness of platform work correlate with self-reported job satisfaction and positive social relationships?

RQ2: How does the isolating nature of remote gig work shape workers' social capital and, in turn, influence work meaningfulness?

This article frames meaningfulness as a livelihood-level phenomena, rather than a sole property of work tasks. Methodologically, the article also employs a mixed-methods design, including a structured survey of 52 Kenyan freelancers that provides quantitative evidence for descriptive statistics, exploratory factor analysis, and multiple regression. Meanwhile, 20 semi-structured interviews offer narrative depth through qualitative evidence. The paper explains why precarious platform conditions can lead to divergent interpretations of work meaningfulness among Kenyan platform workers.

1.3.4.4 AI-Driven Transformation of Platform Work: A Task-Based Model for Measuring Labour Disruption and Vulnerability, with Early Evidence from Online Freelancing in Kenya

Chapter 5 is a comprehensive study on the impact of generative AI on platform work. The article presented in this chapter is substantially longer and more comprehensive than a standard journal article, both in terms of length and scope. While analyzing field data for my paper on the impact of artificial intelligence on workers' livelihoods, I found that most emerging studies on AI's impact on work focused on traditional occupations. However, these frameworks proved inadequate, as the

structural and functional differences between traditional jobs and platform-based freelance work were too significant to overlook. The lack of relevant theoretical and modelling foundations compelled me to undertake additional conceptual work beyond the original scope of my research.

This article presents a granular, task-level model for understanding how generative AI tools are reshaping platform work livelihoods in Kenya's digital platform economy. Contributing to core research question 3, it fills the gap in the existing literature on the impact of AI on platform work. It argues that standard occupation-wide AI exposure metrics conceal the ways platform labour is decomposed into paid and unpaid tasks, as well as how platform work jobs differ in their task composition from traditional job titles. To capture the nuances associated with platform work, this article proposes an assessment methodology and an Integrated Disruption–Vulnerability Measurement Model to evaluate the impact of AI on the livelihoods of platform workers. Similar to the other two empirical articles, this article also uses a mixed-methods design that validates the quantitative model against the lived experiences of platform workers. This article addresses the following research questions.

RQ1: How can we systematically measure AI-driven disruption and livelihood vulnerability across different platform occupations?

RQ2: To what extent do AI's task-enhancing functions offset its substitution and automation effects within different platform work occupations?

RQ3: Which core tasks drive disruption and vulnerability patterns in platform work occupations, and how do these drivers vary by occupation?

RQ4: How well do the model's disruption and vulnerability scores align with freelancers' reported experiences and economic outcomes?

The quantitative segment of this paper identifies core and supporting tasks in four freelance occupations (writing, virtual assistance, web/software development, and transcription), and scores each task's characteristics to compute automation, substitution and enhancement indices. These calculations are used to create composite disruption and vulnerability metrics at both the task and occupation levels. Field data from 52 surveys and 20 semi-structured interviews enrich and ground the metric, using focused thematic analysis to validate theoretical assumptions with empirical data and surface contextual nuances.

1.3.4.5 Dissertation Conclusions

The last chapter (Chapter 6) revisits the findings from the four research articles through a lens of livelihood sustainability, a perspective that informed not only the interpretation of results but also the initial selection of subtopics and analytical focus areas throughout the dissertation. This chapter highlights how platform work intersects with broader livelihood pathways in the Global South, with a focus on the Kenyan context. It consolidates the theoretical and empirical contributions of the dissertation to identify core themes of sustainability, such as exit options and technological disruption. Lastly, these findings are translated into evidence-based policy recommendations aimed at fostering more equitable and resilient forms of digital labour in Kenya.

1.4 Researcher Positionality

I approach this study as a man with substantial social mobility and a history of living in multiple high and medium-income countries. My privileges, strong passports, stable income, and academic capital stand in sharp contrast to many of the Kenyan platform workers whose livelihoods are constrained by geography, race, gender, currency volatility, and patchy social protection. At the same time, I share some dimensions of marginalization as I am racialized in the Global North, have lived and worked in economically developing regions, and have navigated immigrant precarity myself. These overlaps and gaps shape every conversation I have in the field and remind me that my insider knowledge of development projects never erases the fact that I am not a platform worker earning by the task.

My interest in digital freelancing grew out of a decade of working on ICT for development policy and ground initiatives that pursued livelihood gains and achieved varying levels of success. Those experiences taught me that development progress is negotiated in the small, practical choices people make under constraints, not in the grand narratives that often convey a sense of truth but remain somewhat disjointed from the complexity of real-world realities. This insight underpins my pragmatic epistemology as I treat partial, situated accounts as legitimate knowledge if they illuminate what actually helps workers secure decent, sustainable income. Accordingly, in this research, I paired survey data with semi-structured in-person interviews, adapting interview questions on the fly as needed, and maintained a reflexive journal that tracked how my interpretations evolved with each conversation.

I started this field research with the awareness that contacting freelancers through the very platforms that mediate their income would replicate the power asymmetries I seek to analyze, and risk turning participation into just another poorly paid task. I deliberately limited in-platform recruitment. Instead, I relied on peer referrals, visited co-working hubs to connect with workers, and utilized community and social media networks to find participants who often remain inaccessible to online research studies. I met participants in spaces and at times they chose. I shared plain language summaries and treated the resulting transcripts as co-owned material. In doing so, I aimed to convert my positional advantages into a channel that amplified, rather than filtered, the everyday expertise of Kenyan digital workers, while still delivering scholarship that meets rigorous academic standards.

Chapter 2
Short-Term Digital Platform Work's Long-Term Impact on Livelihoods: A Global South Literature Review and an Analysis Framework

2.1 Introduction

The growing size of the digital platform economy is renewing the discourse on how leveraging global digital labour could create attractive livelihood opportunities and fill institutional gaps in economically disadvantaged regions (Rossotto et al., 2018). This development narrative is built on the evidence that digitalization is transforming traditional jobs while creating geographically dispersed employment opportunities with varying levels of quality and stability (Martin & Zysman, 2015). The digital nature of these opportunities carries some potential to help boost service sector employment in developing regions (Elbanna & Idowu, 2021a; Melia, 2020). However, the temporary and precarious nature of these opportunities also demonstrates a decline in employment security (Zhou, 2022). Such work may leave workers without a meaningful corporate narrative to give to their professional lives (Standing, 2016), deepen global inequalities (Wood et al., 2019), and create new forms of marginalization for developing regions (Graham, Hjorth, et al., 2017). Digitalization is often seen as an influential tool for globalization (Schilirò, 2020). Hence, the rapid expansion of digital connectivity denotes that the development implications of the continually changing global labour market for the Global South are inevitable, as global skills demand trends and employment quality now have a stronger influence on local livelihoods among connected regions of the Global South.

There are parallel developments in the reorganization of work, digitalization, and digital connectivity, creating both pull and push factors that affect the growth of digital platform labour. On the one hand, digitalization and the emergence of online digital labour platforms have accelerated neoliberal globalization, enabling firms and individuals to break down and frictionlessly outsource tasks to an on-demand global workforce crowd, effectively bypassing the regulatory frameworks that exist within geographic boundaries and the traditional collective labour action that was the hallmark of employment security in the Global North (Graham et al., 2017; Standing, 2019). On the other hand, the growing skilled workforce in the Global South outpaces the local capacity to effectively harness

human capital for innovation, partly due to institutional gaps and the hegemony of Western innovation systems (Warhurst et al., 2017). A combination of interrelated developments in the Global South, such as higher education advancements, the expansion of digital connectivity, reduced costs of devices, and yet a persistent scarcity of decent local employment opportunities, has driven individuals towards engaging in digital platform labour (Bonina et al., 2021; De Reuver et al., 2018; Mika, 2020).

Central to this discourse is the mounting instability and insecurity in labour markets, a trend partly attributed to the proliferation of platform-mediated work arrangements. Some research points out how platform work structures may contribute to the casualization of labour, eroding the stability and protections typically associated with standard employment relationships (De Stefano, 2015). Hence, whether the livelihood opportunities enabled by platforms are a form of decent work, deliver a fair income, security in the workplace, and social protection is a critical and ongoing concern (D'Cruz, 2017; Graham et al., 2019). In response, there are growing yet fragmented bodies of literature emphasizing the need for decent and equitable platform work indicators and measurement projects that serve as a pillar for upholding core labour standards in the ever-evolving digital platform economy (Graham et al., 2019; Heeks et al., 2021; Rothschild et al., 2022). Recently, some platform-side initiatives, e.g., Fairwork (Graham et al., 2019), have attempted to constitute a baseline for what it may take for different types of platform-mediated work arrangements to be considered decent and fair.

However, the labour end of the platform value chain has a local development dimension. Here, the uneven employment opportunities may result in a subjective and relative perception of what constitutes better quality, more desirable, and meaningful work, making the quality of employment contingent on the extent to which it supports achieving individual development aspirations and improves individual capabilities (Fields, 2003). Additionally, the impact of engaging in digital platform work on workers' career progression and skill development can significantly vary across different social contexts (Bonina et al., 2021). Workers may see the livelihood outcomes differently based on how it may or may not enable them to have more choices to pursue the opportunities that align with their local development landscape (Idowu & Elbanna, 2021b). Central to the policy relevance of these scholarly perspectives is the fragmented nature of the literature, necessitating a more integrated approach to better inform and guide policy-making (Bonina et al., 2021; Sutherland & Jarrahi, 2018).

Against the backdrop of these parallel developments, this paper aims to mitigate this fragmentation by employing a livelihood lens. It builds on the argument that engaging in digital platform work in the Global South may yield disproportionate livelihood outcomes, thereby problematizing the generalizability of platform work's impact. These livelihood outcomes are context-dependent, and their recognition requires broader development framing. While acknowledging that access to a fair platform environment is critical in enabling a healthy macro labour environment, individual experiences and outcomes may largely depend on local contextual factors, such as local labour market conditions and access to capital assets, which are shaped by socio-cultural realities and institutional structures. As a result, the local and long-term livelihood potential of online platform labour in low-resource environments requires a close examination of the narratives of workers in the Global South to understand the range of livelihood outcomes and targeted actions that may improve these outcomes.

In this paper, I first build on this argument by examining the extent to which digital platform work offers a fulfilling and decent livelihood choice for workers in different developing regions, the extent to which engaging in short-term digital platform work influences workers' ongoing skills development, and the long-term career development prospects in the platform labour economy. I examine the published empirical studies in the Global South to synthesize arguments by focusing on the variation in local perspectives and different literature bodies. Second, I utilize the findings to refine a capabilities-centred Sustainable Livelihoods Framework (SLF) for digital platform work as a transdisciplinary lens to recognize how contextual factors such as local economic conditions, access to capital assets, and socio-cultural arrangements influence platform workers' livelihood outcomes.

This interdisciplinary work advances the field of community informatics (CI). It provides a valuable lens to examine these dynamics, emphasizing how communities utilize information and communication technologies (ICTs) to address local needs and foster development. This paper contributes to the concept of CI by examining how digitalization affects livelihoods in the Global South, specifically in terms of access to decent work, skill development, and worker resilience. It offers a nuanced understanding of how digital platform work can mitigate or exacerbate existing socio-economic inequalities and how community-level interventions can enhance positive outcomes. The Sustainable Livelihoods Framework (SLF) is refined to include digital capital and socio-cultural

assets, bridging CI with digital labour studies to provide a comprehensive view of the interplay between technology, work, and community development.

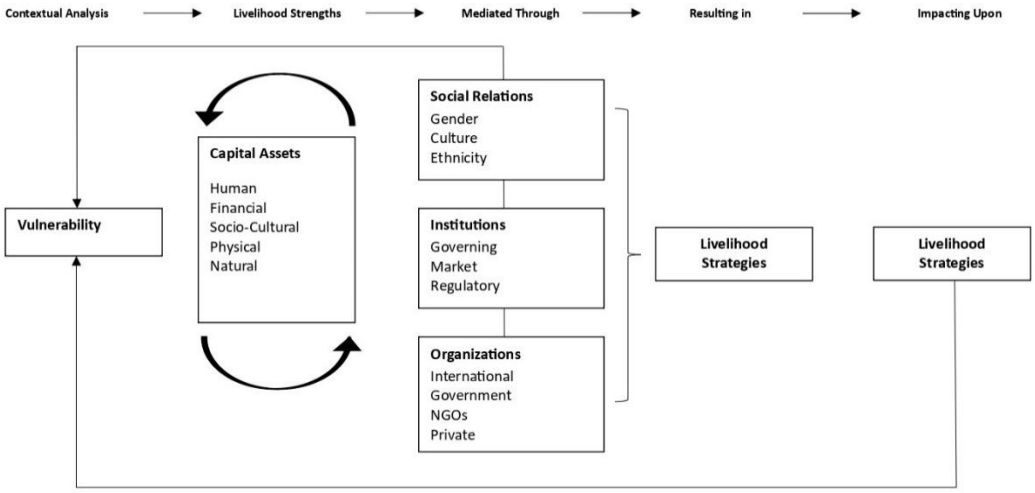
2.2 Sustainable Livelihoods Approach Towards Digital Platform Work

There are few examples in the existing platform literature examining digital platform work from a livelihood lens. The concept of livelihood is an umbrella term used in academic literature and development practice to describe what people do to make a living, the context in which they make these choices, and the structural processes that influence them (Natarajan et al., 2022). Chambers and Conway (1992) first defined a livelihood as the capabilities, assets, and activities needed to make a decent living and reach one's potential. Chambers (1995) further described that a livelihood is sustainable when it is resilient against disruptions, supports advancing capabilities and assets, and adds value to other livelihoods at the local and global levels in the short and long term. Over the period, this livelihood approach has transformed into a framework and a methodology that has directed a range of development interventions by state and non-state actors (Scoones, 2015). Fundamentally, the livelihood framework acknowledges that individual choices related to livelihood strategies and outcomes are influenced by the distinct vulnerabilities individuals encounter and their varying access to capital resources that help cope with those vulnerabilities (Chambers & Conway, 1992).

In recent years, the SLF has been tailored and revised for its utility in understanding livelihoods in the digital economy. Among these versions is Duncombe's conceptualization, which focuses on ICT-driven microenterprises (Duncombe, 2007), and Gilger's alternative evaluation framework to understand digital technology's impact on developing populations (Gigler, 2015). The SLF conceptualization presented by Duncombe (2007) holds the most relevance for investigating digital platform work compared to other versions. Notably, Duncombe (2007) distinctly incorporates political capital, acknowledging the disenfranchised groups' difficulties in accessing market opportunities, and asserts that social relations such as gender, culture, and ethnicity critically influence vulnerabilities and shape livelihood strategies (Figure 2.1).

Figure 2.1

The Livelihood Framework of Analysis by Duncombe, 2007



Some digital labour studies have utilized this SLF in the study of digital work, e.g., Malik et al. (2017). However, SLF has also received criticism for being too rural and poverty-focused (Mensah, 2011), not capturing the globalized nature of structural influences, and being too presumptuous towards livelihood context as a mere form of vulnerability (Mensah, 2011; Natarajan et al., 2022; Scoones, 2015). Considering this critique, the latter half of this paper builds on the review's findings and the critique of SLF. It extends a Sustainable Digital Platform Livelihoods Framework as a starting point for an SLF suitable for analyzing the broader livelihood impact of digital platform work in developing regions.

Two motivating factors inspire the creation of this framework. First, the absence of broader frameworks in the study of platform labour is well-acknowledged in the literature (Bonina et al., 2021; Kenney & Zysman, 2016). Most platform labour studies have employed piecemeal strategies to investigate digital platform work, where specific theories guide analyses without any broader framing of contexts (see Table 1 for a detailed list of theories and frameworks). The application of the livelihood framework could potentially fill this gap, acting as a dynamic tool that widens the spectrum of research by considering a multitude of factors intrinsic to livelihood decisions and

outcomes. Second, the livelihood framework is closely linked with the prolonged efforts to improve employment opportunities in the Global South development, making it a great tool to bridge the gap between academic research and development practice (Duncombe, 2007; Gigler, 2015).

2.3 Methods

I primarily utilize an interpretative qualitative review method to select and analyze relevant empirical studies. This approach amalgamates primary empirical research to interpret and compare findings, fostering new insights and potentially forming new understandings (Seers, 2015). One of the evolving qualitative review methodologies is a realist review or realist synthesis that considers both context and outcomes while compiling appropriate literature to facilitate the review of complex social interventions (Rycroft-Malone et al., 2012). This literature review method considers the context, acknowledging that identical opportunities can yield varying outcomes across different environments or population groups (Edgley et al., 2016; Pawson et al., 2005).

2.4 Data Extraction

A comprehensive search of multiple databases was conducted to find relevant empirical studies. It was last updated on May 10, 2023. This search was initially conducted using the SCOPUS and Web of Science literature databases, which yielded 243 and 518 relevant studies, respectively. Different combinations of relevant keywords used in this search included “online digital labour,” “digital platform labour,” “platform work,” “online gig work,” “crowd work,” “online freelancing,” “microwork,” and “development.” Due to the interdisciplinary nature of digital platforms, an effort was made to include studies from various disciplines, including but not limited to information systems, labour economics, management, governance, and development studies. Following the suggestion of Mallett et al. (2012), highlighting the significance of research published by development sector institutes, I included papers from think tanks and development policy institutes to account for development sector research outside traditional academic journals.

To supplement this search and capture emerging literature, Google Scholar (32 studies) was also utilized, along with emerging literature forest discovery techniques as described by Sharma et al. (2022), employing tools such as ResearchRabbit (68 studies). This process resulted in the discovery of a total of 861 studies. After removing 59 duplicates, 802 studies were selected for initial screening of abstracts and titles. 540 irrelevant studies were removed, and 262 were selected for a full-text

review. The selection of studies was based on specific criteria for inclusion and exclusion. Only empirical studies explicitly focusing on the role of digital platform labour in local development, such as access to work opportunities, skills upgrading, and employment conditions in countries in the Global South, were included. Studies failing to meet these criteria were excluded. After three rounds of literature selection, this process yielded 29 studies (Table 2.1), while 233 were excluded.

Out of the excluded studies, 71 were excluded because they were not empirical in nature. Additionally, 53 studies primarily focused on location-based platforms, making them irrelevant to the study's scope. 29 were related to e-commerce and sharing economy platforms, and 40 concentrated on the Global North or a mix of Global North and South countries. Furthermore, 36 studies exploring a mix of location-based and online platforms were removed due to their mismatch with the study's focus. Lastly, 33 studies primarily focused on the technical structure of digital platforms or emphasized platform statistics without a reasonable human development context were also removed.

Table 2.1

List of Key Empirical Studies Examining Platform Labour in the Global South

	Study	**Topic**	**Countries and Regions**	**Key Theories/Framework**
1	Varanasi et al., 2022	Low-income women's experiences with crowd work	India	
2	Panaligan & Curran, 2022	Racial biases in platform teaching gigs	Philippines	
3	Idowu & Elbanna, 2021a	Crowdwork employment strategies in Nigeria	Nigeria	
4	Idowu & Elbanna, 2021b	Crowd workers' affirmation and identity-building strategies	Nigeria	Social Identity Theory
5	Elbanna & Idowu, 2021	Digital liminality and precarity alternatives	Nigeria	Indigenous Theory of Liminality
6	Gurumurthy et al., 2021	Microwork framing in the Indian context	India	
7	Elbanna & Idowu, 2021	Crowdwork and human capital development in low-resource environments	Nigeria	Sustainable Development Goals and Human Capital Theory.

	Study	Topic	Countries and Regions	Key Theories/Framework
8	Leung et al., 2021	Freelancing strategies and impact	China, India	Putting-Out System
9	Beerepoot & Oprins, 2022	Online Freelancing and impact sourcing in the context of outsourcing trends	Philippines	
10	Wang et al., 2020	Chinese crowd workers' experience with Platforms and digital work perceptions	China	Job Resources model, the Work Design Questionnaire, the Oldenburg Burnout Inventory, the Utrecht Work Engagement Scale
11	Melia, 2020	Digital employment strategies in low-resource environments	Kenya	
12	Idowu & Elbanna, 2020	The shaping of career paths in the digital platform labour economy	Nigeria	Don Super theory
13	Anwar & Graham, 2020	African gig workers' perspectives towards access and quality of work	South Africa	Resistance, Resilience, and Reworking
14	Nawaz et al., 2020	Part-time e-lancing strategies	Pakistan	Value Proposition Theory.
15	Soriano & Cabañes, 2020	Filipino digital workers' collective strategies	Philippines	
16	Chidoori & Van Belle, 2020	Digital Labour Prevalence in South Africa	South Africa	Technology Acceptance Model (TAM), Self-Determination Theory (SDT)
17	Malik et al., 2021a	Digital labour platforms in rural Pakistan	Pakistan	Institutional Theory and Institutional Voids.
18	Sultana et al., 2019	The impact of IT freelancing in Bangladesh	Bangladesh	Theory of Planned Behavior.
19	Idowu & Elbanna, 2019	Nigerian Crowd Workers Career Trajectory	Nigeria	Life Rainbow Model and Super's Model.
20	Eskelund et al., 2019	Online freelancing training in the Philippines	Philippines	Choice Framework and Choice Theory.

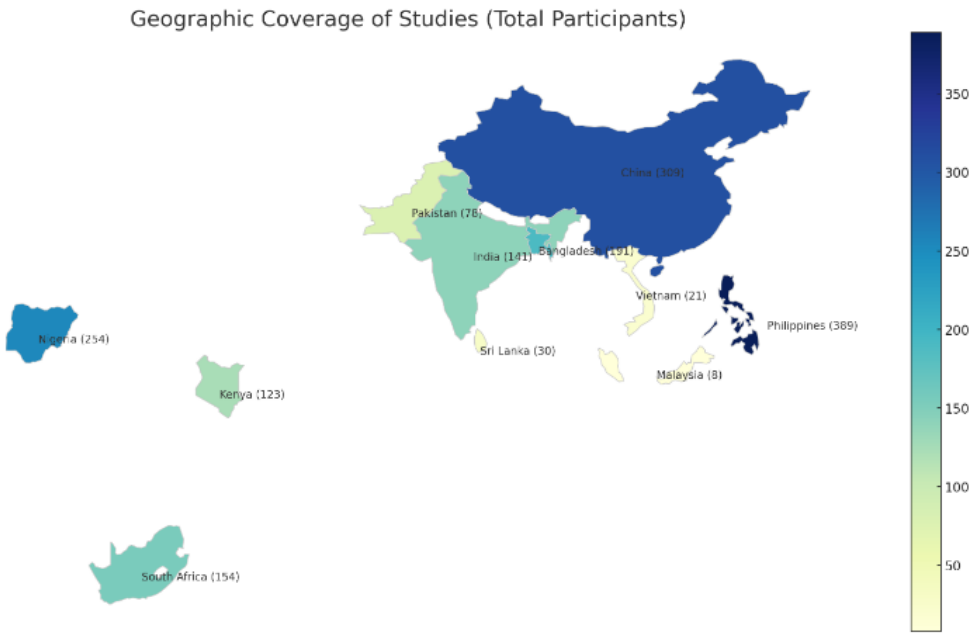
	Study	Topic	Countries and Regions	Key Theories/Framework
21	Lehdonvirta et al., 2019	Global platform economy growth	Philippines, Vietnam, Malaysia, South Africa, Kenya, Nigeria	Transaction Cost Economics (TCE), Signaling Theory.
22	Soriano & Panaligan, 2019	Influence as a career growth strategy among successful platform workers	Philippines	
23	Romke & Sayed, 2018	Freelancing impact in Bangladesh	Bangladesh	Hypodermic Needle Theory
24	Galpaya et al., 2018	Microwork Potential in Sri Lanka	Sri Lanka	
25	Malik et al., 2018	The institutional push toward digital labour in Pakistan	Pakistan	Sustainable Livelihoods Framework
26	Graham, Hjorth et al., 2017	Digital labour and workers' livelihood strategies	Philippines, Malaysia, Vietnam, South Africa, Nigeria	
27	Graham, Hjorth et al., 2017	Global margins and online gig work	Kenya, Nigeria, South Africa, Vietnam, Malaysia, Philippines	
28	D'Cruz, 2017	Empowerment and work quality complexities in online labour	India	Critical Hermeneutic Phenomenology
29	D'Cruz & Noronha, 2016	Indian crowd workers' multifaceted experiences	India	

2.5 Data Analysis

The studies were read in-depth, and key themes and patterns related to digital platform labour and development were identified and categorized. A standardized data extraction form was developed in the first phase to gather consistent information from each included study. The extracted data included the geographical region of focus, theoretical framework, theories used in the empirical studies, and the key findings related to the impact on local development.

Figure 2.2

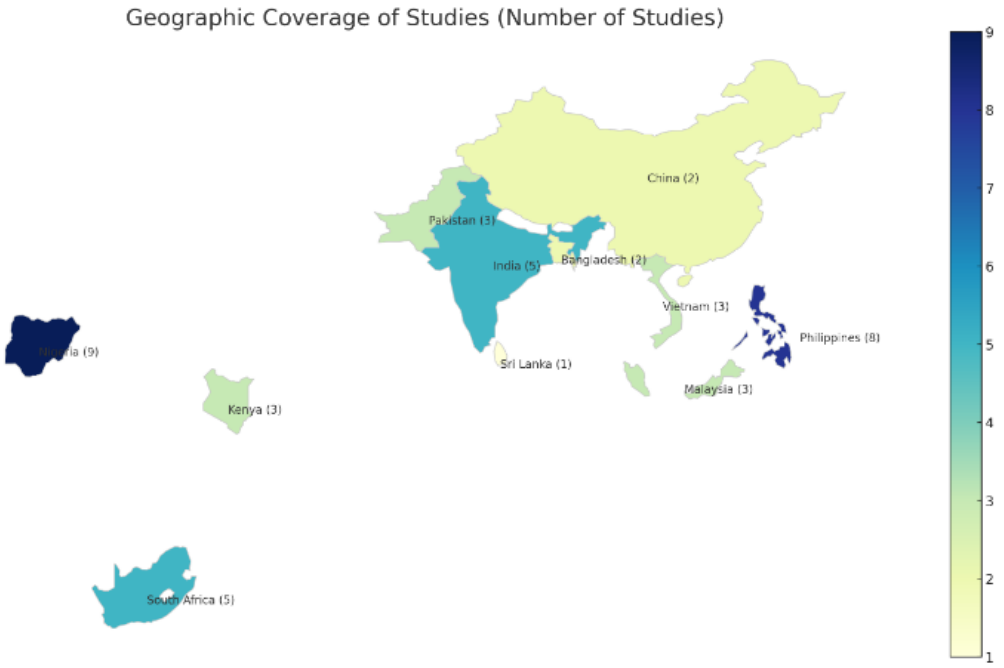
Geographic Coverage (Number of Studies)



Figures 22 and 2.3 illustrate the varying scales of research participation and study numbers across developing countries. The average number of participants per study is approximately 39. The number of participants per country ranges from a low of 8 in Malaysia to a high of 389 in the Philippines, indicating a substantial variation in the size of research participants. Interestingly, this does not correlate directly with the number of studies conducted in each country. For instance, despite not having the highest participant count, Nigeria leads in the number of studies conducted, with 9. In contrast, with a significantly higher participant count, China only has 2 studies.

Figure 2.3

Geographic Coverage (Number of Participants)



In the second data analysis phase, NVivo software was used to systematically construct relevant themes within the collected studies pertinent to the three core focus areas, including decent and meaningful work, opportunities for career development, and employability skills development. NVivo facilitated an in-depth textual analysis, allowing the extraction of emergent sub-themes, patterns, and trends. This process involved scanning statements and phrases while using the Sustainable Livelihoods Framework by Duncombe (2007) as the analytical lens to form arguments on how and which contextual factors may shape experiences in the digital platform labour economy. As a result, the analysis highlighted the interconnectedness of these themes and their distinct characteristics within the context of various study regions.

2.6 Findings

The analysis of these 29 empirical studies unveils considerable diversity in worker experiences and a varied ecosystem of platform labour across developing countries, differing notably in the type of work accessed through digital platforms, workers' skills, motivations, and how local and external socio-economic structures shape experiences in the platform economy. Dissecting the nuanced

differences and similarities across various developing regions, the analyses below illustrate key themes related to decent work, career development prospects, and skills development, building on the narratives that emerged during the analysis.

2.6.1 Access to Decent Work in Digital Platform Labour Economy

Adequate access to decent work opportunities significantly varies by sector and region. Notably, the notion of adequacy is often not about the volume of opportunity, but rather largely depends on individual needs. While some workers in South Asia and Kenya view digital platform work as a supplement to full-time employment or studies (Galpaya et al., 2018; Melia, 2020), others consider it their primary source of income. Despite the instability concerning work availability, workers often leverage their socio-cultural capital to overcome the precarious nature of platform work, forming collaborative networks to secure a larger volume of work (Idowu & Elbanna, 2021; Melia, 2020).

As highlighted in Table 2. 2, several studies suggest that barriers to entry for platform work are significant, especially for individuals lacking higher education credentials. Studies from sub-Saharan Africa and South Asia highlight these challenges, where the initial promise of abundant work often fails to materialize for many individuals who train to become platform workers (Anwar & Graham, 2020; Malik Fareesa et al., 2018). Furthermore, new platform workers frequently face significant difficulties in showcasing their skills and may spend months without securing any work opportunities (Anwar & Graham, 2020).

Table 2.2

Key Empirical Studies on Workers' Access to Decent Work

Notable Observation	Studies	Core Argument
Barriers to entry for platform work	Anwar & Graham (2020); Fareesa et al. (2018)	Lack of higher education credentials hampers initial access to work opportunities
Challenges in showcasing skills	Anwar & Graham (2020)	New workers face significant difficulties in securing work without client ratings
Global platforms perceived as a better option	Chidoori & Van Belle (2020)	Global platforms are seen as offering more accessible work compared to local platforms with smaller market bases

Notable Observation	Studies	Core Argument
Dependence on platform work due to local employment market instability	Graham, Hjorth et al. (2017); Tintiangko & Soriano (2020)	Local employment instability drives reliance on platform work
Intermittent platform work is the only knowledge work option for some migrants	Graham, Hjorth et al. (2017)	Some migrants in medium-income countries often rely on platform work to bypass legal barriers to access knowledge work
Shared unpredictability in employment	Beerepoot & Oprins (2022)	Instability is common in both online and offline work in regions and markets that depend on outsourcing
Varied perspectives on the adequacy of platform work	Galpaya et al. (2018); Melia (2020)	Depending on whether workers see platform work as a primary or supplementary source of work opportunities, there are significant differences in how workers view platform work's adequacy
Sociocultural capital aiding work precarity	Idowu & Elbanna (2021); Melia (2020)	In some regions, collaborative social networks at the local level help secure more work when direct access to work is precarious

Literature suggests that the success of platform workers can be influenced by the platform's own ability to attract clients. Workers in different African countries often perceive global platforms as offering better work opportunities than local digital platforms (Chidoori & Van Belle, 2020). This perception is crucial, as the local employment market in many developing regions is unstable, pushing individuals to rely on global platforms to fill employment gaps (Graham, Hjorth et al., 2017; Tintiangko & Soriano, 2020).

Platform work, though precarious, could bypass opportunity inequalities in some unique ways. For instance, in some medium-income countries, intermittent platform work is the only earning option for migrants who cannot secure formal employment in the knowledge work economy due to legal status issues (Graham, Hjorth et al., 2017). Yet the division between platform work and locally available jobs is often not straightforward as locally available knowledge work jobs and platform work are more closely intertwined in some countries than others. This trend is more pronounced in

regions like the Philippines, where platform labour and local employment are both contingent upon outsourced projects, creating a landscape of unpredictability and inconsistency in work availability (Beerepoot & Oprins, 2022).

2.6.1.1 Wage Conditions and Employment Quality

The fairness of wages is a critical determinant of the quality of work on digital platforms and elsewhere. Table 2.3 below highlights the empirical studies examining the wage disparities and compromises in the platform work economy. The geographic location of workers significantly influences their relative wage satisfaction. For instance, workers in India and China recognize that they are paid less than their Western counterparts for the same work and skill sets. However, some find the remuneration attractive due to the currency conversion rate, which makes relative wages acceptable (D'Cruz, 2017; Leung et al., 2021). Conversely, this currency conversion advantage can also lead to frustration, resulting in wage competition among workers from different developing countries (Malik et al., 2021b; Wang & Huang, 2022).

Table 2.3

Wage Quality and Conditions in the Platform Economy

Notable Observation	Studies	Core Argument
Fairness of wage based on the relative and comparative lens	D'Cruz (2017); Leung et al. (2021)	Lower wages in developing countries but often seen as acceptable by workers due to currency conversion
Frustration with wage differences	Malik et al. (2021b); Wang & Huang (2022)	Currency conversion benefits some Global South workers more than others, resulting in wage competition among workers from different developing countries
Classification of workers into categories	Malik et al. (2018)	Dividing workers into distinct groups based on skill and experience demonstrates how wage conditions and employment quality are experienced differently and often contingent upon workers' broader profiles
Challenges for medium-skill platform workers	Sison & Lavilles (2018)	Oversupply of medium-skilled workers results in challenging market dynamics, and workers struggle with low wages and poor work conditions

Notable Observation	Studies	Core Argument
Career progression through platform work	Elbanna & Idowu (2021b); Idowu & Elbanna (2019)	The goal of securing stable income through platforms requires going through a demanding and underpaid path to learning new in-demand skills
Proactive initiatives by workers	Idowu & Elbanna (2021b); Melia (2020)	Workers' strategies to circumvent platform policies and improve work conditions show how worker agency materializes differently in some regions
Relational power imbalance	Graham & Anwar (2019); Soriano (2021)	Platform work may be global, but social and geographical inequalities continue to impact work conditions

Some studies categorize digital platform workers by skill and experience to understand the varied quality of employment conditions and wage disparities. For instance, Malik et al. (2018) divided potential digital workers in Pakistan into ‘sinkers, strugglers, survivors, and swimmers,’ illustrating the spectrum of experiences from struggling to find work to establishing a strong portfolio with reasonable earnings. Similarly, the categorization by Sison and Lavilles (2018) in the Philippines reflects stages from ‘noob’ to ‘super-rockstar,’ highlighting the cyclical process required to maintain a rewarding work environment.

Workers’ financial reliance on platform work significantly influences their experience and income stability. Those with the flexibility to not entirely depend on platforms may gradually transition into full-time platform work without excessive hardship. On this subject, the studies by Elbanna and Idowu (2021b; 2019) examining the work conditions of Nigerian platform workers are viewed as a liminal journey through stages of untrusted worker, trusted professional, veteran, and post-career stage. However, following such a path often requires patience, a substantial amount of time, and continuous skill training. Yet, these transitional strategies may not be applicable to all workers, as some may not compromise their desired pay and instead rely solely on a good work ethic and skills (D’Cruz, 2017).

Worker agency is limited in this type of work, but it is not entirely absent. Some platform workers undertake proactive initiatives to improve their work conditions, such as circumventing platform policies by directly exchanging contact details with clients for future jobs, thereby avoiding

platform fees (Idowu & Elbanna, 2021b). These strategies are viewed as crucial in mitigating the imbalanced relational power dynamics between clients, global platforms, and workers, which frequently lead to social and geographical inequalities (Graham & Anwar, 2019). Scholars also point to the differences between global platforms and local platforms, noting that in regions with more developed outsourcing markets, local digital platforms may offer better work conditions that align with local welfare needs (Soriano, 2021).

2.6.1.2 Conditions of Equity, Respect, and Non-discrimination

The highlighted observations in Table 2.4 show how, similar to the traditional employment market, gender inequality and patriarchy significantly impact women's participation in digital platform work. Unsurprisingly, these disparities are more pronounced in countries with higher levels of patriarchy. For instance, studies examining women platform workers' local work conditions in Pakistan and India suggest how securing social and cultural approval for engaging in formal work and managing gender-based domestic responsibilities can lead to increased work-related stress and obstruct participation in the platform labour market (Malik Fareesa et al., 2018; Varanasi et al., 2022). However, engaging in paid employment may also cultivate a sense of self-empowerment and enhance personal agency at the local level, helping to reshape cultural norms (Varanasi et al., 2022).

Table 2.4

The State of Equity and Non-Discrimination in The Platform Work Economy

Notable Observation	Studies	Core Argument
Multilayered gender inequality and patriarchy	Fareesa et al. (2018); Varanasi et al. (2022)	Significant local challenges for women platform workers in patriarchal societies
Increased work-related stress for women	Varanasi et al. (2022)	Gender-based domestic responsibilities put heightened pressure on women platform workers
Online work stigma in some countries	Elbanna & Idowu (2021)	Social disapproval for digital work in some regions is gendered but applies specifically to men in some regions, e.g., Nigeria
Global biases and platform inequalities	Gurumurthy et al. (2021); Idowu & Elbanna (2021b); Lehdonvirta et al. (2019)	Location and ethnicity continue to affect and dictate opportunity access

Notable Observation	Studies	Core Argument
Significant discrimination and harassment from employers	Holtgrewe (2014); Pinto (2018); Cini (2023); Malik et al. (2021b)	Widespread equality and discrimination issues on digital platforms, mostly from employers but sometimes from fellow workers due to excessive competition
Discrimination faced on platforms differs by region	Leung et al. (2021); Wang et al. (2020)	Less racial and gender discrimination faced by certain minority groups compared to others
Role of local platform market conditions	Wang et al. (2020)	The strength of Local platforms may result in lower discrimination and better work conditions for local workers

The legacy of how online work has evolved in different regions may play a vital role in the social acceptance of platform work. For instance, in Nigeria, societal norms and perceptions about digital work can lead to social disapproval for male digital platform workers, often associating their work with internet fraud (Elbanna & Idowu, 2021). This stigma, compounded by a lack of institutional support and social awareness, prompts digital platform workers to conceal their work from public visibility (Elbanna & Idowu, 2021). These social landscapes highlight the constraints of associating empowerment universally with certain types of work, as the dignified and equitable nature of work is also measured by how it is experienced within unique societal and cultural contexts.

There is a consensus among scholars that global biases and platform-based inequalities constrain opportunities based on workers' location and ethnicity. Platforms may limit registrations from specific geographic areas and systematically exclude workers based on native language requirements, regardless of their skill level (Gurumurthy et al., 2021; Idowu & Elbanna, 2021b; Lehdonvirta et al., 2019). This stereotyping extends beyond language skills, creating an environment of distrust toward the technical competence of workers from specific regions (Graham, Lehdonvirta, et al., 2017). Discrimination and harassment in the digital platform labour economy often manifest as a new form of neocolonialism facilitated by the anonymity of digital networks (Holtgrewe, 2014; Pinto, 2018). Excessive competition and an oversupply of workers exacerbate hostilities among platform participants (Cini, 2023; Malik et al., 2021b). Interestingly, some comparative studies suggest that Chinese platform workers report comparatively less racial and gender discrimination, potentially due to a robust domestic demand-side platform market that reduces the power imbalance prevalent in globalized platform ecosystems (Leung et al., 2021; Wang et al., 2020).

2.6.1.3 Workers' Agency in the Digital Labour Market

Table 2.5 highlights the limits and complexity of exercising agency on the platform. Workers in the digital labour market may exercise agency by altering their online identities to overcome cultural, racial, and gender biases. For example, women in the Philippines may suppress their ethnic identities to secure teaching gigs, while workers in Nigeria and Kenya may buy accounts registered in more privileged countries or create multiple profiles to secure work (Panaligan & Curran, 2022; Idowu & Elbanna, 2021b; Melia, 2020). These strategies reflect a utilitarian approach to online identities, where the primary goal is to enhance economic capabilities rather than displaying personal achievements (Idowu & Elbanna, 2021b; Melia, 2020).

Table 2.5

Notable Studies Examining Workers' Agency

Notable Observation	Studies	Core Argument
Altering online identities to overcome biases	Panaligan & Curran (2022); Idowu & Elbanna (2021b); Melia (2020)	Workers may revert to altering platform identities to overcome cultural, racial, and gender biases
Utilitarian use of online identities	Idowu & Elbanna (2021b); Melia (2020)	Platform profiles are often more about enhancing economic capabilities rather than displaying personal achievements
Leveraging cultural understanding to secure stable work	Panaligan & Curran (2022)	Workers' level of cultural awareness may help them navigate the biases in the digital labour market

Research studies show that leveraging cultural understanding and anticipating client biases are critical for workers navigating the digital labour market. By altering their online personas, workers in various regions may increase their chances of securing stable and well-paying jobs, effectively overcoming selection biases and networked discrimination (Panaligan & Curran, 2022; Idowu & Elbanna, 2021b; Melia, 2020).

2.6.2 Employability Skills Development

Faced with the pressures for rapid industrialization, much of the developing world has to address the accompanying skill constraints and deskilling by promoting continuous skills development and reskilling to ensure ample formal employment opportunities (Cunningham et al., 2006). The rapidly

growing population further necessitates striking a delicate balance between increasing economic efficiency and reducing unemployment. Unsurprisingly, the potential of digital platform work in reconfiguring the skills landscape is a significant area of discussion in the empirical works examined. Research unveils diverging narratives on the range of skill acquisition landscapes, with some empirical studies highlighting varying levels of improvement while others emphasize potential constraints. Evidently, full-time platform workers may develop their technical skills more than those working part-time (Wang et al., 2020). Although this should be an obvious assertion, it is still an important consideration, as there is a significant variation in the work hours of different platform workers in different regions and work domains (Kässi et al., 2021).

For some workers, platform work may lead to an increased awareness of shifting skill demands. For instance, Melia (2020) shares the experiences of Kenyan workers transitioning from non-technical opportunities, such as working as a security guard, to creative and knowledge-intensive occupations in the platform economy, including content writing on emerging technologies and trends. In such scenarios, platform work may provide an early mover advantage, allowing workers to leverage the remoteness of their geographic location and establish industry-specific knowledge and skills, thereby establishing their niche.

However, for most workers, a superior level of human capital, achieved through good-quality education and professional training, is a prerequisite for developing new skills through digital platform work. The literature demonstrates the critical utility of foundational skills that provide the foundation for learning new skills through diverse platform tasks (Elbanna & Idowu, 2021a). However, regarding self-directed learning and development, some research studies suggest that individuals with health concerns and lower educational levels may be at an advantage. The study by Wang et al. (2020) in China demonstrates that workers without a postgraduate degree scored higher in terms of motivation and ability to utilize platform work as a source of self-development than those with a graduate degree. Their work also demonstrates that workers in high-income groups and with higher education may have a less fulfilling experience on platforms, as they may have already acquired sufficient knowledge and expertise through their formal education, which would weaken the skills-development potential of digital platforms. How this assumption compares to other countries is unclear as fewer studies have taken a similar quantitative approach to study this subject. That said,

these arguments do reflect the ceiling of platform work's skills development potential at a macro level.

Opportunities for skills development may be limited or absent in the context of microwork, primarily due to the repetitive nature and narrow scope of such work (Idowu & Elbanna, 2019; Rani & Singh, 2019). However, the potential for skills development in this context is closely tied to the existing level of local human capital. More specifically, as the previous section highlighted the role of education levels on skills development prospects, the possibilities for skill advancement are also contingent on whether microwork is undertaken by individuals who already possess superior digital and informational skills or by those with little to no digital capital. For instance, studies examining the skills development potential of microwork in India (Varanasi et al., 2022) and Namibia (Keskinen et al., 2022) demonstrate how the structured approaches to introducing microwork may cultivate digital and informational capabilities among those grappling with more significant digital inequalities and skill gaps. Some scholars suggest that the process of scanning work opportunities and navigating digital platform structures may help increase informational and digital capabilities, which is particularly important for reducing barriers for novice workers (Elbanna & Idowu, 2021a). A notable distinction in these viewpoints is the varying levels of existing digital capital and the differentiated local technology landscapes, which may noticeably alter the potential for skills advancement in this form of work and the effectiveness of accompanying skill development programs.

2.6.2.1 Entrepreneurial and Management Skillset Development

Digital platform work has the potential to develop entrepreneurial skills, but this is contingent on the type and complexity of tasks, local organization of platform work, and individual attributes. While such work may build resilience, continuous instability can lead to burnout, decreasing resilience over time (Nawaz et al., 2020). Literature suggests that digital platform work may foster entrepreneurial skills, particularly in the IT sector. In Bangladesh, skills and mindsets, such as risk-taking and proactiveness, are positively associated with worker performance and success (Sultana et al., 2019). Attracting clients and building solid portfolios also requires an entrepreneurial mindset, as seen in studies from Pakistan (Malik et al., 2021). Workers may enhance these skills by independently managing projects, solving problems, and meeting deadlines (Elbanna & Idowu, 2021a).

Table 2.6

Literature Examining Entrepreneurial Skill Development Through Platform Work

Notable Observation	Studies	Core Argument
Positive association with entrepreneurial skills	Sultana et al. (2019)	IT sector work in Bangladesh shows a positive association between entrepreneurial skills development and platform work engagement
Independent management of projects	Elbanna & Idowu (2021a)	All platform work enhances management skills such as project management and problem-solving skills
Building social capital	Leung et al. (2021)	Engaging with international clients and networking help build social capital critical for entrepreneurial ventures
Supporting off-platform ventures	Chidoori & Van Belle (2020); D'Cruz & Noronha (2016)	Platform workers routinely utilize networks built through platforms to enhance business prospects outside the platform ecosystem
Risks of complacency	Rani & Singh (2019); Nawaz et al. (2020)	Entrepreneurial skills development contingent on task complexity. Low-skilled, repetitive platform work tasks can hinder entrepreneurial skills
Resilience and multitasking	Elbanna & Idowu (2021b); Sultana et al. (2019)	Adapting to irregular income and workloads may build workers' resilience to unpredictability
Creativity and innovative thinking	Galpaya et al. (2018)	Competitive platform work markets necessitate and improve creativity and innovative thinking

The observations in Table 2.6 suggest that building resilience and multitasking skills are crucial for platform workers, given their irregular income and unpredictable workloads (Elbanna & Idowu, 2021b; Sultana et al., 2019). Creativity and innovative thinking are also essential for distinguishing oneself in competitive markets, thereby further supporting entrepreneurial growth (Galpaya et al., 2018). Continuous efforts to improve social capital are crucial for digital platform workers to enable swift engagement with international clients and expand networking opportunities.

This social capital may support off-platform ventures, with workers utilizing their networks to enhance their business prospects (Chidoori & Van Belle, 2020; D'Cruz & Noronha, 2016). However, the nature of work still plays a crucial role, as the repetitive nature of low-skilled tasks may lead to complacency, hindering the development of entrepreneurial skills (Rani & Singh, 2019).

2.6.2.2 Domain-Focused Skills Upgrading

Full-time digital platform workers tend to develop their technical skills more than part-time workers, as observed in China (Wang et al., 2020). This trend is also significant in developing regions such as East Africa, where workers may transition from non-technical jobs to knowledge-intensive occupations such as content writing on emerging technologies (Melia, 2020).

Table 2.7

Studies Examining Domain-Specific Skills Upgrading

Notable Observation	Studies	Core Argument
Technical skills development is uneven and depends on the workload	Wang et al. (2020)	Full-time workers enhance technical skills more than part-time workers
Awareness of skill demand among workers	Melia (2020)	Workers constantly learn new skills and switch between knowledge-intensive occupations to remain competitive
Foundational skills and capabilities	Elbanna & Idowu (2021a)	Regardless of degree requirements, good-quality education and training are still crucial for platform workers to be successful
Self-directed learning	Wang et al. (2020)	Lower education levels may show higher motivation to learn new skills
Constraints of microwork	Idowu & Elbanna (2019); Rani & Singh (2019)	Limited skills development potential in microwork
Digital and informational skills	Varanasi et al. (2022); Keskinen et al. (2022)	Most workers enhance digital capabilities through microwork
Vocational training systems	Malik Fareesa et al. (2018); Lehdonvirta et al. (2019); Wood et al. (2019)	Support from state and non-state actors for platform work-related skills training is noticeable in several developing countries, but outcomes are mixed

Notable Observation	Studies	Core Argument
Social media and online forums	Soriano & Cabañes (2020); Elbanna & Idowu (2021b)	Collaborative learning spaces show local skills development ecosystems where experienced workers' support enables new workers to be successful
Firm-supported HR development	Elbanna & Idowu (2021a); Leung et al. (2021)	The practice of sub-contracting platform work may provide functional upgrading opportunities
Platform-provided training programs	Margaryan (2016)	Formal platform work training programs' broader and long-term Impact on livelihood capabilities is inconclusive

Table 2.7 illustrates how scholars have approached the topic of skills development from various perspectives. Although learning new skills to find new and better gigs is common, motivation among workers differs. Self-directed learning is more prominent among workers with lower education levels, who often exhibit higher motivation to utilize platform work for self-development (Wang et al., 2020). However, the potential to learn new skills is limited when workers primarily engage in microwork tasks, as such work typically involves repetitive tasks (Idowu & Elbanna, 2019; Rani & Singh, 2019). Despite this limitation, some scholars suggest that microwork can still enhance digital and informational skills, particularly for workers grappling with significant digital inequalities (Varanasi et al., 2022; Keskinen et al., 2022).

Many studies highlight the vital role that vocational training systems, supported by both state and non-state actors, play in skill development in developing regions. Examples include sponsored training centers in Pakistan, Kenya, and Malaysia, which work with international development organizations to facilitate skills training for digital platform workers (Malik Fareesa et al., 2018; Lehdonvirta et al., 2019; Wood et al., 2019). Beyond such formal skills development ecosystems, social media groups and online forums also serve as collaborative learning spaces, enabling seasoned and novice workers to share strategies and support each other (Soriano & Cabañes, 2020; Elbanna & Idowu, 2021b).

Due to the short-term nature of work contracts, firm-supported human resource development is not common in the platform work economy. However, some functional upgrading opportunities still exist, as workers forming informal SMEs (Small and medium-sized enterprises) and

subcontracting work may provide a learning space for novice workers, as observed in studies examining such work redistribution trends in Nigeria and India (Elbanna & Idowu, 2021a; Leung et al., 2021). Additionally, some digital platforms offer training and certification programs. However, the impact of these credentials on improving workers' livelihood capabilities remains inconclusive (Margaryan, 2016).

2.6.3 Career Development and Upward Mobility Prospects

In the traditional organization of work, career advancement is commonly associated with climbing the hierarchical ladder through job performance and superior work ethics or transitioning into higher roles in other firms (Carmeli et al., 2007; Stroh & Reilly, 1997). In the realm of digital platform labour, growth opportunities are highly uneven, self-supported, and less structured, but they do exist. Some digital platform workers are able to utilize their experience on platforms to progressively increase their income each year by increasing the sophistication of the work they perform and moving towards higher-value-added work chains (Beerepoot & Oprins, 2022; D'Cruz, 2017). For this group of workers, career development opportunities may resemble those of a traditional worker (Elbanna & Idowu, 2021a). However, opportunities for upward mobility are more constrained in certain work domains and regions than others. For instance, language teachers on digital platforms in the Philippines may envision fewer opportunities to develop their careers further or gain pay progression through experience (Panaligan & Curran, 2022).

While having a broad skill set, as an indication of human capital, is helpful, individual attributes and interests play a crucial role in achieving a fulfilling livelihood on these platforms. Harnessing a specific skill niche is crucial in fostering upward mobility and a strategic move to enhance career trajectory, as Melia (2020) noted in one study focusing on Kenyan workers' various strategies to achieve success in the platform labour economy. However, platforms also present an employment ecosystem that theoretically enables the pursuit of unique, specialized work that may not have any local demand or, arguably, may not even command a high demand on a global scale, possibly amounting to only a few hours per week. In addition to the typical platform work career path characterized by portfolio enhancement leading to higher-paying roles, the studies indicate the adoption of diverse entrepreneurial strategies by workers across different regions. As evident from the examples below, these strategies, both within and outside digital platforms, may include assuming

leadership roles in projects, functioning as subcontractors, initiating off-platform business ventures, and cultivating themselves as skill builders in the digital platform economy.

2.6.3.1 Sub-Contracting as a Career Progression Approach

The observations in Table 8 reflect that sub-contracting in the platform work ecosystem may serve as a critical career progression approach for some workers. This horizontal expansion allows workers to subcontract tasks to other workers, effectively becoming intermediaries who handle substantial projects through their more robust platform profiles and network of relationships (Idowu & Elbanna, 2021b; Melia, 2020). This process is often compared to that of project management roles in specialized teams, where workers organize and oversee work assignments, demonstrating their ability to navigate complex projects (Wood et al., 2019; Melia, 2020).

Table 2.8

Empirical Studies Examining Sub-Contracting Practices in the Platform Economy

Notable Observation	Studies	Core Argument
Horizontal expansion of work opportunities through sub-contracting	Idowu & Elbanna (2021b); Melia (2020)	Career advancement through subcontracting in Kenya and Nigeria is common, where acquiring more of the same work and redistributing it may provide a career advancement pathway
Platform intermediation and reintermediation complexities	Chen & Sun (2020); De Reuver et al. (2018b)	Experienced platform workers may opt to become intermediaries to handle substantial projects and manage other platform workers on behalf of clients
Virtual SMEs in Africa	Wood et al. (2019); Melia (2020)	Transitioning from intermittent gigs to established enterprises through sub-contracting work may be considered an organic career progression
Formal Platform Work SMEs and social capital	Beerepoot & Oprins (2022); Malik Fareesa et al. (2018)	Building formal SMEs and powering outsourcing networks through platform work is common among platform workers in Pakistan
Physical SMEs and Local Adaptation of Platform Work	Idowu & Elbanna (2021b)	Renting physical workplaces to transform virtual platform work

Notable Observation	Studies	Core Argument
		into work that resembles traditional work done in offices is common in countries such as Nigeria
Sub-contracting as a form of exploitation	Chidoori & Van Belle (2020); Graham Hjorth et al. (2017)	Sub-contracting ethics is a grey area, and the risks and challenges of subcontracting remain vague

As highlighted in Table 2.8, the empirical studies suggest how digital platform work can lead to the creation of virtual SMEs. Experienced platform workers, particularly in knowledge-intensive domains such as tech and software development, transition from intermittent gigs to established enterprises by subcontracting work to meet client demands or increase profit margins (Wood et al., 2019; Melia, 2020). This transition is facilitated by the robust social capital and professional networks built through digital platforms (Beerepoot & Oprins, 2022; Malik Fareesa et al., 2018).

The concept of platform intermediation and reintermediation is a livelihood strategy in the platform work economy, where workers may secure work opportunities to become visible or shadow intermediaries. This involves leveraging their platform profiles to assemble specialized teams capable of handling substantial projects, effectively operating as virtual SMEs (Chen & Sun, 2020; De Reuver et al., 2018b). Additionally, in countries such as Nigeria, groups of digital platform workers may rent physical workplaces, creating informal physical SMEs that provide structured work environments and support career growth (Idowu & Elbanna, 2021b).

While sub-contracting offers significant career progression opportunities, it also presents risks and challenges. Some studies view subcontracting as a form of exploitation, where subcontracted workers struggle to showcase their experience, limiting their career growth prospects (Chidoori & Van Belle, 2020; Graham Hjorth et al., 2017). These contrasting perspectives highlight the complexity of subcontracting outcomes and underscore the need for balanced regulation to protect workers from potential exploitation.

2.6.3.2 Off-Platform Career Growth Opportunities

Literature highlights how platform work may lead to workers often pursuing off-platform career growth opportunities, such as becoming independent trainers within their communities. For instance, in Nigeria and Kenya, experienced workers guide and support aspiring platform workers, sharing their knowledge and expertise (Elbanna & Idowu, 2021b). Similarly, as noted in Table 2.9, successful digital workers in regions with a more significant presence of development agencies often find employment as formal trainers with skills development institutions, thereby bridging the gap between development agencies and local communities (Malik et al., 2021b; Malik Fareesa et al., 2018).

Table 2.9

Studies Examining Workers' Career Growth Opportunities Beyond Platform Work

Notable Observation	Studies	Core Argument
Platform workers becoming independent trainers in communities	Elbanna & Idowu (2021b)	Guiding new and struggling workers is seen as a career next step among some digital platform workers in Nigeria
Formal trainers and employment	Malik et al. (2021b); Fareesa et al. (2018)	Successful Pakistan workers may become trainers employed by development agencies and skills development institutions
Personal branding for career growth	Soriano & Panaligan (2019); Soriano (2021)	Monetizing platform work success through social media is a common trend linking knowledge work and influencer work segments of the platform work economy
Transferability of skills and experience between the platform and traditional employment market	Beerepoot & Oprins (2022); D'Cruz (2017); Leung et al. (2021)	Varied levels of acceptability of experience and skills gained through platform work
Hybrid entrepreneurs and dream chasers	Idowu & Elbanna (2020); D'Cruz & Noronha (2016); Elbanna & Idowu (2021a)	The practice of leveraging platform work to support individual entrepreneurial ventures shows the ambitious nature of many who choose to work as platform workers
Correlation between digital workers and entrepreneurship	Burke & Cowling (2019); Sultana et al. (2019)	Short-term freelancing as a strategy for new entrepreneurs

Notable Observation	Studies	Core Argument
Challenges of local economic stability	Desai (2011); Naudé et al. (2011)	The long-term success of workers still depends on the strength of the local economy and the stability of the employment market
Self-marketing strategies and social acceptance	Bogatyreva et al. (2022); Malik et al. (2021b)	The personality traits, ability to build a personal brand, and social acceptance to do so are essential for off-platform career success

Personal branding has become a vital career growth strategy for digital platform workers. Self-marketing strategies and social acceptance are crucial for achieving off-platform career success, underscoring the importance of robust personal branding and networking skills (Bogatyreva et al., 2022; Malik et al., 2021b). For example, by monetizing their success through social media, workers in the Philippines may utilize the influencer economy to promote digital work and offer training materials to followers (Soriano & Panaligan, 2019; Soriano, 2021). This intertwined relationship between digital gig work and the influencer economy highlights the potential for additional income streams and career diversification.

Literature suggests a significant correlation between digital platform work and entrepreneurship, with short-term freelancing serving as a strategy for new entrepreneurs to mitigate risk and enhance productivity (Burke & Cowling, 2019; Sultana et al., 2019). Workers may leverage their platform experience to become 'hybrid entrepreneurs' using accumulated financial and social capital to pursue entrepreneurial ventures (Idowu & Elbanna, 2020; D'Cruz & Noronha, 2016; Elbanna & Idowu, 2021a). However, the success of such ventures still depends on local economic stability, which is often challenged by stringent lending criteria, limited infrastructure, and regulatory hurdles (Desai, 2011; Naudé et al., 2011).

2.6.3.3 Skills and Experience Transferability between Platform Work and Local Markets

The empirical literature listed in Table 2.10 suggests that the transferability of skills and experience gained from digital platform work significantly varies across regions and sectors. In the Philippines, workers often find their platform-based experience less valuable in local job markets, whereas in India and China, platform work is viewed positively by local employers (Beerepoot & Oprins, 2022; D'Cruz, 2017; Leung et al., 2021). In some regions, such as sub-Saharan Africa and South Asia, local

job markets often do not fully recognize the value of skills developed through platform work (Graham et al., 2017; Lehdonvirta et al., 2019). This limited recognition poses a challenge for platform workers seeking formal employment opportunities, as local employers may undervalue their experience (Malik et al., 2021b; D'Cruz, 2017).

Table 2.10

Skills and Experience Transferability in the Platform Work Economy

Notable Observation	Studies	Core Argument
Skill transferability varies across regions and sectors	Graham et al. (2017); Lehdonvirta et al. (2019)	Significant Differences in how skills to work on platform-provided jobs are valued in local job markets
Limited recognition of platform work in local job markets	Malik et al. (2021b); D'Cruz (2017)	Local employers may undervalue platform work experience
Mismatched expectations between platform work skills and local market demands	Beerepoot & Oprins (2022); Wood et al. (2019); Sultana et al. (2019)	There is a disconnect between skills developed through and for digital platform work and local market needs
Valued skills in local markets	Wood et al. (2019); Sultana et al. (2019)	Tech skills and digital literacy through platforms are generally highly valued locally
Challenges in translating platform success to local employment	Rani & Singh (2019); Idowu & Elbanna (2019)	Difficulty in demonstrating success on platforms to local employers
Hybrid career paths	Galpaya et al. (2018); Leung et al. (2021)	Combining platform work with traditional employment is a common middle ground for many workers
Regulatory and institutional barriers	Graham & Anwar (2017); Desai (2011)	Significant and long-term constraints for platform workers entering formal employment

Studies reveal a common disconnect between the skills acquired through platform work and the requirements of local economic markets. For instance, while tech skills and digital literacy are highly valued, other skills acquired through platform work may not align with local market needs, leading to mismatched expectations (Beerepoot & Oprins, 2022; Wood et al., 2019; Sultana et al., 2019). This mismatch can result in difficulties for platform workers trying to translate their success

on digital platforms to traditional job settings (Rani & Singh, 2019; Idowu & Elbanna, 2019). Despite these challenges, some platform workers successfully combine platform work with traditional employment, creating hybrid career paths. In regions such as South Asia and China, workers leverage their digital skills to enhance their employability in local markets, effectively bridging the gap between platform work and formal employment (Galpaya et al., 2018; Leung et al., 2021).

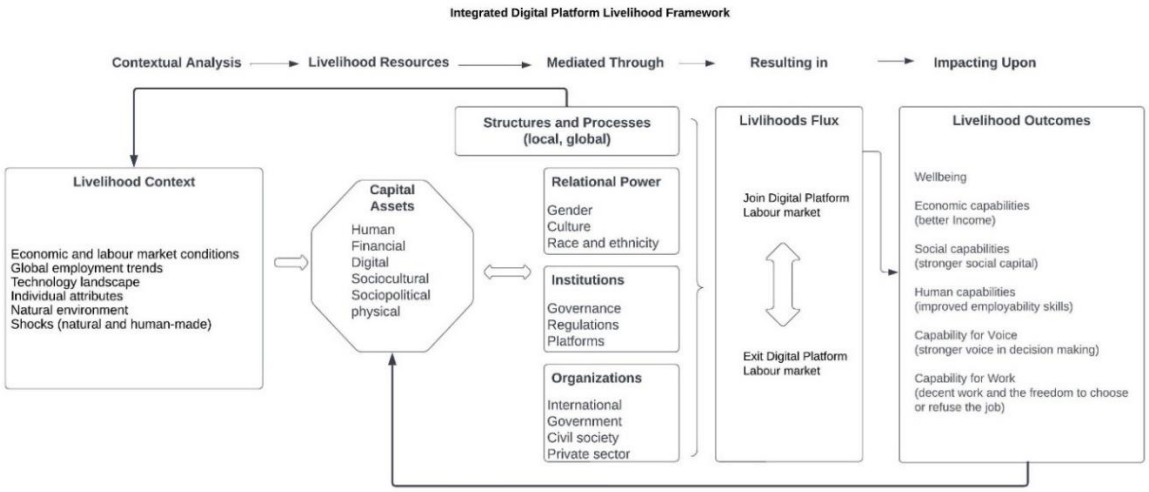
2.7 Sustainable Livelihoods Approach Towards Digital Platform Work

The empirical studies examined here present a diverse range of viewpoints, underscoring the multifaceted nature of digital platform work and its far-reaching implications for workers, societies, and economies. The diversity of disciplinary approaches, while highlighting a fragmented view of platform labour realities, presents an opportunity to apply transdisciplinarity to enrich multifaceted development agendas that focus on livelihood development and gains in human capabilities as their ultimate outcomes. Nevertheless, the question remains: which theoretical frameworks are adequately equipped to support this complex process?

Notably, some studies have applied broader development frameworks such as Sustainable Development Goals (Elbanna & Idowu, 2021), Sustainable Livelihoods Framework (Fareesa Malik et al., 2018), and Choice Framework (Eskelund et al., 2019), signifying the interest in the potential of a capabilities-driven research agenda to understand the implications of platform work for development in low-resource environments. However, a noticeable number of studies (12 out of 29) have not employed an explicit theory or framework while providing valuable empirical insights (Table 1). This decision could be seen as a potential gap in the theoretical landscape, suggesting the need to develop more suitable frameworks that specifically address the unique characteristics and implications of digital platform work and associated micro-data. To support this discourse, the synthesis of these empirical studies provides an opportunity to leverage nuanced differences in how individual experiences of workers are shaped for conjecturing a detailed representation of the relationships that shape livelihood outcomes.

Figure 2.4

Sustainable Digital Platform Livelihoods Framework



This research proposes a Sustainable Integrated Digital Platform Livelihood Framework (Figure 2.4) that builds on the learnings from this empirical analysis and previous works and critiques of the Sustainable Livelihoods Framework (Duncombe, 2007; Gigler, 2015; Mensah, 2011; Natarajan et al., 2022). This adaptation of SLF emphasizes the importance of socio-cultural and digital capital in shaping livelihood outcomes (Williams & Durrance, 2008). Similar to other concepts of SLF, the proposed framework is strongly influenced by the Capability Approach, which signifies the importance of enhancing people's capabilities, which refers to their real freedom to make life choices they would value (Nussbaum, 2005; Sen, 2001). It does not take a normative position on the strength or direction of interconnections between livelihood, contexts, resources, and outcomes. Instead, it offers an approach to reduce oversights in fully recognizing the environment in which workers make a living within the platform economy and how it may affect their development aspirations.

2.7.1 Livelihood Contextual Analysis

The SDPLF emphasizes examining a range of livelihood contextual factors from a local lens as the starting point for recognizing the push and pull factors that shape workers' livelihood outcomes in the platform work economy. The proposed framework broadens the perception of livelihood context as a form of vulnerability (Solesbury, 2003) to account for the versatility and historical composition of socio-economic and labour market systems, technology landscapes, and resource environments

representing different ways of being and doing. Following the philosophical approach towards livelihood analysis by Natarajan et al. (2022), this approach towards contextual factors does not take a normative position on the function of platform labour in improving or impeding local labour market systems and economic structures. Instead, it offers openness and flexibility to examine such linkages through empirical evidence and theory, recognizing the uneven distribution of livelihood outcomes and not just vulnerabilities, but also the opportunities that local socio-economic systems have to offer.

This approach emphasizes examining local market conditions in relation to global employment trends to recognize the nuanced linkages between local livelihood strategies and global labour and skill-demand change (Melia, 2020). While some factors, such as global employment trends in the platform labour economy, may be generalizable, the diverse configurations of local economic and labour markets, individual attributes of workers, and the varying levels of digital divides resist the generalizability of platform work's impact on workers (Idowu & Elbanna, 2019; Van Deursen & Helsper, 2015). Furthermore, the contextual analysis could also consider environmental factors and shocks, whether natural or human-induced, as these elements can make platform-mediated work a relatively better earning option or limit an individual's access to such work. For instance, the prevalence of shocks such as armed conflict and political unrest may result in recurrent internet shutdowns (Mukeredzi, 2017), restricting earning opportunities that largely depend on digital connectivity. These aspects hold particular significance for developing regions, as the remoteness of some regions often results in inadequate access to traditional market opportunities despite the presence of skilled human resources (Malik et al., 2021a).

2.7.2 Livelihood Resources

Livelihood resources are the assets and strengths that empower individuals to make livelihood choices. The analysis of livelihood assets in the form of capital(s) provides an opportunity to recognize measurable and interrelated strengths of individuals in relation to their livelihoods (Duncombe, 2007; Mensah, 2011). These assets may include human capital, financial capital, socio-cultural and sociopolitical capital, physical capital, and, in the case of the platform economy, access to digital capital.[2] The studies in this review paper underscore the significance of human capital,

[2] The concept of Digital Capital, as defined by Ragnedda (2018) is the accumulation of digital competencies (information, communication, safety, content-creation, and problem-solving) and access to digital technology. It is considered a form of capital because, similar to other forms of capital, it can be accumulated and transferred from one arena to another.

characterized by skillsets, knowledge, and health in determining workers' well-being, economic opportunities on digital platforms, and career growth prospects (Eskelund et al., 2019; Malik, Fareesa et al., 2018). As discussed in the previous sections of this paper, some studies, e.g., Idowu & Elbanna (2021a) and Melia (2020), illustrate how workers often utilize their unique socio-cultural strengths to influence their livelihood outcomes and exercise agency, pointing to the significance of adequately accounting for workers' unique socio-cultural resource banks. The importance of socio-cultural capital is also evident in promoting future career growth, as these assets may provide access to networks that enhance opportunity discovery, foster resilience against platform inequalities, and help improve the quality of the work environment (Soriano & Cabañes, 2020).

A significant consideration related to different developing regions is the varying levels of the minimum financial and physical capital required to make the necessary investments for participating in platform labour, such as obtaining access to devices, renting a workplace, or initiating a new entrepreneurial venture (Elbanna & Idowu, 2021b; Gurumurthy et al., 2021; Panaligan & Curran, 2022). Some evidence points to the utility of physical capital and how it shapes the experiences of digital platform workers, e.g., having access to an independent or communal workspace is linked with well-being and career growth (Idowu & Elbanna, 2020). Moreover, recognizing the relationship between the level of the local digital divide and platform work outcomes is critical, as digital capital is a significant determinant of how digital disparities in access and digital skills influence the ability to gain consistent work and potential for career growth prospects (Keskinen et al., 2022; Varanasi et al., 2022).

Recognizing the nature of platform workers' cultural and sociopolitical capital is paramount for understanding workers' actions (or lack thereof) to improve their platform livelihoods. For instance, the lack of sufficient unionization options and the dispersed nature of digital platform labour reveal that workers' agency and voice greatly depend on alternative forms of sociopolitical capital (Wood, Lehdonvirta, et al., 2018). An exploration of how workers establish and employ such capital, for instance, through social media groups, online forums, and informal support groups, illuminates localized strategies that may suggest that the absence of formal civil society structures does not equate to a lack of collective action (Malik et al., 2021a; Melia, 2020; Soriano & Cabañes, 2020).

2.7.3 Structures and Processes

All livelihoods are affected by an array of social relations and structural powers that shape and reshape one's access to livelihood resources (Ashley & Carney, 1999). The framework emphasizes that the transnational character of many digital labour platforms creates a livelihood environment in which workers are exposed to social relations and structural powers at both local *and* global levels. Consequently, the framework suggests examining institutions, organizations, and relational power dynamics at both scales to accurately capture the essence of platform work in distinct geographies.

Relational power dynamics such as gender, culture, and race carry significant implications within the global platform economy since this form of work still builds on the legacy of existing structures of inequalities that shape individual experiences (Graham, Hjorth, et al., 2017). For instance, as the empirical evidence unveiled, local gender and cultural dynamics may drastically shape access to digital work opportunities (Malik et al., 2021a). Similarly, racial and gender relational power imbalances disproportionately impact different developing regions (Panaligan & Curran, 2022). An important consideration is recognizing the layered nature of local and global relational power dynamics affecting platform workers. In a global platform economy, gender, racial, and cultural differences may still influence workers' experiences and access to platform work opportunities. However, workers live and complete work tasks in specific geographic localities where local norms, gender roles, and cultural factors significantly shape their work experiences and access. In certain instances, this interaction between local and global relational power may reveal a novel positive impact, necessitating a cautious evaluation by researchers and policymakers (Varanasi et al., 2022).

Empirical studies highlight the varied nature of governance and regulatory regimes that interface with platform work ecosystems. For instance, the absence of institutional support may prompt some platform workers to perform platform work in secret and face legal difficulties, such as transferring platform earnings to a local bank (Idowu & Elbanna, 2021b). The diversity of institutional support or revulsion may necessitate targeted local research to highlight the roles of both local and global institutions in enhancing the livelihoods of platform workers. The framework also envisages platforms as institutions, emphasizing their broad yet not fully defined role in shaping livelihoods in developing regions (Bonina et al., 2021; Kenney & Zysman, 2016). This viewpoint towards public or private-sector platforms acknowledges that, in some instances, platforms may step

in to fill institutional gaps, functioning as social institutions themselves (Malik et al., 2021b). Similar to relational power, the distinction between local and global platforms is also noteworthy, as livelihood outcomes for workers may significantly vary depending on whether the platform operates locally or globally (Beerepoot & Oprins, 2022).

The framework suggests scrutinizing the unique roles that local and global organizations play across various regions and how these roles either enhance or hinder workers' experiences. This analysis is crucial as certain regions witness substantial government and civil society engagement in advocating for and facilitating the expansion of digital platform work. (Graham, Lehdonvirta, et al., 2017; Lehdonvirta et al., 2019). Lastly, the role of the private sector, though often less discussed, is a crucial topic in the discourse of social and ethical responsibility at the client end of the platform work ecosystem.

2.7.4 Livelihood Flux

The notion of flux in the proposed framework indicates the turbulent nature of platform workers' livelihoods, which constantly evolve due to the short-term nature of work opportunities and the ongoing transformations in the macro labour market and technology landscape (Natarajan et al., 2022). This shift could motivate individuals to choose a range of strategies on the continuum of joining and leaving digital platform work, depending on how much their capital assets permit decision-making and the level at which structures and processes operate to facilitate better worker choices.

2.7.5 Livelihood Outcomes

This framework offered an opportunity to recognize how specific contextual factors and access to resources enable opportunities and shape individual choices to join or leave platform work. The framework also emphasized how such choices and livelihood outcomes are mediated through global and local relational power, institutions, and organizations. While the examination of the specific livelihood outcomes may differ based on specific research questions, a broad development perspective on the impact of digital platform work could envision these outcomes as a function that promotes access to decent and meaningful work, improves well-being, enhances workers' social and economic capabilities, offers opportunities for skill development, and fosters a stronger voice in decision-making. This flexibility enables the potential to conduct empirical examination through a

spectrum of theoretical perspectives, such as the Capability Approach towards work and workers' voice (Bonvin, 2012) or a decent work lens for digital platform work and well-being (Heeks et al., 2021; ILO, 2013).

2.8 Conclusions

This review examined the diversity of digital platform workers' livelihood conditions across various developing regions. Integrating community informatics perspectives provided a deeper understanding of the structural and contextual factors shaping platform workers' livelihood outcomes in various parts of the Global South. The findings suggest a complex interplay between digital platform ecosystems and development, where platform workers are simultaneously empowered and disempowered by platform structures, socio-relational power, and institutional arrangements at both local and global levels. The layered nature of gendered, cultural, and racial relational power, combined with local institutional constraints, highlights region-specific barriers to exercising worker agency in the platform economy.

The digitally connected yet isolated work environment and the often-concealed nature of digital platform workers' livelihoods in the Global South underscore the need for integrated support systems that involve government agencies, NGOs, digital platforms, and the private sector. A targeted approach towards strengthening these systems could help provide continuous training, access to financial resources, and legal support to digital platform workers.

As this review indicates, much of the digital platform work literature is based on empirical studies that are relatively small in size, underscoring the limitations in forming broader perspectives that can adequately represent entire population groups. The broad range of participant selection in the examined studies also highlights the critical need to better understand the impact of digital platform work on traditionally marginalized groups, including women, ethnic minorities, and individuals in remote areas. This research gap is particularly pronounced in regions undergoing large-scale development interventions to leverage platform labour to reduce widespread employment deficits.

As a proposed tool for evaluating the livelihoods of digital platform workers, the Sustainable Digital Platform Livelihoods Framework emphasizes examining livelihood contexts as the starting point for recognizing how platform workers' livelihood outcomes may transpire and differ for different groups. Future research should prioritize in-depth, localized studies that consider specific

skill sets and cultural and institutional contexts to avoid overgeneralization and provide insights into the unique challenges and opportunities faced by platform workers in different developing regions. Expanding the participant base could provide a more representative understanding, helping policymakers with statistically significant data that accounts for community contexts. Reducing this research gap could also support the development of localized policy frameworks that address the multifaceted nature of digital platform work, promoting forward-looking skills development opportunities, social protection, and equitable access to livelihood opportunities in different developing regions.

Chapter 3

Between Opportunity and Precarity: Decent Work and Capability Formation in Kenya's Online Freelance Platform Work Economy

3.1 Introduction

Freelancing through online labour platforms such as Upwork and Fiverr has experienced significant growth in recent years, reshaping employment opportunity landscapes in many economically developing regions. Due to the hidden nature of platform work and the absence of robust data collection mechanisms, precise size and growth estimates remain challenging, but some existing studies indicate approximately 30 percent annual growth in developing regions (Heeks et al., 2021; Kässi et al., 2021).

In Kenya, particularly, there is growing interest in platform-based freelancing among individuals seeking to sustain their livelihoods (Melia, 2020). Despite robust economic growth and a significant business process outsourcing industry, unemployment and employment instability in Kenya[3] have made freelancing through digital platforms an attractive alternative. This appeal underscores structural challenges within the Kenyan economy, notably the persistent mismatch between job seekers' skills and emerging industry demands (The World Bank, 2024). Consequently, a young, educated workforce gravitates towards digital freelancing gigs, attracted not only by financial incentives but also by perceived benefits such as greater temporal autonomy, global connectivity, and potentially superior working conditions compared to traditional employment opportunities (Graham, Hjorth, et al., 2017; Lehdonvirta et al., 2021).

While digital platforms offer income-earning opportunities and access to international markets, the growth of this type of work also presents substantial structural challenges in cultivating a sustainable career. For instance, the short nature of platform gigs and an oversupply of workers means that sustained access to work is a constant challenge for many workers (Berg, 2016). The global scope and concentrated market power of platforms foster intense competition, exacerbating precarious conditions for freelancers whose livelihoods heavily rely on fluctuating ratings and

[3] Kenya has experienced robust economic expansion over the past decade, with GDP growth averaging around 5.0% but this growth has not translated into a commensurate improvement in unemployment rate that has risen steadily from about 3.2% in 2015 to roughly 5.7% in 2024 (The World Bank, 2025)

reputations. This competitive environment significantly impacts the quality of work, often limiting workers' bargaining power, restricting career advancement opportunities, and frequently subjecting them to volatile income streams and unequal earning opportunities (Graham, Hjorth, et al., 2017; Gray & Siddharth, 2019). Several work quality challenges have been identified by existing research, pointing out vulnerabilities inherent to platform work, including, algorithmic management of workers, higher susceptibility to labour market shocks, and exclusion from traditional employment benefits such as social security and pensions, thereby intensifying worker vulnerability (Berg & Rani, 2021; De Stefano, 2015; Van Deursen & Helsper, 2015).

Parallel to the growth of this precarious and globalized platform work economy, organized efforts to enhance working conditions within and outside the digital platform economy are also evident. Notably, the International Labour Organization (ILO) has actively promoted the global Decent Work Agenda (DWA), emphasizing comprehensive labour protections, social dialogue, and robust social security systems applicable to both conventional workers and freelancers. Empirical research specifically addressing online platform work from the perspective of decent work remains limited (Ayentimi et al., 2022). However, some studies on this subject indicate significant divergence between platform labour conditions and the decent work indicators, reflecting the inherent limitations, primarily arising from the framework's historical design for traditional employment relationships rather than digital freelancing arrangements, which typically involve remote, project-based work by independent contractors (Ayentimi et al., 2022; D'Cruz, 2017).

To address these gaps, recent initiatives, such as the Fairwork Project, have developed a complementary framework that sets clear benchmarks for digital platforms, addressing aspects including fair pay, transparent contracting, safety, and worker representation (Graham et al., 2020; Heeks et al., 2021). This approach has proven effective for understanding the rights gaps within location-based platform work by offering concrete guidelines that empower platform workers and encourage platforms to improve their labour practices (Graham et al., 2020; Heeks et al., 2021). However, online freelancers often work in a much more fragmented global market that is fundamentally different than location-based platforms[4]. Consequently, understanding how work

[4] The role and scope of online knowledge-work platforms fundamentally distinguishes them from location-based platforms. While location-based platforms (e.g., ride-hailing or food delivery) involve physical interactions and intense algorithmic oversight, and could be subject to local labour regulations, online

conditions of online freelancers materialize requires a deeper examination to ensure comprehensive protection for this growing segment of the digital labour force (Ayentimi et al., 2022; Heeks, 2017a).

Considering these complexities, two motivations drive this research paper. First, the oversupply of workers on digital platforms requires a closer examination of how various worker groups experience varying levels of decent work conditions within the platform economy. A focus on differentiating platform worker groups is important to recognize the drivers of work conditions, as the platform economy's low barriers to entry make contextual factors such as sociocultural background, technical skills, individual motivations, and socioeconomic status crucial determinants of varied worker experiences (Latif, 2024). Empirical evidence from other regions underscores notable disparities in access to stable, higher-paying opportunities, with some freelancers consistently securing better outcomes due to more favourable contextual and personal attributes, while others face precarious employment conditions and inconsistent income (Malik et al., 2021).

The heterogeneity of platform labour outcomes highlights the need for a more granular and contextualized analysis of platform worker experiences, one that considers the interplay between local socioeconomic constraints, varying levels of worker engagement, and differentiated livelihood trajectories. Importantly, shifting the analytical lens to workers' own perspectives on work quality enables a more people-centred approach to understanding how platform work both supports and limits individual aspirations. Such an orientation moves beyond the deficit-focused paradigms that dominate much of the decent work literature, which often prioritize the absence of protections or formal employment conditions (Pereira et al., 2019). By foregrounding how platform workers actively navigate economic insecurity and structural constraints to sustain livelihoods, especially in low-income settings, this study reorients the informational basis of judgment in justice, a conceptual filter that determines which facts count when we appraise the quality of work (Sen, 1993). Here, the notion of informational basis of judgment in justice stipulates the morally relevant evidence for claims about

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freelancing platforms operate entirely in a digital space. Here, it is not always the platforms, but work providers that often self-select freelancers, creating a bifurcated market in which highly rated workers secure stable, lucrative opportunities. In contrast, others face irregular work patterns, lower pay, and diminished bargaining power. As a result, labour rights issues, such as fair compensation, employment terms, and discrimination, are distinctly different in the online freelancing context.

fairness, shifting the assessment lens from objective measures of quality to workers' own accounts and experiential narratives (Bonvin, 2012).

The second motivating factor centers on the intrinsic role of work in enhancing the quality of life and helping workers live a life they would value. Work is not just an end but a means to achieve a better quality of life. Work is critical to human experience and intrinsically associated with well-being and individual capabilities (I. Ahmed, 2003; Ragadu & Rothmann, 2023). Decent quality and sustainable work should expand workers' choices and provide them with a broad spectrum of intrinsic and extrinsic rewards, such as social status, personal identity, skills enhancement, autonomy, and a sense of community and purpose (Blustein et al., 2023; Klink et al., 2016). Consequently, even when employment meets baseline decent work criteria, its ultimate value lies in its capacity to enhance individual well-being and capabilities within the contextual realities of workers' lives (I. Ahmed, 2003; Blustein et al., 2016; Sen, 2001).

This holistic perspective underscores the importance of evaluating employment opportunities not solely on economic and measurable standards, but through a comprehensive livelihood lens that acknowledges the multidimensional impacts of employment on human agency and capabilities within a local context (Chambers & Conway, 1992; Duncombe, 2007; Latif, 2024). This understanding of work also provides a useful measure to account for the context and motivations of individuals who depart from the status quo of finding employment in the traditional labour market and instead seek flourishing through cultivating a career through non-traditional employment sources, such as freelancing through platforms. Aligned with these motivations, this study adopts a development-oriented approach to examining platform work, connecting normative decent work standards with workers' subjective experiences and development outcomes within specific socioeconomic contexts in Kenya. This inquiry is guided by the following interconnected research questions.

RQ1: To what extent do digital platform work conditions in Kenya align with the established Decent Work Substantive Elements, and where do they diverge?

The first question in this research paper seeks to establish a foundational and quantified understanding of the extent to which the working conditions experienced by Kenyan freelancers on digital platforms align with the globally recognized Decent Work Substantive Elements (ILO, 2013). By evaluating alignment and divergence with these benchmarks, the research aims to identify which

elements of decent work, such as decent income, social protection, and stability, are upheld or undermined within the platform economy. This question forms a critical baseline for interpreting the adequacy of digital work as a sustainable livelihood option.

RQ2: How do interactions between workers' demographic characteristics (age, education, gender, and platform experience) and their labour-input intensity (weekly paid hours, unpaid platform hours, and time devoted to skill development) shape variations in decent work outcomes among Kenyan digital freelancers?

The second question focuses on the heterogeneity of decent work in the Kenyan platform work economy. By modelling the interaction between these dimensions, the second question recognizes that opportunities and constraints in the platform economy are relational rather than uniform. It seeks to identify patterns, for instance, whether certain profiles (e.g., highly educated women who invest substantial time in skill development) consistently attain higher scores on decent work indicators. In contrast, whether others (e.g., new entrants with limited education who rely heavily on unpaid labour) remain more precariously positioned. Highlighting such heterogeneity counters homogenizing narratives about decent work and provides an evidence base for targeted policy or training interventions.

RQ3: How do the decent work alignments or divergences in the platform work economy intersect with the well-being and capabilities of platform workers in Kenya?

The last question shifts the focus from external standards to internal experiences by exploring how variations in decent work conditions intersect with and affect the subjective well-being of platform workers. Drawing on the Capability Approach (CA) by Amartya Sen and others (Bonvin, 2006, 2012; Klink et al., 2016; Nussbaum, 2005; Sen, 1993, 2001), it assesses the extent to which working through digital platforms supports broader life aspirations and individual capabilities. The focus on individual capabilities is particularly important in this research as it seeks to recognize whether platform work can be considered developmentally supportive or merely a survivalist strategy in resource-constrained settings.

Although many aspects of this research could be generalized to various developing regions with a thriving digital freelancing industry and a relatively weaker local labour market, this inquiry is context-specific. It utilizes Kenya as a case study, a nation where rapid technological integration

intersects with significant socio-economic challenges. Drawing on a survey (n = 52) and qualitative interviews (n = 20) with Kenyan digital freelancers, this study fills an important gap in the literature on digital platform work, particularly within the Global South.

This study contributes to three bodies of literature. First, it advances discussions surrounding the intersection of traditional labour protections and digital platform work conditions in Kenya (Ayentimi et al., 2022; D'Cruz, 2017; Heeks et al., 2021). Second, by integrating a capabilities-based well-being perspective, it enriches the discourse linking normative decent work indicators with subjective worker experiences, providing nuanced insights into how employment shapes individual capabilities (A. Austin, 2018; Bonvin, 2012, 2012; Burchell et al., 2014; Deneulin & McGregor, 2010; Klink et al., 2016). Lastly, the study offers empirical insights into the developmental implications of digital freelancing in Kenya, enhancing knowledge of digital platforms' roles in sustainable human development within the Global South (Anwar, 2022; Anwar & Graham, 2021; Ayentimi et al., 2022, 2022; Chambers & Conway, 1992; Latif, 2024; Melia, 2020).

The remainder of this paper is organized as follows. Section 3.2 reviews the Decent Work Agenda (DWA), Decent Work Substantive Elements (SEs) and key empirical findings on decent work in the digital labour sector. Section 3.3 extends the theoretical underpinning of this research by focusing on well-being and capabilities, particularly the capability for work and the capability for voice. Section 3.4 presents the research methodology. Section 3.5 provides in-depth statistics on the state of decent work in the platform economy. Lastly, Section 3.6 utilizes these quantitative results and qualitative data from interviews to discuss how the state of decent work in the platform economy intersects with workers' lived experiences and explores how platform-mediated labour conditions impact workers' capabilities.

3.2 Decent Work Agenda and Platform Work

Although platform work is often described as precarious work that lacks notable social protections, the growing prevalence of short-term employment, including fixed-term contracts and temporary jobs, in the broader employment market is also a mounting concern (Standing, 2017). This concern is grounded in the context that technological advancements and the capitalist nature of economic growth have not only created more employment opportunities but also increased dependence on ever-expanding large firms, resulting in a growing power imbalance between workers and employers

(Srnicek, 2017; Standing, 2017). In response to these broader employment market challenges, the notion of decent work emerged as a critical institutional framework developed by the International Labour Organization (ILO) in the late 1990s, aiming to counteract the erosion of labour standards and safeguard the quality of employment conditions.

3.2.1 The Decent Work Agenda (DWA)

At its core, decent work represents the aggregate of workers' aspirations regarding their work life. These aspirations extend beyond mere income generation to encompass stability in work, fair wages, the capacity to voice concerns and negotiate conditions, gender equality, and opportunities for personal and professional development (I. Ahmed, 2003). Thus, the aim of decent work becomes twofold. First, it establishes a legal and economic baseline that ensures workers are protected and can participate on an equitable footing in the labour market. Second, it aspires to create a work environment that not only meets economic needs but also nurtures a sense of dignity and social inclusion. In doing so, access to decent work becomes a cornerstone for social justice and democratic participation, transforming the very experience of work into a source of empowerment rather than alienation (Ferraro et al., 2016).

Subsequently, the ILO's Decent Work Agenda (DWA) has the following four main objectives (ILO, 2008). Promoting fundamental rights at work, ensuring that workers' dignity, equality and fair working conditions are protected. Promoting processes that create good quality jobs that ensure equality of opportunity. Improving access to social protection, and, lastly, promoting social dialogue to support ongoing improvements in work conditions. It should be noted that the Fairwork project for digital platforms follows a set of principles closely aligned with the DWA, including fair and decent pay, fair working conditions, fair and clear contracts, fair management of workers at the platform end, and fair opportunities for collective voice (Bertolini et al., 2021).

The legitimacy of the DWA is rooted in its foundation within the International Labour Organization's (ILO) core mandate and its formal incorporation into the United Nations Sustainable Development Goals (SDG 8), which explicitly calls for decent work for all. Decades of policy implementation, coupled with academic interest in examining decent work, have reinforced the agenda's normative foundations. However, some critiques have also emerged, pointing out that while DWA sets important baseline standards, it has deficiencies when it comes to addressing the full spectrum of work quality in a rapidly evolving global labour landscape (Deranty & MacMillan, 2012;

Ferraro et al., 2016). For instance, the DWA, by its very design as a multifaceted and integrative framework, enables various institutions and research streams to adapt and prioritize its components to align with their specific objectives. However, this very flexibility contributes to ongoing debates, as different institutional perspectives continue to shape the concept, redefining decent work along economic, social, and institutional dimensions (Bletsas & Charlesworth, 2013; Di Ruggiero et al., 2014).

More importantly, the DWA's narrow focus on structural conditions largely neglects the qualitative, subjective, and experiential aspects of work. In other words, the informational basis of judgment in decent work is based on a set of objective indicators that do not depend on the subjective opinions of workers. Hence, workers may formally enjoy decent work conditions while still facing overwork, monotonous tasks, and insufficient opportunities for personal development, all of which negatively impact their capability and well-being (Blustein et al., 2016; Standing, 2016). Moreover, much of the research on decent work conceptualization emerged from Western contexts and may not adequately account for diverse cultural and intersectional experiences (Deranty & MacMillan, 2012).

A key research challenge is that much of the empirical work on decent work has focused on identifying the deficits in decent work, and developing regions are under-researched (Pereira et al., 2019). Moreover, the individual level of analysis is generally absent from the existing assessments of decent work (Ferraro et al., 2016). Existing literature specifically notes that research on decent work from different workers' perspectives is an important topic for future research (Pereira et al., 2019), pointing to the suitability of this research, which examines decent work in a developing country context and expands the scope of decent work by utilizing a capabilities-driven wellbeing lens.

3.2.2 Indicators of Decent Work

The ILO methodology for measuring the DWA is quite broad. It suggests building on eleven Substantive Elements (SEs) aimed at capturing the multidimensional nature of decent work at the macro level through regional and country-level studies (ILO, 2008). These SEs include: (1) the availability of job opportunities; (2) the provision of sufficient income through productive work; (3) the assurance of reasonable working hours; (4) the ability to balance professional responsibilities with family and personal life; (5) work that should be abolished; (6) the maintenance of stable and secure employment; (7) the guarantee of equal opportunity and fair treatment in the workplace; (8) the

provision of a safe work environment; (9) the availability of social security benefits; (10) the facilitation of constructive social dialogue; and (11) the establishment of an economic and social framework that supports decent work (ILO, 2008, 2013).

Since the ILO methodology is more focused on a macro-level analysis of work, a micro or worker-level analysis might prioritize those SEs that directly affect daily work conditions (Ferraro et al., 2016). Therefore, while the overall DWA encompasses broader economic and social factors, though significant, these factors might be more effectively addressed through a detailed contextual framework for research studies, such as one based on livelihood analysis (Latif, 2024)**.** Moreover, in the context of platform work, there is little evidence that there is any notable presence of work that should be abolished, such as child labour or forced labour (Heeks, 2017a; Heeks et al., 2021). Table 3.1 provides an overview of the remaining 9 SEs and their relevance to platform work.

Table 3.1

Assessing Decent Work Conditions in the Platform Work Economy (Author's Synthesis)

Decent Work Ses	**Worker-Level Conceptualization**	**Relevance to Online Platform Work**
Employment Opportunities	Individual access to suitable work, measured by the availability of stable work.	Digital platforms broaden access to work globally but often present irregular, on-demand job flows that may affect the consistency of opportunities.
Adequate Earnings and Productive Work	Ensuring that work generates fair, sufficient income to support a decent living standard while providing room for individual growth and skill development.	Platform work may offer flexibility and skill development, but could suffer from intense competition, potentially resulting in earnings that may fall short of ensuring economic security.
Decent Working Time	Maintaining a balance between work and personal time by ensuring that work hours are reasonable and predictable.	Platform work often permits flexible scheduling, but irregular workloads may lead to extended or erratic hours.
Combining Work, Family, and Personal Life	Work arrangements should support a healthy balance between professional responsibilities and personal/family commitments.	The flexibility of digital platforms can help workers integrate family and personal responsibilities, but blurred boundaries between home and work may challenge the separation of work and personal life.
Stability and Security of Work	Addresses job continuity and long-term security, often measured by job	Platform work is typically project-based without long-term contracts, leaving

Decent Work Ses	Worker-Level Conceptualization	Relevance to Online Platform Work
	tenure and the prevalence of temporary versus permanent contracts.	freelancers with high levels of precariousness and uncertainty regarding future work engagements.
Equal Opportunity and Treatment in Employment	All workers receive fair treatment in hiring, promotion, and pay, and that discrimination is minimized in the workplace.	Location and background of workers may result in unequal treatment, hindering access to high-quality opportunities and perpetuating disparities.
Safe Work Environment	Focuses on protecting workers from physical and psychological hazards.	Traditional physical risks are lower; however, issues like digital harassment, cyber-security risks, and isolation could become key safety concerns.
Social Security	Whether workers have access to protection systems, such as pensions, healthcare, and unemployment benefits.	Platform workers are generally excluding them from employer-sponsored social security, which increases their vulnerability during periods of illness, economic downturns, or other disruptions.
Social Dialogue	Workers can participate in decision-making, via collective bargaining and representation.	Freelancers on digital platforms typically work individually with limited opportunities for collective representation.

3.2.3 Measuring Decent Work

The typical approach towards measuring decent work or decent work deficits involves aggregated data on employment and standardized policy-level indicators[5]. Such an approach largely relies on national and regional statistical data, surveys, and composite indices to shape policy frameworks and align policy initiatives with international development agendas such as the SDGs. Within platform work, measuring decent work through interventions such as the Fairwork project follows a somewhat similar approach, measuring meso-level conditions and rating specific platforms against a set of

[5] National and regional measures of decent work, such as the Laeken indicators, OECD metrics, and surveys like the European Working Conditions Survey, rely on macro-level indices and statistical indicators of decent work. These instruments capture dimensions such as job quality, income and employment security, social protection, and overall labour market conditions. These tools are instrumental in aligning public policy with the ILO Decent Work Agenda and SDG 8, but they often fall short of capturing the nuanced, lived experiences of workers. That said, a worker-level assessment of decent work is not an alternative but rather a complementary method. Individual-level tools can enrich our understanding by integrating workers' personal assessments, although they may pose challenges for broad cross-country comparisons due to differences in economic, political, and social contexts. For an in-depth discussion on the difference between macro and individual-level measures of decent work, see Ferraro et al. (2018).

criteria. However, I argue that despite their utility, such instruments often offer only a partial view of decent work by overlooking the nuanced, subjective experiences of individual workers. This challenge is particularly important in the Kenyan digital platform work landscape, where workers may utilize a range of platforms to meet their employment needs.

In contrast, individual-level subjective measurements of decent work focus directly on workers' perceptions of their work conditions and link these perceptions with the objective decent work indicators (Duffy et al., 2017; Ferraro et al., 2018). This emerging approach acknowledges that the lived experience of work is central to understanding the empirical notion of decent work. For sociological and developmental research, such as this paper, a focus on workers' subjectivity helps to center the discussion of decent work on the complex needs of workers in a particular sociocultural and economic context, and how individual experiences lead to deficits or improvement in workers' real freedoms or capabilities.

Existing approaches on individual-level subjective measurements of decent work include a decent work questionnaire by Webster et al. (2015) targeting workers in specific industries in South Africa. Subsequently, psychometric methods have been used to capture a broader spectrum of worker experiences focused on developing and validating a decent work questionnaire among workers in Brazil and Portugal by (Ferraro et al., 2018). Both works draw on the ILO-suggested SEs discussed above. However, besides the differing geographic focus, the methodological approaches differ. Webster et al. (2015) take a diagnostic approach aimed at yielding binary responses to scoring that identify the presence or absence of decent work characteristics, facilitating the aggregation of these responses into an overall decent work index. Whereas Ferraro et al. (2018) employed a Likert scale for a more nuanced capture of degrees of agreement, utilizing a psychometrically robust instrument with a graded response scale that supports nuanced, cross-cultural analysis. The decent work survey in this study builds on these existing survey strategies.

3.2.3.1 Existing Literature on Measuring Decent Work Conditions in the Platform Economy

Scholars have approached the topic of decent work in the platform economy primarily by utilizing selected ILO SEs as the key foundation for identifying and discussing decent work deficits. Among some of the relevant literature, the research by Fırat et al. (2024) targeted freelance translators in Turkey who engage with digital labour platforms. Their methodology employs a quantitative approach, using an online questionnaire grounded in six core ILO Decent Work SEs: adequate

earnings, decent working time, work–life balance, a safe work environment, social security, and social dialogue. Their findings reveal that Turkish platform translators experience significant deficits in decent work. Many earn below the basic living standard, work excessively long hours that exceed ILO guidelines, and face challenges in achieving a sustainable work–life balance. Additionally, limited access to social security and minimal avenues for collective representation underscore the exploitative nature of platform-based translation work (Fırat et al., 2024).

Mokofe (2022) studied South African platform workers and reviewed relevant ILO decent work principles covering both online freelancers and location-based platform workers. The study concluded that platform workers in South Africa face poor working conditions, characterized by low pay, long and irregular hours, and limited collective representation due to their misclassification as independent contractors. Mokofe (2022) argues that achieving decent work for these workers requires broadening the legal definition of "employee," enhanced state intervention, stronger union strategies, and comprehensive regulation of platform work. Without such reforms, the promise of decent work remains elusive for digital platform workers. (Mokofe, 2022).

Furthermore, a research paper by Ayentimi et al., (2022) Utilize the Fairwork principles and the ILO DWA to provide a conceptual note on decent work in the online and location-based gig economy, focusing on Sub-Saharan Africa, and outline policy implications. They discuss how gig work might both exacerbate and alleviate existing challenges. Their work highlights the potential for platforms to document and eventually formalize working conditions. They also point out the regulatory and infrastructural hurdles to achieving decent work. Their research provides a similar conclusion that the current conditions are characterized by irregular assignments, low pay, extensive unpaid job search, and minimal social security and collective representation.

A book chapter by D'Cruz (2017) takes a distinct approach by employing a critical hermeneutic phenomenological methodology to examine the lived experiences of Indian freelancers. Unlike studies that broadly analyze decent work deficits in digital labour markets, D'Cruz's work differentiates between various groups of freelancers, primarily full-timers versus part-timers, and unpacks the heterogeneity in their experiences. The analysis by D'Cruz reveals that full-time freelancers often report a degree of empowerment, evidenced by improved income, better work-life balance, and prospects for upward mobility. These nuanced differences underscore that while some freelancers enjoy relative gains, others remain vulnerable to exploitation, discrimination, and

isolation. However, despite these gains, the study identifies persistent deficits in decent work across key dimensions, including job security, human dignity, social protection, and avenues for social dialogue.

Lastly, Richard Heeks' work, e.g. (Heeks, 2017a; Heeks et al., 2021) assessed the digital gig economy in developing regions through the lens of ILO Decent Work SEs, providing conceptual frameworks and categorization schemas to systematically map the positive impacts, problems, and potential interventions for improving online platform work ecosystem. Heeks concludes that while the digital gig economy provides much-needed employment opportunities and flexibility, it also exacerbates issues like wage disparities, unstable workflows, and significant power imbalances between platforms, clients, and workers.

Collectively, existing works point to three recurring fault lines. First, income volatility, driven by irregular task flow and opaque pricing, emerges as a universal deficit (Fırat et al., 2024; Mokofe, 2022). Second, hidden unpaid labour, hours spent bidding, vetting clients, or maintaining ratings, is consistently flagged as an invisible cost that erodes earnings and well-being (Ayentimi et al., 2022; Heeks, 2017). Third, limited collective voice and weak policy safeguards leave freelancers individually responsible for risk management.

Overall, while the literature has effectively highlighted the broader deficits inherent in platform work, the continuous growth of platform work in developing regions demonstrates the persistent and growing attraction of platform work. While the studies highlighted above have documented the opportunities and challenges associated with digital freelancing, e.g., (Anwar, 2022; Anwar & Graham, 2021; Fardany Faisal et al., 2019; Malik et al., 2021), fewer studies have adopted a worker-centric wellbeing or capabilities lens that examines the gap between normative decent work standards and lived realities. The existing literature predominantly focuses on identifying deficits in decent work within the platform economy, often combining online and location-based platform work, with a strong emphasis on issues such as the short-term nature of gigs, lack of employment status, inadequate benefits and social security, and limited opportunities for unionization.

I build on the argument that deficit-based narratives of decent work tend to assume a direct, one-way relationship between the absence of decent work features and a decline in workers' subjective well-being in developing countries. The prevailing normative stance, therefore, presumes

that a uniform improvement in decent work indicators will automatically translate into enhanced subjective well-being. This perspective does not account for the potential complexities and trade-offs that may exist in developing regions, nor does it address the shortcomings of the DWA, which focuses more on functionings rather than the capabilities of workers (as discussed further in the following section). For instance, improvements in certain work conditions, such as opportunities for collective labour action, might not yield proportional gains in well-being if other factors remain unaddressed or if interactions between such decent work gains and local development conditions produce unfavourable results for workers.

Moreover, a significant gap in the current research is the insufficient differentiation among various groups of platform workers. Despite the inherently low entry barriers of digital platforms, which attract a highly diverse workforce in terms of skills, experiences, and situational contexts, most studies aggregate data under a single category. Although there are a few exceptions, such as the work by D'Cruz, (2017) that delineates experiences among full-time and part-time freelancers, there is a notable lack of attention to how demographic and effort-based differences give rise to heterogeneity in how workers experience varying levels of decent work in the platform work economy. These oversight risks oversimplify the relationship between objective work conditions and subjective well-being.

3.3 A Capabilities Perspective Towards Work and Wellbeing in the Platform Economy

The Decent Work SEs primarily emphasize material indicators and entitlements, including income adequacy, employment security, and access to social protection. While these dimensions are critical, they often reflect externally defined standards and come with the default assumption that any improvement in these standards will translate into a better life for workers (I. Ahmed, 2003). A key development challenge is that even if a work opportunity measures well against decent work criteria, it does not negate the fact that many workers face considerable challenges in embracing their work as a source of well-being (Ragadu & Rothmann, 2023; Sen, 2001). A decent quality work life, however, should foster well-being not only through material outcomes but also expanded freedoms to live a valuable life (Sen, 1993). This gap between the material outcomes and well-being calls for a more nuanced informational basis for measuring the value of any work opportunity, one that captures the

aspirations, agency, and lived realities of individual workers, whose experiences often elude conventional metrics (Bonvin, 2012; Burchell et al., 2014; Sen, 1993).

Well-being, in contemporary development theory, is now widely understood as a multidimensional construct that reaches beyond material affluence to encompass the substantive freedoms individuals enjoy (A. Austin, 2018; Nussbaum, 2005; Sen, 2001). In the context of work, an improvement in well-being is, therefore, reflected in how the nature and outcomes of work enhance or constrain the choices and flourishing of workers (Sen, 1993). In the conceptualization of the Capability Approach (CA) by Amartya Sen and others, the yardstick for measuring well-being is individual capability, the expansion of genuine opportunities and substantive freedom to achieve valued functioning, such as building new skills, improving social capital, or being healthy (Sen, 1993, 2001). The CA, as a normative framework, evaluates the fairness and quality of social arrangements, such as labour ecosystems, by asking whether they expand people's real freedoms rather than merely supplying resources or eliciting satisfaction.

Two key distinctions within the CA contextualize and thereby complement the Decent Work SEs when evaluating job quality in specific socioeconomic contexts. First, functionings should not be confused with capabilities (Sen, 2001). Functionings refer to the actual achievements, resources, and realized entitlements, such as skills, earnings, health, or access to bargaining power. The Decent Work SEs, as discussed in the previous section, provide an effective tool to gauge these entitlements and achievements. Capability, however, is the *potential* achievement open to individuals, and the real freedom to make choices representing not only what a person has or does, but what a person can be or can do (Sen, 2001). For instance, earning $25/hour as a freelance platform worker could be considered a functioning, yet having the real freedom to refuse a $3/hour contract could be seen as a capability.

Second, the translation of resources or entitlements into real freedom and capabilities hinges on conversion factors; the personal, social and environmental circumstances that allow or constrain individuals to use these resources in a way that would enhance their opportunity freedom and capabilities (Sen, 1993). If an individual cannot convert resources into real choices, then the ultimate goal of enhancing capabilities is not met (Deneulin & McGregor, 2010; Sen, 2001). A work opportunity, therefore, merits attention not because it pays wages, a necessary but insufficient

condition, but because it can, depending on the conversion factors, enlarge or constrict the range of a worker's capability set.

3.3.1 Capability for Work

In the context of work, an improvement in capability is, therefore, how the nature and outcomes of work improve or hinder the life choices of workers (Bonvin, 2012). The CA recasts assessments of labour or livelihood quality from an inventory of entitlements to an appraisal of real freedoms. Thus, capability for work denotes the substantive freedom to choose, refuse, and shape one's employment in ways one has reason to value (Bonvin, 2012; Sen, 1993). The capability for work builds on the foundation of three main conditions, namely, opportunity freedom, resulting in choices and resources available to a worker; capability-friendly conversion factors needed to translate resources into desired functionings; and a valuable exit option to escape a valueless work environment (Bonvin, 2012; Bonvin, 2006).

Opportunity freedom in this context denotes the range of valuable jobs that are realistically open to a person. Members of society should be able to freely choose between alternative opportunities that are valuable to them. In the case of platform work, platforms may expand opportunity freedom by exposing workers to global demand and novel gigs (Heeks, 2017b). However, capability for work is not inferred simply from access to an additional stream of work opportunities through platforms; it also rests on the negotiated configuration of resources, conversion factors, and institutional safeguards.

These conversion factors can include personal and individual characteristics, such as physical and mental health, skill levels, education, and self-confidence. In the case of platforms, it is evident that such dispositional factors play a crucial role in determining the level of success on platforms (Malik et al., 2017). Moreover, social conversion factors, such as social norms and power relations, may significantly influence whether opportunities for freedom translate into valued functionings. For instance, gender norms may influence the social acceptance of platform work locally, and racial biases may restrict access to certain platform jobs or hinder the credibility of workers when interacting with international clients (D'Cruz, 2017; Elbanna & Idowu, 2021b).

Lastly, conversion factors are also environmental. For instance, legal, infrastructural, and policy environment either enables or constrains real freedoms to transform resources into valued

functionings. In the context of platform work, environmental factors may encompass the general strength of the local labour market, presence or absence of legal protections for freelancers, the availability of social welfare arrangements such as unemployment insurance or health coverage, and the strength of institutional support systems including dispute resolution mechanisms or digital skills training programs. Environmental factors may also include enabling infrastructure, such as access to reliable and affordable internet, electricity, and public workspaces, that make it materially feasible to participate in the digital economy. Environmental factors could also include the natural environment, as climate change and the disproportionate livelihood risks faced by communities in the Global South may act as critical conversion factors determining the extent to which online platform work influences workers' capabilities (Nussbaum, 2005; Scoones, 2015).

The capability for work also requires that people be adequately equipped to escape from the constraint of valueless work, either through the real possibility to refuse such a job or through the possibility to transform it into something one has reason to value (Bonvin, 2012). Notably, the capability for work implies the notion of a valuable exit option, the freedom not to work a particular job, if one chooses to, without facing excessive hardship (Hirschman, 1987; Sen, 1993). The existence of a valuable exit option, such as decent unemployment benefits, transferable skills, or alternative work opportunities, anchors this freedom of choice, rather than accepting the conditions imposed by employers. In the Kenyan platform economy, where freelancers navigate global markets without the institutional protections of standard employment and the novel work environment of working through platforms, the distinction between resources and capabilities becomes decisive in challenging existing workplace norms.

Bonvin (2006) suggests that the capability for work should be evaluated contextually rather than abstractly since it is not a fixed or universal attribute but a socially situated construct that must reflect the diverse values, needs, and aspirations of individuals within specific environments. Assessing the capability for work, therefore, requires acknowledging that what constitutes valuable work varies across contexts and populations, and thus calls for the inclusion of multiple informational bases of judgment in justice, the set of information considered relevant when assessing individuals (Sen, 2001, 2008). Furthermore, the capability for work cannot be meaningfully isolated from the broader capability set, as it is intertwined with other freedoms such as the ability to balance work with family life or to participate in decision-making. The efforts to measure or enhance the capability for

work must therefore take into account this plurality and embeddedness within the broader landscape of human development (Bonvin, 2012; Sen, 2001).

3.3.2 Capability for Voice

The opportunity freedom translates into improvement in individual capabilities when it is complemented by the capability for voice, the process freedom that determines the extent to which a worker can influence the rules that shape those work opportunities (Bonvin, 2012). In the case of platforms, the capability for voice is concerned with the right and power to influence rule-setting processes, negotiate contract terms, and resolve disputes.

The notion of capability for voice is related to, but analytically distinct from, collective action. Unionization, professional associations, and other forms of collective bargaining supply the political resources that can enhance the capability for voice. However, the capability for voice itself refers to each worker's substantive freedom to express preferences and have them considered in decision-making at all levels. Collective structures that merely substitute one set of imposed functionings for another do not meet this standard; they must expand, rather than curtail, individual participation at every level of governance (Bonvin, 2006). The distinction is especially salient in the platform economy, where sector-wide organizing remains fragile (Wood, Lehdonvirta, et al., 2018) and, more importantly, the negotiation of pay, workload, and conditions unfolds continuously in one-to-one interactions between freelancers and clients.

In addition to collective political resources, the capability for voice rests on the conditions of individual cognitive assets, enforceable entitlements, and the receptiveness of other parties to negotiate (Bonvin, 2012). First, effective participation assumes that workers command critical cognitive resources such as time available, wage literacy, legal awareness, and negotiation skills, which are unevenly distributed across the freelance population (Idowu & Elbanna, 2020). Second, enforcement of entitlement is chronically fragile in the platform economy, where the trans-jurisdictional nature of digital labour complicates the existence and applicability of laws and could make it difficult to compel clients or platforms to honour contractual obligations once disputes arise (Wood, Lehdonvirta, et al., 2018). Third, voice can materialize only if platforms and clients are willing to integrate worker input. When business models privilege customer satisfaction and treat labour as a cost externality and disposable, feedback channels deteriorate into ritual displays; rating dashboards may solicit complaints yet fail to trigger remedial action (Wood et al., 2021a). In such

settings, freedom may become largely symbolic, and workers' capability for voice may remain effectively stagnant.

3.4 Paper Methodology

This paper employs a convergent mixed-methods design, incorporating both an online survey and semi-structured interviews. Convergent mixed methods research refers to a design in which both qualitative and quantitative data are collected during a similar period, analyzed separately using appropriate methods, and then integrated to produce a comprehensive understanding of the research problem (Creswell & Plano Clark, 2011). The aim is to compare or combine findings from each method to strengthen interpretation, validate results, or explore different dimensions of the same phenomenon.

The rationale for methodological integration stems from the intersecting emphases of the study's conceptual framing. The quantitative data, grounded in the Decent Work SEs (ILO, 2008) provide normative benchmarks for employment quality and offer an objective assessment of platform work conditions in Kenya. Subsequently, the qualitative interviews explore how workers interpret and navigate these work conditions within their broader livelihood contexts and how structural conditions and day-to-day realities influence workers' capabilities and overall well-being. The convergent approach, therefore, enables a rigorous and multi-layered understanding of how structural, economic, and social conditions shape workers' livelihoods. This approach also positions this research within the broader methodological tradition of mixed methods, where theoretical pluralism is employed not just for explanatory breadth, but also to challenge narrow or reductive conceptions of work and well-being in the Global South (Creswell, 2014, 2021).

Research participants (N=52) were selected using purposive sampling to ensure variation in gender, age, occupational specialization, and experience with platform work. Survey participant recruitment was conducted through a combination of outreach strategies, including posting calls for participation in online freelancer communities on social media and Upwork, connecting with individuals affiliated with digital skills training programs, engaging attendees at freelancer networking events, and meeting workers at co-working hubs in Nairobi, Kenya. Where possible, participants were selected at random from among eligible participants to reduce selection bias within the purposively targeted groups. Of these, 20 survey participants were randomly selected to participate in follow-up interviews. All participants received cash compensation in recognition of

their time and effort. The names used in the research articles are pseudonyms to protect their identities.

3.4.1 Quantitative Research

The quantitative section examining the decent work conditions employed a customized version of the Decent Work Questionnaire (Duffy et al., 2017; Ferraro et al., 2018), aligning items with the ILO's Decent Work SEs (ILO, 2008, 2013). Each SE encompasses a cluster of items related to a core aspect of job quality, such as fair income, stability, or social protection. The survey instrument included both Likert-scale items and multiple-choice questions. A complete list of the survey questions is provided in Appendix A. The survey was administered to 52 digital platform workers in Kenya between January 2024 and July 2024.

3.4.1.1 Constructing Worker Groups by Demographic and Work Intensity Characteristics

As part of the analysis examining how different groups of workers experience decent work, the first step involved grouping workers based on demographic characteristics (age, platform work experience, education, and gender) and work intensity indicators (weekly hours worked, unpaid labour, time invested in skills development, and reliance on platform work for income). These work intensity indicators were then examined in relation to key demographic variables using bivariate analyses to verify whether any significant variation exists among groups due to demographic differences that might influence the broader interpretation of subsequent decent work survey results.

3.4.1.2 Decent Work Substantive Element Factors

Next, the decent work survey questions were systematically consolidated to shape reliable scales for each Decent Work SE. Given the extensive number of questionnaire items (92), a two-stage analytical strategy was adopted to construct manageable and theoretically coherent scales. In the first stage, Exploratory Factor Analysis (EFA) techniques were applied to organize survey items within each SE domain. EFA is used to identify latent constructs empirically and to combine multiple questions into composite indices, where appropriate (Cudeck, 2000). This method follows previous decent work survey strategies, e.g., Ferraro et al., (2018).

As inter-item correlation was theoretically expected, for each SE with three or more items, EFA was conducted using the principal factor method with oblique rotation (Osborne, 2015). To ensure EFA statistical adequacy, factors that met the following minimum criteria were retained.

Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy is ≥ 0.50 ; Bartlett's Test of Sphericity p-value is < 0.05; retained factor(s) have eigenvalues of ≥ 0.7; and rotated factor loadings is ≥ 0.40 for included items (Costello & Osborne, 2005; Kaiser, 1974; Stevens & Stevens, 2001).

In many cases, EFA was not applicable. Specifically, where only two questions were used to capture a construct, an alternative procedure was adopted. For continuous and ordinal variables with only two items, Pearson correlation (r) matrices were used alongside Bartlett's Test of Sphericity to evaluate the suitability of item sets for factor extraction (Eisinga et al., 2013). For binary variables, tetrachoric correlations were applied to better capture the underlying associations between dichotomous responses (Holgado–Tello et al., 2010). While conventional factor analysis often assumes interval data, established psychometric literature supports the use of tetrachoric and Pearson correlations depending on item type (Eisinga et al., 2013). Given the exploratory nature of this research and the heterogeneity in item formats, combining these methods offered a flexible yet statistically valid approach to construct identification (Eisinga et al., 2013; Fabrigar & Wegener, 2012). Scales created through either method were constructed as the mean of the standardized items.

It should be noted that the scale construction process was conducted primarily to reduce item-level noise and allow for more parsimonious modelling, rather than to establish new psychometric instruments against Decent Work SEs. The purpose of this stage was not to validate the internal consistency of scales, but to organize the questionnaire data into analytically tractable dimensions aligned with the decent work SEs.

3.4.1.3 Regression Modelling for Group-Based Variations and Conditional Effects

After forming the worker groups and constructing Decent Work SE scales, multivariable regression and margins plots were used to explore how different worker groups experience each SE scale. In these models, SE scales serve as the dependent variables, with worker group characteristics as predictors. Variables such as gender, age, and platform experience are included not as conventional controls, but as substantive, theory-driven predictors known to shape platform-based labour outcomes (Anwar & Graham, 2021; Berg & Rani, 2021). Framing these variables as analytically meaningful, rather than as statistical adjustments, is important considering the limited sample size.

Five-point or broader Likert indices were analyzed with ordinary least-squares regression (OLS). Binary outcomes were modelled with logistic regression, and 3-point ordered outcomes with

proportional-odds ordinal logit. The independent variables for recognizing group-based variations included (1) weekly paid working hours, (2) weekly unpaid working hours, (3) the proportion of total income derived from gig work and (4) weekly skill development hours. These variables were selected to capture the intensity, precarity, and economic dependency associated with platform labour. Control variables included (5) age, (6) gender, (7) education and (8) experience in platform work to account for demographic and experiential variation among workers. Predictors were identical across models, so effect directions are directly comparable.

Given the small sample size (n = 52), bootstrapping methods (Kimber et al., 1994) were applied to increase the robustness of the findings. With 52 participants and eight predictors, the model faces recognized statistical constraints, particularly risks of overfitting, low power, and coefficient instability. However, the strategy remains appropriate for an exploratory purpose, where the goal is to identify tentative patterns and associations that can inform qualitative interpretation and guide future research. Although conventional guidance recommends higher case-to-variable ratios (Babyak, 2004; Peduzzi et al., 1996), more recent studies support the use of smaller samples in exploratory models when these are interpreted cautiously and anchored in substantive theory (P. C. Austin & Steyerberg, 2015; Vittinghoff & McCulloch, 2007).

The regression results are used to complement, rather than drive, the analysis, with greater interpretive emphasis placed on the qualitative interview data to understand differences across worker groups. The results section primarily presents bootstrapped results for consistency, and Appendix B provides detailed output tables of both standard and bootstrap regression models.

3.4.2 Qualitative Segment

In-depth, semi-structured interviews were conducted with 20 Kenyan digital platform workers between January 2024 and July 2024 to gain insight into their lived experiences within the gig economy. These participants were randomly selected from survey participants and received additional cash compensation for their participation in the interviews. The guiding interview questions (Appendix C) explored a range of topics, including motivations for entering platform work, perceived benefits and constraints of gig labour, coping strategies, and long-term livelihood aspirations. Interviews were conducted in a hybrid format, either in person or online via Microsoft Teams, depending on the participants' availability, and were audio-recorded with their informed consent.

Qualitative data were analyzed using a thematic analysis approach (Clarke & Braun, 2017), supplemented by narrative analytic techniques to preserve the temporal, affective, and relational dimensions of participants' accounts (Riessman, 2008). The interview data analysis process involved an iterative, multi-stage coding approach. Initial interview transcripts reading sessions focused on developing a holistic understanding of each interview, followed by the construction of a coding framework that combined inductive themes emerging from participants' narratives with deductive categories drawn from the Decent Work SEs. This interpretive strategy focused on how workers construct meaning in relation to both personal trajectories and broader socio-economic structures in Kenya. All qualitative quotes are presented verbatim, with only minimal grammatical corrections made for clarity and readability.

3.4.3 Convergence of Methods

Results from the two strands were analyzed independently and then converged during the interpretation process. Convergence occurred through a capabilities-informed lens and the Sustainable Digital Platform Livelihoods Framework (Bonvin, 2012; Latif, 2024; Sen, 2001). This strategy of integration preserves the epistemological integrity of each framework (capability lens and decent work) while enabling a more comprehensive account of platform work realities in Kenya. This data integration approach not only allowed for triangulation but also helps reveal where quantitative measures fall short in capturing subjective or context-specific elements of Kenyan platform workers' livelihoods.

3.5 Results

The quantitative results are organized into three subsections below. First, descriptive statistics summarize the key characteristics of the research sample group, providing an overview of participants' sociodemographic profiles, work engagement patterns, and earnings distribution, which form the foundation of the worker groups. Second, the bivariate analyses explore demographic differences in reported work hours and earnings composition, examining how gender, age, education, and platform experience relate to variations in paid, unpaid, and skill development labour. The third section elaborates on the disparities in decent work indicators across both demographic groups and work input profiles. Due to the dispersed and widespread nature of the decent work measurement scales, the results section focuses solely on bivariate analyses and relevant variables from the regression models that showed statistical significance. For detailed quantitative results and a full list

of bootstrap and standard error regression tables, please see Appendix B. Qualitative interview narratives are integrated into the discussion section, helping to interpret and contextualize the statistical patterns through the workers' lived experiences.

3.5.1 Descriptive Statistics

The sample consisted of 52 digital platform workers, primarily from Nairobi, with a gender distribution of 55.8% male and 44.2% female (Table 3.2). Most participants fell within the 25–34 age group (51.9%), followed by those aged 35 and above (32.7%), and a smaller proportion aged 18–24 (15.4%). The selected sample was highly educated, with 80.8% holding a bachelor's degree or higher, while 19.2% had some college education or less.

Table 3.2

Research Sample Demographics (N = 52)

Demographic Characteristics	**Frequency**	**Percent**
Gender		
Female	23	44.23%
Male	29	55.77%
Age Group		
18–24	8	15.38%
25–34	27	51.92%
35+	17	32.69%
Education Level		
Some college or lower	10	19.23%
Bachelor's or higher	42	80.77%
Platform Work Experience		
1-3 years	10	19.23%
3-5 years	19	36.54%
More than 5 years	23	44.23%

As reflected in Table 3.2, all participants selected for this study were experienced platform workers with a minimum of one year of engagement in the platform economy. This is an important consideration when interpreting these results, as the study intentionally did not focus on potential platform workers and novice workers with very little experience in the platform labour economy. A substantial proportion (44.23%) of participants had more than five years of experience with platform work, while 46.54% had worked for between three and five years. A smaller segment (19.23%) reported having one to three years of experience in platform-based gig work.

Table 3.3

Work Hours, Earnings, and Skill Development

Work Hours, Earnings, and Skill Development	**Mean**	**SD**	**P50**	**P75**
Income from Gig Work	69.35	25.3	75	90
Paid Work Hours/Week	38.79	18.47	39	52
Unpaid Work Hours/Week	19.72	21.78	10	27.5
Skill Upgrading Hours/Week	16.43	17.31	10	20

On average, participants earned approximately 69% of their total income through platform work, though this varied substantially (SD = 25.30). Participants reported working an average of 38.8 paid hours per week, alongside 19.7 hours of unpaid labour, including tasks such as job search, communication, proposal writing, and a range of labour activities that often go unpaid in the platform work economy. Additionally, participants invested an average of 16.4 hours weekly in skill development activities, highlighting the continuous and self-directed nature of upskilling in digital freelancing. As shown in Table 3.3, the noticeably wide spread between median and 75th percentile values highlights variability in how workers allocate time between paid and unpaid tasks, underscoring differentiated strategies for sustaining platform-based livelihoods.

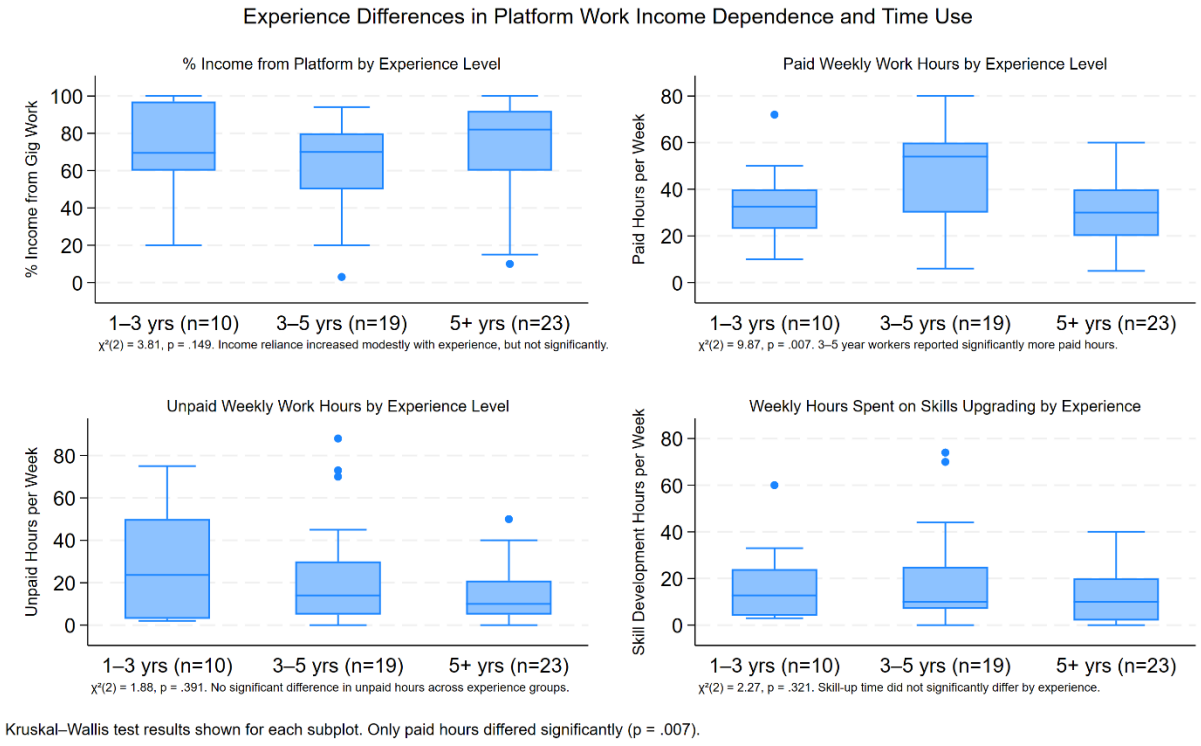
3.5.2 Labour Input Differences Across Demographic Groups

The bivariate analyses explored patterns in how workers with different demographic profiles distribute their labour, offering insight into the extent of economic dependence on platform income, the burden of uncompensated tasks, and variation in opportunities for skills investment across groups.

Overall, the results show that labour input across gender, age, and education groups in this sample group is largely uniform, with no statistically significant differences in income reliance, paid or unpaid hours, or time spent on skill development.

Figure 3.1

Platform Experience Differences in Hours Worked (Paid Work Hours)



Kruskal–Wallis test results shown for each subplot. Only paid hours differed significantly (p = .007).

The only somewhat significant variation emerged around paid work hours (Figure 3.1), with those reporting 3–5 years in gig work logging more hours than those who were newer or more experienced freelancers ($\chi^2(2) = 9.87$, $p = .007$). This relative uniformity in labour input characteristics suggests that any subsequent differences in the experience of decent work are unlikely to stem from demographic variation in work intensity. Please see Appendix B for more detailed results of these bivariate analyses.

3.5.3 Evaluating Decent Work in the Platform Economy

The process of transforming the decent work questionnaire into a benchmarking framework aligned with the ILO's substantive elements (SEs) of decent work presented several methodological

challenges. Contrary to the methodological rationale for constructing a coherent decent work scale, as proposed by Duffy et al. (2017), questions in a comprehensive decent work questionnaire lack sufficient internal coherence to form unified scales. The multidimensional nature of both the questionnaire items and the conceptual structure of decent work hinders the development of unified composite scales for each decent work substantive element (SE) without compromising statistical integrity or theoretical coherence. While this might appear to limit the coherence of the measurement model, it offered an opportunity to maintain greater transparency and fidelity to the distinct constructs embedded in the decent work survey questionnaire.

Rather than imposing overly simplified scores for each SE, the analysis employed exploratory factor analysis to reduce the full questionnaire into a set of statistically valid subscales within each SE. This allowed the construction of internally consistent scales in some domains while retaining meaningful two-item and single-item scales where necessary. Table 3.4 presents the unadjusted means of the survey results on workers' perceptions of work attributes related to decent work SEs.

Table 3.4

The Conditions of Decent Work in the Platform Work Economy

DW SEs and Scales	**Mean**	**SD**	**Range**	**Scale Reliability**[6]
Employment Opportunities				
Work Opportunity Access through Platforms	2.48	0.72	0-4	Two-item scale; r = 0.48
Alternative Work Opportunities	2.38	0.95	0-4	Single-item scale
Extent of Financial Hardship without Platforms	2.75	1.06	0-4	Single-item scale
Adequate Earnings and Productive Work				
Financial Satisfaction	2.37	0.84	0-4	Single-item scale
Income Consistency	1.3	0.97	0-4	Single-item scale
Skill Development and Productive Use	2.6	0.83	0-4	Three-item scale; α = 0.71
Decent Working Time				

[6] For scales with only two items, Pearson's correlation coefficient (r) is reported instead of Cronbach's alpha, due to the known limitations of alpha with very short scales (Eisinga et al., 2013).

DW SEs and Scales	Mean	SD	Range	Scale Reliability[6]
Schedule Autonomy & Negotiation Power	2.18	1.00	0-4	Two-item scale; r = 0.40
Combining Work, Family, and Personal Life				
Work & Life Satisfaction & Fulfilment	2.93	0.7	0-4	Three-item scale; α = 0.80
Stability and Security of Work				
Stability & Growth of Work	2.81	0.73	0-4	Three-item scale; α = 0.76
Equal Opportunity and Treatment				
Perceived Inclusion and Non-Discrimination	3.68	0.53	0-4	Two-item scale; r = 0.38
Platform Policy Protection	1.12	1.34	0-4	Single-item scale
Safe Work Environment				
Physical and Mental Well-Being and Safety	3.07	0.75	0-4	Two-item scale; r = 0.46
Stress from Platform Work	1.54	0.9	0-4	Single-item scale
Social Security				
Perceived Healthcare Access in Traditional Jobs	2.46	1.02	*0-4	Single-item scale
Healthcare Access After Joining Platform Work	1.77	0.98	*0-4	Single-item scale
% of Platform Income Saved	25.25	20.13	0-100	Single-item scale
Social Dialogue				
Opportunities for Collective Action	0.16	0.32	0-1	Two-item scale; r = 0.51
Labour Organizations' Helpfulness	0.31	0.47	0-1	Single-item scale
Participation in Collective Action	0.21	0.33	0-1	Two-item scale; r = 0.37
Public Policy Participation	0.66	0.99	0-4	Two-item scale; r = 0.58
Expression Freedom	2.2	1.1	0-4	Two-item scale; r = 0.40
Client Attention to Labour Concerns	1.62	1.22	0-4	Single-item scale

DW SEs and Scales	Mean	SD	Range	Scale Reliability[6]
Participation in Platform Administrative and Policy Decision	1.07	1.18	0-4	Two-item scale; r = 0.71

* 0 represents the lowest and 4 the highest score; 2 represents no change or neutrality

On average, workers reported moderate levels of access to platform work opportunities (M = 2.48)[7] and alternative income sources (M = 2.38), yet a notable degree of perceived financial hardship in the absence of platform work (M = 2.75). Perceptions of income adequacy were also mixed. Income consistency was rated quite low (M = 1.30), while financial satisfaction remained modest (M = 2.37), pointing to the underlying precarity of platform-based livelihoods. However, workers rated their skill development and productive use opportunities through platform work somewhat high (M = 2.6).

Indicators related to time and autonomy indicate moderate levels of schedule negotiation power (M = 2.18), while perceptions of work–life balance are comparatively more favourable (M = 2.93). Workers expressed a relatively high sense of personal safety while working (M = 3.07) and lower levels of work-induced stress (M = 1.54), indicating an overall positive perception of physical safety and psychosocial well-being.

In terms of fairness and inclusion, scores for the non-discrimination scale were considerably high (M = 3.68), while scores for platform policy protection (M = 1.12) were notably low, suggesting that while workers do not feel discriminated against by immediate clients and colleagues, platform safeguards within the platforms remain weak. Platform work does not come with social security benefits, yet workers rated healthcare access in traditional jobs (that might be available to them) as only slightly better (M = 2.46). The same trend was evident in access to healthcare after transitioning to platform work, where workers rated their change in access as slightly lower (M = 1.77).

Unsurprisingly, the social dialogue dimension received the lowest overall ratings. Although workers feel somewhat free to express their concerns (M = 2.2), formal opportunities for collective action (M = 0.16) and client responsiveness to labour concerns (M = 1.62) are either nonexistent or weak. Workers also rated the helpfulness of labour organizations as particularly limited (M = 0.31).

[7] Responses were measured on a 0-4 scale, with 4 indicating the highest positivity.

The lack of pathways to influence local policies (M = 1.07) and platform rules (M = 1.07) that impact their livelihood highlights the marginal role of intermediary support in the platform economy.

Overall, the survey findings reveal a fragmented landscape of decent work in the platform economy. Several core aspects of platform work appear to show somewhat acceptable conditions, particularly in areas such as work–life balance, perceived inclusion, physical safety, and access to skill development. Access to suitable platform jobs, career stability, and growth options, as well as schedule autonomy, are viewed as moderately adequate among workers. However, this adequacy was tempered by persistent concerns around income consistency and perceived hardship without platforms. Platform policy protections are perceived as weak, with workers expressing minimal confidence in the support systems available when issues arise. While healthcare access did not differ substantially from traditional work, social protections and collective voice remain very limited, as evidenced by consistently low scores related to labour representation, client responsiveness, and participation in platform decisions, indicating key discrepancies in decent work.

A notable observation is the substantial dispersion in responses, where the standard deviations for many scales exceeded 0.90, with several surpassing 1.0. This level of variability, despite a relatively homogeneous sample in terms of labour input, suggested that there is a substantial difference in how different groups of platform workers interpret and evaluate the quality of their work opportunities.

3.5.4 Decent Work Across Demographic and Work Intensity Profiles

Building on the descriptive findings presented above, The regression results and margin plots below explore how intersecting demographic characteristics (e.g., gender, age, education) and labour inputs intensity indicators (e.g., hours worked, time spent on unpaid or skill-building activities) shape divergent experiences of decent work in the platform work, offering exploratory insight into who benefits, who is left behind, and in which dimensions those disparities are most pronounced. Please note that the results below only focus on variables that showed significance or any exploratory trend, with $p < 0.1$. Please see Appendix B for detailed results and complete regression tables.

3.5.4.1 SE 1 Employment Opportunities

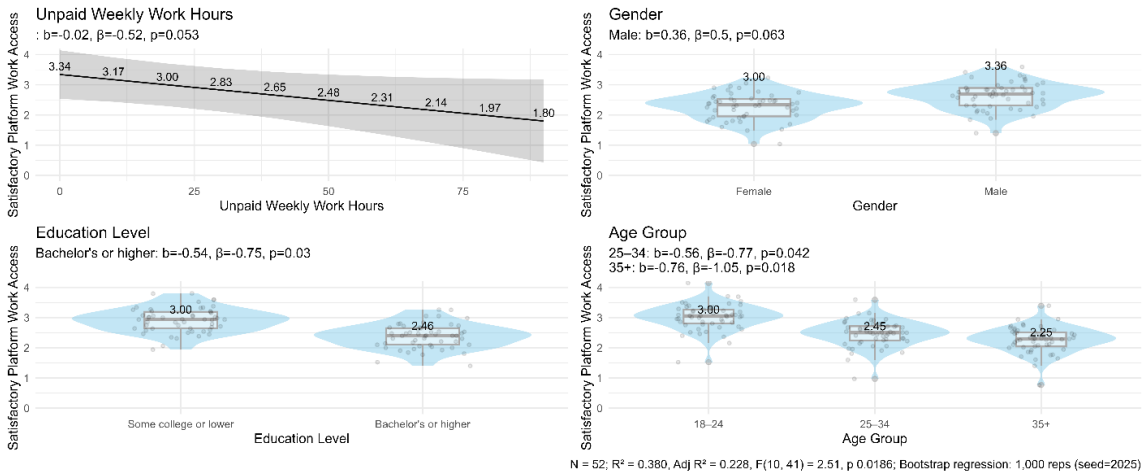
Perceptions of employment opportunities among Kenyan platform workers vary across demographic and work-intensity-related factors. Overall trends showed that access to platform work is rated less

favourably by those with higher unpaid workloads, older workers, and individuals with a university-level education, suggesting a mismatch between expectations and the nature of platform labour. Male workers tend to report slightly more positive work access experiences. In contrast, older workers express greater confidence in finding alternatives outside the platform economy, indicating potential age-related differences in perceived opportunity structures. Workers who rely more heavily on platforms for income also report a heightened sense of vulnerability, viewing platform work as essential to avoiding financial hardship.

All three scales measuring employment opportunities show considerable variation among different groups of platform workers. When it comes to satisfaction with platform work access, as shown in Figure 3.2, higher unpaid work intensity is associated with a lower rating of satisfactory access to platform work (β = –0.52, 95 % CI = –0.034 to 0.000, *p* = .053). Male platform workers reported marginally better access (β = 0.50, 95 % CI = –0.020 to 0.741, *p* = .063). Holding a bachelor's degree or higher corresponded with a significantly lower access score (β = –0.75, 95 % CI = –1.025 to –0.055, *p* = .030). Workers aged 25–34 report lower access (β = –0.77, 95 % CI = –1.091 to –0.020, *p* = .042), and those aged 35 and above exhibited the strongest decline in opportunity access satisfaction (β = –1.05, 95 % CI = –1.376 to –0.137, *p* = .018).

Figure 3.2

Disparities in Platform Opportunity Access (M =2.48)

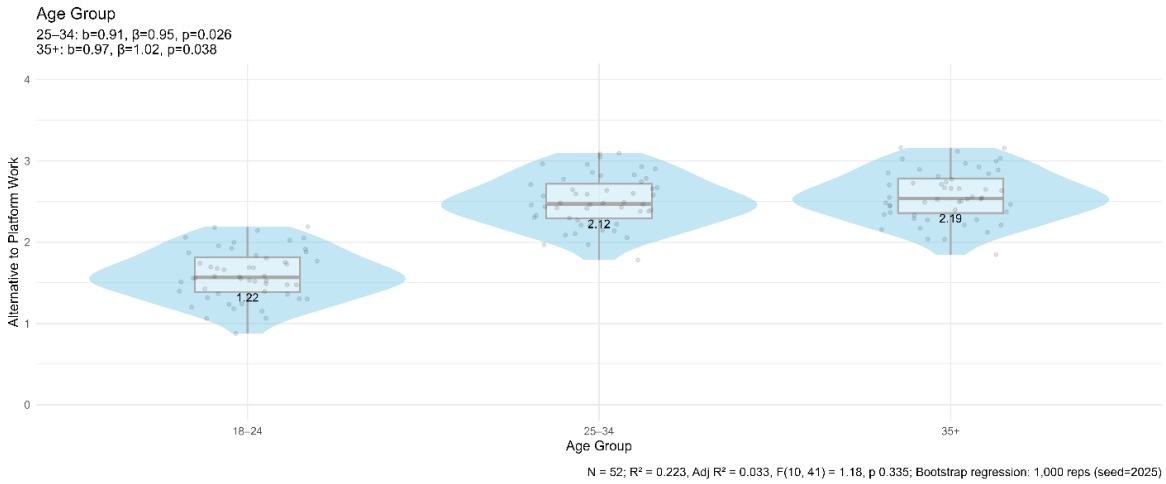


The regression model for alternative work opportunities showed that, compared to the 18–24 reference group, both older cohorts perceived significantly greater availability of non-platform

options. As shown in Figure 3.3, Participants aged 25–34 showed an increase of almost one point on the four-point scale (β = 0.95, 95 % CI = 0.113 to 1.698, *p* = .026). A similar positive association emerged for the 35 + cohort (β = 1.02, 95 % CI = 0.056 to 1.890, *p* = .038).

Figure 3.3

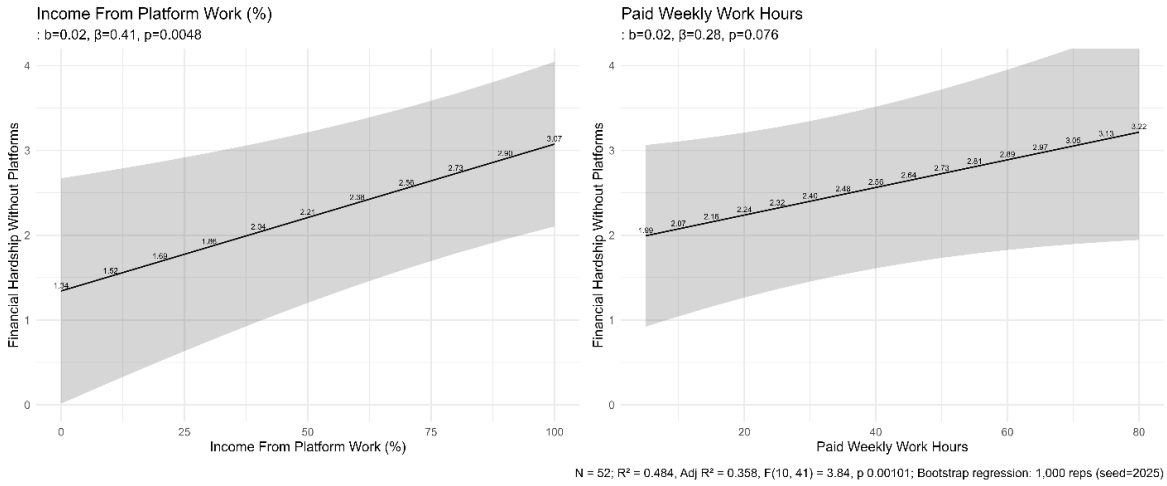
Variation in Non-Platform Work Alternative (M = 2.38)



Perceived hardship without platforms (Figure 3.4) is higher among those earning a higher proportion of total income from platform work (β = 0.41, 95 % CI = 0.006 to 0.029, *p* = .005). More hours worked on platforms also show a positive but only marginal association with a higher perception of hardship without platforms (β = 0.28, 95% CI = –0.002 to 0.034, *p* = .076).

Figure 3.4

Perceived hardship without Platform Work (M=2.75)



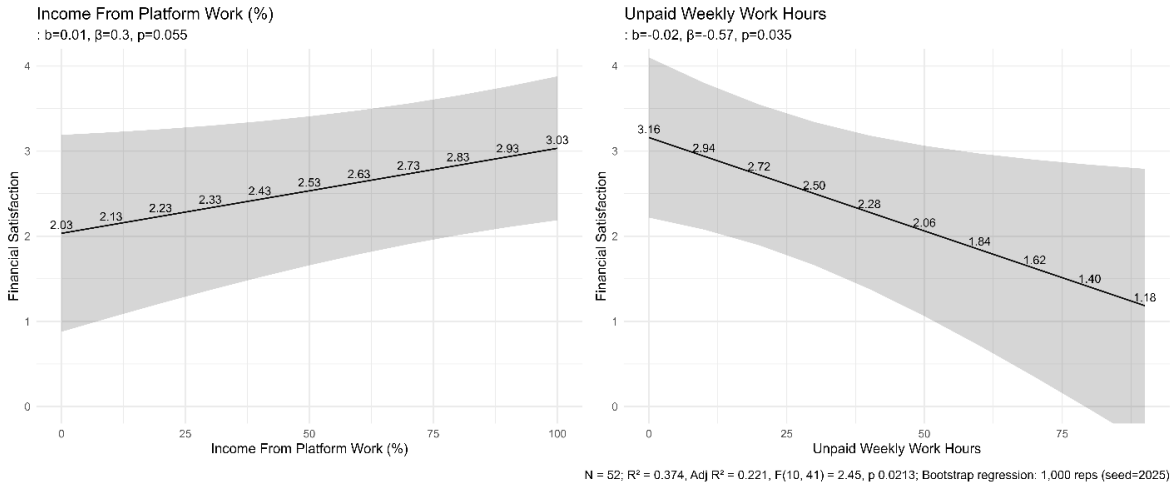
3.5.4.2 SE 2 Adequate Earnings and Productive Work

The notion of adequate earnings and the productive nature of work is measured using three scales that focus on financial satisfaction, income consistency, and perception towards skill development through platforms that distinctly signify work productivity from a worker's perspective. Overall, the data suggest that earning satisfaction is higher when a greater proportion of a worker's income comes from platforms. However, this satisfaction decreases once the burden of unpaid tasks increases. Income consistency is weak for nearly everyone. Skill development perception through platform work reveals that women tend to describe more learning opportunities.

There is moderate financial satisfaction among all workers (2.37), but regression results indicate that a higher share of income through platforms is associated with greater financial satisfaction ($\beta = 0.28$, $p = 0.055$). In contrast, as illustrated in Figure 3.5, a heavier load of unpaid platform-related hours was related to lower satisfaction ($\beta = -0.32$, $p = 0.035$).

Figure 3.5

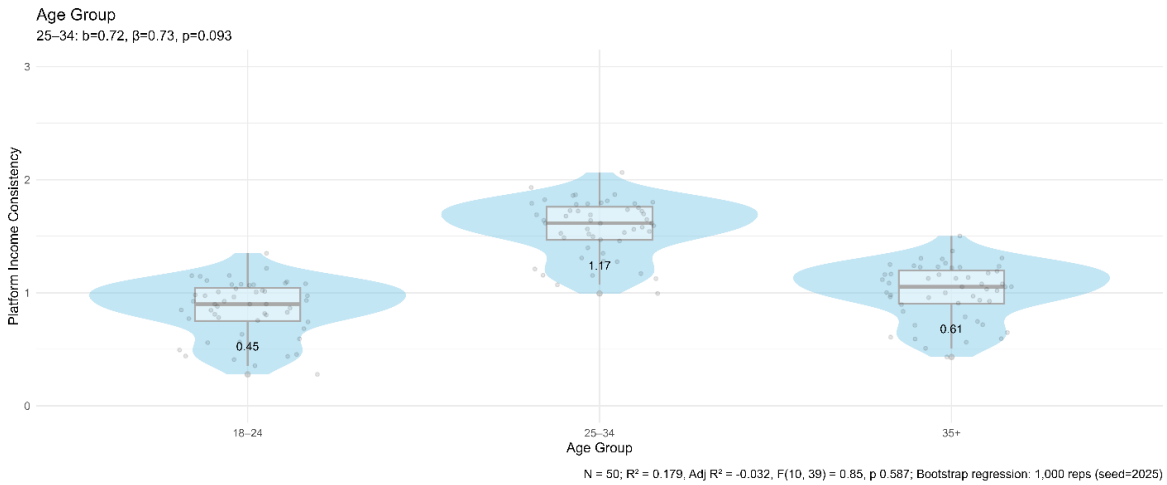
Financial Satisfaction Among Platform Workers (M = 2.37)



The low mean (1.3) for the income consistency scale shows that most workers experience inconsistent income, leaving little between-group variance for predictors to explain. Age emerged as the only near-significant predictor of perceived stability, as shown in Figure 3.6. Compared with the 18–24 reference group, freelancers aged 25–34 reported moderately steadier earnings (β = 0.73, 95 % CI = –0.124 to 1.555, *p* = .094).

Figure 3.6

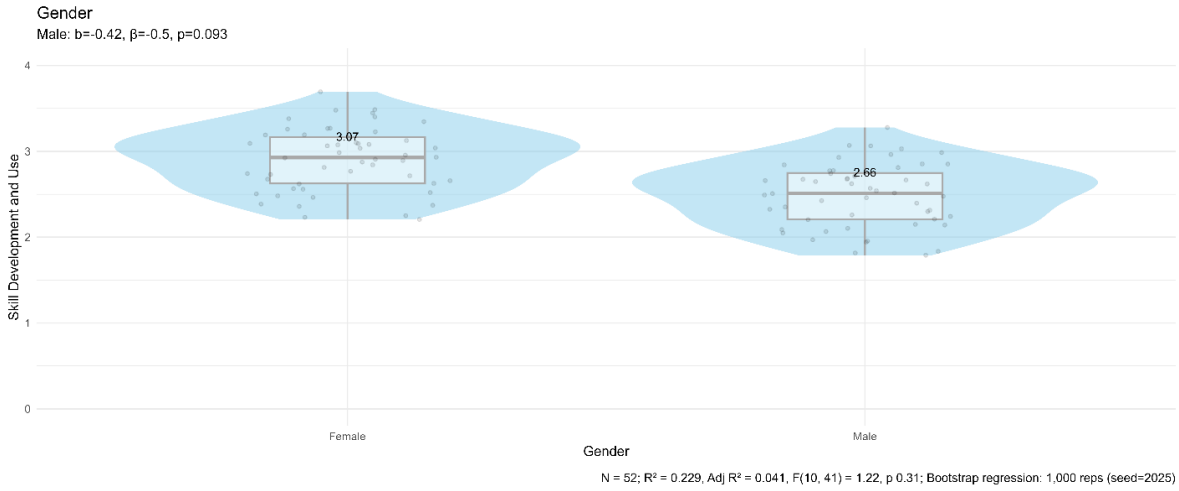
Income Consistency Among Platform Worker Groups (M = 1.3)



Patterns of skill acquisition and productive use of skills show gender differences as shown in the margin plot (Figure 3.7). Male participants were less likely than females to attribute platform work to enhancing their competencies (β = –0.50, 95% CI = –0.905 to 0.073, p = .093). The negative coefficient implies a modest but noteworthy gender gap in perceived professional development opportunities.

Figure 3.7

Differences in Skill Development and Productive Use (M = 2.6)



3.5.4.3 SE 4 Combining Work, Family, and Personal Life

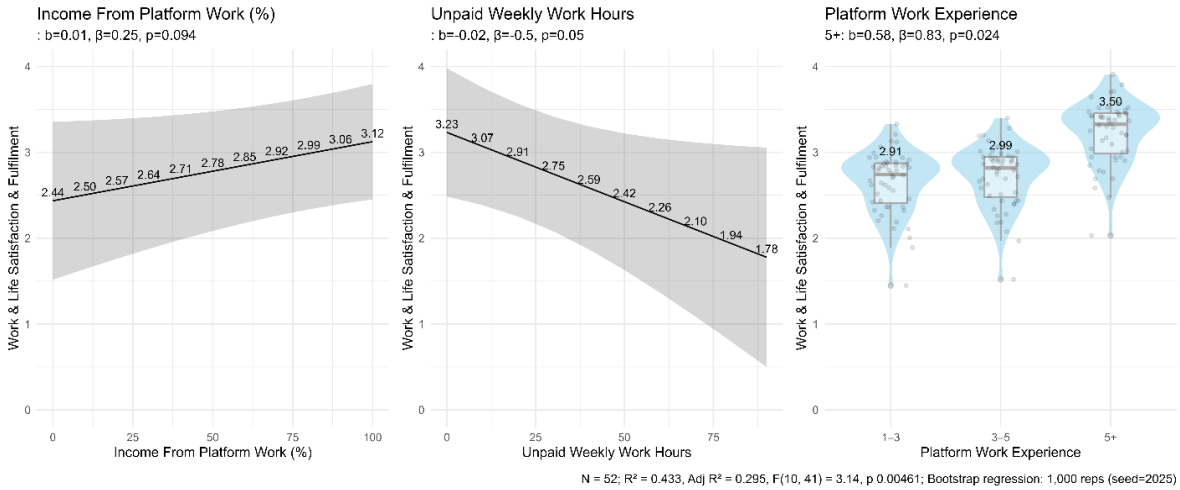
This research measures the combination of work, family, and personal life using a single scale that incorporates questions on satisfaction with work–life balance and fulfillment in the platform economy. The work–life fulfilment scale averaged 2.93. Overall, the regression results showed that those with more than 5 years of experience on platforms exhibit higher subjective work–life fulfillment. Those who derive a larger share of income from platforms also show slightly more fulfilment. However, every extra unpaid hour erodes this benefit, and those working more unpaid hours are less likely to exhibit fulfillment and satisfaction. Demographics such as age, gender, and education show very little effect.

As shown in Figure 3.8, a higher share of total income coming from platforms corresponded with modestly greater work and life satisfaction (β = 0.25, 95% CI = –0.001 to 0.015, *p* = .094). Although the association is only marginally significant, its positive sign suggests that workers who

depend on platform pay may value the flexibility it affords for coordinating family and personal responsibilities.

Figure 3.8

Work and Life Satisfaction Differences (M = 2.93)



However, the burden of unpaid work had the opposite effect. Each additional unit of unpaid workload reduced the satisfaction score by half a point (β = –0.50, 95 % CI = –0.032 to 0.000, *p* = .050), indicating that time spent on bidding, researching work, or client communication without remuneration directly undermines perceived work-life quality.

Lastly, workers with five years or more on platforms reported a boost in work-and-life satisfaction (β = 0.83, 95 % CI = 0.080 to 1.084, *p* = .024), implying that seasoned workers may adopt strategies to harness platform flexibility more effectively, or that those who remain over time in the platform economy tend to be individuals for whom platform work aligns well with broader life domains.

3.5.4.4 SE 5 Stability and Security of Work

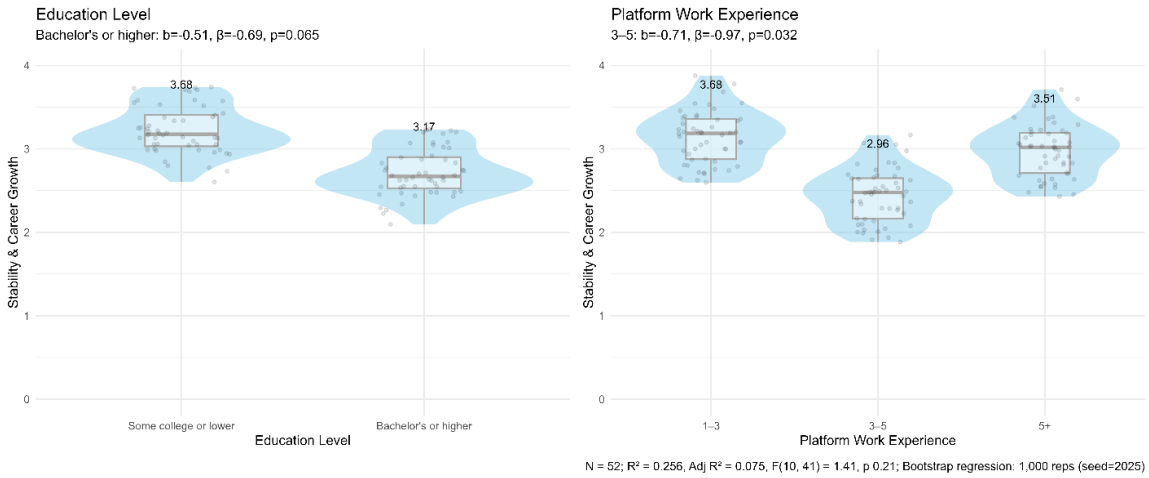
SE 5 is measured using a single scale that combines questions covering career stability and growth, with a noticeably high mean of 2.81 out of 4. Regression results suggested that freelancers with 3-5 years of experience register the sharpest doubts about stability and security. Workers with relatively

more education also show this concern. By contrast, the most seasoned cohort appears to show a rebound.

While the overall model for this scale was not statistically significant (F (10, 41) = 1.41, p = 0.210), two variables, as shown in Figure 3.9, stand out. Workers with 3–5 years of platform experience reported significantly lower perceptions of stability and career growth than newer workers (β = –0.97, p = 0.032). Interestingly, this trend was not observed for those with 5 or more years of experience, who showed no meaningful difference from new entrants, suggesting a possible rebound in satisfaction or adaptation over time. Education also showed a sizeable negative association with perceived career stability. Participants with a bachelor's degree or higher tended to view platform work as offering less stable or growth-oriented opportunities (β = –0.69, p = 0.065).

Figure 3.9

Stability & Growth (M = 2.81)



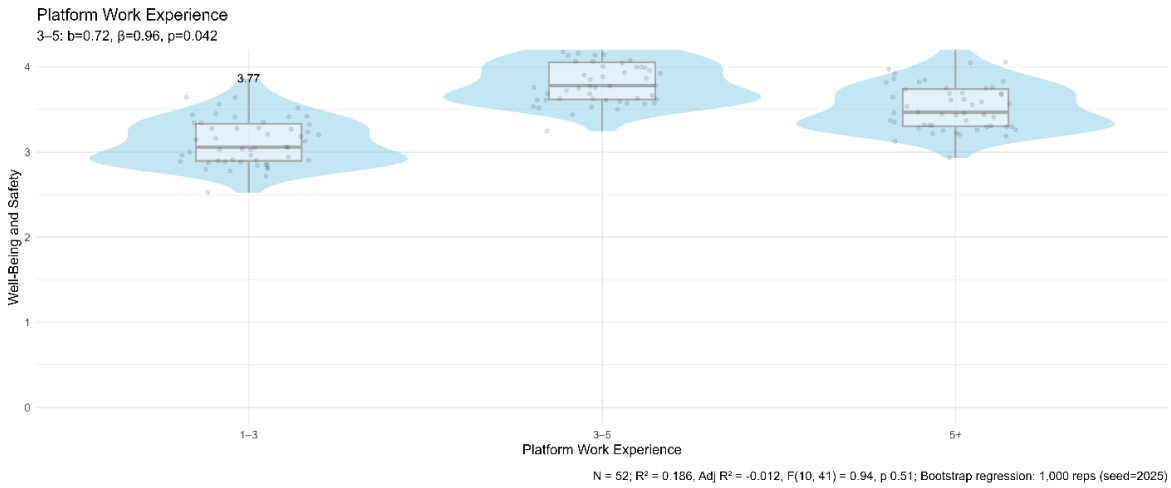
3.5.4.5 SE 7 Safe Work Environment

The safe work environment SE in this research is measured using two scales. The first scale assesses perceptions of physical safety and mental well-being, while the second scale measures perceptions of work-related stress. Overall trends showed that perceptions of safety are high (M = 3.07) and increase with experience. As Figure 3.10 shows, workers with 3–5 years of experience reported higher levels of physical and mental security (β = 0.96, 95% CI = 0.026 to 1.420, p = .042) compared to those with less than 3 years of experience. This difference may suggest that mid-career platform workers may

have developed better coping strategies, established more stable work routines, or become more selective in their engagements, factors that collectively enhance their psychosocial working conditions.

Figure 3.10

Physical Safety and Mental Well-Being Perception Differences (M=3.07)



3.5.4.6 SE 8 Social Security

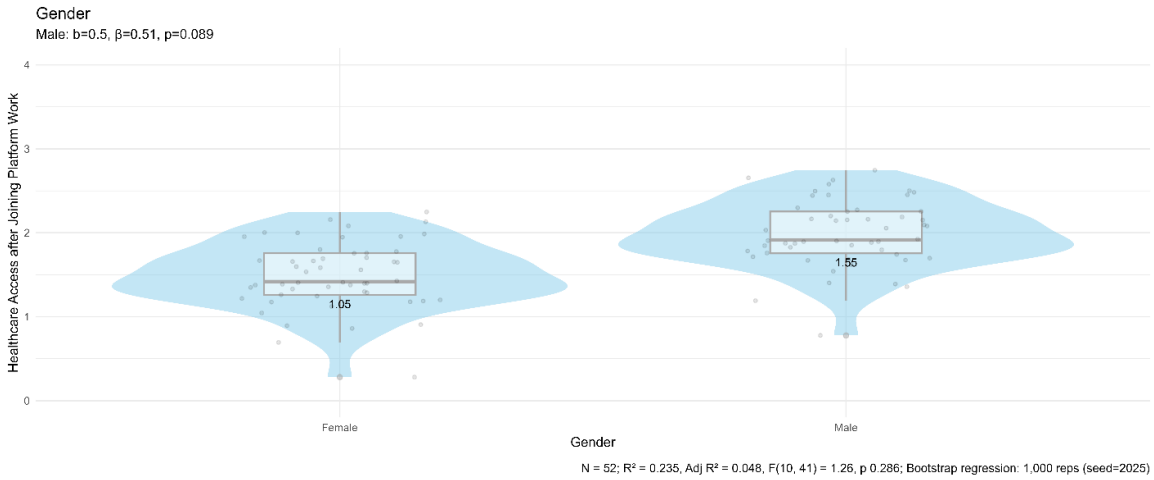
Social security within the platform economy is largely absent, and as such, the questions in this area approached the topic from a slightly different angle. The three scales used to assess this SE included changes in healthcare access after joining platform work, perceptions of healthcare access in traditional jobs accessible to the worker, and the percentage of platform income saved as a proxy for financial buffering and future security. Key trends observed in this exploratory analysis suggest that men perceive their healthcare options as slightly more improved after joining these platforms. Older workers save a larger share of their earnings, and savings are also noticeably higher among freelancers who devote more time to skills development.

Overall, workers see a slight decline in access to healthcare after transitioning to platform work (M = 1.77 < 2). Gender, as evident in the margin plot (Figure 3.11), emerged as a marginally significant predictor of perceived improvements in healthcare access. Male freelancers reported a weak trend showing better access to healthcare services after entering platform work compared to

their female counterparts (β = 0.51, 95 % CI = –0.079 to 1.073, *p* = .089). Although the confidence for the predictor includes zero, the positive coefficient suggests a potential gendered gap.

Figure 3.11

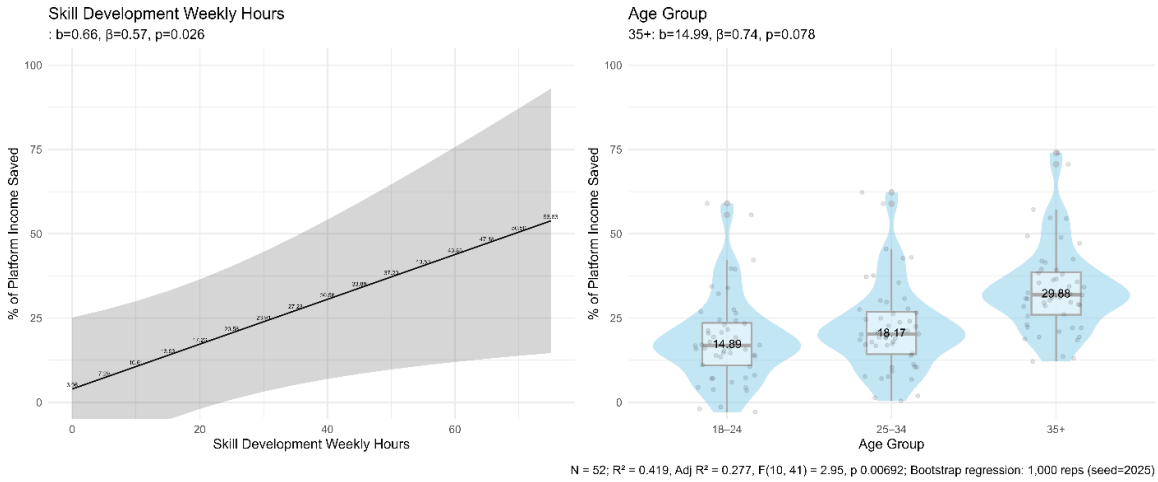
Healthcare Access After Joining Platform Work (M=1.77)



Workers save a considerable proportion (roughly 25%) of platform income, and two predictors were associated with the amount saved. First, a greater intensity of skill development activities was significantly linked to higher savings (β = 0.57, 95% CI = 0.084 to 1.245, *p* = .026). This may suggest that workers who actively invest in upskilling may also adopt more disciplined or forward-looking financial behaviour, treating platform income as a foundation for longer-term stability. Second, freelancers aged 35 and above also reported a higher savings rate (β = 0.74, 95% CI = –1.766 to 31.743, p = .078), as shown in Figure 3.12. However, the very wide confidence interval indicates substantial variability within this group.

Figure 3.12

How Savings Differ Among Different Platform Work Groups (M=25.25)



3.5.4.7 SE 9 Social Dialogue

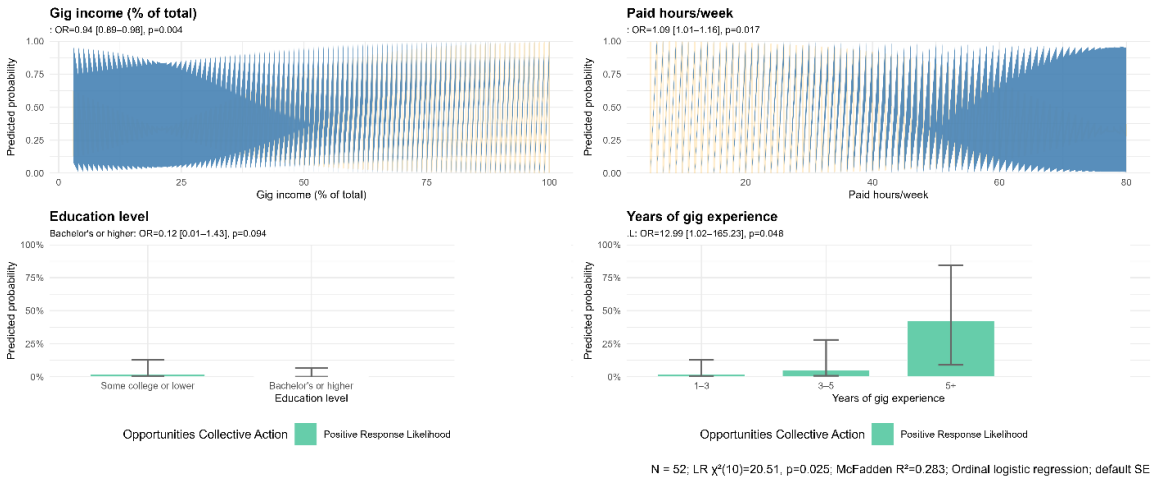
This section had the most (7) number of scales due to the diverse nature of questions that measured distinct constructs. Out of the seven scales, five showed noticeable group differences. Overall trends in the data suggest that engagement in collective action is highly sensitive to reliance on platforms for overall income. As the proportion of income coming from platforms increases, workers show more awareness that there are fewer meaningful opportunities for them to organize, and they are less likely to join any collective action initiatives. There is an observed threshold effect where an increase in weekly paid hours of work beyond 35 hours increases interest in labour mobilization efforts. Workers who focus more on skill development also view labour organizations more favourably, whereas workers who do more unpaid work show skepticism.

Perceived opportunities for organizing and collective action are very low (M= 0.16). However, some group-level differences exist within workers, as shown in the margin plot in Figure 3.13. Greater reliance on platform income was associated with a reduced perceived opportunity (OR = 0.94, 95% CI = 0.89 to 0.98, p = .004). However, those who work more hours, instead of simply relying more heavily on platform work paid platform work to make a living, are more likely to see organizing and collective action opportunities positively (OR = 1.09, 95 % CI = 1.02 to 1.16, p = .017), possibly because more active freelancers are likely more embedded in the platform economy

and better positioned to identify organizing opportunities or they simply have the positive opinion without needing to seek support due to sufficient work availability.

Figure 3.13

Workers' Perception towards Opportunities for Collective Action (M=0.16)

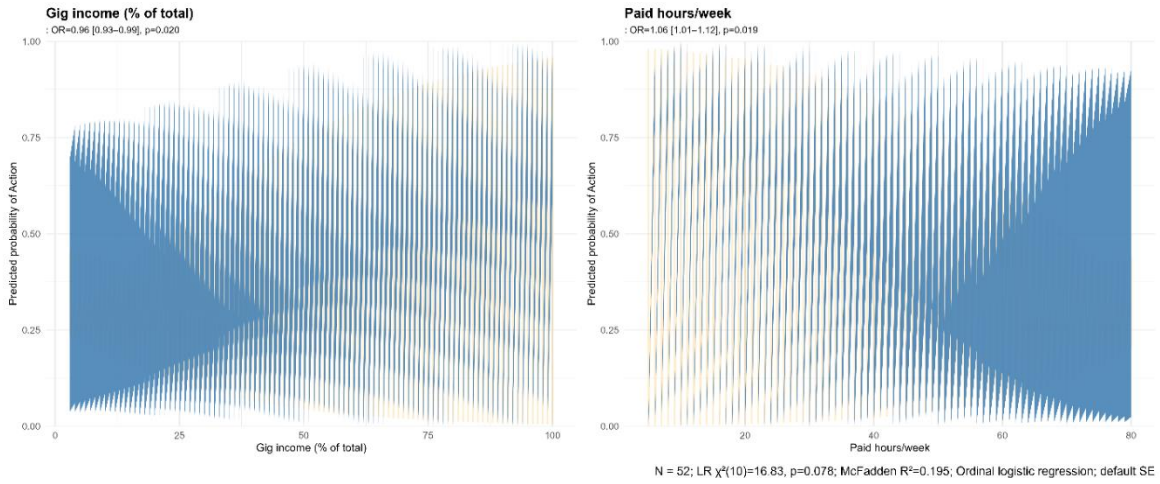


Freelancers with a bachelor's degree or higher were less likely to see avenues for collective action (OR = 0.12, 95 % CI = 0.01 to 1.43, *p* = .094). Though marginal, this large effect size suggests that more educated workers may view platform structures as rigid or unresponsive to reform, or they may simply be more critical of superficial participation mechanisms. In contrast, those with over five years of experience on platforms were more likely to perceive collective-action pathways (OR = 37.6, 95% CI = 1.03 to 1370, p = .048), which likely points to the role of long-term engagement in cultivating a sense of agency, structural awareness, and connections.

Besides the general awareness, actual participation in any form of collective action is extremely low (M = 0.21). Two exploratory trends are noticeable in this data (Figure 3.14), but they should be interpreted cautiously because the overall model has low statistical power. A higher income share coming from platforms reduced the likelihood of actual participation in collective action activities (LogOR = –0.040, p = .020). In contrast, longer paid hours beyond 40 hours boosted the likelihood of collective action (LogOR = 0.059, p = .019).

Figure 3.14

Participation in Collective Action (M=0.21)



While opportunities for collective action are scarce, it is also important to note that workers do not have a positive perception of labour organizations' helpfulness (M = 0.31). Among those who felt slightly more positive about labour organizations' perceived helpfulness, two groups stand out as shown in Figure 3.15. Those who spend more time on skill development are slightly more likely to perceive these bodies as helpful (OR = 1.11, 95 % CI = 1.02 to 1.20, p = .028). On the other hand, greater unpaid work intensity was associated with a marginally lower likelihood of finding such organizations useful (OR = 0.94, 95 % CI = 0.89 to 1.00, p = .091), possibly indicating that those burdened by unpaid work feel discontent towards structures that have underserved them.

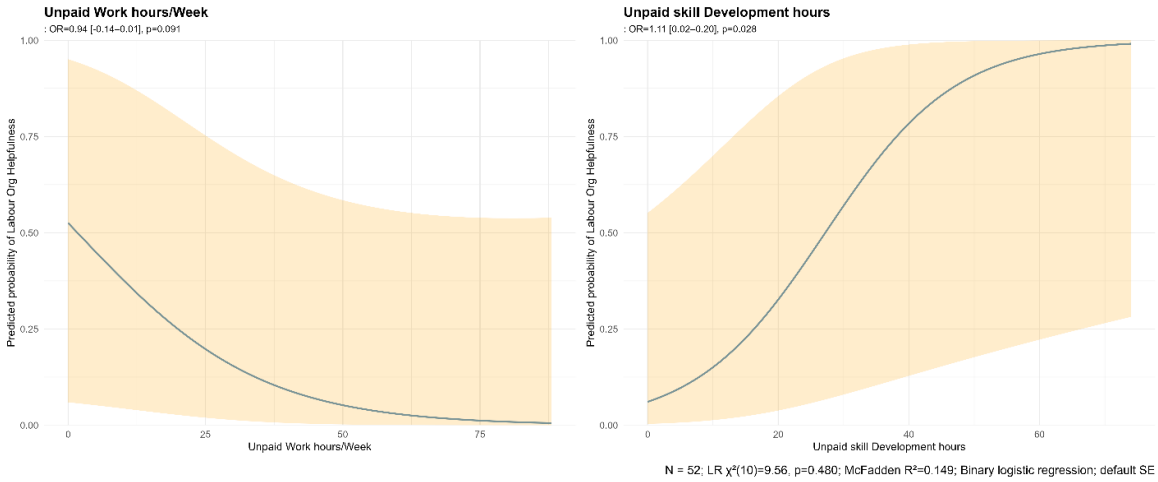
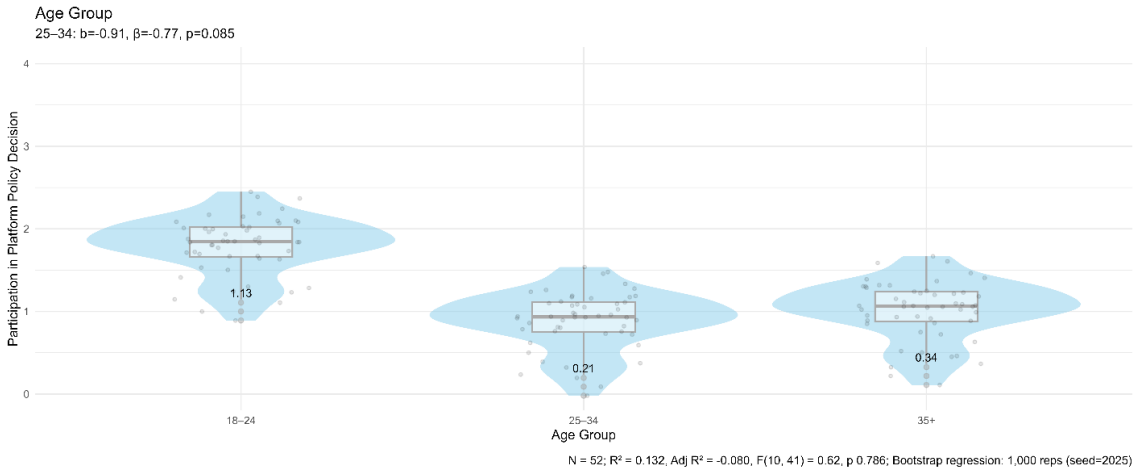


Figure 3.15: Perception about Labour Organizations' Helpfulness (M=0.31)

Most workers reported limited or no involvement in platform decision-making (M = 1.07). Notably, as the margin plot in Figure 3.16 shows, workers aged 25–34 were particularly more likely to express negative perceptions regarding the extent to which platforms involve workers in administrative or policy changes (β = –0.77, 95% CI = –1.951 to 0.130, p = .085). Although this association does not reach conventional levels of statistical significance, the effect size suggests a meaningful trend.

Figure 3.16

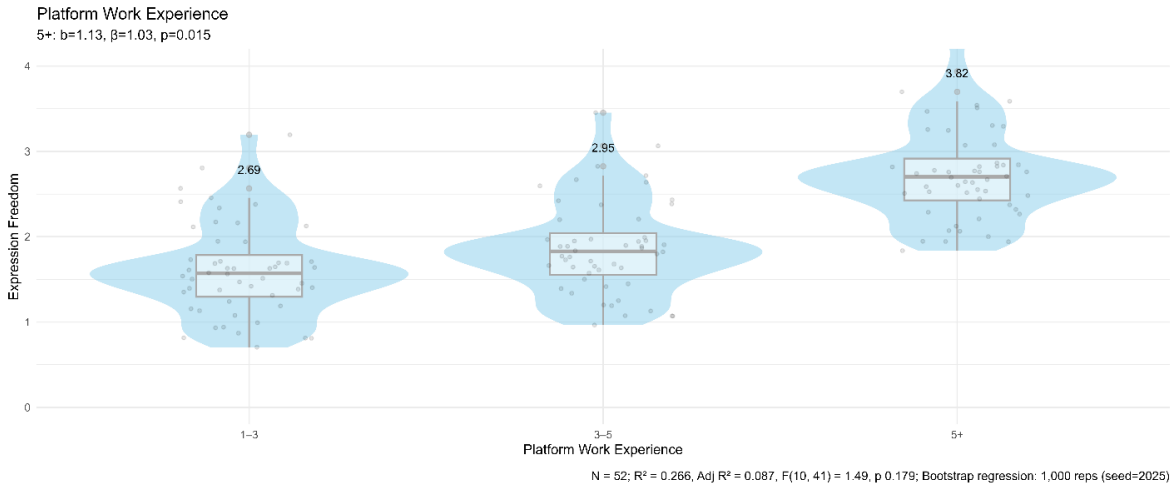
Workers' Perception Towards Platform Policy Participation



Lastly, workers with more than five years of platform experience were significantly more likely to feel free to express their views about platform work (β = 1.03, *p* = .015), suggesting that longer engagement may build confidence or perceived safety in speaking up (Figure 3.17).

Figure 3.17

Workers' Perception Towards Expression Freedom (M=2.2)



3.5.5 Notable Intergroup Work Quality Differences

As the Decent Work SE scale means and the exploratory regression results above indicate, the experience of decent work in Kenya's platform economy is highly uneven. Disaggregated results reveal patterned differences across key social and economic groups, highlighting how age, gender, education, and varying degrees of platform engagement influence decent work outcomes. Table 3.5 summarizes these differentiated effects across the nine Decent Work SEs, highlighting how certain worker profiles face compounded decent work constraints or enjoy relative advantages within the same digital labour environment.

Table 3.5

Heterogeneity in the Perceptions of Decent Work Among Kenyan Platform Workers

	β / OR	**95 % CI**	**p**
SE1 Employment Opportunities			
Satisfactory Platform-Work Access (R^2 = 0.38)			
Unpaid Work Intensity	–0.52	–0.034 , 0.000	0.053
Gender (Male)	0.50	–0.020 , 0.741	0.063
Bachelor's +	–0.75	–1.025 , –0.055	0.030
Age 25 – 34	–0.77	–1.091 , –0.020	0.042
Age 35 +	–1.05	–1.376 , –0.137	0.018
Alternative Work Opportunities (R^2 = 0.223)			
Age 25 – 34	0.95	0.113 , 1.698	0.026
Age 35 +	1.02	0.056 , 1.890	0.038
Financial Hardship Without Platforms (R^2 = 0.484)			
Proportion of income from Platform Work	0.41	0.006 , 0.029	0.005
Paid Platform Work Intensity	0.28	–0.002 , 0.034	0.076
SE2 Adequate Earnings and Productive Work			
Financial Satisfaction (R^2 = 0.374)			
Proportion of income from Platform Work	0.30	–0.000 , 0.020	0.055
Unpaid Work Intensity	–0.57	–0.042 , –0.002	0.035
Income Consistency (R^2 = 0.179)			
Age 25 – 34	0.73	–0.124 , 1.555	0.094
Skill Development & Productive Use (R^2 = 0.229)			

	β / OR	95 % CI	p
Gender (Male)	–0.50	–0.905 , 0.073	0.093
SE4 Combining Work, Family, and Personal Life			
Work & Life Satisfaction / Fulfilment (R^2 = 0.433)			
Proportion of income from Platform Work	0.25	–0.0012 , 0.0150	0.094
Unpaid Work Intensity	–0.50	–0.0323 , 0.0000	0.050
Experience > 5 yr	0.83	0.080 , 1.084	0.024
SE5 Stability and Security of Work			
Stability & Career Growth (R^2 = 0.256)			
Bachelor's +	–0.69	–1.047 , 0.033	0.065
Experience 3–5 yr	–0.97	–1.359 , –0.064	0.032
SE7 Safe Work Environment			
Physical Safety and Mental Well-Being & (R^2 = 0.186)			
Experience 3–5 yr	0.96	0.026 , 1.420	0.042
SE8 Social Security			
Healthcare Access (post-platform) (R^2 = 0.235)			
Gender (Male)	0.51	–0.079 , 1.073	0.089
% Platform Income Saved (R^2 = 0.419)			
Skill Development Intensity	0.57	0.084 , 1.245	0.026
Age 35 +	0.74	–1.766 , 31.743	0.078
SE9 Social Dialogue			
Opportunities for Collective Action (ordinal logit LR $\chi^2(10)$ = 20.51)			
Proportion of income from Platform Work	OR 0.94	0.89 , 0.98	0.004
Paid Platform Work Intensity	OR 1.09	1.02 , 1.16	0.017
Bachelor's +	OR 0.12	0.01 , 1.43	0.094
Experience > 5 yr	OR 37.6	1.03 , 1370	0.048
Participation in Collective Action (ordinal logit LR $\chi^2(10)$ = 16.83)			
Proportion of income from Platform Work	OR -0.04	0.93, 0.99	0.020
Paid Platform Work Intensity	OR 0.06	1.01 , 1.2	0.020
Labour-Organization's Helpfulness (binary logit LR $\chi^2(10)$ = 9.56)			
Skill Development Intensity	OR 1.11	1.02 , 1.20	0.028
Unpaid Work Intensity	OR 0.94	0.89 , 1.00	0.091

	β / OR	95 % CI	p
Expression Freedom (R^2 = 0.266)			
Experience > 5 yr	1.03	0.23 , 2.02	0.015
Participation in Platform-Policy Decisions (R^2 = 0.132)			
Unpaid Work Intensity	OR 0.94	0.89 , 1.00	0.091
Age 25 – 34	–0.77	–1.951 , 0.130	0.085

3.5.5.1 Unpaid Labour and Decent Work

Unpaid work emerges as a consistent drag on multiple dimensions of decent work for Kenyan platform workers. A one-unit increase in unpaid workload is linked to reduced access to suitable platform jobs (β = –0.52, p = .053) and lower financial satisfaction (β = –0.57, p = .035). It also diminishes overall work–life fulfilment (β = –0.50, p = .050) and slightly undermines confidence in collective organizations (OR = 0.94, p = .091). These results highlight the cumulative impact of unpaid labour on both the economic and social dimensions of platform livelihoods.

3.5.5.2 Gender Disparities in Work Conditions

Some gender differences suggest structural advantages in access and security for male workers, but also highlight a perceived trade-off in professional growth. Men perceive somewhat better access to suitable work (β = 0.50, p = .063) and a modest improvement in healthcare access after joining platforms (β = 0.51, p = .089), compared to women. However, they are also more likely to view platforms as less beneficial for skill development (β = –0.50, p = .093), suggesting potential disillusionment with long-term learning opportunities.

3.5.5.3 Education-Based Variation in Work Quality

Formal education does not guarantee better platform outcomes for many platform workers. Degree holders report lower satisfaction with work access (β = –0.75, p = .030) and express higher concern about long-term stability and career growth (β = –0.69, p = .065). They also perceive significantly fewer avenues for collective action (OR = 0.12, p = .094).

3.5.5.4 Age-Based Differences in Work Quality

Workers aged 25–34 echo the same skepticism as degree holders and reported lower perceived access to suitable work (β = –0.77, p = .042). However, they seem more optimistic about alternative job options (β = 0.95, p = .026) and report somewhat more consistent earnings (β = 0.73, p = .094) compared to other age groups. In contrast, workers aged 35 and above report the lowest access to suitable platform work (β = –1.05, p = .018), yet express more substantial confidence in their ability to exit the platform economy if platform work was not an option for them anymore (β = 1.02, p = .038). They also demonstrate a greater capacity to save income through platform work to build safety nets (β = 0.74, p = .078).

3.5.5.5 Decent Work Across Experience Levels

Highly experienced platform workers (with 5+ years of experience) report greater work–life satisfaction (β = 0.83, p = .024) and are more aware of collective action opportunities (OR = 37.6, *p* = .048). Meanwhile, those in the 3–5-year range feel less secure about long-term career prospects (β = –0.97, *p* = .032) despite reporting better physical and mental well-being (β = 0.96, *p* = .042).

3.5.5.6 Income Reliance and Work Conditions

Workers who depend more heavily on platform income perceive themselves as more vulnerable to the platforms' transient nature in Kenya (β = 0.41, *p* = .005). However, this reliance also correlates with greater financial satisfaction (β = 0.30, *p* = 0.055) and higher work–life fulfillment (β = 0.25, p = 0.094). Notably, higher reliance on platform income as total % of income is associated with reduced perception of participation in collective action (OR = 0.94, *p* = .004).

3.5.5.7 Impact of Platform Workload on Work Quality

Similar to high income dependence, those working longer hours on platforms are associated with a heightened perceived vulnerability to livelihood loss if platform work were to disappear (β = 0.28, *p* = .076). However, greater time investment is also linked to more awareness of collective organizing opportunities (OR = 1.09, *p* = .017).

3.5.5.8 Skill Development Effort and Work Quality

Lastly, skill development intensity reveals a specific dispositional orientation among workers, which shows statistically significant associations across multiple SEs. Greater time spent on skill

development is associated with higher financial satisfaction (β = 0.28, p = 0.055), while men report lower perceived skill gains (β = –0.50, p = 0.093), indicating a gendered variation in how upskilling is experienced. Those engaging more in skill development also report saving a significantly higher proportion of their income (β = 0.57, p = .026). Those who invest more time in learning also correspond with more favourable perceptions of labour organizations' helpfulness (OR = 1.11, p = .028).

3.6 Discussion

Drawing on the decent work survey results as an empirical baseline and worker interviews, platform work in Kenya illustrates a fragmented and stratified landscape of decent work and its relationship with workers' capabilities. Since the nine SEs and their corresponding scales encompass a wide range, the discussion into four empirically grounded themes that emerged during the qualitative analysis. Each theme groups the relevant SEs as outlined in Table 3.6 and assesses how the work conditions expand or constrain workers' capabilities. The capability perspective in this discussion functions not as an additional metric but as an interpretive lens that clarifies the practical outcomes of meeting, partially meeting, or falling short of decent work benchmarks.

Table 3.6

Thematic Clustering of Decent Work SEs

Economic Stability, Security, and Growth	**Temporal Autonomy & Work–Life Quality**	**Equity, Inclusion, and Social Protection in the Platform Economy**	**Voice and Agency**
Employment Opportunities Work Opportunity Access, Alternative Opportunities, Financial Hardship)	***Decent Working Time*** Schedule Autonomy & Negotiation Power	***Equal Opportunity and Treatment*** Perceived Inclusion and Non-Discrimination, Platform Policy Protection	***Social Dialogue*** Opportunities for Collective Action, Participation, Expression Freedom, Public Policy Participation
Adequate Earnings and Productive Work Financial Satisfaction, Income Consistency, Skill Development and Productive Use	***Combining Work, Family, and Personal Life***	***Social Security*** Healthcare Access, Savings	

Economic Stability, Security, and Growth	Temporal Autonomy & Work–Life Quality	Equity, Inclusion, and Social Protection in the Platform Economy	Voice and Agency
	Work & Life Satisfaction & Fulfilment		
Stability and Security of Work Stability and Growth of Work		***Safe Work Environment*** Occupational safety, Stress	

3.6.1 Economic Stability, Security and Growth

Employment opportunities, adequate earnings, and work stability represent core building blocks of the capability for work. Among experienced Kenyan platform workers, these decent work indicators show a mixed but cautiously optimistic pattern. Survey scores reveal moderately high perceptions of work access and future stability, with particularly strong evaluations for skill development and long-term growth. At the same time, persistent challenges remain, especially in income consistency and the reliability of alternative employment options.

3.6.1.1 Platforms as an Adequacy Bridge amid Constrained Off-Platform Options

The survey and interview analyses (discussed below) showed a clear trend. Many Kenyan freelancers view digital platforms as a viable pathway to earning a livelihood in an economy where domestic demand for skilled labour remains limited. Although group-level disparities exist, statistically, the mean score for access to work opportunities (2.48 on a 0 to 4 scale) still indicates moderate confidence, suggesting that freelancers perceive platforms as neither universally abundant sources of work nor fully substitutable. This sense of satisfaction is contextual, stemming mainly from widespread dissatisfaction with local employment opportunities, as one participant explained:

> "I was working at an international NGO with children from the slum areas, but I was struggling to make ends meet with the amount of money they were giving me. So, I resigned from that job and decided to start looking for alternative ways to make money" (Triza, 2024).

Triza mentioned how there is a growing disillusionment among Kenyan platform workers, as local employment opportunities are limited; however, even sought-after local jobs often fail to sustain a dignified livelihood. While some conventional jobs may offer elements of affiliation and a sense of purpose, the inadequate remuneration associated with many local jobs undermines the foundational economic conditions necessary to support other valued functionings. Marvin explained:

> "There is the hourly rate, which you can get on the platforms, which is very hard to get on the local jobs" (Marvin, 2024).

Workers like Marvin have reasons to value platform work, not because it is ideal, but because the deficits in decent work are often more pronounced in traditional employment. Considering these deficits, platform work has expanded opportunities and freedom for Kenyan workers; yet, this modest opportunity freedom is only partial and unevenly convertible into lasting economic security. Those working more unpaid hours particularly show higher economic insecurity and lack of sufficient access to suitable work opportunities on platforms.

The average platform income consistency remains low, at 1.30, as indicated in workers' survey responses. Alternative income sources register 2.38, but the expectation of financial hardship without platforms rises sharply to 2.75, revealing that workers are integrated into global labour markets but remain excluded from contractual stability. The asymmetry between satisfaction with access and discontentment with income instability among Kenyan platform workers could be characterized as economic entrenchment or dependence rather than the typically perceived informality of gig work. The reliance on platforms stems from the structural lock-in generated by high national unemployment and platform precarity, both of which are largely outside individual control, underscoring a structural mismatch where domestic demand cannot effectively absorb skilled labour, making workers vulnerable to platform exploitation. As Marvin further pointed out:

> "The people who were in school with me, most of them are still jobless up to today" (Marvin, 2024).

If the domestic structures for skill valorization are weak, they function as adverse social conversion factors, pushing workers to channel their credentials into global digital piecework even when contractual security remains absent and income consistency remains very low. Marvin's experience validates previous studies that Global South freelancers are pulled by transnational

demand only after being pushed by local under-employment (Graham, Hjorth, et al., 2017). One of the participants, Clara, elaborated on these push factors:

> "I worked in offices for 14 years, and I only got promoted twice in 14 years. So, as much as people say there are promotions out there, they don't come that easily" (Clara, 2024).

Workers like Clara, who transitioned to platform work after spending several years in the local economy, often express disillusionment with the prospect of upward mobility in traditional employment, where formal structures may promise progression but rarely deliver it in practice. Hierarchical advancement is often inaccessible to many Kenyan workers, shaping a broader perception that traditional jobs offer limited returns on time and effort. This perception reinforces the appeal of alternative work arrangements, such as freelancing, where perceived merit and effort may yield more immediate, albeit less stable, rewards.

However, when examining the granularity of work access, the uneven dependence and economic stability are evident across worker groups. A heavy reliance on platforms as a primary source of income comes at a cost to livelihood security. Statistically, compared to part-timers, those workers who view platform work as a full-time career exhibit heightened financial vulnerability, as they have fewer alternative income sources and no cushions against lean periods. Theo's arguments highlighted a key issue impacting livelihood security:

> "It is tricky. In December last year, I did not work, there was no work. This January, a lot of work has come. Then the challenge comes when work is too much. Maybe you have sent proposals, and three or four clients respond at the same time, all wanting their work done within a month or so" (Theo, 2024).

The conversation with Theo showed how the immediate opportunity freedom platforms offer can be lucrative. However, it often fails to counter long-term economic insecurity, revealing an absence of genuine security conversation. Unpredictable demand converts this economic reliance into heightened risk, eroding key pillars of career stability, predictable earnings, manageable workloads, and the capacity to plan financially. These are well-documented issues in the global platform economy, e.g., (Anwar & Graham, 2021; Wood & V. Lehdonvirta, 2021). However, the primary challenge for many Kenyan workers remains the shared constraint on capability for work across both conventional and platform settings. Clara noted:

> "With the office work, yeah, it is guaranteed [monthly income], but it is not that guaranteed. You can get fired during the week or maybe during the month. The fact that somebody hired you to be in the office does not mean that you are there forever, it is your performance. The same way it is on the platforms" (Clara, 2024).

Clara points out a fundamental push factor, as the notion of permanent work is not a mature norm in many countries of the Global South, and volatility in the domestic employment market undermines workers' substantive freedom to secure stable, skill-appropriate livelihoods. Clara's perspective also shows that when job loss remains a constant threat, wages and educational qualifications lose their effectiveness as reliable indicators of achieving the valued functioning of economic security. In this context, the instability of both on-platform and off-platform work conditions leads workers to conceptualize employment as a precarious and unpredictable undertaking. However, for many, the relatively higher financial satisfaction associated with platform-based income becomes a decisive factor, offsetting instability through perceived adequacy in earnings. An interesting gender dynamic observed in this research is that while women report slightly lower objective access to suitable work opportunities, they nonetheless perceive their opportunities more positively at a subjective level. As Mable and Joyce noted in the interview:

> "As a woman, I have seen that, and I have realized that women have more opportunities" (Mable, 2024).

> "When you are working on-site, you feel there is an energy where men tend to be favoured over women. But [in] remote work, I am neutral because I have not had that experience" (Joyce, 2024).

There is dissonance between women's objective access to platform opportunities and their subjective perception of relative advantage in the platform work economy. This contradiction is more than a measurement anomaly, and it highlights how gendered experience is always mediated by context, comparison, and prior exclusions. These experiences are shaped by their relational histories with the highly patriarchal labour markets, such as Kenya (Gurumurthy et al., 2021; Julius, 2025; Varanasi et al., 2022). My research provides evidence that gender inequalities faced by workers in countries such as Kenya are layered, and often, when the local layer of inequalities is substantive, platform inequalities seem emancipating. For many women platform workers, especially those with prior experience in discriminatory or male-dominated workplaces, the relative anonymity, financial satisfaction, and flexibility of online platforms may feel empowering, even if structural inequalities

persist in access to high-quality gigs or long-term stability. Hence, where local gender inequalities are deeply entrenched, platform work can appear emancipatory, even as platform-specific inequalities remain.

In the decent work survey, the mean score for financial satisfaction (2.51) sits noticeably above the midpoint, suggesting a moderate sense of adequacy among many platform workers. Notably, those who derive a larger share of their total income from freelancing and report fewer viable alternative income sources express higher financial satisfaction compared to their less embedded counterparts. As Clara highlighted:

> "I cannot be working [in traditional jobs] for 10 hours a day and [they are] giving me 40,000 Kenyan Shillings. My house rent is 25,000. I have other bills: electricity, water, and garbage. What am I left with? I have no money for food, for transport, for taking care of myself, my parents, my son, and the education for him. It is not worth it" (Clara, 2024).

Workers like Clara, who treat platform work as a full-time option and perceive fewer viable alternatives in the local economy, display a pronounced preference for platform work. They also report greater financial satisfaction, a pattern that reflects not only appreciation for platform work but also a deeper estrangement from local employment, including the export-focused BPO industry jobs in Kenya. However, the higher financial satisfaction does not imply stable or predictable earnings; instead, ongoing exposure to platform precarity seems to cultivate an adaptive acceptance of, and resilience to, income volatility, as Clara further noted:

> "Once you get a good client or a job that pays well, try to save as much as you can. Also, budget your life. Do not be extravagant when money comes, and do not change your life abruptly" (Clara, 2024).

These patterns also expose a self-reinforcing cycle of platform dependence, as discussed in previous sections. Higher satisfaction with financial and opportunity satisfaction coincides with a reduced sense of viable off-platform alternatives, further binding workers to digital labour markets that globalize wage competition and disconnect them more from the local labour economy. A key development challenge arising from this dependence is that skills and experience gained on platforms often do not reliably convert into recognized credentials in Kenya's formal labour market, a deficit

that constricts both the transferability of human capital and the exit option that underpins genuine occupational choice. As Deniel observed:

> "If you worked for individual clients, then it [will] be a bit difficult to use that as experience in the local industry, which is a challenge for us because most of our work involves interacting with individual clients rather than companies" (Daniel, 2024).

When platform work experience lacks labour market legitimacy, workers lose a viable exit pathway from platform dependency, shrinking real choice sets. The conversation with Daniel showed that experience only counts toward capability for work if external evaluators, local employers, lenders, and professional bodies recognize it as such. Hidden or unverifiable clients on platforms disrupt the conversion chain, forcing freelancers to rely increasingly on platform markets that do recognize their value, thereby entrenching dependence and foreclosing diversified livelihood pathways.

Although this entrenchment and dependence may be seen as stemming from trading short-term income adequacy for heightened long-term vulnerability (Vallas & Schor, 2020), Kenyan workers themselves stress that viable exit routes were absent long before they turned to platform work. Their engagement with digital freelancing, therefore, exposes rather than creates a pre-existing lack of alternatives in the local labour market. From the perspective of these alienated workers, working in the platform economy represents a net improvement in their economic functioning, even when they are unable to convert these functionings into a fuller sense of capability for work. This financial satisfaction with platform work, however, is uneven among Kenyan freelancers. Seasoned workers report moderately high satisfaction on average, and a closer analysis reveals that one group stands out as distinctly less content. As Kelvin noted:

> "On the platforms, you actually spend a lot of time looking for, compared to the time you spend working, unless your profile is exceptionally good" (Kelvin, 2024).

Well-being appears to depend on the capacity to limit unpaid labour. Regression results confirm this negative association between unpaid hours and satisfaction, where the burden of unpaid work diminishes the perceived value of work. Lack of easy access to adequate paid work leads to more unpaid work, creating a vicious cycle in which unpaid labour further decreases overall satisfaction with work arrangements. This unpaid labour, such as drafting bids, revising deliverables,

and maintaining client communication, acts as a hidden cost that lowers the effective hourly wage and, as a result, reduces satisfaction with work opportunities.

3.6.1.2 The Dual Dynamics of Inclusion and Educational Devaluation in Platform Work

Younger and less formally educated participants reported greater access to online gigs, which reveals a notable incongruity. Platform work appears to flatten traditional hierarchies by prioritizing demonstrable skills over formal qualifications in Kenya. This dynamic opens up income-generating opportunities for individuals, particularly the younger and less formally educated, who are often excluded from conventional labour markets. In doing so, platform work suggests a potential expansion of opportunity freedom for groups that have been historically marginalized in traditional employment systems, as noted by Marvin:

> "If you look at the platforms, they do not judge, mostly, your skills do the talking" (Marvin, 2024).

Marvin regarded the platform economy's focus on practical skills as a beneficial feature. However, this inclusivity comes at an educational penalty, as Kenyan workers with more years of schooling often find their formal credentials undervalued or completely ignored. Consequently, while platforms increase access for some, they simultaneously reduce the returns to education for others. A major part of this educational penalty stems from the disconnect between formal higher education and the skills required in the platform economy, where many specialized degrees have little clear relevance to the task-oriented, client-driven nature of freelance work. As Viola reflected:

> " If you are doing something like marine science, it is very hard to work as a freelancer because they want someone practical" (Viola, 2024).

Viola's arguments revealed that although credentials help build the opportunity potential on platforms, there is a significant decoupling of education from remuneration in the platform market. This decoupling suggests a market logic where price, rather than conventional proficiency indicators, drives client decisions, undermining the conversion of educational qualifications into valued work functionings. Formal education rests on an implicit employment contract. Invest in credentials today, and society will reward you with secure, matching work tomorrow (Spence, 1978). Many Kenyan graduates face a harsh reality where local labour markets underabsorb advanced degrees, and menial work opportunities through global platforms undervalue them, fracturing the trust bond that once

linked study and stable employment, but has never been realized in Kenya. Consequently, graduates whose academic specializations cannot be mapped onto discrete, gig-based tasks suffer diminished returns to their education.

3.6.1.3 Economic (in)Security, Aimed Platform Precarity

For many Kenyan freelancers, platform work is not just a temporary solution but a potentially sustainable livelihood model, at least according to their perceived outlook. Contrary to common narratives of relentless precarity, Kenyan freelancers in this study reported a relatively positive sense of career stability and long-term growth, with the stability and growth scale averaging 2.81 (the third highest among all decent-work scales). These scores suggest that workers' confidence in future planning challenges is not closely tied to general perceptions of instability. Interestingly, the survey analysis revealed a non-linear pattern of perceived stability and growth. Freelancers with 3–5 years of experience on the platform reported a drop in career stability and security, scoring significantly lower than newer entrants and those with more experience, as highlighted by Theo:

> "Today, you may have work, a lot of work, then in the next three months, there are no jobs coming your way. So, let me say, it is very unpredictable" (Theo, 2024).

Theo's perception showed that the mid-career dip for many platform workers marks a critical point where early optimism collides with structural ceiling, the lack of promotion pathways, skill development fatigue, and erosion of motivation due to irregular earnings. It is worth noting that the mid-experience group in this research also worked more paid hours than the other cohorts. These adverse conversion factors strip workers of the freedom to upgrade roles or diversify income, compressing their real choice set just when long-term life commitments usually intensify. Data shows that working in the platform economy beyond five years can restore some sense of stability by crafting individual solutions, such as cultivating repeat clients, finding specialist services as a niche, or running parallel income streams. However, this apparent stability is likely considerably skewed by survivor bias. As Triza and Clara reflected in the interviews:

> "As you build your portfolio and your profile [on platforms], you tend to get long-term clients. Like me, the job I am doing now is full-time. Unless I decide to leave that company, then that would be different. But for me, my job is full-time" (Triza, 2024).

> "There are people that will employ you long term. There are clients that I have worked with since 2018. My very first client, since I joined Upwork, is still my client. And they referred me to, like, four or five more clients" (Clara, 2024).

For many experienced platform workers, permanence arises within the precarious nature of platform work through the strategic buildup of reputation, experience, and occasional luck. As worker profiles and portfolios grow stronger, they tend to shift towards longer-term contracts, intentionally moving beyond fragmented micro-gigs to engagements that resemble the continuity of traditional employment. Yet, this stability remains inherently fragile and depends on individual efforts rather than institutional protections, primarily visible among those with higher risk tolerance who survive long enough to gather social and reputational capital. As Berg et al. (2018) and Wood et al. (2019) argue, platform work offers a form of selective sustainability, rewarding adaptable strategies while excluding those who are unable to manage uncertainty effectively.

This structural gap also highlights a deficit in process freedom, where workers adapt individually because collective mechanisms for career progression or employer accountability are weak or absent. That said, many freelancers who do not secure long-term contracts nevertheless express satisfaction with their growth prospects, suggesting that deeper dynamics allow perceived stability and professional development to coexist with the inherent unpredictability of platform work in Kenya. Sierra contended:

> "As much as it [platform work] does not give me the opportunity [for] career advancement, I can do it with the flexibility to do something on the side" (Sierra, 2024).

Understanding workers, such as Sierra's position, entails recognizing that for many Kenyan workers, most forms of work—whether formal, informal, or platform-based—are experienced as precarious. A single source of employment is no longer seen as a linear or stable pathway to security; instead, livelihood is approached as a form of hustling, where economic security depends not on securing the right job, but on continuously engaging in a portfolio of income-generating formal and informal livelihood activities. Workers engage in many of these activities with the understanding that any opportunity, including platform work, may disappear at any time, and many of these activities do become inaccessible over time.

Much of the current discourse on platform precarity captures the structural insecurity embedded in digital labour markets, where algorithmic allocation, ratings, and global oversupply make both task volume and pay highly volatile (Graham, Hjorth, et al., 2017; Lehdonvirta et al., 2021). Persistent asymmetric information and reputation traps further depress earnings toward the marginal cost of labour (Gray & Siddharth, 2019; Lehdonvirta et al., 2019). While these challenges subtly affect workers' economic security, as Simon's remarks below show, Kenyan platform workers face a more fundamental form of precarity, the transient and unpredictable nature of platform access.

> "I have been working on different platforms, around four or five, and taking their exams to keep adapting. But some platforms have restricted access in our region. For example, RemoTasks shut down access here in February 2024. Verbit and GoTranscript did the same earlier" (Simon, 2024).

Simon identifies the most pressing challenge confronting many platform workers in Kenya. One of the key threats to the sustainability of livelihoods of many platform workers in Kenya and other developing regions is the unstable nature of platform access, where corporate decisions about when to provide or restrict services are driven by algorithmic metrics and business priorities, often made without regard to the sociocultural realities of the Global South workers communities. The regulatory framework underpinning Net Neutrality[8] enables platforms to expand seamlessly and tap into a global labour pool. However, it also permits abrupt and arbitrary geographic exclusions of regions deemed undesirable, often without accountability or consideration for the livelihoods of workers who have invested years building sustainable incomes within these systems.

[8] Net neutrality is the principle that Internet service providers worldwide must treat all data and internet traffic equally, without privileging or blocking particular content, platforms, or users. While this principle ostensibly promotes an open digital commons, its materialization in different regions has profound implications for the asymmetrical power dynamics between the Global North and South. For instance, in an unregulated or weakly regulated environment, Northern platforms, whether new startups or powerful firms, can easily exploit newly connected communities and digital infrastructure to enter new markets smoothly and procure services, such as testing a trial gig labour market in the Global South at minimal cost, with little to no oversight. Conversely, these same platforms can impose sudden, unilateral and arbitrary geographic restrictions, blocking access to entire regions and thereby undermining the livelihoods of workers in the Global South. This type of digital terrain thus becomes a new arena for value extraction through digital infrastructure, whether it be data, labour, or digital participation that flows rapidly northward, echoing traditional colonial patterns of unequal exchange, livelihood disruption, and reinforcing structural dependencies. For more discussion on this, see (Latif, (2022) and Pinto (2018).

When a platform unilaterally and abruptly withdraws from a region, which workers argue is a common practice, they lose more than just a client base; they also lose their hard-earned reputation, metrics, ratings, and experience. Those in the mid experience (3-5 years) group particularly point to these challenges after losing accumulated ratings and experience. Platform membership act like a gatekeeping resource, and its sudden removal shrinks workers' opportunity freedom to zero, regardless of their competence or adaptability. Diversifying across multiple platforms is, therefore, less a strategy of upward mobility than a defensive hedge against exclusionary shocks, underscoring that for many Kenyan platform workers, the fundamental determinant of security is not the nature of precarious gigs but the precarious privilege of remaining inside the platform's boundaries.

3.6.1.4 Continual Reskilling and the Shifting Value of Skills in Platform Work

Skill development also emerges as a moderately positive aspect of platform work in the results of the decent work survey. Average scores on skill improvement (2.65) and productive use of skills (2.58) scales sit above the midpoint, indicating a generally favourable assessment but below a strong endorsement. These results suggest that platform work offers considerable scope for learning and applying skills, a dynamic consistent with the decent work agenda. Overall, the drive for upskilling is amplified by a persistent disconnect between Kenya's formal education system and the skills demanded in the labour market, as suggested by Theo:

> "What the schools are teaching is very different from what companies are looking for. I would say the curriculum is kind of outdated, because most of the things that I do now, I had to learn them myself on YouTube and other sites" (Theo, 2024).

Theo's discontent and adaptive strategies illustrate how a persistent mismatch between institutional curricula and labour-market demand has reduced the signalling power of formal credentials and eroded confidence in education as a pathway to decent work. In response, many workers are turning to self-directed learning and freelancing platforms, where skill requirements are more transparent and learning resources are widely accessible. Interestingly, survey analyses suggest that women report high skill growth in the platform economy while spending comparable hours on skill development. Interviews did not shed light on the underlying drivers, and future work should probe this gender gap using purpose-built interviews or task-level data to determine whether it reflects real learning differences, reporting biases, or task segmentation. However, regardless of gender, many workers suggest that platforms offer an immediate feedback loop, allowing them to

observe job trends and client needs, adjust their training in real-time, and access global markets. Clara highlighted how continuous upskilling thus becomes the vital bridge that converts platform opportunities into tangible economic gains:

> "The competition is very high, so for you to match that, you have to keep on improving your skills when you work online" (Clara, 2024).

A key aspect of skills development discourse should recognize that the value of skills developed through and for platform work differs from the conventional view of deliberately cultivated, transferable assets. In traditional employment settings, skills-building is closely tied to stable job roles and long-term training, ensuring enduring applicability and employability (Soproni, 2023). Instead, they emerge as adaptive competences, a reactive response to ever-changing job trends shaped in real-time by project demands and platform feedback, whose usefulness depends less on strategic career planning by the worker and more on continual responsiveness to shifting client needs. As Clara further pointed out:

> "When you are working with these other people out here, the expectations of those clients are very different. And this client is not short of employees; they can drop you today and, in a few minutes, get a replacement. So, you have to up your game, and that pushes you to learn" (Clara, 2024).

Clara's arguments demonstrate that intense competition renders ongoing skill upgrading indispensable; without it, a platform worker's opportunities shrink rapidly. Sustained employability, therefore, hinges not on initial qualifications alone but on a continual capacity to learn. In the platform economy, skill obsolescence accelerates so swiftly that remaining static becomes synonymous with professional decline. Older workers show lower access to satisfactory platform opportunities. As Triza and Elijah noted:

> "I Just learn new skills and then go to other gigs, because if you stay in the same jobs in the freelancing world, to be honest, it might be a dead end" (Triza, 2024).

> "Even with my experience and top-rated status, getting good-quality, consistent jobs is still a challenge. Before, I used to get more opportunities because whatever was required to do that work, my skills could provide it. I have been upskilled, [but] I have not kept up" (Elijah, 2024).

Skills development is a survival mechanism in the platform labour market defined by rapid technological change and fierce competition. The conversation with Triza and Elijah revealed that the skills functioning in the platform economy are constantly in need of renewal. While continuous learning expands potential functionings, the pressure to reskill is not always a mark of empowerment; it can also be a reflection of unstable opportunity structures where existing skills lose value quickly. The need to remain agile becomes a structural demand, not a voluntary aspiration, placing the burden of adaptability entirely on the individual. Thus, equating platform skill development directly with long-lasting employability risks overstating its benefits and overlooking its context-dependent, transient nature. That said, many Kenyan workers still view continuous upskilling positively, despite the heavy self-investment it demands. For those who never had a clear advancement pathway in the conventional labour market, the near-instant feedback loop between newly acquired skills and additional paid work feels genuinely empowering. Clara explained:

> " [In conventional jobs] you are paid to do a certain thing; you sit there and do it. You don't have time to go online and Google and learn. Other times, when you get home, you are too tired to even look at your laptop" (Clara, 2024).

The perception of workers like Clara points out how work with fewer self-development and growth opportunities can structurally and psychologically distance workers from ongoing skill development. Narrow job scopes and physically or mentally taxing routines leave little time or energy for acquiring new competencies, gradually normalizing skill stagnation and making professional growth appear unattainable. By contrast, the temporal flexibility offered by platform work could promote habits of self-directed learning, reinforcing workers' sense of agency and future orientation. Consequently, many freelancers value the platform economy not only for the opportunity access but also for its continual upskilling outcomes, where avenues for personal and economic advancement kindle hope for a better future. However, the challenge stems not only from the short-lived nature of these skills but also from their limited transferability, which reinforces the thesis of platform ecosystem entrenchment. Jessica Highlighted:

> "They are transferable to other jobs online. Locally, they might not" (Jessica, 2024).

Skills gained through online work are often context-specific and optimized for global digital markets, making them less valuable or unrecognized in local job markets. This mismatch reinforces a

cycle of dependency on platforms, where workers must remain within the digital ecosystem to monetize their expertise, limiting their ability to transition into more stable or locally integrated forms of employment. However, some observation also signals a gradual reconfiguration of the skill conversion landscape. The interviews with Mable and Triza reflected that as remote work has gained global traction, there is an emerging convergence between platform and local labour markets, where prior exclusions are beginning to erode:

> "Now, there are even recruiters who want to find you on LinkedIn, and they will ask you to work, so that's how I know, after COVID, is when the perspective among employers in Kenya changed. But before that, the skills could not be transferred into the job market" (Triza, 2024).

> "They [local employers] see the skills as valuable, but I don't think most Kenyan companies are willing to pay for those skills" (Mable, 2024).

There has been a historical disconnect where online work, despite building valuable competencies, was largely invisible or devalued within local labour markets. This disconnect reinforces a structural dependency on digital platforms, as workers feel they have fewer pathways to translate their experience into stable, locally recognized employment. Platform work could fast-track skill acquisition. Kenya's booming offshore and BPO industry shows considerable compatibility with many skills that platform workers cultivate to pursue different gigs (Melia, 2020). However, the perspective of Triza and Mable, among several other workers, clearly suggests that the transferability of skills may remain impractical if local labour markets continue to significantly undervalue those hard-earned skills.

3.6.2 Temporal Autonomy & Work–Life Quality

Kenyan workers' perspective on the nature of temporal autonomy in the platform economy and its relationship with life quality shows that when formal protections and social support mechanisms are limited, the ability to exert control over time becomes a crucial factor in sustaining livelihoods, maintaining caregiving responsibilities, and investing in skill development, all of which extend the developmental significance of temporal autonomy beyond mere schedule control. Therefore, schedule autonomy and the ability to combine work, family, and personal life represent interdependent dimensions of decent work in the platform economy that underpin the broader capability for work. In

the context of Kenyan platform work, these elements of autonomy function less as discrete benefits and more as complementary enablers, where temporal flexibility expands workers' choice sets. Subsequently, work–life satisfaction signals how effectively that flexibility is converted into valued functioning.

3.6.2.1 The value of Temporal Autonomy is rooted in the Livelihood Sustainability Strategy

Digital labour platforms often position themselves as emancipatory, liberating workers from fixed nine-to-five schedules and promising autonomy over when, where, and how tasks are executed. Among Kenyan platform workers, the mean schedule-autonomy score of 2.18 indicates a noticeable sense of temporal autonomy but falls short of full control. Group-level differences for temporal autonomy were minimal in the results. However, data showed a trend where those who experience greater temporal autonomy are more likely to spend more hours on skill development, indicating a reinforcing cycle in which skill-building expands opportunity freedom, ultimately resulting in greater control and autonomy over work choices and schedules.

By contrast, satisfaction with how the platform works supports a more balanced work, family, and personal life, averaging 2.93, suggesting that workers experience platform flexibility more in terms of life integration than pure temporal sovereignty. These patterns underscore that temporal autonomy is a relative gain where workers assess flexibility by its practical impact on their broader life circumstances, rather than as absolute freedom. Triza noted:

> "As much as I wanted to work in a traditional office job, I usually have other things I am doing on the side, at that time I was freelancing and also baking cakes for sale. So, I wanted the flexibility of being able to deliver cakes to clients, bake, and also go to school, because I am always keen on learning new skills online" (Triza, 2024).

My conversation with Triza and many other workers suggests that Kenyan freelancers view temporal flexibility as a cornerstone of livelihood sustainability. Since freelancing replaces substantial commute time in Nairobi's traffic and prolonged fixed work schedules with a more flexible work schedule, many workers feel motivated to reallocate idle hours to other productive activities, forming a livelihood strategy that meets their economic needs. As Janet's response below shows, in many cases, it is not merely the temporal flexibility that is attractive, but also the reduction in very high overhead costs associated with working in the greater Nairobi metropolitan region.

> "The call center is on Mombasa Road, the other side of town. So, if you're going to work a night shift, you have to, you go to the office at six pm and you leave at six in the morning". (Janet, 2024)

Crucially, it is the perceived reduction in time poverty that broadens platform workers' choice set, giving them the freedom to invest in multiple forms of productive socioeconomic activities, without being locked into a rigid employment routine with long hours and lengthy commutes. The resulting sense of hope for a better future stems from this widened horizon of feasible actions, illustrating how a reasonable schedule and control over time underpin broader capabilities beyond the capability for work, particularly in contexts where hustle culture and informal employment are prevalent. Many workers echoed this mindset, calling for a shift among labour researchers to recognize how livelihood success is conceptualized by Kenyan and many other workers in development regions, i.e., not as linear progression within one job, but as the freedom to navigate across activities that collectively sustain wellbeing, demonstrating how temporal autonomy can be a foundation for adaptive and sustainable livelihoods, particularly in regions where environmental conversion factors to sustain capability for work remain weak.

3.6.2.2 Temporal Autonomy as a Multiplier of Valued Capabilities in Resource-Constrained Contexts

Besides enabling additional economic prospects, the value of temporal autonomy also acts as a capability multiplier in the Kenyan sociocultural environment, where social support mechanisms, such as childcare and maternity leave through formal institutions, remain patchy or inaccessible. Control over one's hours supplies the conversion factors that let workers translate digital gigs into concrete functionings and activities that workers have reasons to value. Rebecca explained:

> "I work according to my schedule. I keep my friendships; family, for me, is very important. I do not miss out on family events. Even if it means I am taking time out, when it comes to my daughter's events, I have attended all of them" (Rebecca, 2024).

Not all functionings or capabilities hold equal value in every context (Sen, 1993). While platform work may constrain some capabilities, temporal autonomy raises Kenyan workers' genuine freedom as they do not have to trade one functioning for another, e.g., being a present parent and being a paid professional (Nussbaum, 2005). Time and income are often competing and scarce resources in almost all regions. However, in resource-scarce environments, this competition is

particularly evident, meaning workers must frequently choose between earning and investing in other central functionings, such as caregiving, learning, rest, or civic participation. When social support systems such as subsidized childcare, public transport, or health coverage are weak or absent, the opportunity cost of time becomes higher, and the freedom to pursue more subjectively meaningful or life-enriching activities narrows significantly (Bonvin, 2012). In this context, even a minor increase in temporal agency and autonomy becomes developmentally significant, as it allows workers to achieve these higher-order capabilities without sacrificing income[9].

3.6.2.3 The Conditional Nature of Work–Life Balance in Platform Work

Although there is a broadly positive assessment of work–life balance and personal fulfillment among research participants, this apparent flexibility masks important group-level differences that reveal disparities in how temporal autonomy is experienced and converted. Two groups particularly stand out: those who perform significant amounts of unpaid work, and those with greater experience in the platform economy.

The quantitative findings from this study reveal a clear trend. Satisfaction with work–life balance and fulfillment are significantly eroded by unpaid work. Freelancers who log the highest number of unpaid hours report the lowest levels of work–life satisfaction, as unpaid labour diminishes not only employment quality but also the time autonomy that platform work supposedly provides. Moreover, in the platform economy, only with profile maturity and experience does temporal autonomy begin to translate into real agency and the ability to say no, to pause, and to prioritize other valued aspects of life without penalty. As Janet delightfully reflected:

> "I am able to travel! All I need is just a laptop, my SIM card" (Janet, 2024).

Workers with over five years of platform experience report the highest satisfaction with how they manage work alongside other life roles, while those in the early and mid-career stages remain largely neutral. This earned entitlement is, in part, a dividend of profile strength as it enables experienced workers to curate client lists, reject low-yield tasks, and structure their schedules more intentionally to pursue more fulfilling life choices.

[9] Please see the chapter on meaningful work for a more detailed discussion on this.

3.6.3 Equity, Inclusion, and Social Protection in the Platform Economy

Experienced Kenyan platform workers describe a working environment that feels polite, yet the structures that would turn that civility into lasting security remain weak. Across the three pillars of this domain, fair treatment in daily exchanges, protection against shocks, and the quality of working life, workers enjoy several basic functionings but struggle to transform them into a more reliable and wider choice set. The capability for work with dignity is, therefore, partially realized, but the capability to remain secure and to steer one's future is constrained by systematic gaps.

3.6.3.1 Interpersonal Respect and Safety within an Ecosystem of Structural Discrimination

The mean score for freedom from client or peer harassment stands very high at 3.68 on a scale of 0 to 4. The perception of physical and mental safety also remains high at 3.07. Most participants, regardless of gender or tenure, report that interactions with clients and colleagues are respectful and non-judgmental, and work provides a sense of physical and mental safety. Clara explained:

> " You don't have to deal with office politics, the backbiting. These things don't happen online. You have that peace of mind" (Clara, 2024).

The remote nature of work could offer a form of interpersonal insulation from the overt hostilities often experienced in formal workplaces, particularly those shaped by rigid hierarchies, deep-rooted gender norms, and institutionalized gatekeeping (D'Cruz & Noronha, 2016; Malik et al., 2017). This negative freedom, as pointed out by Clara, expands the right not to face harassment while earning a living. Objectively, a decent work condition is met to a satisfactory extent. However, interviews also suggest that this day-to-day environment of non-discrimination and respect is not always granted, but rather self-constructed. First, as Mercy pointed out in the interview, experienced platform workers are well aware of the prejudice and discrimination in the platform work economy:

> "Obviously, they discriminate by the graphical regions, that people who will not trust that someone in a third world country has the skills to do the job. They will ask for a sample and then once you submit the sample they come back and say, oh, I am very surprised you are able to do this. I did not think that people from your country could do this" (Mercy, 2024).

In the globalized platform economy, geographic prejudice and exclusionary practices persist and flourish unchecked. Kenyan workers who have been in the industry for a while are acutely aware

that many clients harbour biases toward African workers and often lack trust in their skills. Trust-building is precisely one of the core functions that digital labour platforms are designed to perform. In a multisided market structure, platforms must reduce the uncertainty between unknown clients and service providers, acting as intermediaries that create conditions of calculable trust through reputational systems, escrow payments, standardized communication tools, and algorithmic reputation scores (Kenney & Zysman, 2016).

However, this promise is far from being realized in practice, particularly when it comes to the asymmetries between the Global South and the Global North, as well as between different regions within the Global South. The platforms do not operate in a vacuum but are embedded within and reflect the racialized and geographically stratified global economy. In such a context, the supposed neutrality of platforms often fails to counterbalance inequalities and deeply held stereotypes and may even amplify them (Srnicek, 2017). Due to these biases, having Kenya as a location or even charging competitive rates can be interpreted by clients as signals of lower quality or reliability, despite the presence of strong ratings, verified histories, and demonstrable skills. Elijah revealed:

> "If I change my profile, I retain the same name, everything same, same skillset, same quality, same ratings, but I change my location to the US, you definitely see a better quality of jobs appear" (Elijah, 2024).

What is supposedly a merit-based system risks becoming a thin veil over structurally unequal playing fields, where platforms may actively reinforce the very gaps they claim to close. When geographic discrimination undermines workers' ability to convert their skills and experience into valued employment, their capability for work is constrained not by a lack of competence but by the failure of institutional and social conversion factors. In such an environment, platforms risk becoming conduits for the reproduction of global hierarchies in digital form.

One might ask why, then, many platform workers report experiencing little to no discrimination or harassment in their day-to-day work. In the platform inequality and algorithmic bias discourse, workers are often portrayed as passive victims with limited or no agency, obscuring the everyday strategies they use to navigate, resist, and adapt to precarious conditions (Gray & Siddharth, 2019; Standing, 2017). However, the reality for Kenyan workers is that they are not passive and

helpless when faced with these structural constraints. Mercy explained how workers have developed their own strategies to navigate and minimize exposure to negative encounters:

> "I do not waste time on clients who, I can tell from their work history, are not willing to work with people outside of their own [country]" (Mercy, 2024).

Mercy highlighted how individual tactics, ranging from selective client engagement to self-censorship in communication, serve to construct a curated experience in which the presence of discrimination is muted, deferred, or rendered less tangible. However, these practices are not indicative of a bias-free environment, but rather of adaptive responses to a context where exclusion and mistrust are anticipated, internalized, and proactively managed. What maintains a semblance of civility and politeness in the work environment is that such clients typically avoid hiring Kenyan freelancers, and Kenyan workers do not count on those jobs altogether.

What is evident in the empirical nature of platform labour is that within the planetary digital labour market, multiple segmented markets persist, divided along racial, geographic, and other structural biases. This segmentation is not only the result of algorithmic sorting or platform design but is often actively reinforced by employers themselves. My examination of numerous job postings across different platforms and interviews revealed a clear trend: some clients explicitly exclude workers based on region, ethnicity, age, or nationality, often by stating preferences for native English speakers, specifying no applicants from certain regions, or requesting workers from particular time zones or cultural backgrounds. Such exclusionary practices reproduce and legitimize offline hierarchies within the digital labour economy, embedding structural discrimination into the everyday functioning of global online work.

As a result, only those with fewer prejudices engage with workers, creating a self-selecting dynamic that fosters a practical experience of non-discrimination and mutual respect among. This form of negative freedom, freedom from explicit mistreatment, emerges not from structural inclusion but from the quiet absence of prejudiced clients. The burden of overcoming prejudice, however, is shifted onto the workers themselves. Workers express very low confidence that platform rules will protect them when conflicts arise, which is reflected in a strikingly low score of 1.12 for perceived policy protection. This institutional imbalance not only erodes trust but also reinforces a system where access does not equate to meaningful participation or protection. Clara noted:

> "If you have an issue with the client and it goes to arbitration, 90% of the time Upwork will side with the client because the client is one who is bringing money to the platform" (Clara, 2024).

The contrast between superficial civility and the lack of enforceable protections in the platform economy is a critical deficiency in process freedom, where workers can access platform ecosystems but have limited recourse or influence when facing disputes or discriminatory treatment. The gap pointed out by Clara also underscores the asymmetry of accountability in platform governance, where platforms can swiftly penalize workers based on client feedback or opaque algorithmic assessments. However, workers have limited channels to contest decisions, appeal sanctions, or report discrimination without risking further marginalization.

3.6.3.2 Social Conversion Barriers to the Capability for Work

The issue of social inclusion for Kenyan platform workers extends beyond the structural challenges embedded within the platform economy and includes a local dimension. Workers must also contend with societal expectations at the local level, which pose additional barriers, particularly for women, when attempting to cultivate and sustain a career in the platform economy. Triza and Mable highlighted these struggles:

> "I was really, really judged here. You are working online? What are you doing in the house the whole day? You need to go out there and do something" (Triza, 2024).

> "When I first told my parents I am working [remotely], they actually discouraged me because they did not have so much information about the remote opportunities. My parents actually believe in the nine-to-five jobs or working for the government, which makes it [seem like] an ideal job compared to the remote work" (Mable, 2024).

Norms and community perceptions shape the recognition and legitimacy of work (Berg & Rani, 2021). In the case of Kenyan platform workers, these barriers still exist to a significant extent, as pointed out by Triza and Mable. The social devaluation of platform labour, particularly in contexts where physical presence and conventional employment are viewed as markers of productivity and responsibility, undermines not only external validation but also the worker's ability to convert platform work into social standing and even familial support. The capability for work is not only about earning an income or having autonomy, but also about the genuine freedom to achieve valued

ways of being and doing, including self-respect and dignity. Misrecognition, being devalued or rendered invisible in public life, can be just as capability-limiting as economic deprivation (Sen, 2001).

The challenges associated with the social acceptability and perceived legitimacy of platform work are evident in the experiences of Kenyan workers, a trend that is not unique to Kenya but also reflected in empirical research from countries such as Pakistan and Nigeria (Idowu & Elbanna, 2019; Malik, Fareesa et al., 2018). These shared experience underscores a broader tension in many Global South contexts, where prevailing social norms and cultural expectations continue to frame platform work as less legitimate or respectable than traditional employment. Whether these normative barriers ultimately serve a protective function by discouraging overdependence on precarious digital labour or simply reinforce exclusion and stigma remains to be seen as the long-term implications of platform-based livelihoods unfold over time.

3.6.3.3 Building Social Protection Without Institutional Support

The issue of social legitimacy surrounding platform work in Kenya, and in many other developing regions, is not solely about social standing or identity. In fact, many Kenyan workers also report that freelancing provides them with a desired sense of autonomy and a positive social identity (the next chapter provides more detail on this). However, the deeper challenge lies in how the lack of social legitimacy results in institutional misrecognition of platform work as a legitimate and viable career path. The novelty of these work arrangements means that local systems, from banking to social protection in Kenya, are still ill-equipped to accommodate workers without formal employers or traditional contracts. As one participant explained:

> "Getting access to loans and such kind of financial help, it has been a challenge, because now you do not have an employer, so they do not have any records that can assure [them] that you are going to pay back that amount" (Nora, 2024).

The lack of formal acknowledgment by local institutions, highlighted by Nora above, limits Kenyan workers' ability to build long-term security. This disconnect reflects how conversion factors, such as institutional readiness and recognition, shape the extent to which individuals can translate their work into broader capabilities, including economic resilience, future planning, and social legitimacy. The informal status of digital labour not only restricts immediate livelihood gains but also

weakens longer-term pathways to economic resilience and social inclusion. Even when workers have the necessary skills and income, it is ultimately the local context and conversion factors that help transform these functionings into capabilities.

3.6.3.4 Reframing Job Quality in the Absence of Employment Benefits

There is well-documented evidence that the precarious nature of short-term work, particularly gig work through platforms, lacks social benefits and safety nets such as healthcare, retirement support, and other essential provisions, including vacation pay, paid sick leave, and maternity leave (Ayentimi et al., 2022; Bertolini et al., 2021; Graham et al., 2019; Heeks, 2017a; Mokofe, 2022). These are critical limitations and represent key deficits in decent work within the platform economy. From a development perspective, the case of Kenyan platform workers presents a compelling challenge to conventional indicators of job quality. Standard labour frameworks often treat employment benefits, such as health insurance, retirement contributions, or paid leave, as central markers of decent work (ILO, 2008). However, for many freelancers, these benefits carry limited meaning if not accompanied by an adequate income. Mable commented:

> "If I have remote work that pays me a good amount of money, I will consider saving some money and putting it in my pension or savings account, rather than having an on-site job that pays very little and gives me the pension benefits, which are [often] uncertain" (Mable, 2024).

From Mable's perspective, benefits without a living wage offer little security. It is not that workers do not feel left out of these benefit schemes. The discussion with workers showed that most workers do interpret the absence of employment benefits as a key deficit in the platform economy; however, as Triza's comments below show, many workers emphasize the importance of immediate financial control and prefer higher earnings that they can manage independently, whether to pay out-of-pocket for healthcare, save for retirement, or buffer against emergencies.

> "What I learned is, when you are getting a job or a client, negotiate a higher pay so you can cover some of those benefits for yourself, like health insurance" (Triza, 2024).

The sentiment of Triza revealed how the individualization of risk shifts responsibility from employers (or the state) to the worker, making income adequacy and individual bargaining power prerequisites for accessing basic safeguards. Many Kenyan workers are conditioned to this

individualization. While this can enhance agency for those with higher negotiation power, it also deepens inequality, as those with less leverage may be unable to secure compensation that is sufficiently adequate to support other essential capabilities. Nevertheless, Many Kenyan platform workers see the role of employment benefits as negotiable entitlements rather than fixed institutional provisions or must-haves in a job. This sentiment is also reflected in the survey results, where platform workers perceive that their access to healthcare coverage could be higher in traditional jobs; however, this perception has its limits. The mean score of 2.46 suggests only a modest perceived advantage[10], indicating that traditional employment options available to many are not viewed as offering significantly better healthcare, as many local jobs also do not offer such benefits.

The relationship between health benefits and access to adequate healthcare is quite complex in Kenya and highly dependent on the quality of care through health benefits plans. Many Kenyan platform workers report preferring private medical insurance over the National Health Insurance Fund (NHIF), the plan that is made available to workers through their employers, citing limited access to private clinics, delayed services, and insufficient coverage under the public scheme. Workers felt that this plan falls short of their needs, and those with access to such a benefits plan face persistently high out-of-pocket costs. For instance, the NHIF plan only covers about 30 % of non-communicable disease expenses, forcing households to pay over 70 % themselves (Oyando et al., 2023). This institutional inadequacy discourages reliance on public health plans and conditions workers to have greater personal control over their long-term security and health resilience, often reinforcing a preference for flexible, self-managed alternatives over state-based protection. The same applies to other safety nets, where the value of earnings often outweighs the dim possibility of alternative employment benefits. Clara noted:

> “Money answers everything. Last year was my best year. I made enough money to buy a plot without taking a loan. If I was still in an office job, I wouldn’t have had that freedom. I wouldn’t have been able to pay for that plot outright. Instead, I’d have been forced to go

[10] Participants rated perceived differences in healthcare coverage between platform and traditional jobs on a 0–4 scale, where 0 indicates "much worse" and 4 indicates "much better" in traditional jobs. A score of 2 represents "no change" or "no difference." So, a mean of 2.46 reflects only a slight positive deviation from neutrality.

> to my SACCO[11], take a loan, and still be repaying it right now"
> (Clara, 2024).

Clara's perspective reveals a simple yet easily overlooked means-to-an-end logic that reframes the value of work benefits, not as intrinsically positive, but as conditional functionings that are only valuable when they enhance genuine freedoms. The context of Kenyan workers shows that what matters most is immediate and sufficient earnings, and even more critically, the capacity to build savings as a buffer against predictable and unforeseen life risks. Many platform workers demonstrate this logic in practice as the survey results show that, on average, freelancers save about one-quarter of their platform income. However, significant disparities persist. The data also reveals that it is not simply the number of years spent on platforms that shapes saving behaviour, but rather a combination of age, mindset, and income regularity. Older workers and those who invest consistently in skill development tend to occupy higher-paying or more stable segments of the platform economy. As a result, they are more successful in converting a volatile cash flow into the functioning of economic security and a financial buffer.

3.6.4 Platforms and Workers' Voice and Agency

Unlike traditional employment structures, the platform economy is marked by spatial fragmentation, weak organizational cohesion, and algorithmic control, features that undermine workers' ability to build a collective voice (Wood et al., 2021). The very nature of the platform labour market results in constant competition among geographically dispersed workers, many of whom may never interact with one another, making solidarity and collective action a challenge (Hertwig et al., 2024; Morales-Muñoz & Roca, 2022). Solidarity often collapses under competitive pressure, and income loss deters any form of sustained strikes (Schou & Bucher, 2023). In the case of Kenyan platform workers, a key observation in this research is that workers' voice, solidarity, and collective action tend to manifest in different domains and show limited convergence with one another.

[11] SACCOs (Savings and Credit Cooperative Organizations) are quite popular and mainstream member-owned and controlled financial institutions in Kenya and many other parts of Africa. Members pool their savings, which then form the capital base from which loans are provided to SACCO members at affordable interest rates. Beyond lending, many SACCOs invest in sector-specific ventures, such as dairy and transport, serving both communal and economic objectives. During my work in Kenya with various SACCOs, I did not encounter any that organized freelancers into cooperatives or established dedicated, member-owned platforms for freelance workers. Given the rapid expansion of digital gig work, exploring the potential for freelance-oriented SACCOs represents a compelling avenue for future research.

3.6.4.1 Individual Cognitive Resources as the Foundation for Workers' Voice

Worker solidarity and collective action are traditionally linked to greater bargaining power and the ability to collectively advocate for improved working conditions. However, in the platform economy, the highly individualized and competitive nature of work fosters a climate in which the capability for voice is instead contingent on one's individual leverage, such as reputation scores, specialized skills, or access to high-value clients. As earlier sections have shown, most workers rely on individualized strategies to negotiate better terms, often in isolation, thereby limiting the emergence of shared demands or coordinated action.

Because more favourable work terms are often accessible to highly rated workers, their incentive to engage in collective action is diminished. Collectively mobilization requires not only time but also significant cognitive resources, including emotional investment, political awareness, and coordination efforts (Bonvin, 2012; Heckscher & Carré, 2006). Unsurprisingly, the survey results showed that while workers' perception towards opportunities for collective action is extremely low (0.16 on a scale of 0 to 4), participation in any form of collective action is also very low (mean score is 0.21 on a scale of 0 to 4).

Despite the overall low levels of opportunities and participation in collective action, the data reveal some nuanced patterns that could be helpful in understanding workers' perceptions towards the notion of collective action in the platform work economy. Data suggests that a higher dependence on platform work to make ends meet may condition workers into a more individualistic orientation, gradually diminishing the perceived feasibility or value of organizing efforts. Data also shows that workers with less than five years of platform experience are less likely to participate, likely because the cognitive and emotional demands of building a stronger profile constrain their capacity for collective engagement. That said, due to the limited explanatory power of these statistical models, these patterns should be treated as preliminary insights, requiring validation through further research with a larger and more diverse sample. On this subject, the qualitative interviews revealed that for many experienced workers, it is more rational to allocate cognitive resources toward individual strategies, such as optimizing profiles, cultivating client relationships, skills development, or selectively bidding for projects, where the returns are more immediate and tangible. Marvin reflected:

> "[On the subject of unionization and collective action] it is something that I am not looking for" (Marvin, 2024).

Like Marvin, many platform workers are indifferent to unionization or any other form of collective political action. This disconnect revealed how the platform capitalism fosters a deeply individualized political economy, where success is framed as an individual and personal achievement rather than a collective goal. These findings are in line with previous research showing that the structure of the platform ecosystem thus encourages instrumental rationality among workers over political solidarity among these platform workers, making worker organizing not only difficult but also, for many, seemingly unnecessary (Gandini, 2019). Resultantly, the capability for voice becomes unevenly distributed, with more successful workers more likely to have and exercise voice through market advantage than through political engagement. Those working in gigs with a higher proportion of gig work become more withdrawn from all institutional structures, including labour organizations.

3.6.4.2 Local Solidarity Networks are Less About Discontentment and More About Support

Critical labour research has long associated worker solidarity with a shared sense of discontent toward existing labour conditions, resulting in what Fantasia (1989) called the culture of solidarity, which emerges when workers collectively identify structural injustice and mobilize in response. In the platform economy, however, the individualized pursuit of bargaining power often displaces this shared grievance. Existing research indicates that solidarity is increasingly fractured along occupational lines in platform work, where differences in task complexity, income potential, and client exposure undermine the formation of a unified worker identity (Graham et al., 2019; Lehdonvirta et al., 2019). A collective identity as freelancers or platform workers[12] may have symbolic resonance, but in practice, it often fails to generate the cohesion necessary for sustained political action.

The Kenyan platform work landscape reveals that, despite the individualized nature of bargaining power, solidarity networks exist and thrive in Kenya. However, their nature remains apolitical and less focused on any form of collective action, as these solidarity networks[13] are not

[12] A note to fellow platform researchers: Platform worker is a distinctly academic term, one with little resonance among most workers themselves. Many platform-based workers do not identify with being a platform worker or even traditional occupational titles, such as transcriptionist, web developer, or virtual assistant. Instead, they overwhelmingly choose to call themselves freelancers, finding in that label a stronger sense of identity. Further discussion on this phenomenon follows in the next chapter.

[13] Here, it is useful to recognize that the concept of solidarity has two distinct yet overlapping meanings. One emphasizes political collective action, while the other is grounded in interpersonal support and moral

based on discontentment or rage as conceptualized in some research studies, e.g., (Wood et al., 2021). Instead, as reflected in Theo's comments below, Kenyan freelancers are often united not by grievance but by shared aspirations for opportunity, skills enhancement, and survival within a volatile labour market:

> "I think a few organizations are coming up. I am a member of one community; we are trying to connect as freelancers and share skills. These communities are growing into organizations where we are now trying to teach skills to other youth so that they can also join these online opportunities" (Theo, 2024).

While some workers emphasized the individualistic nature of the platform work journey, many Kenyan freelancers like Theo also expressed how they engage with both digital and physical networks to connect with broader worker communities in Kenya, share opportunities, and navigate challenges collectively. The key difference is that such communities are less concerned with challenging platform power or advocating for structural change, and more focused on facilitating entry into the digital economy, transferring tacit knowledge, and enabling skill acquisition. Janet and Theo's comments below demonstrated that, rather than being driven by collective discontent or political identification, they are motivated by a logic of cooperation rooted in self-betterment, peer encouragement, and incremental improvement of their livelihoods:

> "Like here, we have TikTok communities in Kenya of remote workers. They always update us on what kind of work you can look for" (Janet, 2024).
>
> "What motivates me to talk about freelancing [on social media]... I want to maybe spread the information so that people can learn about

camaraderie. Solidarity entered political discourse as a way to articulate mutual social responsibility. For instance, Émile Durkheim, in The Division of Labour in Society, conceptualized solidarity as a form of social cohesion essential to maintaining societal order. This meaning of solidarity emphasizes its moral and integrative dimensions. In contrast, Marxist and critical labour traditions redefined solidarity as a political force, rooted in class struggle and collective agency. Richard Fantasia (1989), for instance, argued that solidarity does not arise automatically from shared material conditions but must be cultivated through cultures of resistance, often in opposition to managerial control. In the context of precarious and platform work, this distinction remains especially relevant, as expressions of interpersonal support do not always translate into collective political action.

> these platforms. I feel like people have skills in this country, but opportunities for work are limited" (Theo).

My conversations with workers showed that the lived experience of platform workers in Kenya is often less atomized than one might assume, due to their embeddedness in digitally mediated peer communities, which largely explain why workers perceive a noticeable freedom to express their views about the complexities of their platform livelihoods (2.2). The popularity of social media-based local communities among Kenyan platform workers and many other developing regions reflects a growing infrastructure of informal solidarity and peer-based support that counteracts the isolating tendencies of individualized digital labour and functions as a substitute for institutional support. These networked spaces, utilizing platforms such as TikTok, WhatsApp, and Telegram groups, provide dynamic forums for knowledge exchange, emotional validation, and real-time guidance. Jasper organizes in-person networking and support events for fellow freelancers. He explained:

> “I most of the time organize events for these freelancers. Just tell them to come. It's important for you to network with people, talk to them, tell them what you do, where you work, engage in fruitful conversations.” (Jasper, 2024).

In some cases, digital freelancer communities are evolving beyond virtual interactions into organized, in-person gatherings and tangible spaces of connection and mutual support, providing much-needed social infrastructure to an evolving labour market. These gatherings, such as the ones organized by Jasper, serve as grassroots alternatives to institutionalized worker support systems, helping to reconstitute a sense of community within a fragmented labour landscape. This solidarity operates in what could also be termed as a pre-political register, shaped not by ideological confrontation but by the pragmatic need to make work viable in an uncertain labour market. While not organized into collective action, these informal associations could constitute early-stage cohesion, laying the social groundwork for potential future mobilization.

3.6.4.3 From Informal Solidarity to Collective Action

Parallel to this grassroots level local affective solidarity in Kenya, aspirations towards collective action have long existed within the Kenyan platform ecosystem. There is optimism among some Kenyan freelancers that worker-led bodies, anchored in transparent governance and industry expertise, could mediate between freelancers and the state, platforms, and negotiate social

protections, thereby enlarging the capability for voice beyond atomized bargaining. As one participant noted:

> "If they put the right people and stick to their mandate, yes, I see that as a very powerful thing [but] most of them are run by vested interests" (Elijah, 2024).

During the interview, Elijah's account of past and present efforts to organize freelancers in Kenya illustrated both the aspirational and the fractured trajectories of Kenyan worker organizing in the digital sector. As a founding member of an early online work professional association, his reflections made clear that while the foundational vision, to create a collective voice capable of influencing policy and securing rights, is often grounded in lived experience, the operational realities are often fraught where internal fragmentation and low interest among active platform workers undermine the legitimacy and effectiveness of such associations, stalling their ability to function as mediating institutions between freelancers and powerful actors like platforms or the state. Elijah revealed some of these challenges:

> "We were able to register it, but unfortunately, we were unable to really meet the objectives, which was to bring online workers together. We were not able to gather speed." (2024, Elijah).

As Elijah noted, this disillusionment is compounded by low levels of worker engagement, which Elijah attributed to both structural and motivational factors. It should be noted that the survey results showed a clear trend that most workers do not perceive labour organizations as helpful (0.31). This discontentment shows that the functionings for voice (e.g., legal registration, a declared agenda) do not guarantee capability for voice. Without internal cohesion and member engagement, organizations struggle to convert their formal status into effective political power and translating these functionings into sustained political mobilization remains a formidable challenge. The result is that collective action and unity among workers continue to operate in different spaces.

3.6.4.4 The Avenues of Collective Action Beyond Platforms

While most forms of solidarity among Kenyan platform workers remain informal and apolitical, the question of what collective action can realistically aim to achieve is both timely and necessary. The Kenyan context presents a distinctive set of challenges characterized by institutional voids, legal ambiguity, and the marginal visibility of digital labour within corporate social responsibility regimes.

Although existing research has rightly emphasized the need for reforms at the platform level, such as algorithmic accountability and fairer contract terms (Fairwork, 2025; Hertwig et al., 2024; Stylogiannis, 2023), workers themselves point to two additional domains that require urgent attention. These include the social legitimacy of platform work within local institutional and public discourse, as well as the social responsibility of platform clients, who hold disproportionate power yet largely remain unaccountable actors in shaping workers' experiences.

Many Kenyan platform workers attribute the lack of social legitimacy in platform work to their limited access to institutional services, most notably in the domains of finance and healthcare. Because platform workers operate outside conventional employment contracts, they are often rendered invisible to systems designed around formal wage labour, such as banking, insurance, and credit access. Jane and Elijah remarked:

> "You are doing okay as a freelancer, maybe earning better than someone employed, but they [banks] still treat you like a risk because you cannot show them a contract" (Jane, 2024).

> "We were looking for ways where we can partner with insurance companies that offer medical cover that fits into our category of workers. If we can get a good number of freelancers, like say a few thousand, we can talk to insurance companies, and they will listen. They will make something that works for us" (Elijah, 2024).

As Janet and Elijah reveal, workers may possess the economic agency to earn, but they lack the institutional pathways to convert those functionings into long-term security. This institutional invisibility in Kenya not only undermines financial security but also restricts long-term well-being, making freelancers more vulnerable to market shocks. One key objective of collective action, then, must be to secure legal and institutional recognition of platform labour at the local level, enabling inclusion in social protection tools that remain tethered to standard employment models.

The second critical site of action is the platform clients, who often operate as invisible but powerful actors, shape the labour process through task design, payment structures, and recruitment preferences. Kenyan freelancers repeatedly identify clients, the end-users who design tasks, set prices, and approve payments, as the decisive yet least accountable actors in the platform employment chain. Survey results corroborate this perception, where the index measuring client attention to labour

concerns averages just 1.62, signifying that most clients do not feel obliged to uphold decent labour standards. Triza pointed out a key barrier:

> "Most of them [clients] are not keen on trying to improve some of these things you are talking about, like better work environments or better pay" (Triza, 2024).

This key disconnect pointed out by Triza matters because the capability for voice hinges on the conditions of enforceable entitlements and stakeholders willing to negotiate (Bonvin, 2012). Platforms partly supply the first, in the form of escrow payments, formal contracts, and dispute dashboards, but do not have adequate mechanisms or incentives to compel clients to or improve those terms. Another worker further echo the same sentiment. As Sierra mentioned:

> "Right now, everything is left to the discretion of your employer" (Sierra, 2024).

A key barrier to the workers' rights agenda is that corporate clients often operate as invisible yet powerful actors in the platform economy. This invisibility is not incidental but structurally embedded through deliberate platform design choices that prioritize client anonymity and ease of access over transparency or accountability (Lehdonvirta, 2018; Wood, Lehdonvirta, et al., 2018). On many platforms that Kenyan workers typically use, workers have no access to verifiable identity, organizational affiliation, or grievance channels (Berg, 2016). This results in an environment where clients are shielded from social responsibility towards platform workers by jurisdictional gaps (De Stefano, 2015). Nora noted:

> "I would prefer that the governments of the [countries] of the companies that we work with view this thing in a better way [and] consider some benefits, such as the healthcare coverage benefit" (Nora, 2024).

This client identity invisibility obstructs worker voice by making work invisible and rendering those who shape work conditions effectively unaccountable. Crucially, this invisibility also represents a blind spot in the broader push towards corporate social sustainability disclosures, which increasingly emphasize decent work quality, yet often, platform-mediated labour seems to be excluded from scrutiny. This gap indicates that by outsourcing tasks through digital intermediation, companies evade reputational accountability for their labour practices, thereby weakening the broader goal of embedding fairness and social responsibility into global production systems.

3.7 Conclusions

This paper set out to provide a contextualized and worker-centred analysis of decent work in the digital platform economy, situating the Kenyan freelance experience within both normative labour standards and capabilities-centred development theory. The findings underscored that while some Decent Work Substantive Elements, such as access to work, income adequacy, and job stability, remain conceptually relevant, their empirical expressions are fragmented in the platform economy. Some groups of workers report reasonable access to work opportunities, meaningful improvements in autonomy, skills development, and work–life balance, but these gains are contingent and uneven, shaped by dispositional traits, contextual conversion factors, the absence of institutional guarantees, and the very design of the platform economy that amplifies platform dependence.

The empirical evidence presented in this paper suggested that for some workers, particularly those with greater cognitive and material resources, platforms can offer a degree of self-determination and hope. However, for those carrying heavy unpaid workloads or heavily relying on platforms for subsistence, the same environment often intensifies precarity. It diminishes these functionings, preventing them from converting into genuine freedom of choice. Hence, rather than approaching platform labour as inherently precarious or liberating, this study emphasizes its mixed character as a space where new opportunities and enduring constraints intersect in complex and often contradictory ways.

A key insight of this paper lies in shifting the evaluative lens from formal, objective entitlements to real freedoms and lived experiences. The findings underscore that any meaningful assessment of platform work must account for how global and local structural arrangements jointly shape both development needs and the subjectivities of platform workers. Globalized platform labour research involving developing regions increasingly risks generalizing and becoming the dominant framework through which worker and local realities are interpreted. This heightens the importance of examining not just the resources accessed through globalized platform work but also the local conversion processes that determine whether these resources translate into valued outcomes. If research overlooks the specific socio-economic and institutional conditions influencing these dynamics, it can inadvertently flatten or misrepresent the complexity of lived experience. Concurrently, caution is warranted when interpreting workers' subjective reports of satisfaction or perceived opportunities, given the considerable presence of adaptive preferences in workers'

subjective assessments. As Sen (2001) warns, individuals in deprived circumstances may internalize constraints and report contentment not because their conditions are adequate, but because they have adjusted their expectations downward in response to structural limitations. In the context of precarious platform work, such adaptations can obscure deeper forms of deprivation and inequality.

Several limitations exist in this paper that warrant acknowledgement. The study's sample size, although sufficient for exploratory mixed-methods work, constrains generalizability. The analysis also relies heavily on self-reported data from this small sample size, which, although valuable for capturing worker perspectives, may be influenced by recall bias or context-driven optimism. Furthermore, this study relies solely on data from Kenya, which enhances its internal relevance but may restrict its external validity, cautioning against making broad generalisations to other national contexts without careful contextual or comparative analysis.

Chapter 4

Social Capital, Job Quality, and the Making of Meaning in Platform Work: A Mixed-Methods Case Study of Nairobi's Online Freelancing Market

4.1 Introduction

Most people have an intrinsic desire to work towards a livelihood that gives them a sense of purpose and meaning (Steger et al., 2012). This longing to find work that feels meaningful may influence career choices and drastic career changes (Dunn, 2020). However, a deliberate or implicit objective of drawing satisfactory meaning from work-life faces various systemic and circumstantial obstacles. For instance, the capitalist imperative for growth, which emphasizes breaking work down into repetitive tasks to boost productivity, carries a particular consequence. In capitalist production systems, this fragmentation transforms the very nature of work, creating conditions under which it becomes objectively difficult for individuals to derive a meaningful connection or sense of accomplishment from their tasks (Braverman, 1974; Parker et al., 2001). A key accompanying challenge is that the fragmentation of work isolates workers from control over the complete process, thereby undermining their capacity to integrate creativity, diverse skills, and sustained effort (Crawford, 2009). Consequently, meaningfulness, derived from an entire process encompassing both creative and technical dimensions, is diminished when these processes are broken down into repetitive, isolated units.

However, meaningfulness is not solely determined by the structure of work. Instead, it is highly subjective and relative, and significantly shaped by the sociocultural contexts within which individuals perform their work and live their daily lives (Rosso et al., 2010). The cultural values, norms, and societal expectations embedded in these contexts influence workers' perceptions of what constitutes meaningful and purposeful employment (Crawford, 2009; Rosso et al., 2010). Therefore, the multidimensional character of meaningfulness implies that individuals do not uniformly perceive or derive meaning from a specific type of work. Indeed, the same work that one individual considers a calling or a dream job might represent a burdensome and undesirable obligation for another.

Recognizing the subtle difference between the objective quality of work and the meaningfulness experienced by a worker, this research examines whether and how the pursuit of meaningful work materializes in the platform economy. I focus on freelance work through platforms, a work environment where tasks are highly fragmented among a geographically distributed workforce (Heeks, 2017b).

Securing short-term gigs and working online through digital platforms has become an increasingly prominent segment of the labour market (Arcidiacono et al., 2019; Martin & Zysman, 2015). Besides the composition of digital labour markets with low entry barriers, this labour market transformation is fueled by a convergence of factors. On the firm side, organizations are increasingly embracing digitalization to streamline operations, reduce labour costs, and access skilled workers beyond geographical constraints (De Stefano, 2015). Concurrently, economically developing regions, such as Kenya, show notable gains in education and digital connectivity, thereby strengthening the available skill capital. However, despite these improvements, a chronic shortage of quality work, inadequate pay, and unfavourable labour conditions persists (Oranga et al., 2020).

While this digital platform work offers access to international labour markets, the fragmented and precarious nature of these opportunities also imposes challenges. The algorithmic management of platform work has a complex impact on meaningfulness because algorithms may match workers with work that is compatible with their interests, but the same control could also negatively impact workers' agency and identity (Van Zoonen et al., 2024). Besides, the precarious employment conditions, the menial nature of work marked by isolated, remote work, and income instability may leave workers vulnerable, under-protected and negatively impact their well-being (Berg & Rani, 2021; De Stefano, 2015; Van Deursen & Helsper, 2015).

The highly fragmented nature of platform work and the negative impact of algorithmic management would suggest that platform work may, generally, result in a less meaningful livelihood. However, the context of developing regions and the lack of localized empirical research pose a challenge in understanding how the generalized prospects and structural challenges associated with platforms influence the Global South platform workers' perception towards the meaningfulness of their work (D'Cruz, 2017; Heeks, 2017a). The remote and dispersed nature of platform work calls for a deeper and context-specific understanding of which facets of this labour economy may offer

meaningful work opportunities, where its shortcomings lie, and which aspects of this form of work still empower workers (D'Cruz, 2017; Graham, Hjorth, et al., 2017; Latif, 2024).

Considering the above, this research examines Kenyan platform workers' perceptions of the meaningfulness of their gig work and, importantly, which elements of work quality are significantly related to the meaningfulness of work. To achieve this end, the research explores how the perceived meaningfulness of work intersects with work satisfaction, worker well-being and the ability to maintain a healthy social life. The study focuses on Kenyan digital platform workers who navigate the challenges of a precarious gig economy while striving for stable and enriching employment. Grounded in the concept of meaningful work (Blustein et al., 2023; Steger et al., 2012), social dimensions of work (Bertin & Sirven, 2006; Coleman, 1988) and worker well-being (Austin, 2018; Deneulin & (A. Austin, 2018; Deneulin & McGregor, 2010; Sen, 2001), the research addresses the following key research questions.

RQ1: To what extent does the perceived meaningfulness of digital platform work correlate with self-reported job satisfaction and positive social relationships among Kenyan freelancers?

RQ2: How does the isolating nature of remote gig work impact workers' social capital, and how does this social capital influence workers' perception towards work meaningfulness?

The paper uses the terms platform worker, gig worker, and freelancer interchangeably to denote knowledge workers who utilize online digital platforms to find short-term and long-term digital work in fields such as freelance writing, web and software development, and a range of knowledge work tasks typically done remotely.

4.2 Meaningful Work

Whether paid or unpaid, engaging in work can provide individuals with a sense of purpose and contribution beyond mere economic gains. The notion of work to meet a range of psychosocial needs beyond economic necessity dictates that finding meaning in what one does for work is a significant factor in how work influences individual well-being (Blustein et al., 2023). Workers may derive meaning from various aspects of their employment, whether it is the inherent nature of the work itself, the specific roles they play, or the organizational context they belong to (Bailey et al., 2017). Regardless of the sources of work meaningfulness, finding work meaningful is broadly associated

with satisfaction with work, better performance and improved well-being (Clausen & Borg, 2011). However, this sense of meaningfulness is subjective and personal. A good quality job that may score well on objective criteria, such as decent work indicators (I. Ahmed, 2003) may still feel dreadful if engaging in that work does not provide personal satisfaction.

There are various perspectives towards what constitutes meaningful work, as scholars from various disciplines have suggested differing boundaries. Some focus on intrinsic or spiritual rewards, such as personal fulfillment and self-actualization, suggesting that work attains meaning when it nurtures an individual's inner life (Ashmos & Duchon, 2000). Individuals may feel that their work is meaningful if the experience of working is consistent with their perception of themselves and what they want to become (Scroggins, 2008). Workers may derive positive meaning from their work if it provides them with a personal sense of purpose and motivates them to contribute to the greater good (Steger et al., 2012). A meaningful work construct may also encompass a sociocultural values outlook and may refer to the degree to which individuals perceive their work as significant, worthwhile, and aligned with their personal values and goals (Scroggins, 2008).

Scholarship on this topic also emphasizes expanding the notion of meaningful work and incorporating relational dimensions, such as social recognition, and extrinsic factors, such as the organization's social and environmental impact, to demonstrate meaningful work's broader association with the quality of work opportunities, work environment, and worker well-being (Grant, 2007; Lysova et al., 2019). An empirical study by Steger et al. (2012) suggest that work meaningfulness (defined as a combination of positive meaning, meaning-making through work, and greater good motivations) has a positive impact on satisfaction with life and better mental health. Socializing and connecting with others, and creating a shared sense of identity and belonging makes work positively influence well-being (Lips-Wiersma & Morris, 2009; Rosso et al., 2010).

This outlook towards meaningful work suggests that work's influence on a worker's social capital could be significant. However, platform work is generally carried out independently, mediated by algorithms and digital interfaces rather than situated in shared physical or organizational environments. While limited social interactions do exist, such as client communication, online peer exchanges, and support from familial or community networks, they are often fragmented, invisible, or outsourced to the worker's private life (Posada, 2022; Van Doorn, 2017). This makes it a compelling

case for examining how altered or dispersed forms of sociality intersect with perceived meaningfulness in platform work.

In the case of digital platforms, meaningful work is a particularly individualistic topic, as organizational aspects of work are fundamentally absent and social interactions between colleagues are not the norm. Nevertheless, while some workers may take on freelancing gigs through digital platforms out of economic necessity, many may transition toward platform work because alternative employment opportunities seem less meaningful (Latif, 2024; Mousa & Chaouali, 2022; Wood et al., 2019). For some workers, platforms may offer relatively greater freedom of choice and schedule autonomy, enabling individuals to engage in work that aligns more closely with their interests and values. The short-term nature of gigs, while problematic from a job security perspective, may enable workers to explore innovative ideas and express their creativity, resulting in greater work satisfaction (Nemkova et al., 2019). Hence, it is possible that the complexity and novelty of platform work may provide a more meaningful work experience for workers, and workers engaged in multiple types of platform work may find their work more meaningful (H1).

However, the perceived autonomy and agency to choose meaningful gigs may be hindered by the instability of opportunities and heightened competition fueled by the oversupply of workers (Kässi et al., 2021). Besides, not all platform work is geared towards innovative tasks, and since platform work can also be significantly repetitive, menial, and could hinder individual growth, it can also have a countereffect on meaningfulness and worker well-being (Berg & Rani, 2021). Moreover, the intersection of gender, age, and experience level with the broader sociocultural and structural environment may shape how workers perceive and experience the meaningfulness of platform work. Considering this background, this research hypothesizes that for Kenyan platform workers, there is a positive relationship between the meaningfulness of work and the perceived quality of work (H2). In other words, workers who perceive their work as more meaningful are expected to report greater satisfaction with work conditions and remuneration.

Existing literature has taken various positions on how to approach and measure the meaningfulness of work in the platform economy. For instance, a research study by Van Zoonen et al. (2024) perceives the meaningfulness of work as solely a self-actualization feature measured through a combination of importance, personal meaning, and perception towards the meaningfulness of work.

Their study focused on the structure of platforms and how it shapes the meaningfulness of work for European platform workers, offering insight into the noticeable relationship between algorithmic matching, control, and management of workers and how workers perceive the meaningfulness of their work. Their study finds that while algorithmic matching can indirectly contribute to a sense of meaningfulness, by aligning workers with tasks that match their skills or preferences, but this positive effect is tempered by the overarching control exerted by the same algorithms.

Another study by Kost et al. (2018) looked at how US-based platform workers think about the meaningfulness of their work. Their research examines meaningfulness by adopting the notion of meaningful work from Bailey et al. (2017), which posits that the meaning of work is dependent on its nature, the roles performed by workers, social interactions, and the organization itself. Kost et al. (2018) suggest that, since social interactions between platform workers are minimal, platform workers largely perceive meaningfulness as influenced by situational and behavioural factors. Their study also posits whether the highly individualistic nature of meaningfulness in platform work may lead to a work environment where platforms and work providers overlook providing a more meaningful work experience.

It is worth noting that both studies focus on microwork, rather than knowledge work, such as freelance writing, coding, or transcription services. Furthermore, these studies have primarily focused on platform workers in Europe and the United States, whereas research on this topic in the Global South is scarce. Therefore, a deeper understanding of how the meaningfulness of work intersects with the well-being of Kenyan freelance platform workers is a valuable research avenue.

4.3 Social Capital and Platform Work

The very nature of platform work is driven by the distributed nature workforce that requires minimal or no communication between workers, resulting in fewer opportunities to connect with colleagues and build social capital at work (Zhou & Pun, 2022). Social capital is typically viewed as a resource that fosters trust, reduces transaction costs, and ultimately contributes to the growth of individuals and groups; however, a social capital deficit can also threaten one's well-being.

Bourdieu (1980) described social capital as a resource that facilitates social class reproduction, noting that the quality and scale of social capital are critical in determining how individuals can leverage their networks to generate socioeconomic benefits (Bourdieu, 1980;

Coleman, 1988). From this perspective, it is not just about having a strong relationship with contacts, but about who those contacts are and what resources they control. The quality of one's ties and the structure of the network collectively become a mechanism of class maintenance since those already in a better position convert economic and cultural capital into social capital, thus reproducing social inequality (Bourdieu, 1980).

In the work context, social capital serves as a conduit for accessing work support, mentorship, and information that makes work life easier and promotes worker well-being. Since individuals in a particular work environment invest in their social relationships, it could help them gain the right to call upon resources from their network (Bertin & Sirven, 2006; Sen, 1982). The value of these resources, however, depends not only on the overall structure of the network but also on the individual's position within it. Depending on the strength of these individual ties and the network, social capital, when mobilized, can help an individual overcome resource constraints and improve their capability set, thus playing a direct role in enhancing well-being (Sen, 2001, 2008).

Traditionally, the workplace is regarded as a main social environment where people spend a significant part of their waking hours. Regardless of social hierarchies, a traditional workplace fosters social capital, which influences how work is carried out by establishing norms of trust and reciprocity that govern daily interactions (Oksanen et al., 2008). Networks cultivated through professional engagements at work, industry associations, or informal interactions could provide workers with resources that can lead to better opportunities and social connections. These social motives and the interaction with colleagues may make work more meaningful, including platform work, where work conditions are often challenging (Bailey et al., 2017; Kost et al., 2018).

However, platform work is typically done in decentralized, remote environments where workers do not share a common physical workspace. This isolation limits the organic, face-to-face interactions that are critical for building trust, shared norms, and interpersonal networks, all central components of social capital and essential building blocks of well-being (Kuhn & Maleki, 2017; Wood et al., 2019). Short-term and individual work assignments rarely provide opportunities for collaboration and limit workers' ability to form supportive networks. Instead of fostering cooperation, these systems can create competitive atmospheres that inhibit the development of collective trust and reciprocity needed to promote well-being through work (De Stefano, 2015). The result of this

structural issue is that platform work becomes a lonely experience, and some workers may explore off-platform methods, such as engaging in online communities, to fill this social engagement gap (Bajwa et al., 2018; Di Ruggiero et al., 2015).

That said, I build on the argument that a significant dependence on the workplace to nurture social capital is not a universal phenomenon. In many developing countries, strong kinship ties, neighbourhood networks, and local community bonds form the backbone of social support and social capital (Isham et al., 2002; Posada, 2022). Unlike high-income countries, where workplace interactions are often a primary avenue for building social capital, platform workers in the Global South frequently derive much of their social capital from deeply embedded community networks (Elbanna & Idowu, 2021b). Cultural factors in the Global South tend to promote interdependence and solidarity among workers through informal networks (Elbanna & Idowu, 2021a). These networks provide essential support, ranging from emotional resilience to professional assistance, that could compensate for the often fragmented or individualized nature of platform work. Therefore, the sociocultural contexts in some parts of the Global South may shape a platform work environment where the informal nature of platform work may not preclude the flourishing of social capital, resulting in a non-significant negative impact on the meaningfulness of work.

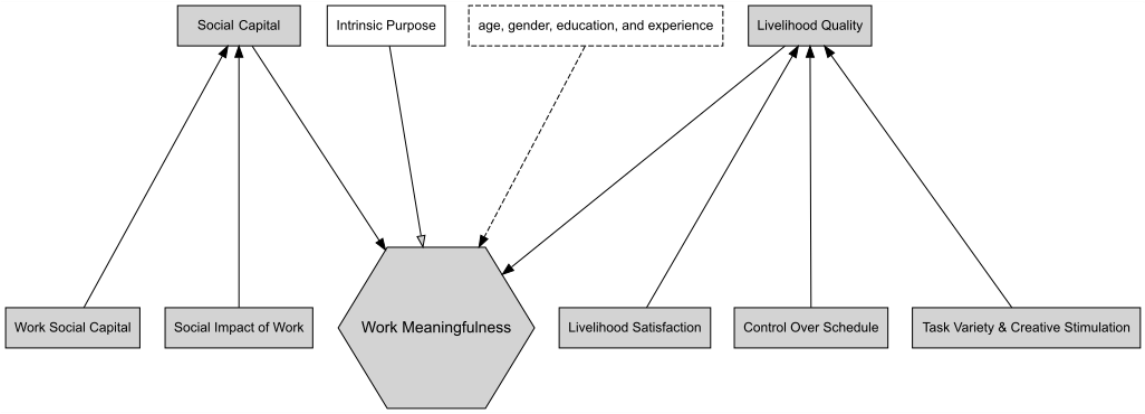
Considering these contentions, this research builds on the position that since the sources and structures of social capital in the Global South countries, such as Kenya, are distinct, research into the relationship between work, social capital, and work meaningfulness should account for these differences. The research tests the hypothesis whether there is a positive relationship between social capital built through work and the perceived meaningfulness of work (H3a). This hypothesis examines whether greater support and higher-quality interactions with peers are associated with higher meaningfulness among platform workers in Kenya. Second, regardless of the direct influence of work social capital on work meaningfulness, work social capital may moderate the relationship between predictors of meaningfulness and the perceived meaningfulness of platform work (H3b), such that the positive association between determinants of meaningfulness may be stronger when work social capital is higher.

4.4 Theoretical Framework

Based on the theoretical discussion above, Figure 4.1 positions personal fulfilment as a foundational dimension of work meaningfulness, reflecting the internal sense of purpose, self-congruence, and personal fulfillment that individuals derive from their work (Ashmos & Duchon, 2000; Scroggins, 2008; Steger et al., 2012). This intrinsic aspect is not reducible to external conditions but complements them. Livelihood quality, shaped by satisfaction with work conditions and income and control over scheduling, represents the material and autonomy-related dimensions through which work supports meaningful living (Scroggins, 2008; Steger et al., 2012). This theoretical perspective underpins H2, which proposes a positive association between the perceived meaningfulness of work and the perceived quality of work.

Figure 4.1

Social, Livelihood, and Intrinsic Dimensions of Work Meaningfulness



Moreover, the diversity of tasks may serve as a creative catalyst that enhances the subjective experience of work meaningfulness (Nemkova et al., 2019). This perspective on meaningfulness forms the basis for testing H1, which suggests that the complexity and novelty of different platform work gigs may enhance workers' experiences of meaningfulness, with those engaged in a wider range of platform work potentially perceiving their work as more meaningful.

Social capital, influenced by work-based social capital and the perceived social impact of work, highlights the role of social connection and recognition in shaping meaning (Lips-Wiersma & Morris, 2009; Rosso et al., 2010). This theoretical view provides the basis for testing H3a, which examines whether work-related social capital is positively associated with the perceived

meaningfulness of work, and H3b, which posits that, beyond any direct effect, work-based social capital may moderate the relationship between key predictors of meaningfulness and the perceived meaningfulness of platform work.

These factors, as illustrated in Figure4.1, show that work meaningfulness is shaped at the intersection of inner values, livelihood conditions, and social embeddedness, while individual attributes such as age, experience, gender, and education may shape how work meaningfulness is perceived and experienced.

4.5 Research Methods

This study adopts a convergent mixed-methods research design. A mixed methods approach was chosen to combine the strengths of both qualitative and quantitative research, capturing the breadth of patterns across a wider subset of platform workers in Kenya while also gaining deep, contextual insight into how workers interpret and navigate their platform-based livelihoods. This approach aligns with best practices in social science research, where complex, multidimensional phenomena such as work satisfaction and meaningfulness are best understood through multiple forms of evidence (Creswell & Plano Clark, 2011). A convergent parallel design (Creswell, 2021) was employed, in which quantitative data (n = 52) and qualitative data (n = 20) were collected between January 2024 and July 2024 and analyzed independently, but integrated during interpretation. This design enabled the study to compare and cross-validate findings from two different strands of data, enhancing the robustness and richness of the conclusions.

Participants were recruited using a mix of snowball and purposive sampling techniques and then screened for diversity sampling to ensure a diverse representation of experienced freelancers across various facets of freelance platform work. The initial screening of participant selection involved ensuring that participants were based in Kenya and engaged in platform work as full-time or part-time workers for at least one year. Interview participants were randomly selected from the list of participants who completed the survey. All participants provided informed consent and received compensation for participating in the research. The study received ethics clearance through the University of Waterloo Research Ethics Board (REB 45638).

4.5.1 Quantitative Component

The quantitative component of this research is exploratory and consisted of a structured survey administered to 52 digital platform workers, most of whom were based in Nairobi. The survey was administered between January 2024 and July 2024 using the Qualtrics platform. Descriptive statistics, exploratory factor analysis (EFA), and multiple regression models were employed to identify patterns, correlations, and predictors associated with meaningful work and overall livelihood outcomes. All quantitative analyses were conducted using Stata and R, with robustness checks including bootstrapping to ensure the stability of coefficient estimates.

The online survey questionnaire, developed for a broader investigation into the sustainability of digital platform work, included Likert-scale and multiple-choice questions that measured various dimensions of work meaningfulness and quality, as well as social elements of work. Please refer to Appendix A for a comprehensive list of questions.

The construction of meaningful work metrics measures is based on work as a meaningful inventory (Steger et al., 2006, 2012) and the purpose and work in livelihood fulfillment (Bailey et al., 2017). The questions measuring the meaningfulness of work included asking workers whether their work opportunities and conditions provide them with a sense of purpose and fulfillment, as well as the perceived impact of platform work on their life satisfaction. Life satisfaction from work is conceptualized as a cognitive evaluation of one's life that is explicitly attributed to work (Duffy et al., 2017; Duffy & Dik, 2013). The survey also included questions focused on measuring workers' satisfaction with work opportunities, conditions, and financial compensation.

The social dimension of work was assessed by capturing the quality and breadth of social relationships developed through and around platform work. Considering the remote nature of platform work, Survey questions focused on social interactions in the gig economy (Di Gangi et al., 2023; Wood, Lehdonvirta, et al., 2018) to measure support received from colleagues or mentors, engagement in digital communities, and the broader impact of platform work on personal relationships outside of work.

4.5.2 Quantitative Data Analysis

The quantitative data analysis proceeded in two primary stages. In the first stage, exploratory factor analysis (EFA) was employed after data screening to consolidate the measured variables into latent

constructs representing meaningful work, livelihood quality, and social capital. The use of aggregation methods, such as EFA, for research on the quality of work questionnaires is considered an appropriate research method (Burchell et al., 2014; Ferraro et al., 2018). Specifically, in this research, I used principal factoring along with an oblique rotation method to account for potential correlations among the constructs. Following the EFA, multiple regression analyses were performed. Control variables, such as age, gender, education, and experience, were used to account for potential confounding effects. Diagnostic tests, including assessments for linearity, normality, homoscedasticity, and multicollinearity, were conducted to ensure the robustness of the regression models. This analytical strategy enabled a detailed examination of both the direct and interactive effects of meaningful work and social capital on well-being, providing insight into the relative contributions of each construct.

4.5.2.1 Scale Development Using Exploratory Factor Analysis

An exploratory factor analysis was conducted to capture the aspects of key variables in this study, i.e., meaningful work, livelihood quality, and social capital. Composite scores were calculated by averaging item responses, resulting in a scale that retains the original Likert range (0–4).

4.5.2.1.1 Meaningful Work Scale

Initially, four items were assessed to create a single scale, theorized to capture aspects of meaningful work. These variables included purpose and fulfillment through work (*purpose*), impact of platform work on life satisfaction (*life satisfaction*), agency and control over work (*control over work*), and satisfaction with growth opportunities (*opportunity satisfaction*). Given the expectation that these items are conceptually related, I employed the principal factors extraction method along with an oblique rotation.

Bartlett's test of sphericity was significant ($p < 0.001$), and the Kaiser-Meyer-Olkin (KMO) measure was 0.550, indicating that the data were suitable for factor analysis. The factor analysis initially extracted two factors based on the Kaiser criterion (eigenvalues > 1) and confirmed via the scree plot. The eigenvalues for the first and second factors were 1.19 and 0.19, respectively, accounting for a combined cumulative variance exceeding 1.35. Given the moderate theoretical overlap among constructs, an oblique oblimin rotation was applied to allow for factor correlation.

Table 4.1

Meaningful Work Rotated Factor Loadings and Uniqueness Values

	Factor 1	**Factor 2**	**Uniqueness**
Sense of Purpose	.724	.101	.43
Life Satisfaction	.631	–.193	.63
Opportunity Satisfaction	.403	.298	.68
Control over Work	.098	.307	.88

The rotated factor solution is presented in Table 4.1. Factor 1 showed strong loadings for *purpose* ($\lambda = .72$) and *life satisfaction* ($\lambda = .63$), while *control over work* and *opportunity satisfaction* loaded weakly across both dimensions, with highest loadings under .31. This pattern suggested a meaningful latent construct primarily defined by *purpose* and *life satisfaction*, which is interpreted as meaningful work variable in this research. Although longer batteries are ideal, two- and three-item reflective scales can achieve acceptable psychometric properties when the construct is narrow and items are highly face-valid (Eisinga et al., 2013). The rotated factor correlation matrix revealed a moderate correlation between factors ($r = 0.42$), justifying the use of an oblique solution. Cronbach's alpha for the two items that strongly loaded on Factor 1 (*purpose* and *life satisfaction*) was .68, indicating acceptable internal consistency for a short scale. Based on these findings, a composite meaningful work scale was constructed by averaging the two retained items. Cronbach's alpha for this scale was ~ 0.7 (0.67), indicating acceptable internal reliability.

4.5.2.1.2 Work Social Capital Scale

Initially, the construct of social capital was examined using three items that were originally expected to capture aspects of social support at work: the impact of platform work on social relationships (*work social impact*), the frequency of interaction with fellow gig workers (*social interaction*), and engagement in digital communities (*community engagement*).

Preliminary diagnostics indicated marginal adequacy for factor analysis. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.573, suggesting mediocre suitability (Kaiser, 1974), and Bartlett's test of sphericity was statistically significant, $\chi^2(3) = 23.10$, $p < .001$, indicating sufficient inter-item correlations. The determinant of the correlation matrix was .625, above the

recommended threshold, further supporting the assumption of multivariate normality and lack of multicollinearity.

The EFA extracted one factor with an eigenvalue of 1.03. As shown in Table 4.2, the rotated (oblimin) factor loadings were highest for *social interaction* (.69) and *community engagement* (.61), while *work social impact* loaded more weakly (.43) and exhibited a high uniqueness value (.82), suggesting it is only modestly related to the underlying construct.

Table 4.2

Work Social Capital Rotated Factor Loadings and Uniqueness Values

Variable	Factor 1	Uniqueness
Social Interaction	.694	.518
Community Engagement	.606	.633
Work Social Impact	.427	.818

A social capital at work scale was constructed by averaging the two retained items. To assess internal consistency, Cronbach's alpha was computed for the two items with the strongest loadings: *social interaction* and *community engagement*. The resulting alpha was .69, with an average inter-item covariance of .68. While slightly below the conventional .70 threshold, this value is still acceptable for exploratory research (Eisinga et al., 2013). The distinct performance of *work social impact* suggests that the perceived impact of work on broader social relationships may represent a separate dimension in our model.

4.5.2.1.3 Livelihood Satisfaction Scale

Livelihood satisfaction reflects workers' subjective evaluation of their employment experiences. The questions focus on measuring perceived satisfaction with key aspects of work, including satisfaction with working conditions (*work satisfaction*), satisfaction with growth opportunities through digital platforms (*opportunity satisfaction*), and satisfaction with financial compensation (*financial satisfaction*).

Preliminary diagnostics supported the factorability of the data. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.685, indicating acceptable adequacy (Kaiser, 1974).

Bartlett's test of sphericity was statistically significant, $\chi^2(3) = 36.19$, $p < .001$, confirming sufficient correlations among items. The determinant of the correlation matrix (.479) was above the threshold for concerns about multicollinearity.

Table 4.3

Factor Loadings and Uniqueness Values for Livelihood Satisfaction Items

	Factor 1	Uniqueness
Satisfaction with Work Conditions	.667	.555
Financial Satisfaction	.639	.592
Opportunity Satisfaction	.720	.482

The EFA extracted a single factor with an eigenvalue of 1.37, accounting for the majority of the common variance. The scree plot displayed a clear elbow after the first factor, reinforcing a one-factor solution. All three items loaded moderately to strongly on the factor, with loadings ranging from .64 to .72, as shown in Table 4.3. Internal consistency of the three-item scale was acceptable, with a Cronbach's alpha of .76. The average inter-item covariance was .38, and item-test correlations ranged from .80 to .84, indicating that each item contributes meaningfully to the overall scale. The results support combining the means of three items into a single index representing satisfaction with livelihood conditions, which encompasses a sum of perceived satisfaction with work conditions, income adequacy, and opportunity for growth within the platform economy.

4.5.3 Qualitative Component

Complementing the survey data, semi-structured interviews were conducted with 20 digital platform workers in Kenya during the same timeframe. Twelve interviews were held in person, while eight were conducted remotely via Microsoft Teams. On average, each interview lasted about 45 minutes and explored how workers make sense of their platform work, focusing on perceptions of work meaningfulness, social dimensions of work, and work characteristics. Pseudonyms are used throughout the research to protect participant identities.

4.5.4 Qualitative Data Analysis

Interview transcripts were coded thematically using a standard four-step Braun–Clarke approach (Clarke & Braun, 2017). The Braun and Clarke approach to thematic analysis involves systematically

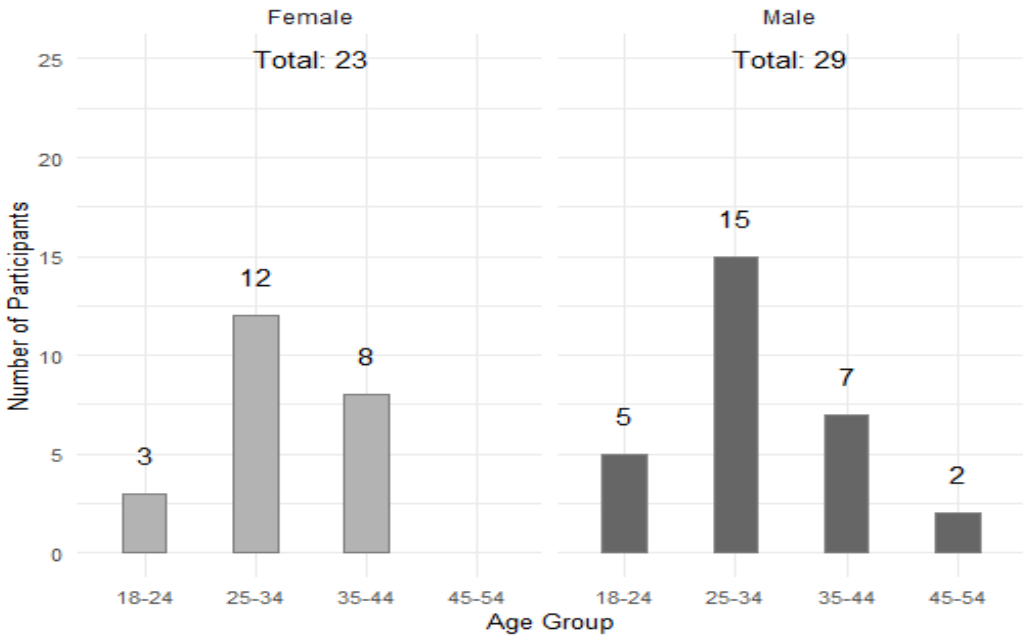
coding qualitative data, organizing these codes into coherent themes, and interpreting those themes to construct meaningful, theory-informed insights about the research question (Clarke & Braun, 2017). This approach applies both inductive and deductive strategies, allowing for points of convergence and divergence to be highlighted during data integration. A narrative analysis approach guided the interpretation, allowing the study to capture how workers construct meaning through personal stories and experiences. Narrative analysis examines not only what participants say but also how they organize and express their experiences, as well as the broader social contexts in which these narratives are shaped (Creswell, 2021; Riessman, 2008). The discussion section is structured around core themes developed through qualitative analysis, allowing empirical findings to be interpreted in close connection with the study's conceptual framing.

4.6 Results

The results section focuses on quantitative findings, while qualitative insights are embedded in the discussion to contextualize and deepen the interpretation of key patterns. The survey results comprised 52 Kenyan digital platform workers, primarily from the Nairobi metropolitan area, with 29 male and 23 female participants. As highlighted in Figure 4.2, the age distribution is concentrated in the 25–34 age bracket for both genders, comprising 15 males and 12 females. The 35–44 age group is the next most represented, with 15 participants (7 males and 8 females). A smaller proportion of participants fall within the 18–24 age group (8 participants: 5 males and 3 females), and very few are in the 45–54 category (2 males, with no females).

Figure 4.2

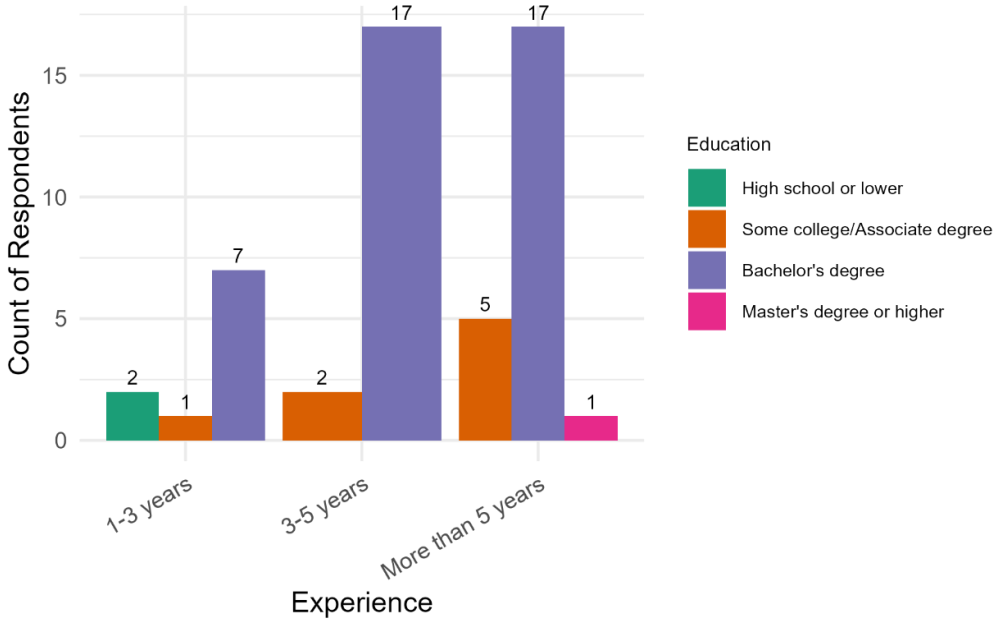
Meaningful Work Study Participants by Age and Gender



The sample primarily comprises young to early mid-career workers; a characteristic commonly observed among digital platform workers in urban settings (Latif, 2024). All participants in the study had at least one year of gig-work experience. Specifically, 10 participants (19.2%) had between one and three years of experience, 19 participants (36.5%) had between three and five years, and 23 participants (44.2%) had more than five years. With respect to educational attainment, the sample was predominantly university educated. As highlighted in Figure 4.3, participants (78.8%) held a bachelor's degree, eight participants (15.4%) had completed a college diploma or associate degree, one participant (1.9%) possessed a master's degree, and two participants (3.8%) reported a high school education.

Figure 4.3

Participants' Education and Experience Level



The study participants engaged in a diverse range of platform gigs, including freelance writing, coding, microwork, transcription, graphic design, and customer service. Interestingly, as shown in Figure 4.4, many participants work various gigs spread across different occupational categories to meet their livelihood needs.

Figure 4.4

Worker Distribution Across Multiple Occupations

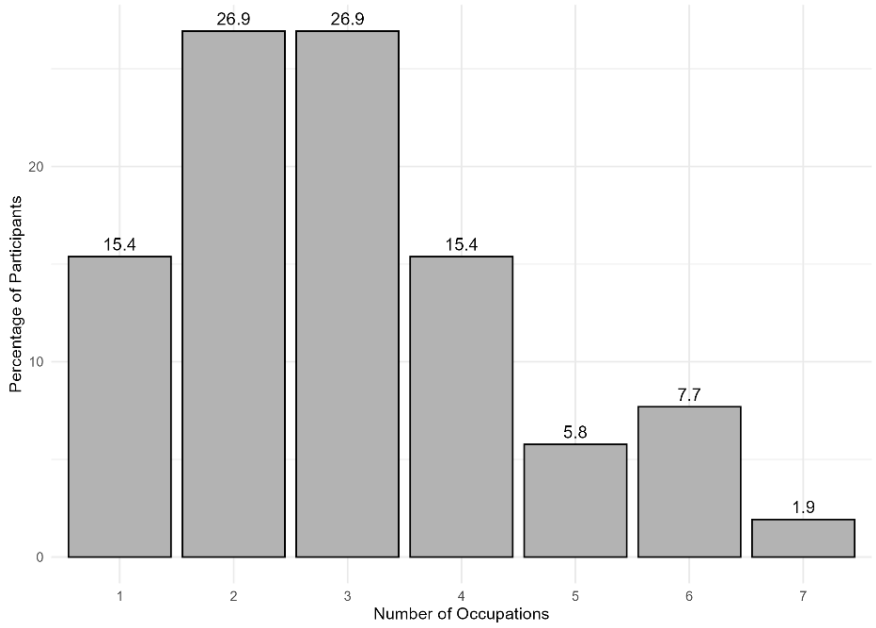


Table 4.4 presents the range of data collected, along with summary statistics. The composite variable denoting meaning and purpose through gig work yielded a high average score (M = 3.07, SD = 0.69), indicating that most participants perceive their platform work as a source of substantial meaning and purpose. The relatively low standard deviation suggests consensus around this positive appraisal.

Table 4.4

Platform Work Meaningfulness and Worker Well-being: Descriptive Statistics

	Mean	**SD**	**Min**	**Max**
Meaning and purpose through gig work[a]	3.07	0.69	1	4
Social Dimension of Work				
Social capital at work[a]	1.84	1.00	0	4
Impact of platform work on social relationships[b]	2.13	1.28	0	4
Livelihood quality				
Livelihood satisfaction[a]	2.48	0.71	0	4
Control over work schedule[a]	2.44	1.23	0	4

n= 52

[a] 0 = lowest; 4 = highest
[b] 0 = most negative 4 = most positive

Unsurprisingly, Social capital at work (0 = lowest, 4 = highest; range = 0–4) had a comparatively low mean (M = 1.84, SD = 1.00), suggesting that many platform workers experience limited networking opportunities through their work. However, the impact of platform work on social relationships (M = 2.13, SD = 1.28) suggest a slight overall positive effect on personal relationships but also substantial variability in workers' experiences.

Livelihood satisfaction is well above the midpoint (M = 2.48, SD = 0.71), indicating moderate satisfaction with income security and overall livelihood. Control over work schedule likewise clustered above the scale's midpoint (M = 2.44, SD = 1.23), reflecting that while workers enjoy substantial autonomy in scheduling, there is still constraint or a lack of predictability.

4.6.1 Work Meaningfulness, Livelihood Quality, and Social Dimension of Work

In examining the interrelationships among five core dimensions of platform work experience through an exploratory correlation matrix (Table 4.5), the strongest positive association emerged between perceived meaningfulness of work and livelihood satisfaction (r = 0.62), indicating that individuals who find greater purpose in their gig work also report higher satisfaction with their work conditions. Social capital at work showed a moderate correlation with social impact (r = 0.32) and livelihood satisfaction (r = 0.31), suggesting that interpersonal networks may enhance both workers' sense of contributing to others and their material outcomes. The relationship between meaningful work and social impact was weak but positive (r = 0.10). In contrast, the correlation between meaningful work and social capital was slightly negative (r = –0.06), suggesting some divergence in how individuals perceive the meaning of work versus the value of social connection in platform work.

Table 4.5

Interrelationship Between Work Meaningfulness and Platform Work

		Social Dimension of Work		**Livelihood Quality**	
	Meaningful Work	*Social Capital*	*Social Impact*	*Livelihood Satisfaction*	*Control over Schedule*
Meaningful Work	1.000				
Social Capital	–0.055	1.000			
Social Impact	0.101	0.323	1.000		
Livelihood Satisfaction	0.617	0.307	0.200	1.000	
Control over Schedule	0.127	–0.068	0.049	0.074	1.000

By contrast, control over one's schedule exhibited weak associations with all other variables (highest r = 0.13), implying that scheduling autonomy operates largely independently of both social and livelihood satisfaction dimensions of platform work.

4.6.2 Regression Analyses

Multiple linear regression models explored whether job diversity, social factors, and livelihood satisfaction predict workers' perceived meaningfulness of gig work, while controlling for gender, age, education, and tenure. Diagnostics indicated no serious multicollinearity (mean VIF = 2.60) and an acceptable residual distribution, allowing for the direct interpretation of coefficients. The overall model was statistically significant, $F(14, 37) = 3.34$, $p = .0017$, and explained approximately 56% of the variance in meaningfulness ($R^2 = .558$, adj. $R^2 = .391$).

Table 4.6

The Relationship Between the Meaningfulness of Work and the Quality of Work

Meaningfulness of Work	B	SE	p	95% conf. Interval of *B*		β
				Lower	Upper	
Engaging in gigs across multiple occupations	–0.040	0.057	0.490	–0.156	0.076	–0.089
Social Dimensions of Work						
Work social capital	–0.121	0.105	0.258	–0.335	0.092	–0.177
Impact of work on social relationships	–0.037	0.075	0.624	–0.189	0.115	–0.069
Livelihood Quality						
Livelihood Satisfaction	0.606	0.125	*< .001	0.353	0.860	0.627
Control Over work schedule	0.007	0.068	0.921	–0.131	0.144	0.012
Demographics & Experience						
Gender (Male =1)[a]	–0.164	0.168	0.334	–0.504	0.176	–0.120
Age (25-34)	–0.032	0.248	0.897	–0.534	0.470	-0.024
Age (35-44)	0.040	0.325	0.903	–0.619	0.699	0.027
Age (45-54)	0.079	0.512	0.878	–0.959	1.118	0.023
Education (Some college/assoc. degree)	0.036	0.493	0.942	–0.962	1.035	0.019
Education (Bachelor's degree)	0.076	0.445	0.865	-0.826	0.979	0.046
Education (Master's degree or higher)	–0.268	0.730	0.716	–1.746	1.211	–0.054
Experience (3-5 years)	0.102	0.250	0.687	–0.405	0.609	0.072
Experience (More than 5 years)	0.482	0.256	0.067	–0.036	1.000	0.352
Intercept	1.751	0.638	0.009	0.459	3.044	—

n=52

[a] Female = 0

R^2 = .558, adj R^2 = .391; F(14, 37) = 3.34, p = .0017

*P = < .001

Reference categories: Age 18–24, Education = High school or lower, Gig-experience = 1–3 years.

4.6.2.1 Work Task Diversity and Work Meaningfulness

These findings in Table 4.6 do not provide *preliminary* evidence in favour of Hypothesis 1 (H1), which proposes that engaging in a greater variety of platform work types would be associated with a higher perceived meaningfulness of gig work. Contrary to expectations, the coefficient for working across multiple occupations was negative and statistically non-significant: B = –0.040, SE = 0.057, t(37) = –0.70, p = .490, with a 95% confidence interval ranging from –0.156 to 0.076. The standardized beta coefficient (β = –0.089) also indicated a small effect size, suggesting that job diversity was not a meaningful predictor of perceived work meaningfulness in this model.

4.6.2.2 Livelihood Quality and Work Meaningfulness

Livelihood satisfaction emerged as the most influential variable of meaningful work. These results align with the expectations of Hypothesis 2 (H2), suggesting a strong association between greater satisfaction with work conditions and perceptions of the meaningfulness of work.

In the model, a one-point increase in the livelihood satisfaction index was associated with a 0.606-point rise in perceived meaningfulness (B = 0.606, SE = 0.125, t = 4.84, p < .001; β = 0.627), representing the largest standardized effect in the equation. Since the livelihood index measures satisfaction with growth opportunities, overall work conditions, and financial compensation, this result suggests that workers perceive work as meaningful and fulfilling when the platform meets their concrete economic and career development needs. In other words, meaningfulness appears to grow out of good quality gigs, work that not only pays adequately but also offers scope for skill development and acceptable day-to-day conditions, rather than from the sheer variety of tasks.

As shown in Table 4.6, none of the demographic or experience-related control variables were significantly associated with perceived meaningfulness in this exploratory analysis. Gender had no meaningful effect (B = –0.164, p = .334), and no significant differences emerged across age or education levels (all p > .70). Experience in the 3–5 year range also showed no association (B = 0.102, p = .687), while only those with more than five years of platform experience approached statistical significance (B = 0.482, p = .067; β = 0.352), suggesting a potential but not conclusive trend. Overall, these findings reinforce the notion that meaningfulness in platform work is not solely a function of worker identity or tenure but is instead shaped primarily by the structural and material qualities of the work.

4.6.2.3 Social Dimension of Work and Work Meaningfulness

For the social dimension of work, neither factor was significantly associated with perceived meaningfulness, as shown in Table 5.6. Accordingly, Hypothesis 3A is not supported in this exploratory quantitative dataset. Work social capital (B = –0.121, SE = 0.105, p = .258; β = –0.177) and the perceived impact of platform work on social relationships (B = –0.037, SE = 0.075, p = .624; β = –0.069) both exhibited small, non-significant effects. These findings suggest that the strength of peer networks and the perceived social spillovers of gig work do not meaningfully shape how workers evaluate the meaningfulness of their platform-based labour. In this sample, the exploratory results suggest that social connectedness, whether through colleagues or perceived benefits to personal relationships, did not translate into a stronger sense of purpose or fulfillment in platform work.

4.6.2.4 Interaction Effects of Livelihood Satisfaction and Social Capital on Work Meaningfulness

Since the direct impact of the social dimensions of work on work meaningfulness is statistically non-significant, the notion of social capital requires a more in-depth examination. To test whether the positive link between livelihood satisfaction and work meaningfulness depends on the strength of peer networks, I introduced an interaction between centred livelihood satisfaction and centred work social capital. The expanded model was statistically significant, $F(14, 37) = 3.87$, $p = .001$, and explained 59 % of the variance in meaningfulness ($R^2 = .594$; adjusted $R^2 = 0.441$).

Table 4.7

Interaction Effect of Livelihood Satisfaction and Work Social Capital

Meaningfulness of Work	**B**	**SE**	**p**	**95% conf. Interval of B**	
				Lower	Upper
Interaction					
Livelihood Satisfaction × Social Capital Interaction	0.263	0.135	0.059	–0.010	0.538
Demographics & Experience					
Gender (Male =1)[a]	–0.206	0.162	0.212	–0.535	0.123
Age (25-34)	0.008	0.229	0.974	–0.457	0.473
Age (35-44)	–0.019	0.307	0.951	–0.642	0.604

Meaningfulness of Work	B	SE	p	95% conf. Interval of B	
				Lower	Upper
Age (45-54)	0.078	0.48	0.872	–0.895	1.051
Education (Some college/assoc. degree)	0.03	0.471	0.949	–0.923	0.984
Education (Bachelor's degree)	0.071	0.427	0.87	–0.794	0.935
Education (Master's degree or higher)	–0.386	0.702	0.585	–1.808	1.035
Experience (3-5 years)	0.184	0.242	0.451	–0.306	0.674
Experience (More than 5 years)	0.608	0.254	0.022	0.094	1.122
Intercept	2.552	0.754	0.002	1.023	4.080

n=52
[a] Female = 0
R^2 = .594, adj R^2 = .4405; F(14, 37) = 3.87, p = <.001.
Reference categories: Age 18–24, Education = High school or lower, Gig-experience = 1–3 years

As Table 4.7 shows, the interaction term was positive and marginally significant (b = 0.263, p = 0.059), indicating that the effect of job satisfaction on perceived work meaningfulness is strengthened when workers also report higher levels of social capital. This interaction is consistent with Hypothesis H3b, indicating that the combination of high-quality work conditions and strong peer connections enhances the sense of purpose derived from platform work.

Among the control variables, experience remains an important covariate in this model. Workers with more than five years of platform tenure reported substantially higher meaningfulness than the 1–3-year reference group (B = 0.608, p = .022). This suggests that, independent of job quality and social factors, prolonged exposure to platform work may foster a deeper sense of purpose, likely through accumulated expertise, better client fit, or a self-selection process in which those who fail to find meaning exit the sector earlier.

4.6.3 Robustness Checks

To ensure the reliability and stability of regression results, robustness checks were conducted using bootstrap methods. Given the relatively small sample size (N = 52), these checks were particularly important to verify that the regression findings were not an artifact of sampling variability.

Bootstrapping is a resampling technique that repeatedly draws samples (with replacement) from the dataset and re-estimates the model and is seen as especially useful in studies with small samples or where assumptions of normality may be weakly met (Mooney & Duval, 1993). The bootstrap approach provides more accurate standard error estimates by resampling the data and recalculating coefficients across many simulated samples (Kimber et al., 1994). Using 1,000 bootstrap replications, bootstrap estimates were obtained for each of the regression models presented in the results section, including both the baseline and interaction specifications. The results are given below.

The bootstrap results closely mirrored the OLS regression findings, predicting the relationship between the meaningfulness of work and the quality of work. Livelihood satisfaction remained a robust and statistically significant predictor ($B = 0.606$, boot-SE = 0.160, $z = 3.80$, $p < .001$; 95% CI [0.293, 0.919]). All other predictors, including job diversity, social factors, and scheduling control, remained non-significant (all $z < 1$, $p > .26$), and the model's explanatory power was stable (bootstrap Wald $\chi^2(14) = 40.54$, $p < .001$; $R^2 = .558$).

However, while the overall model fit remained strong ($R^2 = 0.594$), in the resampled model predicting the interaction effects of livelihood satisfaction and social capital on work meaningfulness, no predictors reached conventional significance levels. The interaction term between livelihood satisfaction and work social capital, which was marginally significant in the OLS model ($B = 0.264$, SE = 0.135, $p = .059$), was attenuated under bootstrapping ($B = 0.264$, boot SE = 0.177, $z = 1.49$, $p = .137$; 95% CI [–0.084, 0.612]). Similarly, the main effect of work social capital also weakened ($B = –0.815$, boot SE = 0.473, $z = –1.72$, $p = .085$). Livelihood satisfaction, while positive, remained non-significant in the bootstrapped model ($B = 0.213$, boot SE = 0.277, $z = 0.77$, $p = .442$). The overall model fit remained strong and virtually unchanged (bootstrap Wald $\chi^2(14) = 48.1$, $p < .001$; $R^2 = 0.594$).

These findings suggest that while the interaction between economic and social factors warrants further exploration, its observed effect in this sample is sensitive to resampling and should be interpreted with caution. Accordingly, this relationship in this research is treated as exploratory and replication with a larger number of participants is recommended for future studies.

4.7 Discussion and Qualitative Synthesis

Most of the survey participants perceived their platform-dependent freelance work as moderately to highly meaningful (Table 4.4). At first glance, this finding is surprising, given the precarious nature of platform work, which is often viewed as menial and exploitative, characterized by intense competition for irregular gigs and algorithmic controls that undermine meaningfulness (Berg & Rani, 2021; Van Zoonen et al., 2024). However, interviews with workers provided deeper insights into why such precarious work may still be perceived as meaningful.

Interview participants repeatedly described individual tasks as monotonous, devoid of intrinsic purpose and psychologically mechanical, echoing classical critiques of labour fragmentation (Crawford, 2009; Parker et al., 2001). The conversations with the workers suggested a broader notion that, at a task level, platform work lacks meaning, but work overall still provides meaning. Generally, platform livelihoods may help create conditions in low-resource environments where the function of platform work can provide primary or supplementary, yet sustained, support in pursuing a more meaningful livelihood.

This distinction between the meaningfulness of work as a set of tasks and livelihood meaningfulness as a holistic set of activities one undertakes to make a living partly explains why some seasoned platform workers may perceive their work as meaningful. As the qualitative evidence in the following sections highlights, when considering the meaningfulness of work, the perspective of Kenyan platform workers is shaped by three key considerations. First, the building block role of platform work in pursuing a meaningful livelihood; second, the function of comparative work quality in enabling a more meaningful life; and third, the role of work in alleviating hardship, contributing to a broadly positive perception of platform work that workers associate with meaning. These distinctions point to a critical distinction between task meaning and livelihood meaning in meaningful work theory (Rosso et al., 2010; Steger et al., 2006).

4.7.1 Lack of Meaningfulness in Platform Work

The discussions with platform workers suggested that many of them do not find inherent meaning in the gig tasks themselves. When reflecting objectively, they do not view their work as spiritually fulfilling or as part of a purposeful ecosystem. As one participant stated:

> "You have to work even when you do not feel like working. In the beginning, there are these advantages when you are interested. Because it is your first job, but when you start working, you realize you are mostly doing it for the money" (Theo, 2024).

When asked about the meaningfulness of work, Theo reflected that, while the novelty of gigs and exposure to a global work environment offer brief excitement, this quickly fades under harsh, mechanical work conditions and clients' indifference to workers' individuality. Theo began freelancing immediately after college, when COVID-19 made it challenging to find local employment. His reflections highlight the challenges of navigating the impersonal nature of platform work; however, more experienced workers also noted that task repetition can lead to a sense of meaninglessness. Some of the other participants also note a similar perception:

> "When I started out, it was [meaningful]. Yeah, so with time, you have to find something else to do. I need to try something else to challenge my mind because it is intellectually unchallenging. So yes, it is a means to an end of getting money" (Sierra, 2024).

> "Work online can be very monotonous; it can be very boring, to say the least. But it is upon yourself, as an individual, to actually step out, find out what else you can be able to do, and go for it" (Joyce, 2024).

Joyce has worked in the platform work sector for over 15 years, well before platform work gained exponential traction. For her, a passive hope of finding meaning in monotonous tasks is a redundant exercise, but actively trying to expand the scope of work is a critical factor that could help experience a more meaningful livelihood. In her case, platform work opened doors to contractual roles in the nonprofit sector, where she trains at-risk youth in digital and employability skills while continuing her freelance work. Similarly, Sierra transitioned to a full-time remote customer service role obtained through a platform but noted that the monotony of routine tasks in her permanent job felt even less fulfilling than short-term contracts, which at least end sooner. Sierra works full-time in customer service but continues to seek marketing gigs through platforms that better align with her interests.

A theme emerging from some workers' experiences is the post-COVID blurring of boundaries between remote employment and freelancing through platforms. As more firms adopt remote work and become open to hiring beyond geographic borders, workers like Joyce, Sierra, and

others have secured long-term gigs through digital platforms. This shift has enhanced the stability of work opportunities, with some workers finding that their platform portfolios and networks now offer greater consistency as digital work becomes more embedded in the broader labour market. However, increased stability and the absence of short-term gigs do not alleviate the dullness and meaninglessness associated with monotonous work for these workers.

4.7.2 Platform Work as a Building Block towards a Meaningful Livelihood

For many workers, only a subset of gig tasks aligns closely with their passions or personal interests. However, the dynamics of local labour markets in developing regions may condition workers to derive substantial fulfillment even from this limited alignment, making their overall platform-based livelihood feel meaningful. As Clara and Tessa reflected:

> "When you get a good client, it is a good feeling, it is very satisfying. It gives you like a sense of belonging and a sense of being employed" (Clara, 2024).

> "I like Wowzi [a Kenyan platform] because of content creation [jobs]. I have a passion for content creation, and then, for Toloka [crowdsourcing platform], the tasks are actually very easy. So, I usually use them also to pass time. Then for Remotask, it does not bring a lot of tasks to me. So, anytime I log in during my free time, if I find a task, I usually just do it" (Tessa, 2024).

Finding one's work meaningful does not imply that all aspects of the work are inherently meaningful, particularly in contexts where the experience of meaningfulness is not rooted in attributing a higher purpose to specific tasks, but rather in the sense of fulfillment that arises when work aligns with one's vision of an engaging or fulfilling livelihood. For workers like Tessa and Clara, engaging in a range of gigs across multiple platforms helps manage the drudgery of short-term work. Most gigs are too brief for workers to feel the need to convince themselves that the tasks contribute to some greater good or carry deeper meaning. However, moments of fulfillment, whether through a positive client interaction or an interesting task that better aligns with one's passions, can help workers derive meaning from their broader livelihood.

Tessa's reflections on engaging across multiple platforms and work types further illuminate why Hypothesis 1, proposing that work diversity enhances perceived meaningfulness, is not supported. It is probable that juggling multiple gig roles dilutes, rather than enriches, workers' sense

of purpose. When it comes to the diversity of work increasing meaning, only specific combinations of work types deliver meaning. Alternatively, the lack of a detectable effect could reflect unmeasured confounders. For example, workers who take on multiple roles out of necessity rather than by choice may experience less meaningfulness. Future research should explore non-linear or threshold effects and consider qualitative insights into how diversification of platform work shapes the experience of meaningful labour.

In many cases, the significance of platform work in achieving a meaningful livelihood in the Global South is also evident when it serves as a means to an end, e.g., supporting the pursuit of a different, more desired line of work. As many interview participants noted:

> "Being involved in implementing a program [that is] training people in freelancing, it is good to have what I can call moral authority. So, I have the skill and have the experience, but I can also show you that I am still doing it. It is usually very important if I am able to log in to my Upwork and able to show that, as we speak here during this session, I have this many clients and this many projects. It also helps me keep sharp and keep abreast of changing trends on different platforms" (Owen, 2024).

> "With those platforms, it was a good journey for me to understand that freelancing is a good place for me to get started. [Now] I am running my own agency. It's been operational for over five years now, and currently I have nine people working with [me]" (Jasper, 2024).

Workers like Jasper feel differently about developing meaning and satisfaction from gig work. For workers like Jasper, there is little point in seeking meaningfulness in platform work, as competition and isolation make it harder to grow or pursue a fulfilling career. For him and many other workers with entrepreneurial ambitions, platform work is merely a building block toward a more fulfilling livelihood. Owen, on the other hand, works as both a trainer and a freelance platform worker. His idea of meaningfulness through platform work is shaped by his ability to showcase his platform skills and portfolio, while he derives arguably more meaningful experiences from his role as a trainer with a nonprofit organization.

Although the quantitative analysis did not support the notion that occupational diversity contributes to a more positive perception of work's meaningfulness, some participants reflected that

the novelty of gigs makes their work more fulfilling and interesting. For example, Iris and Sierra explained:

> "Ok this one [gig] I just did recently. It was so interesting. It was on farming. I've never done farming before, but when I got this [gig], this guy, he wanted someone to just put up this put up a small space in your home and take care of some vegetables for 30 days and see how it performs here in Kenya. So, I think I really liked it and I enjoyed it because I've never done farming before. Even if you want to just send me out for an errand. I'll still apply. So, you get many different kinds of works" (Iris, 2024).

> "Since I already have a common job [traditional full-time job], so [I]treat my Upwork to be more marketing related jobs because otherwise it can get really boring" (Sierra, 2024).

Interviews with workers suggest that those who are less financially dependent on platform work, often because they hold a primary, long-term job, are more likely to find gig work meaningful. This is largely because they have greater autonomy to select gigs that better align with their interests and meet their cognitive needs. For these workers, creative stimulation and enjoyment are central motivations for engaging with platforms, allowing them to pursue diverse projects within their areas of interest. In contrast, workers who rely heavily on platform income to make ends meet often experience job scarcity and are compelled to engage across multiple platforms and job types. For them, the pressure to secure any available work, regardless of fit, makes it harder to align work with personal preferences, thereby reducing the potential for fulfillment and perceived meaningfulness.

4.7.3 Livelihood as a Foundation for a Meaningful Life

A key observation in this research is that the line between finding meaning in work and living a meaningful life is often more blurred in economically developing regions, supporting the position that in low-resource contexts, external job features (e.g., security, temporal autonomy, pay) dominate intrinsic task features in shaping meaning (Blustein et al., 2023). For many workers, it is not the work itself that gives much meaning, but how work supports what matters most in their lives, giving their lives a more positive meaning. As one participant explained:

> " [A friend], she introduced me to Upwork. We met in town for coffee. She met me with two of her friends, and I looked at them and I say those ladies looked classy! and I was inspired.. and I thought,

> God! Someday, I will be like this. I can wake up at my time, make money come back, have dinner. I did not look back" (Clara, 2024).

Clara's and many other workers 'perceptions of platform work are shaped less by the nature of the work itself and more by how it might enhance their social identity and class status. For them, this is not about the meaningfulness of the work tasks, but rather how the nature of the work may generate meaningfulness in life. For some workers, platform work erodes their sense of professional identity (Standing, 2019), while for others, freelancing through platforms becomes a source of identity. Particularly in regions like Kenya, the professional identity of platform workers is often shaped less by the nature of the work itself and more by how the work is organized. It is common for individuals to identify primarily as freelancers rather than by their specific roles, such as writers, transcriptionists, or web developers. In such sociocultural contexts, being a successful freelancer symbolizes freedom from commuting constraints, fixed low wages, and time poverty.

For some workers, the fulfilment of platform work lies less in the nature of the work itself and more in the practicality it offers for their lifestyle. The agency and control embedded in platform labour, including the ability to set one's own schedule, choose preferred tasks, and manage professional commitments flexibly, become instrumental in supporting the aspects of life that matter most to them. As Mercy and Joyce highlighted:

> "It is life-changing. As a woman and a mother with two children, working remotely has given me so much time to be able to do the things I need to do as a mother while I am still working. I don't have to give up on either of those things. Working remotely, for me, has been life-changing. The fact that I'm able to spend more time with my kids, take care of my household while I'm still working, I don't know if I can describe the impact. It's worth the risk of not having, like, what can I say... guaranteed income, just to have the opportunity to do what I need to do, both as a mother and as a professional" (Mercy, 2024).

> "I'm a mother. So for me, it has given me room to be able to raise my child from home as I do my work. I have been able to carry out my responsibilities and just be available. So, for me, it has positively impacted me, as a parent, [and] as a wife, it has really impacted [me] because I have been present" (Joyce, 2024).

For work to feel meaningful, it must first provide the essential conditions necessary for living a meaningful life. For many workers, especially those in the Global South, the pursuit of meaningful

work is closely tied to meeting basic needs. In this sense, meaningfulness is not grounded in abstract ideals but in work's ability to alleviate material hardship and provide agency over daily life. Mable shared a similar sentiment:

> "What brought me into remote work is the work-life balance that is lacking in the on-site jobs in Kenya. I get to spend time with family when I'm working remotely. I get to have a lot of free time, and I'll have family around" (Mable, 2024).

In contexts where social safety nets are limited and financial survival is a daily concern, time flexibility and stable earnings rarely align. The ability to provide for one's family while remaining physically present emerges as a key incentive shaping how platform workers perceive the meaningfulness of their work and the positive relationship between meaningfulness and work satisfaction. These social determinants of platform work fulfillment also point to a gendered dimension of meaning-making in platform work. As highlighted in the quantitative analyses, while gender may not significantly affect the proportion of workers who report their work as meaningful, the motivations and contextual factors informing this perception likely vary by gender. As Nora explained:

> "I also have a family, so I decided to work online so that I can have time to take care of my children. Yeah, and also have a lot of time with my family. In an office setup, you don't have the freedom to spend time with the people that you love " (Nora, 2024).

Women platform workers, particularly those with caregiving responsibilities, often view time flexibility not just as a convenience but as a core determinant of meaningfulness. Their narratives centre on how platform work enabled them to fulfill familial roles while earning an income, a form of practical agency often denied by traditional employment.

The findings above highlight the material and social foundations of meaningful work, where the meaningfulness of work cannot be disentangled from the social and economic contexts in which it is embedded. Particularly in collectivist cultures, personal fulfillment cannot be separated from the ability to fulfill collective obligations tied to family, community, and sociocultural expectations, an insight congruent with studies linking schedule control to work–family enrichment and life meaning (Lips-Wiersma & Morris, 2009; Van Deursen & Helsper, 2015). Even precarious platform work can

feel fulfilling when the flexibility it offers enables workers to live more meaningful lives, for instance, by being more present with their families.

4.7.4 Workers' Positive Perceptions of Platform Work Amid Socioeconomic Hardship

Workers also perceive the meaningfulness of platform work through a comparative lens, where work that may not align with dominant notions of decent work, especially those rooted in Global North standards, can still feel meaningful in contexts where local labour market options severely restrict workers' agency and choices. As the quantitative results demonstrate, there is a strong association between the perceived meaningfulness of work and its subjective quality, understood as a combination of satisfaction with work opportunities, conditions, and financial compensation. The way workers perceive the relative quality of their work significantly informs how they interpret the meaningfulness of platform work, and this perception is deeply rooted in their broader sociocultural experiences.

For instance, one of the interview participants, Clara, takes on a variety of gigs in social media marketing, writing, and virtual assistance. Her sense of belonging and purpose in platform work is rooted in earlier employment struggles and the way those experiences shaped how she finds meaning in tasks that might otherwise seem mundane. Her reflections highlight the limited alternatives she faced and explain why platform work feels meaningful.

> "After school, I found myself working as a waiter in a hotel. Because of the timing, you have to wake up very early to make it to work, and you leave late. So, me being a young girl, I was like, no, let me get something else. I started a nail salon. I ran it for almost two and a half years. It's very chaotic, and leases expire, and people are not straight. There's a lot of scamming. You rent a place from someone, [and] later you realize that they've just been sublet by someone else. So now when the original owner comes by, you are left wondering, who do I turn to? And they evict you. So, I got evicted, and I took my things and went to the house. I got a job next to the airport. You'd be there exactly [at] seven in the morning, and your time to leave work is not definite. So, I went there for four days, and I quit. It was a challenge because these kids have to go to school and come back and not find me. They need someone to bathe them, to do homework, to cook for them, and I just looked around and I said, no, it's not the life I want for my son or even my niece. So, I left that work and I started selling what we call mitumba [second-hand clothes]. It was good, but it was not that fine. The sun, the dust, the time it takes to

> sell... People just tell you, oh, give it to me, I'll pay you by the end of the week, and they don't pay" (Clara, 2024).

The agonizing struggle to build a meaningful career around personal interests can render even the most appealing occupations unviable. Clara's experiences remind us how a livelihood rooted in passion cannot feel meaningful if it fails to meet basic needs or exposes a worker to excessive hardship. In such contexts, satisfaction with work conditions that enable individuals to make ends meet without excessive hardship has a far greater influence on perceptions of meaningfulness, especially when alternative opportunities are harsh or unsustainable. Clara, for example, repeatedly reflected on how running a small business, such as a nail salon or spa, seemed like a fulfilling and desirable path. However, the immense challenges of starting and sustaining such a livelihood ultimately made it an unfeasible option.

During the interviews, participants often used terms such as needing a break from their traditional jobs, the desire for a better work-life balance, and dissatisfaction with local employment, highlighting how the lack of good-quality jobs and growth opportunities in traditional roles influences their perception of the platform economy. Enduring struggles and building resilience against challenging livelihood conditions, where the odds seem stacked against them, reshape how individuals derive meaning from their livelihoods. For some workers, these struggles are not merely economic but also social. As Janet explained:

> "They [local office job] reward loyalty and experience, but they tend to overlook skills. I will be in a position to deliver very fast. But now I'm being fought because the moment I'm given, like, a promotion, it becomes an issue. And it is seen as favoritism, [or] tribalism. What I like about freelance [work] is that I don't get to experience those kinds of backbiting and stuff, because no one cares who I talk to, how I look when I am walking, as long as the work is done, perfectly done. But now when you are up against other people in the office you're working [in], people start talking, and you become demoralized" (Janet, 2024).

The role of social interactions in shaping work meaningfulness is noticeable in the theories of meaningful work (Bailey et al., 2017; Clausen & Borg, 2011; Van Zoonen et al., 2024). However, this research highlights the multifaceted nature of this role. While a supportive network of peers can enhance one's work experience, toxic or discriminatory environments can undermine it. In such cases, the absence of social interactions, or the absence of negative social interactions, may actually

enhance the perceived meaningfulness of work. Platform workers, particularly in sociocultural contexts where work-related social capital is limited or exclusionary, tend to evaluate the social dimension of work through this comparative lens. This helps explain why work social capital shows a weaker association with perceived meaningfulness in the quantitative analysis. The common assumption that social connection enhances meaningfulness overlooks the reality that social interactions are not always positive. When workplace relationships are marked by exclusion or judgment, lower social engagement may be a more desirable alternative.

4.7.5 Social Dimension of the Platform Labour Economy

In the platform economy, workplace social capital, such as solidarity networks, peer support, and positive interactions, exists but remains limited. The quantitative findings indicate that a weaker work social dimension of platform work does not have a strong relationship with perceived meaningfulness of work. The null finding of Hypothesis 3a is plausible in the platform context for two reasons. First, algorithmic matching atomizes tasks, conditioning workers to keep work and personal life separate, so workers expect little collegiality and thus do not gauge purpose by it (Kuhn & Maleki, 2017). As a result, the sense of purpose and meaningfulness workers derive from the job is unlikely to hinge on co-worker support or on how the job shapes their social circle. Second, workers in survival mode also view platform labour instrumentally, as a vehicle to finance the life they aspire to live. Under this logic, purpose is anchored less in collegial ties and more in whether the work yields the income and flexibility that enables the desired lifestyle.

As discussed in the previous sections, the sociocultural complexity surrounding work social capital in developing countries such as Kenya may partly explain why platform work's weaker social capital is a less potent determinant of meaningful work. Platform and remote workers' ability to spend more time with family and friends significantly shapes their positive perception of platform work opportunities, as they derive social capital from kinship and local community rather than the workplace (Elbanna & Idowu, 2021a; Isham et al., 2002; Posada, 2022). During the interviews, workers expressed diverse perspectives on the social dimensions of platform work, which can be grouped into three distinct categories.

The first group, including Triza, Kelvin, and Theo, emphasized a sense of social disconnection, describing how the absence of collegial interactions diminished their work experience.

> “You don't get, like, the human touch, you know? You just talk to people. For me, my clients are in the US and some of them in the Philippines, so [you] just get to see them on the laptop. But in the traditional market, you get to go for workshops with them, see them. And, you know, you can be able to have a human connection” (Triza, 2024).

> “So, not being able to maintain regular hours. Something like, oh, you cannot be able to sleep at a regular hour. Maybe the people you're working for, our hours do not align—our time zones do not align—so that does mess up your health a bit, where you're not sleeping regular hours, or you're working either too late. You're not able to meet, uh, family, because, you know, they are working a regular job. Like, they're sleeping, you're awake, you're working. So, I do think there is also that psychological perspective to working online” (Kelvin, 2024).

> “I wish to get a job at an actual local place, because freelancing kind of isolates you from the world. I can spend the whole month in my house, because I'm working from my office in my room. So, I don’t get to interact with people” (Theo, 2024).

The younger workers I interviewed were more likely to express concerns about the limited opportunities to build social capital through platform work, often describing it as one of the more isolating and psychologically taxing aspects of their experience. As Triza highlighted, the absence of human touch and embodied interaction with clients marks a loss of relational depth that traditional work environments provide. Kelvin highlights how asynchronous time zones, a lack of structured routines, and social disconnection from family contribute to a breakdown of the work-life rhythm and emotional strain. Similarly, Theo’s reflection reveals how prolonged physical isolation and lack of casual social engagement can diminish one’s broader sense of connectedness.

While these concerns do not significantly influence the perceived meaningfulness of platform work as a livelihood strategy, they highlight how diminished social interaction can impair psychological well-being and constrain the non-material aspects of work. This suggests that for many younger workers, what troubles them most is not the lack of professional networking or career support (work social capital), but rather the absence of meaningful social interaction and emotional connection that usually make work feel more human and fulfilling.

The second group adopted a coping orientation, acknowledging the lack of social capital but focusing on individual strategies to manage its emotional or professional effects. Simon and Rebecca explained:

> "I enjoy being outdoors and meeting people. When I transitioned to remote work, there were times I'd leave my desk was to find food, drink, or take a small walk. At first, it affected me negatively. [pause] ok, during the first few months, I almost sought mental health support because I was dealing with anxiety. There is the post-work trauma of leaving a traditional job and then the stress of freelancing, trying to find tasks alone and not knowing where to turn for help. Most people I knew didn't understand what I was doing. They often felt that online work didn't amount to anything, so I didn't even tell many people about it. I would just say I was "consulting," which sounded easier to explain. Eventually, I learned to separate work from my personal life by scheduling my time better. I decided on specific work hours and took breaks to walk or do other activities. Initially, it was hard, but now I don't feel any negative effects" (Simon, 2024).

> "I've made friends. So apart from just working in isolation, we have side chats here and there, getting to know more about them and interacting. So yes, it is isolated, but you make it intentional; you make your social life intentional—you work on it, yeah" (Rebecca, 2024).

A subset of mature platform workers acknowledged the limitations of social capital in online work but adopted intentional strategies to manage its psychological and professional implications. These workers do not passively accept the isolating nature of platform labour; instead, they engage in adaptive practices to restructure their social and emotional realities. A recurring theme is the emotional toll experienced during the early stages of transitioning to platform work, often marked by anxiety, identity ambiguity, and a lack of social validation from peers or family. For many, this is compounded by the cultural illegibility of freelancing, which is not always recognized as real work within their social groups.

To mitigate these challenges, some workers employ temporal and spatial boundary-setting to reclaim a sense of normalcy and psychological control. Others opt for long-term gigs that cultivate virtual relationships with colleagues, leveraging chat functions, informal conversations, or transnational collaborations to restore a sense of community. These self-directed efforts illustrate how

social connection in the platform work economy must often be constructed, rather than assumed. For such workers, these virtual networks built through online work play an instrumental role in accessing future opportunities. These interactions may function similarly to the traditional form of work social capital, resulting in professional growth opportunities. However, this form of capital remains unevenly distributed, often dependent on the nature and stability of gigs, suggesting that while platform work can generate new relational assets, these are not universally accessible.

The third group demonstrated proactive engagement, actively seeking to cultivate alternative forms of social connection, such as building virtual peer communities or establishing mentoring networks, to reconstruct social capital within the platform economy. For instance, Jasper routinely organizes in-person events for freelancers in central Nairobi. His perspective on the lack of social capital in platform work highlights how the platform labour ecosystem may require collegial support from fellow workers. However, in-person social networking with those who are socio-culturally closer to you remains an important factor that impacts platform workers' well-being. More specifically, Jasper and Theo highlighted:

> "[I] just tell them to come. It's important for you to network with people—talk to them, tell them what you do, where you work, engage in fruitful conversations. Probably you might lose a job, and one of the freelancers who's at a networking session is going to tell you, "No worries, I can actually help you get a job." We just bring in a sense of community for these guys, so that they can actually see, "I think I am very okay fitting in this particular community. And it's joy for them. When they come over here and network, they get to realize, "This is a friend I can actually talk to." And with time, you find that these guys, believe me, they come back and they're very happy, because now they've been able to spark fruitful conversations. Now, with that sense of community, just one person makes you feel happy" (Jasper, 2024).

> "What motivated me to share, what I do on social media, and maybe talk about freelancing or social media could be the boredom, because mostly I am alone. This has helped me connect with people. Most freelancers now are coming up online, and that is where this world is now. People have started joining communities. I also feel like people have good skills, but they don't know how to market them or put them into work. So, I think that's what motivates me to talk about freelancing" (Theo, 2024).

When platform work is examined in isolation, the lack of opportunities for collegial connection stands out as a significant shortcoming, validating the existing literature position on this subject (Arcidiacono et al., 2019; Fagioli, 2021). However, in Kenya and similar contexts, experienced freelancers like Jasper and Theo are increasingly bridging this gap by forming digital communities and organizing peer-led events. These grassroots initiatives replicate many of the functions traditionally associated with workplace-based social capital, such as peer support, shared identity, and informal learning, serving as alternative infrastructures for an otherwise atomized form of labour (Arcidiacono et al., 2019; Wood, Lehdonvirta, et al., 2018). For some workers, the act of building or participating in these networks provides a sense of purpose and contributes to the sustainability of platform livelihoods.

Nevertheless, as the Hypothesis H3a findings indicate, engagement in peer communities does not consistently translate into a stronger perception of meaningful work. While some workers are able to cultivate local or virtual ties through digital communities, co-working spaces, or informal networks that partially address the social isolation of remote platform work, these experiences remain uneven and often fall short of replicating the depth of in-person human connection. Those who do form such ties frequently describe them as sources of emotional support and belonging, which help mitigate isolation and foster a sense of shared purpose. However, for many others, the absence of meaningful social connection persists. This suggests that platform work fundamentally reconfigures the relationship between sociality and work meaningfulness. Even when workers recognize that social engagement could enhance their experience, they may not explicitly evaluate the meaningfulness of their work through that social lens.

These findings also offer further validation of Hypothesis H3b, showing that even in platform work settings, where workplace social ties are limited, the presence of social capital indirectly enhances workers' sense of purpose and fulfillment. While job quality, particularly satisfaction with tasks, compensation, and conditions, remains the strongest predictor of perceived meaningfulness, its impact is significantly amplified when workers have access to supportive peer networks. Conversely, in low-social-capital environments, high job quality alone may be insufficient to make the platform work feel meaningful.

Collectively, the proactive strategies and mindset of workers reflect a broader redefinition of what it means to have colleagues or to participate in a professional community that would provide a more meaningful work experience. The absence of workplace-based social capital does not necessarily diminish the possibility of finding meaning in work, but this systemic individualization does require workers to work their own to find compensatory mechanisms that are socially contingent. The experience of meaningfulness, therefore, is not only shaped by the presence or absence of workplace interactions but also by the individual capacity to navigate and reconstruct social connections in fragmented and transnational labour spaces that is often indifferent to workers' psychosocial needs.

Importantly, the discourse on the meaningfulness of work in this research raises a fundamental question: to what extent is it the moral responsibility of platforms or work providers on platforms to foster a sense of purpose and fulfilment for workers? In platform-based labour, opportunities for deriving meaning through social relationships are largely absent. But does the responsibility of cultivating such a connection rest with the platforms, especially given their limited capacity to understand the diverse social values and community support needs of a globally dispersed workforce?

In practice, local informal networks and semi-organized labour initiatives in Kenya are stepping in to fill some of this gap. While collective mobilization for labour rights is one important function of labour networks, these efforts also play a vital role in addressing the social capital void created by the individualized and task-oriented nature of platform work. By fostering solidarity, shared identity, and mutual support, these community-based efforts help reconstruct the social dimensions of work that online platforms often overlook. Their significance lies not only in advocating for better working conditions but also in making remote, platform-based livelihoods more meaningful and socially sustainable.

4.8 Conclusion

This study aimed to understand why many Kenyan platform workers describe gig-based, algorithmically mediated labour as meaningful, despite its well-documented precarity. Guided by two research questions, first, the extent to which perceived work meaningfulness correlates with self-reported job satisfaction and positive social relationships among Kenyan freelancers; and second, how the isolating nature of remote gig work affects social capital and, in turn, shapes perceptions of meaningfulness, this mixed-methods analysis combines survey data with in-depth interviews to offer a nuanced understanding of this apparent paradox.

The findings reveal a strong positive correlation between perceived meaningfulness and job satisfaction. However, a greater diversity of gig work, on its own, does not consistently enhance the sense of meaningfulness unless accompanied by improved access to opportunities and adequate financial remuneration. Furthermore, work-related social capital within the Kenyan platform economy tends to be localized. While it contributes to the perception of meaningfulness when coupled with high-quality work opportunities, its overall influence on how workers derive meaning from their work remains limited.

Beyond testing established relationships, the study offers several novel insights. First, the distinction between tasks meaningfulness and livelihood meaningfulness is critical. Most participants found little inherent purpose in the gigs themselves; what felt meaningful was the function those gigs served, as building blocks that eased financial pressure, expanded professional horizons, or enabled a lifestyle aligned with family and community commitments. The livelihood meaning often supersedes the task meaning. Platform work is judged less by its intrinsic content and more by its ability to reduce hardship, enhance agency, and support roles that matter outside work.

Second, comparative evaluations shape perception. Even imperfect platform opportunities can appear attractive when local labour markets offer scarce, low-paying, and time-intensive jobs. Quantitatively, perceived meaningfulness rose sharply with workers' satisfaction about pay, task variety, and autonomy, suggesting that quality remains decisive, but is assessed against a backdrop of constrained alternatives. These findings echo a capability-based view in which agency to pursue valued doings and beings, rather than task content per se, defines meaningfulness (Sen, 2001).

Third, the study highlights a relational reconfiguration of work social capital. Limited collegial interaction on platforms is widely felt, yet its impact on meaning depends on context. Where traditional workplaces are marred by discrimination or rigid hierarchies, the absence of daily politics can be liberating. Meanwhile, freelancers who proactively cultivate digital or local peer communities often restore a sense of belonging and open new income channels, though these benefits accrue unevenly.

Please note that this study is context-specific, drawing exclusively on a modest sample of 52 Kenyan freelancers. Consequently, quantitative statistical power is exploratory and limited. The findings may not extrapolate to economies with stronger welfare systems, different labour regulations, or alternative cultural norms. Because the data are cross-sectional, they capture only a snapshot of workers' experiences; longitudinal evidence is needed to demonstrate how perceptions of meaningfulness evolve as careers mature, platform policies change, or global demand fluctuates. Future research should broaden the concept of work-related social capital to include relationships with platform clients, investigating how the diversity and quality of client interactions shape both opportunity structures and social capital, as well as the subjective value of work. Comparative studies, across gender, sector, platform type, and national context, are also warranted to test whether the livelihood-over-tasks logic observed here holds in other parts of the Global South and in the Global North.

Chapter 5

AI-Driven Transformation of Platform Work: A Task-Based Model for Measuring Labour Disruption and Vulnerability, with Early Evidence from Online Freelancing in Kenya

5.1 Introduction

This paper seeks to analyze the complex impact of generative artificial intelligence (AI) driven change on the livelihood sustainability of Kenyan freelance platform workers. The rapid evolution and widespread availability of general-purpose AI tools, such as ChatGPT, Midjourney, Google Gemini, DeepSeek, and Anthropic Claude, is creating possibilities to restructure work and rethink work productivity through integrated human-AI partnerships. This technological transition introduces questions about its potential to influence how work is performed, with significant uncertainty surrounding its effects on job availability, skills demand, and wages (Agrawal et al., 2019). As general-purpose Artificial Intelligence (AI) tools continue to evolve and grow in adoption, their complex impact on labour markets demands deeper, evidence-based analysis.

The practical impact of this technological transition on worker livelihood remains unclear without empirical investigation (Hui et al., 2023; Liu et al., 2023). This uncertainty arises from several research gaps and challenges. There are significant differences between theoretical AI exposure and its practical impact on jobs (Albanesi et al., 2023; Gmyrek et al., 2023). The adoption of AI tools across firms, regions, and individual workers remains uneven, while the capabilities of these tools are constantly evolving and advancing with each update (E. W. Felten et al., 2023). More importantly, these tools have a multifaceted impact on workers' livelihoods, as they simultaneously function to substitute and complement work tasks (Agrawal et al., 2019).

It is likely that AI-driven automation may depress wages and reduce job quality by narrowing the range of tasks where human expertise remains indispensable (Occhipinti et al., 2024). However, historically, theoretical models predicting technology's impact, including widespread labour market disruption and job losses, often remain disconnected from the actual effects on the labour market (Agrawal et al., 2019). Yet, competing perspectives also argue that this time around, the disruptive impact on the economy and labour market would be different since the ability of AI tools to handle

non-routine cognitive tasks offers the type of productivity growth and labour market disruption that may not self-correct, leading to labour redundancy and broader recessionary pressure (Occhipinti et al., 2024).

Recognizing the impact of this technological change on occupations and employment, the recent discourse on AI's potential impact on jobs (Acemoglu et al., 2022; George et al., 2023; Gmyrek et al., 2023) has primarily focused on exploring the risks and impacts within conventionally recognized occupational categories and job titles. While building a macro-level understanding of potential AI risks and opportunities, this broad perspective often overlooks the nuanced ways in which work is organized (e.g., platform work) within the same occupations and industries, potentially leading to varied AI effects on skills and tasks within a given occupation.

While AI tools could alter work processes and productivity metrics, the platformization of knowledge work[14] fundamentally transforms how labour is organized as platforms deconstruct traditional jobs into task-based units, challenging labour norms and traditional occupational categories (De Stefano, 2015; Graham, Hjorth, et al., 2017). I build on the understanding that even when job and occupation titles stay the same, the nature and frequency of tasks, methods, and tools used can differ significantly among workers, depending on how work is organized. These variations suggest that AI technologies may differentially impact worker groups, reshaping the demand for specific skills and the remunerative potential of tasks while leaving others largely unchanged. As a result, a more granular, task-level analysis is essential to accurately assess AI's true impact on workers within an occupation.

This need for detailed examination is particularly acute in the domain of knowledge work, where precarious working conditions are increasingly evident, such as freelancing through digital platforms. The growth of online labour platforms has transformed the employment landscape, especially in developing regions where education gains and digital connectivity have significantly

[14] The notion of Knowledge work here refers to labour that primarily involves a higher level of cognitive complexity and specialized expertise, rather than manual or routine tasks. It is commonly defined as work in which knowledge serves as both the principal input and output (Allison Woodruff et al., 2023; Alvesson, 2001). Within the platform economy literature, this distinction is particularly salient, as it helps differentiate cognitively demanding and interactive gigs, such as writing, software development, graphic design, and customer service, from highly repetitive or routine tasks such as image tagging, clickwork, as well as manual services such as ride-hailing and delivery work (Huws, 2014; Kalleberg & Dunn, 2016).

improved, but decent work opportunities are relatively scarce (Bonina et al., 2021). Freelancers operating on platforms such as Upwork and Fiverr engage in a variety of tasks across different occupations, requiring a range of digital skills, making them uniquely susceptible to the nuanced effects of AI on specific tasks and work availability.

Although these freelancers in developing regions have historically leveraged competitive pricing to secure offshored jobs (Graham, Hjorth, et al., 2017), the growth of AI systems capable of handling tasks at scale could threaten to disrupt this advantage, potentially reshaping global demand for and pricing of human labour. The precarious nature of platform work and the lack of employment safety nets could further amplify these vulnerabilities, making this group of the workforce particularly exposed to rapid technological shifts and global market fluctuations (Standing, 2019). Despite extensive discussions on AI's potential impact on employment, there is a lack of empirical research that systematically assesses this disruption and how AI affects specific tasks within various freelance occupations, especially in developing regions (Hui et al., 2023). Understanding which tasks are most susceptible to AI disruption and recognizing the nature of this disruption is essential for freelancers, policymakers, and platform operators to develop strategies that mitigate risks and leverage AI for sustainable employment.

In this research, the notion of generative artificial intelligence (AI) refers to computational systems designed as interactive products capable of generating seemingly new, meaningful content, such as text and images, from training data (Brown et al., 2020). These products are built on recent breakthroughs in machine learning that have paved the way for large language models (LLMs) that harness vast datasets to produce human-like text and perform sophisticated language and data tasks (Brynjolfsson et al., 2023; Sutton & Barto, 2018). A generative AI model can be either general-purpose or specialized (i.e., industry-specific), built on a machine-learning architecture that is designed to create content by identifying and replicating complex patterns in data (Acemoglu & Restrepo, 2019).

However, the automation aspect of AI also encompasses AI agents. These somewhat autonomous software entities recognize the common digital environments, such as using a web browser to perform certain tasks, make decisions, and execute actions to achieve specific goals based on given objectives, which could contribute to the automation of common workplace tasks (Kolt,

2025). It represents a different level of automation, as traditional automation primarily involved programming systems to perform repetitive, rule-based tasks, thereby optimizing operational efficiency (Acemoglu & Restrepo, 2020; Brynjolfsson & McAfee, 2014). By contrast, the newer conceptualization of AI is characterized by adaptive learning capabilities that extend its influence beyond synthetic content creation and routine task execution (Brown et al., 2020; Kolt, 2025).

In this paper, I focus on how AI's capabilities in enhancing labour productivity, automating tasks, and substituting human labour pose both opportunities and challenges for freelance platform workers who rely on digital platforms for employment. I assess the extent to which this technological shift reshapes work and whether this change results in livelihood vulnerabilities for those working in platform-dependent jobs. The occupations examined in this analysis include freelance writing, web and software development, virtual assistance, transcription, and freelance transcription services.

I take the approach to structure this inquiry around two interrelated yet distinct dimensions of AI's impact on freelance work: disruption and vulnerability. In digital labour markets, disruption and vulnerability are not incidental by-products but embedded within the design of platform work structures. Disruption operates on two levels. First, it fragments work into decontextualized, modular tasks that decouple execution from decision-making, flatten occupational hierarchies, and enable new forms of remote oversight and productivity tracking (Gray & Siddharth, 2019; Kellogg et al., 2020). And second, it restructures labour relations through algorithmic control, flexible contracting, and the externalization of risk (Graham et al., 2019; Srnicek, 2017). AI, however, may introduce additional layers of change and reshape the interaction between workers and the worker providers. This duality makes it challenging to differentiate the incremental impact of AI from the systemic instability already present in the platform economy.

In the context of this research, disruption refers to any drastic departure from the established status quo regarding both the nature of work and its potential for remuneration. It denotes the overall transformation in how tasks are configured and executed, encompassing both opportunities (e.g., enhanced productivity, new work modalities, the need for reskilling) and challenges (e.g., task reorganization, shifting skill requirements) (Autor, 2015; Brynjolfsson et al., 2018; Huang & Rust, 2021). From a platform work perspective, disruption is not merely a technical adjustment but a continuous restructuring of work, one that obliges platform workers to navigate new regimes of

control, competition and compensation and impose significant transition costs (De Stefano, 2015; Wood et al., 2019). This deskilling and reskilling due to continuous reorganization of work remains a hallmark of platform work (Latif, 2024; Srnicek, 2017).

This conceptualization of platform work disruption builds on the understanding that disruption is a multifaceted process that involves significant, often rapid, reconfigurations of established practices, processes, and structures within workplaces and industries (Christensen, 1997; De Stefano, 2015). Significant changes in work practices, whether introduced through new tools and technologies such as labour substitution via generative AI or organizational arrangements like the platformization of work, are not neutral innovations but deliberate shifts that unsettle established labour processes. While such a form of disruption is not inherently harmful and can open up opportunities for worker groups to reposition themselves within emerging opportunities, it nonetheless demands a period of adjustment that may precipitate struggles at the worker level.

Vulnerability, on the other hand, refers to the structural exposure of workers to factors that collectively reduce their livelihood opportunities by causing wage cuts and job losses (Cingolani, 2021). The conceptualization of vulnerability focuses specifically on the adverse economic outcomes that may arise from these changes, such as job loss, wage reduction, or the sudden devaluation of skill capital (De Stefano, 2015; Standing, 2019). Unlike disruption, which broadly denotes the reconfiguration of work practices, vulnerability in this context emphasizes the economic risks and livelihood insecurities that arise when new forms of production render work opportunities inaccessible or less economically competitive.

This paper quantifies disruption and vulnerability in the platform work economy. The disruption score in this study quantifies the extent to which AI is likely to alter a task, reflecting the overall magnitude of change in how work is performed. This metric is crucial because it highlights the need for reskilling as the retooling of tasks potentially demands retraining, regardless of whether the impact is perceived as positive or negative. The focus on disruption underscores that AI will bring about significant shifts in task execution, necessitating greater adaptability among workers. The vulnerability score assesses how susceptible a task is to being affected by AI in ways that directly impact workers' access to work, particularly for those in the Global South. This metric is important

because it sheds light on the potential risks to income and employment stability for freelancers who may already be in precarious economic situations.

I examine the potential likelihood of disruption and vulnerability within the selected platform work categories using a task-based analysis model. By adopting a task-based analysis of AI impact, which provides a framework for isolating AI's specific effects from the broader disruptions inherent to other aspects of platform-mediated work, this model disentangles these intertwined influences, thereby offering a more precise understanding of how AI contributes to both the disruption and vulnerability of platform workers. The following key questions guide this research.

RQ1: How can we systematically measure the magnitude of AI-related occupational disruption and the extent of worker vulnerability across different platform work occupations?

RQ2: To what extent do AI's task-enhancing capabilities mitigate its labour substitution effects across different occupational categories within platform work?

RQ3: Which core tasks within selected platform work occupations drive levels of disruption and vulnerability, and how does this susceptibility vary across occupational categories?

RQ4: How well do these disruption and vulnerability metrics correspond with freelancers' experiences and economic outcomes on digital platforms?

The first section addresses question 1 by building on existing research to develop and validate quantitative measures that capture both the overall disruption and the vulnerability induced by AI across different freelance occupations. Existing measurement techniques that rely solely on platform labour market statistics often fall short of capturing these nuanced dynamics (see, e.g., Gmyrek et al., 2023; Jing Liu et al., 2023) highlighting the need for more refined metrics (discussed further in the literature review section). I introduce a measurement model that builds on the nature of tasks, such as cognitive routine and non-routine tasks (Autor, 2015; Frey & Osborne, 2017) and the potential impact of AI, such as substitution, automation risk, and worker performance enhancement (Eloundou et al., 2023; Mäkelä & Stephany, 2024).

The second section operationalizes this model to answer questions 2 and 3. The second question recognizes the dual nature of AI: its capacity to both substitute for and enhance human labour, potentially mitigating the adverse effects on vulnerable workers. This question aims to assess

the extent to which AI's task-enhancing capabilities can mitigate its displacement effects on the selected occupational categories. The third question examines a range of core tasks within selected freelance occupations to identify the drivers of both disruption and vulnerability across occupational categories. A granular understanding of these drivers is critical for explaining why freelancers may shift between occupational categories or experience divergent outcomes, and it offers valuable insights for freelancers, skill trainers, and policymakers alike.

The third section examines the empirical validity of these assumptions by analyzing both qualitative (n = 20) and quantitative data from my field study, which involved 52 platform workers in Nairobi, Kenya. This section is a direct response to question 4 and addresses the empirical gap as highlighted by scholars (Hui et al., 2023; Liu et al., 2023). It examines how well these disruption and vulnerability metrics correspond with freelancers' experiences and economic outcomes on digital platforms. By linking task-level assessments to workers' direct perspectives, I evaluate the external validity of these measures and illuminate their lived experiences.

This study contributes to multiple bodies of literature by advancing the understanding of AI's impact on digital platform work at both task and occupation levels. First, it extends the literature on the task-based measurement methods to capture the magnitude of the AI-driven labour market transition by providing empirical data and a methodology identifying tasks vulnerable to AI disruption (Acemoglu et al., 2022; Agrawal et al., 2019; Autor, 2015). Second, it builds on the scholarship on digital platform labour markets and the impact of AI on platform-mediated knowledge work (Graham, Hjorth, et al., 2017; Hui et al., 2023; Liu et al., 2023; Melia, 2020) by analyzing how AI reshapes tasks that form the livelihood of freelance platform workers. Third, by highlighting both the challenges and opportunities AI presents, ranging from the need to upskill workers and redesign tasks to the potential for enhanced productivity, this research informs workers and development agents seeking to foster resilience in the digital economy. The study uses the terms freelancers, gig workers, and platform workers interchangeably to denote the global workforce of knowledge workers who leverage digital platforms to find gig work that is typically done remotely.

5.2 Literature Review

Recent literature highlights a growing interest in measuring the early-stage effects of generative artificial intelligence in reshaping the nature of work, e.g., Acemoglu & Restrepo, 2019; Felten, Raj,

Manav, et al., 2023; Frey & Osborne, 2017; Gmyrek et al., 2023. Current research has generally followed two methodological streams.

5.2.1 Methodological Approaches and Perspectives in AI and Labour Research

On the one hand, some studies analyze job market data to track changes in skill demand and labour supply over time. e.g., (Acemoglu & Restrepo, 2019; Hui et al., 2023). These studies adopt an approach that emphasizes the use of observable market-level trends and dynamic changes in labour demand to understand the broad influence of AI tools.[15]

On the other hand, another set of studies takes a task-based perspective, focusing on the underlying occupational structures (Eloundou et al., 2023; E. W. Felten et al., 2023; Frey & Osborne, 2017; Liu et al., 2023). These bodies of literature examine the broader impacts of AI on occupations and labour markets, concentrating on stable, well-defined roles and skills (Frey & Osborne, 2017; Webb, 2019). For example, the International Labour Organization's report on AI's potential effects on jobs (Gmyrek et al., 2023) offers a global analysis of AI's potential impact on jobs. Following the techniques of Eloundou et al. (2023), their method builds on sequential GPT-4 API calls to generate task-level automation scores aggregated at the occupation level. Their findings highlight, for instance, that clerical support occupations exhibit high automation potential, while other occupational groups show much lower exposure.

Frey & Osborne (2017) and Felten, Raj, Manav, et al. (2023) both draw on standardized O*NET[16] data to assess the susceptibility of occupations to AI automation, yet they employ distinct methodological approaches. Frey and Osborne employ a Gaussian process classifier to estimate the probability of computerization across 702 detailed occupations, examining task characteristics to distinguish between routine and non-routine tasks, as well as manual and cognitive tasks. Their analysis suggests that jobs requiring creative or social intelligence appear more resilient.

In contrast, Felten, Raj, Manav, et al. (2023) adapt the AI Occupational Exposure (AIOE) framework to capture the impact of recent advances in large language models (LLMs), such as those

[16] ONET (Occupational Information Network) is an online database sponsored by the U.S. Department of Labour that offers detailed, standardized information on job requirements, worker attributes, and occupational characteristics. (*O*NET Resource Center*, n.d.)

embodied by different versions of ChatGPT3. By assigning weights to the AI models and human skills within their exposure matrix, they reveal that specific education-related roles and digital work, such as telemarketing, are notably vulnerable. However, they find a positive correlation between higher wages and exposure to these technologies. Although both studies leverage ONET data, Frey and Osborne offer a broad, generalized risk assessment. In contrast, Felten et al. provide a technology-specific perspective highlighting how task reconfiguration within particular domains may evolve. Notably, neither study captures the contextual occupational variability, such as differences between traditional and remote or freelance work, pointing to a gap that future research should address.

While these approaches towards the task-based assessment of AI impact on work offers a deeper understanding of the intrinsic automation potential in various occupational structures, it is important to also consider the differences that emerge when work is organized differently. A traditional understanding of occupational structures differs from, and may sometimes overlook, the operational nuances in digital work contexts (Wood et al., 2019). Hence, I contend that by aggregating data at the occupational level, the analysis, when applied to platform work, may overlook critical nuances within digital work contexts or the enhancement impact of the same technology.

5.2.2 Existing Literature on the Impact of AI on Platform Work

Among the relevant quantitative research studies covering digital platforms, Jing Liu et al. (2023) utilized a dataset of jobs, bids, transactions, and freelancer profiles from Upwork to analyze how generative AI reshapes labour demand and supply. They created submarkets (in lieu of occupations) based on skill tags and applied difference-in-differences and triple-differences methods to capture the impact of ChatGPT's availability on these submarkets. Their findings reveal a significant drop in labour demand (fewer jobs posted and fewer participating clients) for text-based and coding-related submarkets and fewer new freelancers entering them. Jing Liu et al. (2023) note that many text-oriented freelancers also begin bidding on programming tasks, citing ChatGPT's ability to lower coding barriers. Notably, their analysis shows no such effect for image-based work. According to Jing Liu et al. (2023), this is presumably because current image-generation tools remain narrow in scope. These results highlight the fluid and uncertain boundaries of general-purpose AI, underscoring freelancers' adaptability through skill transitions in response to rapid technological change.

While Liu et al. (2023) provide valuable market-level evidence on how ChatGPT reduces demand for certain skill-based submarkets and reshapes freelancer bidding, their analysis remains at a relatively aggregated scale, focusing on broad submarkets (e.g., text versus programming) rather than the specific tasks that vary within an occupation. Moreover, they do not employ dedicated metrics to pinpoint the magnitude of disruption or worker vulnerability arising from AI adoption. This gap is precisely where the present research intervenes, conducting a task-level inquiry into freelance work to capture how AI reshapes both the nature of tasks and workers' livelihood security.

Among the studies focusing on job availability data, Xiang Hui et al. (2023) using Upwork platform job availability data shows that after ChatGPT's release, freelancers offering writing-related services experienced a decline in work. They highlight that among those freelancers who receive work, the study documents a 4.7% decrease in the number of jobs and a 5.1% reduction in monthly income. Notably, their results suggest that higher-quality freelancers are less adversely affected by these technological shifts. In a complementary analysis, they extend their approach to image-generation technologies (including DALL-E 2 and Midjourney) and find that freelancers in design, image editing, and art services experience similarly negative impacts on job counts and compensation. It is worth noting that these findings related to graphic work contradict the findings by Jing Liu et al. (2023) that estimated lower disruption among image-related work, demonstrating the limits and complexity of measuring impact on freelance work on a granular level.

5.2.3 Macro-Level and Theoretical Impact of AI on Work

Broadly, a central question emerging from the literature involves whether AI tools merely boost productivity or substantially displace human labour (Acemoglu & Restrepo, 2019; Agrawal et al., 2019; Brynjolfsson et al., 2018). The outcome can vary significantly across different occupations and tasks depending on how the technology is integrated, whether as an assistant or a near-total replacement. Key scholars in this field argue that large language models can perform a wide array of tasks at or near human-level quality, suggesting they can serve as both substitutes for and complements to human labour (Agrawal et al., 2019; Eloundou et al., 2023; Mäkelä & Stephany, 2024).

On the one hand, some studies suggest that AI can function as a powerful complement to human labour rather than complete automation or substitution (Agrawal et al., 2019). By automating repetitive or lower-value tasks, AI frees individuals to devote more time and cognitive resources to

creative, strategic, or social dimensions of their work, areas in which human judgment remains indispensable (Huang & Rust, 2021; Mäkelä & Stephany, 2024). On the other hand, a competing view warns that dependence on AI may erode essential worker capabilities, a phenomenon referred to as skill atrophy, where individuals may become less adept at certain tasks when they overly rely on algorithms and automated systems (E. Felten et al., 2023).

Increasingly, however, the scope of AI raises fresh concerns. According to (Eloundou et al., 2023), large language models can handle both routine and some non-routine cognitive tasks[17], challenging the notion that labour markets will naturally absorb disruptions by creating entirely new, offsetting roles. This creates a paradox where rapid productivity gains, if not matched by the development of new tasks requiring human intervention, could intensify labour-market frictions and potentially create recessionary pressures (Acemoglu & Restrepo, 2020; Brynjolfsson et al., 2021). Still, the ability to automate a task does not automatically translate to immediate or universal adoption, as cultural, economic, and policy factors often mediate its real-world impact (Acemoglu, 2021). Although this macro-level AI impact has significant policy value, the realities of individual workers facing displacement and deskilling and their reskilling struggles are context-specific and require a microlens to examine this technological disruption.

5.2.4 Limitations of Traditional Occupational Aggregation in Digital Platform Work

This emphasis on traditional employment categories can obscure the intricacies of freelance or gig-based work, where individuals frequently perform a significantly different set of tasks, sometimes under the same occupation label, as discussed in the existing literature on the occupational impact of AI (Tolan et al., 2019). The traditional occupation-centric lens has been critiqued for its limited applicability to fragmented and diverse platform work, where boundaries between these categories can blur because many online workers take on diverse tasks that do not always fit neatly into a single traditional occupation (Kässi & Lehdonvirta, 2018; Wood et al., 2019).

These scholars argue that standardized occupational titles, while useful for large-scale labour market analyses, may poorly capture the granular task mix that defines freelancing. Consequently, the

[17] Routine tasks are activities that involve repetitive, predictable, and well-structured processes, often requiring little to no creativity or complex decision-making. Non-routine tasks, on the other hand, involve problem-solving, critical thinking, or creative decision-making and are less predictable. (Autor, Levy, & Murnane, 2003).

theoretical predictions derived from mapping traditional occupations to AI exposure may not align with the actual work experiences of freelancers, particularly in low- and middle-income countries where digital platform labour is rapidly expanding. This misalignment underscores the necessity of applying a more dimensional approach centred on freelancing-specific tasks and worker experiences rather than relying solely on static occupational labels.

In platform-based freelancing, questions of AI exposure and displacement risk are particularly complex and multifaceted. Even workers formally grouped under the same occupational title (for instance, freelance writer) may carry out a portfolio of tasks such as drafting marketing copy, researching content, editing standardized documents, producing keyword-rich web content, administrative work, and repetitively applying for jobs (Kässi & Lehdonvirta, 2018). Each task presents its own degree of complexity, creativity, and susceptibility to the impact of AI. The occupational exposure index by Felten, Raj, et al. (2023) provides a starting point, but such an approach risks misinterpretation if applied to freelance work through digital platforms, where activities often diverge widely from those of traditional employees with the same job title.

These perspectives suggest that the real-world impact of generative AI on freelance occupations, particularly in the Global South, is influenced by an interplay of economic, social, and technological factors. Critically, there is a need to measure not only the potential for displacement but also the degree to which AI tools might augment and diversify existing worker capacities (Brynjolfsson et al., 2021; Eloundou et al., 2023).

5.3 Conceptual and Analytical Framework for Task-Based AI Impact Measurement

I build on the understanding that the collection of platform work tasks within an occupation category is similar but not the same as the tasks within a traditional occupation category. Therefore, grasping the layered reality of platform workers requires going beyond conventional occupational tasks, focusing instead on the distinct tasks that define the work a platform worker performs. A task-level assessment model of AI impact, therefore, offers a granular gauge of how AI might disrupt or augment platform-mediated work while accounting for the proportion of time or weight each subtask represents, acknowledging that a single occupation might include both easily automated duties (e.g., routine data entry) and highly creative functions (e.g., brand storytelling) (Frey & Osborne, 2017).

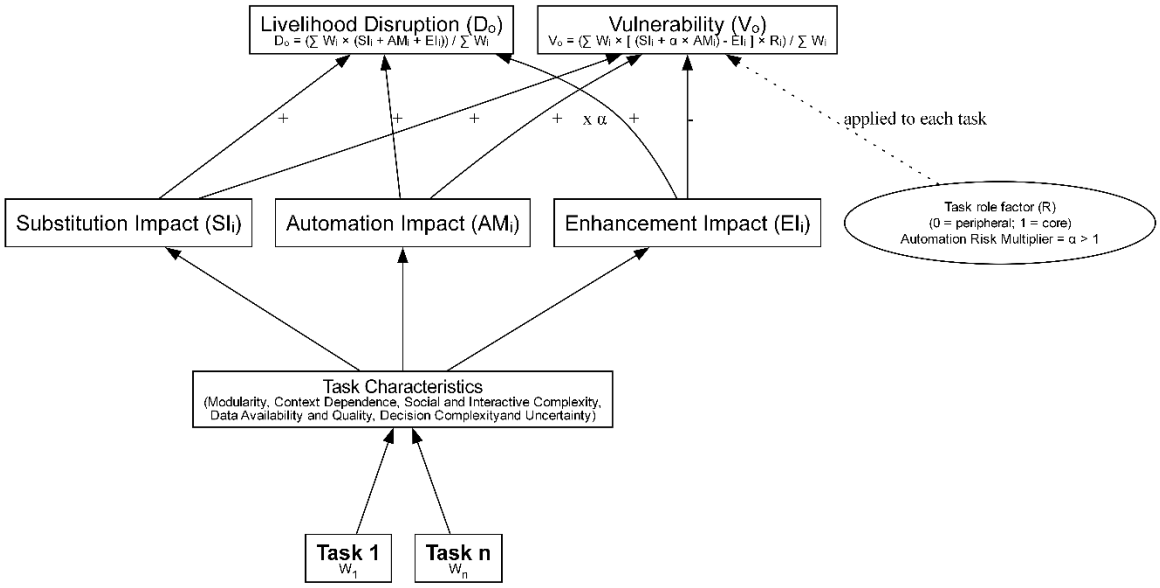
Simultaneously, the early stage of this research topic underscores the need to align empirical investigation with theoretical models that are flexible enough to accommodate AI's rapidly evolving capabilities.

The suggested framework below (Figure 5.1) quantifies the likelihood of how individual tasks within a particular category of platform work are being transformed by AI, capturing the nuanced interplay among automation, substitution, and enhancement impacts. It implies that an objective analysis of the characteristics of tasks within an occupation can clarify the nature of AI's impact on those tasks. Additionally, determining the relative significance of each task and accounting for often-overlooked unpaid tasks can ensure a more balanced understanding of this impact at the occupational level, helping to recognize the magnitude of disruption and potential livelihood vulnerability.

Rather than treating the impact dimensions as binary outcomes, the model calculates probabilistic scores for work tasks, reflecting that slight variations in task characteristics can shift the balance between being entirely automated, substituting the majority of human labour, or only benefiting the worker but enhancing their abilities. This framework provides a tool to generate robust occupation-level disruption and vulnerability scores by aggregating these task-level probabilities through task weightings that account for both economic significance and unpaid labour. In doing so, it identifies which tasks and occupations are most likely susceptible to AI-driven change and reveals the underlying trade-offs, such as the constrained potential for worker enhancement when a task already exhibits high automation characteristics

Figure 5.1

Task-Based Model to Measure AI-Driven Platform Work Disruption and Vulnerability



5.3.1 Task Characteristics Examination

The approach to examining the work task characteristics draws on seminal works (Autor, 2015; Autor et al., 2003; Goodhue & Thompson, 1995) and more recent contributions (Acemoglu & Restrepo, 2019; Frey & Osborne, 2017). Earlier studies have primarily relied on dichotomous or fixed criteria, such as those distinguishing between routine[18] versus non-routine or manual versus cognitive tasks, to gauge the computerization-driven automation potential of occupations (Autor, 2015; Autor et al., 2003).

However, emerging research suggests that the increased capabilities of AI and the blurring of boundaries between such legacy distinctions require a more nuanced approach (Acemoglu & Restrepo, 2019; Frey & Osborne, 2017). The framework presented above primarily draws on this emerging body of literature. The framework proposes assessing occupational tasks associated with

[18] Routine tasks adhere to established, clearly defined protocols that enable them to be codified and executed automatically through algorithmic processes (Autor et al., 2003)

different categories of platform work, including unpaid periphery tasks, along the following five dimensions.

5.3.1.1 Task Modularity and Granularity

Prediction tasks that are highly modular and discrete may be easier to automate fully, leading to a strong substitution effect. In contrast, tasks interwoven with other activities might be less amenable to complete automation but could benefit from AI augmentation. This conceptualization builds on the insights from the Task Technology Fit literature (Goodhue & Thompson, 1995) and the well-acknowledged routine versus non-routine and cognitive versus manual task distinctions by Autor and Murnane (Autor, 2015; Autor et al., 2003) to explain how technological change affects job tasks.

5.3.1.2 Context Dependence

Tasks that require high sensitivity to environmental, cultural, or situational cues are less likely to be entirely substituted by AI, even if certain components can be automated. In contrast, low context-dependent tasks might face higher substitution as prediction and decision-making abilities can both be performed by AI tools (Acemoglu & Restrepo, 2019; Agrawal et al., 2019).

5.3.1.3 Social and Interactive Complexity

Tasks that involve significant social interaction, negotiation, or emotional labour are more likely to experience enhancement, where AI tools support human decision-making, rather than outright replacement (Brynjolfsson et al., 2021).

5.3.1.4 Data Availability and Quality

The extent to which a task is data-driven plays a crucial role. Tasks with abundant, high-quality data can be more effectively learned and replicated by AI systems, increasing the likelihood of automation and substitution, whereas tasks reliant on tacit knowledge may be less affected (Agrawal et al., 2019). The lower quality of data may result in unreliable performance and utility of AI tools (Mohammed et al., 2022) resulting in a greater need for human decision-making.

5.3.1.5 Decision Complexity under Uncertainty

Finally, tasks that involve multi-step decision-making under uncertainty may be only partially automatable, as AI may offer decision support and augment human performance, rather than fully

substitute or automate it. Even as AI systems improve their ability to forecast outcomes, the difficulties of consecutive decision-making under uncertainty require human intervention to manage residual ambiguity (Brynjolfsson et al., 2018; Huang & Rust, 2021).

5.3.2 The Dimensions of AI Impact

In developing this model, I heavily draw on the dimensions of AI impact as conceptualized by Agrawal et al., (2019). Their framework differentiates between the three direct effects mentioned below, through which advances in AI's prediction capability could influence the future of work. These three dimensions are the building blocks for this task-based impact measurement model. In this framework, each task within an occupation is evaluated along substitution, automation, and enhancement vectors, and their relative importance is adjusted using two key parameters, i.e., task weightage (*W*) and role factor (*R*).

5.3.2.1 Substitution Impact (SI)

AI could directly substitute capital for labour in prediction tasks that depend on using existing data to fill information gaps (Agrawal et al., 2019). For instance, freelance transcription platforms increasingly employ AI-powered speech-to-text tools that substitute for human transcribers. As the cost of high-quality prediction decreases, AI tools can replace human labour in the bulk of this work, thereby reducing the need for human labour to do the *entire* work, boosting productivity and shrinking human labour demand. However, I suggest that, for substitution to be viable, enabling factors such as data availability and task modularity must surpass a minimum level. Moreover, excessive uncertainty may encompass high decision complexity and contextual and social challenges that make it difficult for AI to operate reliably, thereby reducing its substitution potential.

5.3.2.2 Automation Impact (AM)

When automated prediction increases the relative returns to capital versus labour in complementary decision tasks, it can lead to the complete automation of those tasks (Agrawal et al., 2019). For instance, for micro-tasks, algorithms and AI agents may themselves complete the job or validate task completion, effectively automating decisions that were previously made by human supervisors. In such cases, AI not only predicts outcomes more quickly than a human but also automates the subsequent decision-making process, ultimately reducing the need for the worker. In this context, I suggest that for automation, not only must data availability and the modular nature of tasks be

sufficiently high, but they must often exceed a minimal threshold level to enable AI to perform both prediction and decision-making. Excessive levels of hindering factors (e.g., context dependence and social complexity) can drastically reduce the automation potential for AI to take over tasks, regardless of how strong the enabling conditions might otherwise be.

5.3.2.3 Enhancement Impact (EI)

Alternatively, the impact of AI on tasks may enhance, rather than replace, human decision-making when it does not replace labour with capital (i.e., AI). When the enabling factors (such as data quality and availability, and the modularity of a task) exist but do not reach the threshold required to achieve substitution or automation levels, it will likely result in AI being a helpful tool for labour without impacting wages.

I suggest that enhancement without substitution tends to be most effective within a balanced range of conditions. When enabling factors are too low, AI adds little value to tasks. On the other hand, when enabling factors are very high, particularly alongside strong hindering factors such as extreme social complexity, tasks may become so unstructured that even augmentation becomes difficult. In this case, by providing accurate, real-time recommendations, AI can augment human productivity in prediction and decision-making tasks without diminishing the value of human labour. For instance, freelance writers can utilize AI-based grammar and style checkers to refine their drafts, thereby enhancing efficiency while maintaining creative control. Here, the prediction provided by AI enables a more nuanced and effective human response, thereby increasing labour productivity.

5.3.3 Unpaid Work and Task Significance

Not all tasks within an occupation hold the same value[19], particularly in freelance work. To account for the significance of each task, the framework assigns a weight (W) that reflects its significance in contributing to overall work output. Additionally, the role factor (R) is employed to adjust for the economic impact of individual tasks, ranging from unpaid work that is considered peripheral functions (R close to 0) to those that are fully income-generating (R equal to 1).

[19] In this context, value refers to the relative importance or contribution of a task to the overall work output within an occupation. This value may be economic (e.g., income-generating potential or client willingness to pay), effort-based (e.g., time intensity or complexity), or skill-based (e.g., level of expertise or specialized knowledge required). It recognizes that not all tasks are equal in their demands or returns, particularly in freelance settings where workers often engage in a mix of high-skill and routine tasks.

Traditional occupational analyses often overlook a critical dimension of platform work, the unpaid labour inherent in platform-mediated environments (Bonina et al., 2021; Cingolani, 2021; Standing, 2017). Unpaid work tasks, such as developing proposals and applying for jobs, a constant need for upskilling to complete new work, and a range of project management responsibilities that come with being a freelance worker, are essential for securing and executing paid work but are rarely captured in standard job descriptions. The role of unpaid labour in the job quality of Kenyan platform workers is also important, since workers in developing regions do a disproportionate amount of unpaid labour (Howson et al., 2023). Recognizing the significance of this gap, this model incorporates these hidden tasks alongside conventional work tasks to provide a more comprehensive picture of occupational dynamics and the impact of AI on these tasks.

5.3.4 AI-Induced Livelihood Disruption

The disruption construct in this framework encompasses any change from the status quo, even if such change is perceived as beneficial, as it necessitates new skills (e.g., learning skills to utilize AI) or adaptation. In this model, disruption is driven by the combined effects of substitution *(SI)* and automation *(AM)* impacts, as well as by any worker enhancement *(EI)* in the sense that even changes beneficial to a worker require adjustment. Disruption score (d_i) for each task within an occupation is calculated as:

$$d_i = (1 - SI_i) \times (1 - AM_i) \times (1 - EI_i)$$

Measuring the disruption score using a multiplicative (complementary) method captures the combined impact of its enabling factors, ensuring that the overall disruption score will be high if any single enabling factor is high. The disruption score (D_o) at the occupation level is calculated by aggregating the weighted task disruption scores as follows:

$$D_o = \frac{\sum_{i=1}^{n} W_i d_i}{\sum_{i=1}^{n} W_i} = \frac{\sum_{i=1}^{n} W_i \times [(1 - SI_i) \times (1 - AM_i) \times (1 - EI_i)]}{\sum_{i=1}^{n} W_i}$$

Note: Here, di is the disruption score for a task. Wi is the weight assigned to the task. SIi, AMi, and EIi are the Substitution, Automation, and Enhancement impact scores for task i, respectively. n is the total number of tasks within the occupation.

5.3.5 AI-Induced Livelihood Vulnerability

Vulnerability captures the net negative impact on an occupation or work category. Specifically, the risk that the expansion of AI may influence work availability and remuneration for completing that

work. It focuses on the adverse effects of substitution and automation on workers while recognizing that enhancement may, to some degree, mitigate these adverse outcomes by complementing human labour. Thus, for each task, the vulnerability contribution is derived by subtracting the mitigating effect of enhancement from the combined disruptive effects. Rather than viewing these scores as absolute measures of a task's automation, substitution, or enhancement potential, I interpret the final vulnerability score as a probabilistic indicator of risk. The vulnerability score (v_i) for each task within an occupation is calculated as:

$$v_i = (Weighted\ SI_i + \alpha\ \times Weighted\ \ AM_i) \times \frac{R_i - 1}{R_{max} - 1} - Weighted\ \ EI_i\ - \times \beta\ \times (1 - \frac{R_i - 1}{R_{max} - 1})$$

Subsequently, the overall vulnerability score for an occupation (V_o) is computed as:

$$V_o = \frac{\sum_{i=1}^{n} W_i v_i}{\sum_{i=1}^{n} W_i} = \frac{\sum_{i=1}^{n} W_i\ \times (Weighted\ SI_i + \alpha\ \times Weighted\ \ AM_i) \times \frac{R_i - 1}{R_{max} - 1} - Weighted\ \ EI_i\ - \times \beta\ \times (1 - \frac{R_i - 1}{R_{max} - 1})}{\sum_{i=1}^{n} W_i}$$

Here α is a multiplier, α>1 may increase the weight of the Automation Impact score, based on the notion that automation tends to have a more significant adverse effect on job security than substitution[20]. This research proposed setting the initial α value at 1.5. R_i is the role factor for task i. This factor adjusts the negative impact of a task based on its monetary significance (unpaid tasks offset automation and substitution impact). β scales the impact of the portion of the task less directly tied to income (to account for the positive impact of unpaid work in this case) on the vulnerability calculation.

5.3.6 Limitations

While this framework offers a detailed process for dissecting and analyzing AI's impact on various platform work categories, it has several limitations. First, measuring latent variables, such as disruption and vulnerability, inevitably involves subjective judgment, which can introduce variability in interpreting results. Second, accurately determining task weightings and assessing task characteristics requires a systematic and context-specific approach, as the nuances of each occupation must be carefully examined. Nevertheless, the granularity of this framework is also a strength, as it enables the integration of rich contextual information into the model, thereby enhancing its overall relevance and precision.

[20] Automation often implies the removal of the human element entirely and could replace entire processes rather than merely altering tasks. This is supported in literature such as Acemoglu and Restrepo (2018), who highlight that automation can lead to significant labour displacement. A multiplier greater than 1 (i.e., α>1) is a way to capture that asymmetry but could be adjusted based on empirical observations and sensitivity analysis

5.4 Methods

This study employs a mixed-methods design to operationalize the Task-Based Model for Measuring AI-Driven Disruption and Vulnerability in the Platform Work Economy, introduced earlier. The identification of paid and unpaid tasks across the selected occupational categories was iteratively completed by reviewing online job listings on Upwork, Freelancer, and participant portfolios (n = 22), as well as relevant literature on identifying unpaid tasks between March 2024 and July 2024. These categories included freelance writing, virtual assistance, web and software development, and transcription services.

In the quantitative modelling component, identified tasks for these occupations were first analyzed and scored against their relative significance (weight) and task characteristics criteria. The Analytic Hierarchy Process (AHP) was employed to quantify task characteristics and assign weightage scores, resulting in impact scores across the three dimensions of AI exposure (i.e., automation, substitution, and enhancement). AHP, as a multi-criteria decision-making tool, is well-suited for scenarios like this research, where subjective judgments about weightage must be rationally quantified. AHP breaks down the decision-making process into a hierarchy of more easily comprehended sub-problems that can be analyzed independently (Brunelli, 2014; Salomon & Gomes, 2024; Vargas, 1990). This method is particularly suitable for this study, as it provides a clear and logical framework for comparing the relative importance of different criteria to determine weightages. Utilizing the processes presented in the task-based framework, this analysis generated two key metrics: a disruption score, which quantifies the magnitude of AI impact, and a vulnerability score, capturing the qualitative aspects of AI impact on primary income-generating and unpaid auxiliary tasks for each occupation.

5.4.1 Task Identification, Weightage, and AI Impact Calculation

In the first step, core and supporting tasks within each occupation were identified by reviewing job postings on freelance platforms and examining participant portfolios, ensuring the selected tasks accurately reflect available opportunities and actual freelancer experiences. Note that the occupations included are not exhaustive of the platform work economy.

Leveraging the conceptual framework and criteria presented earlier, task characteristics (i.e., task modularity and granularity, context dependence, social and interactive complexity, data availability and quality, and decision complexity under uncertainty) were scored on a scale of 1–10 through a

series of calls to context-informed GPT-4 model between September 2024 and January 2025. This scoring process was also used to compute the task weightage role factor (R), which accounts for the contribution of unpaid tasks. These initial scores were then manually verified and calibrated based on a review of empirical data and observations. This included adjusting context information where model outputs diverged from grounded realities, such as revising the unpaid task ratio based on direct feedback from platform workers and cross-checking the listed tasks against documented work samples and field interviews.

This method follows the previous research by Gmyrek et al. (2023). Gmyrek et al. (2023) utilized ChatGPT4 API prompts to generate work task scores, predicting the automation potential of generative AI. In their work, the model was prompted to analyze a uniform set of tasks for each occupation, after which the outputs were used to calculate mean automation scores. In contrast, my methodology employs a similar context-specific prompt strategy. However, rather than relying on AI judgment to gauge a task's automation potential, it focuses on scoring task characteristics and pairwise matrix relationships against a refined set of theoretically grounded criteria to mitigate technology capability biases and enhance replicability and transparency (Karger et al., 2023). For detailed task scoring against task characteristics with clear justification, see Appendix D. For detailed weightage and paid-unpaid task ratio scoring, see Appendix E.

While some elements of scoring involved subjective judgment, these judgments are grounded in empirical observations I performed during my fieldwork in Kenya, direct insights from Upwork and Freelancer, where I registered and applied for jobs as a platform worker to gain a better insight into validated job postings, and interviews with workers (n=20). Besides the empirical evidence-driven adjustments, a sensitivity analysis was conducted to ensure the robustness of the model.

5.4.2 AI Impact Calculation using AHP

A hierarchical model using the Analytic Hierarchy Process (AHP) was developed to assess the potential impact of AI on tasks within an occupation along three dimensions: Substitution Impact (SI), Automation Impact (AM), and Enhancement Impact (EI). These dimensions quantify how AI will likely affect tasks by measuring both the overall disruption and the net vulnerability. The following steps were taken to calculate different dimensions of AI impact, i.e., automation (AM), substitution (SI), and enhancement impact (EI) score for each task.

5.4.2.1 Step 1: Hierarchy

As a first step, a hierarchy was developed to structure the decision-making process into levels:

Level 1 (Goal): Determine the automation, substitution, and enhancement impact of AI on each task.

Level 2 (Criteria): Identify and compare the task characteristics that influence AI impact dimensions *(e.g., SI, AM, EI)*. The five key characteristics are:

Task Modularity and Granularity (TMG): Highly modular and discrete tasks can be automated or substituted by AI. In contrast, tasks that are interwoven with other activities may require higher human judgment and thus be less amenable to full automation.

Context Dependence (COD): Tasks that rely on sensitivity to environmental, cultural, or situational cues are less susceptible to full automation as they require human judgment, whereas those with low context dependence can be more easily replaced by AI.

Social and Interactive Complexity (SIC): Tasks requiring significant social interaction, negotiation, or emotional labour tend to be either enhanced through AI support or are not impacted by AI.

Data Availability and Quality (DAQ): Tasks supported by abundant, high-quality data are more amenable to automation, while those dependent on tacit knowledge or lower-quality data may continue to require human judgment.

Decision Complexity under Uncertainty (DCU): Tasks involving multi-step decision-making under uncertainty are likely only partially automatable but may still see significant substitution. AI can provide decision support, but human intervention remains essential to address residual ambiguities. Tasks with simple, rule-based decisions are easier to automate.

Level 3 (Alternatives): The individual core tasks within the occupation.

5.4.2.2 Step 2: Pairwise Comparison of Criteria

For each AI Impact dimension (SI, AM and EI), a pairwise comparison of the five criteria (i.e., task modularity and granularity, context dependence, social and interactive complexity, data availability and quality, and complexity under uncertainty) is conducted to determine their relative importance. Each pairwise matrix is normalized by dividing each element by its respective column total.

$$Normalized\ Value_{ij} = \frac{Element\ Value_{ij}}{Column\ Total_j}.$$

The relative weights w_i of each criterion i are calculated by taking the average of the normalized values in its row, which yields a set of relative weights that reflect the judgments in the pairwise comparisons.

$$w_i = \frac{\sum_{j=1}^{n} Normalized\ Value_{ij}}{n}$$

Here n is the number of criteria

5.4.2.3 Step 3: Consistency Check

A consistency check is performed to ensure the reliability of the judgments. The weighted sum vector (*s*) is calculated by multiplying each row of the original pairwise comparison matrix by the corresponding criterion weight (*w)*. This yields the weighted sum vector, where each element represents the aggregated importance for a criterion.

$$S_i = \sum_{i=1}^{n} a_{ij} \times w_j, for\ i = 1,2, \dots, n.$$

For each criterion, the consistency vector element (λ_i) is calculated by dividing the weighted sum for that criterion by its corresponding weight.

$$\lambda_i = \frac{s_i}{w_i}$$

The Consistency Index (CI) is calculated as: $CI = \frac{\lambda max - n}{n-1}$

Where λmax is the largest eigenvalue of the pairwise comparison matrix calculated as $\boldsymbol{\lambda}_{max} = \frac{1}{n}\sum_{i=1}^{n} \lambda_i$
n is the number of criteria.

The Consistency Ratio (CR) is calculated as $CR = \frac{CI}{RI}$

RI is the random consistency index, which is determined based on the number of criteria. If CR < 0.10, the judgments in the pairwise comparison matrix are considered consistent.

5.4.2.4 Step 4: Incorporating Threshold Effects using Gaussian Functions

I incorporate threshold adjustments via Gaussian functions to better reflect the nuanced conditions under which AI impacts tasks. It reflects the notion that each criterion has an optimal level, and any deviation (either too low or too high) results in a proportionally lower contribution. Before calculating

the weighted impact scores for each AI impact dimension, the raw scores (on a 1–10 scale) for each criterion are transformed into effective scores using a Gaussian transformation.

$$f_i(r_i) = \exp\left(-\frac{(r - r_{opt})^2}{2\sigma^2}\right.$$

Here, r_i is the raw score of a particular criterion. σ is the standard deviation that controls the width of the sweet spot.

This transformation peaks at 1 when the raw score equals the optimal value (r_{opt}) and decays exponentially as the raw score deviates from this optimum. This Gaussian transformation (with a sigma value of 1.5, determined via sensitivity analysis results below) ensures that tasks far from the ideal conditions receive substantially lower effective scores. This adjustment captures the concept of the sweet spot, as explained in the conceptual framework section, reflecting that only scores near the optimum contribute maximally to the subsequent impact calculations.

For each AI impact dimension, optimal values are set based on theoretical expectations and empirical insights into task structure and complexity. Substitution is most effective when tasks are highly modular and supported by robust data while exhibiting minimal contextual, social, and decision complexity. Therefore, for factors that enable automation and substitution potential, such as Task Modularity and Data Availability, I set r_{opt} = 8 (on a scale of 1 to 10). This reflects the expectation that tasks scoring near 8 on these dimensions are ideally structured for AI to fully substitute human labour. Conversely, lower values facilitate substitution for hindering factors (Context Dependence, Social and Interactive Complexity, and Decision Complexity). I set r_{opt} = 2 for these criteria, meaning that tasks ideally should score close to 2 to minimize the need for human judgment. Deviations from these optima result in proportionally lower effective scores, reducing the overall substitution impact.

Automation requires nearly perfect enabling conditions, as the process involves prediction and autonomous decision-making. To reflect this, I set r_{opt} =10 for enabling factors, indicating that only tasks with high modularity and data quality are optimal for full automation. For hindering factors, where even minor increases in complexity can thwart automation, I set r_{opt} =1. These choices underscore that even slight deviations from the ideals, such as a modest rise in contextual or decision complexity, can significantly diminish automation potential.

Enhancement occurs when AI augments rather than replaces human labour (Acemoglu & Restrepo, 2019). This dimension is most effective when tasks possess a balanced mix of structure and complexity; that is, when enabling factors are present but not at levels high enough to favour substitution or automation, and hindering factors are moderate enough to require human judgment without overwhelming the AI's supportive role. Accordingly, I set r_{opt} =5 for both enabling and hindering factors in the context of enhancement. A score of 5 represents a mid-range condition where AI can effectively augment human performance.

5.4.2.5 Step 5: Weighted Task Score Calculation for AI Impact Dimension

Effective scores are combined with the AHP-derived weights to compute the impact score for each task. This process is repeated separately for *SI, AM, and EI.* The relative weight from the pairwise matrix is then applied to calculate the weighted scores. For each AI impact dimension *X* (where *X*stands for SI, AM, or EI), the weighted impact score for a task is computed as:

$$\text{Weighted Imapct Score}_{\text{X}} = \sum_{i=1}^{5} (f_i(r_{i,X}) \times w_i)$$

Where X represents the impact dimension (SI, AM, or EI), $ri_{,X}$ is the score assigned for the i_{th} criterion for dimension *X*, and w_i is the corresponding weight. This process results in three separate weighted scores per task: weighted substitution impact (SI), weighted automation impact (AM), and weighted enhancement impact (EI).

5.4.2.6 Disruption and Vulnerability Scores

Using the computed weighted impact scores for SI, AM, and EI, I derived the overall task-level impact measures. Disruption in the model is calculated as a multiplicative (complementary) method and represents the combined impact of three abstract dimensions, i.e., substitution, automation, and enhancement.

$$d_{task} = 1 - [(1 - Weighted\ SI)(1 - Weighted\ AM)(1 - Weighted\ EI)]$$

This multiplicative method ensures that the combined disruption score is sensitive to the highest individual impact and reflects the interdependent, competing nature of the risks posed by substitution, automation, and enhancement.

Vulnerability captures the net negative (economic) impact on the occupation. Since automation tends to have a more detrimental effect, an automation multiplier α (α=1.5) is applied to the automation scores to compute vulnerability. In addition, to reflect that not all tasks are equally

economically important, a role factor *R* (derived from the task identification process) is incorporated, where *R* is closer to 1 for core or income-generating tasks and less than 1 for supportive tasks. The vulnerability score for a task is calculated as:

$$v_{task} = (SI + \alpha \times AM) \times \frac{R-1}{R_{max}-1} - Weighted\ EI\ - \times \beta \times (1 - \frac{R-1}{R_{max}-1})$$

Raw scores for vulnerability can range from a potentially protective extreme (negative) to a highly vulnerable extreme (positive). In the results, this score is normalized to a [−1, +1] scale for clarity. Specifically, −1 indicates the theoretical maximum advantage (where enhancement strongly outweighs substitution and automation), while +1 reflects the theoretical maximum vulnerability (where substitution and automation dominate).

5.4.3 Task weightage using AHP

A key distinction I make in this research is that each task within a given occupation may hold a different weightage in terms of its significance and the value it adds to the overall workload of a platform worker. In this research, I theorize that this significance and value are dependent on four key factors i.e., frequency (how often a task is performed in a particular category of platform work), duration (the time required for a task), complexity (the skill and effort needed), and client prioritization (the task's importance from the client's perspective).

Pairwise comparisons of these factors were conducted to assess their relative importance, yielding a set of weighted values. Each core task was then scored against these criteria, and the scores were multiplied by the corresponding weights. Finally, the aggregated scores were normalized to produce percentage weightings that reflect the relative significance of each task within the occupation. This structured approach ensures a transparent, reproducible, and justifiable means of prioritizing tasks in line with the role's demands.

5.4.3.1 Task Weightage AHP Step 1: Hierarchy

As a first step, I developed a hierarchy that structures the decision-making process into levels: the overall goal, the criteria, and the alternatives (i.e., the core tasks within each occupation).

Level 1 (Goal): Determine the weightage for each core task.

Level 2 (Criteria): Frequency (F), Duration (D), Complexity (C), Client Prioritization (P). Where Frequency (F) reflects how often a task is performed in the freelancer's workflow; Duration (D) reflects the average amount of time required to complete a task; Complexity (C) reflects the perceived cognitive and technical difficulty of the task; and Client Prioritization (P) reflects how important the task is seen by clients in the platform economy (from a workers' perspective.

Level 3 (Alternatives): The core task identified for each occupation.

5.4.3.2 Step 2: Pairwise Comparison of Criteria

Next, a pairwise comparison of the criteria (*F, D, C, P*) is conducted. The aim is to create a pairwise matrix to compare the criteria based on their relative significance in the context of the specific occupation while ensuring that the relative importance of the criteria is grounded in the realities of the platform economy (as compared to traditional job descriptions).

To derive the relative weights of the criteria, the pairwise matrix is normalized by dividing each element of the matrix by its respective column total, thereby normalizing the matrix.

$$Normalized\ Value_{ij} = \frac{Element\ Value_{ij}}{Column\ Total_j}.$$

Finally, the relative weight of each criterion *I* is calculated by taking the average of the normalized values in its row, yielding a set of relative weights that reflect the expert judgments expressed in the pairwise comparisons.

$$Weight\ of\ Criterion_i = \frac{\sum_{j=1}^{n} Normalized\ Value_{ij}}{n}$$

Where n is the number of criteria.

Step 3: Consistency Check

A consistency check is performed to ensure the reliability of the judgments made. In this step, the Weighted sum vector (*s*) is calculated by multiplying each row of the original pairwise comparison matrix by the corresponding criterion weight (*w)*. This yielded the weighted sum vector, where each element represented the aggregated importance for a criterion.

$$s_i = \sum_{i=1}^{n} a_{ij} \times w_j, for\ i = 1,2, \dots, n.$$

For each criterion, I calculated the consistency vector element (λ_i) by dividing the weighted sum for that criterion by its corresponding weight.

$$\lambda_i = \frac{s_i}{w_i}$$

The Consistency Index (CI) is calculated as: $CI = \frac{\lambda max - n}{n-1}$

λmax is the largest eigenvalue of the pairwise comparison matrix calculated as: $\boldsymbol{\lambda}_{max} = \frac{1}{n}\sum_{i=1}^{n} \lambda_i$
n is the number of criteria.

The Consistency Ratio (CR) is calculated as $CR = \frac{CI}{RI}$

Here, RI is the random consistency index, which is determined based on the number of criteria. If CR < 0.10, the judgments in the pairwise comparison matrix are considered consistent.

5.4.3.3 Step 4: Weighted Task Score Calculation

The pairwise table is then used to calculate the weighted scores for each task within each occupation. This step quantifies the overall significance of each task based on its performance across the criteria. These scores are subsequently normalized and converted into percentage values. The weighted score for each task is calculated using the following formula:

$$\text{Weighted Score for Task} = (\text{F score} \times \text{F weight}) + (\text{D score} \times \text{D weight}) + (\text{C score} \times \text{C weight}) + (\text{P score} \times \text{P weight})$$

The weighted scores are normalized by dividing each task's weighted score by the total score for all tasks:

$$\text{Normalized Score for Task} = \frac{\text{Weighted Score for Task}}{\text{Total Weighted Score for All Tasks}} \times 100$$

The collective results of this process ensured that the assigned weightages for tasks within each occupation are systematic, justified, and consistent with the underlying criteria.

5.4.4 Occupation Level Impact Scores

Scores across all tasks within the occupation were aggregated using this task weightage to capture occupation-level impact. The occupation-level measures are expected to shed light on the composite constructs of disruption and vulnerability, recognizing the individual dimensions of AI impact (SI, AM, and EI) and differences between occupations. Such disaggregated information is helpful for understanding which aspect of AI impact (e.g., substitution vs. automation) is most pronounced within an occupation. Scores are aggregated at the occupation level and normalized to a scale of 0 to 1, providing insight into the relative contributions of each AI impact dimension across occupations.

$$SI_o = \frac{\sum_{i=1}^{n} W_i \times SI_i}{\sum_{i=1}^{n} W_i} \quad AM_o = \frac{\sum_{i=1}^{n} W_i \times AM_i}{\sum_{i=1}^{n} W_i} \quad EI_o = \frac{\sum_{i=1}^{n} W_i \times EI_i}{\sum_{i=1}^{n} W_i}$$

SIo is Occupation-Level Substitution Impact, and SIi is the weighted Substitution Impact score for each task i AMo is the Occupation-Level Substitution Impact, and AMi is the weighted Substitution Impact score for each task i. EIo is Occupation-Level Substitution Impact and AMi is the weighted Substitution Impact score for each task i. Wi the task weightage (obtained from the Task Weightage AHP process).

Using the task-level disruption and vulnerability scores, occupation-level measures for Disruption and Vulnerability are computed as:

$$D_o = \frac{\sum_{i=1}^{n} W_i d_i}{\sum_{i=1}^{n} W_i} = \frac{\sum_{i=1}^{n} W_i \times [(1 - SI_i) \times (1 - AM_i) \times (1 - EI_i)]}{\sum_{i=1}^{n} W_i}$$

$$V_o = \frac{\sum_{i=1}^{n} W_i v_i}{\sum_{i=1}^{n} W_i} = \frac{\sum_{i=1}^{n} W_i \times (Weighted\ SI_i + \alpha \times Weighted\ AM_i) \times \frac{R_i - 1}{R_{max} - 1} - Weighted\ EI_i - \times \beta \times (1 - \frac{R_i - 1}{R_{max} - 1})}{\sum_{i=1}^{n} W_i}$$

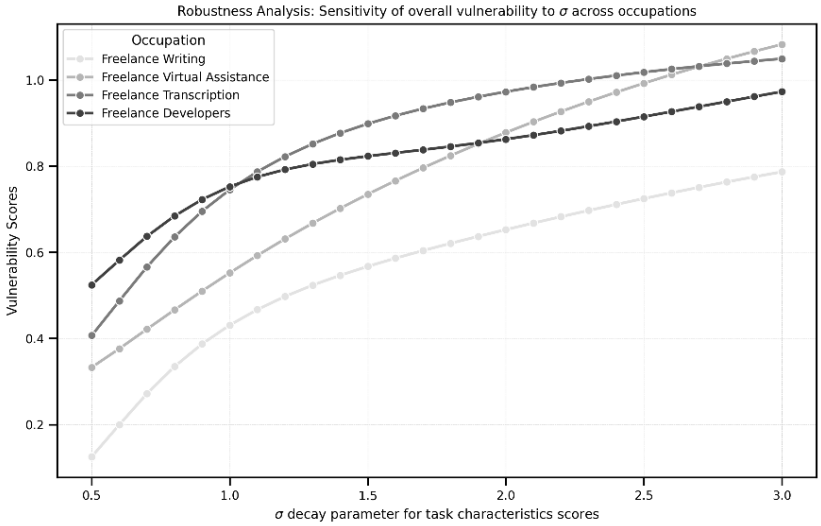
5.5 Consistency and Robustness Checks

All AHP pairwise comparisons yielded CR values below 0.10, indicating acceptable consistency (Salomon & Gomes, 2024). Specifically, for Freelance Writing, the CRs were 0.072 for the substitution impact, 0.039 for the automation impact, 0.067 for the enhancement impact, and 0.026 for the task weightage. For Freelance Virtual Assistance, the CRs were 0.072 (substitution), 0.039 (automation), 0.067 (enhancement), and 0.017 for the task weightage. In Freelance Transcription, the CRs were 0.071, 0.040, 0.067, and 0.026, respectively, while for Freelance Developers they were 0.072, 0.040, 0.067, and 0.043. These results confirm that the input judgments in the AHP comparisons are internally consistent.

To assess the robustness of the vulnerability metric with respect to the sigma parameter in the Gaussian transformation, I conducted a sensitivity analysis across four occupational groups. The analysis shows that as σ increases from 0.5 to 3.0, the overall paid work vulnerability score rises dynamically. Notably, at σ = 1.5, the vulnerability scores are significantly lower, reflecting a steeper decay in effective task scores when raw scores deviate from their optimum. This steep decay supports the theoretical expectation that even minor deviations markedly reduce automation potential. Consequently, selecting σ = 1.5 establishes a robust threshold that effectively distinguishes tasks likely to be automated from those that are not.

Figure 5.2

Sensitivity Analysis of Vulnerability Index to Sigma Parameter



As shown in Figure 5.2, the sensitivity analysis indicates that as σ, the decay parameter controlling how rapidly the effective score decreases as raw scores for task characteristics deviate from the optimum, increases from 0.5 to 3.0. Overall, these results confirm that while the absolute vulnerability values are sensitive to sigma, as expected given its role in modulating the decay rate, the qualitative trends remain consistent across occupational groups. The modest range of variation, particularly for Freelance Developers, lends confidence to the stability of this model. Consequently, the chosen baseline sigma value (e.g., 1.5) is well justified, and the consistent behaviour across occupations supports the robustness of our analytical framework.

5.5.1 Empirical Fieldwork

The fieldwork was conducted to understand workers' perspectives on the impact of AI on their livelihoods and to validate and enrich the theoretical assumptions underlying the AI impact modelling. The field research data were collected in Kenya from January 2024 to July 2024, using a survey of 52 freelance platform workers, from which 20 participants were selected for follow-up, semi-structured interviews. Survey participants were recruited using purposive and snowball sampling techniques, targeting active freelance platform workers across different sectors to capture a range of experiences and work arrangements in Kenya. The aim was to capture a diverse sample in terms of occupation, gender, experience level, and engagement with AI tools. The survey captured information, including the frequency of generative AI tool use, perceived helpfulness of AI tool use, and perceived job loss concern. For a detailed list of survey questions, please see Appendix A.

Please note that the results of the field study are incorporated into the discussion section, while the results section in this article primarily focuses on the theoretical modelling and projections of AI's impact on selected freelance occupations. This structure was chosen to support clearer interpretation, allowing the theoretical modelling in the results section to be complemented by the field study insights in the discussion section.

5.5.1.1 Fieldwork Data Analysis

Descriptive statistics were used to profile and cross-tabulate key indicators by occupation. Bivariate analyses, including t-tests and Pearson correlations, explored associations among AI use, job-loss concern, and labour input variables. An exploratory factor analysis using principal-axis factoring with oblique rotation was conducted to assess whether AI-use frequency and perceived helpfulness could be meaningfully combined into a single AI-Utility index, based on acceptable factor loadings and internal reliability. Ordinary least squares (OLS) regressions were then conducted to examine two outcomes: first, whether AI-Utility predicts job-loss concern; and second, which factors, including AI concern, paid hours, age, gender, education, platform tenure, work control, and financial satisfaction, explain workers' confidence in securing future platform work. All regression models were tested for linearity, homoscedasticity, and multicollinearity (VIF < 5), and confirmed to have normally distributed residuals. Bootstrap standard errors, based on 1,000 replications, were used to improve the robustness of coefficient estimates. This analytical sequence provided a rigorous quantitative

foundation for interpreting how Kenyan freelancers perceive and respond to AI-driven changes in the platform labour market.

A narrative approach was used to examine and contextualize workers' accounts of how AI is reshaping their work. Interview recordings were transcribed verbatim and reviewed for accuracy and clarity. A narrative approach is a qualitative method that examines how individuals construct meaning through the stories they tell, focusing on both the content and structure of their accounts within broader social and cultural contexts (Riessman, 2008). The analysis focused on how participants constructed meaning around AI through personal experiences, language choices, and the sequencing of events. This approach made it possible to capture not only what workers said about AI, but also how they positioned themselves within evolving technological landscapes and shifting labour dynamics. Direct quotes from the interviews are used, and all participant names are pseudonyms to protect their identities.

5.6 Results

The analysis reveals that AI-driven work reconfiguration has a significant impact on all platform work categories (Table 5.1). The overall disruption factor registers an exceptionally high average score of 0.913, with paid (0.906) and unpaid work (0.929) exhibiting similarly elevated means, indicating the substantial ongoing and anticipated transformation in platform work practices. Various dimensions of this impact, automation (mean = 0.534), enhancement (mean = 0.542), and substitution (mean = 0.649, all yield high values, reflecting the widespread and dual-faceted (both positive and negative) influence of AI. Notably, vulnerability emerges as a critical factor: while the overall vulnerability measure remains relatively low (mean = 0.214), unpaid work vulnerability presents a more pronounced negative value (mean = –0.493), highlighting distinct dynamics in unpaid labour contexts.

Table 5.1

Impact of AI on Freelance Platform Work (Multiple Occupation Categories)

Variable	Mean	Minimum	Maximum	SD
Vulnerability	0.214	0.054	0.368	0.129
Paid Work Vulnerability	0.482	0.324	0.662	0.145
Unpaid Work Vulnerability	-0.493	-0.657	-0.411	0.111

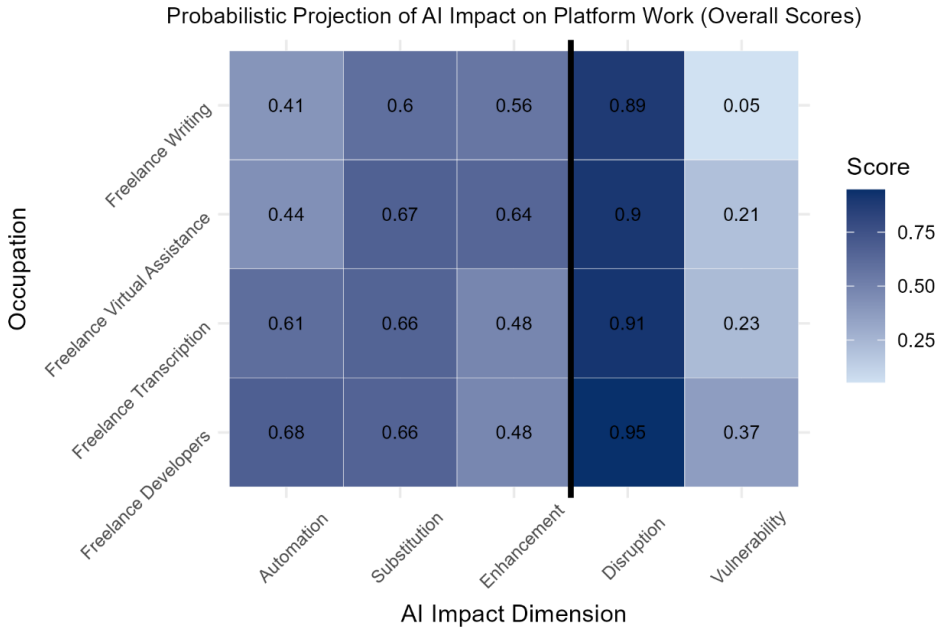
Variable	Mean	Minimum	Maximum	SD
Disruption	0.913	0.887	0.947	0.025
Paid Work Disruption	0.906	0.891	0.944	0.025
Unpaid Work Disruption	0.929	0.878	0.96	0.038
Automation	0.534	0.411	0.682	0.132
Unpaid Work Automation	0.464	0.334	0.603	0.145
Enhancement	0.542	0.478	0.644	0.078
Paid Work Enhancement	0.496	0.408	0.627	0.101
Unpaid Work Enhancement	0.654	0.627	0.714	0.041
Substitution	0.649	0.601	0.675	0.033
Paid Work Substitution	0.646	0.616	0.696	0.035
Unpaid Work Substitution	0.648	0.573	0.724	0.077

5.6.1 Occupation Level Impact Results

At the occupational level, automation risk is notably higher for jobs characterized by routine and structured execution, such as web and software development (0.68) and transcription (0.61), reflecting their greater susceptibility to automation (Figure 5.3). In contrast, types of work that require complex decision-making and adaptability, such as freelance writing (0.41) and virtual assistance (0.44), exhibit a considerable but comparatively lower risk, indicating greater resilience against automation.

Figure 5.3

AI Impact on Platform Work (Overall Scores)



As highlighted in Figure 5.3, at the occupational level, automation risk is particularly pronounced in roles characterized by routine and structured execution, such as web and software development (0.68) and transcription (0.61). This reflects their greater susceptibility to AI-driven automation, as these tasks often involve repetitive processes that machine learning models can efficiently handle. In contrast, occupations requiring greater adaptability and complex decision-making, such as freelance writing (0.41) and virtual assistance (0.44), exhibit lower but notable automation risks. This suggests that while AI may enhance productivity in these roles, complete automation remains less feasible due to the need for creativity, contextual judgment, and human interaction.

Disruption scores across occupations indicate consistently high levels of AI-driven impact, with all four freelance occupations registering values above 0.88. Web and software development (0.95) and transcription (0.91) exhibit the highest disruption scores, underscoring the substantial transformation potential of these fields. Virtual assistance (0.90) and freelance writing (0.89) follow closely, suggesting that while these roles may be relatively less susceptible to full automation, they are nonetheless experiencing profound shifts in task execution, workflow dynamics, and required skill

sets. This highlights the pervasive influence of AI across diverse freelance occupations, affecting not only technical and repetitive tasks but also roles traditionally reliant on adaptability and human judgment.

A key insight from this analysis is that AI-driven changes do not uniformly translate into heightened livelihood vulnerability across all occupations. Notably, freelance writing registers a low vulnerability score (0.05), suggesting that AI's overall impact on job security in this field may be relatively marginal. In contrast, transcription (0.23) and virtual assistance (0.21) exhibit higher vulnerability scores, indicating that these occupations face more significant risks due to AI-driven automation. This suggests that while these roles may persist, the increasing integration of AI could significantly alter their demand, potentially reducing human labour needs or reshaping job functions.

Freelance developers exhibit the highest vulnerability score (0.37), indicating that platform workers in this field may face substantial challenges as AI-driven automation reshapes their work. However, the factors that mitigate or amplify this vulnerability warrant closer examination. While substitution and automation risks are significantly higher in these occupations, they do not always correspond to equally high vulnerability. This suggests that other dynamics, such as the demand for specialized skills, adaptability, or the evolution of AI-human collaboration, may influence the extent to which workers experience job displacement or transformation.

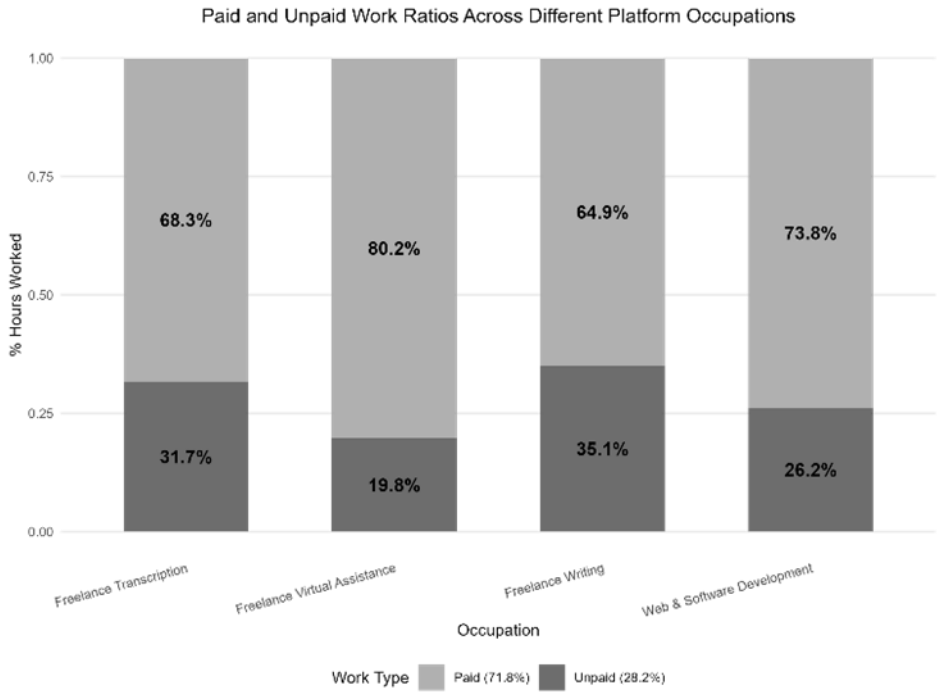
5.6.2 Unpaid Work as a Balancing Factor

All four occupations examined carry a significant share of unpaid work, although to varying degrees (Figure 5.4). This assessment was based on rating each task within the four occupations for its contribution to paid or unpaid work (R factor), allowing for an occupation-specific calculation of the share of unpaid tasks and the identification of which tasks fall into each category. The proportion of unpaid work varies significantly across occupations, influencing the overall impact of AI. Virtual assistance has the lowest unpaid work share (19.8%), followed by developers (26.2%). In contrast, writing (35.1%) and transcription (31.7%) involve a substantial unpaid workload. These differences highlight how unpaid tasks alter the overall composition of freelance work (see the task-level analyses for more detailed information on specific paid and unpaid tasks). The prominence of these tasks creates a complex dynamic for how AI tools might reshape practices and opportunities in

platform-based work.

Figure 5.4

Paid and Unpaid Work Ratio in Platform Work



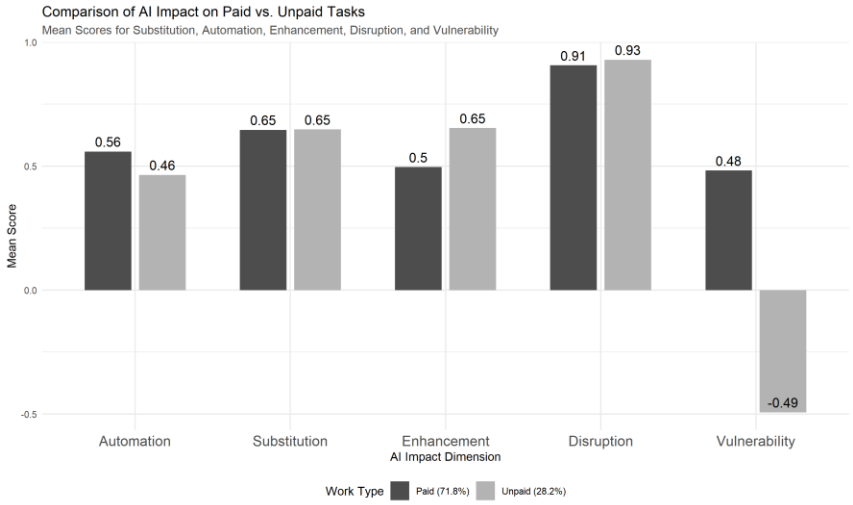
While both paid and unpaid work experience are significantly disrupted by AI, unpaid tasks exhibit a pronounced counterbalancing effect. The results indicate that automation and substitution effects are moderately high across both work types (Automation: 0.56 vs. 0.46; substitution: 0.65). However, enhancement scores are notably higher in unpaid tasks (0.65) than in paid work (0.50). This suggests that AI integration may offer more significant efficiency gains in non-remunerated activities, such as proposal development and client communication.

A key distinction emerges in disruption and vulnerability. Disruption scores remain similarly high for both paid (0.91) and unpaid work (0.93), underscoring the broad impact of AI across task categories. However, vulnerability trends diverge because unpaid tasks counter vulnerability (Figure 5.5). Paid work exhibits a positive vulnerability score (0.48), whereas unpaid work registers a negative score (-0.49), indicating a net offset effect. Despite this mitigating factor, the lower

proportion of unpaid work (28.2%) limits its ability to substantially reduce overall vulnerability. These findings suggest that while unpaid tasks may help buffer against AI-driven displacement, their influence is constrained by their relative share within the overall work structure.

Figure 5.5

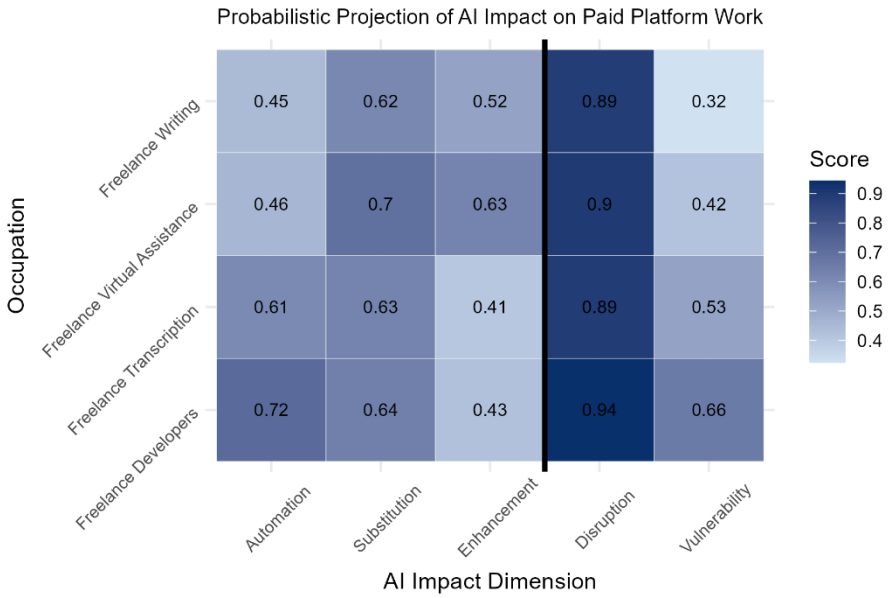
Impact of AI on Platform Work: Paid vs Unpaid Tasks



While the overall results suggest a somewhat similar offset effect in vulnerability and substitution scores, a closer examination at the occupational level reveals significant variation. Automation scores are consistently higher for paid work across all occupations, indicating that routine and repetitive tasks within paid labour are more susceptible to AI-driven automation. Freelance developers exhibit the highest automation score for paid work (0.72), followed by transcription (0.61), reflecting the structured nature of tasks in these fields (Figure 5.6).

Figure 5.6

AI Impact on Paid Work Tasks

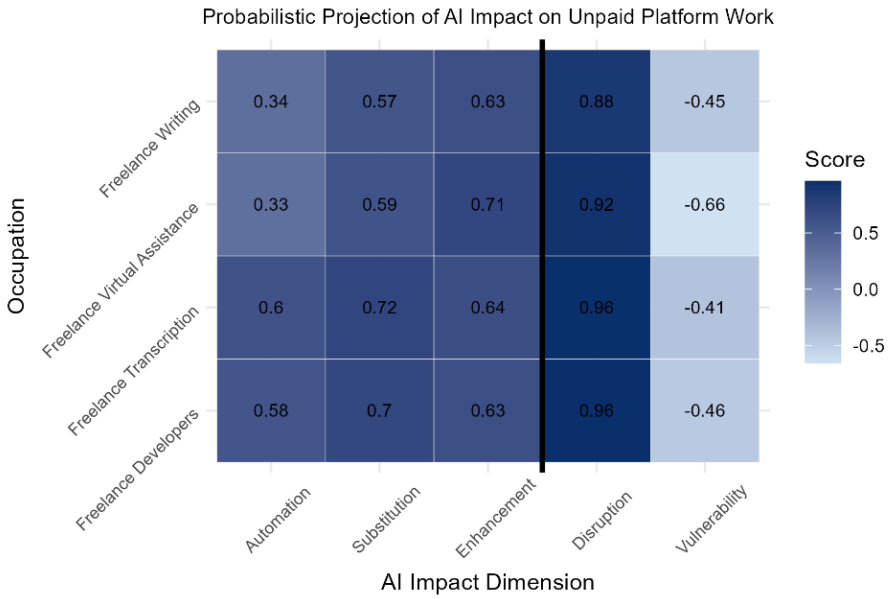


In contrast, automation scores for unpaid work are comparatively lower across all occupations, suggesting that non-remunerated tasks, often involving administrative, preparatory, or interpersonal components, are less likely to be replaced by AI (Figure 5.7). Among unpaid tasks, virtual assistance registers the lowest automation score (0.334), reinforcing the notion that tasks with lower economic value and requiring human discretion and adaptability remain resistant to automation.

Substitution effects reveal contrasting patterns across paid and unpaid work. In freelance development and transcription, unpaid tasks exhibit a higher potential for substitution than paid tasks (0.70 and 0.72 for unpaid work, compared to 0.64 and 0.63 for paid work, respectively). Conversely, virtual assistance and writing show the opposite trend, with unpaid substitution scores (0.59 and 0.57) slightly lower than their paid counterparts (0.70 and 0.62).

Figure 5.7

AI Impact on Unpaid Tasks



A notable trend across all observed platform-based occupations is the significantly higher enhancement scores for unpaid tasks compared to paid work, with an average difference of approximately 10 points. This suggests that AI-driven improvements are more likely to augment, rather than replace, the efficiency of tasks in proposal development, research, administrative, or coordination-related activities. Despite these variations, disruption scores remain consistently high across paid and unpaid work, suggesting that AI-driven changes profoundly affect both work categories, regardless of differences in automation, substitution, or enhancement effects.

A key finding in this comparison is the varying vulnerability scores across work categories. Unpaid tasks in freelance writing exhibit a vulnerability score of 0.45 (represented as -45 to indicate directionality), compared to 0.32 for paid tasks. This suggests that unpaid work within writing gigs benefits more from AI-driven transformations than paid tasks in the same occupation. Notably, freelance writing has the highest proportion of unpaid work (35.1%) among the occupations examined, contributing to a substantial offset effect. This is reflected in the overall livelihood

vulnerability score (0.05) for freelance writing, indicating that the presence of unpaid tasks mitigates some of the adverse effects of AI on job security within this occupation.

Similarly, vulnerability scores for unpaid virtual assistance (0.66) and transcription work (0.41) are notably higher than paid tasks, which register scores of 0.42 and 0.53, respectively. The analyses in my research suggest that unpaid tasks in these occupations offset a portion of the impact of paid work vulnerability. As a result, the net vulnerability score for virtual assistance (0.21) and transcription work (0.23) remains more pronounced compared to freelance writing (0.05), where unpaid work plays a more substantial mitigating role.

Lastly, freelance developers exhibit a statistically higher vulnerability score in paid work (0.66) than in unpaid work (-0.46). Notably, the paid work vulnerability score for developers is the highest among all occupations examined, contributing to a significantly elevated net vulnerability score of 0.37. This highlights the heightened exposure of developers to AI-driven disruptions, particularly in revenue-generating coding tasks, where automation and substitution effects are more pronounced.

5.6.3 Task-Level Impact Across Occupations

The key argument in this research is that AI's transformative impact is deeply intertwined with the intrinsic characteristics of tasks, shaping overall disruption and vulnerability at the occupational level. The analyses conform to the theoretical considerations that tasks with high modularity and extensive data availability, such as coding, proofreading, or drafting text, are particularly susceptible to automation and substitution when they do not require complex social context or a compensatory enhancement effect, resulting in high disruption and elevated vulnerability. Conversely, tasks demanding rich contextual understanding and significant social interaction, such as in-depth client consultations and communications, tend to resist automation. Their complexity and reliance on human judgment naturally mitigate some of the risks of automation. Additionally, the significance and nature of each task, reflected in its weight (W) and the proportion of paid work (R), further refine the impact of AI.

As detailed in the task-level results below, this integrated perspective, which links task characteristics such as modularity, context dependence, social complexity, data availability, and

decision complexity to AI impact indices, offers a comprehensive framework for understanding how the nuanced nature of work influences occupation-level outcomes in digital platform labour.

5.6.3.1 Freelance Writing

Although the overall vulnerability score for freelance writing is relatively low (0.05), the interaction between task characteristics and AI impact reveals a more nuanced picture. Specific tasks within freelance writing, particularly those with high modularity and substantial data availability, such as proofreading and research, pose livelihood income risks for workers when they lack a compensatory enhancement effect. However, as evident in Table 5.2, a substantial proportion of freelance writing tasks require high contextual sensitivity and social interaction, providing greater resilience against automation and substitution risks.

Table 5.2

Writing Tasks Characteristics Scoring

Freelance Writing Task Characteristics[21]	**TMG**	**TCD**	**SIC**	**DAQ**	**DCU**	**W_i**	**R_i**
Engage in initial client consultations to clarify project requirements, target audience, and desired tone or style.	4	8	9	5	7	0.09	0.50
Conduct comprehensive research on various topics tailored to the client's needs using credible sources to develop content ideas and detailed outlines tailored to the assignment.	7	6	3	8	7	0.15	0.87
Draft articles, blog posts, website content, academic papers, etc., adapting the writing style to suit various formats (creative, technical, academic, or copywriting).	8	5	3	4	5	0.19	1.00
Proofread the content thoroughly to eliminate grammatical, punctuation, and formatting errors, ensuring high-quality final output.	8	2	1	9	3	0.12	0.87
Regularly communicate with clients to provide progress updates, clarify requirements, and address feedback.	7	4	6	7	7	0.08	0.71

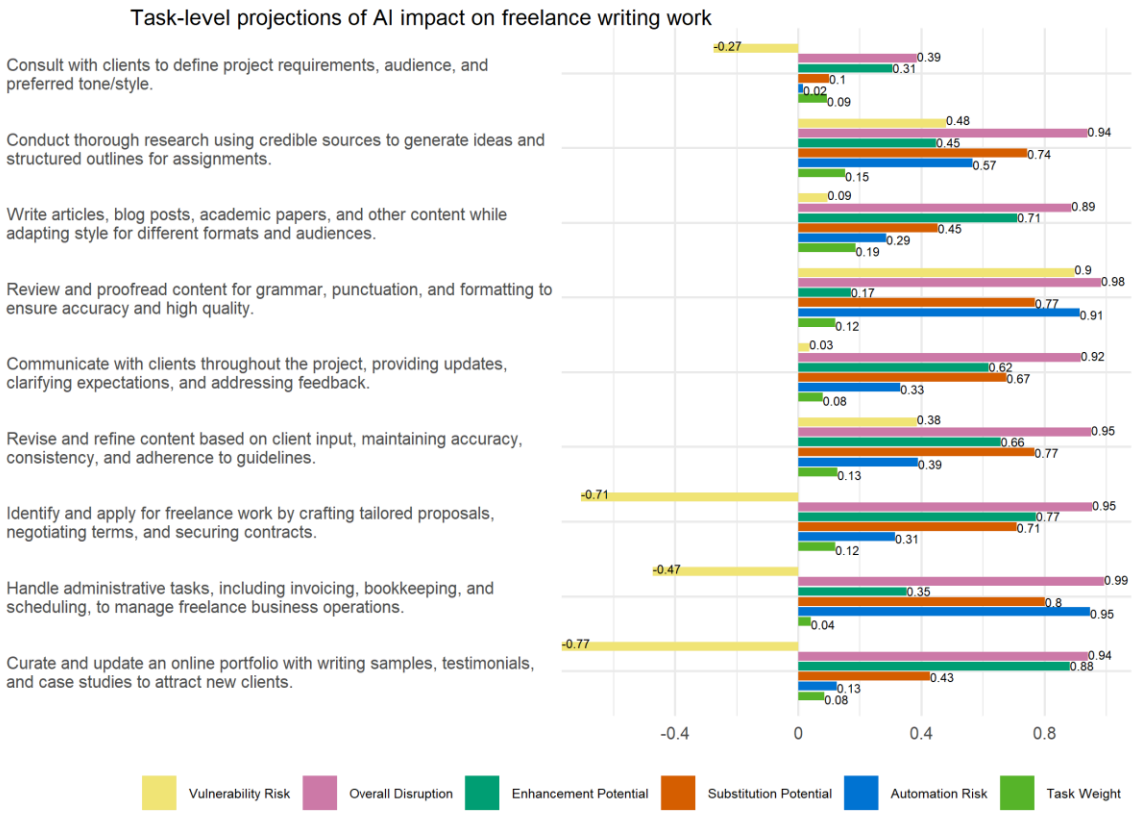
[21] For clarity, Wi represents the weight of the task, indicating its overall significance in the work process; and Ri is the ratio of paid work, distinguishing income-generating activities from unpaid functions. TMG (Task Modularity and Granularity), TCD (Context Dependence), SIC (Social & Interactive Complexity), DAQ (Data Availability & Quality), and DCU (Decision Complexity & Uncertainty). Annex D provides a comprehensive analysis to support the scoring presented in this table.

Freelance Writing Task Characteristics[21]	TMG	TCD	SIC	DAQ	DCU	W_i	R_i
Revise and edit content based on client feedback, ensuring accuracy, tone, and adherence to guidelines.	7	6	3	7	5	0.13	1.00
Proactively search for and apply to new work opportunities by developing and submitting tailored proposals on freelance platforms and negotiating contracts, project terms, and rates with clients.	7	5	6	7	6	0.12	0.00
Manage administrative tasks such as invoicing, bookkeeping, and scheduling to sustain smooth business operations.	9	3	3	9	3	0.04	0.00
To attract potential clients, maintain and update an online portfolio and professional profile by regularly showcasing recent writing samples, client testimonials, and case studies.	6	4	4	5	5	0.08	0.00

A closer look at task-level impact reveals significant variations in disruption and vulnerability. For instance, drafting, a core task with high weight (W = 0.19, Ri = 1), exhibits high modularity (TMG = 8) and moderate context dependence (TCD = 5). Its moderate data availability (DAQ = 4) results in a relatively low automation score (0.29) and a moderate substitution score (0.45). However, a high enhancement score (0.71) drives strong disruption (0.89) while keeping vulnerability low (0.09). This suggests that the structured nature of drafting work enables AI support without exposing workers to excessive risk.

Figure 5.8

Task-Level projections of AI impact Freelance Writing Work



Contrastingly, proofreading (W = 0.12) demonstrates a markedly different risk profile. Despite sharing high modularity (TMG = 8) with drafting, proofreading benefits from very high data availability (DAQ = 9) but has minimal social complexity (SIC = 1) and low context dependence (TCD = 2). As a result, it becomes highly susceptible to automation (0.91) and substitution (0.77). Furthermore, limited enhancement potential (0.17) fails to counterbalance these risks, leading to near-maximal disruption (0.98) and high vulnerability (0.90). This illustrates how even structurally similar tasks can diverge in risk when enhancement effects are absent (Figure 5.8).

In contrast, client consultations exhibit a distinctly protective profile. With low modularity (TMG = 4) but very high context dependence (TCD = 8) and social complexity (SIC = 9), this task

naturally resists automation (0.02) and substitution (0.10). Modest enhancement (0.31), coupled with its intrinsic interpersonal demands, results in low disruption (0.39) and even negative vulnerability (-0.27), indicating a protective effect partly due to its mixed paid ratio (Ri = 0.50).

Similarly, research work, characterized by high modularity (TMG = 7) and robust data availability (DAQ = 8) yet lower social complexity (SIC = 3) and moderate context dependence (TCD = 6), exhibits elevated substitution (0.74) and automation (0.57) scores. These factors drive near-maximal disruption (0.94) and moderately high vulnerability (0.48), particularly due to its significant weight (W = 0.15) and high paid ratio (Ri = 0.87). In contrast, client communication, which involves moderate modularity (TMG = 7), modest context dependence (TCD = 4), and higher social complexity (SIC = 6), maintains a low automation potential (0.33) while benefiting from a strong enhancement score (0.62). This combination results in high disruption (0.92) yet minimal vulnerability (0.03), underscoring the buffering effect of interpersonal interaction.

These findings, shown in Figure 5.8, illustrate that while freelance writing as an occupation remains relatively insulated from AI-driven vulnerability, task-level differences reveal significant disparities in exposure. Highly modular, data-rich tasks like proofreading and research are disproportionately susceptible to automation and substitution. In contrast, tasks requiring human judgment, social interaction, and contextual understanding, such as client consultations and communication, are more resistant. Notably, the degree of enhancement plays a crucial role in determining whether disruption translates into vulnerability. These dynamics suggest that AI's role in freelance writing will likely be augmentation rather than wholesale replacement, with human expertise remaining a central component in many core tasks.

5.6.3.2 Freelance Virtual Assistance

At the occupational level, freelance virtual assistance exhibits the highest substitution score (0.61) and enhancement score (0.64) among the examined occupations. These trends are closely linked to the underlying characteristics of tasks within this role (Table 5.3 and Figure 5.9). While client-facing and decision-oriented tasks (e.g., consultations, project management) demonstrate greater resistance to automation, structured and repetitive tasks (e.g., scheduling, correspondence, and administrative duties) are highly vulnerable to substitution.

For instance, initial client consultations, which involve direct engagement with clients, display low modularity (TMG = 4) but high context dependence (TCD = 8) and strong social complexity (SIC = 9). These features naturally shield the task from automation and substitution, as reflected in its low automation (0.02) and substitution (0.10) scores. Consequently, it experiences only modest disruption (0.39) and even negative vulnerability (-0.15) due to its relatively balanced paid work ratio (Ri = 0.87).

Table 5.3

Freelance Virtual Assistance Task Characteristics Scoring

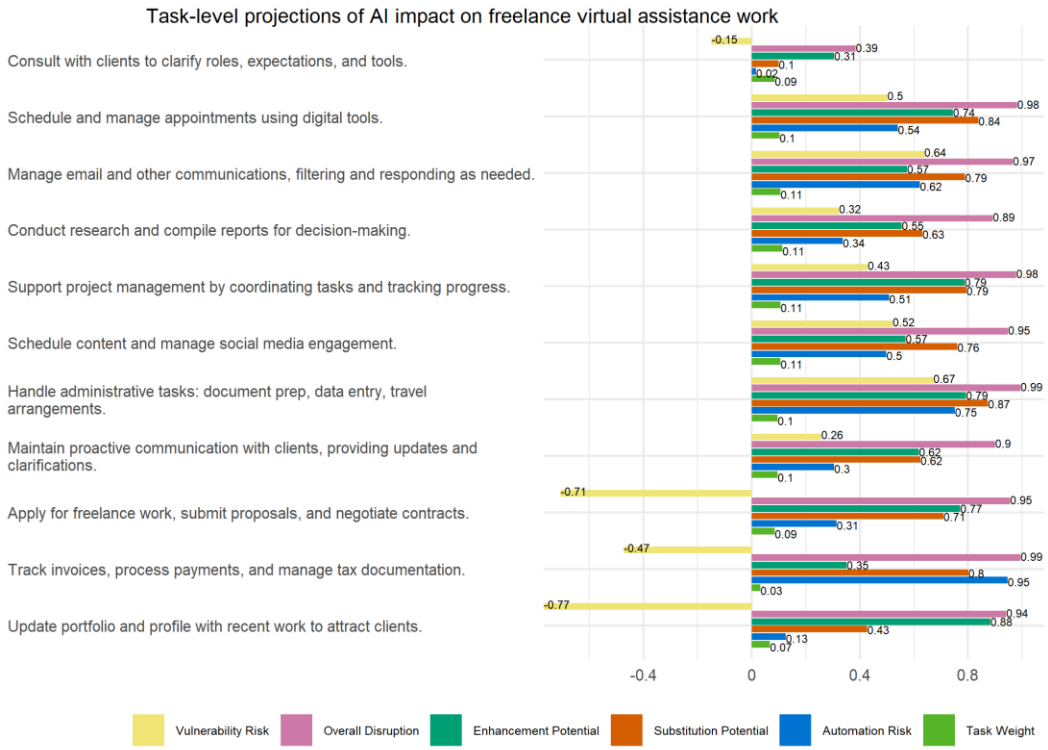
Freelance Virtual Assistance	**TMG**	**TCD**	**SIC**	**DAQ**	**DCU**	**W_i**	**R_i**
Engage in initial client consultations to clarify project requirements, communication expectations, and preferred tools, establishing clear roles for long-term or short-term engagements.	4	8	9	5	7	0.09	0.87
Manage and organize schedules and appointments using digital calendaring and scheduling software to ensure optimal time management and timely coordination of meetings or tasks.	7	5	4	8	6	0.10	1.00
Handle email correspondence and other communications, liaising between clients and their contacts by filtering, prioritizing, and responding to messages as needed.	8	6	4	8	7	0.11	1.00
Conduct targeted research and compile data to prepare reports, presentations, or summaries that support the client's decision-making and project objectives.	7	7	4	7	7	0.11	1.00
Assist with project management by coordinating tasks, tracking progress using project management software, and ensuring deadlines and milestones are met.	7	6	5	8	6	0.11	1.00
Manage social media accounts by scheduling content, monitoring engagement, and performing essential updates per the client’s brand guidelines.	7	6	7	8	6	0.11	1.00

Freelance Virtual Assistance	TMG	TCD	SIC	DAQ	DCU	W_i	R_i
Perform administrative tasks, such as document preparation, data entry, travel arrangements, and running errands, while coordinating with other freelancers or team members to ensure seamless execution of projects.	8	5	5	9	4	0.10	1.00
Maintain regular and proactive communication with clients by providing progress updates, clarifying requirements, and promptly addressing any concerns or emerging issues.	7	6	6	7	7	0.10	1.00
Actively search for new work opportunities by researching freelance platforms, developing and submitting tailored proposals, and negotiating contracts, project terms, and rates with clients.	7	5	6	7	6	0.09	0.00
Manage financial and administrative systems by tracking invoices, processing payments, and maintaining tax documentation to support smooth business operations.	9	3	3	9	3	0.03	0.00
Maintain and update an online portfolio and professional profile by regularly showcasing recent work.	6	4	4	5	5	0.07	0.00

By contrast, routine digital organization tasks, such as scheduling and appointment management, exhibit high modularity (TMG = 7) and strong data availability (DAQ = 8) but only moderate context dependence (TCD = 5) and low social complexity (SIC = 4). These characteristics make such tasks highly susceptible to substitution (0.84) and moderately automatable (0.54). However, despite a strong enhancement effect (0.74), a moderate vulnerability level (0.50) highlights how structured, repetitive tasks are at risk despite AI-driven efficiency gains.

Figure 5.9

Task-level projections of AI impact on Freelance Virtual Assistance



Similarly, handling correspondence and communication shares a high modularity score (TMG = 8) and strong data availability (DAQ = 8) but only moderate context dependence (TCD = 6) and low social complexity (SIC = 4). As a result, it faces significant automation (0.62) and high substitution potential (0.79). Its moderate enhancement score (0.57) is insufficient to fully counterbalance these pressures, leading to high disruption (0.97) and elevated vulnerability (0.64).

Conversely, project management tasks, which involve tracking progress and ensuring a timely execution of projects, demonstrate a more balanced risk profile. With moderate modularity (TMG = 7), moderate context dependence (TCD = 6), and moderate social complexity (SIC = 5), project management tasks benefit from robust data availability (DAQ = 8). These attributes contribute to very high substitution (0.79) and moderate automation (0.51), yet high enhancement (0.79) helps offset some risks. While the overall disruption score remains exceptionally high (0.98) due to the

magnitude of change, vulnerability is also significant (0.43) because of the heightened substitution risk, which may lead to skill degradation and financial instability.

Finally, administrative tasks, while essential for operational efficiency, are among the most vulnerable due to their highly routine nature. These tasks score high in modularity (TMG = 8) and data availability (DAQ = 9) but exhibit low context dependence (TCD = 5) and moderate social complexity (SIC = 5). As a result, they record high substitution (0.87) and automation (0.75) scores. Even with a strong enhancement effect (0.79), the nearly maximal disruption (0.99) leads to high vulnerability (0.67), making administrative functions one of the most at-risk categories in virtual assistance work.

5.6.3.3 Transcription Services

Transcription work is shaped by strict accuracy requirements and adherence to client guidelines, which influence its exposure to AI-driven changes. The core task of converting audio or video recordings into text is fully remunerated (Ri = 1.00, W = 0.16). It involves a high degree of context dependence (TCD = 8) and considerable decision complexity (DCU = 7) due to the need for precise transcription with minimal errors (Table 5.4). These characteristics result in moderate automation (0.24) and high substitution (0.40) scores, with modest enhancement potential (0.35). Consequently, this task registers a moderately low vulnerability (0.23), indicating that while AI may aid transcription, full automation remains constrained by the necessity for accuracy and compliance with client specifications.

Table 5.4

Transcription Service Task Characteristics Scoring

Freelance Transcription Service	TMG	TCD	SIC	DAQ	DCU	W_i	R_i
Convert audio or video recordings into text following client formatting guidelines, including any required timestamps and speaker identifications.	6	8	2	5	7	0.16	1.00
Research and integrate domain-specific terminology and contextual details, especially for technical or specialized content.	7	8	3	8	8	0.14	0.87
Rigorously review transcripts to correct errors in grammar, punctuation, and spelling.	8	2	1	9	3	0.15	1.00
Consult with clients to clarify unclear or ambiguous audio segments, ensuring the final transcript accurately reflects the original content.	6	7	6	7	7	0.12	0.71
Update and refine transcripts in response to client corrections and detailed feedback.	7	6	3	7	5	0.13	1.00
Provide regular updates and clarifications during transcription to align the final output with client expectations.	6	5	4	7	5	0.07	0.50
Proactively search for and submit tailored proposals on freelance platforms while negotiating client contracts, project terms, and rates.	7	5	4	7	6	0.10	0.00
Manage administrative tasks such as invoicing, bookkeeping, and scheduling to sustain smooth business operations.	9	3	2	9	3	0.05	0.00
Maintain and update your professional profile.	6	4	3	5	5	0.08	0.00

A notable contrast emerges when examining proofreading and transcript review, both of which are crucial tasks for ensuring quality. It exhibits high modularity (TMG = 8) and very high data availability (DAQ = 9) but minimal social complexity (SIC = 1) and low context dependence (TCD = 2). These characteristics make it highly susceptible to automation (0.84) and substitution (0.54). Furthermore, limited enhancement potential (0.17) fails to counterbalance these risks, resulting in near-maximal disruption (0.98) and high vulnerability (0.90). This highlights that even tasks integral

to transcription can become increasingly at risk when they lack contextual or interpersonal complexity.

Similarly, research tasks, which involve integrating domain-specific terminology and contextual details, exhibit high modularity (TMG = 7), high context dependence (TCD = 8), and slightly elevated social complexity (SIC = 3) due to the specialized knowledge required for industry-specific transcripts. These characteristics, coupled with robust data availability (DAQ = 8) and high decision complexity (DCU = 8), lead to high automation (0.77) and substitution (0.63) scores. As a result, this task experiences significant disruption (0.94) and high vulnerability (0.68), illustrating that even knowledge-intensive transcription tasks remain highly susceptible to AI replacement.

A different pattern emerges in peripheral work, such as consultation with clients to clarify ambiguous audio segments, which, although performed on a needs basis (W = 0.12, Ri = 0.71), relies on moderate modularity (TMG = 6), high context dependence (TCD = 7), and moderate social complexity (SIC = 6). These attributes yield some automation potential (0.51) and high substitution (0.70). However, strong enhancement (0.58) helps mitigate some of these risks, resulting in high disruption (0.94) but comparatively lower vulnerability (0.17). This underscores how tasks that incorporate interpersonal judgment remain relatively resilient to full AI displacement.

Similarly, routine revision tasks, such as updating transcripts based on client feedback, a fully paid task (Ri = 1.00, W = 0.13), exhibit moderate modularity (TMG = 7), context dependence (TCD = 6), and social complexity (SIC = 3). However, high automation (0.73) and substitution (0.90) scores indicate that AI can significantly streamline revision processes. Despite a moderate enhancement potential (0.66), the rapid pace of AI-driven transcription correction leaves workers vulnerable, resulting in a high vulnerability score (0.74). This suggests that even tasks benefiting from enhancement remain at considerable risk due to AI's growing efficiency in transcription-based revisions.

Overall, the task-level analysis of transcription work that many platform workers do shows contrasting impacts of AI, depending on the nature of the tasks. While core transcription activities exhibit moderate automation and substitution risks, tasks with high modularity and robust data availability, such as proofreading and transcript revisions, face substantially higher displacement risks due to their repetitive and structured nature (Figure 5.10).

Figure 5.10

Task-level projections of AI impact on Transcription Work



However, tasks requiring interpersonal communication and domain-specific expertise, such as client consultations and research-based transcription, remain more resilient due to their contextual dependencies and specialized decision-making processes. Nonetheless, the overall vulnerability of transcription work remains high, particularly for tasks that AI can rapidly enhance but also replace, leading to heightened job insecurity for freelancers in this occupation.

5.6.3.4 Freelance Developers

Among the occupations examined, freelance software and web development stand out with the highest automation score (0.68) and vulnerability score (0.37), reflecting the diverse nature of tasks and their susceptibility to AI-driven transformation (Table 5.5). The highly structured nature of core

technical tasks, such as coding and software maintenance, makes them particularly exposed to automation.

For instance, developing and maintaining code, a fundamental core paid task (Ri = 1.00, W = 0.14), exhibits high modularity (TMG = 8) and robust data availability (DAQ = 8), while displaying low social complexity (SIC = 3) and moderate context dependence (TCD = 6). These characteristics predispose coding to high automation (0.83) and moderate substitution (0.64). Despite some enhancement potential (0.43), the resulting near-maximal disruption (0.97) leads to high vulnerability (0.81)—a risk further intensified by its fully paid nature and substantial task weight.

A similar pattern emerges in tasks such as website and application optimization, where the interplay of high modularity (TMG = 7), strong data availability (DAQ = 8), and elevated context dependence (TCD = 8) leads to substantial automation (0.75) and moderate enhancement (0.40). This combination results in high disruption (0.95) and considerable vulnerability (0.76), illustrating how even tasks requiring some degree of context adaptation remain highly susceptible to AI-driven changes.

Table 5.5

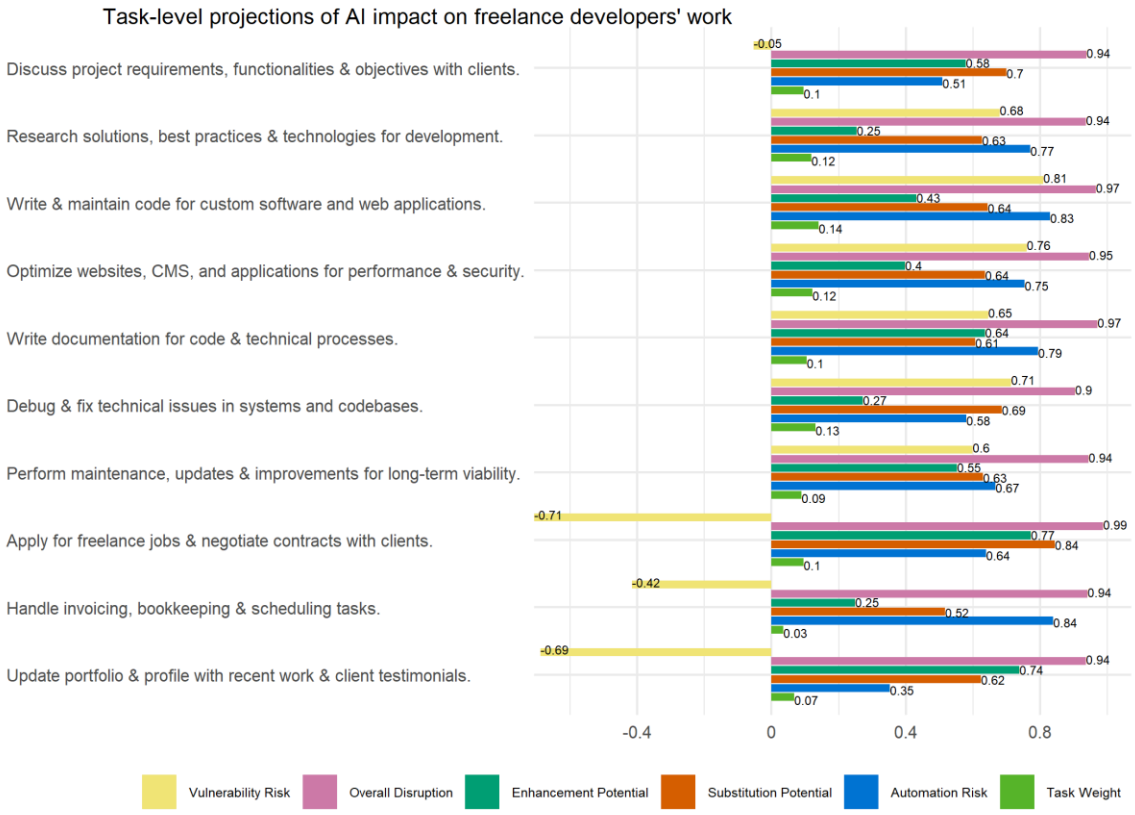
Web and Software Development Task Characteristics Scoring

Freelance Developers	**TMG**	**TCD**	**SIC**	**DAQ**	**DCU**	**W_i**	**R_i**
Communicate with clients to clarify project requirements, desired functionalities, and target objectives, ensuring a clear understanding of the assignment.	6	7	6	7	7	0.10	0.50
Conduct technical research to identify effective solutions, best practices, and appropriate technologies to inform the development process.	7	8	3	8	8	0.12	0.87
Develop and maintain code to meet specific client requirements related to custom software and web applications.	8	6	3	8	7	0.14	1.00
Optimize websites, content management systems (e.g., WordPress, Drupal), and applications for performance, speed, security, and reliability as needed or per client request.	7	8	4	8	8	0.12	1.00
Document code and technical processes to ensure quality and maintainability.	8	5	3	9	5	0.10	1.00
Troubleshoot and resolve technical issues in existing systems and codebases, including debugging and addressing production challenges.	6	8	3	7	9	0.13	1.00
Provide ongoing maintenance, updates, and improvements to ensure the long-term viability and scalability of the project.	6	7	4	8	7	0.09	1.00
Proactively search for and apply to new work opportunities by developing and submitting tailored proposals on freelance platforms and negotiating contracts, project terms, and rates with clients.	7	5	6	7	6	0.10	0.00
Manage administrative tasks such as invoicing, bookkeeping, and scheduling to sustain smooth business operations.	9	3	2	9	3	0.03	0.00
To attract potential clients, maintain and update an online portfolio and professional profile by regularly showcasing recent work samples, client testimonials, and case studies.	6	4	3	5	5	0.07	0.00

In contrast to the high automation risks observed in technical tasks, those involving direct client communication, such as clarifying project requirements, demonstrate greater resilience (but less income-generating value). With moderate modularity (TMG = 6), high context dependence (TCD = 7), and balanced social complexity (SIC = 6), this task is less susceptible to automation (0.51) and substitution (0.70). These factors, combined with a moderate enhancement potential (0.58), result in high disruption (0.94) but near-neutral vulnerability (-0.05), primarily because this task is only partially paid (Ri = 0.50).

Figure 5.11

Task-Level projections of AI impact on Web and Software Development Work



Other structured but essential tasks, such as documenting code, present a unique case. This task benefits from very high data availability (DAQ = 9) and high modularity (TMG = 8), while

maintaining moderate context dependence (TCD = 5) and low social complexity (SIC = 3). Here, moderate automation (0.79) combined with a more substantial enhancement effect (0.64) lowers vulnerability to moderate levels (0.65), even though disruption remains near-maximal (0.97).

Meanwhile, troubleshooting technical issues exemplifies the complex trade-offs in AI's impact on development work. With moderate modularity (TMG = 6), high decision complexity (DCU = 9), and strong context dependence (TCD = 8), this task faces moderate automation (0.58) and substitution (0.69) scores. However, its limited enhancement potential (0.27) results in high disruption (0.90) and elevated vulnerability (0.71). This suggests that while troubleshooting remains a critical function, AI-driven diagnostics and debugging tools are increasingly encroaching on aspects of this work.

Unlike other occupations examined, freelance development work presents a paradoxical relationship with AI. The high modularity, strong data availability, and structured nature of technical tasks make them prime candidates for automation, leading to significant disruption and vulnerability (Figure 5.11). However, tasks requiring decision complexity, adaptation, and client interaction remain somewhat insulated from full automation, though they still face substantial shifts in workflow and skill demands.

5.7 Discussion and Empirical Synthesis

In this research, I thoroughly examined the task characteristics of platform work to assess the potential impact of generative AI on the nature of available work and the livelihoods of platform workers. The results in this study particularly highlight the significant differences between platform-based labour and conventional employment by demonstrating how key work tasks across various platform work categories differ due to the nature of work available and the ratio of unpaid tasks. Analyzing these differences offers valuable insights into how professional identities and job titles in the digital economy may mirror those in traditional labour markets; however, the structure of available work and the burden of unpaid labour create nuanced variations in workers' exposure to transformations in the labour market.

While occupations such as web development, personal assistance, and content writing may seem similar to traditional professional identities, their nature within the platform economy is fundamentally different. In the platform economy, these professions heavily depend on hyper-

digitalized, fragmented, and data-driven job tasks that enable firms to profit from precarious labour while making low-commitment gigs attractive to workers. However, the precariousness of platform-based work extends beyond inconsistent job availability and fluctuating wages; it reflects a structural constraint within the labour market. The very factors that enable task fragmentation, letting firms and freelancers operate within this ecosystem of precarious work, also increase workers' exposure to market volatility and technological disruptions.

5.7.1 Contextualizing Uneven AI Disruption and Its Perceived Impact

As the findings of the theoretical analysis suggest, AI-driven automation in data-intensive tasks could result in considerable direct replacement of labour with capital (AI). Even in cases where the social and decision complexity of tasks decreases the likelihood of full automation, the partial substitution of human labour may have a dual impact. While it could enhance productivity, it may also introduce particular livelihood vulnerabilities by suppressing wages and diminishing the skill premium.

Several key practical questions arise from the theoretical projections of AI's impact on categories of platform work. For instance, if the livelihood vulnerability (0.214) associated with generative AI is expected to suppress roughly a fifth of platform work, and the mean disruption score of 0.913 (both on a scale of 0 to 1) indicates a significantly high level of disruption, what observable early-stage changes in the job market might emerge at this stage? Moreover, how does this transformation align with the adoption of AI tools? Some studies estimate a 24% decline in job supply on a major digital platform within two years of ChatGPT's introduction (Liu et al., 2023). This demand-side contraction, representing approximately a quarter of platform jobs, along with the theoretical inference from my analysis that AI-induced livelihood vulnerability could be of a similar magnitude, suggests that occupations most susceptible to AI disruption are already facing a sharp decline in job availability.

However, to what extent is this early-stage transformation evident in the perceptions of workers? To explore this question, I conducted field research with Kenyan platform workers from January 2024 to September 2024, which included examining their views on the impact of AI on their livelihood. Their responses, however, reveal a different story.

Table 5.6

Perceived Job Insecurity Due to AI Among Freelance Platform Workers (N=41)

Occupation	Mean	SD	Min	Max
Freelance Writing	2.44	1.15	0	4
Transcription	1.28	0.95	0	3
Virtual Assistance	1.76	1.30	0	3
Web and Software Development	2.00	1.41	0	4

0 = not at all concerned, 4 = extremely concerned

As shown in Table 5.6, survey responses from my research indicate that freelancers engaged in writing gigs, who, according to these theoretical projections, face the lowest livelihood vulnerability (0.05), express the highest level of concern about AI's impact on their future work opportunities[22]. Web and software development workers follow as the second most concerned group. However, the overall concern among workers remains moderate, which is not expected if a quarter of their livelihood opportunities have already disappeared. This does not necessarily contradict the observed decline in job availability or the broader impact of AI but suggests that additional factors may influence workers' perceptions and concerns.

First, market fluctuations likely affect different groups of workers unevenly. Those who have established a clientele and a surplus of work have more control over their opportunities, making them less susceptible to early-stage disruption. It should be noted that the platform labour market is widely recognized as oversupplied, with significantly more workers seeking opportunities than available job postings (Kässi et al., 2021). A conventional labour supply perspective, focusing primarily on the job-to-worker ratio, may overlook a crucial aspect of platform work: the signalling power of workers' profiles. The established trust, reinforced by indirect network effects and review-based credibility, is critical in shaping employment outcomes and the amount of work available to workers.

More specifically, the exponential growth of many digital platforms with a two-sided market is significantly influenced by indirect network effects and the pivotal role of ratings and reviews in

[22] Please note that the timing of the survey is important for interpreting the findings. The data were collected between January and July 2024, and it is possible that workers' views have since evolved.

user decision-making, resulting in a winner-takes-most scenario for both platforms and workers. Indirect network effects occur when the value of a platform increases for one user group as the size of another user group expands (Lee & Wellman, 2012). For instance, increasing the number of work providers in digital labour platforms leads to more job opportunities, attracting more freelancers. Conversely, a larger pool of freelancers offers clients a broader selection of skills, enhancing the platform's appeal to employers. This reciprocal relationship fosters a self-reinforcing cycle of growth, conveying a sense of confidence to both sides of the market that their business needs will be met.

Sustaining this growth and user engagement, however, depends on mechanisms that demonstrate continued trust. One of the primary mechanisms for building this trust in the platform economy is through ratings and reviews. Empirical studies have shown that online reviews have a significant impact on key platform decisions, such as purchasing a product or hiring a worker (Pulignano et al., 2025; Yoganarasimhan, 2013). This creates a feedback loop where well-reviewed freelancers secure more projects, leading to greater control over their work options and additional reviews that further enhance their attractiveness to potential clients.

As a result, freelancers with stronger signalling power are more likely to attract a surplus of clients and have greater confidence in their ability to sustain adequate work access under disruptive conditions, as well as find work on favourable terms in the future. Unlike traditional employment and many location-based work platforms, a worker on a digital labour platform does not appear busy, engaged in a task, or employed full-time. Thus, a well-positioned worker could theoretically accumulate a significant amount of work. In some instances, a well-placed individual profile could technically gather enough work for a whole team of workers (Idowu & Elbanna, 2021b).

In the survey, I asked workers about their confidence in finding sufficient work through digital platforms over the next six months. Table 5.7 displays the results of a linear regression model that examines relevant factors.

Table 5.7

Determinants of Workers' Confidence in Future Digital Platform Employment[23]

Work Access Confidence	***b***	**SE**	***p***	**95% confidence interval of *b***		**beta**
				Lower	Upper	
AI Job Loss Concern	-0.103	0.075	0.174	-0.254	0.047	-0.174
Paid Work Hours	0.0005	0.005	0.925	-0.01	0.009	-0.012
Age	0.089	0.136	0.519	-0.186	0.363	0.094
Education Level	0.057	0.174	0.743	-0.294	0.409	0.043
Gig Experience	0.037	0.13	0.780	-0.226	0.3	0.039
Work Control	0.275*	0.074	0.001	0.127	0.424	0.475
Financial Satisfaction	0.35*	0.11	0.003	0.128	0.572	0.414
Gender	-0.182	0.178	0.312	-0.542	0.177	-0.127
Intercept	1.141	0.808	0.165	-0.49	2.772	-

n=51
*p<.05

Among the predictors listed in Table 5.7, control over workload, schedule, and financial satisfaction emerge as the only significant factors influencing workers' confidence in securing future platform jobs. Work control (B = 0.275, SE = 0.074, p = 0.001, β = 0.475) has the strongest positive effect, demonstrating that workers who feel they have greater autonomy over their tasks, schedules, and job selection exhibit significantly higher confidence in their ability to secure future digital platform work. These findings suggest that platform workers with greater control over their workflow perceive their employment as more stable and predictable, thereby reducing their vulnerability to job insecurity and fluctuations in demand.

Likewise, workers' negotiating power leading to financial satisfaction (B = 0.350, SE = 0.110, p = 0.003, β = 0.414) is positively linked to confidence in continuing to find suitable work.

[23] The model explains 40.35% of the variance in confidence to access work ($R^2 = 0.4035$, Adjusted $R^2 = 0.2899$), with the overall model being statistically significant ($F(8, 42) = 3.55$, $p = 0.0032$). Pre-estimation checks confirmed that multicollinearity is not a concern (VIF < 5 for all predictors). The Shapiro-Wilk test ($p = 0.556$) indicates that residuals are normally distributed. The Breusch-Pagan test ($p = 0.7114$) found no evidence of heteroskedasticity, supporting the use of standard errors. The Ramsey RESET test ($p = 0.3404$) suggests the model does not suffer from omitted variable bias.

This suggests that financially secure workers tend to be more optimistic about their ability to keep earning through digital platforms in the future, irrespective of the ongoing transformation. This finding is consistent with broader labour market trends, where financial stability is a buffer against economic uncertainty. In the context of platform work, it may suggest that workers who have attained financial security by enhancing their platform profiles view their income streams as reliable and replicable. In contrast, those experiencing financial instability and difficulties attracting sufficient clients might perceive more significant risks in sustaining their platform-based employment, especially if automation and substitution reduce available work opportunities.

Other variables, such as hours worked, age, education level, total experience, and gender, do not show significant effects on workers' confidence in securing future platform jobs ($p > 0.05$ for all predictors). The findings suggest that demographic factors and work history alone do not dictate confidence in maintaining digital platform work. It is particularly noteworthy that gig experience does not show a significant impact, indicating that time spent on platform work does not necessarily lead to increased confidence in future opportunities. This reflects the precarious nature of digital labour, where even experienced workers may still encounter instability and uncertainty in obtaining jobs if their years of experience do not result in greater control over platform work conditions and bargaining power.

Importantly, concerns regarding AI-related job loss ($B = -0.103$, $SE = 0.075$, $p = 0.174$, $\beta = -0.174$) do not have a statistically significant impact, indicating that worries about automation and AI replacing jobs on digital platforms exist but do not currently align with workers' confidence in their ability to secure future employment. However, it is possible that as automation advances, this effect could become more pronounced over time. My research indicates that workers' confidence in their ability to secure future employment is also a function of their resilience in the face of persistent labour market precariousness. The inherent instability of platform work conditions them to adapt to emerging transformations. Theo, one of the research participants I spoke to, explained this:

> "Freelancing is very tricky because you don't have a regular schedule. So today, you may have work, a lot of work, then in the next three months there are no jobs coming your way. So, let me say it's very unpredictable (Theo, software and web developer)"

Theo started freelancing during his undergraduate studies; for him, unpredictable workloads and finding work through platforms amid uncertainty have become defining features of his career, particularly after graduating in 2020 when COVID-19 restrictions severely limited his local job opportunities. His experience working through disruption explains the reason for relatively lower concern among workers. As he noted:

> "Initially, I was a bit concerned because most of the tasks that we used to do manually are now done by AI, especially writing. Most of it is done by AI. A client has a website, and they want to write content. So, most of these big things are done by AI. Initially, the workload went down, especially in those tasks. But what I have learned is, AI is still developing; I think it's still in the early stages. What happened is, most of the clients who tried using it, I think, realized there were still issues with quality. So, they still needed someone who is keen on writing to edit and maybe generate more accurate content than AI" (Theo, software and web developer).

Platform workers like Theo are often conditioned to adapt to shifting market dynamics, including technological disruptions. In the platform economy, adaptability is not just an edge but often a necessity, as workers face direct livelihood risks when they fail to adjust to changing client demands or emerging technology transitions, like AI. However, adaptation is a less risk-free process for firms. For clients, adopting AI too hastily carries its own set of risks, such as reduced quality, unforeseen costs, or workflow disruptions, especially when AI proves an imperfect substitute for human labour. This interplay of risks on both sides means that fluctuations in labour demand are a part of an ongoing recalibration process. As both workers and clients navigate these uncertainties, significant variation in the nature and volume of available work is likely before any semblance of stability emerges in the platform labour market. Amid this uncertainty, some workers go beyond reactive adjustment by actively anticipating market shifts and repositioning themselves accordingly, when their circumstances permit. Jasper, who transitioned from a solo platform freelancer to a successful entrepreneur and mentor by establishing his firm with a group of workers, explained:

> "The websites we used to work on, like three websites [in] a full month. But now, we can do three websites in a week. Traditionally, if someone wanted to do like an SEO copy for like, a landing page [of] a website, it's probably going to take you, like, three days before the project is done, but nowadays, with AI and just a few hours with proper prompt engineering[,] you have [it] done. I'm not really so worried about artificial intelligence, because it's here and we have to

> adapt to it. There's no way we can actually say it's not going to be part of us anymore, because [already] businesses, corporations, and even big companies, are actually using it. So, we also have to adapt to it and understand how we can actually include it in what we do as professionals" (Jasper, graphic designer, web developer, entrepreneur and trainer).

For professionals with established positions, such as Jasper and his team, recognizing emerging trends and staying ahead of ongoing labour market disruptions is essential to maintaining a competitive edge. Consequently, continuous upskilling, reskilling, and effective repositioning of their skills, combined with hard-earned credibility that attracts a steady stream of work, serve as vital safety nets against the disruptions. However, not all workers share this experience. For instance, Iris explained:

> "You might get to work today; tomorrow, you don't have work, and then you have bills here to pay. I see most of [the tasks] going to automation because most of [the clients], sometimes, they even tell you to test apps for them. Someone develops an app and wants it to be tested, like some here locally in Kenya. So, I think something [will change] in [the] future. It should be easier to test it, just wherever you are; you won't need someone in Kenya to do it for you. I think in [the] future, it won't be easy to work online. It concerns me a lot. Because I'm now thinking I have to think outside the box… what will I do if now we can't get to work online because maybe AI has replaced us and things like that?" (Iris, virtual assistant).

The volatile labour market and the transient nature of platform jobs can raise concerns about maintaining a consistent workload, particularly as automation and general-purpose AI increasingly compete with human tasks. For example, Iris turned to virtual assistance jobs through a platform after the very short three-month maternity leave made it challenging to return to her marketing job while caring for a newborn with health complications. In Kenya's rapidly developing economy, she seeks diverse opportunities where her local presence in Kenya offers her a competitive advantage. Still, the precarious nature of work availability, combined with the growing role of AI, remains a significant concern for her.

The contrasting experiences of Jasper, Iris, and many other workers demonstrate how AI-induced livelihood insecurities intensify when access to suitable work is already restricted, both on and off digital platforms. However, workers who are already in a position to maintain robust control

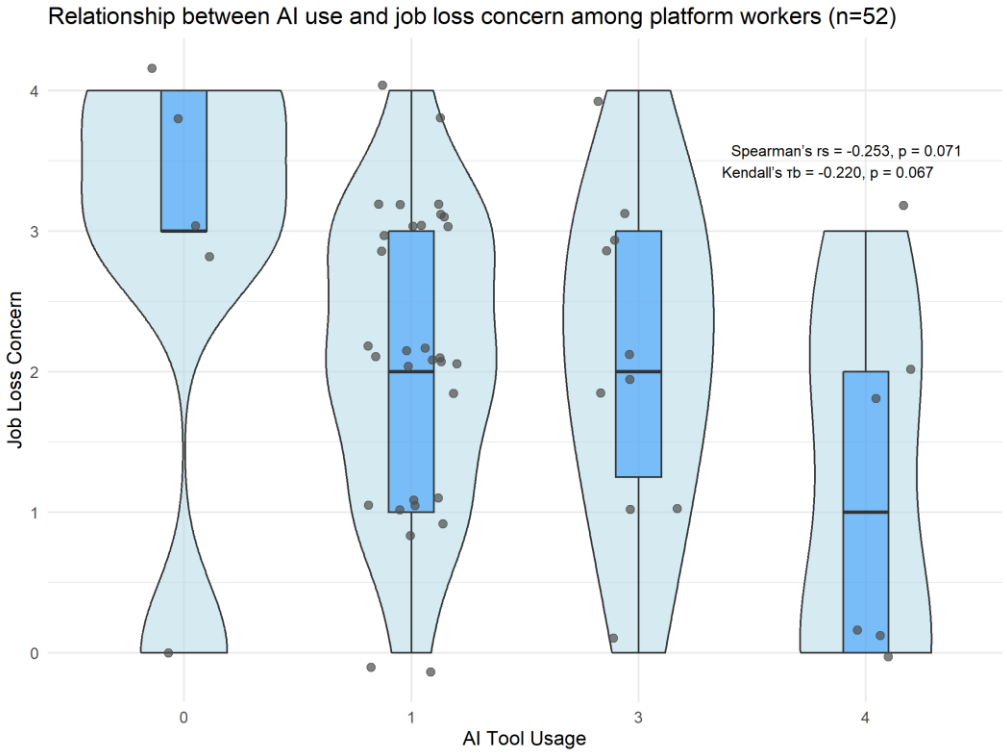
and stability over their work prove more adept at navigating the disruptions driven by AI and the vulnerabilities it introduces. As a result, AI's impact on digital platform work is decidedly uneven. Its benefits or drawbacks hinge on each worker's unique livelihood context and are shaped by their ability to cultivate trust, leverage established profiles, and swiftly adapt to shifting market dynamics. In this rapidly evolving landscape, resilience and adaptability are not just assets but essential survival skills for sustaining a decent livelihood.

5.7.2 The Gap Between AI Usage and AI Livelihood Impact Perception

While the interpretations above provide a plausible understanding of how early-stage empirical evidence on the impact of AI might be perceived, they also raise the question of what other factors could be at play if perceived job security is not always a significant determinant of concerns regarding AI-related job loss among workers. As illustrated in Figure 5.12, the empirical analysis of the relationship between levels of AI concern and AI usage shows that worry about AI is highest among those who use it the least.

Figure 5.12

AI Usage and Job Loss Concerns Among Kenyan Platform Workers[24]



A likely explanation is that a lack of familiarity with AI and barriers to effectively utilizing AI tools to support workflow heighten uncertainty, exacerbating worker apprehension. These results, although somewhat statistically significant (p = .073), also indicate that usage alone accounts for only a small portion (6.3%) of this variation.

During the interviews, it became clear that although the narrative on AI often emphasizes productivity gains and potential job losses to automation, workers' views on the potential AI-driven work transformations were significantly shaped by their awareness that AI represents an advancement

[24] A simple linear regression was conducted to examine the relationship between AI tool usage and job loss concern. The model was marginally significant, $F(1, 50) = 3.35$, $p = .073$, explaining 6.3% of the variance ($R^2 = .063$). AI tool usage was negatively associated with job loss concern ($\beta = -0.24$, $SE = 0.13$, $t = -1.83$, $p = .073$), suggesting that higher AI tool usage is likely linked to lower job loss concern, though the effect was weak, likely due to the smaller sample group of this study.

with the potential to create additional job opportunities for Kenyan workers. When asked how the expansion of AI is changing access to work, Marvin explained:

> "We have projects based on AI [,for example,] since last week, Freelancer is hiring a lot of Kenyans who are going to help AI determine the best responses based on languages. So, like, the Swahili language is mostly spoken in East Africa, [and] best African people have a higher chance of getting these jobs. So yes, we can be replaced on the high-paying skills and the low-paying ones for the AI; they are coming, but I feel we are going to be, at some point, replaced" (Marvin, web developer).

Marvin monitors emerging trends and opportunities as part of his livelihood strategy. Based on my interviews, Marvin and several other workers demonstrated greater awareness of AI's impacts on work, as well as the nature of outsourced digital jobs in Kenya, which shapes their outlook.

Leading AI models have increasingly depended on freelance and BPO (business process outsourcing) workers from key outsourcing hubs such as Kenya, the Philippines, and India for critical tasks such as data labelling, content moderation, and linguistic annotation (Graham, Lehdonvirta, et al., 2017; Gray & Siddharth, 2019; Melia, 2020). These contributions are essential for optimizing AI performance, and for many platform workers, particularly in Kenya, the surge in AI-related work is seen as a significant opportunity, undermining any broader perception of AI as a livelihood threat. Interviews indicate that many workers strategically engage in short-term gigs (e.g., annotation, data labelling) as a gap-fill strategy, enabling them to secure income while exploring broader, more sustainable opportunities on digital platforms.

5.7.3 The Delayed Onset of Automation and Substitution Impact

Linking empirical data on work demand and supply with the theorical projections of AI impact requires recognizing that any theoretical projections of automation and substitution assume highly efficacious AI tools and widespread AI adoption. That level of product reliability and adoption has not yet occurred and may not materialize to the extent predicted, depending on how firms and workers adapt to these technological changes and how regulations are implemented to mitigate adverse impacts on labour. The delayed onset of automation can also be attributed to the inherent flexibility of labour roles within firms, which enables companies to reassign workers to alternative

tasks when specific roles become less relevant due to automation, thereby buffering the immediate displacement of workers. Sierra explained:

> "When we automated our customer service system, I was pushed to the back end. So, I do — I don't interact with customers like I used to. So, at the moment, I just, if a customer wants something changed, they create a ticket, [and] AI [creates] a ticket, it comes to us, and then we make the changes. The owners find an opportunity, or somewhere they can use you, because, as much as AI can do the front end and reply to customers automatically, that means that on the back-end side, where, if a customer has a request, someone needs to actually get the request done because the AI can only respond. Luckily for the company I work for, yes, there is [something] at risk, but they always have a way of trying to get something else for you if they decided to go the automated area" (Sierra, virtual assistant and customer support agent).

Sierra transitioned into virtual assistance work after feeling burned out from a local marketing job in Nairobi, but she found a long-term remote gig in customer service. Her perspective towards the livelihood risks of early-stage automation and labour substitution demonstrates how the flexibility of labour roles within firms can delay the immediate onset of automation. This reaffirms the position in existing literature that technological change often leads to a reallocation of labour rather than immediate replacement, as firms adjust by shifting workers to tasks that complement automation (Acemoglu & Restrepo, 2019). That said, another critical factor that must be considered is the relative cost of platform labour.

Many firms are drawn to a global workforce because it provides access to significantly lower-cost human labour (Graham & Anwar, 2019). This phenomenon mirrors the rapid expansion of the BPO industry in the past, which leveraged digitalization and task fragmentation to reduce costs by employing workers in developing regions. During the interview, while Sierra felt grateful that the American firm she worked for found her another role as the firm transitioned towards automation, she also showed her frustration towards the wage and benefits inequality that makes such work arrangements attractive for firms:

> "You know, they don't recognize local holidays. So, that's one thing. They don't, they don't also recognize the benefits of, probably generally, because in the companies that I work[for], Americans get medical benefits. But remote workers do not; they get pension

> benefits that remote workers, they do not" (Sierra, virtual assistant and customer support agent).

Cost competitiveness often serves as a key rationale for moving away from traditional practices, such as offshoring work to BPO firms, hiring freelancers through digital platforms, or outsourcing tasks to AI. The decision to fully automate or substitute labour ultimately depends on the relative costs of human labour versus technology. Automation can yield significant cost savings and boost productivity in environments where labour is expensive. Conversely, when labour costs are low, the economic incentives for automation diminish, as the marginal efficiency gains may not justify the capital outlay and ongoing expenses (Autor, 2015; Howson et al., 2022).

In the case of AI-driven automation and labour substitution, cost-effectiveness is determined by a complex interplay of factors, such as acceptable level of AI advancements, capital availability, and labour market conditions. The result of this interplay is that the relative cost of platform labour is more competitive than traditional labour and, in many cases, AI-automation. While such automation might promise higher productivity, its adoption is currently curtailed in low-wage settings where the marginal gains do not outweigh the initial costs and associated AI risks for firms. Consequently, the effects of automation and substitution are unlikely to be immediately revealed in their true form in many segments of the gig economy while the relative cost of platform labour remains low, and if AI adoption remains low among firms due to a range of socio-technical reasons, including the error-prone nature of AI tools[25].

5.7.4 The Interplay of Paid and Unpaid Work

One of the key premises of this research is recognizing that AI tools affect the unpaid components of freelance work, potentially transforming conditions for workers, but only if AI adoption, accessibility, and user proficiency remain largely frictionless. Unpaid work accounts for a significant portion of human productive effort, often comparable in duration and impact to paid work. Unpaid work is an

[25] A pressing barrier to the utility of generative AI is that the predicted text output often appears authentic and factual at the surface level, yet its fabricated or falsified nature only becomes evident upon closer examination. This phenomenon, often referred to as AI hallucinations, indicate the useability barriers. Such hallucinations can lead to misleading information, underscoring the automation risks for firms and the continued need for expert oversight. For more on this, see (Emsley, 2023; Salvagno et al., 2023). Also see (Gosmar & Dahl, 2025) on how recent advances have demonstrated promising strategies to mitigate these errors by refining and clarifying speculative content, yet significant challenges remain.

inherent feature of platform-based freelancing, functioning as a hidden cost necessary to secure sufficient paid opportunities while simultaneously reducing the time available to complete remunerated tasks. In the context of the platform economy, this invisibility is particularly problematic, as many gig workers invest significant time in auxiliary tasks.

In the field research survey, I asked workers which aspects of their jobs could be made more efficient with AI-based tools. A significant proportion of responses pointed to the perceived role of AI tools in transforming unpaid work. Roughly 10% of responses emphasized using AI tools solely for job application processes, such as drafting proposals, writing cover letters, and searching for suitable gigs, which this research classifies as unpaid tasks despite requiring considerable time and energy. Additionally, about 48% of participants highlighted AI's role in supporting activities such as extensive research, idea generation, and client communications. While these functions are crucial for securing paid gigs, they often remain auxiliary and largely uncompensated, underscoring the hidden labour costs inherent in the freelance platform economy.

Could AI reduce the burden of unpaid work for freelance workers and help them overcome the autonomy paradox?[26] The significantly high automation, substitution, and enhancement scores for unpaid tasks across various platform work categories indicate that a widespread adoption of AI is likely to substantially reduce a large amount of unpaid work in all categories. It should not be overlooked that unpaid work also requires considerable creativity and a personal touch, and it can often set a freelancer apart from the rest in a saturated labour market. Unpaid work in the platform economy also includes emotional labour, the strategic personalization of interactions used by workers to cultivate client relationships necessary for building long-term career growth opportunities (Alacovska et al., 2024). While AI's capacity to decrease unpaid work could provide substantial support, it also creates a new dilemma. The reduction in unpaid work relies on the same extensive adoption of AI in the workplace, which poses a risk of labour substitution and automation in paid positions.

[26] The autonomy paradox refers to the contradiction in which digital platform workers, attracted by promises of flexibility and the ability to be their own boss, ultimately discover that they must work long, irregular, and unsocial hours. Instead of enjoying true autonomy over their schedules, these workers are compelled to remain constantly available to secure work and maintain high ratings on the platform. This situation traps them in a cycle where their "free" time is effectively consumed by unpaid labour, undermining the very freedom they sought. For more on this, see (Alacovska et al., 2024; Mazmanian et al., 2013; Pulignano, Marino, et al., 2024)

I refer to this phenomenon as the enabling-obsolescence paradox, where the automation of both paid and unpaid tasks mutually reinforces each other. More importantly, it also produces the composite consequences of unpaid labour automation, resulting in the collective dehumanization of work, irrespective of its paid or unpaid status. By using the term enabling-obsolescence paradox, I emphasize how, in the early stages, AI support can reduce the tediousness of writing numerous job proposals to secure limited work or assist with the error-prone aspects of managing client communication in globalized work environments. However, these efficiency gains come at a significant cost of reducing the already limited human element of worker-work provider interactions that underpin organic interpersonal interactions, synergistic creativity, and authentic workplace engagement. Suppose the significance of such meaningful professional relationships diminishes; it will be a substantial leap towards replacing paid human labour with AI capital, and platforms are at the forefront of this change.

My position is that the drive for the deeper integration of AI in freelance work is inherently connected to the platformization of work and the business model of platforms that promote hasty technology acceptance (Silva Neto, 2019). Unsurprisingly, digital labour marketplaces are actively reshaping freelance work through this deeper integration of AI[27]. These platforms promote and integrate AI utility for freelancers, providing them with helpful tools for drafting proposals, collaboration with clients, and streamlining communication that not only supports workers but also redefines workplace norms.

However, by normalizing the broader use of these tools, the platforms condition the labour market to a broader acceptance of AI tools (even if both sides of the labour market recognize the involvement of AI tools), gradually accepting dehumanized interactions[28] and work processes as the

[27] For instance, Upwork, one of the largest freelancing platforms, is evolving from a destination for on-demand hiring of human labour to one for on-demand work outcomes. This change is subtle but important. The platform offers integration support for a range of third-party AI tools, as well as its own AI model, called “Uma”. On the workers' end, these features are expected to assist with tasks such as drafting proposals, brainstorming, data management and streamlining communication. Concurrently, Upwork now offers clients fully managed AI services that include the creation of custom AI agents tailored to handle a variety of tasks. (Upwork Global Inc., n.d). This development not only streamlines project management and outcome delivery but also signifies a shift in platform mediation of human labour to increasingly transitioning toward mediation of AI agents.

[28] In the broader context of technological substitution, work dehumanization is a threat to employee–employer relationships. This concern is twofold: first, the transition to algorithmic processes erodes the nuanced human presence fundamental to authentic interpersonal interactions; second, the values inherent in human judgment

new normal and replacing the nuanced and empathetic aspects of interaction with automated processes. Simultaneously, these platforms extend AI-driven solutions to work providers, transforming the traditional mediation between human labour and clients into one where AI agents increasingly assume the roles held by human workers and ultimately pave the way for AI capital to supplement human labour.

5.7.5 The Forms of Early-Stage Automation and Substitution in the Platform Economy

While empirical observations reveal workers' perceptions of AI's impact, a critical gap remains in identifying and understanding the early-stage shifts in the job market that signal the onset of automation and task substitution. When it comes to reshaping existing tasks, a more plausible empirical scenario is that the initial phases of automation and substitution would manifest instead as task enhancement, benefiting workers more before the labour market adjusts to these transformations.

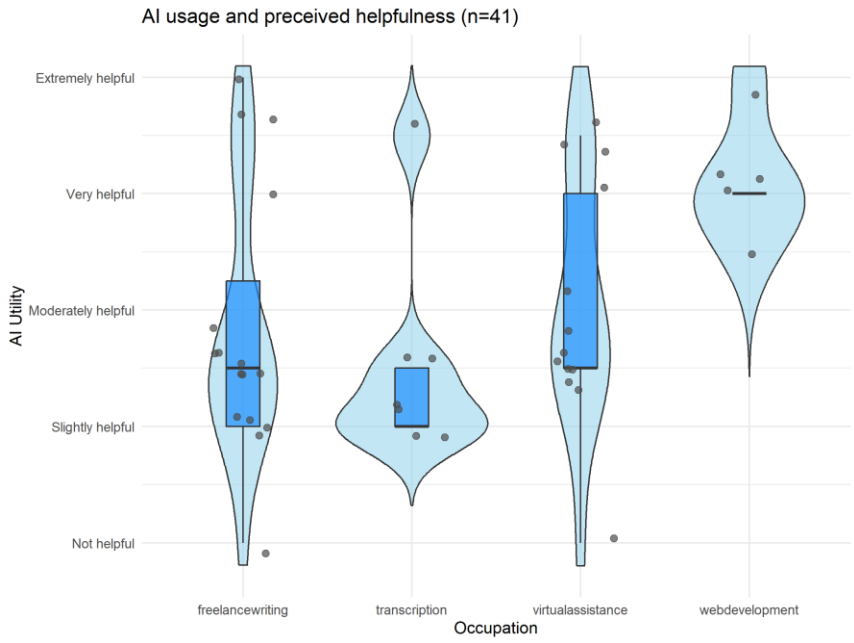
In the early stages, the AI-driven tools may improve productivity, increasing output without immediately displacing workers. However, as market pricing mechanisms and the skill premium evolve in response to AI adoption, the long-term implications for job security and income distribution may become more pronounced. Under this scenario, work that is likely to see higher automation and substitution under peak-AI would experience early adoption and increased utility of these tools, gradually reducing the skill premium for tasks that impact the livelihood of workers if they cannot transition to other, higher-paying gigs.

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often diverge from the vague metrics embedded in algorithms. See (Fritts & Cabrera, 2021) on how the use of recruitment algorithms results in such dehumanization.

Figure 5.13

Perception of AI Utility Among Kenyan Platform Workers



This delayed automation impact hypothesis is grounded in empirical data presented in Figure 5.13 and the theoretical analysis results presented in the previous section. It indicates that, regarding AI helpfulness, workers involved in work categories with a higher proportion of automatable tasks that lead to greater livelihood vulnerability, such as those in software and web development gig work (Figure 5.14), are more likely to perceive AI tools as helpful. In contrast, freelance writers (Figure 5.15) are less likely to experience a similar long-term impact involving automation, substitution, and vulnerability.

Figure 5.14

Impact of AI on Freelance Web and Software Development Work

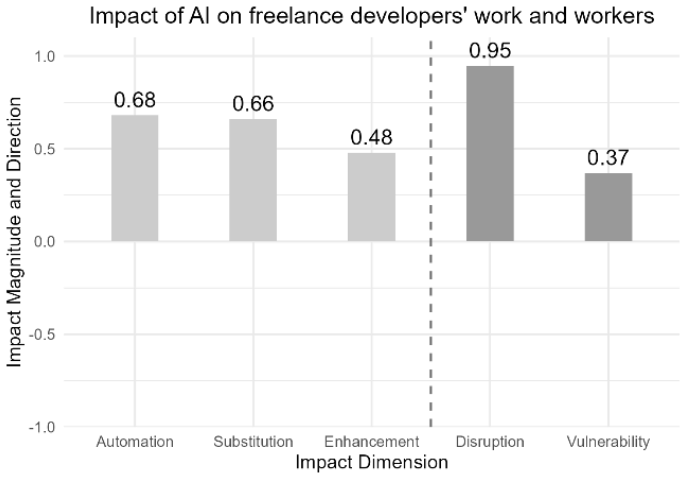
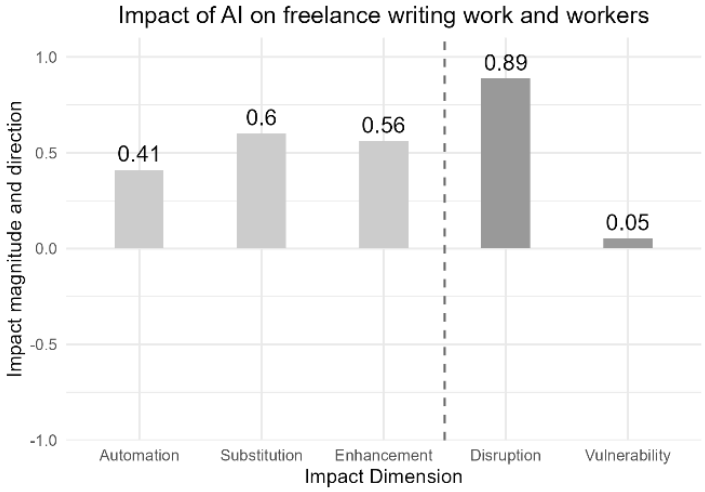


Figure 5.15

Impact of AI on Writing Jobs



The interview data also provides support for this argument, suggesting that when access to the amount of work is not a concern, the perspective of tech workers such as Jasper and Theo revealed how the benefits of AI have a considerable positive impact on their work:

> "For me, AI is a development in the right place, because now things [tasks] that we used to do, we used to take a long time to actually do. We can actually automate very easily and have them done within,

> like, maybe [a] few days" (Jasper, graphic designer and web developer).
>
> "I feel like AI is like making everything easier"[29] (Theo, software and web developer).

Jasper and Theo express a utilitarian perspective, where the immediate benefits of efficiency and ease of work outweigh concerns about the long-term sustainability of short-term, often transitory, platform-based tasks. When the focus is on productivity and efficiency, workers tend to assess AI in a largely positive light, even if they are aware of potential long-term risks. However, some workers exhibited a notable indifference toward these technological transitions. For them, while automation and substitution may compromise the attractiveness or availability of certain types of work, these changes do not pose fatal threats to their overall livelihood. The consistently high disruption scores across all work categories further illuminate this perspective. For example, Mable and Clara explained:

> "I'm not concerned because now, if I find out that it [AI] is replacing some aspect, I go on to the next thing and look for something that is going to help me move further and become better" (Mable, Freelance writer and accountant).
>
> "For me, it is not a big challenge; it is just about being open-minded. Things are going to change always, just have that in mind. They're gonna change either in your way or in another person's way, not necessarily the way you like it or the way you want it. That acceptance is what makes you move forward" (Clara, freelance writer).

A notable observation from the theoretical measurement of AI impact presented in the previous section is the exceptionally high level of disruption, with scores ranging from 0.89 to 0.95 on a scale of 0 to 1. Such elevated disruption levels reflect that, regardless of whether AI's impact manifests as substitution, enhancement, or automation, workers must proactively adopt strategies to remain competitive in an increasingly dynamic labour market.

[29] Theo shared this perspective during our interview in March 2024. By the end of September 2024, he contacted me to express that he was struggling to secure similar software and web development gigs and was considering a transition into video editing and marketing.

To empirically contextualize this high level of platform work disruption, and Clara and Mable's comments, it is worth noting that Kenyan platform workers have historically operated within a gig economy characterized by inherent instability, where technological disruptions extend beyond recent advancements in AI technology (Melia, 2020). Although platform work could be segmented into various categories to understand the magnitude of such technology's impact on platform work, the transitory nature of platform work persuades workers to remain vigilant, continually seeking new niches and switching work categories when their current gigs become less lucrative. This precariousness conditions workers to view work categories as temporary, driving them to adapt swiftly and cultivate resilience in the face of constant disruption and livelihood risks. Ultimately, the fluid landscape of platform work compels Kenyan workers to adopt an opportunistic mindset, enabling them to worry less and navigate disruptions effectively, continually reshaping their career trajectories in response to evolving market demands.

5.7.6 Navigating AI Disruption Through Upskilling and Adaptability

Platform workers are acutely aware that the evolving nature of their tasks necessitates attentiveness to changing market dynamics and the need for reskilling. In my survey, over 92% of participants strongly agreed that acquiring AI-related skills is essential for maintaining job security in the face of potential job displacement due to AI. In the survey, participants were asked an open-ended question about how aspects of their work might be replaced by AI-based tools and the support or training required to navigate this transition. Responses primarily highlighted the need for a better understanding of AI integration into their workflows, emphasizing the development of skills as a priority in an evolving job market.

A semantic analysis of these responses revealed that approximately 60% of participants emphasized specialized technical skills, such as prompt engineering, programming, and data analytics, as crucial for preparing to work with AI. Roughly half of the responses focused on practical AI integration, indicating a desire for concrete guidance on incorporating AI into writing, design, and planning tasks. About 40% highlight the need for ongoing, technology-oriented learning and accessible resources, often referencing cost concerns and the importance of formal or informal programs to adapt effectively to AI-based tools. A smaller portion, around 20%, mentioned business or soft skills training, including marketing and creative thinking, as equally vital in staying relevant alongside AI. Finally, a subset of around 10% explicitly referenced ethical and societal

considerations, underscoring the importance of responsible AI usage and professional standards for freelancers. These proportions illustrate that while the majority prioritize direct technical training to utilize AI tools, there is also notable interest in broader skill development, continuous education, and ethical awareness in an AI-driven landscape.

Evidently, platform workers in Kenya demonstrate remarkable resilience in navigating evolving labour market dynamics, particularly in response to technological transformations. While concerns about AI-driven displacement are widespread, this does not necessarily indicate an adaptability crisis; instead, it reflects workers' awareness of the changes reshaping digital labour. Evidence from the survey (Table 5.8) shows that a substantial majority, 78.85%, express confidence in their ability to transition to new job opportunities if AI-based tools were to replace some aspects of their current work. In contrast, 17.31% remain uncertain, and only 3.85% anticipate significant challenges to adaptability.

Table 5.8

Perceived Adaptability of Skills to New Job Opportunities Amid AI Disruption

	Frequency	**Percentage**	**Cumulative**
Probably yes	23	44.23	44.23
Definitely yes	18	34.62	78.85
Might or might not	9	17.31	96.15
Definitely not |	2	3.85	100.00
Total	52	100.00	

This elevated level of confidence aligns with findings from digital labour research, which indicate that platform workers consistently engage in upskilling, diversifying their tasks, and strategically navigating their careers to maintain employability in an unpredictable market (Elbanna & Idowu, 2021b; Graham, Hjorth, et al., 2017; Melia, 2020). Unlike workers in traditional employment structures, freelancers operating in the digital gig economy, particularly in countries such as Kenya, are conditioned to embrace adaptability as a core survival strategy. They often juggle multiple tasks across different skill levels and industries to hedge against market volatility. As evident from the interviews, several workers shared this sentiment:

> “One of my strengths is adaptability. If AI starts taking over, I’d want to learn how to use it and find my place within that system. So, yes, it might take my job, but [it] will not take my ability to take on other jobs by using it” (Simon, freelance transcriptionist).

> “Already, like for me, [we're] already getting into machine learning, data science, [and] also getting into artificial intelligence itself, because it's already here. And for us to say, to stay sustainable and to also stay in business, we also have to adapt. So, for me, I force everyone around me to get started with artificial intelligence as early as now” (Jasper, freelance web developer and graphic designer).

> “Quite concerned, but maybe not worried, because I have also integrated AI into my workflow. [My] thinking is that freelancing is a one-person business, so we are actively including aspects of AI which we think would help the beneficiary” (Owen, freelance transcriptionist and trainer).

Concern and confidence coexist among experienced workers like Simon, Jasper and Owen. Their concern stems from a clear understanding of the potential disruptions introduced by AI, which necessitate continuous upskilling, diversification of services, and exploration of new opportunities emerging from technological change. At the same time, confidence arises from their adaptive orientation. Workers are structurally conditioned to embrace adaptability not just as a strategy but as a fundamental requirement for survival and advancement in an uncertain and rapidly evolving labour market.

The significance of this adaptability is evident in many workers, such as Owen, who has worked in the transcription services field since 2007. Reflecting on his early career, Owen described transcribing voicemails and converting them into written text for clients in the United States, a clear example of how hidden human labour has always underpinned seemingly automated digital processes for decades, and workers continue to cultivate transition pathways. Today, alongside his continued roles as a transcriptionist and virtual assistant, Owen's primary job is to provide skills training to refugees in Dadaab and Kakuma, equipping them with the diverse skills needed to succeed on freelance platforms. His optimism about adaptability and managing technological transition extends to his trainees, as he explains:

> “They [workers] have the fortitude to persevere and innovate. Some skills, especially language-related skills like Dadaab and Somali, are protected niches. With adequate support and mentorship, they

> [workers] can transition" (Owen, freelance transcriptionist and trainer).

Owen's cautiously optimistic response illustrates not only Kenyan platform workers' inherent capacity to adapt but also their perceived need to do so in order to sustain their livelihoods. This dual dynamic helps explain why many view AI-driven disruptions less as existential threats and more as manageable challenges within the evolving platform economy. These perspectives also reveal a critical distinction between the vulnerability of individual workers' livelihoods and the broader vulnerability associated with specific categories of platform work. While specific types of platform tasks and work may be more immediately vulnerable to AI-driven disruption, similar technological shocks are reshaping work globally by fragmenting traditional permanent roles into discrete, task-based units. Some of these tasks might be automated, while others could shift to different labour structures, including digital platforms, and Kenyan freelancers seem ready to adapt and strategically position themselves within this changing landscape.

5.8 Conclusions

This research emphasizes the adoption of a nuanced, context-sensitive approach to understanding and managing AI's impact on digital platform labour. By bridging theoretical insights with empirical realities, the study contributes to contemporary debates on technological transformation, worker vulnerability, and adaptive strategies within the rapidly evolving digital economy. It discusses the gaps between theoretical and empirical understanding of AI's impact on work. The task-based analytical framework employed in this research offers a robust methodological approach to identifying which occupational tasks are more susceptible to automation and which may effectively resist it. This framework presents a replicable model for future studies exploring the labour impacts of AI in diverse contexts while leveraging novel research technologies, such as using LLM models to support analyses.

The AI impact scores derived from the presented model indicate substantial occupational changes driven by AI, highlighting high automation risks in coding tasks, significant substitution effects in transcription services, and notable enhancements in virtual assistance roles. These findings underscore AI's dual role in simultaneously augmenting and potentially displacing human labour, reinforcing the complexity of its impact, which is heavily mediated by the intrinsic characteristics of specific tasks.

Empirical evidence from surveys and interviews with 52 Kenyan freelancers partly validates the theoretical predictions. However, these projections remain inherently probabilistic, assuming frictionless and extensive AI adoption, a scenario not fully realized in empirical contexts and an assumption that may not materialize uniformly. Still, the empirical section of the study highlights concrete shifts in freelancers' job tasks, increased reliance on AI tools for paid and unpaid tasks, and varied concerns about future job security and adaptability. This alignment particularly emphasizes the resilience and adaptive capacity of Kenyan platform workers, who consistently perceive technological disruptions as manageable challenges rather than existential threats. Such resilience is not mere optimism but is deeply rooted in structural realities of platform workers, including limited institutional safety nets and continuous exposure to job volatility, which have historically conditioned freelancers to develop proactive skills, be flexible, and engage in continuous learning.

Despite strong findings in this article, several limitations remain. Notably, disruption vulnerability formulas depend on multiplicative models and Gaussian thresholds, where hyperparameters are determined by subjective judgment. A similar replication limitation affects the novel research methods that utilize LLM-based scoring against task characteristics, such as task modularity and social complexity. Additionally, a sole focus on specific tasks may misjudge broader political-economic factors and underestimate systemic drivers of AI adoption. Future research should broaden its geographic scope, include longitudinal analyses to track the evolving impacts of AI, and consider client-side dynamics.

Chapter 6
Conclusions

This dissertation set out to examine whether, how, and for whom digital platform work supports sustainable livelihoods in the Global South. Through a Kenya-based mixed-methods study, it advances a worker-centred understanding of platform work, emphasizing the improvement of human capabilities as the ultimate goal of work, the significance of lived experiences, and long-term development trajectories. It examines objective and subjective measurement of platform work quality, utility and resilience against labour market shocks. It challenges binary framings of platform work as either precarious or empowering. Instead, it reveals a shifting continuum shaped by institutional conditions, unpaid labour burdens, and unequal access to meaningful exit options.

6.1 Sustainable Livelihoods Framing of Platform Work

This research reoriented the analysis of digital platform work by embedding it within a sustainable livelihoods perspective. Rather than treating work as an isolated economic transaction, the study foregrounded how platform work is lived, navigated, and reinterpreted by workers within the broader context of their life trajectories. This approach highlighted how workers in the Global South draw upon, adapt to, and are constrained by the quality of platform work in relation to their long-term livelihood strategies, including risk management, future planning, and social responsibilities.

The Sustainable Digital Platform Livelihoods Framework (IDPLF), presented in this reached adapted the classical Sustainable Livelihoods Framework to the realities of digitally mediated labour (Chambers & Conway, 1992; Duncombe, 2007). Unlike the traditional SLF, the IDPLF explicitly incorporate the layered institutional and relational power structures that characterize the global platform economy. It captures how local and transnational asymmetries jointly shape access to resources, the distribution of risk, and the capacity of platform workers to build sustainable livelihoods over time (Natarajan et al., 2022). This framework offered a contextually grounded lens for examining how workers perceive precarity, opportunity, and value within an increasingly digitized and unequal labour market.

6.2 Decent Work in the Platform Economy

The first research question in this research examined the extent to which digital-platform workers in the Global South achieve decent work, and how these outcomes vary across different worker groups. This dissertation advances a grounded and differentiated understanding of how decent work manifests in the platform economy, moving beyond binary judgments of platform work as either empowering or precarious. Drawing on the experiences of Kenyan workers, it demonstrates that decent work is not a fixed standard for platform workers, but a dynamic continuum shaped by a constellation of factors, including experience, profile capital, time autonomy, and unpaid labour intensity.

The findings reiterate the context of Kenyan platform workers, where work secured through digital platforms improves access to much-needed income-generating opportunities and enables some degree of time flexibility and skill acquisition, but falls short in delivering security, stability, and recognition of credentials, particularly for newer entrants. Notably, experienced workers with strong portfolios are better positioned to negotiate terms, refuse undesirable gigs, and minimize unpaid labour. In contrast, others remain exposed to relying on less dependable platforms, global competition, and unstable earnings.

This research has demonstrated that, among a broad base of platform workers, persistent and visible differences and inequalities in livelihood quality persist as a defining feature of the platform work landscape in Kenya and many other developing regions. However, these inequalities do not always have a linear relationship with changes in workers' well-being. Hence, when it comes to decent work evaluations, rather than conforming to conventional dichotomies of job quality, platform work reveals a complex interplay of constraints and opportunities that influence the diverse livelihood outcomes for different worker groups. These findings reconceptualize decent work on platforms as a dynamic continuum rather than a fixed threshold, one along which different workers move up and down in response to socially defined hierarchies, changes in experience, profile strength, unpaid labour intensity, and market fluctuations.

6.3 Meaningfulness of Work in the Platform Economy

The second research question examined the extent to which platform work in the Global South is perceived as meaningful, and what factors contribute to variations in these perceptions. This study finds that platform workers in Kenya often perceive their work as meaningful, not because of the

intrinsic content of the tasks themselves, but because of how those tasks contribute to sustaining livelihoods, alleviating material hardship, and enabling longer-term personal and professional goals.

This research showcases a development-oriented understanding of meaningful work by shifting the focus from task-based logic to livelihood-based assessments, integrating psychosocial fulfilment into the material dimensions of livelihood sustainability. In doing so, it positions meaningfulness as a defining attribute of high-quality work, enabling individuals to pursue and advance their development aspirations that align with their own values and prioritization of goals. Rather than deriving purpose from the atomized nature of platform gigs, Kenyan freelancers find meaning when their work alleviates material hardship, enables them to fulfill personal or family responsibilities, or expands future possibilities. In this context, meaningfulness is not located in the job itself, but in its role as a building block toward greater stability, autonomy, and dignity.

This perspective differs from research on meaningful work in the Global North, which views meaningfulness of work as a form of positive freedom, a quality inherent to tasks, socializing opportunities, identity, passion, or organizational values (Bailey et al., 2017; Blustein et al., 2023). In the Global South platform labour market, the meaningfulness benchmark is not always the pursuit of a permanent, specific type of job; instead, it is more concerned with negative freedoms, the work arrangement that alleviates economic pressure and replaces time poverty that causes excessive hardship in making ends meet and achieving basic development aspirations.

Furthermore, from the perspective of platform livelihood sustainability, livelihood meaningfulness is not just a present trait of work but also a future-oriented notion linked to the perceived potential for long-term fulfillment, growth, and stability. Kenyan platform workers often view their work as meaningful despite ongoing hardship and struggles. Their perspective remains future-oriented, where precarious platform work is often perceived to serve as a stepping stone toward larger, more meaningful goals, such as pursuing more appealing side ventures or preparing for more stable or rewarding types of employment in the future. In this way, within limited opportunity environments, meaningfulness could arise not only from the nature of the tasks but also from the perceived potential of work to expand capabilities in the future.

6.4 Platform Work and AI

The third research question explored how, and to what extent, generative AI–driven labour market disruption is reshaping the livelihood sustainability of platform workers in the Global South. The study extends beyond occupation-level generalizations by decomposing platform jobs into their constituent tasks and presenting a theoretically grounded model of AI impact that also accounts for the unpaid nature of some platform work tasks. This study highlights that the impact of AI on digital livelihoods should be understood not in terms of job titles but in terms of how specific tasks are restructured or devalued under new technological regimes.

The concept of enabling–obsolescence paradox in this research draw attention to how AI tools offer an immediate appeal by reducing unpaid burdens like drafting, scheduling, or proposal writing, yet in doing so, they gradually displace the relational and human-centred aspects of work, such as trust-building and client rapport, that are essential for long-term livelihood sustainability of the Global South platform workers. As platforms increasingly embed AI into both client and worker interfaces, they automate not just support tasks but also the mediating functions once performed by human freelancers, thereby positioning AI agents as substitutes for labour itself. Still, Kenyan freelancers display a high degree of confidence and adaptive resilience in the face of AI risks, shaped by their long-standing exposure to everchanging platform work, economic volatility, and weak institutional safety nets.

6.5 Bridging Decent Work and Livelihood Sustainability

This research reveals a critical disjuncture between formal indicators of decent work and workers' lived experiences, as well as their broader livelihood sustainability. While frameworks such as the Decent Work Substantive Elements (SEs) offer important benchmarks, their developmental value, in the form of improved well-being, is contingent on whether workers can translate these entitlements into meaningful life outcomes. The findings demonstrate that in the Kenyan context, the development value of decent work cannot be meaningfully assessed without sufficiently accounting for local socioeconomic conditions, institutional voids, and cultural dynamics that shape what workers are able to do and become through platform work.

A key insight is that work may satisfy formal decent work criteria, such as access to income or skill development without necessarily enhancing well-being if these gains remain unstable, unrecognized, or disconnected from long-term opportunity structures. Conversely, platform work that

falls short of conventional decent work standards may still hold comparatively higher developmental value in contexts of constrained alternatives, particularly when it expands capabilities or reduces time poverty. The analysis also underscores that not all dimensions of decent work carry equal weight for workers. In the Kenyan platform economy, temporal autonomy emerges as a disproportionately valued asset, functioning as a capability multiplier that enables workers to juggle care work, side ventures, and skill acquisition in a volatile and infrastructure-poor labour market. This highlights the need to rethink the hierarchy of decent work indicators and to foreground those aspects most closely aligned with workers' actual pathways to sustainable livelihood.

6.5.1 Unpaid Labour as a Structural Barrier to Livelihood Sustainability

This research establishes unpaid labour as one of the most pervasive and structurally embedded barriers to a sustainable livelihood in Kenya's platform economy. For most platform workers, unpaid labour functions as the hidden cost of economic participation, absorbing nearly 20 hours per week, and represents a privatized mechanism for shifting labour-market adjustment risks from platforms to individuals.

Time spent searching for gigs, drafting proposals, negotiating terms, building relationships, managing reputations, and revising work is not merely auxiliary work; it is integral to sustaining platform visibility and employability. This unpaid labour remains a defining feature of platform capitalism, reflecting the devaluation of locally earned credentials, the erosion of job security, and the platform-driven imperative to signal worth through continuous unpaid effort. Kenyan freelancers, in particular, internalize this burden, interpreting persistent insecurity as personal skill failure rather than systemic exclusion, thus obscuring the deeper structural frictions that sustain digital labour markets. While AI tools could reduce the burden of unpaid tasks to some extent, they also have the potential to further diminish the value of unpaid work by undermining the human interactions that sustain trust, visibility, and repeat work.

This research has also shown that unpaid labour is a valid quantitative indicator of overall platform work quality. Empirical evidence from this study shows that income adequacy and work autonomy are only attainable when the burden of unpaid work is contained, and many workers have to do significantly more unpaid work to reach comparable levels of income adequacy and other decent work standards. These findings reinforce the argument that the extent of unpaid work, on its own, serves as a reliable proxy for assessing the overall quality of platform work.

6.5.2 Platform Dependence as a Structural Variable of Livelihood Sustainability

Platform-mediated work, while expanding income-generating possibilities, often leads to a form of structural dependence that influences the long-term livelihood sustainability of platform workers. Workers become embedded in an economic logic that rewards immediate responsiveness to worker skills while offering limited pathways for professional mobility, skills recognition, or integration into stable employment systems.

Throughout the discussions, it is evident that platform-mediated online work, whether done intermittently or full-time, has significant long-term effects on workers' ability to create secure and dignified ways of earning a living. Platform work is increasingly viewed by Kenyan workers as a distinct profession, not merely a stopgap. Yet, this professionalization reinforces reliance on a shaky digital infrastructure that workers or regional regulatory institutions do not control and that can withdraw access without warning. The structural dependencies observed in platform-mediated work resonate with key arguments of broader dependence theory, particularly regarding how global economic structures constrain economically developing regions by embedding them in unequal relationships that limit their sustainable development (Cardoso & Faletto, 1979; Dos Santos, 1996).

Critically, the livelihood sustainability problem is the platform's control over workers' visibility, reputation, and access to opportunities. Workers cannot carry their work histories across platforms, nor are they guaranteed continued access to the profiles they have painstakingly developed. Accounts may be blocked, platforms may exit specific regions, or algorithms may suddenly deprioritize long-serving workers in search rankings, severing livelihoods with little recourse. These dependencies underscore the urgency of developing structurally viable exit routes, not only within local economies but also beyond the Global North platform intermediation (Howson et al., 2023; Wood, Graham, et al., 2018).

6.5.3 Livelihood Sustainability and Valued Exit Options

This research reiterates that valued exit options are crucial for livelihood sustainability, not because platform-acquired skills must seamlessly transfer into local jobs, but because workers require viable, structurally supported alternatives when platform work becomes inaccessible, inadequate, or unsustainable. The case of Kenya demonstrates that platform work and local labour markets, although

rhetorically intertwined, often evolve in parallel and disconnected ways. In Kenya, even as the domestic economy grows and the BPO sector expands, workers report a perceived lack of alignment between freelancing on digital platforms and employment in local tech-related industries.

Although this study involved a limited number of participants, there is no indication that workers perceive a strong or desirable match between the skills used in online freelancing and those required in the Kenyan BPO industry. Low wages and limited career mobility diminish the appeal of BPO jobs, even when there is skill overlap. This disconnect is further exacerbated by geographic barriers, as many promising tech hubs, including the highly celebrated Silicon Savannah, are located several hours away from where most workers reside and operate.

The Kenyan case illustrates that alignment between globally dispersed digital labour markets and domestic labour markets is neither automatic nor necessarily desirable. The challenge is not simply that the skills mismatch is a policy gap or an indicator of the underdeveloped nature of a local labour market. Rather, it signals deeper structural tensions between the fragmented, task-based logic of platform work, which demands specific skills, and the complex, often institutionally mediated skill demands of local economies. In many developing contexts, including Kenya, national development goals increasingly depend on higher-order technical skills and capabilities, such as professional judgment, leadership, and long-term project ownership, that platform work neither fosters nor rewards.

Crucially, the fragmentation between growing platform work and local employment pathways risks institutionalizing a narrow skills development agenda focused on meeting evolving foreign demand. This not only deepens dependency on external platforms but also sidelines domestic innovation and undermines inclusive development. If left unaddressed, it may reinforce a platform-driven neocolonial dynamic, where the Global South becomes a flexible labour reserve for remote digital tasks without parallel investment in domestic economic resilience (Howson et al., 2023).

Ultimately, the livelihood sustainability of platform workers cannot be reduced to the question of whether local economies in the Global South complement skills acquired through platform work. Instead, it must be understood in terms of whether workers can access alternative, contextually relevant pathways that are not structurally subordinated to the logic of global digital labour markets. Building meaningful exits for platform workers, therefore, requires recognizing that

platform work and local economic development may reflect fundamentally divergent trajectories, and that sustainability depends on creating bridges, not enforcing alignment.

6.5.4 Improving Platform Work Without Exit Options May Reinforce Exclusion

This research highlights a critical distinction between two types of platform reform agendas: equity-oriented reforms that address structural disparities, such as racialized ranking systems, geographic bias, disproportionate unpaid labour, and gendered patterns of opportunity access; and benefits-oriented reforms that improve material conditions, including pay rates, contractual protections, and algorithmic transparency. While both dimensions are essential, improving only the latter without redressing embedded inequities in a labour ecosystem where local exit options are weak can inadvertently reinforce livelihood exclusion.

While improving rights, pay, and conditions on digital labour platforms is a necessary goal, this research cautions against viewing such unilateral platform reform as sufficient for achieving a just livelihood sustainability (Agyeman, 2008). If digital platforms enhance pay and protections without dismantling the global hierarchies that disadvantage workers in the Global South, the competition for higher-quality jobs will intensify. In such scenarios, freelancers from contexts like Kenya and many other countries in the Global South may remain structurally marginalized, unable to fully access or retain improved opportunities due to the compounded effects of global oversupply and limited local alternatives. This bifurcated reform trajectory risks entrenching a stratified digital labour regime in which better conditions exist but are disproportionately captured by already-advantaged segments of the global workforce.

6.6 Policy Recommendations

The findings of this dissertation underscore the urgent need for context-sensitive policy responses that move beyond generalized prescriptions for digital labour. Platform work in the Global South, as exemplified by the Kenyan case, reveals both new opportunities and structural vulnerabilities that cannot be addressed solely through platform-level reforms. A sustainable and equitable platform economy requires interventions that respond to the complex interplay between technological disruption, unpaid labour burdens, institutional exclusion, and limited exit options. The following policy recommendations are grounded in empirical evidence and aim to support not only the

improvement of work conditions on digital platforms but also the broader development of livelihoods, social protections, and resilient economic alternatives for platform workers in Kenya.

6.6.1 Introduce Portable Micro-Benefit Packs for Freelancers

As of 2024, most platform freelancers in Kenya contribute to the country's tax revenue under its digital economy reforms; however, they largely remain excluded from core social protection mechanisms. The current Social Health Insurance Fund (SHIF) and National Social Security Fund (NSSF) frameworks categorize them as other informal workers, overlooking the instability of their work and their revenue contributions (Oyando et al., 2023).

To address this gap, the Social Health Insurance Act and the NSSF Act should be amended to support micro-benefit schemes that adjust contributions in proportion to the actual income of platform workers. Verified through digital earnings or tax filings, these small contributions would be recognized over time as part of full health and pension entitlements, enabling a more realistic and inclusive pathway for digital informal workers. In the short term, a tiered SHIF contribution discount for tax-compliant platform workers, offering reduced rates for a limited period, would encourage uptake and build trust in the system. These measures would align social protection with the ground realities of platform work, reward formalization efforts, and create a portable benefits system that allows freelancers to build long-term security.

6.6.2 Public-Telecom Compact for Affordable Connectivity in Kenya’s Platform Economy

Kenyan online freelancers consistently cite the high cost of internet data as a binding constraint on their earnings and their capacity to sustain digital work. Since July 2023, platform income has also been brought under new withholding and digital economy tax regimes (The Finance Act, 2023). The combination of rising statutory deductions and volatile, shrinking work wage rates has deepened frustration among workers and eroded their margins.

A balanced and equitable remedy is to ring-fence a portion of the platform income tax and Significant Economic Presence tax. For instance, 10 percent of this tax revenue could be allocated toward an internet tax credit. Under this scheme, telecom operators would be eligible to claim a refundable credit only when they provide regulator-approved, high-capacity data bundles to verified freelancers at a discounted rate. The credit would match the value of the discount, ensuring fiscal

neutrality. By redirecting part of the tax extracted from digital labour into its single most significant operational cost, this mechanism lowers freelancers' monthly expenses without introducing new subsidies or administrative complexity. It also directly enhances their capability to earn by improving access to a basic digital infrastructure input, thereby aligning tax policy with inclusive development goals.

6.6.3 Launch a Gender-Responsive Gig to SME Transition Grant

Women freelancers in my sample report lower access to work opportunities yet higher skill gains, signalling gendered conversion-factor barriers. While existing training programs, such as Ajira Digital, train large cohorts, they offer no seed funding for scaling up from solo gigs to microenterprises (ILO, 2024). The National Treasury, in partnership with the Women Enterprise Fund and the Africa Guarantee Fund, could issue competitive transition grants to female-led freelancer teams that formalize as small businesses. Grants could be disbursed in milestone-linked tranches conditioned on mentorship completion and matched in-kind by the applicants. Such an intervention could convert high but under-realized skill-development efforts and hidden platform work into concrete enterprise growth, addressing both the study's gender gap and the wider national priority of female economic empowerment. Such interventions could also enhance the social legitimacy of platform work and help reduce societal resistance stemming from the perception that it is not a credible or acceptable form of employment.

6.6.4 Bridge the BPO–Freelancing Divide through Joint Job Fairs and Skills Development Coordination

Kenya's BPO industry and online freelancing sector both rely on a shared foundation of technical and soft skills, yet they remain essentially detached in practice. The BPO Association of Kenya (BPOAK), which supports export-facing firms in formal outsourcing markets and national BPO policy frameworks, has opportunities to engage meaningfully with the online freelancing ecosystem.

The BPOAK and the National Policy on Business Process Outsourcing should collaborate with established freelancing associations, civil society groups, and digital skills programs[30]. Together, they should co-host recurring job fairs, mentoring events, and training sessions to integrate

[30] Such as Ajira Digital, Jitume, Ajira Youth Empowerment Centers, and Refugee Employment and Skills Initiative (RESI) in Dadaab and Kakuma

freelancers into broader local labour strategies and improve talent flow between the two sectors. Such collaboration would not only optimize the utilization of publicly funded digital skills programs but also foster smoother transitions between freelance, contract, and formal employment. It would signal a shift toward a coordinated digital employment ecosystem that recognizes freelancing and BPO not as siloed markets, but as complementary pillars of Kenya's digital services economy.

6.6.5 Support the Formation of SACCOs for Online Freelancers

Existing freelance civil society associations should support and amplify current worker-led initiatives by helping transform mentorship networks and informal meetups into more structured and sustained forms of collective engagement that meet the needs of workers. A natural extension of such initiatives is the formation of freelancer SACCOs (Savings and Credit Cooperative Organizations), which would understand the income structure of freelancers and enable members to pool savings, access affordable loans, and insure against financial shocks. It also serves a deeper social function by formalizing mutual support, providing a shared institutional identity, and building a platform for future collective action.

Establishing SACCOs for platform workers not only improves their economic security but also contributes to the broader legitimacy of platform work. It signals that digital freelancing is not just viable but deserving of institutional recognition, community investment, and long-term sustainability. Through these worker-led cooperatives, civil society can help lay the foundation for a more stable, respected, and socially embedded form of digital self-employment.

6.6.6 Mandate Verified Business Identity for Commercial Use of Digital Freelance Labour

The lack of client-side transparency in digital freelance markets exposes platform workers to significant risks, including non-payment, fraud, and abuse. While freelancers are subject to identity verification, public rating systems, and strict platform surveillance, clients, particularly businesses, can operate with minimal accountability, often using pseudonymous profiles. This asymmetry limits the enforceability of contracts, deters redress in disputes, and perpetuates structural opacity in the platform economy.

To address this imbalance, regulatory frameworks and platform governance standards should require that work commissioned for business purposes be processed under a verified legal business

name. This requirement would apply to clients acting on behalf of companies, whether domestic or foreign. It would compel platforms and intermediaries operating in Kenya to disclose verified business status at the point of job posting. Verification could be conducted through platform-facing mechanisms using existing business registries or payment records, without compromising public privacy.

Anchoring commercial transactions to identifiable entities enhances traceability, reduces the incidence of fraud, and fosters the institutional conditions for dispute resolution and enforcement of social protection. It also aligns with emerging global standards on responsible platform governance, sustainable supply chains, and ESG due diligence. Far from excluding small enterprises, such a rule can include flexibility for low-threshold onboarding and simplified registration for microbusinesses. By requiring businesses to stand behind the work they commission, this intervention enhances trust, fairness, and accountability in digital outsourcing markets, particularly for freelancers in the Global South who have limited legal recourses.

6.6.7 Regulate Platform Opt-Out Restrictions to Protect Freelancer Autonomy and Enable Fair Transitions to Off-Platform Work

As distributed workforce models become more mainstream, many platform workers, particularly those who have secured longer-term contracts, seek to continue client relationships outside of platforms. My research revealed that this shift is often driven by practical considerations, such as avoiding continuous high service fees, adapting to client-preferred workforce management tools, or minimizing administrative friction. However, most digital labour platforms maintain restrictive opt-out clauses, which either prohibit off-platform engagement entirely or impose very high, arbitrary opt-out fees and penalties, including account suspension or bans. These policies function as anti-competitive barriers, limiting worker autonomy and reinforcing platform dependency.

To address this, platform governance frameworks should regulate opt-out restrictions by establishing clear, enforceable limits on non-circumvention clauses. Freelancers and clients should have the right to move their contractual relationship off-platform upon mutual consent, without incurring punitive fees. Where exit fees exist, they should be transparent, proportionate, and capped in relation to the actual value added by the platform.

Such regulation would align with broader digital rights and competition principles, particularly in the context of platform-to-business (P2B) fairness laws such as the EU's Platform to Business Regulation or emerging frameworks under the EU Platform Work Directive. It would also reflect the changing structure of digital work, where off-platform expansion of distributed labour is a legitimate and increasingly common model. Enabling smooth, fair transitions from platform to direct client work respects the value workers create, reduces unnecessary friction in the digital economy, and ensures that platforms serve as facilitators, not gatekeepers and rent-seekers, of work.

6.6.8 Introduce Entitlement-Based Stability Mechanisms in Platform Governance Frameworks

Platform workers remain vulnerable to sudden deactivation, service withdrawal, or platform exits from regional markets, often with no warning or compensation. Despite years of consistent work and contributions, freelancers typically have no claim to the platforms they help sustain. This lack of stability undermines livelihoods and perpetuates the power imbalance between platforms and workers.

Multilateral institutions and regulatory coalitions, such as the EU Platform Work Directive, should promote the adoption of earned entitlements within platform governance frameworks. Under this model, a small percentage of platform fees (such as 10 percent fee collected from each completed project) would be set aside as a deferred entitlement, accessible only if a worker is deactivated, if the platform halts operations in a region, or if the worker voluntarily exits after a sustained period of engagement.

If a platform's decision to suspend services or exit a market disrupts access for a significant number of active workers, it should trigger enhanced accountability measures. Large-scale service changes magnify economic harm and signal systemic instability, warranting mandatory compensation or regulatory penalties to deter abrupt disengagement and ensure responsible wind-down processes. This structure fosters long-term participation, eliminates arbitrary termination, and establishes a shared responsibility model.

6.6.9 Mainstream ESG and Sustainability Standards to Recognize Digital Platform Labour as a Separate Reportable Value-Chain Category.

Current environmental, social, and governance ESG and sustainability regimes, including the Global Reporting Initiative (GRI), Sustainability Accounting Standards Board (SASB), and International Sustainability Standards Board (ISSB), and the EU's Corporate Sustainability Due Diligence Directive (CSDDD), require companies to account for labour impacts across their value chains, including contractors and non-employee workers (GRI, 2023; O'Brien, 2024). However, based on my review of the sustainability standards, none of these frameworks have any explicit tools to recognize platform-mediated freelance labour in the labour supply chain. This omission creates a visibility loophole that allows corporate clients to benefit from low-cost, outsourced digital work while remaining invisible in ESG disclosures and shielded from social accountability.

To close this gap, standard-setters such as GRI and International Financial Reporting Standards (IFRS) should issue clarification notes requiring companies to include spending on platform-based freelancers in workforce disclosures. Firms should report three key indicators: the average effective hourly pay (net of platform fees), the share of contracts with verified dispute-resolution channels, and the geographic distribution of platform workers. These metrics would help reduce anonymity and location-based exclusion while making working conditions auditable and material.

In parallel, ESG rating agencies should develop scoring tools that assess corporate platform labour practices based on compliance rates and grievance-resolution outcomes published by platforms or third parties. Incorporating these factors into social-pillar ratings would reward firms that scrutinize their digital labour supply chains and penalize those that rely on opacity. For investors, this metric would mitigate reputational and regulatory risk exposure.

6.7 Key Research Contributions

The four papers in this thesis advance literature on sustainable livelihoods, decent work, meaningful employment, and automation by examining these issues through the lens of Kenya's platform economy. In doing so, they deepen the broader understanding of digital gig work in development contexts and make several notable contributions.

The first paper in this thesis consolidated fragmented empirical research on digital gig work in the Global South. It introduced a new analytical framework for understanding how short-term platform gigs translate into long-term livelihood outcomes. By refining the Sustainable Livelihoods Framework to include digital capital, socio-cultural assets, and relational power, the study promoted a context-sensitive approach for examining how platform work influences livelihood trajectories in various development settings. This contribution not only bridges gaps between community informatics and digital labour studies but also provides a transdisciplinary perspective that highlights local conditions, structural inequalities, and worker agency in shaping platform work experiences.

A key contribution of the second paper is its thorough empirical analysis of platform work quality in Kenya's platform economy, enhancing understanding of how decent work and well-being are connected in Kenya. By introducing Decent Work Substantive Element (SE) scales and a structured evaluation methodology, it provides a replicable quantitative approach for examining group differences in experiences of decent work. The paper also advances labour research by highlighting the gaps between the ideals of decent work and the lived realities of platform work, critically examining what these gaps reveal about the developmental value of a platform work ecosystem.

The third paper contributes to the discourse on meaningful work by offering a developmental perspective on meaning-making within the platform economy. It introduces a new perspective by empirically differentiating between work meaningfulness and livelihood meaningfulness, and by examining how meaning-making processes are shaped in contexts marked by limited social safety nets and restricted access to quality employment opportunities. The paper also broadens the existing conversation on how social capital affects workers' experiences in platform-mediated labour markets.

The thesis breaks new ground in assessing how generative artificial intelligence (AI) is transforming platform-based work. The fourth paper introduces an innovative task-based model for measuring AI-driven disruption and worker vulnerability in online freelancing, filling a significant gap in automation research. This methodological contribution expands the task-based automation literature by providing empirical tools to identify which aspects of platform work are most vulnerable to AI and how the presence of unpaid work influences overall outcomes. By validating the model with field data, the paper offers early evidence of how workers experience and respond to AI-driven

changes. It contributes to digital labour economics by showing that AI's impact varies across tasks rather than being uniform, and by emphasizing workers' resilience and adaptability.

Finally, this thesis advances policy discussions on digital labour by translating its empirical and conceptual insights into a clear agenda for fair and sustainable platform work in Kenya. These recommendations extend beyond generic calls for improved platform work, providing specific, evidence-based guidance that development agencies, social institutions, platforms, and firms can operationalize to enhance work quality, boost worker resilience, and align platform growth with sustainable development agendas.

6.8 Future Research Suggestions

Building on the findings and conceptual contributions of this thesis, several directions for future research emerge. The following suggestions emphasize important areas where further study is needed to enhance understanding of platform work's effects on livelihoods, labour conditions, and technological disruption in the Global South.

6.8.1 Quantifying Group Differences in Decent Work Experiences

While this research identified statistically significant group differences in decent work experiences, the quantitative analyses were exploratory, with a small number of participants. Future research should build on this by applying robust statistical approaches to a larger sample to better measure variations in decent work experiences across groups. Such studies could move beyond arbitrary group distinctions used in past research by employing empirical techniques to identify measurable categories. This would improve the ability to develop concrete policies and interventions that address disparities in decent work outcomes.

6.8.2 Examining Interrelations Among Decent Work Substantive Elements (SEs)

This study highlighted that Decent Work SEs include a broad spectrum of worker aspirations but lack a consistent theoretical basis. Future research could investigate how different SEs interact, particularly how achieving one SE may impact others. This approach would move beyond a deficit-focused analysis of decent work to enhance the theoretical significance of Decent Work SEs. Identifying which SEs have the most significant influence on overall well-being could provide valuable insights for both policy and practice.

6.8.3 Investigating Gendered Dynamics in Platform Work

Preliminary quantitative findings in this study reveal gender disparities in access to employment opportunities and skills development outcomes within platform work in Kenya. Future research should investigate how these gendered patterns vary across different regional, occupational, and demographic contexts. Particularly, an in-depth understanding of the factors that shape gender differences in how platform work impacts workers' transferable and employability skill development outcomes could help in creating more inclusive policies and support systems tailored to the needs of marginalized groups.

6.8.4 Exploring Systemic Dependence in Platform Work

This study confirmed that systemic dependence on the Global platform often isolates workers from local labour markets. Future research could extend this analysis by theorizing platform dependence as a distinct mode of labour intermediation in the global economy, assessing whether classical dependency frameworks adequately capture the dynamics of platform work or whether new conceptual tools are needed. Comparative studies, particularly across regions and platform types, would be valuable, as highlighted in the first review paper of this thesis, which notes that stronger local platform ecosystems (e.g., in China and the Philippines) produce noticeably different decent work outcomes for workers. Such research could illuminate how worker agency manifests under varying structural conditions, and whether it reflects adaptive resistance, negotiated dependence, or individualized coping within constrained systems. Such comparative work would also help test and refine the thesis's proposed framework, i.e., the Sustainable Digital Platform Livelihoods Framework, in diverse settings and determine whether unique conceptual tools are needed to understand platform work in different development contexts.

6.8.5 Addressing the Evidence Gap Between Past and Present Platform Work Studies

Given the inherently evolving nature of digital work, another clear avenue for research is longitudinal and broader-scope studies on the evolving quality of platform work. The current body of platform work research often mixes outdated insights with newer empirical findings, obscuring the rapidly evolving realities of platform-mediated labour. Future research must explicitly differentiate between historical analyses and contemporary conditions, particularly given the rapid changes driven by AI.

Longitudinal studies tracking the transformation of platform work over time are urgently needed to understand these shifts and to inform timely, context-sensitive policy responses.

6.8.6 Applying a Justice-Oriented Lens to Platform Work Sustainability

Findings from this research caution against viewing linear improvements in platform work quality (e.g., better material benefits) as universally positive, given the risk of entrenching inequalities among already disadvantaged workers. Future research should adopt a justice-oriented perspective to explore how platform labour sustainability can bridge the gap between decent work and critical labour theories, ensuring that reform agendas do not exacerbate existing disparities.

6.8.7 Differentiating the Meaningfulness of Work and the Meaningfulness of Livelihood

The thesis's insights into meaningful work and social context also open up several research possibilities. This research introduced the conceptual distinction between the meaningfulness of work and the meaningfulness of livelihood, an important differentiation in contexts with weak social safety nets. Further empirical studies could examine how income thresholds and the absence of social protections influence workers' sense of meaning from work, as well as the relative impact of this meaning-making process on overall well-being. Another recommendation is to investigate the social and relational dimensions of platform work more deeply. Specifically, future research should broaden the concept of work-related social capital to include not only peer networks but also relationships with clients and other stakeholders.

6.8.8 Expanding the Task-Based AI Impact Assessment Model

The task-based AI impact model developed in this research provides a theoretical framework for evaluating AI's role in transforming work ecosystems, particularly in task-based occupations that defy traditional job categorizations. Future studies could expand this model to other occupational categories, providing empirical evidence on how the enabling and hindering effects of AI balance out in different contexts. This line of inquiry is critical for informing policy, labour advocacy, and development interventions aimed at mitigating adverse impacts and leveraging technological change for inclusive development.

6.8.9 Advancing the 'Enabling-Resilience Paradox' in Platform Work

The research introduced the Enabling-Resilience Paradox, which highlights the tension between diminishing human relationships in work processes and their critical role in securing work, particularly in the Global South. Future theoretical and empirical work could explore how the erosion of human connections, driven by platform-mediated work, disproportionately affects communities where relational labour is pivotal for access and resilience, yet remains constrained by systemic biases.

6.8.10 Examining the Uptake and Impact of Platform Work Policy Recommendations

Lastly, a crucial direction for future research is to critically examine the effectiveness and uptake of policy recommendations and practice-oriented proposals emerging from the growing body of academic work on platform labour. While scholarship from diverse disciplines has produced extensive analyses of platform work and offered numerous recommendations for improving labour conditions, regulatory frameworks, and development interventions, little is known about how these recommendations influence actual policy, platform structure, client behaviour, platform governance, or worker outcomes. Research that assesses the translation of scholarly insights into practice, including their adoption by policymakers, platforms, and development actors, would provide valuable evidence on the practical impact of academic work in this field and highlight to what extent all these research-driven recommendations are making a ground-level impact (or identifying why they might not be).

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Appendix A

Survey Questionnaire

Decent Work, Meaningful Work, and AI Impact on Work

Start of Block: Decent Work Opportunities

DWO1 How frequently do you find platform work opportunities that match your skills and work preferences?

- Never (4)
- Rarely (5)
- Often (6)
- Most of the time (7)
- Always (8)

DW02 On a scale of 1 to 5, how satisfied are you with the opportunities for growth and advancement in and through your platform work?

- Not at all satisfied (1)
- Slightly satisfied (2)
- Moderately satisfied (3)
- Very satisfied (4)
- Extremely satisfied (5)

DW03 How consistent is your income from digital platform work?

- Very unpredictable monthly income (6)
- Monthly income often either less or more (7)
- Sometimes monthly income is less or more (8)
- Monthly income rarely changes (9)
- Fixed monthly income (10)

DW04 Roughly what proportion of your total income comes from platform work?

0 10 20 30 40 50 60 70 80 90 100

% of income through online freelancing on digital platforms ()	

DW05 What challenges did you face when seeking gig work through digital platforms in the last six months? (Select all that apply)

- Limited access to suitable jobs (9)
- High competition (10)
- Inadequate compensation (11)
- Job insecurity (12)
- Lack of benefits (13)
- Difficult clients (14)
- Other (15)

DW06 To what extent would you face financial hardship without being able to access digital platform work?

- Very significant hardship (5)
- Significant hardship (6)
- Moderate hardship (7)
- Slight hardship (8)
- No hardship (9)

DW07 How often do you interact with fellow gig workers (online or in-person) to exchange information and share experiences?

Never (15)
Sometimes (16)
Most of the time (17)
Almost Always (18)
Always (19)

DW08 In the past 6 months, how was your experience with the work environment while working through platforms?

	Yes, frequently (4)	Sometimes (5)	Never (14)	unsure (9)	I am not comfortable answering this question (10)
Faced any discrimination or harassment from clients (6)					
Faced any discrimination or harassment from other platform workers (7)					
Received any support or guidance from colleagues or mentors (8)					

DW09 Think of how decision makers value your opinions in matters that affect your work environment

	Always (1)	Frequently but not always (2)	Sometimes (3)	Never (5)	Unsure (4)
Do you feel involved in decision-making processes related to any platform changes? (1)					
Do you feel your opinions and concerns are considered in local or national policy debates and regulations related to the freelancing and platform work economy? (2)					
Do you provide, or you are asked to provide input on the policies, terms, and conditions of the digital platforms you work with? (3)					
Do you believe your platform administration considers your concerns when making decisions? (4)					
Do you believe your employers/clients on the platform consider your concerns when making decisions? (5)					

DW10 Think about the extent to which your work environment allows you to voice your concerns to make a better living through your platform work

	Always (1)	Frequently but not always (2)	Sometimes (3)	Never (4)	Unsure (5)
Do you feel comfortable expressing your concerns related to your platform work? (1)					
Do you have suitable opportunities to negotiate better working conditions or contracts for your gig work? (2)					
Are you comfortable voicing your concerns and defending your rights as a freelance platform worker? (3)					

DW11 How often do you negotiate contracts for better working conditions for your gig work?

- Never (9)
- Sometimes (10)
- About half the time (11)
- Most of the time (12)
- Always (13)

DW12 Consider how some workers benefit from the support provided by campaign groups, collaboration with other workers, or organizations such as labour unions that are dedicated to improving labour rights

	Yes (1)	No (2)	Unsure (3)	Does not apply to me (4)	Prefer not to answer (6)
Do you have opportunities for you to participate in any campaigns or actions to improve your platform work conditions? (1)					
Are you aware of any organizations or associations that represent the interests of gig workers like yourself? (2)					
Are you a member of any such organization or association? (3)					
Do you feel such organizations and associations are helpful in representing your interests and improving your work conditions? (5)					
Do you collaborate with other gig workers or organizations for mutual support and advocacy? (6)					

DW13 Please reflect on your personal experiences and knowledge of legal rights, the effectiveness of government labour laws, and the policies of your work platforms

	Low (3)	Medium (4)	High (5)	Unsure (6)	Prefer not to answer (7)
To what extent do you feel protected by government labor laws and regulations as a platform worker? (8)					
How would you rate your understanding of labor laws and legal rights for gig workers like yourself? (9)					
How satisfied are you with the current legal and regulatory environment for platform workers? (such as local government policies) (10)					
To what extent do you feel protected by the policies of platforms you use to find work? (11)					
In the past 6 months, how frequently have you faced any legal disputes or challenges related to your platform work, such as wage theft or misclassification? (12)					

End of Block: Decent Work Opportunities

Start of Block: MW

MW1 Think of how working as a freelancer through digital platforms has impacted your health in the past 6 months

	Yes (1)	No (2)	Unsure / Prefer Not to Answer (3)
Have you faced any health risks or challenges related to your platform work? (1)			
Have you faced any emotional challenges related to your platform work? (2)			

MW2 Think of how access to health care requires either money or healthcare plan that some traditional jobs (but not all) provide. To what extent has working on digital platforms changed your access to adequate healthcare services?

Significantly decreased access (9)
Decreased access (10)
No change (11)
Increased access (12)
Significantly increased access (13)

MW3 Do you feel your access to health care would be better, worse, or the same if you were to work in a traditional/non-platform-based employment that matches your skills?

Much worse (14)
Somewhat worse (15)
About the same (16)
Somewhat better (17)
Much better (18)

MW4 Think of how working as a freelancer and doing gig work through platforms has impacted your well-being in the last six months

	very low (1)	low (2)	medium (3)	high (4)	very high (5)
This work provided you with a sense of purpose or fulfillment? (1)					
How much stress do you experience as a result of your platform work? (2)					
How much control do you have over your workload and schedule? (3)					
Faced cyberbullying or online harassment due to your work-related online activities (5)					
How satisfied are you with your platform work? (4)					

MW5 On a scale of 1 to 5, how does your platform work impact your overall satisfaction with life?

- Negative impact (4)
- Slightly negative impact (5)
- Neutral (6)
- Slightly positive impact (7)
- Positive impact (8)

MW6 On a scale of 1 to 5, how has your platform work impacted your social relationships?

- Negative impact (9)
- Slightly negative impact (10)
- Neutral (11)
- Slightly positive impact (12)
- Positive impact (13)

End of Block: MW

Start of Block: Demographic and Platform Work Experience

DWE1 Which age range do you fall into?

- 18-24 (4)
- 25-34 (5)
- 35-44 (6)
- 45-54 (7)
- 55 and above (8)

DWE2 What is your gender identity?

- Male (6)
- Female (7)
- Another option not specified (8)
- Prefer not to say (9)

DWE3 Besides working on digital platforms, which of the following categories best describes your current circumstances?

- Student (4)
- Unpaid houseworker (5)
- Unemployed searching for work (outside digital platform labour) (6)
- Employed (outside digital platform labour) (7)
- Independent worker with employees (8)
- Unpaid family worker (9)

DWE4 What is your highest level of education completed?

- High school or lower (4)
- Some college/associate degree (5)
- Bachelor's degree (6)
- Master's degree or higher (7)
- Prefer not to say (8)

DWE5 Please provide the name of your city/town

_____

DWE6 Do you consider your city to be an urban or rural area?

- large urban city / metropolitan area (1)
- small city / Town (2)
- Rural area / village (3)

DWE7 How long have you been working in the freelance gig economy?

- Less than 1 year (4)
- 1-3 years (5)
- 3-5 years (6)
- More than 5 years (7)

DWE8 Think of how much paid work and unpaid work (applying for jobs, updating profile, learning a new skill to complete a task etc.) you do to find and complete freelancing jobs In the last 6 months. Can you tell me roughly how many hours did you work for the digital platforms each week?

0 10 20 30 40 50 60 70 80 90 100

paid work - average weekly hours ()	
average Unpaid weekly hours (work such as applying for jobs, communication, updating profile and other paperwork, except skills development) ()	
average unpaid weekly hours (Skills development, learning a new skill, researching how to do a task) ()	

DWE9 What types of gig work have you engaged in through digital platforms in the last six months? move the slider to select approximate percentage

0 10 20 30 40 50 60 70 80 90 100

Freelance writing ()	
Graphic design ()	
Web development ()	
Customer service ()	
Online tutoring/teaching ()	
Virtual assistance ()	
Microtasks (data entry, picture tagging, AI training, surveys etc.) ()	
Other ()	

DWE10 Which digital platforms do you normally use to acquire work from clients? Please list all

_____

_____

_____

_____

_____

DWE11 How much of your freelancing work is given to you by other platform workers and freelancers (not the end clients)?

All of it (4)
A large portion (5)
About half (6)
A small portion (7)
None of it (8)

DWE12 Do you outsource a part of your work to other freelancers and platform workers?

All of it (4)
A large portion (5)
About half (6)
A small portion (7)
None of it (8)

DWE13 How often do you have reliable, high-speed internet access at home for your work tasks?

Never (4)
Rarely (5)
Sometimes (6)
Often (7)
Always (8)

DWE14 In the last six months, how often were you unable to access important online resources or services for your work due to lack of equipment or poor connectivity?

Never (4)
Rarely (5)
Sometimes (6)
Often (7)
Always (8)

DWE15 How often do you engage with digital communities or networks (such as social media groups or in-person groups of professionals) to share knowledge or collaborate on new work projects?

Never (4)

Rarely (5)

Sometimes (6)

Often (7)

Always (8)

End of Block: Demographic and Platform Work Experience

Start of Block: 5. Skills Development Impact of Digital Platform Work

SKILL1 Think of how effectively your education and training align with the work you do through digital platforms

	Not at all (1)	A little (2)	Moderately (3)	Very much (4)	Significantly (5)
Do you feel that your education and training have prepared you adequately for the gig work you are doing? (1)					
Do you feel your current work allows you to use and improve your employment-related skills and abilities? (2)					
you accessed any training or educational opportunities because of your platform work in the past six months? (3)					
how much has your platform work contributed to your current education and overall skill development? (4)					
Do you feel the new skills you learn for completing platform-related work are helpful for your overall career opportunities beyond platform work? (5)					

SKILL2 Please list up to three top skills or areas of knowledge you have gained through or because of your platform work

_____

_____

_____

_____

_____

End of Block: 5. Skills Development Impact of Digital Platform Work

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Start of Block: Work Experience and Local Labour Market Integration

WELB1 Reflect on the impact of your experience with digital platform work on your future career prospects

	Not at all (1)	A little (2)	A moderate amount (3)	Very much (4)	Significantly (5)
how much do you think your platform work experience will contribute to your long-term career development and prospects, in terms of gaining new opportunities? (1)					
how confident are you in your ability to find work through digital platforms in the next six months? (2)					
How satisfied are you with the financial benefits (e.g., income, bonuses) you receive from your platform work? (3)					

Q49 5.3On average, what percentage of your platform work income are you able to save each month? (think of last six months)

	0 10 20 30 40 50 60 70 80 90 100
% savings from platform income ()	

Q50 Do you feel the local employers in Kenya value the experience you get from working on digital platforms?

- Employers value this experience more than local employment (4)
- Employers value this experience as much as local employment (5)
- Employers somewhat value this experience, but less than local employment (6)
- Employers rarely or don't value this experience (7)
- Employers see this experience negatively compared to local employment (8)

Q51 To what extent does the availability or unavailability of relevant and good paying local jobs influence your decision to continue working through digital platforms?

- The unavailability of good local jobs strongly drives me towards or away from working on digital platforms (7)
- The presence of suitable local employment has a moderate impact on my decision to work on digital platforms (8)
- The availability or lack of local jobs does not influence my decision to work through digital platforms (9)
- Unsure (10)

Q52 If you were not working on digital platforms, what other employment opportunities would be available to you?

- No other opportunities (8)
- Few opportunities, but not in my field (9)
- Some opportunities in my field (10)
- Many opportunities in my field (11)
- Unsure (12)

End of Block: Work Experience and Local Labour Market Integration

Start of Block: Labour Market Resilience - Generative AI Impact

Q53 On a scale of 1 (not concerned) to 5 (extremely concerned), how concerned are you about the possibility of AI-based tools or technologies (such as Chat GPT, Google Bard) replacing your remote gig work in the future?

- Not concerned (4)
- Slightly concerned (5)
- Moderately concerned (6)
- Very concerned (7)
- Extremely concerned (8)

Q54 Do you think your current skill set would allow you to adapt to new job opportunities if AI-based tools or technologies were to replace some or all aspects of your remote gig work?

- Definitely not (9)
- Probably not (10)
- Might or might not (11)
- Probably yes (12)
- Definitely yes (13)

Q55 Thinking of the last question about the impact of AI of the type of work you do, what kind of support or training do you believe would help you prepare for such a transition?

_____

_____

_____

_____

_____

Q56 Do you currently use any AI-based tools or technologies to support your digital platform work?

- Never (9)
- Sometimes (10)
- About half the time (11)
- Most of the time (12)
- Always (13)

Q57 On a scale of 1 (not helpful) to 5 (extremely helpful), how helpful do you find AI-based tools or technologies in improving the efficiency and quality of your remote gig work?

- Not at all helpful (9)
- Slightly helpful (10)
- Moderately helpful (11)
- Very helpful (12)
- Extremely helpful (13)

Q58 What tasks or aspects of your remote gig work do you think could be improved or made more efficient with the use of AI-based tools or technologies?

_____

_____

_____

_____

_____

Q59 Do you believe that acquiring new skills related to AI technologies can help you maintain job security in the face of potential job losses due to AI?

- Definitely not (19)
- Probably not (20)
- Might or might not (21)
- Probably yes (22)
- Definitely yes (23)

End of Block: Labour Market Resilience - Generative AI Impact

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Start of Block: Interview

InterviewP Would you like to be contacted for the one-on-one Interview portion of this study?

- Yes (1)
- No (2)
- Maybe (3)

End of Block: Interview

END OF APPENDIX A

Appendix B

Decent Work in the Platform Labour Economy Extended Results

Margin plots and regression output tables for both standard and bootstrap regression models

Descriptive Statistics

The sample consisted of 52 digital platform workers, primarily from Nairobi, with a gender distribution of 55.8% male and 44.2% female. Most participants fell within the 25–34 age group (51.9%), followed by those aged 35 and above (32.7%), and a smaller proportion aged 18–24 (15.4%). In terms of educational attainment, the selected sample was highly educated, with 80.8% holding a bachelor's degree or higher, while 19.2% had some college education or less.

Table 32: Research Sample Demographics (N = 52)

Demographic Characteristics	Frequency	Percent
Gender		
Female	23	44.23%
Male	29	55.77%
Age Group		
18–24	8	15.38%
25–34	27	51.92%
35+	17	32.69%
Education Level		
Some college or lower	10	19.23%
Bachelor's or higher	42	80.77%
Platform Work Experience		
1-3 years	10	19.23%
3-5 years	19	36.54%
More than 5 years	23	44.23%

As reflected in Table 1, all participants selected for this study were experienced platform workers with a minimum of one year of engagement in the platform economy. This is an important consideration when interpreting these results, as the study did not focus on potential platform workers

and novice workers with very little experience in the platform labour economy. A substantial proportion (44.23%) had more than five years of experience, while 46.54% had worked for between three and five years. A smaller segment (19.23%) reported having one to three years of experience in platform-based gig work.

Table 33: Work Hours, Earnings, and Skill Development

Work Hours, Earnings, and Skill Development	Mean	SD	P50	P75
Income from Gig Work	69.35	25.3	75	90
Paid Work Hours/Week	38.79	18.47	39	52
Unpaid Work Hours/Week	19.72	21.78	10	27.5
Skill Upgrading Hours/Week	16.43	17.31	10	20

On average, participants earned approximately 69% of their total income through platform work, though this varied substantially (SD = 25.30). Participants reported working an average of 38.8 paid hours per week, alongside 19.7 hours of unpaid labour, such as job search, communication, proposal writing, and a range of labour activities that go unpaid in the platform work economy. Additionally, participants invested an average of 16.4 hours weekly in skill development activities, highlighting the continuous and self-directed nature of upskilling in digital freelancing. The wide spread between median and 75th percentile values highlights variability in how workers allocate time between paid and unpaid tasks, underscoring differentiated strategies for sustaining platform-based livelihoods.

Labour Input Differences Across Demographic Groups

The bivariate analyses below identify patterns in how workers with different demographic profiles distribute their labour, offering insight into the extent of economic dependence on platform income, the burden of uncompensated tasks, and variation in opportunities for skills investment across groups. Overall, the results show that labour input across gender, age, and education groups is largely uniform, with no statistically significant differences in income reliance, paid or unpaid hours, or time spent on skill development. The only significant variation emerged around paid work hours, with mid-experience freelancers working more than others. Overall, this relative uniformity in labour input suggests that any subsequent differences in the experience of decent work are unlikely to stem from demographic variation in work intensity.

Gender Variation in Platform Work and Earnings

There is minimal variation across the sample when it comes to gender-based patterns in income dependence and time use. In this sample group, women and men derived nearly identical proportions of their income from platform work, with averages of 69.26% (SD = 24.79) and 69.41% (SD = 26.13), respectively, t(50) = -0.02, p = .983, d = -0.01. Weekly paid work hours were also similar across genders, though slightly higher for women (M = 40.18, SD = 15.24) than men (M = 37.69, SD = 20.87), t(50) = 0.48, p = .634, d = 0.13. In contrast, women reported fewer unpaid work hours (M = 15.62, SD = 17.09) than men (M = 22.97, SD = 24.69), a difference that, while not statistically significant, may point to modest differences in non-remunerated platform-related tasks (t(50) = -1.21, p = .231, d = -0.34). Time spent on skill development was nearly indistinguishable across genders, with women averaging 16.33 hours (SD = 12.16) and men 16.52 hours (SD = 20.72), t(50) = -0.04, p = .969, d = -0.01. Overall, the results in Figure 1 suggest that gender does not play a significant role in shaping how platform workers in this sample allocate their weekly labour time or derive income from digital work, although some slight differences in unpaid labour may warrant closer examination.

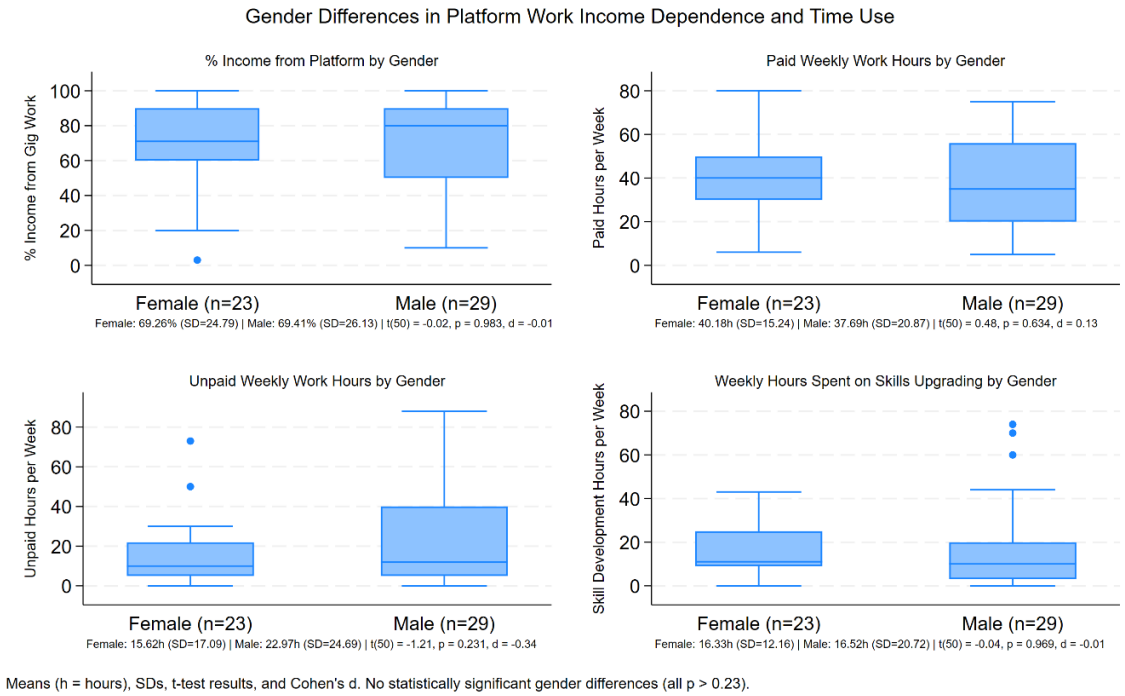
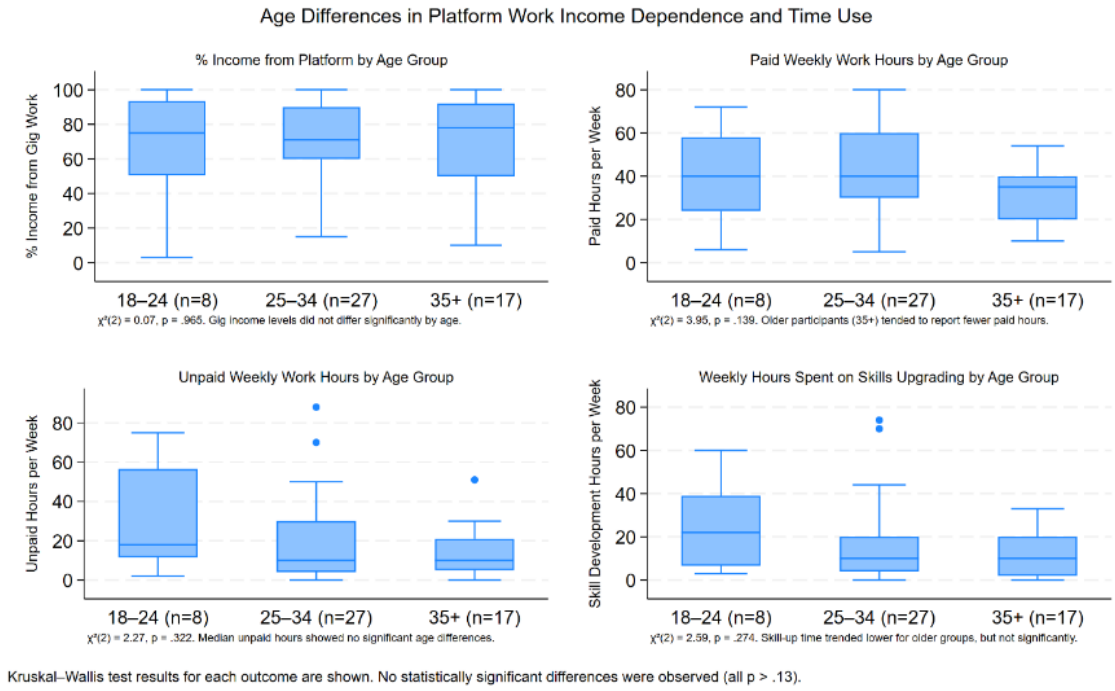


Figure 41: Gender Differences in Income Reliance and Time Use Among Platform Workers

Age-Based Differences in Platform Work Engagement

Similarly, patterns of time use and income dependence across age groups revealed subtle differences, though none reached statistical significance. As shown in Figure 2, younger freelancers aged 18–24 and those aged 25–34 reported similar levels of platform income reliance, averaging around 68–70%



of total income, while those aged 35 and older showed only a marginal decline ($\chi^2(2) = 0.07$, $p = .965$

Figure 42: Age-group differences in income reliance and weekly hours

). Weekly paid work hours showed more noticeable variation. Participants aged 25–34 reported the highest average, while those aged 35 and older reported markedly fewer hours ($\chi^2(2) = 3.95$, $p = .139$), suggesting a possible shift in platform engagement among older workers. A similar age gradient appeared in unpaid work hours, with younger participants (18–24) ranking highest and those in the 35+ group reporting the least ($\chi^2(2) = 2.27$, $p = .322$).

Time spent on skill development followed the same trajectory, with younger workers investing more time in upgrading their skills compared to older participants ($\chi^2(2) = 2.59$, $p = .274$). While none of these age-based differences were statistically significant, the directional patterns hint that there could be generational differences in work intensity and upskilling behaviour within the platform economy.

Experience and Labour Intensity in Platform Work

Figure 3 shows that differences in time use and income reliance across experience levels in the platform economy revealed one statistically significant pattern, alongside some subtle trends. Notably, weekly paid work hours varied meaningfully by experience, with those reporting 3–5 years in gig work logging significantly more hours than newer or more experienced freelancers ($\chi^2(2) = 9.87$, $p = .007$).

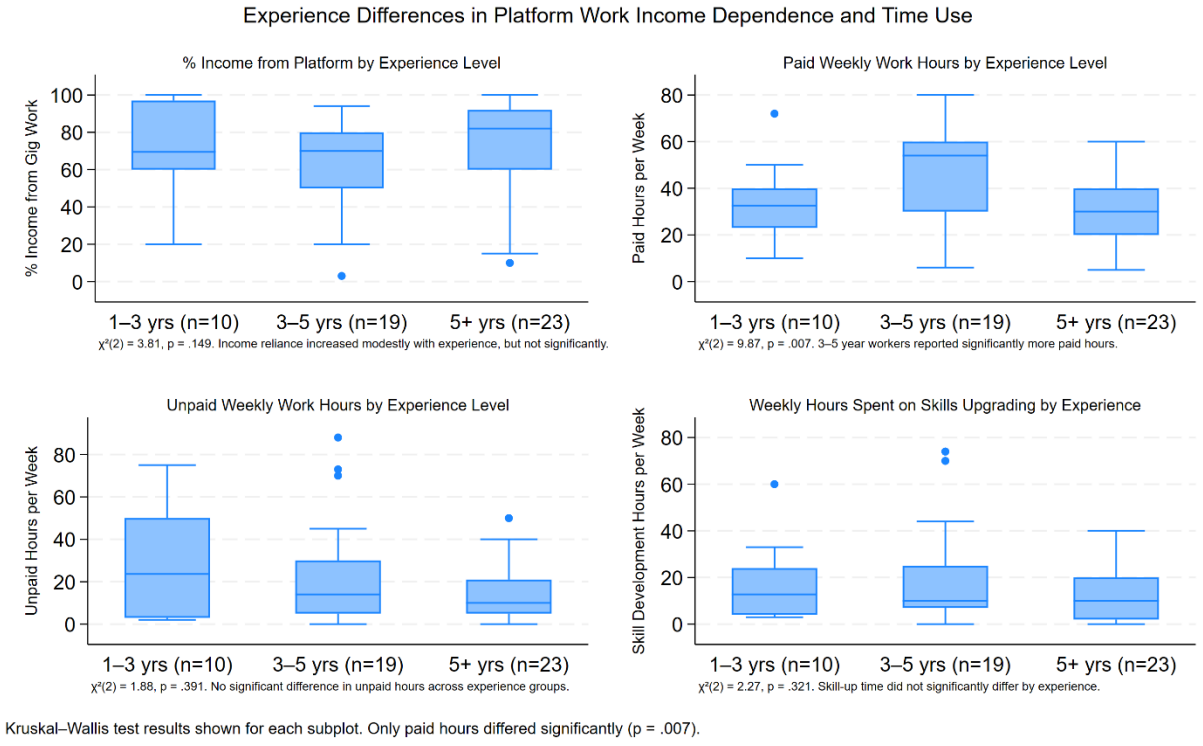


Figure 43: Platform-experience differences in paid hours

While not statistically significant, reliance on platform income tended to increase with experience. Workers with over five years of experience had the highest income share from platform gigs, followed by those with 3–5 years of experience, and lastly those with 1–3 years of experience ($\chi^2(2) = 3.81$, $p = .149$). Differences in unpaid work hours ($\chi^2(2) = 1.88$, $p = .391$) and time spent on skill development ($\chi^2(2) = 2.27$, $p = .321$) were negligible across groups. These findings suggest that accumulated experience in the platform economy may be associated with greater paid labour intensity, though other aspects of time use remain relatively stable.

Education-Based Differences in Platform Work Engagement

Bivariate analyses comparing platform workers by education level revealed no statistically significant differences in income reliance or time use, though some moderate patterns were observed. As shown in Figure 4, those with some college or less reported a slightly higher share of income from platform work (M = 75.20%, SD = 27.25) than those with a bachelor's degree or higher (M = 67.95%, SD = 24.96), $t(50) = 0.81$, $p = .421$, $d = 0.29$. Paid work hours were nearly equivalent across groups, $t(50) = -0.34$, $p = .737$.

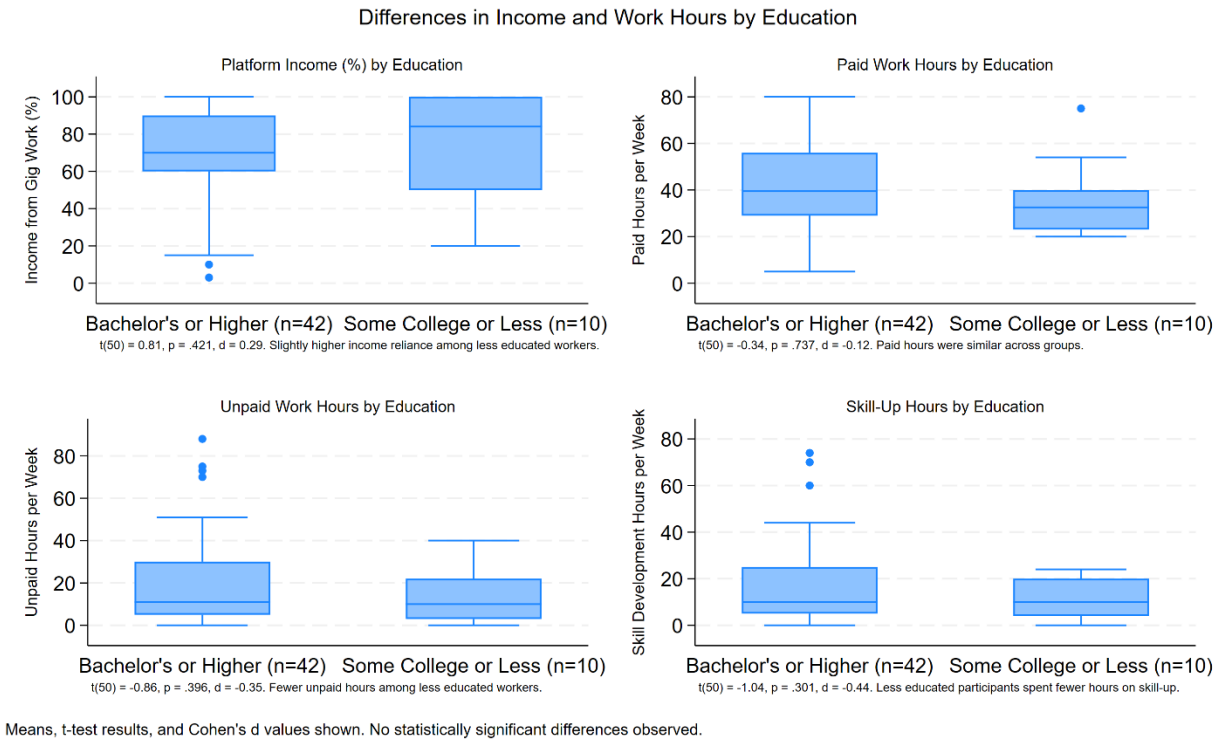


Figure 44:Education Impact on Platform Income Reliance and Work Hours

However, workers with less formal education reported fewer unpaid hours (M = 14.40, SD = 13.31) compared to their more educated counterparts (M = 20.98, SD = 23.29), $t(50) = -0.86$, $p = .396$, $d = -0.35$. A similar pattern emerged in the time spent on skill development, with participants holding less education averaging 11.30 hours (SD = 9.13) compared to 17.65 hours (SD = 18.61) among those with higher education, $t(50) = -1.04$, $p = .301$, $d = -0.44$.

Decent Work Across Demographic and Work Intensity Profiles

Building on the descriptive findings presented above, The analysis used regression and margin plots to demonstrate how intersecting demographic characteristics (e.g., gender, age, education) and labour inputs intensity indicators (e.g., hours worked, time spent on unpaid or skill-building activities) shape divergent experiences of decent work in the platform work, offering insight into who benefits, who is left behind, and in which dimensions those disparities are most pronounced. Please note that the results below only display bootstrap regression results and margin plots for variables that showed significance. Please see Appendix B for detailed regression tables with standard error and bootstrap regression output. Because the study is exploratory and the sample is small (N = 52), several regression models do not reach conventional significance. Nevertheless, effect directions and magnitudes offer some exploratory clues about where structural inequalities or work-intensity patterns may concentrate advantages or risks. The discussion section cautiously revisits these provisional signals in light of qualitative evidence from the interviews.

SE 1 Employment Opportunities

Employment Opportunities SE was measured using three scales. Overall, the results show that younger freelancers and those without university degrees consistently feel more satisfied with opportunities within the platform economy and perceive fewer viable alternatives outside of it. Older and more educated workers feel comparatively lower opportunity satisfaction but also show higher confidence in finding work outside the platform economy. Moreover, heavy reliance on platform earnings and long paid hours deepens financial vulnerability, showing that the very investment that brings short-term income also magnifies risk.

Two of the three models measuring this SE reached conventional significance (Platform-Opportunity Access and Financial Hardship), while Non-Platform Alternatives was non-significant and explained only 3 % of the variance. This low explanatory power likely reflects a restricted range in the outcome (most workers report only moderate alternatives) rather than the absence of real group differences. Please see below for more details on SE 1 scale results.

SE1.1 Work Opportunity Access through Platforms

An ordinary least squares (OLS) model with demographic and labour-input covariates accounted for 23 percent of the variance in perceived access to suitable work opportunities through platforms, $F(10, 41) = 2.51$, $p = .019$. Participants holding at least a bachelor's degree reported markedly lower access (standardized $\beta = -0.51$, $p = .030$) than those with less formal education. Age showed a similar

pattern; participants aged 25–34 and those 35 or older recorded lower access than the 18–24 group (β = −0.38, *p* = .042 and β = −0.43, *p* = .018, respectively). Gender presented a small positive trend, with men perceiving greater access (β = 0.27, *p* = .063). Platform tenure of five years or more exhibited a modest positive but non-significant association (β = 0.19, *p* = .209). Each additional unpaid work hour per week was related to a slight decline in access (β = −0.29, *p* = .053). Paid work hours, share of income from platforms, and the remaining controls had near-zero coefficients with *p* > .25. Adjusted means for the significant categorical variables are illustrated in Figure 5.

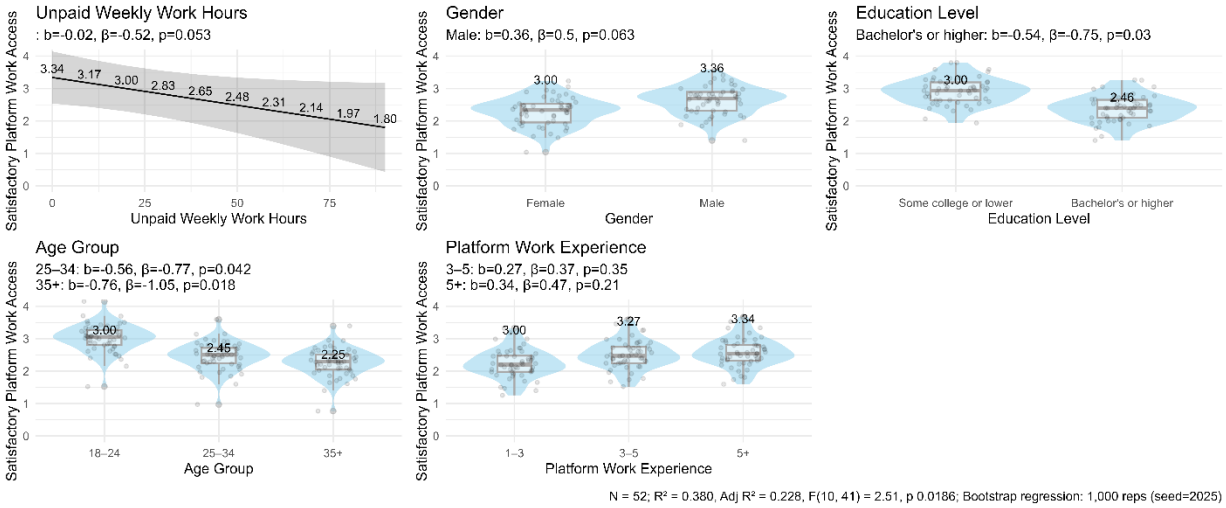


Figure 45: Disparities in Platform Opportunity Access (M =2.48)

SE1.2 Non-Platform Work Alternatives

The OLS model for this scale was not statistically significant and explained only 3% of the variance in perceived alternatives, F(10, 41) = 1.18, p = .335, Adj R^2 = .03. As shown in Figure 6 below, age is the only variable that shows clear separation by group. Workers aged 25–34 reported higher confidence in viable non-platform options than the 18–24 reference group (*p* = .026), and the difference was even larger for those 35 or older (*p* = .038). Gender showed a small positive estimate favouring men (*p* = .182). Hours spent on skills development showed a positive but weak association (*p* = .331) while unpaid hours showed a negative trend (*p* = .180). Education level, platform income share, paid work hours and platform tenure produced near-zero effects in this mode with *p* > .25 for these variables.

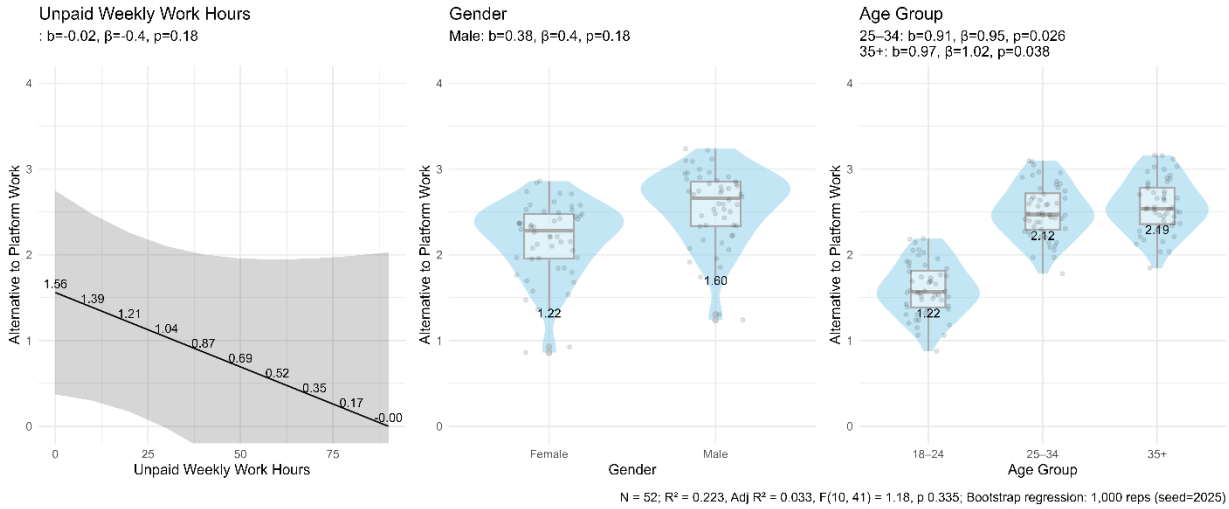


Figure 46: Variation in Non-Platform Work Alternative (M = 2.38)

SE 1.3 Financial Hardship without Platform-Based Income

The model for perceived hardship was statistically significant, $F(10, 41) = 3.84$, $p = .001$, explaining a considerable thirty-six percent of outcome variance. A higher share of income from platforms related strongly to greater anticipated hardship ($p = .005$). Paid weekly platform hours also carried a positive coefficient that shows some significance ($p = .076$). As shown in Figure 7 below, education exhibits a negative trend, indicating a lower perception of hardship among those with a degree ($p = .285$). Age groups displayed positive but non-significant estimates relative to the youngest workers ($p = 0.144$ for 25–34; p = 0.213 for 35 and older).

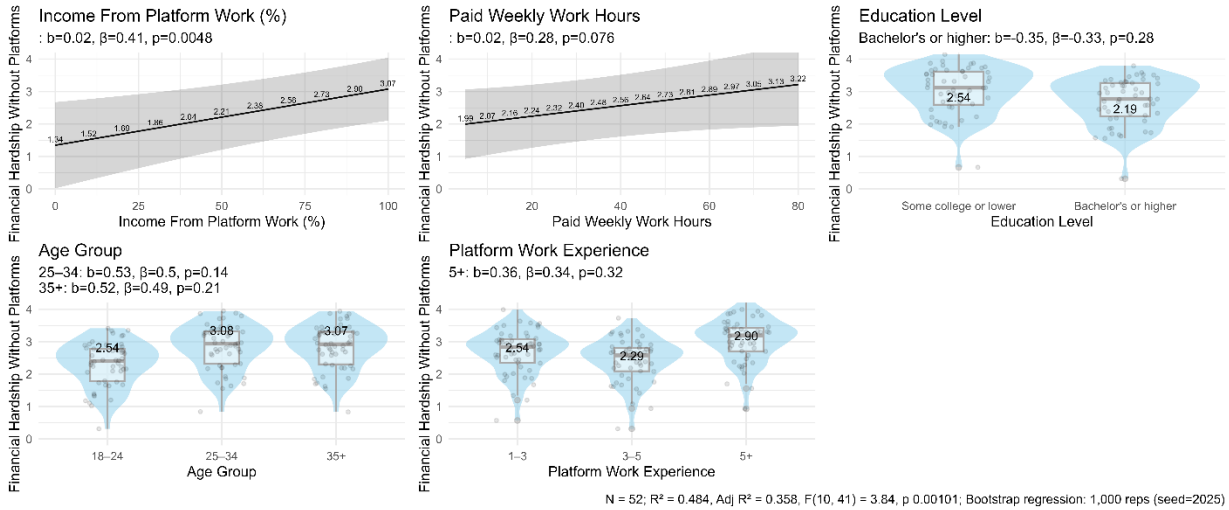


Figure 47: Predicted Financial Hardship Across Platform Worker Groups (2.75)

SE 2 Adequate Earnings and Productive Work

SE 2 is measured using three scales that focus on financial satisfaction, income consistency, and perception towards skill development through platforms that distinctly signify work productivity from a worker's perspective. Overall, data suggested that earnings satisfaction improved when most of a worker's income comes from platforms, but it reduces once the burden of unpaid tasks grows. Income stability remains weak for nearly everyone. Skill growth yields a mixed picture where women and those who work more paid hours describe more learning.

Please note that only the Financial-Satisfaction model in SE 2 was somewhat significant. Income Consistency and Skill Development were non-significant despite several βs bordering on $p \approx .10$. The null finding for the Income Consistency scale is unsurprising given its very low mean (1.3) and compressed variance, leaving little room for predictors to operate. Please see below for more details on SE 2 analysis results.

SE2.1 How Does Financial Satisfaction Vary in the Platform Economy?

Regression results indicate that a higher share of income through platforms is associated with greater financial satisfaction ($\beta = 0.28$, $p = 0.055$). In contrast, a heavier load of unpaid platform-related hours was related to lower satisfaction ($\beta = -0.32$, $p = 0.035$). The overall model reached significance, with $F(10, 41) = 2.45$, $p = 0.021$, explaining 22% of the variance. Coefficients for gender and education suggested modest trends; men reported slightly higher satisfaction, $\beta = 0.19$, $p = 0.143$, and participants with more education showed a negative association, $\beta = -0.24$, $p = 0.103$. Age group and platform tenure produced near-zero effects. These patterns are visualized in Figure 8 below.

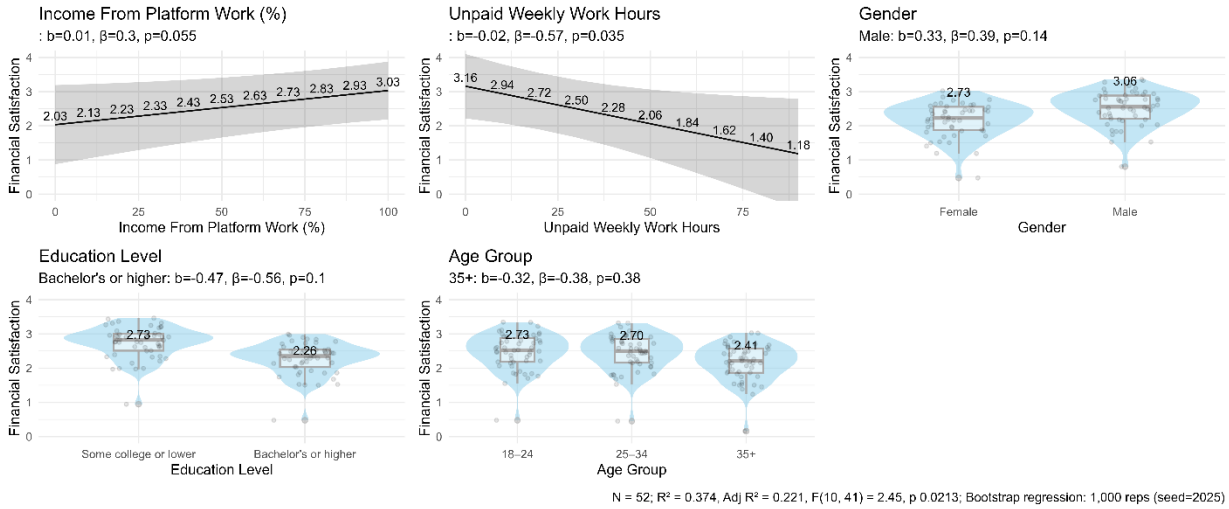


Figure 48: Financial Satisfaction Among Platform Workers (M = 2.37)

SE2.2 Income Consistency

The low mean (1.3) for this scale indicates most workers experience inconsistent income, leaving little between-group variance for predictors to explain. Hence, the regression did not achieve statistical significance, $F(10, 39) = 0.85$, $p = 0.587$, Adj $R^2 = -0.03$. Nonetheless, workers aged 25–34 indicated a positive coefficient, $\beta = 0.73$, $p = 0.093$, hinting that early mid-career workers may feel marginally more stable than the youngest cohort. Platform experience of three to five years and five or more years each yielded identical estimates, $\beta = 0.50$, with p-values of 0.310 and 0.298, respectively. Exploratory age and experience contrasts are illustrated in Figure 9 below.

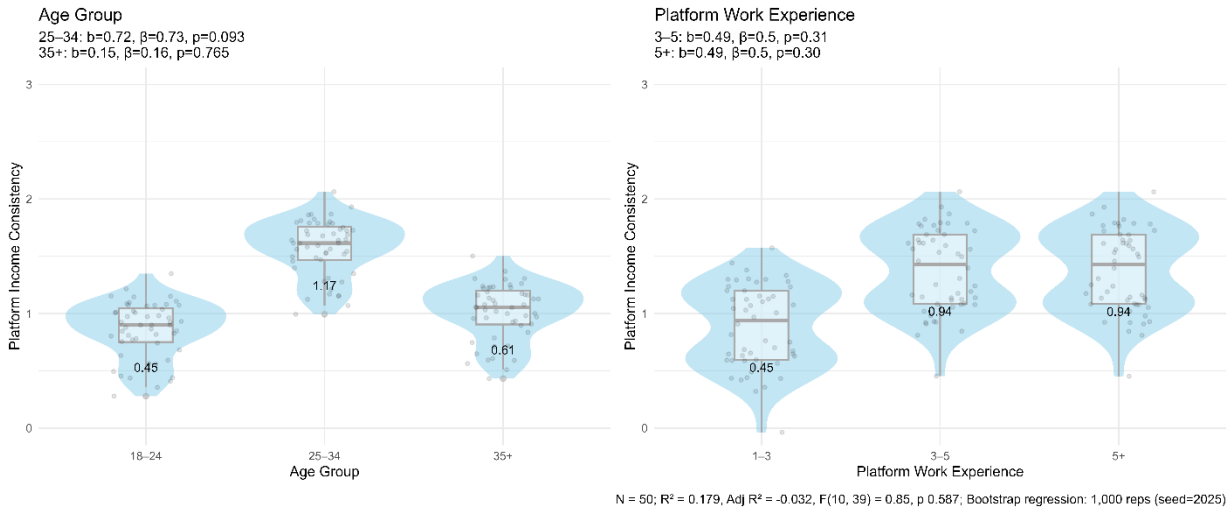


Figure 49:Income Consistency Among Platform Worker Groups (M = 1.3)

SE2.3 Patterns of Skill Acquisition and Use Among Platform Workers

The skill-development model produced $F(10, 41) = 1.22$, $p = 0.310$, with four percent of variance explained. Gender returned the largest single coefficient; men rated their skill growth lower than women, $\beta = -0.50$, $p = 0.093$. Hours worked per week showed a positive but weak estimate, $\beta = 0.31$, $p = 0.110$. Age 25–34 carried $\beta = 0.40$, $p = 0.341$. As Figure 10 shows, a dip appeared for those with three to five years of platform tenure, $\beta = -0.71$, $p = 0.119$. Education, income reliance, and unpaid hours offered negligible contributions in this scale.

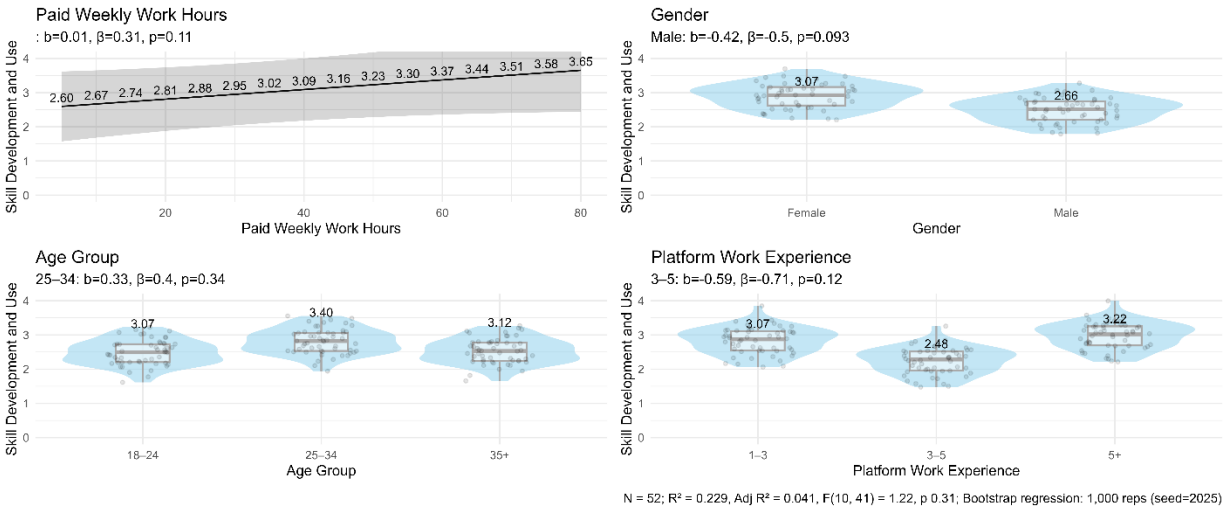


Figure 50: Skill Development and Productive Use (M = 2.6)

SE 3 Decent Working Time

Since freelancing through platforms does not follow a fixed time schedule, and time zone differences pose significant challenges, this analysis uses scheduling autonomy and negotiating agency of workers as a proxy for decent working time. Most participants report moderate control over their work schedule, and this level of control does not vary significantly across gender, education, or income share. The only noticeable increase in autonomy of schedule appears among freelancers who spend more time on up-skilling, suggesting that workers who invest in themselves also negotiate schedules more confidently. Experience and age offer no automatic advantage, demonstrating that schedule autonomy is earned on a case-by-case basis rather than being a product of seniority.

The scheduling autonomy and negotiating agency scale averaged 2.18. The OLS regression model for this scale provided limited explanatory power, F(10, 41) = 0.98, p = 0.466, adjusted R-squared = 0.05. These results indicate that perceived control over working time shows only modest variation within the observed demographic and labour input categories.

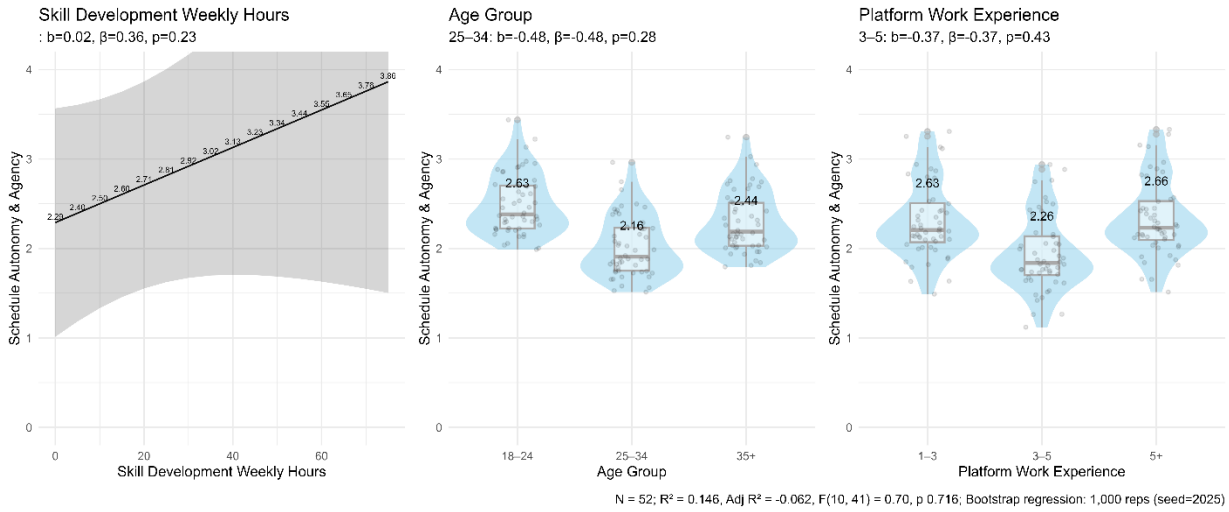


Figure 51: Schedule Autonomy & Negotiation Power Differences (M = 2.18)

The margin plot for this scale, as shown in Figure 11, indicates that investment in skill building displayed a positive but statistically insignificant signal, β= 0.36, p = 0.232. In contrast, gender, education, unpaid hours, paid hours, and platform income share each produced small coefficients with p values above 0.40. Workers aged 25–34 recorded a standardized β of −0.48, p = 0.277 when compared with the 18–24 reference group.

SE 4 Combining Work, Family, and Personal Life

Combining work, family, and personal life in this research is measured using a single scale that combines questions on satisfaction with work–life balance and fulfillment in the platform economy. The work–life fulfilment scale averaged 2.93 on its zero-to-four range. Overall, the regression Results showed that those with more than 5 years of experience on platforms exhibit higher subjective work–life fulfillment, while those with lower experience are rather neutral. Those who derive a larger share of income from platforms also show slightly more fulfilment. Importantly, every extra unpaid hour erodes this benefit, and those working more unpaid hours are less likely to exhibit fulfillment and satisfaction. Demographics such as age, gender, and education show very little effect.

This regression reached significance with $F(10, 41) = 3.14$, $p = .005$, adjusted $R^2 = .30$, explaining 30 % of the variance, the strongest fit outside SE 1. As shown in Figure 12, greater reliance on platform income related to slightly higher fulfilment ($\beta = 0.25$, $p = .094$), whereas each additional unpaid hour corresponded with lower scores ($\beta = -0.50$, $p = .050$). Platform tenure showed the clearest pattern where workers engaged for five years or more reported markedly higher satisfaction than newcomers ($\beta = 0.83$, $p = .024$) while those at three to five years did not differ appreciably. Age, education, gender, paid hours, and skill-building time produced coefficients near zero with p-values above 0.20.

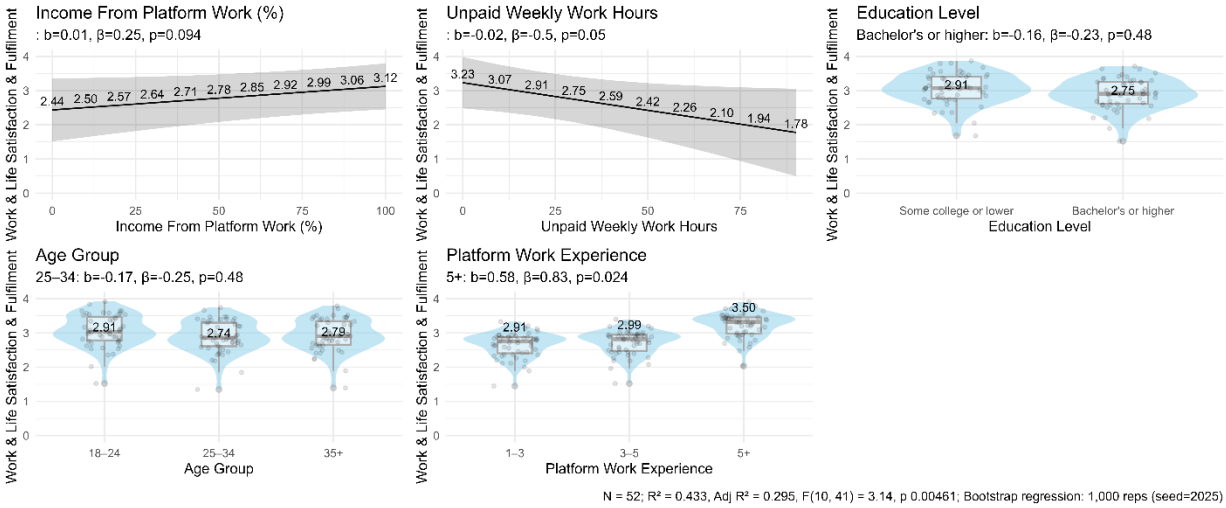


Figure 52:Work and Life Satisfaction Differences (M = 2.93)

SE 5 Stability and Security of Work

SE 5 is measured using a single scale that combines questions covering career stability and growth, with a noticeably high mean of 2.81 out of 4. Regression results suggested that freelancers in the three-to-five-year window register the sharpest doubts about stability and security. Workers with relatively more education also show this concern. By contrast, the most seasoned cohort appears to show a rebound.

While the full model for Stability & Growth of Work was not statistically significant ($F(10, 41) = 1.41$, $p = 0.210$), several plotted variables in Figure 13, particularly education and platform work experience, show meaningful variation that helps explain how different groups evaluate career

prospects within the platform economy.

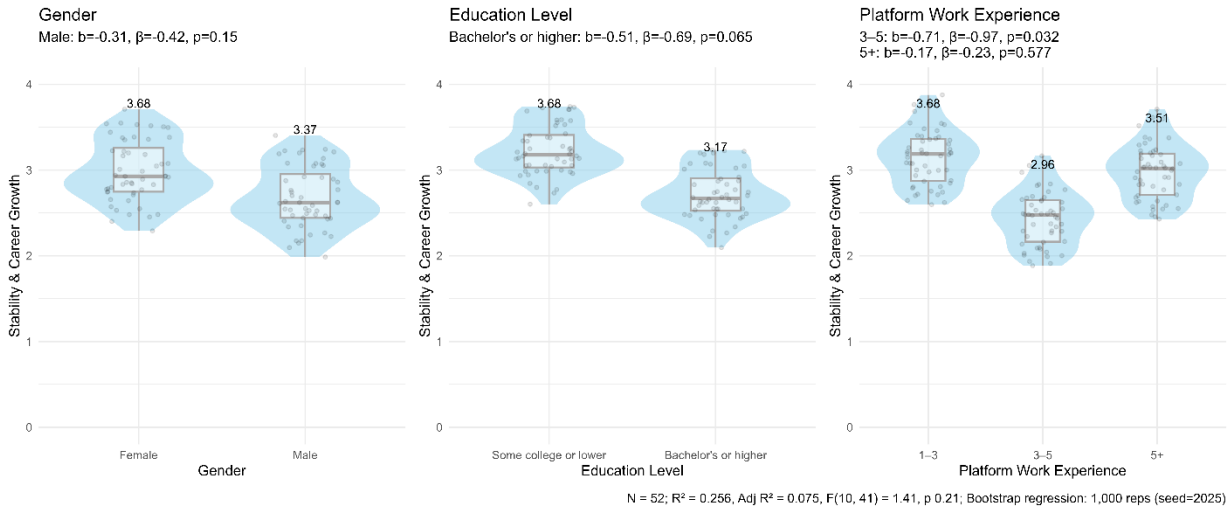


Figure 53: Stability & Growth (M = 2.81)

Among the most notable results, workers with 3–5 years of platform experience reported significantly lower perceptions of stability and career growth than newer workers (β = –0.97, p = 0.032). Interestingly, this trend was not observed for those with 5 or more years of experience, who showed no meaningful difference from new entrants (p = 0.577), suggesting a possible rebound in satisfaction or adaptation over time. Education also showed a sizeable negative association with perceived career stability. Participants with a bachelor's degree or higher tended to view platform work as offering less stable or growth-oriented opportunities (β = –0.69, p = 0.065). For gender, male participants reported slightly lower perceived stability (β = –0.42, p = 0.153), though this effect did not reach significance. Still, the direction of the coefficient suggests that gendered experiences may influence long-term outlooks.

SE 6 Equal Opportunity and Treatment in Employment

SE 6 used two scales, where the first scale focused on perceptions of inclusion and discrimination related to platform clients and colleagues, and the second scale focused on platform policy protection. The analyses below show that perceptions of inclusion, non-discrimination, and formal policy protection are high (mean = 3.68) but broadly flat across most worker groups. Small, non-significant dips among university-educated freelancers and men indicate pockets of discontent, but no variable in this sample shows a significant variation. In contrast, the structural safeguards provided by the

platforms themselves score especially low, and this perception does not vary across the board. Consequently, neither scale yielded significant models. Both outcomes exhibit either ceiling effects (mean 3.68 for inclusion) or floor effects (mean 1.12 for policy protection), compressing variance and muting group contrasts. Please see below for more details on SE 6 results.

SE6.1 Perceived Inclusion and Non-Discrimination

Mean inclusion scores varied little across groups, and the model explained very little variance, F(10 41) = 0.58, p = .819, adjusted R^2 = –.09. The largest coefficient appeared for education; participants with a bachelor's degree or higher registered lower inclusion perceptions, β = –0.50, p = .213. Age groups 25–34 and 35 and above had small negative coefficients, β = –0.24 and β = –0.34, respectively, both with p > .50. Platform tenure, gender, hours worked, income share, and skill-building time showed no consistent direction. Figure 14 below visualizes these almost flat relationships.

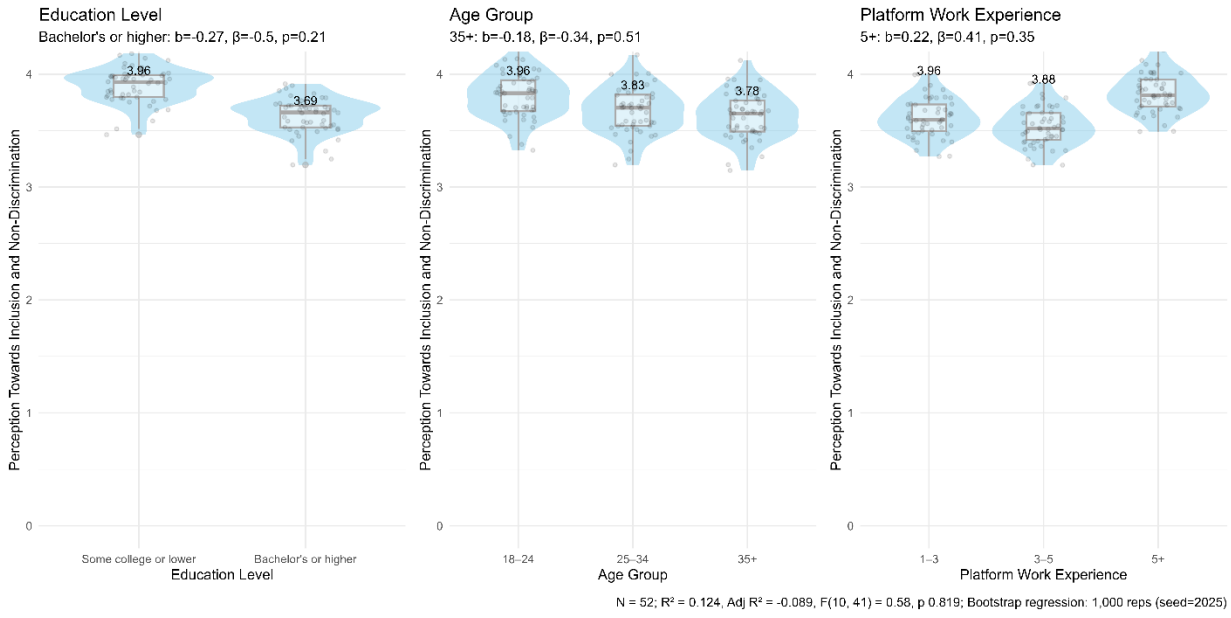


Figure 54: Perception of Inclusion and Non-Discrimination (M=3.68)

SE 6.2 Platform Policy Protection

The regression offered little explanatory power with F(10, 41) = 0.51, p = .870 and an adjusted R^2 of –.11. No covariate approached conventional significance. Predicted values for the explored variables are visualized in Figure 15 below.

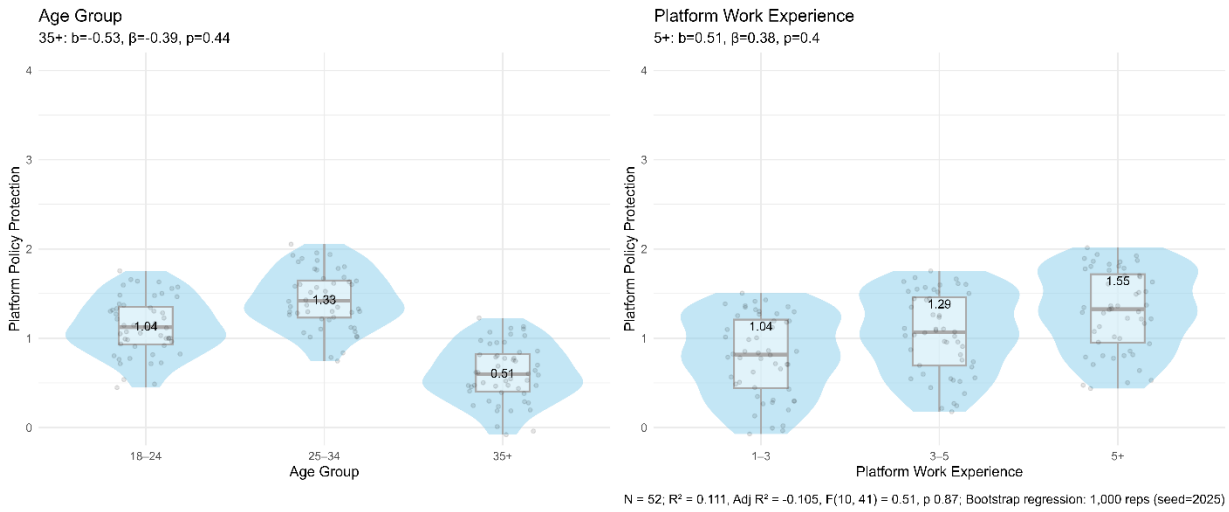


Figure 55: Perception Towards Platform Policy Protection (M=1.12)

SE 7 Safe Work Environment

The safe work environment in this research is measured using two scales. The first scale examines perceptions of physical safety and psychosocial well-being, while the second scale measures perceptions of stress from work. Overall trends showed that perceptions of safety grow with experience. Freelancers in their third to fifth year report the highest sense of well-being and safety, while newer and much older workers lag in this scale. The stress scale shows some distinct results. Reported stress levels are higher among those who do more unpaid work, and reported stress is also slightly higher for men and for the 25–34 age band. However, it should be noted that neither model reached statistical significance. Means at opposite ends of the scales (high for safety, low for stress) reduced statistical leverage.

SE 7.1 Wellbeing and Safety

This regression model offered no explanatory power, with $F(10, 41) = 0.94$, $p = .510$, and an adjusted R^2 of –0.01. Figure 16 below shows the predicted well-being and safety scores against the main covariates. Among some noteworthy trends, participants holding at least a bachelor's degree recorded lower scores than their peers ($\beta = –0.57$, $p = .143$). Compared to the 18-24 age group, both older age groups trended downward, 25–34, $\beta = –0.62$, $p = .150$ and 35 plus, $\beta = –0.56$, $p = .257$.

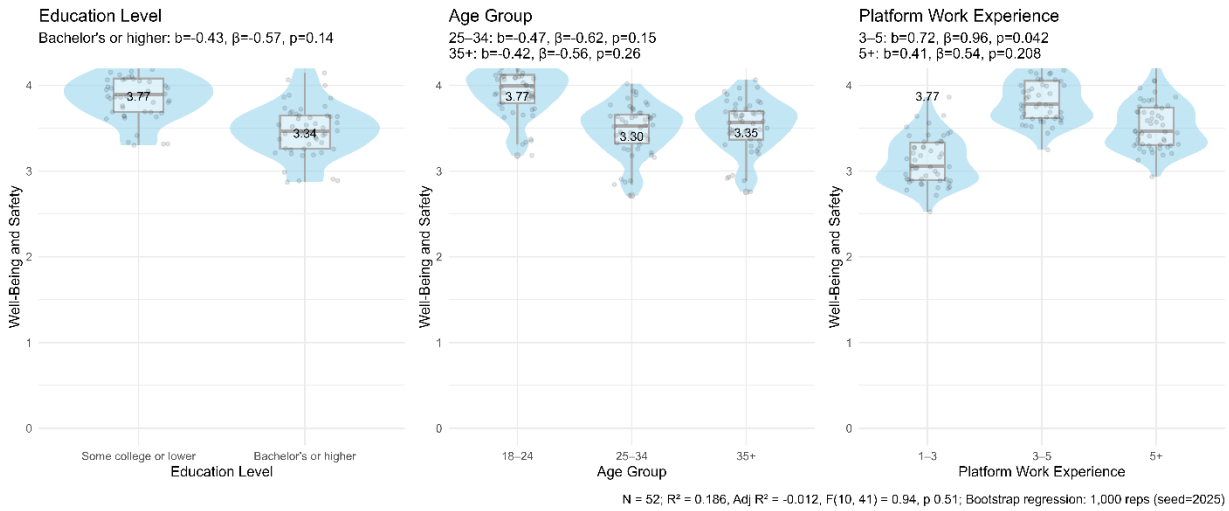


Figure 56: Well-Being and Safety Perception Differences (M=3.07)

SE 7.2 Stress from Platform Work

This model was also not significant, F(10, 41) = 1.03, p = .437, adjusted R^2 = .01. The overall stress mean is 1.54, producing a left-skew that reduced detectable group differences. Figure 17 highlights two exploratory patterns. First, men indicated higher stress than women, β = 0.40, *p* = .184. Second, a higher number of unpaid hours is related to a noticeable rise in stress, β = 0.41, p = 0.170.

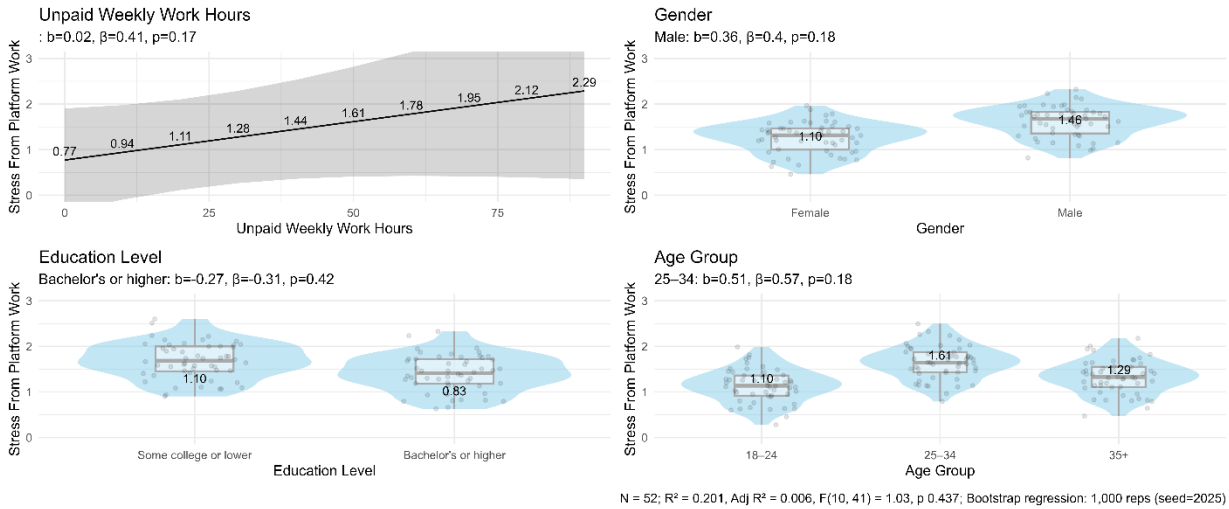


Figure 57: Stress from Platform Work (M=1.54)

SE 8 Social Security

Social security within the platform economy is largely absent, and as such, the questions in this area approached the topic from a slightly different angle. The three scales used to assess this SE included changes in healthcare access after joining platform work, perceptions of healthcare access in traditional jobs accessible to workers, and the percentage of platform income saved as a proxy for financial buffering and future security. Key trends observed in this exploratory analysis indicate that men perceive their pre-platform healthcare options as weaker, yet they also experience marginal improvements after joining platforms. Older workers save a larger share of their earnings. Savings are noticeably higher among freelancers who devote more time to skills development. The savings scale had ample variance (SD > 20 %) and allowed some predictors to show statistical significance. In contrast, healthcare items capture nuanced access differences that may require finer measurement or a larger sample to detect.

SE8.1 Perceived Healthcare Access Through Traditional Jobs

The regression model was not significant, $F(10, 41) = 0.80$, $p = .630$, and had an adjusted R^2 of –0.04. Figure 18 shows that education and age produced the widest confidence bands, yet none of their estimates crossed the customary threshold. Men tended to rate their traditional-job healthcare options lower than women, $\beta = –0.34$, $p = .272$. Workers aged 35 plus leaned higher than the youngest cohort, $\beta = 0.71$, $p = .159$, whereas the 25–34 group resembled newcomers. Platform tenure, income share, work hours, and skill-building time hovered near zero with p values above .40, suggesting minimal group differentiation on this item.

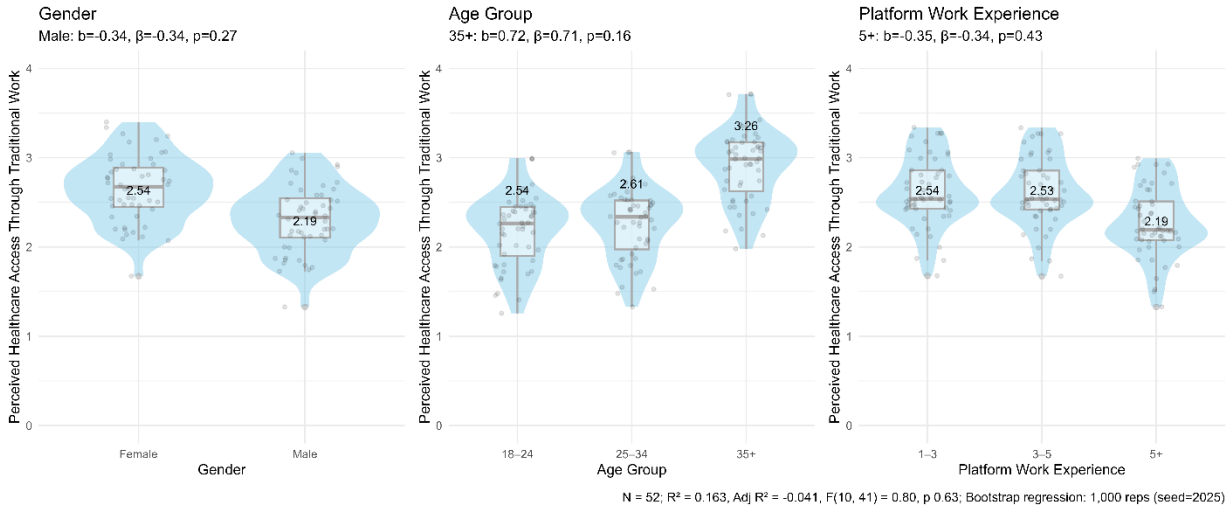


Figure 58: Perceived Healthcare Access in Traditional Jobs (M=2.46)

SE 8.2 Healthcare Access After joining Platform Work

This model showed limited fit, $F(10, 41) = 1.26$, $p = .286$, adjusted $R^2 = .05$. In Figure 19, the most visible contrast lies between genders. Male participants reported noticeably better post-platform healthcare access, $\beta = 0.51$, $p = .089$, a moderate effect. A smaller uplift was observed for workers with at least five years of experience on platforms, $\beta = 0.49$, $p = 0.240$.

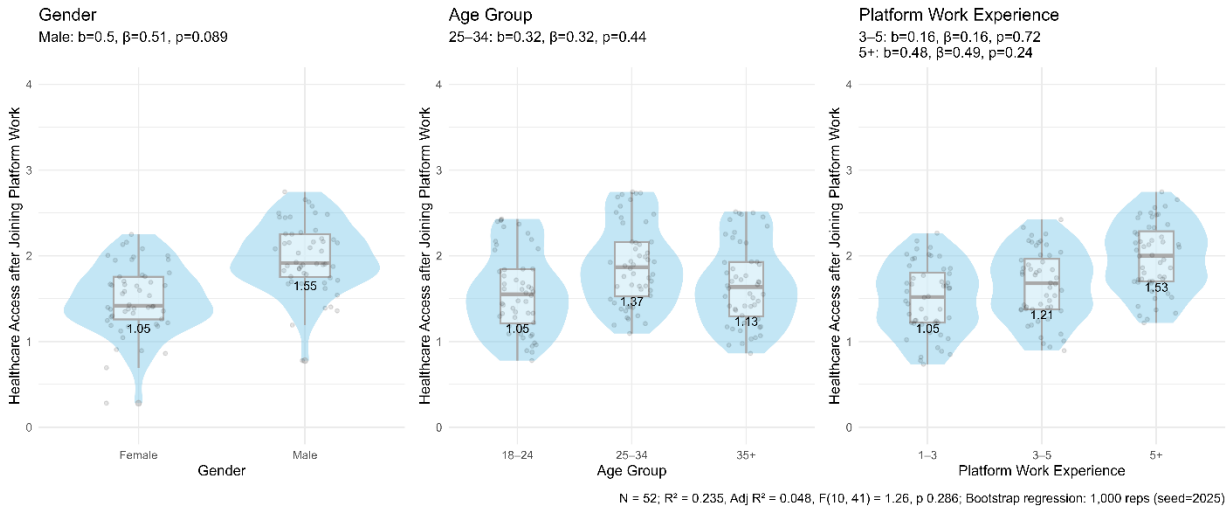


Figure 59: Healthcare Access After Joining Platform Work (M=1.77)

SE 8.3 Savings

Savings displayed far more structure compared to other social security scales. The model was somewhat significant with $F(10\ 41) = 2.95$, $p = .007$ and an adjusted R^2 of .28. In Figure 20, the upward slope for skill-development hours stands out, $\beta = 0.57$, $p = .026$, indicating that freelancers who invest in learning tend to save larger share of their income. Paid weekly hours reinforced this positive link though less decisively, $\beta = 0.22$, $p = .183$. Older workers also appeared to save more; the 35-plus group showed a β of 0.74, $p = 0.078$. Gender, education, and most tenure categories clustered near the origin in this sample.

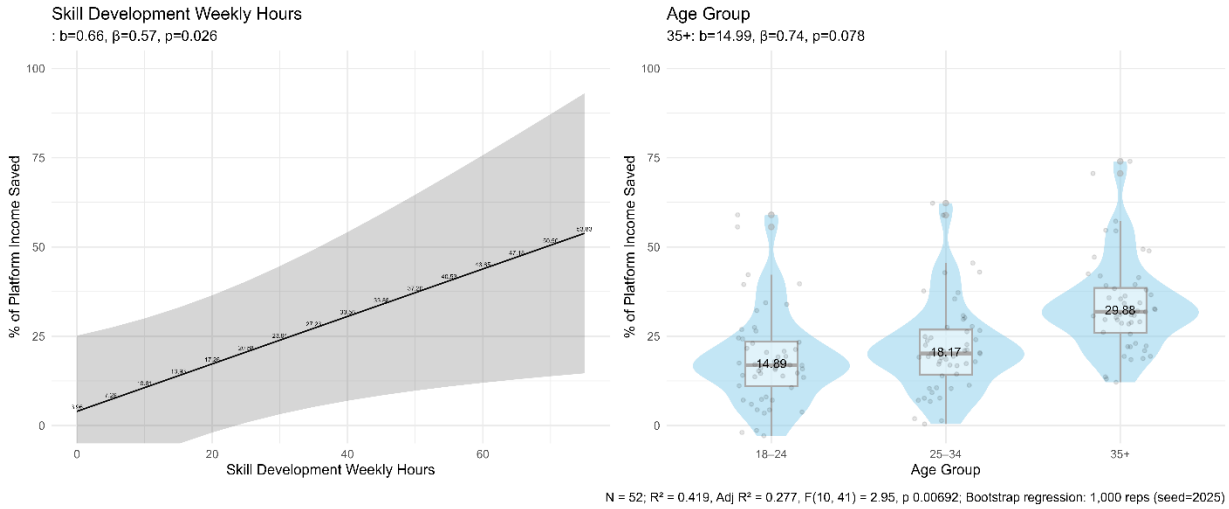


Figure 60: Savings (M=25.25)

SE 9 Social Dialogue

This section had the most number of scales (7) due to the diverse nature of questions that measured distinct constructs. Trends in data suggest that engagement in collective action is highly sensitive to platform dependence. As the proportion of income coming from platforms increases, workers become less likely to join collective initiatives. An increase in weekly paid hours of work reduces interest in labour mobilization efforts. Workers who focus more on skill development also view labour organizations more favourably, whereas workers who do more unpaid work show skepticism.

Among the seven scales measuring the social dialogue dimension of decent work, Opportunities for Collective Action produced a significant logistic regression model, and Participation in Collective Action was marginally significant. The remaining five scales were non-significant. This is

unsurprising, given their very low means (e.g., 0.16 for opportunities for collective action, 0.31 for labour-organization helpfulness) and the binary or four-point response format in some questions, which limits the available variance.

SE 9.1 Opportunities for Collective Action

This model used logistic regression due to the lower number of categories in the data. The model was statistically reliable, with LR $\chi^2(10) = 20.51$ ($p = .025$) and McFadden $R^2 = .28$, explaining a moderate share of the variation. A higher dependence on platform income is negatively associated with perceived opportunities for collective action. (LogOR = –0.067, p = .004). In contrast, each additional paid platform hour was related to a higher odds of perceiving such opportunities (LogOR = 0.083, p = .017). Figure 21 shows these opposing gradients. Workers with more than five years of experience are vastly more likely to report higher perceived opportunities for collective action (LogOR = 3.63, p = .048)

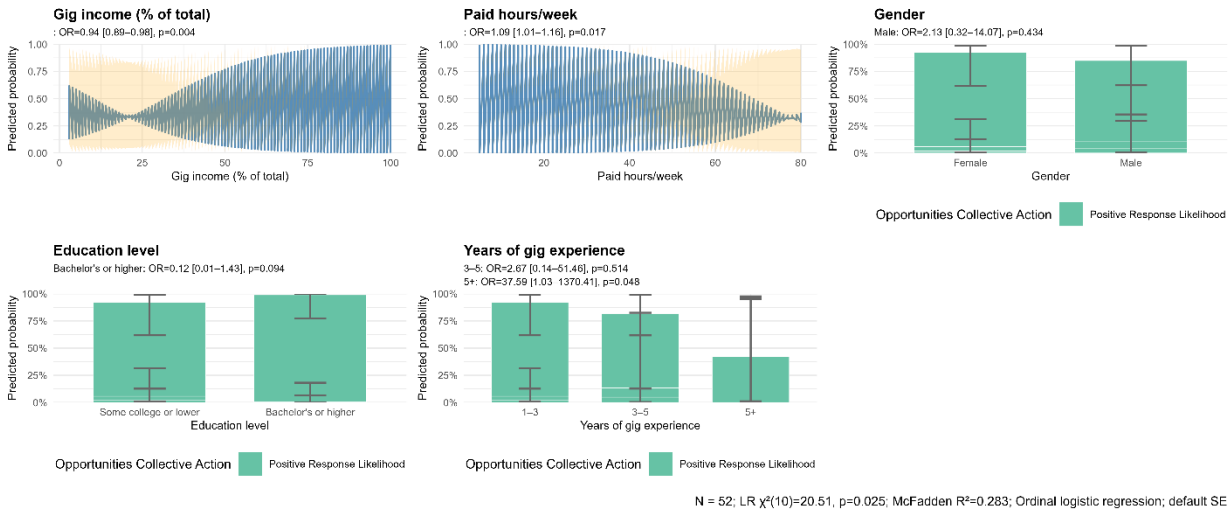


Figure 61: Opportunities for Collective Action (M=0.16)

SE 9.2 Participation in Collective Action

The overall fit for this model reached the margin of significance, with LR $\chi^2(10) = 16.83$ ($p = .078$) and McFadden $R^2 = .20$. Figure 22 below highlights two continuous drivers that are also observed in the previous scale. A higher income share from platforms reduced the likelihood of actual participation in collective action activities (LogOR = –0.040, p = .020), whereas longer paid hours

boosted the likelihood of collective action (LogOR = 0.059, p = .019).

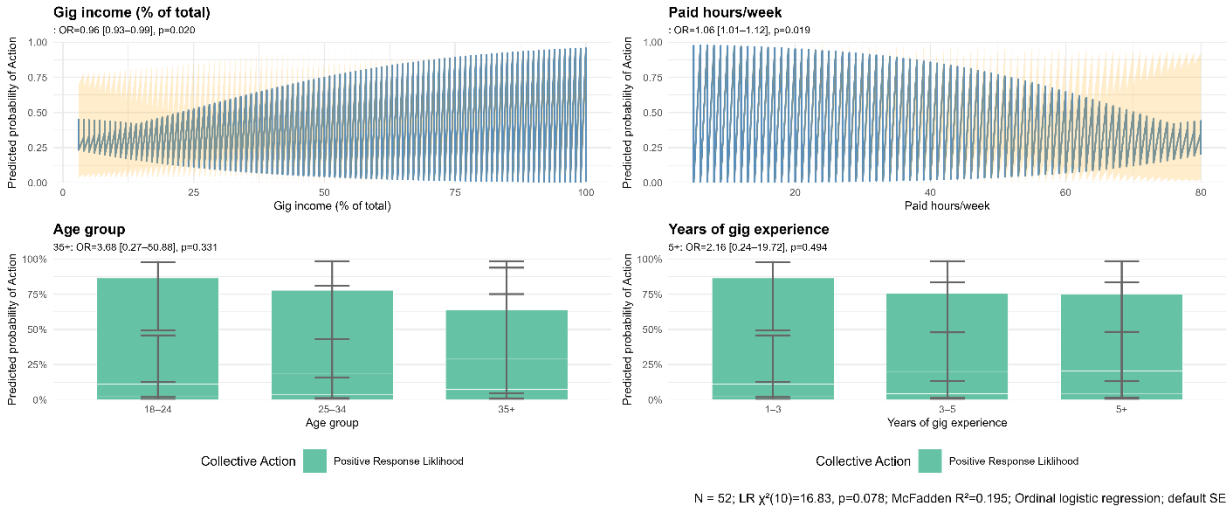


Figure 62: Participation in Collective Action (M=0.21)

SE 9.3 Labour Organizations' Helpfulness

This logistic model was weak, LR $\chi^2(10) = 9.56$ ($p = .480$) with McFadden $R^2 = .15$, though one variable stood out. Figure 23 shows that skill development hours displayed a clear positive slope (LogOR = 0.10, p = 0.028), indicating a similar pattern where those who spend more time on skill development also perceive support mechanisms more optimistically. A heavier unpaid workload showed the opposite tendency (LogOR = –0.060, p = .091).

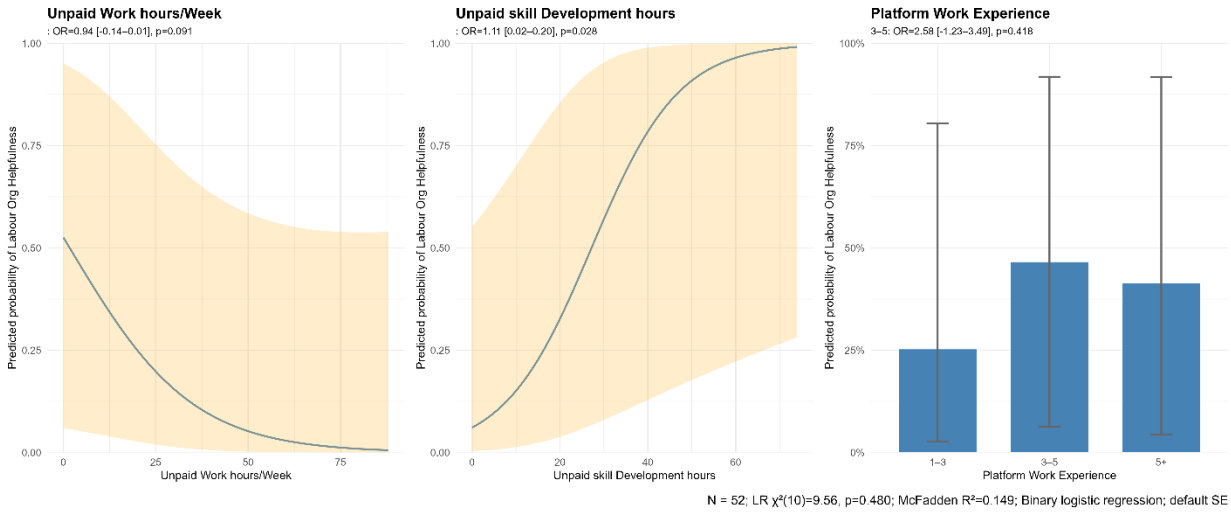


Figure 63: Labour Organizations' Helpfulness (M=0.31)

SE.9.4 Policy Participation

The linear regression yielded minimal explanatory value, F(10, 41) = 0.25 (p = .989) and adjusted R^2 = –.17. As Figure 24 confirms, estimates for gender (β = 0.26, p = .425), education (β = –0.17, p = .680), both age groups (β = –0.11 and –0.28), and tenure (β = 0.28 and 0.35) were small with wide confidence intervals.

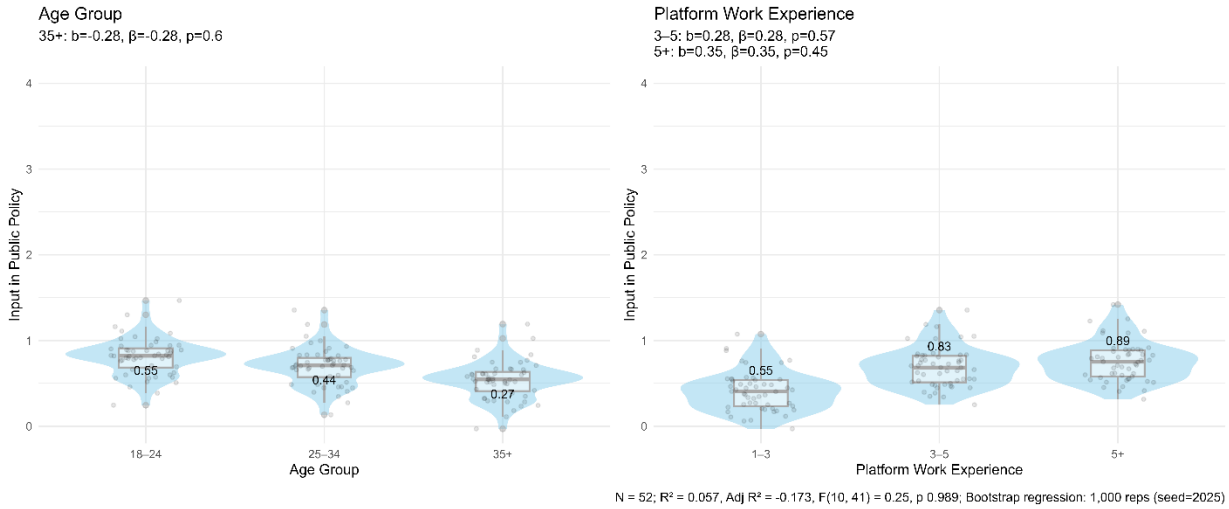


Figure 64: Public Policy Participation (M=0.66)

SE 9.5 Expression Freedom

The model was also not statistically significant (F(10, 41) = 1.49, p = 0.179; Adj R^2 = 0.087). Among the plotted variables, platform workers with over 5 years of experience reported significantly higher expression freedom (β = 1.03, p = 0.015), indicating greater comfort in voicing opinions or concerns. Those with 3 to 5 years of experience showed a smaller, non-significant positive trend (β = 0.24, p = 0.591). Higher education exhibited a downward trend (β = –0.60, p = .103).

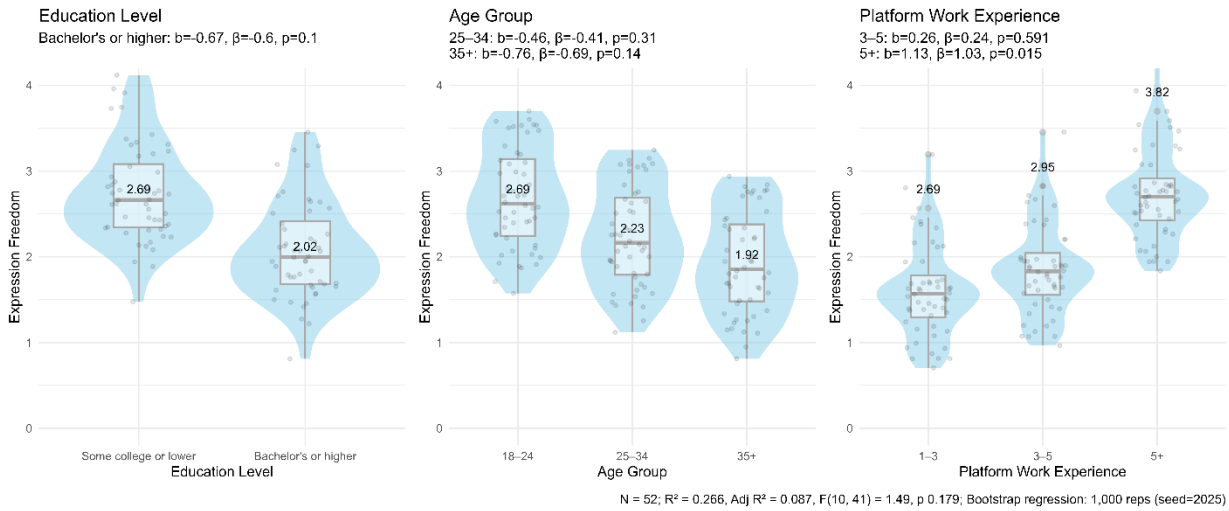


Figure 65: Perception Towards Expression Freedom (M=2.2)

SE 9.6 Client Attention to Labour Concerns

With F(10, 41) = 0.81 (p = .622) and adjusted R^2 = –.04, this model revealed subtle variation. As Figure 26 illustrates, participants holding a bachelor's degree or higher perceived slightly more client attentiveness to workers' concerns (β = 0.42, p = .281). Gender displayed a small positive estimate in favour of men (β = 0.19, p = .532), and the middle age group, 25–34, showed a dip (β = –0.40, p = .359).



Figure 66: Client Attention to Labour Concerns (M=1.62)

SE 9.7 Participation in Platform Administrative and Policy Decision

The model was also not statistically significant (F(10, 41) = 0.62, p = 0.786; Adj R^2 = –0.080). In Figure 27, the largest absolute coefficient was observed for the age group 25–34, which was linked to lower participation (β = –0.77, p = .085). Age 35 and older also showed a negative trend, though smaller (β = –0.66, p = .198). A tenure of five years or more leaned positive (β = 0.63, p = .159). Overall, the data indicate only modest group differences in perceptions toward direct policy engagement among these platform workers.

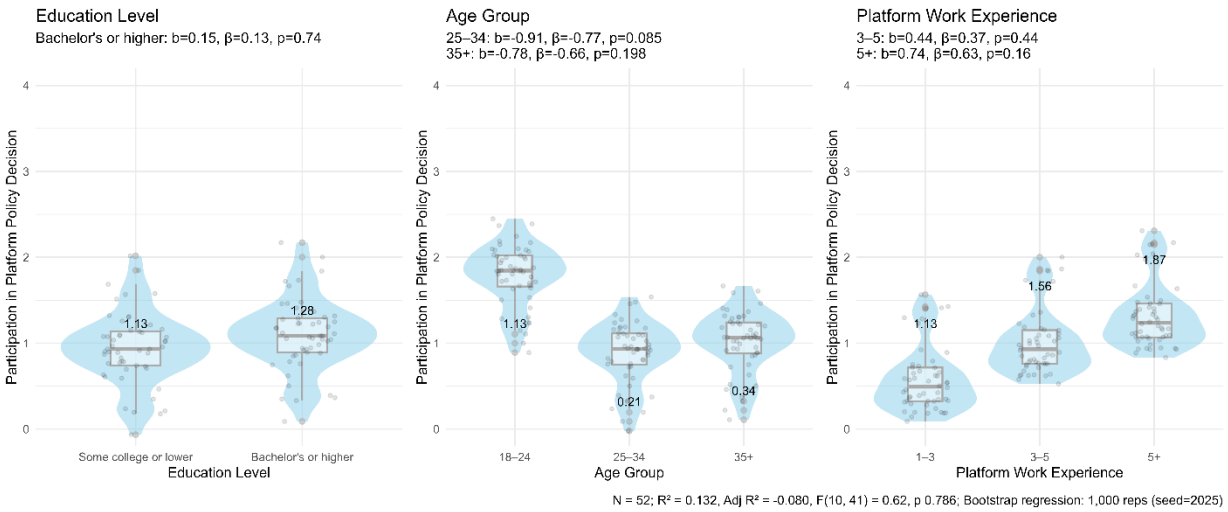


Figure 67: Perceived Participation in Platform Administrative and Policy Decision (M=1.07)

Standard Errors and Bootstrap Regression Tables

SE1: Employment Opportunities

SE1.1 Satisfactory Platform Work Access

Bootstrap Regression Results

Bootstrap regression: 1,000 reps (seed=2025)

N = 52; R^2 = 0.380, Adj R^2 = 0.228, F(10, 41) = 2.51, p 0.0186

Satisfactory Platform Work Access

Source	Sum of Squares	DF	Mean Square	F	Pr(>F)	R^2	Adj R^2	Root MSE
Model	10.05559	41	0.2452582	2.510043	0.01863284	0.38	0.228	0.633
Residual	16.42518	10	1.6425182					
Total	26.48077	51	0.5192308					

Coefficient Estimates

Satisfactory Platform Work Access

Variable	b	β	95% CI Low	95% CI High	p-value
dw04_gigincomeperc	0.005080155	0.1783604	-0.003624936	0.0137852459	0.24536340
e_paidworkhours	0.006115175	0.1567181	-0.007280047	0.0195103959	0.36194363
e_unpaidworkhours	-0.017133009	-0.5177993	-0.034482642	0.0002166238	0.05279487
e_skilldunpaidhours	0.009052203	0.2174282	-0.012411282	0.0305156874	0.39930654
e_genderMale	0.360321529	0.5000461	-0.020172644	0.7408157024	0.06281931
eduBachelor's or higher	-0.540000804	-0.7494009	-1.024876805	-0.0551248021	0.02993857
age_grouped25–34	-0.555617301	-0.7710731	-1.090827489	-0.0204071124	0.04224649
age_grouped35+	-0.756068741	-1.0492551	-1.375651778	-0.1364857041	0.01800469

Satisfactory Platform Work Access					
Variable	b	β	95% CI Low	95% CI High	p-value
e_gigexp3–5	0.269499421	0.3740052	-0.311577836	0.8505766785	0.35442414
e_gigexp5+	0.340827844	0.4729932	-0.197909449	0.8795651380	0.20856130

Standard Errors Regression Results

Table: OLS Regression Results on Platform Work Opportunity Access (N = 52)

Normal SD

Model Statistics

Number of observations: 52
F-statistic (df = 10, 41): 2.51
p-value (overall model): 0.0186
R-squared: 0.3797
Adjusted R-squared: 0.2284
Root MSE: 0.633

Variable	Coefficient	Std. Error	t	p-value	95% Confidence Interval
dw04_gigincomeperc	0.0051	0.0043	1.18	0.245	[−0.0036, 0.0138]
e_paidworkhours	0.0061	0.0066	0.92	0.362	[−0.0073, 0.0195]
e_unpaidworkhours	−0.0171	0.0086	−1.99	0.053	[−0.0345, 0.0002]
e_skilldunpaidhours	0.0091	0.0106	0.85	0.399	[−0.0124, 0.0305]
Gender: Male	0.3603	0.1884	1.91	0.063	[−0.0202, 0.7408]
Education: Bachelor’s or higher	−0.5400	0.2401	−2.25	0.030	[−1.0249, −0.0551]
Age: 25–34	−0.5556	0.2650	−2.10	0.042	[−1.0908, −0.0204]
Age: 35+	−0.7561	0.3068	−2.46	0.018	[−1.3757, −0.1365]
Experience: 3–5 years	0.2695	0.2877	0.94	0.354	[−0.3116, 0.8506]

Experience: >5 years	0.3408	0.2668	1.28	0.209	[−0.1979, 0.8796]
Constant	2.6020	0.4598	5.66	0.000	[1.6734, 3.5306]

SE1.2: Alternative Opportunities

Standard Errors Regression Results

Table: OLS Regression Results for Alternative Work Opportunities (N = 52)

Variable	Coefficient	Std. Error	t	p-value	95% Confidence Interval
dw04_gigincomeperc	−0.0050	0.0064	−0.79	0.436	[−0.0179, 0.0079]
e_paidworkhours	−0.0035	0.0098	−0.36	0.721	[−0.0234, 0.0163]
e_unpaidworkhours	−0.0173	0.0127	−1.36	0.180	[−0.0430, 0.0083]
e_skilldunpaidhours	0.0155	0.0157	0.98	0.331	[−0.0163, 0.0472]
Gender: Male	0.3785	0.2789	1.36	0.182	[−0.1848, 0.9417]
Education: Bachelor’s or higher	0.2476	0.3554	0.70	0.490	[−0.4701, 0.9654]
Age: 25–34	0.9053	0.3923	2.31	0.026	[0.1131, 1.6976]
Age: 35+	0.9730	0.4541	2.14	0.038	[0.0559, 1.8902]
Experience: 3–5 years	0.0727	0.4259	0.17	0.865	[−0.7875, 0.9328]
Experience: >5 years	−0.1330	0.3949	−0.34	0.738	[−0.9305, 0.6645]
Constant	1.7900	0.6806	2.63	0.012	[0.4155, 3.1646]

Model Summary

- Number of observations: 52
- F-statistic (df = 10, 41): 1.18
- p-value (overall model): 0.3347
- R-squared: 0.2228
- Adjusted R-squared: 0.0332
- Root MSE: 0.9369

Bootstrap Regression Results

Regression Results for Alternative to Platform Work

Bootstrap regression: 1,000 reps (seed=2025)

N = 52; R^2 = 0.223, Adj R^2 = 0.033, F(10, 41) = 1.18, p 0.335

Alternative to Platform Work								
Source	Sum of Squares	DF	Mean Square	F	Pr(>F)	R^2	Adj R^2	Root MSE
Model	10.31724	41	0.251640	1.175331	0.3347153	0.223	0.033	0.937
Residual	35.99045	10	3.599045					
Total	46.30769	51	0.907994					

Coefficient Estimates

Alternative to Platform Work					
Variable	b	β	95% CI Low	95% CI High	p-value
dw04_gigincomeperc	-0.005018926	-0.13325119	-0.01790474	0.007866888	0.43604170
e_paidworkhours	-0.003528704	-0.06838555	-0.02335714	0.016299732	0.72113951
e_unpaidworkhours	-0.017335525	-0.39618999	-0.04301753	0.008346476	0.18025796
e_skilldunpaidhours	0.015475573	0.28109108	-0.01629601	0.047247152	0.33103490
e_genderMale	0.378472484	0.39718499	-0.18475855	0.941703514	0.18218520
eduBachelor's or higher	0.247626608	0.25986981	-0.47011687	0.965370082	0.48988730
age_grouped25–34	0.905328427	0.95008984	0.11307717	1.697579681	0.02613274
age_grouped35+	0.973025244	1.02113374	0.05588008	1.890170411	0.03813220
e_gigexp3–5	0.072677961	0.07627132	-0.78746857	0.932824490	0.86534551
e_gigexp5+	-0.132981480	-0.13955637	-0.93045377	0.664490813	0.73801109

SE 1.3: Financial Hardship Without Platforms

Bootstrap regression Results

Bootstrap regression: 1,000 reps (seed=2025)

N = 52; R^2 = 0.484, Adj R^2 = 0.358, F(10, 41) = 3.84, p 0.00101

Financial Hardship Without Platforms								
Source	Sum of Squares	DF	Mean Square	F	Pr(>F)	R^2	Adj R^2	Root MSE
Model	27.93811	41	0.6814174	3.842301	0.00101415	0.484	0.358	0.853
Residual	29.81189	10	2.9811888					
Total	57.75000	51	1.1323529					

Coefficient Estimates

Financial Hardship Without Platforms					
Variable	b	β	95% CI Low	95% CI High	p-value
dw04_gigincomeperc	0.017316921	0.41170063	0.005589218	0.02904462	0.004802756
e_paidworkhours	0.016291242	0.28271827	-0.001755115	0.03433760	0.075580917
e_unpaidworkhours	0.002858262	0.05849505	-0.020515571	0.02623209	0.806172412
e_skilldunpaidhours	-0.003529729	-0.05741062	-0.032445839	0.02538638	0.806508990
e_genderMale	-0.040143750	-0.03772481	-0.552754434	0.47246693	0.875111060
eduBachelor's or higher	-0.350503067	-0.32938280	-1.003739401	0.30273327	0.284867949
age_grouped25–34	0.532162688	0.50009615	-0.188885044	1.25321042	0.143745668
age_grouped35+	0.522510199	0.49102530	-0.312206617	1.35722701	0.213306008
e_gigexp3–5	-0.258210831	-0.24265182	-1.041051756	0.52463009	0.509064187
e_gigexp5+	0.359397636	0.33774141	-0.366401896	1.08519717	0.323163772

Standard Errors Regression Results

Model Summary

- Number of observations: 52
- F-statistic (df = 10, 41): 3.84
- p-value (overall model): 0.0010
- R-squared: 0.4838
- Adjusted R-squared: 0.3579
- Root MSE: 0.8527

Table: OLS Regression Results for Financial Hardship Without Platforms (N = 52)

Variable	Coefficient	Std. Error	t	p-value	95% Confidence Interval
dw04_gigincomeperc	0.0173	0.0058	2.98	0.005	[0.0056, 0.0290]
e_paidworkhours	0.0163	0.0089	1.82	0.076	[−0.0018, 0.0343]
e_unpaidworkhours	0.0029	0.0116	0.25	0.806	[−0.0205, 0.0262]
e_skilldunpaidhours	−0.0035	0.0143	−0.25	0.807	[−0.0324, 0.0254]
Gender: Male	−0.0401	0.2538	−0.16	0.875	[−0.5528, 0.4725]
Education: Bachelor's or higher	−0.3505	0.3235	−1.08	0.285	[−1.0037, 0.3027]
Age: 25–34	0.5322	0.3570	1.49	0.144	[−0.1889, 1.2532]
Age: 35+	0.5225	0.4133	1.26	0.213	[−0.3122, 1.3572]
Experience: 3–5 years	−0.2582	0.3876	−0.67	0.509	[−1.0411, 0.5246]
Experience: >5 years	0.3594	0.3594	1.00	0.323	[−0.3664, 1.0852]
Constant	0.7126	0.6195	1.15	0.257	[−0.5385, 1.9636]

SE2: Adequate Earnings and Productive Work

SE2.1: Financial Satisfaction

Bootstrap regression Results

Bootstrap regression: 1,000 reps (seed=2025)

N = 52; R^2 = 0.374, Adj R^2 = 0.221, F(10, 41) = 2.45, p 0.0213

Financial Satisfaction								
Source	Sum of Squares	DF	Mean Square	F	Pr(>F)	R^2	Adj R^2	Root MSE
Model	13.48743	41	0.3289618	2.450060	0.02132325	0.374	0.221	0.742
Residual	22.57026	10	2.2570257					
Total	36.05769	51	0.7070136					
Financial Satisfaction								

Financial Satisfaction							
Source	Sum of Squares	DF	Mean Square	F	Pr(>F)	R^2	Adj R^2	Root MSE
Variable	b		β		95% CI Low	95% CI High	p-value	
dw04_gigincomeperc	0.0099868682		0.30048113		-0.0002175083	0.020191245	0.05485210	
e_paidworkhours	0.0009052809		0.01988200		-0.0147970112	0.016607573	0.90787850	
e_unpaidworkhours	-0.0219435113		-0.56832955		-0.0422812868	-0.001605736	0.03513369	
e_skilldunpaidhours	0.0107001404		0.22025075		-0.0144600193	0.035860300	0.39540453	
e_genderMale	0.3301221937		0.39260954		-0.1159048264	0.776149214	0.14263934	
eduBachelor's or higher	-0.4688596651		-0.55760800		-1.0372462879	0.099526958	0.10335484	
age_grouped25–34	-0.0253692484		-0.03017128		-0.6527591597	0.602020663	0.93531245	
age_grouped35+	-0.3160464261		-0.37586943		-1.0423407962	0.410247944	0.38463028	
e_gigexp3–5	-0.2048778789		-0.24365829		-0.8860345850	0.476278827	0.54691123	
e_gigexp5+	0.0559776877		0.06657345		-0.5755468053	0.687502181	0.85881150	

Standard Errors Regression Results

Model Summary

- Number of observations: 52
- F-statistic (df = 10, 41): 2.45
- p-value (overall model): 0.0213
- R-squared: 0.3741
- Adjusted R-squared: 0.2214
- Root MSE: 0.7420

Table: OLS Regression Results for Financial Satisfaction (N = 52)

Variable	Coefficient	Std. Error	t	p-value	95% Confidence Interval
dw04_gigincomeperc	0.0100	0.0051	1.98	0.055	[−0.0002, 0.0202]
e_paidworkhours	0.0009	0.0078	0.12	0.908	[−0.0148, 0.0166]
e_unpaidworkhours	−0.0219	0.0101	−2.18	0.035	[−0.0423, −0.0016]
e_skilldunpaidhours	0.0107	0.0125	0.86	0.395	[−0.0145, 0.0359]
Gender: Male	0.3301	0.2209	1.49	0.143	[−0.1159, 0.7761]
Education: Bachelor's or higher	−0.4689	0.2814	−1.67	0.103	[−1.0372, 0.0995]
Age: 25–34	−0.0254	0.3107	−0.08	0.935	[−0.6528, 0.6020]
Age: 35+	−0.3160	0.3596	−0.88	0.385	[−1.0423, 0.4102]
Experience: 3–5 years	−0.2049	0.3373	−0.61	0.547	[−0.8860, 0.4763]
Experience: >5 years	0.0560	0.3127	0.18	0.859	[−0.5755, 0.6875]
Constant	2.2557	0.5390	4.18	0.000	[1.1672, 3.3443]

SE2.2 Income Consistency

Bootstrap Regression Results

Bootstrap regression: 1,000 reps (seed=2025)

N = 50; R^2 = 0.179, Adj R^2 = -0.032, F(10, 39) = 0.85, p 0.587

Platform Income Consistency								
Source	Sum of Squares	DF	Mean Square	F	Pr(>F)	R^2	Adj R^2	Root MSE
Model		41		0.8478543	0.5871489	0.179	-0.032	0.99
Residual	38.1962	10	3.81962					
Total		51						

Platform Income Consistency					
Variable	b	β	95% CI Low	95% CI High	p-value
dw04_gigincomeperc	0.0031181037	0.08026293	-0.01099481	0.01723102	0.65742435
e_paidworkhours	0.0041608867	0.08046662	-0.01681966	0.02514144	0.69050480
e_unpaidworkhours	0.0008868065	0.02012435	-0.02730264	0.02907625	0.94958871
e_skilldunpaidhours	-0.0043679263	-0.07868047	-0.03942800	0.03069215	0.80236817

Platform Income Consistency							
Source	Sum of Squares	DF	Mean Square	F	Pr(>F)	R^2	Adj R^2	Root MSE
e_genderMale	0.1336528421		0.13719863	-0.47911465	0.74642033		0.66152173
eduBachelor's or higher	-0.0796263667		-0.08173884	-0.88386140	0.72460866		0.84231458
age_grouped25–34	0.7156199765		0.73460524	-0.12378958	1.55502953		0.09255452
age_grouped35+	0.1536969800		0.15777453	-0.87872189	1.18611585		0.76492299
e_gigexp3–5	0.4903816340		0.50339136	-0.47431474	1.45507800		0.31019575
e_gigexp5+	0.4886141881		0.50157703	-0.44845414	1.42568252		0.29805800

Standard Errors Regression Results

Model Summary

- Number of observations: 50
- F-statistic (df = 10, 39): 0.85
- p-value (overall model): 0.5871
- R-squared: 0.1786
- Adjusted R-squared: −0.0320
- Root MSE: 0.9896

Table: OLS Regression Results for Income Consistency (N = 50)

Variable	Coefficient	Std. Error	t	p-value	95% Confidence Interval
dw04_gigincomeperc	0.0031	0.0070	0.45	0.657	[−0.0110, 0.0172]
e_paidworkhours	0.0042	0.0104	0.40	0.691	[−0.0168, 0.0251]
e_unpaidworkhours	0.0009	0.0139	0.06	0.950	[−0.0273, 0.0291]
e_skilldunpaidhours	−0.0044	0.0173	−0.25	0.802	[−0.0394, 0.0307]
Gender: Male	0.1337	0.3029	0.44	0.662	[−0.4791, 0.7464]
Education: Bachelor’s or higher	−0.0796	0.3976	−0.20	0.842	[−0.8839, 0.7246]
Age: 25–34	0.7156	0.4150	1.72	0.093	[−0.1238, 1.5550]

Variable	Coefficient	Std. Error	t	p-value	95% Confidence Interval
Age: 35+	0.1537	0.5104	0.30	0.765	[−0.8787, 1.1861]
Experience: 3–5 years	0.4904	0.4769	1.03	0.310	[−0.4743, 1.4551]
Experience: >5 years	0.4886	0.4633	1.05	0.298	[−0.4485, 1.4257]
Constant	0.1320	0.7267	0.18	0.857	[−1.3378, 1.6019]

SE 2.3 Skill Development and Utility

Bootstrap Regression Results

Bootstrap regression: 1,000 reps (seed=2025)

N = 52; R^2 = 0.229, Adj R^2 = 0.041, F(10, 41) = 1.22, p 0.31

Skill Development and Productive Use

Source	Sum of Squares	DF	Mean Square	F	Pr(>F)	R^2	Adj R^2	Root MSE
Model	8.056953	41	0.1965110	1.216115	0.3096309	0.229	0.041	0.814
Residual	27.163133	10	2.7163133					
Total	35.220085	51	0.6905899					

Skill Development and Productive Use

Variable	b	β	95% CI Low	95% CI High	p-value
dw04_gigincomeperc	-0.002708760	-0.08246357	-0.013903349	0.008485829	0.62767963
e_paidworkhours	0.014083119	0.31295315	-0.003142892	0.031309130	0.10636370
e_unpaidworkhours	0.008972489	0.23513150	-0.013338824	0.031283801	0.42139162
e_skilldunpaidhours	-0.008370991	-0.17434461	-0.035972642	0.019230661	0.54360017
e_genderMale	-0.416147277	-0.50076843	-0.905455867	0.073161313	0.09341882
eduBachelor's or higher	-0.251525564	-0.30267184	-0.875067288	0.372016160	0.41998145
age_grouped25–34	0.328639662	0.39546665	-0.359630911	1.016910235	0.34054762
age_grouped35+	0.042310466	0.05091406	-0.754462057	0.839082990	0.91511982
e_gigexp3–5	-0.589318433	-0.70915294	-1.336573223	0.157936358	0.11890897
e_gigexp5+	0.149032164	0.17933700	-0.543774203	0.841838530	0.66625338

Standard Errors Regression Results

Table: OLS Regression Results for Skill and Productivity (N = 52)

SE 3: Decent Working Time

Bootstrap Regression Results

Schedule Autonomy & Agency

Bootstrap regression: 1,000 reps (seed=2025)

N = 52; R^2 = 0.146, Adj R^2 = -0.062, F(10, 41) = 0.70, p 0.716

Schedule Autonomy & Agency								
Source	Sum of Squares	DF	Mean Square	F	Pr(>F)	R^2	Adj R^2	Root MSE
Model	7.463024	41	0.182025	0.7025813	0.7164406	0.146	-0.062	1.031
Residual	43.551399	10	4.355140					
Total	51.014423	51	1.000283					

Schedule Autonomy & Agency					
Variable	b	β	95% CI Low	95% CI High	p-value
dw04_gigincomeperc	-0.009816264	-0.24830563	-0.02399114	0.004358612	0.1694654
e_paidworkhours	0.008151871	0.15051733	-0.01366015	0.029963889	0.4547013
e_unpaidworkhours	-0.006381474	-0.13895290	-0.03463263	0.021869683	0.6506670
e_skilldunpaidhours	0.020982774	0.36311425	-0.01396715	0.055932694	0.2322747
e_genderMale	-0.134565663	-0.13454664	-0.75414078	0.485009452	0.6632363
eduBachelor's or higher	0.072339157	0.07232893	-0.71720540	0.861883716	0.8541154
age_grouped25–34	-0.475779513	-0.47571225	-1.34728541	0.395726379	0.2766637
age_grouped35+	-0.194122512	-0.19409507	-1.20301636	0.814771338	0.6995957
e_gigexp3–5	-0.369902189	-0.36984989	-1.31609541	0.576291035	0.4343541
e_gigexp5+	0.022807172	0.02280395	-0.85444206	0.900056402	0.9583813

Standard Errors Regression Results

Model Summary

- Number of observations: 52
- F-statistic (df = 10, 41): 0.70
- p-value (overall model): 0.7164
- R-squared: 0.1463
- Adjusted R-squared: −0.0619
- Root MSE: 1.0306

Table: OLS Regression Results for Schedule Autonomy and Negotiability (N = 52)

Variable	Coefficient	Std. Error	t	p-value	95% Confidence Interval
dw04_gigincomeperc	−0.0098	0.0070	−1.40	0.169	[−0.0240, 0.0044]
e_paidworkhours	0.0082	0.0108	0.75	0.455	[−0.0137, 0.0300]
e_unpaidworkhours	−0.0064	0.0140	−0.46	0.651	[−0.0346, 0.0219]
e_skilldunpaidhours	0.0210	0.0173	1.21	0.232	[−0.0140, 0.0559]
Gender: Male	−0.1346	0.3068	−0.44	0.663	[−0.7541, 0.4850]
Education: Bachelor's or higher	0.0723	0.3910	0.19	0.854	[−0.7172, 0.8619]
Age: 25–34	−0.4758	0.4315	−1.10	0.277	[−1.3473, 0.3957]
Age: 35+	−0.1941	0.4996	−0.39	0.700	[−1.2030, 0.8148]
Experience: 3–5 years	−0.3699	0.4685	−0.79	0.434	[−1.3161, 0.5763]
Experience: >5 years	0.0228	0.4344	0.05	0.958	[−0.8544, 0.9001]
Constant	2.7804	0.7487	3.71	0.001	[1.2683, 4.2925]

SE 4: Combining Work, Family, and Personal Life

Bootstrap Regression Results

Work & Life Satisfaction & Fulfilment

Bootstrap regression: 1,000 reps (seed=2025)

N = 52; R^2 = 0.433, Adj R^2 = 0.295, F(10, 41) = 3.14, p 0.00461

Work & Life Satisfaction & Fulfilment

Source	Sum of Squares	DF	Mean Square	F	Pr(>F)	R^2	Adj R^2	Root MSE
Model	10.91789	41	0.2662900	3.137323	0.00461355	0.433	0.295	0.59

Work & Life Satisfaction & Fulfilment								
Source	Sum of Squares	DF	Mean Square	F	Pr(>F)	R^2	Adj R^2	Root MSE
Residual	14.26801	10	1.4268008					
Total	25.18590	51	0.4938411					

Work & Life Satisfaction & Fulfilment					
Variable	b	β	95% CI Low	95% CI High	p-value
dw04_gigincomeperc	0.006889180	0.24801369	-0.001224164	0.015002523656	0.09392737
e_paidworkhours	0.009245185	0.24294759	-0.003239467	0.021729838077	0.14243733
e_unpaidworkhours	-0.016163227	-0.50089009	-0.032333482	0.000007027567	0.05009508
e_skilldunpaidhours	0.011897821	0.29303237	-0.008106638	0.031902279733	0.23659034
e_genderMale	-0.011245088	-0.01600181	-0.365874358	0.343384183113	0.94925081
eduBachelor's or higher	-0.160175546	-0.22793057	-0.612091067	0.291739976124	0.47817202
age_grouped25–34	-0.174930181	-0.24892649	-0.673758316	0.323897954520	0.48281757
age_grouped35+	-0.127373008	-0.18125241	-0.704838568	0.450092551520	0.65833414
e_gigexp3–5	0.072451146	0.10309833	-0.469126147	0.614028437876	0.78838462
e_gigexp5+	0.582140448	0.82838867	0.080024970	1.084255925659	0.02415215

Standard Errors Regression Results

Model Summary

- Number of observations: 52
- F-statistic (df = 10, 41): 3.14
- p-value (overall model): 0.0046
- R-squared: 0.4335
- Adjusted R-squared: 0.2953
- Root MSE: 0.5899

Table: OLS Regression Results for Life and Work Satisfaction (N = 52)

Variable	Coefficient	Std. Error	t	p-value	95% Confidence Interval
dw04_gigincomeperc	0.0069	0.0040	1.71	0.094	[−0.0012, 0.0150]
e_paidworkhours	0.0092	0.0062	1.50	0.142	[−0.0032, 0.0217]

Variable	Coefficient	Std. Error	t	p-value	95% Confidence Interval
e_unpaidworkhours	−0.0162	0.0080	−2.02	0.050	[−0.0323, 0.0000]
e_skilldunpaidhours	0.0119	0.0099	1.20	0.237	[−0.0081, 0.0319]
Gender: Male	−0.0112	0.1756	−0.06	0.949	[−0.3659, 0.3434]
Education: Bachelor's or higher	−0.1602	0.2238	−0.72	0.478	[−0.6121, 0.2917]
Age: 25–34	−0.1749	0.2470	−0.71	0.483	[−0.6738, 0.3239]
Age: 35+	−0.1274	0.2859	−0.45	0.658	[−0.7048, 0.4501]
Experience: 3–5 years	0.0725	0.2682	0.27	0.788	[−0.4691, 0.6140]
Experience: >5 years	0.5821	0.2486	2.34	0.024	[0.0800, 1.0843]
Constant	2.2005	0.4286	5.13	0.000	[1.3350, 3.0660]

SE 5: Stability and Security of Work

SE 5 Stability & Career Growth

Bootstrap Regression Results

SE Stability & Career Growth

Bootstrap regression: 1,000 reps (seed=2025)

N = 52; R^2 = 0.256, Adj R^2 = 0.075, F(10, 41) = 1.41, p 0.21

Stability & Career Growth								
Source	Sum of Squares	DF	Mean Square	F	Pr(>F)	R^2	Adj R^2	Root MSE
Model	7.02278	41	0.1712873	1.411273	0.2097141	0.256	0.075	0.705
Residual	20.40243	10	2.0402433					
Total	27.42521	51	0.5377493					

Stability & Career Growth					
Variable	b	β	95% CI Low	95% CI High	p-value
dw04_gigincomeperc	-0.003450867	-0.11905292	-0.01315282	0.006251087	0.47662993
e_paidworkhours	0.011484984	0.28922182	-0.00344419	0.026414158	0.12795901
e_unpaidworkhours	0.006113375	0.18155118	-0.01322305	0.025449799	0.52670225

Stability & Career Growth							
Source	Sum of Squares	DF	Mean Square	F	Pr(>F)	R^2	Adj R^2	Root MSE
e_skilldunpaidhours	-0.005781044		-0.13644517	-0.02970242	0.018140330		0.62810766
e_genderMale	-0.305678130		-0.41684486	-0.72974456	0.118388302		0.15308021
eduBachelor's or higher	-0.507009224		-0.69139453	-1.04741076	0.033392313		0.06519269
age_grouped25–34	0.076150246		0.10384400	-0.52034949	0.672649985		0.79783686
age_grouped35+	0.040446230		0.05515541	-0.65008831	0.730980768		0.90641611
e_gigexp3–5	-0.711373980		-0.97008112	-1.35899325	-0.063754707		0.03212784
e_gigexp5+	-0.167316052		-0.22816430	-0.76774680	0.433114698		0.57665923

Standard Errors Regression Results

Model Summary

- Number of observations: 52
- F-statistic (df = 10, 41): 1.41
- p-value (overall model): 0.2097
- R-squared: 0.2561
- Adjusted R-squared: 0.0746
- Root MSE: 0.7054

Table: OLS Regression Results for Stability and Growth (N = 52)

Variable	Coefficient	Std. Error	t	p-value	95% Confidence Interval
dw04_gigincomeperc	−0.0035	0.0048	−0.72	0.477	[−0.0132, 0.0063]
e_paidworkhours	0.0115	0.0074	1.55	0.128	[−0.0034, 0.0264]
e_unpaidworkhours	0.0061	0.0096	0.64	0.527	[−0.0132, 0.0254]
e_skilldunpaidhours	−0.0058	0.0118	−0.49	0.628	[−0.0297, 0.0181]
Gender: Male	−0.3057	0.2100	−1.46	0.153	[−0.7297, 0.1184]
Education: Bachelor’s or higher	−0.5070	0.2676	−1.89	0.065	[−1.0474, 0.0334]
Age: 25–34	0.0762	0.2954	0.26	0.798	[−0.5203, 0.6727]
Age: 35+	0.0404	0.3419	0.12	0.906	[−0.6501, 0.7310]
Experience: 3–5 years	−0.7114	0.3207	−2.22	0.032	[−1.3590, −0.0638]
Experience: >5 years	−0.1673	0.2973	−0.56	0.577	[−0.7677, 0.4331]

Variable	Coefficient	Std. Error	t	p-value	95% Confidence Interval
Constant	3.4435	0.5125	6.72	0.000	[2.4086, 4.4785]

SE 6: Equal Opportunity and Treatment in Employment

SE6.1: Perception Towards Inclusion and Non-Discrimination

Bootstrap Regression Results

Perception Towards Inclusion and Non-Discrimination

Bootstrap regression: 1,000 reps (seed=2025)

N = 52; R^2 = 0.124, Adj R^2 = -0.089, F(10, 41) = 0.58, p 0.819

Perception Towards Inclusion and Non-Discrimination								
Source	Sum of Squares	DF	Mean Square	F	Pr(>F)	R^2	Adj R^2	Root MSE
Model	1.80480	41	0.04401951	0.5822109	0.8188173	0.124	-0.089	0.557
Residual	12.70962	10	1.27096230					
Total	14.51442	51	0.28459653					

Perception Towards Inclusion and Non-Discrimination					
Variable	b	β	95% CI Low	95% CI High	p-value
dw04_gigincomeperc	-0.0039458841	-0.187124769	-0.011603341	0.003711573	0.3041275
e_paidworkhours	0.0046905565	0.162367895	-0.007092586	0.016473699	0.4260767
e_unpaidworkhours	0.0030985321	0.126487960	-0.012163119	0.018360183	0.6839245
e_skilldunpaidhours	-0.0086512813	-0.280677391	-0.027531693	0.010229131	0.3601816
e_genderMale	-0.0008710051	-0.001632698	-0.335573729	0.333831718	0.9958322
eduBachelor's or higher	-0.2674246370	-0.501287198	-0.693947117	0.159097843	0.2125784
age_grouped25–34	-0.1297442567	-0.243205472	-0.600543339	0.341054826	0.5808593
age_grouped35+	-0.1794163366	-0.336315733	-0.724434223	0.365601550	0.5098882
e_gigexp3–5	-0.0766467836	-0.143674315	-0.587792957	0.434499390	0.7635492
e_gigexp5+	0.2201898856	0.412745707	-0.253711825	0.694091596	0.3535632

Standard Errors Regression Results

Table: OLS Regression Results for Work Environment (Reversed Scale) (N = 52)

Model Summary

- Number of observations: 52
- F-statistic (df = 10, 41): 0.58
- p-value (overall model): 0.8188
- R-squared: 0.1243
- Adjusted R-squared: −0.0892
- Root MSE: 0.5568

Variable	Coefficient	Std. Error	t	p-value	95% Confidence Interval
dw04_gigincomeperc	−0.0039	0.0038	−1.04	0.304	[−0.0116, 0.0037]
e_paidworkhours	0.0047	0.0058	0.80	0.426	[−0.0071, 0.0165]
e_unpaidworkhours	0.0031	0.0076	0.41	0.684	[−0.0122, 0.0184]
e_skilldunpaidhours	−0.0087	0.0093	−0.93	0.360	[−0.0275, 0.0102]
Gender: Male	−0.0009	0.1657	−0.01	0.996	[−0.3356, 0.3338]
Education: Bachelor’s or higher	−0.2674	0.2112	−1.27	0.213	[−0.6939, 0.1591]
Age: 25–34	−0.1297	0.2331	−0.56	0.581	[−0.6005, 0.3411]
Age: 35+	−0.1794	0.2699	−0.66	0.510	[−0.7244, 0.3656]
Experience: 3–5 years	−0.0766	0.2531	−0.30	0.764	[−0.5878, 0.4345]
Experience: >5 years	0.2202	0.2347	0.94	0.354	[−0.2537, 0.6941]
Constant	4.1286	0.4045	10.21	0.000	[3.3117, 4.9454]

SE6.2: Platform Policy Protection

Bootstrap Regression Results

Bootstrap regression: 1,000 reps (seed=2025)

N = 52; R^2 = 0.111, Adj R^2 = -0.105, F(10, 41) = 0.51, p 0.87

Platform Policy Protection								
Source	Sum of Squares	DF	Mean Square	F	Pr(>F)	R^2	Adj R^2	Root MSE
Model	10.16660	41	0.2479659	0.513711	0.870484	0.111	-0.105	1.407
Residual	81.14109	10	8.1141090					
Total	91.30769	51	1.7903469					

Platform Policy Protection					
Variable	b	β	95% CI Low	95% CI High	p-value
dw04_gigincomeperc	-0.0083562292	-0.157995059	-0.02770434	0.01099188	0.3881696
e_paidworkhours	0.0005742104	0.007924887	-0.02919828	0.03034670	0.9691192
e_unpaidworkhours	-0.0016881110	-0.027475170	-0.04024976	0.03687354	0.9299818
e_skilldunpaidhours	0.0028985163	0.037492893	-0.04480667	0.05060370	0.9029401
e_genderMale	-0.3160663647	-0.236216204	-1.16176052	0.52962779	0.4546977
eduBachelor's or higher	-0.0540227056	-0.040374554	-1.13171806	1.02367265	0.9198570
age_grouped25–34	0.2985927527	0.223157079	-0.89097640	1.48816190	0.6149243
age_grouped35+	-0.5273709742	-0.394137382	-1.90446895	0.84972700	0.4437223
e_gigexp3–5	0.2497544451	0.186657150	-1.04175979	1.54126868	0.6981584
e_gigexp5+	0.5090905004	0.380475239	-0.68831807	1.70649907	0.3955377

SE 7: Safe Work Environment

SE7.1 Well-Being and Safety

Bootstrap Regression Results

Bootstrap regression: 1,000 reps (seed=2025)

N = 52; R^2 = 0.186, Adj R^2 = -0.012, F(10, 41) = 0.94, p 0.51

Well-Being and Safety

Source	Sum of Squares	DF	Mean Square	F	Pr(>F)	R^2	Adj R^2	Root MSE
Model	5.398799	41	0.1316780	0.9373064	0.5102051	0.186	-0.012	0.759
Residual	23.615624	10	2.3615624					
Total	29.014423	51	0.5689103					

Well-Being and Safety

Variable	b	β	95% CI Low	95% CI High	p-value
dw04_gigincomeperc	-0.001513336	-0.05075925	-0.01195135	0.008924679	0.77115234
e_paidworkhours	-0.006163479	-0.15090188	-0.02222529	0.009898332	0.44280499
e_unpaidworkhours	-0.004629424	-0.13366358	-0.02543285	0.016174004	0.65550128
e_skilldunpaidhours	0.004554162	0.10450291	-0.02118206	0.030290387	0.72264900
e_genderMale	0.146548215	0.19429367	-0.30969102	0.602787445	0.52015263
eduBachelor's or higher	-0.429398938	-0.56929725	-1.01079931	0.152001434	0.14347147
age_grouped25–34	-0.466691134	-0.61873925	-1.10844573	0.175063462	0.14956360
age_grouped35+	-0.422802036	-0.56055107	-1.16572560	0.320121530	0.25707964
e_gigexp3–5	0.722822443	0.95831822	0.02607001	1.419574875	0.04238115
e_gigexp5+	0.409035520	0.54229942	-0.23694832	1.055019363	0.20816952

Standard Errors Regression Results

Table: OLS Regression Results for Work Safety Risk (Reversed) (N = 52)

Model Summary

- Number of observations: 52
- F-statistic (df = 10, 41): 0.94
- p-value (overall model): 0.5102
- R-squared: 0.1861
- Adjusted R-squared: −0.0124
- Root MSE: 0.7589

Variable	Coefficient	Std. Error	t	p-value	95% Confidence Interval
dw04_gigincomeperc	−0.0015	0.0052	−0.29	0.771	[−0.0120, 0.0089]

Variable	Coefficient	Std. Error	t	p-value	95% Confidence Interval
e_paidworkhours	−0.0062	0.0080	−0.77	0.443	[−0.0222, 0.0099]
e_unpaidworkhours	−0.0046	0.0103	−0.45	0.656	[−0.0254, 0.0162]
e_skilldunpaidhours	0.0046	0.0127	0.36	0.723	[−0.0212, 0.0303]
Gender: Male	0.1465	0.2259	0.65	0.520	[−0.3097, 0.6028]
Education: Bachelor’s or higher	−0.4294	0.2879	−1.49	0.143	[−1.0108, 0.1520]
Age: 25–34	−0.4667	0.3178	−1.47	0.150	[−1.1084, 0.1751]
Age: 35+	−0.4228	0.3679	−1.15	0.257	[−1.1657, 0.3201]
Experience: 3–5 years	0.7228	0.3450	2.10	0.042	[0.0261, 1.4196]
Experience: >5 years	0.4090	0.3199	1.28	0.208	[−0.2369, 1.0550]
Constant	4.1284	0.5514	7.49	0.000	[3.0149, 5.2419]

SE 7.2 Work Stress

Bootstrap Regression Results

Bootstrap regression: 1,000 reps (seed=2025)

N = 52; R^2 = 0.201, Adj R^2 = 0.006, F(10, 41) = 1.03, p 0.437

Stress From Platform Work

Source	Sum of Squares	DF	Mean Square	F	Pr(>F)	R^2	Adj R^2	Root MSE
Model	8.209575	41	0.2002335	1.02891	0.4370669	0.201	0.006	0.893
Residual	32.713502	10	3.2713502					
Total	40.923077	51	0.8024133					

Variable	b	β	95% CI Low	95% CI High	p-value
dw04_gigincomeperc	0.008256254	0.2331770	-0.004028931	0.02054144	0.1821324
e_paidworkhours	-0.005089197	-0.1049158	-0.023993397	0.01381500	0.5896058
e_unpaidworkhours	0.016851392	0.4096800	-0.007633529	0.04133631	0.1720542
e_skilldunpaidhours	-0.015372310	-0.2970174	-0.045662964	0.01491834	0.3114178
e_genderMale	0.359292270	0.4010965	-0.177685652	0.89627019	0.1840166
eduBachelor's or higher	-0.274842505	-0.3068208	-0.959130797	0.40944579	0.4219675
age_grouped25–34	0.510792407	0.5702239	-0.244530736	1.26611555	0.1794701
age_grouped35+	0.191177050	0.2134208	-0.683218500	1.06557260	0.6611345

Stress From Platform Work							
Source	Sum of Squares	DF	Mean Square	F	Pr(>F)	R^2	Adj R^2	Root MSE
e_gigexp3–5		0.265715356	0.2966317	-0.554338353	1.08576907	0.5165241		
e_gigexp5+		-0.100810807	-0.1125403	-0.861111629	0.65949001	0.7902131		

Standard Errors Regression Results

Table: OLS Regression Results for Work Stress (Reversed) (N = 52)

Model Summary

- Number of observations: 52
- F-statistic (df = 10, 41): 1.03
- p-value (overall model): 0.4371
- R-squared: 0.2006
- Adjusted R-squared: 0.0056
- Root MSE: 0.8933

Variable	Coefficient	Std. Error	t	p-value	95% Confidence Interval
dw04_gigincomeperc	−0.0083	0.0061	−1.36	0.182	[−0.0205, 0.0040]
e_paidworkhours	0.0051	0.0094	0.54	0.590	[−0.0138, 0.0240]
e_unpaidworkhours	−0.0169	0.0121	−1.39	0.172	[−0.0413, 0.0076]
e_skilldunpaidhours	0.0154	0.0150	1.02	0.311	[−0.0149, 0.0457]
Gender: Male	−0.3593	0.2659	−1.35	0.184	[−0.8963, 0.1777]
Education: Bachelor’s or higher	0.2748	0.3388	0.81	0.422	[−0.4094, 0.9591]
Age: 25–34	−0.5108	0.3740	−1.37	0.179	[−1.2661, 0.2445]
Age: 35+	−0.1912	0.4330	−0.44	0.661	[−1.0656, 0.6832]
Experience: 3–5 years	−0.2657	0.4061	−0.65	0.517	[−1.0858, 0.5543]
Experience: >5 years	0.1008	0.3765	0.27	0.790	[−0.6595, 0.8611]
Constant	3.3519	0.6489	5.17	0.000	[2.0413, 4.6624]

SE 8: Social Security

SE8.1 Perceived Healthcare Access Through Traditional Work

Bootstrap Regression Results

Bootstrap regression: 1,000 reps (seed=2025)

N = 52; R^2 = 0.163, Adj R^2 = -0.041, F(10, 41) = 0.80, p 0.63

Perceived Healthcare Access Through Traditional Work								
Source	Sum of Squares	DF	Mean Square	F	Pr(>F)	R^2	Adj R^2	Root MSE
Model	8.638379	41	0.2106922	0.799765	0.6295643	0.163	-0.041	1.039
Residual	44.284698	10	4.4284698					
Total	52.923077	51	1.0377074					

Perceived Healthcare Access Through Traditional Work					
Variable	b	β	95% CI Low	95% CI High	p-value
dw04_gigincomeperc	0.0024648698	0.061215062	-0.01182884	0.01675858	0.7294280
e_paidworkhours	0.0086506357	0.156819895	-0.01334425	0.03064552	0.4316003
e_unpaidworkhours	0.0075319153	0.161018571	-0.02095609	0.03601992	0.5962633
e_skilldunpaidhours	0.0006786065	0.011529815	-0.03456432	0.03592153	0.9691696
e_genderMale	-0.3445656430	-0.338247439	-0.96933505	0.28020377	0.2718547
eduBachelor's or higher	-0.0011694642	-0.001148020	-0.79733328	0.79499435	0.9976475
age_grouped25–34	0.0714202706	0.070110657	-0.80739201	0.95023256	0.8704382
age_grouped35+	0.7222210038	0.708977838	-0.29513105	1.73957306	0.1592470
e_gigexp3–5	-0.0046373002	-0.004552267	-0.95876307	0.94948847	0.9922161
e_gigexp5+	-0.3485390455	-0.342147982	-1.23314282	0.53606473	0.4307830

Standard Errors Regression Results

Table: OLS Regression Results for Perceived Healthcare Comparison (N = 52)

Model Summary

- Number of observations: 52
- F-statistic (df = 10, 41): 0.80
- p-value (overall model): 0.6296
- R-squared: 0.1632
- Adjusted R-squared: −0.0409

- Root MSE: 1.0393

Variable	Coefficient	Std. Error	t	p-value	95% Confidence Interval
dw04_gigincomeperc	0.0025	0.0071	0.35	0.729	[−0.0118, 0.0168]
e_paidworkhours	0.0087	0.0109	0.79	0.432	[−0.0133, 0.0306]
e_unpaidworkhours	0.0075	0.0141	0.53	0.596	[−0.0210, 0.0360]
e_skilldunpaidhours	0.0007	0.0175	0.04	0.969	[−0.0346, 0.0359]
Gender: Male	−0.3446	0.3094	−1.11	0.272	[−0.9693, 0.2802]
Education: Bachelor's or higher	−0.0012	0.3942	−0.00	0.998	[−0.7973, 0.7950]
Age: 25–34	0.0714	0.4352	0.16	0.870	[−0.8074, 0.9502]
Age: 35+	0.7222	0.5038	1.43	0.159	[−0.2951, 1.7396]
Experience: 3–5 years	−0.0046	0.4724	−0.01	0.992	[−0.9588, 0.9495]
Experience: >5 years	−0.3485	0.4380	−0.80	0.431	[−1.2331, 0.5361]
Constant	1.8712	0.7550	2.48	0.017	[0.3464, 3.3959]

SE8.2: Healthcare Access after Joining Platform Work

Bootstrap Regression Results

Bootstrap regression: 1,000 reps (seed=2025)

N = 52; R^2 = 0.235, Adj R^2 = 0.048, F(10, 41) = 1.26, p 0.286

Healthcare Access after Joining Platform Work

Source	Sum of Squares	DF	Mean Square	F	Pr(>F)	R^2	Adj R^2	Root MSE
Model	11.54895	41	0.2816818	1.256593	0.2862137	0.235	0.048	0.959
Residual	37.68181	10	3.7681814					
Total	49.23077	51	0.9653092					

Healthcare Access after Joining Platform Work

Variable	b	β	95% CI Low	95% CI High	p-value
dw04_gigincomeperc	0.001225279	0.03155030	-0.01195984	0.01441040	0.85205817
e_paidworkhours	-0.009201104	-0.17294073	-0.02949011	0.01108790	0.36509290

Healthcare Access after Joining Platform Work							
Source	Sum of Squares	DF	Mean Square	F	Pr(>F)	R^2	Adj R^2	Root MSE
e_unpaidworkhours	0.003210964		0.07117216	-0.02306757	0.02948950	0.80632002		
e_skilldunpaidhours	-0.014922398		-0.26287374	-0.04743195	0.01758716	0.35935101		
e_genderMale	0.496826734		0.50567529	-0.07948680	1.07314026	0.08918392		
eduBachelor's or higher	-0.026109459		-0.02657447	-0.76052439	0.70830547	0.94311220		
age_grouped25–34	0.315921925		0.32154854	-0.49473142	1.12657527	0.43578405		
age_grouped35+	0.083446860		0.08493306	-0.85500138	1.02189510	0.85836871		
e_gigexp3–5	0.157981896		0.16079558	-0.72214377	1.03810756	0.71883590		
e_gigexp5+	0.481651952		0.49023025	-0.33434370	1.29764761	0.24009189		

Standard Errors Regression Results

Table: OLS Regression Results for Healthcare Access After Joining Platforms (N = 52)

Model Summary

- Number of observations: 52
- F-statistic (df = 10, 41): 1.26
- p-value (overall model): 0.2862
- R-squared: 0.2346
- Adjusted R-squared: 0.0479
- Root MSE: 0.9587

Variable	Coefficient	Std. Error	t	p-value	95% Confidence Interval
dw04_gigincomeperc	0.0012	0.0065	0.19	0.852	[−0.0120, 0.0144]
e_paidworkhours	−0.0092	0.0100	−0.92	0.365	[−0.0295, 0.0111]
e_unpaidworkhours	0.0032	0.0130	0.25	0.806	[−0.0231, 0.0295]
e_skilldunpaidhours	−0.0149	0.0161	−0.93	0.359	[−0.0474, 0.0176]
Gender: Male	0.4968	0.2854	1.74	0.089	[−0.0795, 1.0731]
Education: Bachelor’s or higher	−0.0261	0.3637	−0.07	0.943	[−0.7605, 0.7083]
Age: 25–34	0.3159	0.4014	0.79	0.436	[−0.4947, 1.1266]
Age: 35+	0.0834	0.4647	0.18	0.858	[−0.8550, 1.0219]

Variable	Coefficient	Std. Error	t	p-value	95% Confidence Interval
Experience: 3–5 years	0.1580	0.4358	0.36	0.719	[−0.7221, 1.0381]
Experience: >5 years	0.4817	0.4041	1.19	0.240	[−0.3343, 1.2976]
Constant	1.5050	0.6965	2.16	0.037	[0.0985, 2.9115]

SE8.3: Savings

Bootstrap Regression Results

Bootstrap regression: 1,000 reps (seed=2025)

N = 52; R^2 = 0.419, Adj R^2 = 0.277, F(10, 41) = 2.95, p 0.00692

% of Platform Income Saved

Source	Sum of Squares	DF	Mean Square	F	Pr(>F)	R^2	Adj R^2	Root MSE
Model	8,651.14	41	211.0034	2.953195	0.006924458	0.419	0.277	17.116
Residual	12,010.61	10	1,201.0610					
Total	20,661.75	51	405.1324					

% of Platform Income Saved

Variable	b	β	95% CI Low	95% CI High	p-value
dw04_gigincomeperc	0.14994463	0.18846652	-0.08545228	0.3853415	0.20551339
e_paidworkhours	0.24317046	0.22310173	-0.11905364	0.6053945	0.18259336
e_unpaidworkhours	-0.07136929	-0.07721841	-0.54052577	0.3977872	0.76023272
e_skilldunpaidhours	0.66483820	0.57168829	0.08443784	1.2452386	0.02579544
e_genderMale	2.06268118	0.10247871	-8.22637285	12.3517352	0.68768202
eduBachelor's or higher	1.42733292	0.07091316	-11.68434061	14.5390064	0.82708155
age_grouped25–34	3.28177388	0.16304602	-11.19100110	17.7545489	0.64941271
age_grouped35+	14.98854393	0.74466507	-1.76578189	31.7428697	0.07815273
e_gigexp3–5	-1.63645371	-0.08130275	-17.34953349	14.0766261	0.83445423
e_gigexp5+	4.64280711	0.23066525	-9.92534535	19.2109596	0.52340661

Standard Errors Regression Results

Table: OLS Regression Results for Savings (N = 52)

Model Summary

- Number of observations: 52
- F-statistic (df = 10, 41): 2.95
- p-value (overall model): 0.0069
- R-squared: 0.4187
- Adjusted R-squared: 0.2769
- Root MSE: 17.1160

Variable	Coefficient	Std. Error	t	p-value	95% Confidence Interval
dw04_gigincomeperc	0.1499	0.1166	1.29	0.206	[−0.0855, 0.3853]
e_paidworkhours	0.2432	0.1794	1.36	0.183	[−0.1191, 0.6054]
e_unpaidworkhours	−0.0714	0.2323	−0.31	0.760	[−0.5405, 0.3978]
e_skilldunpaidhours	0.6648	0.2874	2.31	0.026	[0.0844, 1.2452]
Gender: Male	2.0627	5.0947	0.40	0.688	[−8.2264, 12.3517]
Education: Bachelor’s or higher	1.4273	6.4924	0.22	0.827	[−11.6843, 14.5390]
Age: 25–34	3.2818	7.1664	0.46	0.649	[−11.1910, 17.7546]
Age: 35+	14.9885	8.2961	1.81	0.078	[−1.7658, 31.7429]
Experience: 3–5 years	−1.6365	7.7805	−0.21	0.834	[−17.3495, 14.0766]
Experience: >5 years	4.6428	7.2136	0.64	0.523	[−9.9253, 19.2110]
Constant	−14.4612	12.4340	−1.16	0.252	[−39.5722, 10.6498]

SE 9: Social Dialogue

SE 9.1 Opportunities for Collective Action

Metric	Value
N (Observations)	52
LR Chi-square (df)	20.51 (10)
LR Chi-square p-value	0.025
McFadden R-squared	0.283
Model Type	Ordinal logistic regression; default SE

term	LogOR	StdError	z_value	P_value	OR	CI_low_OR	CI_high_OR	Std_Coefficient	CI_std_low	CI_std_high
dw04_gigincomeperc	-0.067	0.023	-2.854	0.004	0.936	0.894	0.979	-1.683	-3.018	-0.638
e_paidworkhours	0.083	0.035	2.387	0.017	1.086	1.015	1.163	1.530	0.381	2.942
e_unpaidworkhours	0.015	0.038	0.406	0.685	1.015	0.943	1.094	0.334	-1.290	1.991
e_skilldunpaidhours	0.041	0.049	0.838	0.402	1.042	0.947	1.146	0.705	-0.882	2.465
e_genderMale	0.754	0.964	0.782	0.434	2.126	0.321	14.072	0.754	-1.092	2.786
eduBachelor's or higher	-2.084	1.246	-1.673	0.094	0.124	0.011	1.430	-2.084	-4.960	0.208
age_grouped25–34	-0.194	1.260	-0.154	0.877	0.823	0.070	9.730	-0.195	-2.670	2.452
age_grouped35+	-0.725	1.722	-0.421	0.674	0.484	0.017	14.145	-0.725	-4.388	2.640
e_gigexp3–5	0.984	1.509	0.652	0.514	2.675	0.139	51.457	0.984	-1.837	4.450
e_gigexp5+	3.627	1.835	1.977	0.048	37.587	1.031	1370.415	3.627	0.594	7.977

SE 9.2 Participation in Collective Action

Bootstrap Regression Results

Table: Ordered Logistic Regression Results for Collective Action (N = 52, Bootstrap Reps = 965)

Model Summary

- Log-likelihood: −34.748
- Wald $chi^2(10)$: 0.14
- p-value: 1.000
- Pseudo R^2: 0.1949
- Number of Bootstrap Replications: 965
- Note: 35 replications failed; SEs are based only on successful replications.

Variable	Coefficient	Bootstrap SE	z	p-value	95% Confidence Interval
dw04_gigincomeperc	−0.0397	1.8802	−0.02	0.983	[−3.7248, 3.6454]
e_paidworkhours	0.0594	3.1121	0.02	0.985	[−6.0402, 6.1590]
e_unpaidworkhours	0.0051	1.5100	0.00	0.997	[−2.9544, 2.9647]
e_skilldunpaidhours	0.0329	3.3465	0.01	0.992	[−6.5262, 6.5920]
Gender: Male	−0.0018	32.7209	−0.00	1.000	[−64.1335, 64.1299]
Education: Bachelor's or higher	−0.5556	54.3598	−0.01	0.992	[−107.0989, 105.9877]
Age: 25–34	0.6085	38.8631	0.02	0.988	[−75.5619, 76.7788]
Age: 35+	1.3026	38.6061	0.03	0.973	[−74.3639, 76.9691]
Experience: 3–5 years	0.7365	77.2977	0.01	0.992	[−150.7643, 152.2373]
Experience: >5 years	0.7711	46.7051	0.02	0.987	[−90.7691, 92.3114]

Cut Points

- /cut1: 2.0538 (SE = 37.9341)
- /cut2: 4.0097 (SE = 82.9463)

Standard Errors Regression Results

SE Participation in Collective Action

Metric	Value
N (Observations)	52
LR Chi-square (df)	16.83 (10)
LR Chi-square p-value	0.078
McFadden R-squared	0.195
Model Type	Ordinal logistic regression; default SE

term	LogOR	StdError	z_value	P_value	OR	CI_low_OR	CI_high_OR	Std_Coefficient	CI_std_low	CI_std_high
dw04_gigincomeperc	-0.04	0.02	-2.34	0.02	0.96	0.93	0.99	-1.01	-1.90	-0.18
e_paidworkhours	0.06	0.03	2.34	0.02	1.06	1.01	1.12	1.10	0.22	2.08

e_unpaidworkhours	0.01	0.03	0.17	0.86	1.01	0.95	1.07	0.11	-1.20	1.42
e_skilldunpaidhours	0.03	0.04	0.89	0.37	1.03	0.96	1.11	0.57	-0.68	1.86
e_genderMale	0.00	0.70	0.00	1.00	1.00	0.26	3.91	0.00	-1.38	1.39
eduBachelor's or higher	-0.56	0.90	-0.62	0.54	0.57	0.10	3.36	-0.56	-2.36	1.27
age_grouped25–34	0.61	1.07	0.57	0.57	1.84	0.22	15.01	0.61	-1.36	3.00
age_grouped35+	1.30	1.34	0.97	0.33	3.68	0.27	50.88	1.30	-1.23	4.16
e_gigexp3–5	0.74	1.10	0.67	0.50	2.09	0.24	18.16	0.74	-1.34	3.12
e_gigexp5+	0.77	1.13	0.68	0.49	2.16	0.24	19.72	0.77	-1.31	3.26

SE9.3 Labour Organizations Helpfulness

Metric	Value
N (Observations)	52
LR Chi-square (df)	9.56 (10)
LR Chi-square p-value	0.480
McFadden R-squared	0.149
Model Type	Binary logistic regression; default SE

term	LogOR	StdError	z_value	P_value	OR	CI_low_OR	CI_high_OR	Std_Coefficient	CI_std_low	CI_std_high
dw04_gigincomeperc	-0.014	0.015	-0.931	0.352	0.986	-0.046	0.016	-0.361	-1.153	0.398
e_paidworkhours	-0.023	0.026	-0.874	0.382	0.978	-0.077	0.027	-0.418	-1.422	0.493
e_unpaidworkhours	-0.060	0.036	-1.690	0.091	0.942	-0.137	0.006	-1.308	-2.978	0.127
e_skilldunpaidhours	0.101	0.046	2.198	0.028	1.106	0.018	0.201	1.742	0.310	3.480
e_genderMale	0.584	0.741	0.788	0.431	1.792	-0.831	2.131	0.584	-0.831	2.131
eduBachelor's or higher	-0.629	0.917	-0.686	0.493	0.533	-2.450	1.246	-0.629	-2.450	1.246
age_grouped25–34	-0.412	0.975	-0.422	0.673	0.663	-2.352	1.589	-0.412	-2.352	1.589

age_grouped35+	-0.527	1.136	-0.464	0.642	0.590	-2.880	1.702	-0.527	-2.880	1.702
e_gigexp3–5	0.947	1.168	0.810	0.418	2.577	-1.225	3.488	0.947	-1.225	3.488
e_gigexp5+	0.736	1.122	0.656	0.512	2.088	-1.339	3.203	0.736	-1.339	3.203

SE 9.4: Input in Public Policy

Bootstrap Regression Results

Bootstrap regression: 1,000 reps (seed=2025)

N = 52; R^2 = 0.057, Adj R^2 = -0.173, F(10, 41) = 0.25, p 0.989

Input in Public Policy

Source	Sum of Squares	DF	Mean Square	F	Pr(>F)	R^2	Adj R^2	Root MSE
Model	2.830269	41	0.06903096	0.2467367	0.9889532	0.057	-0.173	1.071
Residual	47.030308	10	4.70303076					
Total	49.860577	51	0.97765837					

Input in Public Policy

Variable	b	β	95% CI Low	95% CI High	p-value
dw04_gigincomeperc	-0.0027109731	-0.06936389	-0.01744112	0.01201918	0.7120442
e_paidworkhours	-0.0006696636	-0.01250702	-0.02333612	0.02199680	0.9527117
e_unpaidworkhours	-0.0024690863	-0.05438144	-0.03182693	0.02688875	0.8659636
e_skilldunpaidhours	0.0109681869	0.19199198	-0.02535083	0.04728720	0.5452985
e_genderMale	0.2568715281	0.25978999	-0.38697420	0.90071726	0.4250500
eduBachelor's or higher	-0.1685898678	-0.17050531	-0.98906326	0.65188352	0.6803253
age_grouped25–34	-0.1120851030	-0.11335856	-1.01773050	0.79356029	0.8038789
age_grouped35+	-0.2751932383	-0.27831986	-1.32360849	0.77322201	0.5989025
e_gigexp3–5	0.2800197601	0.28320122	-0.70323869	1.26327821	0.5683396
e_gigexp5+	0.3451361826	0.34905746	-0.56647754	1.25674990	0.4488904

Standard Errors Regression Results

Model Summary

- Number of observations: 52
- F-statistic (df = 10, 41): 0.25
- p-value (overall model): 0.9890
- R-squared: 0.0568
- Adjusted R-squared: −0.1733
- Root MSE: 1.0710

Table: OLS Regression Results for Policy Participation (N = 52)

Variable	Coefficient	Std. Error	t	p-value	95% Confidence Interval
dw04_gigincomeperc	−0.0027	0.0073	−0.37	0.712	[−0.0174, 0.0120]
e_paidworkhours	−0.0007	0.0112	−0.06	0.953	[−0.0233, 0.0220]
e_unpaidworkhours	−0.0025	0.0145	−0.17	0.866	[−0.0318, 0.0269]
e_skilldunpaidhours	0.0110	0.0180	0.61	0.545	[−0.0254, 0.0473]
Gender: Male	0.2569	0.3188	0.81	0.425	[−0.3870, 0.9007]
Education: Bachelor’s or higher	−0.1686	0.4063	−0.41	0.680	[−0.9891, 0.6519]
Age: 25–34	−0.1121	0.4484	−0.25	0.804	[−1.0177, 0.7936]
Age: 35+	−0.2752	0.5191	−0.53	0.599	[−1.3236, 0.7732]
Experience: 3–5 years	0.2800	0.4869	0.58	0.568	[−0.7032, 1.2633]
Experience: >5 years	0.3451	0.4514	0.76	0.449	[−0.5665, 1.2568]
Constant	0.6320	0.7781	0.81	0.421	[−0.9393, 2.2033]

SE 9.5 Expression Freedom

Bootstrap Regression Results

Bootstrap regression: 1,000 reps (seed=2025)

N = 52; R^2 = 0.266, Adj R^2 = 0.087, F(10, 41) = 1.49, p 0.179

Expression Freedom

Source	Sum of Squares	DF	Mean Square	F	Pr(>F)	R^2	Adj R^2	Root MSE
Model	16.54812	41	0.4036127	1.488477	0.1786359	0.266	0.087	1.054
Residual	45.58169	10	4.5581686					

Expression Freedom								
Source	Sum of Squares	DF	Mean Square	F	Pr(>F)	R^2	Adj R^2	Root MSE
Total	62.12981	51	1.2182315					

Expression Freedom					
Variable	b	β	95% CI Low	95% CI High	p-value
dw04_gigincomeperc	-0.009534042	-0.21853142	-0.02403556	0.004967474	0.19160599
e_paidworkhours	0.000708621	0.01185604	-0.02160602	0.023023266	0.94917657
e_unpaidworkhours	0.001276279	0.02518190	-0.02762589	0.030178444	0.92937302
e_skilldunpaidhours	0.018717561	0.29351218	-0.01703773	0.054472853	0.29660496
e_genderMale	-0.099114341	-0.08979902	-0.73296669	0.534738011	0.75376240
eduBachelor's or higher	-0.666774453	-0.60410723	-1.47451296	0.140964050	0.10311731
age_grouped25–34	-0.455498369	-0.41268806	-1.34708689	0.436090151	0.30823666
age_grouped35+	-0.763568135	-0.69180370	-1.79571052	0.268574255	0.14282334
e_gigexp3–5	0.259404093	0.23502383	-0.70859282	1.227401009	0.59130039
e_gigexp5+	1.131773374	1.02540293	0.23430917	2.029237579	0.01472176

Standard Errors Regression Results

Table: OLS Regression Results for Freedom of Expression (N = 52)

Model Summary

- Number of observations: 52
- F-statistic (df = 10, 41): 1.49
- p-value (overall model): 0.1786
- R-squared: 0.2663
- Adjusted R-squared: 0.0874
- Root MSE: 1.0544

Variable	Coefficient	Std. Error	t	p-value	95% Confidence Interval
dw04_gigincomeperc	−0.0095	0.0072	−1.33	0.192	[−0.0240, 0.0050]
e_paidworkhours	0.0007	0.0110	0.06	0.949	[−0.0216, 0.0230]
e_unpaidworkhours	0.0013	0.0143	0.09	0.929	[−0.0276, 0.0302]

Variable	Coefficient	Std. Error	t	p-value	95% Confidence Interval
e_skilldunpaidhours	0.0187	0.0177	1.06	0.297	[−0.0170, 0.0545]
Gender: Male	−0.0991	0.3139	−0.32	0.754	[−0.7330, 0.5347]
Education: Bachelor’s or higher	−0.6668	0.4000	−1.67	0.103	[−1.4745, 0.1410]
Age: 25–34	−0.4555	0.4415	−1.03	0.308	[−1.3471, 0.4361]
Age: 35+	−0.7636	0.5111	−1.49	0.143	[−1.7957, 0.2686]
Experience: 3–5 years	0.2594	0.4793	0.54	0.591	[−0.7086, 1.2274]
Experience: >5 years	1.1318	0.4444	2.55	0.015	[0.2343, 2.0292]
Constant	2.9874	0.7660	3.90	0.000	[1.4405, 4.5344]

SE 9.6: Client Attention to Labour Concerns

Bootstrap Regression Results

Bootstrap regression: 1,000 reps (seed=2025)

N = 52; R^2 = 0.165, Adj R^2 = -0.039, F(10, 41) = 0.81, p 0.622

Client Attention to Labour Concerns

Source	Sum of Squares	DF	Mean Square	F	Pr(>F)	R^2	Adj R^2	Root MSE
Model	12.55915	41	0.3063207	0.8077441	0.6224452	0.165	-0.039	1.247
Residual	63.74854	10	6.3748543					
Total	76.30769	51	1.4962293					

Client Attention to Labour Concerns

Variable	b	β	95% CI Low	95% CI High	p-value
dw04_gigincomeperc	0.005136993	0.10624578	-0.01201258	0.02228657	0.5485562
e_paidworkhours	0.008823535	0.13320917	-0.01756589	0.03521296	0.5033069
e_unpaidworkhours	-0.011831065	-0.21063608	-0.04601093	0.02234880	0.4884697
e_skilldunpaidhours	0.009403632	0.13305719	-0.03288078	0.05168804	0.6557061
e_genderMale	0.233954497	0.19126360	-0.51564286	0.98355185	0.5319877
eduBachelor's or higher	0.517196776	0.42282118	-0.43803932	1.47243287	0.2805805
age_grouped25–34	-0.484350870	-0.39596884	-1.53874846	0.57004672	0.3589917

Client Attention to Labour Concerns							
Source	Sum of Squares	DF	Mean Square	F	Pr(>F)	R^2	Adj R^2	Root MSE
age_grouped35+		0.512245296	0.41877323	-0.70837209	1.73286269			0.4016246
e_gigexp3–5		0.351631264	0.28746727	-0.79312733	1.49638986			0.5384703
e_gigexp5+		-0.017048009	-0.01393717	-1.07839422	1.04429820			0.9742793

Standard Errors Regression Results

Table: OLS Regression Results for Participation in Decision-Making with Clients (N = 52)

Model Summary

- Number of observations: 52
- F-statistic (df = 10, 41): 0.81
- p-value (overall model): 0.6224
- R-squared: 0.1646
- Adjusted R-squared: −0.0392
- Root MSE: 1.2469

Variable	Coefficient	Std. Error	t	p-value	95% Confidence Interval
dw04_gigincomeperc	0.0051	0.0085	0.60	0.549	[−0.0120, 0.0223]
e_paidworkhours	0.0088	0.0131	0.68	0.503	[−0.0176, 0.0352]
e_unpaidworkhours	−0.0118	0.0169	−0.70	0.488	[−0.0460, 0.0223]
e_skilldunpaidhours	0.0094	0.0209	0.45	0.656	[−0.0329, 0.0517]
Gender: Male	0.2340	0.3712	0.63	0.532	[−0.5156, 0.9836]
Education: Bachelor’s or higher	0.5172	0.4730	1.09	0.281	[−0.4380, 1.4724]
Age: 25–34	−0.4844	0.5221	−0.93	0.359	[−1.5387, 0.5700]
Age: 35+	0.5122	0.6044	0.85	0.402	[−0.7084, 1.7329]
Experience: 3–5 years	0.3516	0.5668	0.62	0.538	[−0.7931, 1.4964]
Experience: >5 years	−0.0170	0.5255	−0.03	0.974	[−1.0784, 1.0443]
Constant	0.4105	0.9059	0.45	0.653	[−1.4189, 2.2399]

SE9.7 Platform Policy Participation

Bootstrap Regression Results

Bootstrap regression: 1,000 reps (seed=2025)

N = 52; R^2 = 0.132, Adj R^2 = -0.080, F(10, 41) = 0.62, p 0.786

Participation in Platform Policy Decision								
Source	Sum of Squares	DF	Mean Square	F	Pr(>F)	R^2	Adj R^2	Root MSE
Model	9.428597	41	0.2299658	0.6226421	0.7856782	0.132	-0.08	1.231
Residual	62.085826	10	6.2085826					
Total	71.514423	51	1.4022436					

Participation in Platform Policy Decision					
Variable	b	β	95% CI Low	95% CI High	p-value
dw04_gigincomeperc	-0.005656418	-0.12084579	-0.02258086	0.01126803	0.50348827
e_paidworkhours	0.002262537	0.03528374	-0.02378046	0.02830554	0.86158844
e_unpaidworkhours	-0.012405402	-0.22814298	-0.04613657	0.02132577	0.46187852
e_skilldunpaidhours	0.014165454	0.20704301	-0.02756387	0.05589478	0.49685248
e_genderMale	0.102611568	0.08665320	-0.63714554	0.84236867	0.78078623
eduBachelor's or higher	0.154148981	0.13017540	-0.78854737	1.09684533	0.74290486
age_grouped25–34	-0.910749717	-0.76910797	-1.95130583	0.12980640	0.08456829
age_grouped35+	-0.781286366	-0.65977904	-1.98588025	0.42330752	0.19753795
e_gigexp3–5	0.436570999	0.36867454	-0.69315991	1.56630191	0.43962196
e_gigexp5+	0.743787915	0.62811243	-0.30362560	1.79120143	0.15912324

Standard Errors Regression Results

Model Summary

- Number of observations: 52
- F-statistic (df = 10, 41): 0.62
- p-value (overall model): 0.7857
- R-squared: 0.1318
- Adjusted R-squared: −0.0799
- Root MSE: 1.2306

Table: OLS Regression Results for Platform Participation (N = 52)

Variable	Coefficient	Std. Error	t	p-value	95% Confidence Interval
dw04_gigincomeperc	−0.0057	0.0084	−0.67	0.503	[−0.0226, 0.0113]
e_paidworkhours	0.0023	0.0129	0.18	0.862	[−0.0238, 0.0283]
e_unpaidworkhours	−0.0124	0.0167	−0.74	0.462	[−0.0461, 0.0213]
e_skilldunpaidhours	0.0142	0.0207	0.69	0.497	[−0.0276, 0.0559]
Gender: Male	0.1026	0.3663	0.28	0.781	[−0.6371, 0.8424]
Education: Bachelor’s or higher	0.1541	0.4668	0.33	0.743	[−0.7885, 1.0968]
Age: 25–34	−0.9107	0.5152	−1.77	0.085	[−1.9513, 0.1298]
Age: 35+	−0.7813	0.5965	−1.31	0.198	[−1.9859, 0.4233]
Experience: 3–5 years	0.4366	0.5594	0.78	0.440	[−0.6932, 1.5663]
Experience: >5 years	0.7438	0.5186	1.43	0.159	[−0.3036, 1.7912]
Constant	1.4417	0.8940	1.61	0.114	[−0.3637, 3.2471]

Appendix C

Interview Guide

Interview Guiding Questions

Warm-up Question: Introduction: minutes 00 - 05

- Tell me briefly about your background and how you started doing online platform work.

Decent and Meaningful Work: minutes 05-18

- What motivates you to continue working on online platforms rather than working locally with a company?
- How would you rate the quality of the platform work opportunities available to you when compared to local jobs, in terms of providing stable income, benefits, and career advancement prospects?
- What are the biggest challenges you face in accessing decent quality platform work opportunities that meet your needs?
- To what extent would you face financial hardship if you did not have access to platform work?

Skills Development: minutes 18-30

- In what ways has your platform work allowed you to develop new skills or knowledge? Can you give examples?
- How has working on digital platforms influenced your long-term career goals?
- How transferable do you feel the skills you gain from platform work are to employment opportunities available locally?
- Do you think local employers value and recognize the skills and experience you gain from online platform work? Why or why not
- Do you think local employers value and recognize the skills and experience you gain from online platform work? Why or why not?
- What opportunities do you see for improving your career prospects through platform work?
- What strategies are you using to build resilience and adaptability in case of disruptions to the types of platform work you currently do?

AI and Remote Work: minutes 30-38

- How concerned are you about AI or automation replacing aspects of your platform work?
- Do you think your current skillset would allow you to transition to new opportunities if some of your work was automated?
- What kinds of training or support do you think would be helpful in preparing you for such a transition?

- Do you think remote work trends globally are improving or worsening the availability of online platform jobs?

Local employment market: minutes 38-45

- Has your platform work experience so far helped open up additional local job opportunities that you didn't previously have access to?
- How transferable do you feel the skills you gain from platform work are to employment opportunities available locally?
- How does the income and job security you have through platform work compare to employment opportunities available to you locally?

Conclusion: minutes 45-55

- What role do you think local organizations (unions, NGOs, government) could play in promoting the rights of platform workers?
- What policies or regulations would you like to see implemented to improve conditions for platform workers?
- Is there anything else you'd like to add about your experiences as a platform worker?

Appendix D

Platform Work and AI: Task Characteristic Scoring Criteria

Descriptive Anchors

Task Modularity and Granularity (TMG):

Measures how easily a task can be broken down into independent, discrete sub-tasks. A score of 1 indicates that the task is highly integrated with little separation between components, while a score of 10 means it can be segmented into clear, modular parts with well-defined boundaries.

Context Dependence (CD):

Assesses the extent to which a task relies on situational, cultural, or environment-specific details. A score of 1 signifies that the task is largely standardized and context-independent, whereas a score of 10 indicates that success in the task requires nuanced interpretation of context-specific cues and information.

Social & Interactive Complexity (SIC):

Evaluates the level of interpersonal interaction and collaborative effort required to complete a task. A score of 1 means the task is performed almost entirely independently with minimal social engagement, while a score of 10 reflects tasks that demand significant real-time interaction, negotiation, and collaborative problem-solving.

Data Availability and Quality (DAQ):

Reflects how much reliable, structured, and high-quality data is accessible to support task execution. A score of 1 denotes that data is scarce, poorly organized, or unreliable, whereas a score of 10 indicates abundant, well-structured, and dependable data that facilitates efficient task completion.

Decision Complexity under Uncertainty (DCU):

Captures the degree of cognitive effort and uncertainty involved in making decisions related to the task. A score of 1 implies that decisions are straightforward, well-defined, and made under clear conditions, while a score of 10 indicates highly complex decision-making that requires extensive judgment and adaptation under ambiguous or uncertain circumstances.

Substitution Impact (SI) Pairwise Matrix

Substitution Impact (SI) Pairwise Matrix **Criteria**	**TMG**	**CD**	**SIC**	**DAQ**	**DCU**
TMG	1	3	3	1/3	1
CD	1/3	1	3	1/5	1/3
SIC	1/3	1/3	1	1/5	1/5
DAQ	3	5	5	1	5
DCU	1	3	5	1/5	1

Data Availability and Quality (DAQ)

DAQ vs. TMG (3 vs. 1/3):

Prediction tasks are heavily data-driven, and improved data quality directly reduces the cost and increases the accuracy of substitution. High-quality, abundant data is fundamental for accurate AI predictions. Even if a task is modular (TMG), without sufficient data the AI cannot reliably substitute for human judgment. Thus, DAQ is roughly three times more critical than TMG for enabling substitution.

DAQ vs. CD (5 vs. 1/5):

Reliable data is the bedrock of AI substitution; even in context-rich environments, having robust data can sometimes help approximate context, whereas a lack of data precludes effective substitution entirely. While both factors matter, a task's context dependence (CD) poses a barrier because nuanced, environment-specific cues are harder for AI to capture. However, the absence of rich data is an even greater problem—without data, prediction tools cannot function at all. We rate DAQ as five times more enabling than low context dependence.

DAQ vs. SIC (5 vs. 1/5):

Social and interactive complexity (SIC) is a severe challenge for substitution because AI struggles with tasks that require human interaction or emotional nuance. Yet, without high-quality data, even routine tasks cannot be automated. Thus, DAQ is assigned a weight of 5 relative to SIC. In examples like AI-powered transcription, abundant and clean data enables the system to reliably predict speech, even if a human review is needed for nuanced errors; however, if social cues are central to the task, substitution would fail regardless of data quality.

DAQ vs. DCU (5 vs. 1/5):

Decision complexity under uncertainty (DCU) hinders substitution because multi-step, uncertain decisions require human judgment. Nonetheless, having excellent data can sometimes simplify decision rules. Therefore, DAQ is set as five times more enabling than low decision complexity. When prediction costs are low due to good data, even tasks with moderate decision complexity become more amenable to substitution, as the AI can reliably forecast outcomes, leaving only the "edge cases" for human review.

Task Modularity and Granularity (TMG)

TMG vs. CD (3 vs. 1/3)

Highly modular tasks (TMG) are more clearly defined and separable, making them easier for AI to

automate. In contrast, tasks with high context dependence (CD) require human sensitivity to environmental cues. I rated TMG as three times more enabling than low context dependence. Discrete, modular tasks (e.g., isolated prediction steps in transcription) lend themselves well to substitution, whereas tasks needing adaptation to context reduce the scope for full automation.

TMG vs. SIC (3 vs. 1/3):

Similarly, the modular nature of a task is a positive for substitution. Tasks that involve heavy social or interactive complexity (SIC) inherently require human insight and are less amenable to being replaced. Thus, TMG is considered three times more enabling than low social complexity. Even if a task is modular, if it requires interpersonal interactions (as in customer service), substitution becomes less effective.

TMG vs. DCU (1 vs. 1):

For substitution, task modularity and low decision complexity (DCU) are both important, and we consider them roughly equally critical. A modular task that still involves multi-step decisions under uncertainty may not be fully substitutable, balancing the enabling effect of modularity with the hindrance of complex decisions.

Context Dependence (CD)

CD vs. SIC (3 vs. 1/3):

AI systems can sometimes be engineered to handle structured contextual information better than the nuanced, interactive elements of human behavior. While both high context dependence and high social complexity reduce substitutability, tasks with lower context dependence are somewhat more conducive to substitution than those with lower social complexity. Thus, we assign low context dependence a weight three times greater than low social complexity.

CD vs. DCU (1/3 vs. 3):

In direct comparison, low decision complexity (DCU) is seen as more enabling for substitution than low context dependence. A task with simple, straightforward decisions is easier to substitute even if it has moderate contextual requirements, so we set DCU as three times more enabling than low context dependence. Predictive tasks with minimal sequential decision challenges are far more amenable to automation than those that, even if context-light, involve complex decision-making.

Social and Interactive Complexity (SIC) vs. DCU

SIC vs. DCU (1/5 vs. 5)

Finally, when comparing low social complexity and low decision complexity, low decision complexity is far more enabling for substitution. Tasks that are simple in decision-making (DCU) are much easier for AI to substitute than tasks that require minimal social interaction (SIC), where the human element is still critical. Even if a task has low social demands, a high level of uncertainty or multi-step decisions (DCU) can hinder effective substitution, making low decision complexity a much stronger facilitator.

Automation Impact (SI) Pairwise Matrix

Automation Impact (SI) Criteria	TMG	CD	SIC	DAQ	DCU
TMG	1	3	3	1/3	3
CD	1/3	1	1/2	1/5	1/2
SIC	1/3	2	1	1/5	1/2
DAQ	3	5	5	1	5
DCU	1/3	2	2	1/5	1

Data Availability and Quality (DAQ) Comparisons

DAQ vs. TMG (3 vs. 1/3):

For automation, abundant and high-quality data are critical not only for accurate prediction but also for informing and streamlining automated decision rules. Even if a task is highly modular (TMG), without robust data, an AI system cannot reliably operate end-to-end. Thus, DAQ is considered three times more enabling than TMG.

DAQ vs. CD (5 vs. 1/5):

While context dependence (CD) poses a big barrier (because nuanced, environment-specific cues are difficult for AI to capture) having excellent data can sometimes help approximate or infer aspects of context. However, without data, automation is virtually impossible. This makes DAQ far more enabling (rated five times higher) compared to low context dependence.

DAQ vs. SIC (5 vs. 1/5):

Social and interactive complexity (SIC) is a major challenge for automating task (decision-making component in particular), as AI systems typically struggle with the subtleties of human interaction and emotional cues. Still, high-quality data is a prerequisite for even initiating automation. Therefore, DAQ is weighted as five times more enabling than having low social complexity.

DAQ vs. DCU (5 vs. 1/5):

Decision complexity under uncertainty (DCU) directly impacts whether an AI can fully replace human decision-making. Even moderate complexity can obstruct automation. Yet, exceptional data quality can mitigate some of these challenges by clarifying decision rules. Hence, DAQ is deemed five times more enabling than low decision complexity.

Task Modularity and Granularity (TMG) Comparisons

TMG vs. CD (3 vs. 1/3):

Highly modular tasks can be broken into discrete, well-defined units that are more readily automated. In contrast, tasks with high context dependence (CD) require constant adaptation to environmental cues, making full automation more difficult. Thus, TMG is considered three times more enabling than low context dependence.

TMG vs. SIC (3 vs. 1/3):

Modularity (TMG) allows tasks to be segmented and automated in parts, whereas tasks requiring significant human interaction (SIC) are inherently challenging to automate. As such, TMG is rated three times more enabling than low social complexity.

TMG vs. DCU (3 vs. 1/3):

Even when tasks are modular, high decision complexity (DCU) may still block full automation because the AI must handle multi-step, uncertain decisions. Here, we rate TMG as three times more enabling than low decision complexity, acknowledging that even modular tasks face hurdles if their decision-making demands are high.

Context Dependence (CD) Comparisons

CD vs. SIC (1/2 vs. 2 from the reciprocal):

Both high context dependence and high social complexity hinder automation. However, in many cases, structured contextual information can be approximated by AI (given enough data), whereas the subtleties of social and interactive nuances are harder to replicate. Thus, we set low context dependence at a lower enabling weight than low social complexity—implying that SIC is twice as critical as CD for enabling automation.

CD vs. DCU (1/2 vs. 2 from the reciprocal):

When comparing context dependence and decision complexity, the latter is more crucial for

automation. Even if a task is relatively low in context dependence, if it involves complex, multi-step decisions (DCU), full automation becomes far more challenging. Therefore, low decision complexity is considered twice as enabling as low context dependence.

Social and Interactive Complexity (SIC) vs. Decision Complexity under Uncertainty (DCU)

SIC vs. DCU (1/2 vs. 2 from the reciprocal):
While both factors are barriers, decision complexity (DCU) poses a particularly steep challenge because it covers the entire chain of decision-making that automation must replicate. Even if social interactions are minimal, a task with high decision complexity is much harder to automate. Therefore, low decision complexity is weighted as twice as enabling as low social complexity.

Enhancement Impact (EI) Pairwise Matrix

Enhancement Impact (EI) Criteria	TMG	CD	SIC	DAQ	DCU
TMG	1	1/3	1/5	1/3	1/3
CD	3	1	1/3	3	1/3
SIC	5	3	1	5	1
DAQ	3	1/3	1/5	1	1/3
DCU	3	3	1	3	1

Task Modularity and Granularity (TMG) Comparisons

TMG vs. CD (TMG = 1, CD = 3):
Highly modular (discrete) tasks are easier to automate or substitute. For enhancement, a task that is less modular (i.e. high context dependence) benefits more from human judgment aided by AI. Thus, CD is deemed about three times more enabling for enhancement than TMG.

TMG vs. SIC (TMG = 1, SIC = 5):
A task that is highly modular is clearly segmented and hence more likely to be replaced. In contrast, tasks that are socially complex require nuanced human interaction. Therefore, SIC is assigned a weight of 5 relative to TMG, indicating that high social and interactive complexity is a strong driver for enhancement.

TMG vs. DAQ (TMG = 1, DAQ = 3):

While abundant, high-quality data (DAQ) is crucial for AI prediction, it tends to favor substitution. For enhancement, a lower effective DAQ is preferable. In comparing TMG and DAQ, we assign DAQ a weight of 3 relative to TMG, suggesting that even though both favor substitution when high, the modular nature of a task (TMG) is particularly adverse for enhancement.

TMG vs. DCU (TMG = 1, DCU = 3):
High decision complexity (DCU) implies tasks involve multi-step, uncertain decisions—conditions under which full automation is challenging and enhancement becomes more valuable. Thus, DCU is seen as three times more enabling for enhancement than high modularity.

Context Dependence (CD) Comparisons

CD vs. SIC (CD = 1, SIC = 3):
Both context dependence and social/interactive complexity hinder complete automation. However, the subtleties involved in social interactions (SIC) tend to require even more human judgment. Therefore, we judge SIC as roughly three times more enabling for enhancement than CD.

CD vs. DAQ (CD = 3, DAQ = 1/3):
High context dependence reinforces the need for human oversight, favoring enhancement. In contrast, high data availability can make tasks more prone to substitution. We rate CD as three times more enabling than DAQ in the context of augmentation.

CD vs. DCU (CD = 1, DCU = 3):
Although both factors support enhancement by reducing the feasibility of full automation, multi-step decision complexity (DCU) has a stronger effect because complex decisions are particularly resistant to full automation. Thus, DCU is taken as three times more enabling than context dependence.

Social and Interactive Complexity (SIC) Comparisons

SIC vs. DAQ (SIC = 5, DAQ = 1/5):
A high degree of social and interactive complexity strongly favors enhancement, as these tasks cannot be easily replaced by AI. Conversely, high data availability pushes towards substitution. In our matrix, SIC is considered five times more enabling than DAQ.

SIC vs. DCU (SIC = 1, DCU = 1):
Both high social complexity and high decision complexity are critical in resisting full automation and

promoting the use of AI as an augmentative tool. Here, we consider them roughly equal in their ability to enhance human work.

Data Availability and Quality (DAQ) vs. Decision Complexity under Uncertainty (DCU)

DAQ vs. DCU (DAQ = 1, DCU = 3):

While high data availability is generally positive for AI performance, in the context of enhancement it can lead toward substitution if it drives effective automation. In contrast, high decision complexity (DCU) strongly necessitates human judgment and therefore is more enabling for enhancement. We assign DCU a weight three times that of DAQ.

Freelance Writing

Freelance Writing Task Description	Task Modularity and Granularity (TMG)	Context Dependence (TCD)	Social & Interactive Complexity (SIC)	Data Availability & Quality (DAQ)	Decision Complexity & Uncertainty (DCU)
Engage in initial client consultations to clarify project requirements, target audience, and desired tone or style.	4	8	9	5	7
Conduct comprehensive research on a wide range of topics tailored to the client's needs using credible sources to develop content ideas and detailed outlines tailored to the assignment.	7	6	3	8	7
Draft articles, blog posts, website content, academic papers, and other forms of written communication adapting the writing style to suit various formats such as creative, technical, academic, or copywriting.	8	5	3	4	5
Proofread the content thoroughly to eliminate grammatical, punctuation, and formatting errors, ensuring high-quality final output.	8	2	1	9	3
Maintain regular communication with clients to provide progress updates, clarify requirements, and address feedback.	7	4	6	7	7
Revise and edit content based on client feedback, ensuring accuracy, tone, and adherence to guidelines.	7	6	3	7	5
Proactively search for and apply to new work opportunities by developing and submitting tailored proposals on freelance platforms and negotiating contracts, project terms, and rates with clients.	7	5	6	7	6
Dedicate scheduled time for continuous professional development to keep skills and knowledge current.	3	6	3	6	3
Manage administrative tasks such as invoicing, bookkeeping, and scheduling to sustain smooth business operations.	9	3	3	9	3
Maintain and update an online portfolio and professional profile by regularly showcasing recent writing samples, client testimonials, and case studies to attract potential clients.	6	4	4	5	5

Engage in initial client consultations to clarify project requirements, target audience, and desired tone or style

Task Modularity and Granularity (TMG = 4)

Although the consultation might seem like a single meeting, its very nature is an ongoing, iterative dialogue. Rather than comprising neatly separable sub-tasks, it involves continuous back-and-forth exchanges where each conversational turn can reshape the discussion. This interdependence means the task is not easily broken down into discrete, independent modules. As a result, its granularity is relatively low.

Context Dependence – (TCD = 8)

The success of the consultation hinges on the freelancer's ability to interpret nuanced, often unstructured cues from the client. Understanding cultural, situational, and personal communication styles is essential to truly grasp the client's needs. Because the conversation is steeped in contextual subtleties, such as tone, nonverbal cues, and industry-specific and cultural references, the task is highly context dependent.

Social and Interactive Complexity (SIC = 9)

This task involves high levels of interpersonal interaction. The freelancer must engage in active listening, negotiation, and sometimes even mediation to resolve ambiguities. The interactive complexity is amplified by the need to build rapport, adjust communication style on the fly, and ensure mutual understanding throughout the dialogue. The task's reliance on real-time social dynamics justifies a very high score.

Data Availability and Quality (DAQ = 5)

During an initial consultation, the "data" generally consists mainly of unstructured, qualitative information provided in real time. There may be pre-existing, high-quality data that can be leveraged to clarify the client's requirements. Although, in contexts where abundant, clear data is available, the need for extensive consultation diminishes. Here, the relative lack of structured, reliable data means the freelancer must rely heavily on human judgment, resulting in a medium score for data availability.

Decision Complexity and Uncertainty (DCU = 7)

Consultation is designed to reduce uncertainty; it inherently involves making critical decisions under ambiguous conditions. The freelancer must decide how to interpret vague client input, negotiate the

project scope, and identify key priorities, all of which can have cascading effects on later stages of work. While the consultation aims to bring clarity, the decisions taken during this phase are complex and carry significant implications, warranting a higher score in decision complexity.

Conduct comprehensive research on a wide range of topics tailored to the client's needs using credible sources to develop content ideas and detailed outlines tailored to the assignment.

Task Modularity and Granularity (TMG = 7)

Research process can be segmented into sub-tasks—such as information sourcing, evaluating credibility, synthesizing findings, and outlining content—the boundaries between these phases are often blurred. Insights gained during synthesis may prompt revisiting earlier steps, making the process inherently iterative but still compartmentalized, this prevents a neat segmentation into fully independent modules. As a result, the process exhibits a moderate level of modularity.

Context Dependence (TCD = 6)

The research task is strongly shaped by the specific needs of each assignment. It requires tailoring content ideas and outlines to match the client's subject matter, target audience, and stylistic preferences. This reliance on situational cues and specialized domain knowledge means the process is dependent on some contextual factors that may not be embedded in LLMs, warranting a medium high score.

Social and Interactive Complexity (SIC = 3)

The core of comprehensive research is a largely solitary endeavor. Although occasional interactions, like clarifications with the client or consulting with subject matter experts, can occur, these are peripheral to the main task. The bulk of the activity is performed individually, resulting in low social and interactive complexity.

Data Availability and Quality (DAQ = 8)

Freelance writers generally have access to a wide array of credible sources, academic databases, and reputable publications, ensuring a robust supply of high-quality data. However, the variability in data quality across different topics and the occasional need for additional validation or supplementary sources mean that while data is abundant, it is not uniformly consistent, thus earning a moderate-to-high score.

Decision Complexity and Uncertainty (DCU = 7)

Research involves some critical decisions under conditions of uncertainty. Freelance writers must determine which data sources to trust, decide on the relevance of diverse pieces of information, and continuously refine their understanding as new insights emerge. This iterative decision-making process—where each choice can significantly influence the subsequent content creation and overall quality of the deliverable—justifies a somewhat high score in decision complexity.

Draft articles, blog posts, website content, academic papers, and other forms of written communication adapting the writing style to suit various formats such as creative, technical, academic, or copywriting.

Task Modularity and Granularity (TMG = 8)

Drafting process can be notionally divided into segments—such as individual paragraphs, sections, or even sentence-level decisions. Maintaining narrative coherence, thematic consistency, and stylistic fluidity across the entire text can be neatly segmented into fully independent modules. This interconnectedness results in a relatively high modularity score.

Context Dependence (TCD = 5)

The drafting process is sensitive to contexts that are generally well known but can be more nuanced that give some freelance workers a social advantage. These writers adapt tone, style, and structure to suit a wide variety of formats and audiences. Whether the task involves crafting a creative narrative, a technical explanation, an academic argument, or persuasive copy, the effectiveness of the draft hinges on a deep understanding of the subject matter, audience expectations, and client-specific requirements. This reliance on situational cues and domain-specific nuances justifies a medium score.

Social and Interactive Complexity (SIC = 3)

Drafting is predominantly a solitary, introspective activity. Thers is some emotional labor but while external feedback is often sought later in the revision process, the initial creation of content typically occurs in isolation. The process demands minimal real-time interpersonal interaction, leading to a low score in social and interactive complexity.

Data Availability and Quality (DAQ = 4)

Similar to research, drafting relies on the freelance writer's internal repository of ideas, language proficiency, and creative intuition combined with available data. External data, such as style guides or content briefs, may provide guidance, however, the core of the process is supported internally rather

than entirely drawn from structured, high-quality datasets. This limited reliance on external data sources results in a medium score.

Decision Complexity under Uncertainty (DCU = 5)

Drafting involves continuous decision-making but not excessive uncertainty (when information is already available). Choices, ranging from word selection and sentence structure to the overall organization and flow of ideas, affects the final outcome but . The process is inherently iterative and sometimes uncertain, as writers navigate multiple layers of creativity, audience engagement, and adherence to client requirements.

Proofread the content thoroughly to eliminate grammatical, punctuation, and formatting errors, ensuring high-quality final output.

Task Modularity and Granularity (TMG = 8)

Proofreading can be segmented into distinct sub-tasks, such as checking grammar, punctuation, and formatting, which can each be addressed independently. Although the overall process must ensure consistency and coherence across the entire document, the discrete nature of these checks supports a high degree of modularity.

Context Dependence (TCD = 2)

The proofreading process largely follows well-established grammatical rules and style conventions. While client-specific style guides (and the topic specific words)may introduce some contextual nuances, the task is primarily governed by standardized criteria. This results in a relatively low reliance on contextual interpretation.

Social and Interactive Complexity (SIC = 1)

Proofreading is predominantly a solitary task. Although occasional consultations may occur to clarify stylistic preferences or resolve ambiguities, the core activity is executed individually, thereby involving minimal interpersonal interaction.

Data Availability and Quality (DAQ = 9)

The task benefits from abundant, high-quality data in the form of established language rules, style guides, and formatting standards. This structured and reliable information underpins the proofreading process, resulting in a high score for data availability and quality.

Decision Complexity under Uncertainty (DCU = 3)

While proofreading largely involves applying fixed rules, it still requires some nuanced decision-making to distinguish between errors and stylistic choices, especially in texts with technical or ambiguous elements. The iterative nature of reviewing and cross-checking introduces a moderate level of decision complexity.

Maintain regular communication with clients to provide progress updates, clarify requirements, and address feedback.

Task Modularity and Granularity (TMG = 7)

This communication task can be segmented into discrete interactive and response dependent interactions—such as scheduled emails, brief phone calls, or chat messages automatic notifications—that each focus on specific aspects of the project. Although these individual updates are modular, they form part of a continuous engagement with the client. This recurring yet separable structure results in a high modularity score.

Context Dependence (TCD = 4)

The effectiveness of client communication hinges on understanding and adapting to project-specific nuances, such as client preferences, project stage, and industry context. But standard templates and protocols often guide these interactions, a certain degree of situational interpretation is required to address emerging issues accurately. This results in a medium level of context dependence.

Social and Interactive Complexity (SIC = 6)

Regular client communication involves routine interpersonal exchanges that require clarity, active listening, and appropriate responsiveness. Although these interactions demand basic social skills and relationship management, they are generally straightforward and less complex than tasks involving high-stakes negotiation or in-depth consultation, leading to a relatively moderate score.

Data Availability and Quality (DAQ = 7)

The information exchanged during these communications—such as progress updates, client feedback, and clarification queries is typically highly data driven. Sufficient for guiding project adjustments, the variability in clarity and completeness of this data yields a medium score in data availability and quality's impact on the task.

Decision Complexity under Uncertainty (DCU = 7)

Although interpreting ambiguous feedback may introduce some uncertainty, the overall decision-making process is relatively straightforward. However, the key function of such communication is to deal with uncertainty, resulting in a moderate high for complexity.

Revise and edit content based on client feedback, ensuring accuracy, tone, and adherence to guidelines.

Task Modularity and Granularity (TMG = 7)

The revision process can be segmented into discrete components, such as error detection, structural changes, tone adjustments, and stylistic refinements. However, these components are interdependent; maintaining overall consistency and cohesiveness requires iterative integration of these elements. This balance between modular sub-tasks and the holistic revision process results in a moderately high modularity score.

Context Dependence (TCD = 6)

Revisions are strongly driven by client feedback (that may involve cultural or situational context) and established style guidelines. The task requires careful interpretation of nuanced feedback, which often reflects specific expectations regarding tone, accuracy, and message. This reliance on situational cues and domain-specific context necessitates a medium-high score in context dependence.

Social and Interactive Complexity (SIC = 3)

While the act of revising and editing is largely a solitary task, it is inherently linked to interpersonal communication through client feedback. The writer must interpret and integrate this feedback, which introduces a moderate level of interactive complexity even though the execution is primarily independent.

Data Availability and Quality (DAQ = 7)

The revision process draws on data from multiple sources—the original draft, client comments, and style guidelines. Although these sources are directly relevant, the variability in clarity and completeness of client feedback could create challenges. This results in a moderate-high score for data availability and quality.

Decision Complexity under Uncertainty (DCU = 5)

Revising content involves a series of decisions but less uncertain conditions since revision is a direct response to the previous ambiguity. The writer and client mutually determine which aspects of the feedback to incorporate, resolve conflicting suggestions, and decide how best to enhance the content without compromising its intended message. The lower uncertainty supports a medium decision complexity score.

Proactively search for and apply to new work opportunities by developing and submitting tailored proposals on freelance platforms and negotiating contracts, project terms, and rates with clients.

Task Modularity and Granularity (TMG = 7)

This task could be segmented into discrete modules, such as scanning for job postings, developing tailored proposals, and engaging in negotiations through structured response. Although these components are distinct, they are interdependent; for example, feedback from initial proposal submissions may lead to refining search strategies or reworking proposal content. This iterative yet compartmentalized structure results in a high modularity score.

Context Dependence (TCD = 5)

The process is moderately dependent on context. Proposals must be customized to align with the specific requirements of each job posting, which involves understanding industry norms, client expectations, cultural aspects and project-specific details. Although standard templates often guide the process, tailoring and negotiation require sensitivity to nuanced situational cues, warranting a medium-high score.

Social and Interactive Complexity (SIC = 6)

Negotiating contracts, project terms, and rates involves interpersonal interaction that, while generally structured through written communication on platforms, still requires persuasive dialogue and strategic engagement. This task demands a moderate level of social and interactive complexity as freelancers balance automated responses with personalized communication to secure favorable terms.

Data Availability and Quality (DAQ = 7)

Freelancers have access to a wealth of structured data through job postings, client profiles, and platform analytics, which inform proposal development and negotiation strategies. However, the clarity and completeness of this information can vary, and sometimes key details may be ambiguous or incomplete. This variability yields a moderately high score for data availability and quality.

Decision Complexity under Uncertainty (DCU = 6)

Tailoring proposals that stand out and negotiating contracts require a series of decisions, such as determining which opportunities to pursue, how to position one's skills, and what terms to negotiate, under conditions of uncertainty. Although the process benefits from established strategies and templates, the inherent variability in client expectations and market conditions introduces moderate decision complexity.

Dedicate scheduled time for continuous professional development to keep skills and knowledge current.

Task Modularity and Granularity (TMG = 3)

Although professional development activities can be segmented into discrete modules—such as online courses, webinars, reading sessions, and practice exercises, but these are largely cognitive activities. While these activities are individually identifiable, they collectively form an integrated, ongoing learning routine that is interdependent and continuously evolving. This balance results in a low modularity score.

Context Dependence (TCD = 6)

The need for professional development is driven by both self-determined career goals and external industry trends. While the learning objectives are generally set by the freelancer's personal assessment of skill gaps, they are also shaped by the broader market and technological context. This dual influence warrants a medium score in context dependence.

Social and Interactive Complexity (SIC = 3)

Continuous professional development is predominantly a self-directed, but a social and often interactive process. It always requires the presence of a freelancer for it to happen, and freelancers may occasionally engage in group discussions, online forums, or virtual workshops to enhance their

learning, although the core activity involves individual study (using materials developed by others and sometimes by generative systems). This results in a low level of social and interactive complexity.

Data Availability and Quality (DAQ = 6)

There is an abundance of high-quality educational resources available online, including courses, webinars, articles, and tutorials. However, the quality and relevance of these materials can vary, requiring the freelancer to evaluate and select the most appropriate resources. This environment of plentiful yet variable data yields a medium score.

Decision Complexity under Uncertainty (DCU = 3)

Choosing which skills to develop and which resources to pursue involves a series of decisions that, while guided by market trends and personal objectives, still carry a moderate level of uncertainty.

Manage administrative tasks such as invoicing, bookkeeping, and scheduling to sustain smooth business operations.

Task Modularity and Granularity (TMG = 9)

Administrative tasks are highly modular. Functions such as logging hours, invoicing, bookkeeping, and scheduling can be clearly delineated into discrete, independent modules. Each task follows a standardized process—often supported or even fully executed by automation—which enables them to be managed separately with minimal interdependency.

Context Dependence (TCD = 3)

These tasks are largely routine and follow established protocols or software workflows. While there may be minor variations based on specific client requirements or internal systems, the core processes remain standardized, resulting in a very low dependency on unique situational factors.

Social and Interactive Complexity (SIC = 3)

The execution of administrative tasks is predominantly solitary and structured (some interaction with clients and others is required). They require minimal interpersonal interaction as most functions—such as data entry or scheduling—are automated or follow clear procedural guidelines, leading to extremely low social and interactive complexity.

Data Availability and Quality (DAQ = 9)

Administrative work relies on well-structured, reliable data. Financial records, time logs, and scheduling information are typically standardized and maintained in digital formats, ensuring high data quality and ease of access. This high degree of structured data supports the efficiency and consistency of these tasks.

Decision Complexity under Uncertainty (DCU = 3)

Decisions in administrative tasks are generally straightforward and rule-based (although writing reviews and ratings are subjective). The overall processes are generally guided by clear, established procedures with minimal ambiguity, resulting in very low decision complexity under conditions of uncertainty.

Maintain and update an online portfolio and professional profile by regularly showcasing recent writing samples, client testimonials, and case studies to attract potential clients.

Task Modularity and Granularity (TMG = 6)

The process can be segmented into distinct modules—such as updating profile with skills, links to writing samples, refreshing client testimonials, and adding new case studies. Although each component can be managed independently, together they form an integrated, cohesive profile. However, often there is no connection between some of these tasks (if using more than one platform). This structured yet flexible nature results in a moderate modularity score.

Context Dependence (TCD = 4)

While maintaining an online portfolio requires alignment with current industry trends and personal branding, the process is largely standardized. The selection and presentation of work are guided by general best practices rather than highly variable contextual cues, yielding a low-to-moderate score in context dependence.

Social and Interactive Complexity (SIC = 4)

Updating an online portfolio is primarily a solitary task (but collection reviews require social interaction). Occasional feedback or consultation may occur, the core activity involves self-directed curation and content management, resulting in lower social and interactive complexity.

Data Availability and Quality (DAQ = 5)

The data for this task—comprising previous work samples, client testimonials, and case studies—is readily available and typically of good quality. However, variability in how the data is presented and the need for careful curation to maintain a professional image contribute to a moderate overall score.

Decision Complexity under Uncertainty (DCU = 5)

Decisions regarding which pieces to feature and how to update the profile are strategic, although made under relatively stable conditions. The criteria for selection are generally clear, and the process involves limited uncertainty, justifying a moderate decision complexity score.

Freelance Virtual Assistance

2. Freelance Virtual Assistance Task Description	Task Modularity and Granularity (TMG)	Context Dependence (TCD)	Social & Interactive Complexity (SIC)	Data Availability & Quality (DAQ)	Decision Complexity & Uncertainty (DCU)
Engage in initial client consultations to clarify project requirements, communication expectations, and preferred tools, establishing clear roles for either long-term or short-term engagements.	4	8	9	5	7
Manage and organize schedules and appointments using digital calendaring and scheduling software to ensure optimal time management and timely coordination of meetings or tasks.	7	5	4	8	6
Handle email correspondence and other communications, acting as a liaison between the client and their contacts by filtering, prioritizing, and responding to messages as needed.	8	6	4	8	7
Conduct targeted research and compile data to prepare reports, presentations, or summaries that support the client's decision-making and project objectives.	7	7	4	7	7
Assist with project management by coordinating tasks, tracking progress using project management software, and ensuring that deadlines and milestones are met.	7	6	5	8	6
Manage social media accounts by scheduling content, monitoring engagement, and performing basic updates in line with the client’s brand guidelines.	7	6	7	8	6
Perform administrative tasks, such as document preparation, data entry, travel arrangements, and running errands, while coordinating with other freelancers or team members to ensure seamless execution of projects.	8	5	5	9	4
Maintain regular and proactive communication with clients by providing progress updates, clarifying requirements, and addressing any concerns or emerging issues promptly.	7	6	6	7	7
Actively search for new work opportunities by researching freelance platforms, developing and submitting tailored proposals, and negotiating contracts, project terms, and rates with clients.	7	5	6	7	6
Manage financial and administrative systems by tracking invoices, processing payments, and maintaining tax documentation to support smooth business operations.	9	3	3	9	3
Dedicate time for continuous professional development by learning new software tools, staying updated on virtual assistance best practices, and keeping abreast of emerging industry trends.	3	6	3	6	5

Maintain and update an online portfolio and professional profile by regularly showcasing recent work.	6	4	4	5	5

Engage in initial client consultations to clarify project requirements, communication expectations, and preferred tools, establishing clear roles for either long-term or short-term engagements.

Task Modularity and Granularity (TMG = 4)

Although consultation is a discrete event, it is not easily broken into independent, modular sub-tasks. Instead, it is an integrated, fluid dialogue where each conversational turn builds on the previous one. This is particularly true for many virtual assistance jobs where a range of responsibilities are expectations need to discussed. This interdependence makes it difficult to segment, resulting in a relatively low modularity score.

Context Dependence (TCD = 8)

The success of the consultation hinges on interpreting nuanced, client-specific cues. Understanding the client's unique requirements, cultural nuances, and specific operational context is essential to build a positive relationship and to deliver on a range of assistance tasks. This reliance on situational details and unstructured input warrants a high score for context dependence.

Social and Interactive Complexity (SIC = 9)

This task is highly interactive and involves real-time negotiation, active listening, and dynamic interpersonal communication. Establishing rapport and adapting communication styles in a virtual setting, especially across diverse cultural or remote environments, adds significant social and interactive complexity.

Data Availability and Quality (DAQ = 5)

Information exchanged during consultations is largely qualitative and unstructured, relying on real-time verbal and written cues rather than standardized data sources. While some clients may provide detailed briefs or background documents, the variability in the quality and completeness of this information typically results in a moderate score for data availability and quality.

Decision Complexity under Uncertainty (DCU = 7)

Client consultations require freelancers to make critical decisions under conditions of ambiguity—such as interpreting unclear directives or balancing conflicting client inputs. In the context of freelance virtual assistance, where multiple responsibilities might converge during a single consultation, the need to negotiate project scope and prioritize requirements in real time contributes to a high decision complexity score.

Manage and organize schedules and appointments using digital calendaring and scheduling software to ensure optimal time management and timely coordination of meetings or tasks.

Task Modularity and Granularity (TMG = 7)

While scheduling can be broken down into discrete activities (e.g., adding appointments, adjusting meeting times, setting reminders), these tasks are interrelated and often interdependent—conflicts, recurring events, and time zone considerations require integrated management. In the context of virtual assistance, where daily calendar updates are essential, the task exhibits a moderately high modularity score, as each component can be individually managed but still influences the overall schedule.

Context Dependence (TCD = 5)

The effectiveness of scheduling depends partly on standardized digital tools (e.g., calendar apps) and established procedures, yet it must be tailored to client-specific needs such as preferred meeting times, time zone differences, and specific deadlines. This blend of standardized automation with contextual adjustments justifies a moderate score for context dependence.

Social and Interactive Complexity (SIC = 4)

Although scheduling involves interpersonal communication—such as negotiating meeting times and resolving conflicts—it is largely mediated by automated tools and email exchanges. The task requires basic social skills but is less demanding in terms of real-time interaction compared to tasks like client consultations or negotiations, resulting in a relatively low social and interactive complexity score.

Data Availability and Quality (DAQ = 8)

Scheduling data (calendar entries, meeting invites, deadlines) is typically well-structured and highly reliable, as it is managed through digital platforms with standardized formats. This abundance of high-quality, readily available data supports efficient task execution, meriting a high score.

Decision Complexity under Uncertainty (DCU = 6)

Despite the structured nature of scheduling, virtual assistants frequently face uncertainties such as conflicting appointments, last-minute changes, and time zone challenges. Balancing these elements requires timely decision-making and problem-solving, resulting in a moderately high decision complexity score.

Handle email correspondence and other communications, acting as a liaison between the client and their contacts by filtering, prioritizing, and responding to messages as needed.

Task Modularity and Granularity (TMG = 8)

While individual email and text interactions are discrete and can be managed as separate events (e.g., reading, filtering, drafting a reply), they are often interconnected through ongoing threads and context. In virtual assistance, where multiple communication channels (email, chat, video calls) are used simultaneously, the task is moderately modular—each email is a unit, but its meaning and response may depend on the broader conversation.

Context Dependence (TCD = 6)

Effective email management requires understanding client instructions, subtle cues in message tone, and the context of previous communications. Although standardized templates often guide responses, each interaction must be adapted to the client's specific needs and evolving project details. This reliance on situational context earns a moderate-to-high score for context dependence.

Social and Interactive Complexity (SIC = 4)

Most email correspondence is asynchronous and relies on written communication, reducing the immediacy of interpersonal interaction compared to live meetings. However, the task still requires active listening, prioritization, and occasional negotiation—especially when handling urgent or conflicting messages. This results in a relatively moderate level of social and interactive complexity.

Data Availability and Quality (DAQ = 8)

Email data is highly structured, with clear fields for sender, subject, timestamp, and content, which facilitates efficient processing and filtering. Despite some variability in message clarity, the overall availability and quality of data are high, supporting effective task execution.

Decision Complexity under Uncertainty (DCU = 7)

Managing email correspondence involves a series of decisions under uncertainty—such as determining which messages require immediate action, which can be delegated, and how to interpret ambiguous or incomplete information. The necessity to balance prompt responses with thoughtful prioritization and tone adjustment contributes to a high decision complexity score.

Conduct targeted research and compile data to prepare reports, presentations, or summaries that support the client's decision-making and project objectives.

Task Modularity and Granularity (TMG = 7)

Research tasks in virtual assistance can be segmented into discrete phases—such as information sourcing, evaluating credibility, synthesizing findings, and outlining summaries. Although each phase functions as an individual module, the interdependence of these sub-tasks (where insights from synthesis might prompt additional sourcing) means that the task is not completely independent, warranting a moderately high modularity score.

Context Dependence (TCD = 7)

Effective research in this setting requires tailoring information to the specific needs of each client and project. Freelance virtual assistants must understand the client’s industry, target audience, and project objectives to select and synthesize relevant data. This reliance on nuanced, project-specific cues results in a high level of context dependence.

Social and Interactive Complexity (SIC = 4)

While research is primarily an individual task, it occasionally involves some interaction—such as consulting with subject matter experts or seeking clarifications from clients. However, these interactions are infrequent compared to the bulk of the work, so the overall social and interactive complexity remains low.

Data Availability and Quality (DAQ = 7)

Research tasks benefit from a wealth of readily accessible and high-quality data sources (e.g., academic journals, reputable websites, and industry reports). Although there may be challenges with data gaps or inconsistent quality that require field research, the overall availability and reliability of external data are high.

Decision Complexity under Uncertainty (DCU = 7)

The research process requires critical evaluation and judgment in selecting credible sources and determining the relevance of diverse pieces of information. Freelance virtual assistants must navigate uncertainties in data quality and interpret ambiguous information, resulting in a moderately high decision complexity score.

Assist with project management by coordinating tasks, tracking progress using project management software, and ensuring that deadlines and milestones are met.

Task Modularity and Granularity (TMG = 7)

Project management tasks can be broken down into distinct components—such as scheduling check-ins, tracking progress updates, and managing deadlines. In a virtual assistance setting, these sub-tasks are supported by digital tools that compartmentalize responsibilities. However, the interconnected nature of these modules (for example, the outcome of a scheduling task can affect progress tracking) limits the complete independence of each sub-task. This balance between discrete components and their inherent interdependencies warrants a moderately high modularity score of 7.

Context Dependence (TCD = 6)

While standard project management software provides a consistent framework, effective coordination still requires tailoring to each client's unique requirements. Virtual assistants must adapt scheduling, communication protocols, and milestone tracking to diverse industries, client preferences, and time zone differences. This blend of standardized processes with the need for contextual customization leads to a moderate score of 6 in context dependence.

Social and Interactive Complexity (SIC = 5)

Project management in freelance virtual assistance involves periodic interpersonal interactions—such as client meetings, team check-ins, and collaborative updates—but much of the work is conducted asynchronously or through automated systems. Although effective communication and negotiation are required, these interactions are relatively structured and less spontaneous than in more dynamic, real-time environments. Thus, the social and interactive complexity is moderate, with a score of 5.

Data Availability and Quality (DAQ = 8)

The data needed for project management—such as task lists, deadlines, progress metrics, and

calendar entries—is typically well-organized and stored in digital systems. These systems provide high-quality, structured information that facilitates efficient tracking and coordination. The reliability and accessibility of this data support a high score of 8.

Decision Complexity under Uncertainty (DCU = 6)

Even though many project management decisions follow established protocols (e.g., rescheduling a meeting or updating a task status), virtual assistants often encounter uncertainties such as conflicting appointments, last-minute changes, or varying client priorities. The need to quickly evaluate these factors and adjust plans dynamically contributes to a moderately high decision complexity, which is captured with a score of 6.

Manage social media accounts by scheduling content, monitoring engagement, and performing basic updates in line with the client's brand guidelines.

Task Modularity and Granularity (TMG = 7)

Social media management can be broken down into discrete activities—such as scheduling posts, responding to comments, and updating profiles—but these modules are interdependent. For instance, content scheduling affects engagement monitoring and vice versa. In the context of virtual assistance, where maintaining a consistent online presence is critical, this integrated yet segment-able nature earns a moderately high modularity score.

Context Dependence (TCD = 6)

While many social media tasks rely on standardized digital tools and protocols, their effectiveness depends on tailoring content to specific audience preferences, brand voice, and real-time market trends. Virtual assistants must adjust strategies based on client-specific guidelines and evolving circumstances, which results in a moderately high context dependence score.

Social and Interactive Complexity (SIC = 7)

Although individual actions like posting or replying may be brief, managing social media as a whole requires active engagement, creative content creation, and occasional real-time interaction with audiences. This combination of creative and interpersonal demands, especially when aligning with diverse client brands, results in a moderately high social and interactive complexity.

Data Availability and Quality (DAQ = 8)

Digital platforms provide well-structured, reliable data—from engagement metrics to scheduling logs—that supports efficient social media management. The ready availability of high-quality data (e.g., analytics dashboards, performance reports) justifies a high score in this dimension.

Decision Complexity under Uncertainty (DCU = 6)

Decision-making in social media management involves adjusting strategies based on audience responses and emerging trends. Although best practices and digital tools offer guidance, uncertainties such as sudden shifts in engagement or unexpected feedback necessitate real-time judgment, resulting in a moderate level of decision complexity.

Perform administrative tasks, such as document preparation, data entry, travel arrangements, and running errands, while coordinating with other freelancers or team members to ensure seamless execution of projects.

Task Modularity and Granularity (TMG = 8)

Administrative tasks in virtual assistance are typically well-defined and can be segmented into discrete components—such as preparing documents, entering data, or arranging travel. Although these modules are individually straightforward, the need to coordinate among multiple tasks (and sometimes with team members) introduces a degree of interdependency. This blend of discrete, modular tasks with the occasional need for integrated coordination results in a moderately high modularity score.

Context Dependence (TCD = 5)

These tasks are generally standardized and follow established procedures or software workflows but preference of clients are often nuanced. While specific client requirements might introduce minor variations (for instance, unique formatting in document preparation or specific travel preferences), the bulk of the administrative work is routine. This limited reliance on situational nuances warrants a relatively medium context dependence score.

Social and Interactive Complexity (SIC = 5)

Although many administrative activities are performed independently, coordination with other freelancers, vendors, or team members adds an element of interaction. This collaborative aspect—ensuring that all administrative components align with broader project objectives—introduces

moderate social complexity, though the interactions are typically structured and infrequent compared to more dynamic tasks.

Data Availability and Quality (DAQ = 9)

Administrative tasks rely on well-organized, structured data such as schedules, invoices, and digital records. The high quality and reliability of this data—often managed by dedicated software—facilitate efficient task execution. This abundance of high-quality, readily accessible data supports a very high score for data availability and quality.

Decision Complexity under Uncertainty (DCU = 4)

These tasks are largely rule-based and follow clear, established procedures. Although occasional adjustments may be required (for example, handling an unexpected scheduling conflict or a last-minute travel change), the overall decision-making process is straightforward and involves minimal uncertainty. Thus, the decision complexity under uncertainty is low.

Maintain regular and proactive communication with clients by providing progress updates, clarifying requirements, and addressing any concerns or emerging issues promptly.

Task Modularity and Granularity (TMG = 7)

While the overall communication process can be divided into discrete interactions (e.g., sending status updates, clarifying specific requirements, and addressing concerns), these individual exchanges are interdependent and collectively form an ongoing engagement. In the virtual assistance context—where timely updates are crucial for managing remote projects—the modular elements work together to form a cohesive communication strategy, warranting a moderately high modularity score.

Context Dependence (TCD = 6)

Effective communication in virtual assistance depends on understanding each client's specific needs, project context, and industry nuances. Although many interactions follow established protocols (like using email templates or scheduled updates), adapting to evolving project requirements and client feedback requires situational awareness. This balanced reliance on standardized methods and context-specific adjustments results in a moderate context dependence score.

Social and Interactive Complexity (SIC = 6)

Managing client communications involves interpersonal skills such as active listening, clarity in messaging, and sometimes negotiating changes. Although many interactions occur asynchronously

(via email or chat), the need to build trust and promptly resolve issues introduces a moderate level of social and interactive complexity. This is particularly important in virtual environments where real-time, face-to-face cues are absent.

Data Availability and Quality (DAQ = 7)

Communication data—such as email threads, chat logs, and status updates—is generally well-structured and reliably recorded in digital platforms. This readily available and high-quality data facilitates efficient communication management. However, variability in message clarity or occasional incomplete information requires some interpretive effort, yielding a moderately high score.

Decision Complexity under Uncertainty (DCU = 7)

The task requires making decisions in real time, such as determining which messages need immediate attention, resolving ambiguous client instructions, and adjusting plans based on evolving feedback. Despite established communication protocols, the need to interpret nuanced information and respond effectively under uncertain conditions leads to a moderately high decision complexity score.

Actively search for new work opportunities by researching freelance platforms, developing and submitting tailored proposals, and negotiating contracts, project terms, and rates with clients.

Task Modularity and Granularity (TMG = 7)

This task can be segmented into distinct phases—such as identifying opportunities, drafting proposals, and negotiating terms—but these phases are interdependent. In freelance virtual assistance, while each component (e.g., research, proposal writing) is clearly defined, they continuously inform and modify one another as market feedback is received. This iterative and cohesive structure results in a moderately high modularity score.

Context Dependence (TCD = 5)

Tailoring proposals requires some adjustment to the specific requirements of each opportunity, including understanding industry norms and client expectations. However, many aspects of the process are guided by standard templates and typical market practices. Thus, while the task relies on context, it does so at a moderate level.

Social and Interactive Complexity (SIC = 6)

Although much of the work is performed asynchronously (via emails or online platforms), the negotiation component introduces interpersonal complexity. Freelancers must engage in persuasive

dialogue and strategic communication during contract negotiations, which adds a moderate level of social and interactive complexity compared to more solitary tasks.

Data Availability and Quality (DAQ = 7)

Freelancers have access to structured information from job postings, client profiles, and platform analytics that help in formulating proposals. However, the quality and completeness of this data can vary, necessitating additional research or interpretation. This mix of readily available yet sometimes variable data supports a moderately high score.

Decision Complexity under Uncertainty (DCU = 6)

Crafting tailored proposals on platforms and negotiating terms require balancing various factors, such as market competition, client budgets, and personal skill level. While established templates and practices guide many decisions, the inherent uncertainty in client needs and market dynamics demands thoughtful judgment. This results in a moderate decision complexity score.

Manage financial and administrative systems by tracking invoices, processing payments, and maintaining tax documentation to support smooth business operations.

Task Modularity and Granularity (TMG = 9)

Administrative functions in freelance virtual assistance are highly modular. Billing, invoicing, bookkeeping, and documentation can be clearly separated into distinct, standardized processes. Each sub-task follows established routines and is often executed independently, allowing for clear segmentation even though they collectively contribute to overall business operations.

Context Dependence (TCD = 3)

These tasks largely follow predefined protocols and software workflows. While there might be minor client-specific requirements (e.g., preferred invoicing formats or specific tax documentation details), the core processes remain consistent across projects. This limited reliance on situational nuances results in a relatively low context dependence score.

Social and Interactive Complexity (SIC = 3)

Administrative tasks are mostly solitary and process-driven. Although occasional coordination with clients or team members may be necessary, these interactions are typically brief and structured. As a result, the level of interpersonal engagement is low compared to tasks that require dynamic, real-time communication.

Data Availability and Quality (DAQ = 9)

Financial records and administrative data are usually well-organized and maintained in digital systems. The availability of standardized tools and platforms ensures that high-quality, reliable data is readily accessible for tasks such as invoicing and bookkeeping, justifying a high score.

Decision Complexity under Uncertainty (DCU = 3)

The decision-making process in managing finances and administrative systems is largely rule-based and follows clear procedures. While accuracy is paramount, the choices involved are straightforward with minimal ambiguity. Thus, the overall decision complexity under uncertainty is low.

Dedicate time for continuous professional development by learning new software tools, staying updated on virtual assistance best practices, and keeping abreast of emerging industry trends.

Task Modularity and Granularity (TMG = 3)

Although professional development can be conceptually segmented into discrete modules (e.g., attending webinars, completing online courses, or self-study sessions), these activities are largely integrated into a continuous learning routine. In the context of virtual assistance, where skill enhancement is an ongoing process rather than a set of isolated tasks, the activity is less modular and more interwoven with daily routines. This interdependency leads to a relatively low modularity score.

Context Dependence (TCD = 6)

Continuous professional development is driven by both internal career goals and external industry trends. While standard courses and webinars offer structured content, the relevance and application of new tools and practices often depend on the specific context of a virtual assistant's work environment. The need to adapt learning to emerging technologies and client-specific requirements warrants a moderate context dependence score.

Social and Interactive Complexity (SIC = 3)

Much of professional development is self-directed—through online courses, reading, or video tutorials—resulting in limited interpersonal interaction. Although virtual assistants might occasionally participate in group discussions or collaborative workshops, the core learning process is primarily solitary. This relatively low level of interaction supports a low social and interactive complexity score.

Data Availability and Quality (DAQ = 6)

There is an abundance of high-quality educational resources available online; however, the quality and relevance of these materials can vary. Virtual assistants must evaluate and select the most appropriate resources, which introduces some variability. Thus, while data is plentiful, its inconsistent nature justifies a moderate score in data availability and quality.

Decision Complexity under Uncertainty (DCU = 5)

The process of professional development involves significant cognitive engagement. Freelancers must decide which new skills or tools to prioritize, sometimes unlearning outdated methods and integrating complex new concepts into their workflow. The need to navigate rapidly evolving information and make strategic learning decisions under uncertainty contributes to a medium decision complexity score.

Maintain and update an online portfolio and professional profile by regularly showcasing recent work.

Task Modularity and Granularity (TMG = 6)

Although the task can be broken down into discrete actions—such as uploading new samples, revising biographical information, and refreshing client testimonials—these components collectively contribute to a unified professional image. In the context of virtual assistance, while each update is a stand-alone module, the overall process is integrated into a broader branding strategy, resulting in a moderate modularity score.

Context Dependence (TCD = 4)

Maintaining an online portfolio requires alignment with current industry trends and the freelancer's personal branding. While standard practices (such as updating after major projects) are generally followed, the selection and presentation of work samples often depend on the specific context of client expectations and market demands. This reliance on situational cues and strategic branding decisions justifies a low-to-moderate context dependence score.

Social and Interactive Complexity (SIC = 4)

Although updating a portfolio is primarily a solitary, self-directed task, it does occasionally involve social elements—such as gathering testimonials or incorporating feedback from peers. These interactions are minimal and structured, leading to a moderate level of social and interactive complexity.

Data Availability and Quality (DAQ = 5)

The information used for portfolio updates (work samples, testimonials, case studies) is generally available, though its quality and consistency may vary. Freelancers must curate and sometimes reformat this content to maintain a professional presentation. This balance of readily available data with the need for careful curation supports a moderate score.

Decision Complexity under Uncertainty (DCU = 5)

Decisions regarding which work to feature, how to update the profile, and when to refresh content involve strategic judgment but are typically made under relatively stable conditions. While these choices are important for marketing purposes, they are guided by clear best practices, leading to a moderate decision complexity score.

Freelance Transcription Services

3. Freelance Transcription Services Task Description	Task Modularity and Granularity (TMG)	Context Dependence (TCD)	Social & Interactive Complexity (SIC)	Data Availability & Quality (DAQ)	Decision Complexity & Uncertainty (DCU)
Convert audio or video recordings into text following client formatting guidelines, including any required timestamps and speaker identifications.	6	8	2	5	7
Research and integrate domain-specific terminology and contextual details, especially for technical or specialized content.	7	8	3	8	8
Rigorously review transcripts to correct errors in grammar, punctuation, and spelling.	8	2	1	9	3
Consult with clients to clarify unclear or ambiguous audio segments, ensuring the final transcript accurately reflects the original content.	6	7	6	7	7
Update and refine transcripts in response to client corrections and detailed feedback.	7	6	3	7	5
Provide regular updates and clarifications during the transcription process to align the final output with client expectations.	6	5	4	7	5
Proactively research, seek, and submit tailored proposals on freelance platforms while negotiating contracts, project terms, and rates with clients.	7	5	4	7	6
Manage administrative tasks such as invoicing, bookkeeping, and scheduling to sustain smooth business operations.	9	3	2	9	3
Maintain and update your professional profile.	6	4	3	5	5
Dedicate scheduled time for continuous professional development by learning new transcription tools and staying updated on industry practices.	3	6	3	7	7

Convert audio or video recordings into text following client formatting guidelines, including any required timestamps and speaker identifications.

Task Modularity and Granularity (TMG = 6)

While the transcription process can be segmented into discrete parts (e.g., dividing the audio into time-stamped chunks or speaker segments), the overall task remains inherently continuous. Maintaining context and ensuring consistency across segments limits the extent to which the task can be completely modular. In freelance transcription, this balance between chunking the work and preserving an integrated narrative leads to a moderately high modularity score.

Context Dependence (TCD = 8)

The task's success relies heavily on interpreting a range of contextual factors. Transcriptionists must navigate poor audio quality, diverse accents, and technical jargon while adhering to strict formatting guidelines. This reliance on nuanced, situation-specific information—such as understanding speaker intent and contextual cues—results in a high context dependence score.

Social and Interactive Complexity (SIC = 2)

Transcription is predominantly a solitary activity. Freelance transcriptionists typically work independently, with minimal real-time interpersonal interaction. While occasional client clarifications or consultations may occur, these are infrequent. Consequently, the task exhibits very low social and interactive complexity.

Data Availability and Quality (DAQ = 5)

The quality and clarity of the input data—i.e., the audio or video recordings—vary considerably. While some files may be of excellent quality, others suffer from background noise or unclear speech. This variability means that, although data is available in a digital format, its reliability is moderate, resulting in a moderate score for data availability and quality.

Decision Complexity under Uncertainty (DCU = 7)

Transcription requires significant decision-making under uncertainty. Freelancers must repeatedly decide how to interpret unclear or ambiguous speech, often re-listening to segments and making judgment calls about speaker identification and proper timestamp placement. This continuous evaluation of uncertain information results in a high decision complexity score.

Research and integrate domain-specific terminology and contextual details, especially for technical or specialized content.

Task Modularity and Granularity (TMG = 7)

While the research process can be divided into distinct sub-tasks—such as identifying unfamiliar terms, consulting authoritative sources, and integrating the verified terminology into the transcript—the overall activity is interdependent. Each phase influences subsequent steps, particularly in specialized content where precise integration is critical. This balance of discrete, modular components with necessary integration yields a moderately high modularity score.

Context Dependence (TCD = 8)

The task is highly context-dependent. Transcriptionists must tailor their research to the specific technical or specialized content of each project. Understanding industry-specific jargon, client expectations, and subject nuances is essential to accurately reflect the intended meaning in the transcript. The reliance on situational details and precise contextual knowledge justifies a high score in context dependence.

Social and Interactive Complexity (SIC = 3)

Research and data compilation in this context is predominantly a solitary activity. Although occasional consultation with experts or client clarifications may occur, these interactions are infrequent compared to the core individual research work. Consequently, the social and interactive complexity remains relatively low.

Data Availability and Quality (DAQ = 8)

For specialized content, authoritative data is generally available through academic journals, technical manuals, or reputable online sources. Although the quality of available information can sometimes vary, the overall reliability and abundance of high-quality data sources support a high score in data availability and quality.

Decision Complexity under Uncertainty (DCU = 8)

This task demands significant cognitive engagement. Transcriptionists must determine which terms require additional verification, interpret ambiguous terminology, and decide on the most appropriate contextual integration. The need for critical analysis, judgment under uncertainty, and occasional consultation of industry literature contributes to a high decision complexity score.

Rigorously review transcripts to correct errors in grammar, punctuation, and spelling.

Task Modularity and Granularity (TMG = 8)

Proofreading can be subdivided into distinct sub-tasks—such as checking grammar, punctuation, and spelling—each of which can be executed independently. However, these components must ultimately be integrated to ensure overall textual coherence. In the transcription context, while the process is segmented into clear steps, the necessity to maintain consistency across the entire transcript leads to a high, but not perfect, modularity score.

Context Dependence (TCD = 2)

This task relies primarily on well-established grammatical rules and style conventions rather than on variable contextual factors. Although client-specific style guides may occasionally influence decisions, the core activity remains standardized, resulting in a low score for context dependence.

Social and Interactive Complexity (SIC = 1)

Proofreading is predominantly a solitary task. Although a transcriptionist might occasionally consult with a client or colleague to resolve minor ambiguities, the bulk of the work is performed independently. Consequently, the social and interactive complexity is very low.

Data Availability and Quality (DAQ = 9)

The task benefits from highly reliable and structured data sources such as grammar rules, dictionaries, and established style guidelines. This wealth of high-quality, standardized information supports the proofreading process, resulting in a very high data availability and quality score.

Decision Complexity under Uncertainty (DCU = 3)

While proofreading requires sustained attention to detail, the decisions involved are generally straightforward—based on fixed linguistic rules with minimal ambiguity. Even though the process demands meticulous review, the overall decision complexity remains low to moderate due to the clear-cut nature of the corrections required.

Consult with clients to clarify unclear or ambiguous audio segments, ensuring the final transcript accurately reflects the original content.

Task Modularity and Granularity (TMG = 6)

While the act of consulting can be separated into sub-tasks (e.g., identifying ambiguous segments, drafting clarifying questions, and reviewing client responses), these sub-tasks are tightly interwoven.

In freelance transcription, resolving uncertainty requires that each consultation inform subsequent parts of the transcript, reducing the possibility of complete independence between modules.

Context Dependence (TCD = 7)

This task is highly dependent on context. Transcriptionists must accurately interpret unclear audio—often affected by background noise, overlapping speech, or unfamiliar accents—and tailor their questions based on the specific client's field, preferences, and the nuances of the recording. The need for detailed, situational understanding results in a high context dependence score.

Social and Interactive Complexity (SIC = 6)

Although consultations are typically brief (via email or phone) and occur infrequently, they demand effective interpersonal communication skills. Freelance transcriptionists must articulate their uncertainties clearly and adapt their queries to obtain the most relevant clarifications. This task involves moderate social and interactive complexity because it requires precise communication despite being a short interaction.

Data Availability and Quality (DAQ = 7)

The data involved in this task consists of the audio recording (which may be ambiguous) and any pre-existing client documentation or style guides. While the audio data itself may be of variable quality, the additional client-provided materials usually help clarify uncertainties. Thus, data quality is moderate-to-high, but the inherent variability of audio quality keeps the score from being at the very top.

Decision Complexity under Uncertainty (DCU = 7)

Determining which segments are ambiguous—and deciding how to frame the clarifying questions—requires significant judgment under uncertainty. Transcriptionists must evaluate incomplete or unclear audio and decide on the best course of action for clarification, balancing the need for precision with time constraints. This complex decision-making process leads to a high score in decision complexity.

Update and refine transcripts in response to client corrections and detailed feedback.

Task Modularity and Granularity (TMG = 7)

Incorporating client feedback can be segmented into distinct sub-tasks—such as identifying errors, reformatting text, and adjusting content—but these elements must be integrated to produce a cohesive

final transcript. In freelance transcription, where revision cycles are standard, the process is clearly delineated yet interdependent, justifying a moderately high modularity score.

Context Dependence (TCD = 6)

This task relies on interpreting sometimes ambiguous client feedback and aligning it with the original content. Transcriptionists must understand the context behind each correction—whether it's related to tone, technical accuracy, or formatting nuances—to make appropriate adjustments. This reliance on client-specific, situational details results in a moderate context dependence score.

Social and Interactive Complexity (SIC = 3)

Although the revision process is primarily a solitary activity, it is indirectly shaped by prior client interactions. While there may be occasional follow-up communications to clarify feedback, the bulk of the work is performed independently. Thus, the social and interactive complexity remains relatively low.

Data Availability and Quality (DAQ = 7)

The data for this task includes the initial transcript and the client's written feedback, both of which are typically available in digital, structured formats. While the clarity and completeness of client feedback can vary, overall the quality of available data is sufficiently high to support accurate revisions, yielding a moderately high score.

Decision Complexity under Uncertainty (DCU = 5)

Incorporating client feedback involves a series of decisions—such as determining which corrections to implement and resolving any ambiguous instructions. Although many of these decisions are straightforward when feedback is clear, occasional uncertainties require additional judgment. This results in a moderate decision complexity score.

Provide regular updates and clarifications during the transcription process to align the final output with client expectations.

Task Modularity and Granularity (TMG = 6)

This task can be segmented into individual communication events (e.g., sending a progress update, clarifying a specific issue, or following up on a query), yet these discrete interactions function as parts of a cohesive, ongoing communication strategy. In freelance transcription—where keeping the client

informed is essential but not continuous—this integrated structure results in a moderate modularity score.

Context Dependence (TCD = 5)

Effective communication requires tailoring messages to the specific project context and client expectations. Although many updates may follow standardized templates, adjustments are necessary when unexpected issues arise or when the project scope shifts. This balanced reliance on standard practices and situational customization yields a moderate context dependence score.

Social and Interactive Complexity (SIC = 4)

While interpersonal communication is key, the interactions in this task are typically brief and asynchronous (e.g., emails or short messages). Although the task demands clarity and timely responses, it involves lower levels of live, dynamic interaction compared to more complex negotiations. Hence, the social and interactive complexity is low-to-moderate.

Data Availability and Quality (DAQ = 7)

Communication data—such as email threads, chat logs, and status updates—are generally well-structured and readily accessible through digital platforms. The high quality and reliability of this data support efficient management and tracking of project progress, resulting in a high score.

Decision Complexity under Uncertainty (DCU = 5)

Deciding what information to share, when to provide an update, and how to articulate potential issues involves some uncertainty. However, established communication protocols often guide these decisions. While there is some need for judgment—especially when handling ambiguous or evolving project details—the overall decision-making process is moderately complex.

Proactively research, seek, and submit tailored proposals on freelance platforms while negotiating contracts, project terms, and rates with clients.

Proactively research, seek, and submit tailored proposals on freelance platforms while negotiating contracts, project terms, and rates with clients.

Task Modularity and Granularity (TMG = 7)

This business development activity can be divided into distinct sub-tasks, including scanning job postings, crafting customized proposals, and engaging in contract negotiations. In the context of

transcription work, these phases are clearly identifiable yet interdependent—insights gained during proposal drafting may inform negotiation strategies, for example. This iterative and compartmentalized structure warrants a moderately high modularity score.

Context Dependence (TCD = 5)

While proposals generally rely on standard templates and established market practices, the process does require some customization to match the specifics of each job posting. For transcriptionists, the contextual demands are moderate; although the bulk of proposals follow a similar format, nuances such as client industry, audio complexity, and pricing guidelines require situational adjustments.

Social and Interactive Complexity (SIC = 4)

The task primarily involves asynchronous, written communication on freelance platforms. Although there is some interpersonal interaction—particularly during negotiations—the overall social complexity is lower compared to live consultations. The cognitive effort is more focused on crafting persuasive text rather than managing dynamic interpersonal exchanges, leading to a relatively low-to-moderate social complexity score.

Data Availability and Quality (DAQ = 7)

Freelancers have access to structured data via job postings, client profiles, and platform analytics that inform proposal development. However, the quality and completeness of this data can vary, especially when job descriptions are vague or incomplete. This balance of abundant yet sometimes inconsistent data supports a moderately high score in data availability and quality.

Decision Complexity under Uncertainty (DCU = 6)

Developing tailored proposals and negotiating contracts require moderate cognitive engagement. Transcriptionists must decide which opportunities to pursue, tailor their pitch to client needs, and determine acceptable terms—all under conditions of market competition and variable client expectations. Although the overall process is guided by standard practices, the inherent uncertainty in client requirements and negotiation outcomes results in a moderate decision complexity score.

Manage administrative tasks such as invoicing, bookkeeping, and scheduling to sustain smooth business operations.

Task Modularity and Granularity (TMG = 9)

Administrative tasks in freelance transcription are highly modular. These functions—such as logging hours, invoicing, and bookkeeping—are distinct, discrete activities that can be executed independently. Moreover, many digital platforms used by transcriptionists automate a significant portion of these processes, further emphasizing their compartmentalized nature. This clear segmentation results in a very high modularity score.

Context Dependence (TCD = 3)

These tasks are largely standardized, following predefined workflows and utilizing automation tools available on freelance platforms. While there may be minor variations based on specific client preferences or internal processes, the overall procedures remain consistent. Thus, the task exhibits a low dependency on unique contextual cues, yielding a low context dependence score.

Social and Interactive Complexity (SIC = 2)

Administrative tasks are mostly performed individually and rely on routine digital interactions, such as submitting invoices or updating schedules. Although some minimal coordination with clients or team members may be required, these interactions are generally brief and structured. Therefore, the social and interactive complexity is very low.

Data Availability and Quality (DAQ = 9)

These functions are supported by well-organized and reliable data. Freelance platforms typically provide standardized tools for logging hours, processing payments, and managing financial records. The abundance and quality of this structured data contribute to a very high score in data availability and quality.

Decision Complexity under Uncertainty (DCU = 3)

Decisions in managing administrative tasks are largely routine and governed by established protocols. Although accuracy is essential, the choices involved (such as reconciling invoices or updating records) are straightforward, with minimal ambiguity or need for complex judgment. This results in a low decision complexity score.

Maintain and update your professional profile.

Task Modularity and Granularity (TMG = 6)

This task can be segmented into clear, discrete actions—such as uploading updated work samples, revising biographical information, and adding recent testimonials. However, these sub-tasks collectively contribute to a single, cohesive professional image across multiple platforms. In the context of freelance transcription, where updates typically occur only after major projects or skill upgrades, the activity is modular but not continuous, yielding a moderate modularity score.

Context Dependence (TCD = 4)

Updating an online profile largely follows standardized formats and best practices, though there is a need to tailor content to reflect industry-specific experience. While the overall process is relatively consistent, minor adjustments based on current market trends or unique client expectations do introduce some context dependence, resulting in a low-to-moderate score.

Social and Interactive Complexity (SIC = 3)

This task is predominantly solitary. Although a freelancer might occasionally seek feedback or collaborate with peers to refine their presentation, the core activity of updating a profile is executed independently. Consequently, the social and interactive complexity remains low.

Data Availability and Quality (DAQ = 5)

The data required for portfolio updates—such as past work samples, ratings, and testimonials—is generally accessible via digital platforms. However, the quality and consistency of this information can vary between platforms or projects. This mix of readily available but variable data supports a moderate score.

Decision Complexity under Uncertainty (DCU = 5)

While the task involves standard procedures, freelancers must make strategic decisions about which projects to highlight, how to present their skills, and when to refresh their profiles. These choices, though guided by clear industry norms, still involve moderate uncertainty—particularly in a competitive market—resulting in a moderate decision complexity score.

Dedicate scheduled time for continuous professional development by learning new transcription tools and staying updated on industry practices.

Task Modularity and Granularity (TMG = 3)

Although professional development activities can be broken down into distinct components—such as

attending webinars, self-study sessions, and practicing new tools, these activities tend to be interwoven into an ongoing, integrated learning routine. In the context of freelance transcription, where staying current is critical yet not compartmentalized into isolated, billable tasks, the overall process is less modular, resulting in a low score.

Context Dependence (TCD = 6)

Professional development is driven both by the freelancer's internal goals and by rapidly evolving industry standards. While many training modules and online courses offer structured content, the relevance and application of new skills depend on the specific challenges and technological trends encountered in transcription work. This mix of standardized learning and situational adaptation leads to a moderate score for context dependence.

Social and Interactive Complexity (SIC = 3)

The majority of professional development is self-directed—through online courses, tutorials, or reading—requiring minimal real-time interpersonal interaction. Although occasional collaborative sessions (like virtual workshops or group discussions) occur, the core activity remains solitary. Thus, the task has low social and interactive complexity.

Data Availability and Quality (DAQ = 7)

A wealth of educational resources (e.g., online courses, tutorials, webinars) is readily available for learning new transcription tools and practices. However, the quality and applicability of these resources can vary, so while data is abundant and generally high quality, some variability exists. This supports a moderately high score in data availability and quality.

Decision Complexity under Uncertainty (DCU = 7)

Choosing which skills or tools to focus on in an ever-changing technological landscape involves significant decision-making. Transcriptionists must weigh the benefits of adopting new practices against the time investment required, often in a context of uncertain future client demands. This continuous evaluation and strategic adjustment under conditions of uncertainty contribute to a high decision complexity score.

Freelance Developers

Freelance Developers Task Description	**Task Modularity and Granularity (TMG)**	**Context Dependence (TCD)**	**Social & Interactive Complexity (SIC)**	**Data Availability & Quality (DAQ)**	**Decision Complexity & Uncertainty (DCU)**

Communicate with clients to clarify project requirements, desired functionalities, and target objectives, ensuring a clear understanding of the assignment.	6	7	6	7	7
Conduct technical research to identify effective solutions, best practices, and appropriate technologies to inform the development process.	7	8	3	8	8
Develop and maintain code to meet specific client requirements related to custom software and web applications.	8	6	3	8	7
Optimize websites, content management systems (e.g., WordPress, Drupal), and applications for performance, speed, security, and reliability as needed or per client request.	7	8	4	8	8
Document code and technical processes to ensure quality and maintainability.	8	5	3	9	5
Troubleshoot and resolve technical issues in existing systems and codebases, including debugging and addressing production challenges.	6	8	3	7	9
Provide ongoing maintenance, updates, and improvements to ensure long-term viability and scalability of the project.	6	7	4	8	7
Proactively search for and apply to new work opportunities by developing and submitting tailored proposals on freelance platforms and negotiating contracts, project terms, and rates with clients.	7	5	6	7	6
Manage administrative tasks such as invoicing, bookkeeping, and scheduling to sustain smooth business operations.	9	3	2	9	3
Maintain and update an online portfolio and professional profile by regularly showcasing recent work samples, client testimonials, and case studies to attract potential clients.	6	4	3	5	5
Dedicate scheduled time for continuous professional development to keep skills and knowledge current.	3	7	3	8	8

Communicate with clients to clarify project requirements, desired functionalities, and target objectives, ensuring a clear understanding of the assignment.

Communicate with clients to clarify project requirements, desired functionalities, and target objectives, ensuring a clear understanding of the assignment.

Task Modularity and Granularity (TMG = 6)

Although the initial and follow-up communications can be broken down into distinct phases—such as gathering requirements, resolving ambiguities, and confirming technical specifications—the process is highly interdependent. In freelance development, these consultations form a cohesive dialogue that informs subsequent coding, debugging, and project planning. The modularity is moderate because while individual exchanges are identifiable, they must collectively maintain a coherent project vision.

Context Dependence (TCD = 7)

Successful technical communication depends heavily on understanding the unique context of each project. Freelance developers must interpret client inputs—often delivered in non-technical language—and convert them into precise, actionable specifications. This task requires sensitivity to industry-specific details, client priorities, and potential technical constraints, yielding a high score in context dependence.

Social and Interactive Complexity (SIC = 6)

Although these interactions typically occur via scheduled calls or written communications (emails, chats), effective dialogue in technical projects demands both interpersonal skills and technical literacy. Developers must negotiate nuances, clarify ambiguous points, and sometimes bridge gaps between non-technical client language and technical implementation requirements. This level of interpersonal negotiation, while not as dynamic as real-time collaborative brainstorming, results in a moderate social and interactive complexity score.

Data Availability and Quality (DAQ = 7)

The information exchanged during these communications—such as project briefs, requirement documents, and follow-up clarifications—is often available in structured digital formats. However, the quality and completeness of this data can vary, particularly when initial client instructions are vague or incomplete. This mixture of reliable yet sometimes inconsistent data contributes to a moderately high score in data availability and quality.

Decision Complexity under Uncertainty (DCU = 7)

Determining how to interpret and translate client requirements into actionable technical specifications involves significant decision-making under uncertainty. Freelance developers must balance differing interpretations, resolve ambiguities, and decide on priorities—all in real time. The need for such critical judgment under uncertain conditions warrants a high decision complexity score.

Conduct technical research to identify effective solutions, best practices, and appropriate technologies to inform the development process.

Task Modularity and Granularity (TMG = 7)

Technical research can be segmented into distinct phases—such as identifying relevant sources,

evaluating emerging trends, synthesizing information, and performing risk assessments—but these phases are closely interdependent. In freelance development, the research is often an iterative process that continuously informs design decisions, so while each sub-task is identifiable, they are not entirely independent. This integrated yet segmentable structure justifies a moderately high modularity score.

Context Dependence (TCD = 8)

The effectiveness of technical research depends heavily on the specific context of each project. Developers must tailor their research to address unique client requirements, industry standards, and technological constraints. For instance, solutions appropriate for a startup might differ significantly from those for an enterprise client. This strong reliance on contextual nuances and the need for customized evaluation results in a high context dependence score.

Social and Interactive Complexity (SIC = 3)

Technical research is primarily a solitary activity. Although there might be occasional interactions—such as consulting with experts or discussing findings with a team—the majority of the work involves individual analysis and synthesis. As a result, the social and interactive complexity is relatively low in this task.

Data Availability and Quality (DAQ = 8)

Developers have access to a wide range of high-quality data sources, including academic journals, industry reports, online forums, and technology blogs. This abundance of structured and reliable information supports thorough technical research. However, given that the quality of data can vary by topic and source, a very high but not perfect score is warranted.

Decision Complexity under Uncertainty (DCU = 8)

The task demands significant decision-making under conditions of uncertainty. Freelance developers must critically evaluate competing technologies, weigh the trade-offs of various solutions, and predict the future viability of emerging tools. These decisions—often made with incomplete information—require deep technical understanding and strategic judgment, leading to a high decision complexity score.

Develop and maintain code to meet specific client requirements related to custom software and web applications.

Task Modularity and Granularity (TMG = 8)

Coding tasks are inherently modular. Developers often break down the overall solution into discrete components (e.g., functions, classes, modules) that can be developed, tested, and maintained independently. Even though the final product is an integrated system, the ability to segment the work into clear, manageable parts supports a high modularity score. This is especially true for freelance developers who work on varied projects using different frameworks and coding languages.

Context Dependence (TCD = 6)

Custom software and web development require a deep understanding of the client's specific needs, industry standards, and target audience but this understanding is often explicit and not always nuanced. Developers must adapt their approach and design choices based on the particular context of each project—whether it's tailoring a user interface, integrating third-party APIs, or ensuring compliance with client-specific security protocols. This reliance on situational details warrants a medium context dependence score.

Social and Interactive Complexity (SIC = 3)

The development process is predominantly solitary. While code reviews, collaborative debugging sessions, and client meetings occur, the bulk of the work—writing, testing, and refactoring code—is completed independently. Thus, the social and interactive demands are relatively low compared to tasks that require continuous, dynamic interpersonal interaction.

Data Availability and Quality (DAQ = 8)

Freelance developers benefit from access to a wealth of structured technical documentation, coding standards, libraries, and robust testing frameworks. These high-quality resources support efficient coding practices and help ensure adherence to best practices. Although some projects may require additional research to fill information gaps, the overall reliability of available data is high, justifying a high score.

Decision Complexity under Uncertainty (DCU = 7)

Developing and maintaining code involves complex decision-making under uncertainty. Developers must select appropriate technologies, design architecture, and optimize performance while handling ambiguous or incomplete client specifications. The need to balance trade-offs—such as speed versus security or maintainability versus innovation—requires substantial cognitive effort and strategic judgment, resulting in a high decision complexity score.

Optimize websites, content management systems (e.g., WordPress, Drupal), and applications for performance, speed, security, and reliability as needed or per client request.

Optimize websites, content management systems (e.g., WordPress, Drupal), and applications for performance, speed, security, and reliability as needed or per client request.

Task Modularity and Granularity (TMG = 7)

Optimization tasks can be broken down into discrete activities—such as profiling code, identifying bottlenecks, implementing caching strategies, and enhancing security measures. However, these sub-tasks are closely interrelated; improvements in one area often affect overall system performance. In the context of freelance development, where every optimization contributes to the final deliverable, this interconnected yet segmentable structure justifies a moderately high score.

Context Dependence (TCD = 8)

The effectiveness of optimization depends heavily on the specific technical environment and client requirements. Developers must tailor their approaches based on the existing system architecture, current performance issues, and industry standards. For instance, solutions appropriate for an e-commerce site under heavy traffic may differ significantly from those for a content management system with low usage. This deep reliance on contextual details results in a high score.

Social and Interactive Complexity (SIC = 4)

Although optimization is primarily a technical and solitary activity, there is some degree of interaction—such as collaborating with client IT teams or consulting with other developers to resolve challenging issues. However, most of the work is conducted individually using automated tools and performance metrics, leading to a relatively low-to-moderate social and interactive complexity.

Data Availability and Quality (DAQ = 8)

Optimization efforts benefit from structured, high-quality data provided by performance profiling tools, server logs, and analytics dashboards. While there can be variability in the data quality depending on the client's system, overall, the abundance and reliability of such information support informed decision-making, justifying a high score.

Decision Complexity under Uncertainty (DCU = 8)

Optimization requires complex decision-making to balance competing priorities—speed versus

security, performance versus resource usage, and stability versus innovation. Developers must make iterative adjustments under conditions of uncertainty, such as variable traffic loads or unforeseen system limitations. This dynamic and multifaceted decision process results in a high decision complexity score.

Document code and technical processes to ensure quality and maintainability.

Task Modularity and Granularity (TMG = 8)

Documentation can be divided into discrete components—such as documenting individual modules, APIs, and architectural decisions—but these elements must ultimately integrate into a cohesive guide. In freelance development, clear documentation is essential for long-term maintainability and often forms a defined deliverable. Although the task is not performed continuously, its modular sub-tasks combine to create a comprehensive reference, justifying a high modularity score.

Context Dependence (TCD = 5)

The effectiveness of documentation hinges on capturing project-specific details, including unique design choices, coding standards, and client-specific requirements. While some aspects follow standard documentation practices, each project's unique technical context necessitates tailored explanations. This reliance on contextual and situational details results in a medium context dependence score.

Social and Interactive Complexity (SIC = 3)

Documenting code is primarily an individual, solitary task. Although it may occasionally involve brief interactions—such as gathering clarifications from team members or clients—the bulk of the work is executed independently. Therefore, the social and interactive complexity remains relatively low.

Data Availability and Quality (DAQ = 9)

Documentation benefits from access to well-structured data such as codebases, design documents, and existing style guides. This information is generally reliable and of high quality, which facilitates the creation of accurate and detailed documentation. The structured nature of the data supports a high score for data availability and quality.

Decision Complexity under Uncertainty (DCU = 5)

Effective documentation requires critical decisions about the level of detail to include, how to balance

comprehensiveness with clarity, and which aspects of the code or architecture are most important to convey. Although best practices and templates often guide these decisions, the need to adapt documentation to evolving code and client requirements introduces significant decision-making under uncertainty, yielding a medium complexity score.

Troubleshoot and resolve technical issues in existing systems and codebases, including debugging and addressing production challenges.

Troubleshoot and resolve technical issues in existing systems and codebases, including debugging and addressing production challenges.

Task Modularity and Granularity (TMG = 6)

While troubleshooting can often be broken into discrete modules (such as isolating a bug, replicating the issue, and then applying a fix), many production issues are interrelated and require a holistic understanding of the system architecture. In freelance development, debugging tasks may be compartmentalized, yet their resolution often necessitates integrated changes across multiple components. This balance results in a moderately high modularity score.

Context Dependence (TCD = 8)

The effectiveness of troubleshooting heavily depends on understanding the specific operating environment. Factors such as varying system configurations, network conditions, and unique client setups all play a critical role in identifying and resolving issues. In freelance settings—where projects differ widely—this strong reliance on situational context justifies a high context dependence score.

Social and Interactive Complexity (SIC = 3)

Troubleshooting is primarily a solitary task, with most of the analysis and debugging performed independently. Although there may be occasional interactions (for instance, discussing issues with a client or collaborating briefly with team members), these are generally limited. Thus, the social and interactive complexity remains low.

Data Availability and Quality (DAQ = 7)

Debugging and troubleshooting rely on various sources of structured data, such as system logs, performance metrics, and error messages. While these data sources are typically available, their

quality can be inconsistent—especially if the production environment is not well-maintained. This variability in data reliability supports a moderately high score for data availability and quality.

Decision Complexity under Uncertainty (DCU = 9)

This task involves deep technical analysis and creative problem solving under uncertain conditions. Freelance developers must interpret ambiguous error messages, assess multiple potential causes, and weigh trade-offs between different fixes. The process of making critical decisions under often unpredictable conditions makes the decision complexity very high.

Provide ongoing maintenance, updates, and improvements to ensure long-term viability and scalability of the project.

Task Modularity and Granularity (TMG = 6)

Maintenance tasks can be divided into discrete sub-tasks—such as patching bugs, implementing feature updates, and running performance tests—but these sub-tasks are interconnected. In freelance development, ongoing maintenance is scheduled periodically (e.g., weekly or monthly) and must be coordinated to avoid disruption of existing functionalities. This combination of modular components and their integrated nature results in a moderately high modularity score.

Context Dependence (TCD = 7)

The effectiveness of maintenance efforts is highly dependent on the specific context of the project. Developers must tailor their updates and improvements to the current system architecture, existing codebase, and evolving client requirements. Variations in system complexity and client expectations require a deep understanding of contextual factors, leading to a high context dependence score.

Social and Interactive Complexity (SIC = 4)

While ongoing maintenance is primarily a technical and often solitary activity, there is an element of interaction—such as coordinating with clients or team members to schedule downtime or discuss update priorities. However, these interactions are generally structured and infrequent, resulting in a relatively low-to-moderate social and interactive complexity score.

Data Availability and Quality (DAQ = 8)

Maintenance tasks are supported by abundant, high-quality data from system logs, performance metrics, and error reports. These reliable data sources enable developers to identify bottlenecks, track

system performance, and validate updates efficiently. The structured nature of this data contributes to a high score in data availability and quality.

Decision Complexity under Uncertainty (DCU = 7)

Implementing maintenance and updates involves balancing innovation with stability. Developers must decide which features to update, how to integrate new improvements without disrupting existing functionalities, and how to address unexpected issues. Although established protocols can guide some decisions, the inherent uncertainty in system performance and client needs leads to a high decision complexity score.

Proactively search for and apply to new work opportunities by developing and submitting tailored proposals on freelance platforms and negotiating contracts, project terms, and rates with clients.

Task Modularity and Granularity (TMG = 7)

This task can be divided into discrete modules—for example, scanning job postings, crafting customized proposals, and negotiating terms. However, these modules are interdependent: feedback from initial proposals may require adjustments to subsequent submissions or negotiation strategies. For freelance developers working in a competitive digital marketplace, these phases collectively form an iterative process, resulting in a moderately high modularity score.

Context Dependence (TCD = 5)

While many aspects of proposal creation follow established templates and market practices, tailoring each proposal to the specific requirements of a job posting requires a degree of contextual adaptation. Freelance developers must interpret client specifications, understand industry norms, and adjust their pricing strategies accordingly. This balance between standardized procedures and situational customization yields a moderate context dependence score.

Social and Interactive Complexity (SIC = 6)

Although much of the work is performed asynchronously through online platforms, the task still involves interpersonal negotiation and persuasive communication—especially when discussing contract terms or rates with potential clients. The interactive component, while not as dynamic as real-time client consultations, does require a moderate level of social engagement and negotiation skills, leading to a moderate social complexity score.

Data Availability and Quality (DAQ = 7)

Freelance platforms provide a wealth of structured information such as job postings, client profiles, and platform analytics. This data is generally reliable and well-organized, which supports informed decision-making when preparing proposals. However, variability in the completeness and clarity of job descriptions means that the quality of available data can fluctuate, justifying a moderately high score.

Decision Complexity under Uncertainty (DCU = 6)

Crafting tailored proposals and negotiating contract terms involve significant decision-making under conditions of uncertainty. Freelance developers must choose which opportunities to pursue, determine competitive pricing, and adapt their strategies based on evolving client expectations. Although standard templates and past experience provide guidance, the inherent variability in the market and client requirements results in a moderately high decision complexity score.

Manage administrative tasks such as invoicing, bookkeeping, and scheduling to sustain smooth business operations.

Task Modularity and Granularity (TMG = 9)

Administrative tasks are highly modular. Functions like invoicing, bookkeeping, and scheduling are clearly delineated and can be executed as distinct, independent modules. In freelance transcription, these tasks are typically performed as one-off events at the end of each project or on a periodic basis, and many are supported by automated tools, reinforcing their segmented, modular nature.

Context Dependence (TCD = 3)

These tasks follow standardized procedures and utilize consistent digital platforms (e.g., invoicing software, time-tracking systems). Although there might be minor client-specific variations (such as custom invoicing formats), the core processes remain uniform. This low reliance on unique situational factors results in a low context dependence score.

Social and Interactive Complexity (SIC = 2)

Administrative work is predominantly solitary and routine. Although occasional coordination with clients or team members may occur (for example, confirming a billing cycle or scheduling a follow-up meeting), the interactions are minimal and structured. Consequently, the social and interactive complexity is very low.

Data Availability and Quality (DAQ = 9)

Administrative tasks benefit from highly structured and reliable data—such as digital invoices, time logs, and financial records—provided by automated systems and platforms. The high consistency and accessibility of this data support efficient task execution, justifying a very high score for data availability and quality.

Decision Complexity under Uncertainty (DCU = 3)

The decisions involved in managing administrative tasks are typically straightforward and rule-based. Tasks such as reconciling invoices or updating a schedule follow established protocols, and while precision is important, the cognitive demands are minimal. Therefore, the overall decision complexity under uncertainty is low.

Maintain and update an online portfolio and professional profile by regularly showcasing recent work samples, client testimonials, and case studies to attract potential clients.

Task Modularity and Granularity (TMG = 6)

While updating an online portfolio can be broken down into discrete actions (such as uploading work samples, revising bios, and refreshing testimonials), these components ultimately merge to form a cohesive professional image. In the context of freelance transcription, the updates tend to be straightforward and standardized across different platforms, which supports a moderate modularity score.

Context Dependence (TCD = 4)

The process of updating a portfolio generally follows standardized best practices and platform requirements. Although there is a need to reflect any new skills or client feedback (which introduces some situational nuance), the overall task is relatively consistent regardless of context. This results in a low-to-moderate score for context dependence.

Social and Interactive Complexity (SIC = 3)

Maintaining an online profile is predominantly a solitary activity. Transcriptionists typically update their portfolios independently, with minimal real-time interaction. Occasional consultations or peer feedback may occur, but these do not significantly elevate the overall social complexity, leading to a low score.

Data Availability and Quality (DAQ = 5)

The data required—previous work samples, client testimonials, and case studies—is usually available from past projects. However, the quality and presentation of this data can vary, particularly across different freelance platforms. This variability results in a moderate score for data availability and quality.

Decision Complexity under Uncertainty (DCU = 5)

Updating a portfolio requires strategic decisions, such as determining which samples best represent one's skills and how to update a professional profile to remain competitive. Although the task is guided by established norms, the inherent uncertainty in market competition and client preferences necessitates moderate decision-making, resulting in a moderate score.

Dedicate scheduled time for continuous professional development to keep skills and knowledge current.

Task Modularity and Granularity (TMG = 3)

Professional development activities—such as attending webinars, self-study sessions, or online courses—are generally integrated into the daily or weekly routine rather than being discrete, isolated tasks. For freelance developers, continuous learning is an ongoing process that blends into their work routine rather than being compartmentalized, resulting in a low modularity score.

Context Dependence (TCD = 7)

Staying competitive in technology requires developers to continuously adapt to rapidly evolving tools, frameworks, and industry practices. The relevance of new skills often depends on the specific technological context of the projects they undertake. Freelance developers must evaluate which emerging trends are most applicable to their niche, which introduces significant contextual dependency and justifies a high score.

Social and Interactive Complexity (SIC = 3)

The core of professional development is predominantly self-directed. Although there may be occasional collaborative learning sessions, such as virtual workshops or peer group discussions, the majority of the learning is done individually. Consequently, the social and interactive complexity remains relatively low.

Data Availability and Quality (DAQ = 8)

There is an abundance of high-quality educational resources available for developers, including online courses, tutorials, documentation, and technical blogs. While the quality and relevance of these resources can vary, overall the data supporting professional development is robust and well-structured, leading to a high score in data availability and quality.

Decision Complexity under Uncertainty (DCU = 8)

Choosing which new tools to learn or which skills to upgrade involves significant decision-making under uncertainty. Freelance developers must weigh the benefits of adopting cutting-edge technologies against the time investment required to master them. This process involves high cognitive engagement and strategic judgment, resulting in a high decision complexity score.

Appendix E

Platform Work and AI: Task Weightage Scoring Criteria

Descriptive Anchors

Frequency (F): Reflects how often a task is performed in the freelancer's workflow. A score of 1 means the task is performed very rarely, while a score of 10 indicates it is a routine and very frequent task.

Duration (D): Captures the average amount of time required to complete a task. A lower score (closer to 1) signifies that the task is brief, whereas a higher score (closer to 10) indicates a task that requires extensive time commitment.

Complexity (C): Measures the perceived cognitive and technical difficulty of the task. A score of 1 denotes a task that is very simple and straightforward, while a score of 10 represents a task that demands high expertise, intricate problem-solving, and significant mental effort.

Client Prioritization (P): Reflects how important the task is seen by clients in the platform economy, from the worker's perspective. A low score (near 1) means the task is considered of minimal importance to clients, whereas a high score (near 10) indicates that clients place great value on that task, as it directly impacts project success and satisfaction.

Role Factor (R) (1 = Unpaid Work): Tasks that are completely unpaid. These activities support a freelance workers' business and professional growth, but do not generate revenue for a specific client deliverable and remain unpaid.

Role Factor (R) (2 = Mostly Unpaid work): Tasks that are primarily unpaid. Although they may have a minor impact on the quality or efficiency of the paid work resulting in some paid time used to complete these tasks, but the bulk of the time and effort spent is not directly charged to the client.

Role Factor (R) (3 = Mixed): Tasks that involve a nearly equal mix of paid and unpaid effort. These activities are sometimes included as part of a client's deliverable, but they also require significant unpaid effort from workers.

Role Factor (R) (4 = Mostly Paid Work): Tasks that are predominantly considered paid work hours, meaning the majority of the work is directly tied to delivering client outcomes and almost all hours are billed, though they may include some elements of overhead effort to deal with externalities that make the fixed price contracts more time consuming for a worker than initially anticipated.

Role Factor (R) (5 = Fully Paid Work): Tasks that are completely revenue generating and paid hours. These are core deliverables that are directly invoiced to clients without additional overhead or unpaid work at workers' end.

Freelance Writing

Freelance Writing Task Description	**F**	**D**	**C**	**P**	**R**
Engage in initial client consultations to clarify project requirements, target audience, and desired tone or style.	2	2	6	8	2
Conduct comprehensive research on a wide range of topics tailored to the client's needs using credible sources to develop content ideas and detailed outlines tailored to the assignment.	9	6	7	6	4
Draft articles, blog posts, website content, academic papers, and other forms of written communication adapting the writing style to suit various formats such as creative, technical, academic, or copywriting.	8	9	10	10	5
Proofread the content thoroughly to eliminate grammatical, punctuation, and formatting errors, ensuring high-quality final output.	3	7	6	9	4
Maintain regular communication with clients to provide progress updates, clarify requirements, and address feedback.	3	3	4	6	3
Revise and edit content based on client feedback, ensuring accuracy, tone, and adherence to guidelines.	4	4	7	10	5

Proactively search for and apply to new work opportunities by developing and submitting tailored proposals on freelance platforms and negotiating contracts, project terms, and rates with clients.	9	6	6	2	1
Dedicate scheduled time for continuous professional development to keep skills and knowledge current.	7	7	7	4	1
Manage administrative tasks such as invoicing, bookkeeping, and scheduling to sustain smooth business operations.	2	2	2	2	1
Maintain and update an online portfolio and professional profile by regularly showcasing recent writing samples, client testimonials, and case studies to attract potential clients.	3	2	4	8	1

Freelance Writing Pairwise Matrix

Freelance Writing Criteria	Frequency (F)	Duration (D)	Complexity (C)	Client Prioritization (P)
Frequency (F)	1.00	2.00	0.50	1.50
Duration (D)	0.50	1.00	0.50	1.00
Complexity (C)	2.00	2.00	1.00	1.50
Client Prioritization (P)	0.67	1.00	0.67	1.00

Frequency (F) vs. Duration (D): Value = 2

Freelance writing involves many frequent, short tasks (such as writing blog posts or applying for jobs), while tasks like revising long documents or proofreading extensive work occur less frequently but may take more time. Here, frequency is considered twice as important as duration because high-frequency tasks dominate daily activities and income generation.

Frequency (F) vs. Complexity (C): Value = 0.5

In this comparison, a value of 0.50 indicates that frequency is half as important as complexity. Although simpler, recurring tasks (like basic blog posts or client communications) occur more frequently, tasks that are complex (e.g., writing high-quality white papers or in-depth research articles) add significant value even if they are less frequent. This reflects the notion that complexity, in terms of the skill and intellectual effort required, is highly valued.

Frequency (F) vs. Client Prioritization (P): Value = 1.5

Frequent tasks like applying for jobs, communicating with clients, and producing content are fundamental to maintaining access to consistent work. However, aligning with client priorities (e.g., meeting deadlines and adhering to tone) is critical for success (impacts freelancer's ratings). Freelancers often spend significant time on frequent, client-driven tasks to ensure satisfaction and build relationships. Frequency slightly outweighs client prioritization because the need to perform frequent tasks (e.g., job applications) is essential for sustaining work opportunities.

Duration (D) vs. Complexity (C): Value = 0.5

While long tasks (e.g., editing extensive documents) take more time, they are often less cognitively demanding than creating original, high-quality content. Clients value output quality over time invested, making complexity more critical than duration also because work is often fixed payment and not hourly. Complexity is twice as important as duration because it reflects the intellectual and technical effort required to deliver value.

Duration (D) vs. Client Prioritization (P): Value = 1

In this case, a value of 1.00 means that duration and client prioritization are considered equally important. Tasks that take longer often align closely with client expectations (for instance, larger projects that demand detailed work), thus balancing both the time required and the importance from the client's perspective.

Complexity (C) vs. Client Prioritization (P): Value = 1.5

Complex tasks (e.g., developing intricate content or performing detailed research) not only require high-level skills but also generally yield higher client value. The value of 1.50 indicates that complexity is 1.5 times as important as client prioritization, reinforcing that while client needs are critical, the inherent difficulty and skill requirement of a task can add significant value to the final deliverable.

Engage in initial client consultations to clarify project requirements, target audience, and desired tone or style

R= 2 (Mostly Unpaid Work)

These consultations are critical for establishing project scope and ensuring that the final product meets client expectations. However, work if mostly fixed price and time spent on these consultations is generally not separately invoiced; instead, they often serve as a preparatory activity that sets the stage for subsequent, fully paid work. The time spent here is often considered overhead because it supports future work rather than representing a direct client deliverable.

Frequency (F) = 2

This consultation typically occurs once per project. Although a freelance writer may have multiple projects in a given period, each consultation is a one-off event at the start of a project rather than a daily or repeated task. Thus, compared to tasks performed continuously (e.g., drafting), its frequency is low.

Duration (D) = 2

A client consultation could last between 30 to 60 minutes. When compared to other tasks in freelance writing, such as drafting or revising content, which can span several hours, the time commitment for a consultation is relatively short compared to the rest of the tasks. Therefore, the duration score is low.

Complexity (C) = 6

This task requires effective communication skills, active listening, and the ability to accurately interpret and translate client requirements into actionable project guidelines. Although these skills are essential, the cognitive and technical complexity is moderate compared to more intensive tasks like in-depth research or creative drafting. A score of 5 reflects this balanced level of complexity.

Client Prioritization (P) = 8

The initial consultation is highly prioritized by clients because it sets the foundation for the entire project. Clear and accurate understanding of client needs, objectives, and style preferences directly influences the quality and success of the final deliverable. Given its critical importance in aligning the project with client expectations, this task receives a high score of 8.

Conduct comprehensive research on a wide range of topics tailored to the client’s needs using credible sources to develop content ideas and detailed outlines tailored to the assignment.

R = 4 (Mostly Paid Work)

Research is integral to producing relevant content and is often included as part of the service fee. While some research elements may fall under general overhead as new topic may require a lot of learning and research, the majority of the activity directly informs the content creation process and is therefore predominantly considered paid work in this analysis.

Frequency (F) = 9

Research is a core component of freelance writing and is performed for nearly every project. Freelance writers must consistently engage in thorough research to understand the subject matter and generate fresh, tailored content ideas. Because this activity occurs repeatedly across multiple assignments, its frequency is very high. Therefore, a score of 9 reflects that comprehensive research is a regularly recurring and essential part of the workflow.

Duration (D) = 6

Comprehensive research typically requires a moderate to significant time commitment. While the exact duration may vary, depending on the complexity of the topic and the depth of information required, the average research task often takes several hours. This is shorter than the time needed for drafting long-form content but is still a substantial portion of the overall project. Thus, a score of 7 is appropriate to capture the moderate-to-high time investment.

Complexity (C) = 7

The research task demands high cognitive effort, analytical skills, and sometimes technical expertise. Freelance writers must evaluate multiple sources, verify the credibility of the information, and synthesize the data into coherent content ideas and detailed outlines. Given that the task involves dealing with diverse topics and requires careful judgment in selecting and interpreting information, a complexity score of 8 reflects the substantial intellectual and analytical demands of the task.

Client Prioritization (P) = 6

Clients place a high value on the quality of research because it directly influences the credibility and effectiveness of the final content. Although drafting and revisions are critical to producing the deliverable, thorough research forms the foundation upon which quality content is built. Thus, while research might not always be as immediately visible as a polished draft, its impact on the overall project quality is significant. A score of 7 indicates that research is moderately to highly prioritized by clients.

Draft articles, blog posts, website content, academic papers, and other forms of written communication adapting the writing style to suit various formats such as creative, technical, academic, or copywriting.

R = 5 (Fully Paid Work)

Drafting is the core production activity in freelance writing. Nearly all the time and effort spent on creating the draft directly contribute to a client's deliverable, making this task completely revenue generating and fully billable.

Frequency (F) = 8

Drafting content is the core production activity for freelance writers and is performed for nearly every project. Unlike one-off activities such as initial consultations, drafting occurs repeatedly and continuously as a writer works on each assignment. Because this task is at the very heart of a freelance writer's workflow, its frequency is assigned the maximum score.

Duration (D) = 9

The process of drafting involves generating substantial amounts of original text, which can require several hours per project. While the exact time may vary depending on the assignment's complexity and length, drafting generally takes up a significant portion of the project timeline. Hence, a score of 9 reflects that this task has a high duration relative to other tasks, though it might not always extend to the absolute maximum for every project.

Complexity (C) = 10

Drafting content is not merely a mechanical process of writing; it requires creativity, analytical thinking, and technical skill. Freelance writers must adapt their tone, style, and structure to suit different formats—whether that's a creative narrative, technical documentation, academic paper, or persuasive copywriting. This multi-format adaptability adds considerable complexity to the task, justifying a high complexity score.

Client Prioritization (P) = 10

Clients view the draft as the foundational deliverable that directly influences the overall quality and success of the project. The ability to produce clear, engaging, and well-structured content is of

paramount importance. Because the drafted content forms the primary basis for client satisfaction and subsequent revisions, this task is given the highest score in client prioritization.

Proofread the content thoroughly to eliminate grammatical, punctuation, and formatting errors, ensuring high-quality final output.

R = 4 (Mostly Paid Work)

Proofreading is a critical step that ensures the final content is polished and professional. Since this process directly impacts the quality of the deliverable, it is an essential step. However, depending on the skills of a worker, proofreading may involve significant effort at the worker's end that may not be billable if remuneration is project based and not hourly.

Frequency (F) = 3

Proofreading is generally performed once per project, following the drafting and revision stages. Unlike tasks such as drafting or research, which occur repeatedly throughout the project lifecycle, proofreading is a one-off step per draft cycle. Although it is an essential part of every project, its occurrence is limited, resulting in a relatively low frequency score.

Duration (D) = 7

The time required for proofreading can vary depending on the length and complexity of the document. For longer or more detailed content, proofreading may require a sustained, focused effort to catch all errors. While it is typically shorter in duration than drafting, the process is still time-intensive—especially when ensuring that even minor grammatical, punctuation, or formatting issues are addressed. Thus, a score of 7 reflects a moderate-to-high time investment.

Complexity (C) = 6

Although proofreading is primarily a quality control step rather than a creative process, it demands significant attention to detail, a thorough understanding of language rules, and the ability to catch subtle errors. The cognitive effort is moderate, as the task involves systematic error detection and correction, particularly in content that includes technical or stylistic nuances. A score of 6 appropriately captures this level of complexity.

Client Prioritization (P) = 9

Clients place very high importance on the final quality of the deliverable. A well-proofread document reflects professionalism and directly influences client satisfaction. Any errors can undermine the credibility of the content and, by extension, the freelancer. Given that a polished final output is critical for achieving high client ratings and ensuring repeat business, proofreading is assigned a high client prioritization score of 9.

Maintain regular communication with clients to provide progress updates, clarify requirements, and address feedback.

R = 3 (Mixed)

Regular client communication is essential for keeping projects aligned with client needs, yet these interactions are typically not itemized on invoices. Although they contribute to the overall quality of the service, they are classified as mostly unpaid work because much of the time spent does not directly generate revenue.

Frequency (F) = 3

This communication task occurs repeatedly throughout the project lifecycle but less frequently than other core tasks. Freelance writers may need to often check in with clients on a regular (e.g., daily or several times a week) basis to provide updates and clarify any emerging issues. Although it's not continuous in the way that drafting might be, the recurring nature of these interactions earns a high frequency score.

Duration (D) = 3

While communication happens frequently, each individual interaction is relatively brief, typically lasting a few minutes to perhaps half an hour. Compared to tasks like drafting or in-depth research, the time spent per communication event is limited, so the duration score is lower.

Complexity (C) = 4

Effective communication requires clear writing, active listening, and the ability to interpret and respond to client feedback. Although these skills are important, the cognitive load is generally moderate, less demanding than creating original content or performing detailed research. Thus, a moderate complexity score reflects that while the task is essential, it is not as technically or creatively demanding as other core activities.

Client Prioritization (P) = 6

From a client's perspective, ongoing communication is critical. Regular updates and clarifications help ensure that the project remains aligned with their expectations, minimize misunderstandings, and build trust. Given its direct impact on client satisfaction and project success, this task is highly prioritized by clients.

Revise and edit content based on client feedback, ensuring accuracy, tone, and adherence to guidelines.

R = 5 (Fully Paid Work)

Revisions and edits directly enhance the final product, ensuring it meets the client's specifications and quality standards. Since this activity is a critical component of the deliverable, it is fully billable and represents a core revenue-generating task.

Frequency (F) = 4

Revision and editing are integral to every freelance writing project. Many project goes through at least one revision cycle to refine the draft according to client feedback, whether for minor tweaks or significant overhauls, giving it medium frequency score.

Duration (D) = 4

While the initial drafting process might consume a very large portion of the project timeline, the revision stage still demands a substantial time commitment. Incorporating detailed client feedback, making structural changes, and ensuring that all aspects (accuracy, tone, adherence to guidelines) are met can require considerable hours per project. Although it is less time-intensive than drafting.

Complexity (C) = 7

The revision process is complex in several ways. It requires not only the ability to detect errors and inconsistencies but also the skill to modify content in a way that preserves the intended message while enhancing clarity and style. The task demands a nuanced understanding of language and tone as well as the capability to balance client feedback with creative and technical writing requirements.

Client Prioritization (P) = 10

The final product’s quality is heavily dependent on the thoroughness of the revision process. Clients place maximum value on receiving polished, error-free content that accurately reflects their requirements and desired tone. Because any oversight in the revision stage can compromise client satisfaction and impact future business opportunities, this task is of utmost importance from the client's perspective, justifying a maximum score for client prioritization.

Proactively search for and apply to new work opportunities by developing and submitting tailored proposals on freelance platforms and negotiating contracts, project terms, and rates with clients.

R= 1 (Unpaid Work)

Seeking new work, developing and submitting proposals on platforms, interviewing and negotiating terms with potential clients, are essential for long-term work availability but do not directly contribute to current client deliverables. These efforts are entirely overhead and, therefore, fully unpaid.

Frequency (F) = 9

In the competitive freelance environment, freelancers must apply to numerous job postings daily in order to secure even a few assignments. This task occurs extremely frequently, multiple times per day, since freelancers continuously scan platforms for new opportunities. Therefore, the frequency score is very high.

Duration (D) = 6

While an individual proposal might not take an extensive amount of time to prepare, the cumulative time spent on job searches, tailoring multiple proposals, and engaging in negotiations can be substantial. Freelancers often invest several hours each day in this activity, which justifies a moderate-to-high duration score.

Complexity (C) = 6

Developing tailored proposals and negotiating contract terms require a mix of research, persuasive writing, and strategic thinking. Although the cognitive demands of this task are moderate compared to creative drafting or in-depth research, the need to customize each proposal and negotiate effectively adds a significant level of complexity. Thus, a score of 6 is appropriate.

Client Prioritization (P) = 2

This task is entirely self-initiated and aimed at securing future work; clients do not directly request or prioritize freelancers' efforts in applying for new jobs. As such, despite its critical role in long-term income generation, it is not directly tied to client deliverables and is assigned a low client prioritization score.

Dedicate scheduled time for continuous professional development to keep skills and knowledge current.

R = 1 (Unpaid Work)

Continuous professional development is crucial for long-term career growth and maintaining competitive skills, yet it does not directly result in immediate client deliverables. As a result, the time spent on professional development is considered fully unpaid work.

Frequency (F) = 7

Freelancers engaged in diverse writing topics often integrate learning into their daily or near-daily routine to stay current across multiple domains. Because this ongoing learning activity is embedded in their everyday work, it occurs frequently, and a score of 7 accurately reflects its high occurrence.

Duration (D) = 7:

Given the broad range of subjects that freelance writers must cover, the cumulative time invested in professional development can be substantial. This high level demand to learn new topics and process information requires signfivcnatn time commitment.

Complexity (C) = 7

The process of learning new topics and tools involves assimilating complexes, evolving information and sometimes unlearning outdated methods and writing practices. This high level of cognitive engagement and the need for strategic integration of new skills justify a high complexity rating.

Client Prioritization (P) = 4

Although continuous professional development is crucial for maintaining high-quality service over the long term, its benefits are largely indirect. Clients ultimately receive the advantages of improved skills and updated practices, but the learning process itself is not immediately visible or appreciated by clients. Thus, it is given a moderate-to-low client prioritization score.

Manage administrative tasks such as invoicing, bookkeeping, and scheduling to sustain smooth business operations.

R = 1 (Unpaid Work)

Continuous professional development is crucial for long-term career growth and maintaining competitive skills, yet it does not directly result in immediate client deliverables. As a result, the time spent on professional development is considered fully unpaid work.

Frequency (F) = 2

Administrative tasks in freelance writing are typically performed once per small project, such as marking a work as completed and sharing files with the client after a project is completed or updating hours worked on a platform. Additionally, many platforms automate a significant portion of these functions. As a result, these tasks do not occur on a daily basis but rather as one-off events at the end of each project, leading to a low frequency score.

Duration (D) = 2

The time required to complete administrative tasks is generally short compared to core writing activities. Even when performed through platforms, tasks such as invoicing or updating a schedule are relatively quick, especially when much of the work is automated by freelance platforms. Therefore, the duration score is low.

Complexity (C) = 2

Managing administrative tasks involves basic data entry and routine scheduling functions. These tasks are straightforward and do not require specialized skills or intensive cognitive effort, particularly when automation tools are used. Hence, the complexity is rated low.

Client Prioritization (P) = 2

While essential for smooth business operations, administrative tasks are considered overhead by clients. They do not directly contribute to the creative or deliverable aspects of a project and are not typically a focus of client. As such, these tasks receive low priority from the client's perspective.

Maintain and update an online portfolio and professional profile by regularly showcasing recent writing samples, client testimonials, and case studies to attract potential clients.

R = 1 (Unpaid Work)

Maintaining an up-to-date online portfolio on platforms is important for future opportunities, but it is not a direct revenue-generating activity. The time and effort dedicated to updating the portfolio is thus fully categorized as unpaid work.

Frequency (F) = 3

Although the task is described as being performed "regularly," in practical terms, unlike tasks that are performed on a daily or weekly basis (e.g., drafting or client communications), portfolio updates occur infrequently. Therefore, a frequency score of 3 reflects that this task, while important, is not a continuous daily activity.

Duration (D) = 2

The time required to update an online portfolio or professional profile is relatively modest since giving and receiving ratings and reviews is a relatively quick task. A duration score of 2 indicates that, although necessary, the time investment per update is minimal.

Complexity (C) = 4

Maintaining and updating a profile is not as cognitively demanding as tasks like drafting original content or conducting in-depth research; however, it does require a level of strategic curation and attention to detail. Freelancers must decide how to best represent their work, ensure that the profile is current. This moderate level of decision-making and technical handling justifies a complexity score of 4.

Client Prioritization (P) = 8

A freelancer’s online portfolio and professional profile are critical for attracting new clients and securing future work. Clients often rely heavily on these resources to assess a freelancer's competence, experience, and reliability. Because a well-maintained portfolio can significantly influence hiring decisions and ultimately impact a freelancer's success, this task is highly prioritized from a client perspective. Hence, a client prioritization score of 8.

Freelance Virtual Assistance

Freelance Virtual Assistance Task Description	**F**	**D**	**C**	**P**	**R**

Engage in initial client consultations to clarify project requirements, communication expectations, and preferred tools, establishing clear roles for either long-term or short-term engagements.	3	3	7	8	4
Manage and organize schedules and appointments using digital calendaring and scheduling software to ensure optimal time management and timely coordination of meetings or tasks.	8	6	4	8	5
Handle email correspondence and other communications, acting as a liaison between the client and their contacts by filtering, prioritizing, and responding to messages as needed.	8	6	5	8	5
Conduct targeted research and compile data to prepare reports, presentations, or summaries that support the client's decision-making and project objectives.	6	7	8	7	5
Assist with project management by coordinating tasks, tracking progress using project management software, and ensuring that deadlines and milestones are met.	6	7	6	8	5
Manage social media accounts by scheduling content, monitoring engagement, and performing basic updates in line with the client’s brand guidelines.	7	5	7	7	5
Perform administrative tasks, such as document preparation, data entry, travel arrangements, and running errands, while coordinating with other freelancers or team members to ensure seamless execution of projects.	7	6	5	6	5
Maintain regular and proactive communication with clients by providing progress updates, clarifying requirements, and addressing any concerns or emerging issues promptly.	7	4	5	8	5
Actively search for new work opportunities by researching freelance platforms, developing and submitting tailored proposals, and negotiating contracts, project terms, and rates with clients.	7	6	6	2	1
Manage financial and administrative systems by tracking invoices, processing payments, and maintaining tax documentation to support smooth business operations.	2	2	2	2	1
Dedicate scheduled time for continuous professional development by learning new software tools, staying updated on virtual assistance best practices, and keeping abreast of emerging industry trends.	7	7	7	4	2
Maintain and update an online portfolio and professional profile by regularly showcasing recent work.	3	2	4	8	1

Freelance Virtual Assistance Pairwise Matrix

Freelance Virtual Assistance Criteria	**Frequency (F)**	**Duration (D)**	**Complexity (C)**	**Client Prioritization (P)**
Frequency (F)	1.00	1.50	0.67	1.25
Duration (D)	0.67	1.00	0.67	1.00
Complexity (C)	1.50	1.50	1.00	1.00
Client Prioritization (P)	0.80	1.00	1.00	1.00

Frequency (F) vs. Duration (D): 1.50

Virtual Assistance tasks occur very frequently. However, while duration is important, many tasks (like sending a quick email or updating a calendar) are brief. A ratio of 1.50 (rather than 2.00) reflects that frequency is important but the duration of tasks isn't as variable.

Frequency (F) vs. Complexity (C): 0.67

Routine tasks in Virtual Assistance are generally not highly complex. By setting F vs. C = 0.67, we imply that complexity is about 1.5 times as important as frequency. This acknowledges that while most tasks are simple, the few that require more advanced skills (e.g., managing multiple stakeholders or handling complex scheduling conflicts) are particularly valuable.

Frequency (F) vs. Client Prioritization (P): 1.25

Clients highly value prompt communication and reliability, but because Virtual Assistance work is so routine, frequency is only slightly more important than client prioritization. A value of 1.25 reflects that maintaining a steady workflow is essential, yet client satisfaction remains a close second.

Duration (D) vs. Complexity (C): 0.67

This indicates that complexity (reflecting cognitive and technical demands) is about 1.5 times as important as the time invested in a task. Even if a task takes a bit longer, its value is more tied to its complexity in this occupation.

Duration (D) vs. Client Prioritization (P): 1.00

This suggests that the time a task takes is considered equally important as its alignment with client expectations.

Complexity (C) vs. Client Prioritization (P): 1.00

In Virtual Assistance, while complex tasks are less common, when they do occur they are critical. Here, we assume that complexity and client prioritization are equally important.

Engage in initial client consultations to clarify project requirements, communication expectations, and preferred tools, establishing clear roles for either long-term or short-term engagements.

R = 4 (Mostly Paid Work)

These consultations are essential for setting clear expectations and establishing the framework for the engagement. Since they serve as a preparatory activity for that lays the groundwork for subsequent tasks within hourly gig, it is mostly considered paid work in this analysis.

Frequency (F) = 3

Initial consultations generally occur only once at the start of each engagement. Although every new gig normally requires a consultation, the process is not repeated daily or even weekly within a single project, making its occurrence relatively infrequent.

Duration (D) = 3

While a consultation may last 30–60 minutes, the overall time commitment per project is modest compared to ongoing tasks. The brief yet critical nature of the conversation justifies a low-to-moderate duration score.

Complexity (C) = 7

This task demands a deep understanding of the client's business context, an ability to interpret varied communication styles, and the skill to negotiate and clarify roles. Given the necessity to tailor the consultation to both long-term and short-term engagements—often involving cross-cultural or remote considerations—the cognitive and interpersonal demands are high.

Client Prioritization (P) = 8

Clients regard these consultations as foundational. A successful initial consultation sets the tone for the entire engagement and minimizes the risk of misunderstandings. The clarity and confidence established here significantly influence client satisfaction and project success.

Manage and organize schedules and appointments using digital calendaring and scheduling software to ensure optimal time management and timely coordination of meetings or tasks.

R = 5 (Fully Paid Work)

Scheduling and appointment management are core responsibilities in virtual assistance.

Frequency (F) = 8

This type of work, when assigned, is a daily task. Virtual assistants continuously update and adjust calendars to accommodate meetings, deadlines, and client requests. The regular nature of this activity earns it a high frequency score.

Duration (D) = 6

Although each individual scheduling activity may take only a few minutes, the cumulative time spent

throughout the day is non-trivial. The overall duration is moderate as it forms a recurring part of the daily workflow.

Complexity (C) = 4
Modern calendaring tools automate many aspects of scheduling; however, challenges such as managing conflicting appointments, coordinating across time zones, and adjusting to last-minute changes require problem-solving and a keen eye for detail. These factors add a modest level of complexity.

Client Prioritization (P) = 8
Timely and accurate scheduling is critical for smooth operations and meeting deadlines. Clients rely on virtual assistants to optimize their time, making this task highly important to overall client satisfaction.

Handle email correspondence and other communications, acting as a liaison between the client and their contacts by filtering, prioritizing, and responding to messages as needed.

R = 5 (Fully Paid Work)

Managing tasks such as email correspondence is generally central to the role of a virtual assistant.

Frequency (F) = 8
Communication is continuous in a virtual environment. Virtual assistants often handle a high volume of emails and messages throughout the day, which makes this task very frequent.

Duration (D) = 6
While individual communication events such as email responses and text might be brief, the aggregate time required to process, filter, and respond to a high volume of messages adds up to a significant daily commitment.

Complexity (C) = 5
Although much of the correspondence involves routine filtering and standard replies, the role also demands judgment in prioritizing urgent matters and crafting responses that maintain professional tone and clarity. This mix results in moderate complexity.

Client Prioritization (P) = 8

Effective communication is central to maintaining client relationships. Prompt, clear, and courteous handling of emails directly impacts client trust and satisfaction, hence the high prioritization.

Conduct targeted research and compile data to prepare reports, presentations, or summaries that support the client's decision-making and project objectives.

R = 5 (Fully Paid Work)

Targeted research and data compilation are important for informed decision-making. While some preparatory effort is required (depending on the skill and the background of workers), the majority of this activity directly supports client deliverables, making it predominantly paid work.

Frequency (F) = 6

Research tasks are typically tied to specific projects or deliverables and often become a daily occurrence. While they may be recurring over multiple projects, they are not performed continuously, resulting in a moderate frequency score.

Duration (D) = 7

Quality research and data compilation often demand several hours per project. The investment of time to gather, verify, and synthesize information justifies a moderately high duration score.

Complexity (C) = 8

This task requires critical evaluation of sources, discerning reliable information from less credible information, and the ability to integrate diverse data points into coherent outputs. These intellectual demands place the task at a high complexity level.

Client Prioritization (P) = 7

Although not directly client-facing, the outputs of research heavily influence decision-making and project quality. Clients value well-supported, data-driven insights, thereby assigning significant importance to this task.

Assist with project management by coordinating tasks, tracking progress using project management software, and ensuring that deadlines and milestones are met.

R = 5 (Fully Paid Work)

Providing project management support is vital for keeping client projects on track. The primary effort directly contributes to achieving client objectives and is thus mostly billable.

Frequency (F) = 6

Project management is a typical activity in virtual assistance work and an ongoing function that persists throughout the gig. While not a constant minute-by-minute task, it is performed regularly enough to warrant a moderate frequency score.

Duration (D) = 7

Regular check-ins, status updates, and task coordination cumulatively take up a significant portion of the workday, leading to a moderate overall duration score.

Complexity (C) = 6

Effective project management requires a mix of organizational skills, proficiency with digital tools, and the ability to adapt to dynamic project requirements. The need to balance multiple tasks and deadlines contributes to a moderately high complexity rating as attention to detail is critical.

Client Prioritization (P) = 8

For clients, the assurance that projects will be delivered on time and within scope is critical. Consequently, project management is highly prioritized as it directly impacts the quality and reliability of the service provided.

Manage social media accounts by scheduling content, monitoring engagement, and performing basic updates in line with the client's brand guidelines.

R = 5 (Fully Paid Work)

Task such as social media management (if part of virtual assistance) is a key service for many virtual assistants.

Frequency (F) = 7

Social media management (if required in the contract) involves daily activities, such as developing and posting updates, monitoring comments, and adjusting strategies, making it a frequent part of a virtual assistant's role.

Duration (D) = 5

While individual social media tasks (e.g., posting or responding) are brief, the overall time commitment is moderate due to continuous monitoring and periodic content scheduling.

Complexity (C) = 7

This task blends creative input with technical know-how. Understanding platform-specific dynamics and target audience, ensuring consistency with brand guidelines, and engaging with audiences in a meaningful way adds a notable degree of complexity.

Client Prioritization (P) = 7

A robust social media presence is essential for brand building and customer engagement. Clients recognize the value of maintaining active and professional social media accounts, assigning this task a high level of priority.

Perform administrative tasks, such as document preparation, data entry, travel arrangements, and running errands, while coordinating with other freelancers or team members to ensure seamless execution of projects.

R = 5 (Fully Paid Work)

Administrative tasks in virtual assistance are typically central to the role, as clients rely on these services to streamline their operations. These tasks are performed as part of the agreed service, making them fully billable.

Frequency (F) = 7

Administrative tasks tend to be continuous, performed on an as-needed basis. Their occurrence is frequent and often takes a very large portion of a freelancer's time.

Duration (D) = 6

Although individual administrative tasks are usually quick, the cumulative time—spread across different tasks—is high. However, overall, it is less time-intensive than tasks like research or project management.

Complexity (C) = 5

These tasks are generally straightforward, involving routine procedures that require medium cognitive effort. The primary skills required are attention to detail and basic proficiency with digital tools.

Client Prioritization (P) = 6

While important for internal efficiency, these tasks are largely behind the scenes. They directly impact client satisfaction and trust resulting in a medium-high score.

Maintain regular and proactive communication with clients by providing progress updates, clarifying requirements, and addressing any concerns or emerging issues promptly.

R = 5 (Fully Paid Work)

Ongoing client communication is a core function of virtual assistance. These interactions ensure that client needs are met in real time and are typically integrated into the billed service, making this task fully revenue generating for a freelancer.

Frequency (F) = 7
Ongoing communication is essential throughout the gig. Virtual assistants must frequently update clients to ensure alignment, making this a high-frequency activity.

Duration (D) = 4
Although each communication interaction may be brief, the cumulative duration over the course of a project results in a moderate overall time investment.

Complexity (C) = 5

Maintaining effective communication requires clarity, tact, and the ability to resolve issues promptly. While the task is relatively routine, its importance in managing client expectations adds moderate complexity.

Client Prioritization (P) = 8
Clients highly value consistent, proactive communication because it builds trust and helps prevent misunderstandings. This makes the task critically important from a client's perspective.

Actively search for new work opportunities by researching freelance platforms, developing and submitting tailored proposals, and negotiating contracts, project terms, and rates with clients.

R = 1 (Unpaid Work)

Seeking new work, developing and submitting proposals on platforms, interviewing and negotiating terms with potential clients, are essential for long-term work availability but do not directly contribute to current client deliverables. These efforts are entirely overhead and, therefore, fully unpaid.

Frequency (F) = 7
In the virtual assistance landscape, actively searching for new gigs is an essential, recurring activity. Although virtual assistants often secure longer-term or repeat engagements, the competitive nature of

the platforms means that opportunity scouting occurs several times a week. Many work multiple gigs at a time. This activity is less frenetic than in freelance writing, where the volume of proposals might be extremely high, but still requires regular attention to maintain a steady workflow.

Duration (D) = 6

While individual proposals or negotiations might take only a short time, the cumulative time dedicated to this activity over the week is significant. It requires blocking out several hours weekly to research opportunities, tailor proposals to specific client needs, and engage in contract discussions. This sustained commitment justifies a moderate-to-high duration score.

Complexity (C) = 6

Crafting tailored proposals and negotiating contract terms demands a combination of market research, strategic communication, and persuasive writing. Although the process may be segmented into research, drafting, and negotiation phases, each stage requires thoughtful customization to align with varied client requirements. Thus, the overall cognitive and strategic load is moderate, warranting a complexity score of 6.

Client Prioritization (P) = 2

This task is primarily an internal, self-initiated function aimed at securing future work rather than addressing the immediate needs of current clients. As such, while it is important for long-term income stability, clients do not directly benefit from the process and hence assign it a low priority in their perception of service quality.

Manage financial and administrative systems by tracking invoices, processing payments, and maintaining tax documentation to support smooth business operations.

1 (Unpaid Work)

Administrative tasks are necessary for a freelance business but do not contribute directly to the production of client deliverables. These activities are purely overhead, classifying them as unpaid work.

Frequency (F) = 2

Financial and administrative tasks in freelance virtual assistance business are performed on a periodic basis, often weekly to log hours, or at the end of each gig to close individual projects. Unlike day-to-

day client communication or content creation, these tasks occur infrequently, resulting in a low frequency score.

Duration (D) = 2

Each cycle of billing hours, payment processing, or documentation requires only a relatively short time commitment when compared to ongoing client deliverables. Although accuracy is crucial, the actual hands-on time is limited as platforms generally provide easy to use tools to reduce friction, which justifies a low duration score.

Complexity (C) = 2

The procedures for managing finances and administrative systems are largely routine and supported by digital platforms. These tasks require attention to detail and a basic understanding of financial processes, but they are generally straightforward. Therefore, they are assigned a low complexity rating.

Client Prioritization (P) = 2

Since these functions are internal to the virtual assistant's operations and do not directly affect client-facing work, they are considered necessary overhead (mostly unpaid work). Do they receive a low prioritization score relative to more visible or strategic activities.

Dedicate time for continuous professional development by learning new software tools, staying updated on virtual assistance best practices, and keeping abreast of emerging industry trends.

R = 2 (Mostly Unpaid Work)

Continuous professional development is crucial for long-term career growth and maintaining competitive skills, yet it does not result in immediate client deliverables. Although in some cases, learning new programs and skills is a part of a virtual assistant's work routine. As a result, the time spent on professional development is considered mostly unpaid work.

Frequency (F) = 7

In a rapidly evolving digital landscape, virtual assistants need to integrate learning into their regular routines. This may involve daily brief sessions or dedicated weekly training, making professional development a frequent part of their work life. The high frequency score reflects the necessity of continual learning to stay competitive.

Duration (D) = 7

While not performed continuously throughout every day, professional development requires substantial, focused time blocks to understand new work and stay competitive. The cumulative time investment over weeks or months is considerable, justifying a moderate-to-high duration score.

Complexity (C) = 7

The process of learning new tools and best practices involves assimilating complex, evolving information and sometimes unlearning outdated methods. Virtual assistants must not only understand technical concepts but also apply them contextually to improve efficiency and service quality. This high level of cognitive engagement and the need for strategic integration of new skills justify a high complexity rating.

Client Prioritization (P) = 4

Although continuous professional development is crucial for maintaining high-quality service over the long term, its benefits are largely indirect. Clients ultimately receive the advantages of improved skills and updated practices, but the learning process itself is not immediately visible or appreciated by clients. Thus, it is given a moderate-to-low client prioritization score.

Maintain and update an online portfolio and professional profile by regularly showcasing recent work.

R = 1 (Unpaid Work)

Updating an online portfolio and professional profile supports long-term business growth by attracting new clients, but it is not directly revenue generating. The effort dedicated to this task is fully categorized as unpaid work.

Frequency (F) = 3

Updates to an online platform portfolio or professional profile occur infrequently, typically at the end of each contract. This periodic refresh is sufficient to maintain a current image without requiring continuous attention, resulting in a low frequency score.

Duration (D) = 2

The process of updating the portfolio and profiles by managing ratings and reviews is important but

generally a quick task. Given that the overall time commitment is minimal, justifying a low duration score.

Complexity (C) = 4

Although not as cognitively demanding as creative or strategic content production, maintaining an effective portfolio requires thoughtful curation and attention to detail. Virtual assistants must select representative work, ensure consistency in presentation, and sometimes rebrand themselves to stay competitive. This moderate level of decision-making and technical handling supports a modest complexity rating.

Client Prioritization (P) = 8

A well-maintained online portfolio and professional profile serve as critical marketing tools, forming the first impression for potential clients. In virtual assistance, where trust and demonstrated capability are paramount, this task directly influences hiring decisions. Therefore, despite its low frequency and duration, it is highly prioritized from the client acquisition standpoint.

Freelance Transcription Services

Freelance Transcription Services Task Description	**F**	**D**	**C**	**P**	**R**
Convert audio or video recordings into text following client formatting guidelines, including any required timestamps and speaker identifications.	8	9	6	9	5
Research and integrate domain-specific terminology and contextual details, especially for technical or specialized content.	5	6	7	7	4
Rigorously review transcripts to correct errors in grammar, punctuation, and spelling.	9	6	5	8	5
Consult with clients to clarify unclear or ambiguous audio segments, ensuring the final transcript accurately reflects the original content.	5	3	6	8	3
Update and refine transcripts in response to client corrections and detailed feedback.	6	5	5	9	5
Provide regular updates and clarifications during the transcription process to align the final output with client expectations.	4	2	2	6	2
Proactively research, seek, and submit tailored proposals on freelance platforms while negotiating contracts, project terms, and rates with clients.	7	4	4	2	1
Manage administrative tasks such as invoicing, bookkeeping, and scheduling to sustain smooth business operations.	2	3	2	2	1
Maintain and update your professional profile.	2	2	4	8	1
Dedicate scheduled time for continuous professional development by learning new transcription tools and staying updated on industry practices.	6	6	7	3	1

Freelance Transcription Services Pairwise Matrix

Freelance Transcription Service Criteria	Frequency (F)	Duration (D)	Complexity (C)	Client Prioritization (P)
Frequency (F)	1.00	2.00	0.50	1.50
Duration (D)	0.50	1.00	0.50	1.00
Complexity (C)	2.00	2.00	1.00	1.50
Client Prioritization (P)	0.67	1.00	0.67	1.00

Frequency (F) vs. Duration (D): Value = 2

Tasks such as basic transcription and applying transcription tools occur frequently. However, longer tasks such as domain-specific research or revising complex transcripts require more time. Freelancers on digital platforms need a steady flow of assignments, making frequency twice as important as duration in this line of work.

Frequency (F) vs. Complexity (C): Value = 0.5

Routine transcription tasks, such as straightforward dictations, are frequent but not highly complex. However, handling challenging audio, technical jargon, or multi-speaker dialogues requires higher complexity. Complexity outweighs frequency because high-quality, specialized transcription leads to better pay and more client retention.

Frequency (F) vs. Client Prioritization (P): Value = 1.5

Clients expect fast turnaround times, making frequency crucial for maintaining a steady workflow. However, meeting client-specific instructions and ensuring quality takes precedence over speed. Frequency slightly outweighs client prioritization because freelancers must deliver a high volume of accurate transcripts to sustain work.

Duration (D) vs. Complexity (C): Value = 0.5

Some transcription tasks, such as verbatim legal transcriptions, require more time but are not necessarily more complex. In contrast, understanding specialized terminology or deciphering poor-

quality recordings adds technical complexity, even in shorter assignments. Complexity is twice as important as duration because clients pay more for accuracy and domain expertise.

Duration (D) vs. Client Prioritization (P): Value = 1

Both task duration and client needs are equally important in transcription. Longer projects require sustained attention to meet deadlines, while clients demand accuracy, proper formatting, and adherence to guidelines. Duration and client prioritization are balanced.

Complexity (C) vs. Client Prioritization (P): Value = 1.5

Handling complex medical or legal content demands high skill. While clients appreciate advanced expertise, they ultimately care most about receiving a well-formatted and accurate transcript. Complexity slightly outweighs client prioritization because technical expertise helps freelancers stand out in a competitive market.

Convert audio or video recordings into text following client formatting guidelines, including any required timestamps and speaker identifications.

R = 5 (Fully Paid Work)

This is the core production task of transcription. It directly produces the client deliverable and is completely revenue generating, making it fully billable.

Frequency (F) = 8

This is the primary revenue-generating task. In practice, transcriptionists typically receive multiple files per day. Even if some files are longer and require concentrated focus, the overall workload is dominated by continuous transcription. In a freelance world, maintaining a steady stream of projects necessitates high-frequency engagement.

Duration (D) = 9

Converting audio to text is extremely time-intensive. A one-hour recording might require three to five hours of careful transcription, especially when factoring in pauses to decipher unclear segments. This prolonged duration not only reflects the physical act of typing but also the cognitive load of re-listening and ensuring accuracy.

Complexity (C) = 6

While the process may be repetitive, each file can introduce unique challenges—poor audio quality, multiple speakers, diverse accents, or technical terminology—that necessitate adaptive problem-

solving. From an academic standpoint, this task is methodologically straightforward but practically complex due to variability in content.

Client Prioritization (P) = 9
Clients pay primarily for accurate, well-formatted transcripts. A single transcription error or mis-timed label can compromise the document's utility, especially for legal or research purposes. Hence, this task is of utmost importance to clients, which is reflected in its very high prioritization.

Research and integrate domain-specific terminology and contextual details, especially for technical or specialized content.

4 (Mostly Paid Work)

Ensuring the transcript reflects specialized content accurately is integral to producing a high-quality deliverable. Although additional research may be needed for technical topics, the majority of the effort directly supports the billable outcome.

Frequency (F) = 5
Not every project requires intensive domain research; however, for specialized fields, this becomes a recurring necessity. The frequency is moderate, as transcriptionists may handle a mix of general and specialized files, engaging in research only when the subject matter demands precision.

Duration (D) = 6
The time commitment varies widely. For highly technical files, researching unfamiliar terms, checking authoritative sources, and cross-referencing context can consume considerable time. This investment, while not as prolonged as transcription itself, is substantial enough to merit a moderate-to-high duration score.

Complexity (C) = 7
The cognitive demands here are high. Transcriptionists must not only recognize when a term is unfamiliar but also verify its correct form and usage within context. This involves analytical thinking and sometimes even consultation of industry-specific literature or experts—a process that, academically, would be considered rigorous.

Client Prioritization (P) = 7
Clients expect the final transcript to reflect precise and appropriate terminology. Errors in domain-

specific language can significantly diminish credibility. Although this task happens behind the scenes, its impact on the overall quality is directly visible to clients, thus earning a high prioritization.

Rigorously review transcripts to correct errors in grammar, punctuation, and spelling.

R = 5 (Fully Paid Work)

Quality control is critical in transcription. This detailed review ensures the final transcript meets high-quality standards and is an essential, directly billable component of the service.

Frequency (F) = 9

Every project requires a thorough review, making proofreading a nearly ubiquitous task. Whether minor corrections or extensive edits, this step is invariably repeated with each submission, resulting in an extremely high frequency.

Duration (D) = 6

Proofreading demands careful, line-by-line scrutiny. Although it is typically less time-consuming than the initial transcription, for longer files it still consumes several hours. This moderate-to-high duration reflects the necessary focus to catch even subtle errors.

Complexity (C) = 5

The task is methodologically straightforward—identify and correct mistakes—but it requires sustained concentration and familiarity with stylistic nuances. The complexity is moderate because it relies on attention to detail rather than advanced problem-solving.

Client Prioritization (P) = 8

A transcript that has been thoroughly proofread enhances the client's confidence in the freelancer's professionalism and is important for a workers' ratings. Given that errors can lead to misunderstandings or diminish the document's utility (especially in legal or research contexts), clients place very high importance on error-free output.

Consult with clients to clarify unclear or ambiguous audio segments, ensuring the final transcript accurately reflects the original content.

R = 3 (Mixed - Balanced)

When audio segments are unclear, consulting with the client is necessary for ensuring accuracy. However, these interactions are typically not billed separately, resulting in a balanced mix of direct deliverable work and overhead.

Frequency (F) = 5

Ambiguities do not arise in every file, but a significant fraction of projects, particularly those with challenging audio conditions, require clarifications. Thus, the task occurs moderately frequently, reflecting both routine and occasional needs.

Duration (D) = 3

Typically, these clarifications are handled via brief emails or short phone calls. Although crucial, the time investment for each clarification is relatively small compared to transcription and research, yielding a low duration score.

Complexity (C) = 6

Determining which segments are genuinely ambiguous—and formulating precise questions for clients—requires critical judgment and communication skills. The complexity is moderate since the task involves both problem identification and effective query formulation.

Client Prioritization (P) = 8

Clients appreciate a proactive approach that minimizes errors. When transcriptionists consult to resolve uncertainties, it reinforces the quality and reliability of the final product. As a result, this task is highly prioritized, even though it is not a major time sink.

Update and refine transcripts in response to client corrections and detailed feedback.

R = 5 (Fully Paid Work)

Incorporating client feedback is a direct part of the transcription process that enhances the quality of the final product, making this task fully billable

Frequency (F) = 6

Revision cycles are common in freelance transcription. Most projects involve at least one round of client feedback. Although the frequency varies by client and project, the task is sufficiently recurrent to be rated moderate.

Duration (D) = 5

The duration of revisions may depend on the extent of client feedback. Minor tweaks may be quick, while comprehensive revisions require re-checking segments or reformatting parts of the transcript. On average, the time commitment is moderate.

Complexity (C) = 5

Integrating feedback involves deciphering sometimes vague instructions and then re-aligning the transcript to match client expectations. While the process is straightforward for clear-cut issues, ambiguous feedback may require additional interpretation, resulting in a moderate complexity rating.

Client Prioritization (P) = 9

Clients invest time in reviewing drafts and expect swift, accurate revisions. Meeting these expectations is critical for building trust and ensuring repeat business, which makes this task one of the highest in client prioritization.

Provide regular updates and clarifications during the transcription process to align the final output with client expectations.

R = 2 (Mostly Unpaid Work)

While keeping the client informed is important for ensuring that the transcript meets expectations, these communication activities generally do not generate additional income for freelancers.

Frequency (F) = 4

Regular progress updates are expected by some clients, particularly for longer projects. While not every transcription gig may require such updates, updates occur frequently enough (e.g., at key milestones) to warrant a frequency rating.

Duration (D) = 2

These communications are typically concise—brief emails or messages—so the cumulative time spent is low relative to the core transcription work.

Complexity (C) = 2

Communicating project status is generally straightforward, although it requires clarity and a sense of urgency. The complexity is low-to-moderate because it involves routine messaging rather than strategic decision-making.

Client Prioritization (P) = 6

Clients value transparency, especially when delays or issues arise. Regular updates help manage expectations and reduce client anxiety, thereby ranking this task high in client prioritization.

Proactively research, seek, and submit tailored proposals on freelance platforms while negotiating contracts, project terms, and rates with clients.

R = 1 (Unpaid Work)

Seeking new work, developing and submitting proposals on platforms, interviewing and negotiating terms with potential clients, are essential for long-term work availability but do not directly contribute to current client deliverables. These efforts are entirely overhead and, therefore, fully unpaid.

Frequency (F) = 7

The highly competitive platform work economy requires freelancers to routinely apply to a number of jobs. This task is very frequent in almost all freelance platform work occupations. Since freelancers continuously scan platforms for new opportunities to maintain a steady work pipeline, the frequency score is high.

Duration (D) = 4

While an individual proposal for transcription might not take an extensive amount of time to prepare, the cumulative time spent on job searches, tailoring multiple proposals, and engaging in negotiations can be substantial. Freelancers often invest several hours each day in this activity, which justifies a moderate duration score.

Complexity (C) = 4

The cognitive demands are moderate, as it involves some market research and tailoring one’s pitch to a competitive environment. While crafting effective proposals requires an understanding of the client’s needs and persuasive writing, and strategic pricing, transcription jobs and are more akin to the structure of microtasks where complex project proposals are not required to apply for these jobs.

Client Prioritization (P) = 2

As a business development activity, this task is entirely self-directed. Existing clients do not see this work, and it does not impact ongoing projects, which keeps its client prioritization very low.

Manage administrative tasks such as invoicing, bookkeeping, and scheduling to sustain smooth business operations.

R = 1 (Unpaid Work)

Administrative tasks are necessary for running a freelance business efficiently; however, they do not produce client deliverables and are therefore fully considered unpaid work.

Frequency (F) = 2

Administrative tasks are typically performed once per small project, such as marking a work as completed billing, and sharing transcribed files with the client after a project is completed or updating hours worked on a platform. Additionally, many platforms automate a significant portion of these functions. As a result, these tasks do not occur on a daily basis but rather as one-off events at the end of each project, leading to a low frequency score.

Duration (D) = 3

The time required to complete administrative tasks is generally short compared to core transcription activities. When performed through platforms, tasks such as logging hours and payment processing relatively quick, especially when much of the work is automated by freelance platforms. Therefore, the duration score is low.

Complexity (C) = 2

Managing administrative tasks involves basic data entry and routine scheduling functions. These tasks are straightforward and do not require specialized skills or intensive cognitive effort, particularly when automation tools are used. Hence, the complexity is rated low.

Client Prioritization (P) = 2

Since these functions support internal business operations and are not directly visible to clients, they are assigned a low client prioritization score despite their importance to overall business continuity.

Maintain and update your professional profile.

R = 1 (Unpaid Work)

Updating an online portfolio and professional profile supports long-term business growth by attracting new clients, but it is not directly revenue generating. The effort dedicated to this task is fully categorized as unpaid work.

Frequency (F) = 2

Platform profile updates are not a daily task; they typically occur intermittently—such as after major projects or when new skills are acquired—resulting in a low frequency.

Duration (D) = 2

The time required to update an online portfolio or professional profile is relatively modest since giving and receiving ratings and reviews is a relatively quick task. A duration score of 2 indicates that, although necessary, the time investment per update is minimal.

Complexity (C) = 4

Although updating a profile does not require advanced technical skills, it does require strategic thinking and a keen eye for branding. Freelancers must decide how to best represent their work, ensure that the profile is current. This moderate level of decision-making and technical handling justifies a complexity score of 4.

Client Prioritization (P) = 8

A freelancer’s online portfolio and professional profile are critical for attracting new clients and securing future work. Clients often rely heavily on these resources to assess a freelancer's competence, experience, and reliability. Because a well-maintained portfolio can significantly influence hiring decisions and ultimately impact a freelancer's success, this task is highly prioritized from a client perspective. Hence, a client prioritization score of 8.

Dedicate scheduled time for continuous professional development by learning new transcription tools and staying updated on industry practices.

R = 1 (Unpaid Work)

Continuous professional development is vital for long-term competitiveness, yet it does not result in immediate client deliverables and is fully classified as overhead.

Frequency (F) = 6

Professional development is integrated into a freelance platform workers' daily routine. This is an activity that might not be limited to transcription jobs but to overcome overall preacity and nature of available work. Its frequency is moderate, reflecting the need for continuous improvement and constant engagement.

Duration (D) = 6

While individual training sessions or self-study periods might last a few hours, cumulatively over a month, the time investment can be significant. This justifies a moderate-to-high duration score.

Complexity (C) = 7

Learning new tools or mastering advanced subject matter demands a high degree of cognitive engagement. Transcriptionists must often adapt to rapidly evolving technologies or delve into specialized content areas, which requires a sophisticated level of learning and unlearning, thus a high complexity rating.

Client Prioritization (P) = 3

Although the benefits of professional development manifest in improved service quality, the learning process itself is not directly visible to clients. Hence, while it is crucial for long-term success, it is assigned a low client prioritization.

Freelance Developers

Task Description	**F**	**D**	**C**	**P**	**R**
Communicate with clients to clarify project requirements, desired functionalities, and target objectives, ensuring a clear understanding of the assignment.	4	3	7	9	2
Conduct technical research to identify effective solutions, best practices, and appropriate technologies to inform the development process.	7	7	8	7	4
Develop and maintain code to meet specific client requirements related to custom software and web applications.	9	10	9	7	5
Optimize websites, content management systems (e.g., WordPress, Drupal), and applications for performance, speed, security, and reliability as needed or per client request.	7	7	8	8	5
Document code and technical processes to ensure quality and maintainability.	5	6	7	8	5
Troubleshoot and resolve technical issues in existing systems and codebases, including debugging and addressing production challenges.	7	7	9	9	5
Provide ongoing maintenance, updates, and improvements to ensure long-term viability and scalability of the project.	4	5	6	7	5

Proactively search for and apply to new work opportunities by developing and submitting tailored proposals on freelance platforms and negotiating contracts, project terms, and rates with clients.	8	5	7	2	1
Manage administrative tasks such as invoicing, bookkeeping, and scheduling to sustain smooth business operations.	2	3	2	2	1
Maintain and update an online portfolio and professional profile by regularly showcasing recent work samples, client testimonials, and case studies to attract potential clients.	3	2	4	8	1
Dedicate scheduled time for continuous professional development to keep skills and knowledge current.	7	8	9	3	1

Freelance Developers Pairwise Matrix

Freelance Developers Criteria	Frequency (F)	Duration (D)	Complexity (C)	Client Prioritization (P)
Frequency (F)	1.00	2.00	0.40	1.50
Duration (D)	0.50	1.00	0.50	1.00
Complexity (C)	2.50	2.00	1.00	1.50
Client Prioritization (P)	0.67	1.00	0.67	1.00

Frequency (F) vs. Duration (D): Value = 2

Tasks like debugging code, making minor updates, and integrating new features happen more frequently in web and software development work. In contrast, larger development projects such as full-stack software builds or optimizing entire applications take significantly more time and are less frequent (based on available jobs). Freelancers on digital platforms often juggle multiple short-term contracts, making frequent tasks a core part of their work to ensure consistent income. Frequency is twice as important as duration because maintaining a steady flow of assignments is essential for sustaining work on freelancing platforms, where securing long-term projects is less common.

Frequency (F) vs. Complexity (C): Value = 0.4

Basic coding tasks such as implementing small UI changes or setting up CMS platforms are frequent but do not require high levels of technical complexity. More complex work, such as developing

secure authentication systems or optimizing backend performance, occurs less often but demands specialized expertise. While frequent tasks provide a consistent stream of income, higher-complexity work commands better pay and improves career growth for freelancers. Complexity outweighs frequency because advanced skills are key to securing higher-value projects, even if they are less common.

Frequency (F) vs. Client Prioritization (P): Value = 1.5

Regular tasks like software updates, bug fixes, and client communications are critical for maintaining a continuous workflow. However, meeting client expectations—such as adhering to deadlines and delivering high-quality code—remains vital for sustaining repeat business and a strong reputation. A value of 1.50 means frequency is 1.5 times as important as client prioritization, acknowledging that while client satisfaction is essential, maintaining a steady flow of work is slightly more critical in this context.

Duration (D) vs. Complexity (C): Value = 0.5

Long-duration tasks, such as developing custom web applications or conducting extensive security audits, take significant time but are not necessarily highly complex. In contrast, certain shorter tasks, like troubleshooting backend issues or implementing advanced performance optimizations, require greater technical expertise despite taking less time. Since freelance developers benefit more from skill-intensive tasks than from simply working on long projects, complexity is twice as important as duration. Clients prioritize expertise over time spent, making complexity a stronger determinant of a developer's earning potential.

Duration (D) vs. Client Prioritization (P): Value = 1

Long-term projects require sustained effort and planning, while client needs dictate how and when work is completed. Freelancers must balance duration with deadlines, as failing to meet client expectations can result in lower ratings or contract termination. Since duration and client prioritization are both critical in project-based work, they are equally important. A well-structured, long-term project must align with client expectations while ensuring manageable workloads for the developer.

Complexity (C) vs. Client Prioritization (P): Value = 1.5

Highly complex tasks, such as backend architecture development or cybersecurity implementation, require advanced skills and problem-solving capabilities. While clients may not always understand the complexity of these tasks, they benefit significantly from high-quality, scalable solutions. At the same time, aligning with client preferences, such as user experience considerations and customization requests, ensures project satisfaction. Complexity slightly outweighs client prioritization because technical expertise is a freelancer's primary differentiator in a competitive digital labor market, even though client needs ultimately guide project scope and requirements.

Communicate with clients to clarify project requirements, desired functionalities, and target objectives, ensuring a clear understanding of the assignment.

R = 2 (Mostly Unpaid Work)

This task involves initial consultations that are essential for understanding project scope and setting clear expectations. However, these communications are generally not billed separately; they serve as groundwork that supports the subsequent, fully billable development work, and are therefore considered overhead.

Frequency (F) = 4

This task is fundamental at the project kickoff and may require follow-up clarifications during the early phases of development. Although it may not occur multiple times, it recurs in every new project and often throughout revisions, justifying a moderately low frequency.

Duration (D) = 3

Initial and follow-up discussions are usually time-bound (e.g., a scheduled call or a series of texts). While essential, they generally do not consume a large portion of the daily workload relative to coding or debugging.

Complexity (C) = 7

Effective communication in technical projects requires both technical literacy and strong interpersonal skills. Developers must translate client needs into actionable technical specifications, sometimes resolving ambiguities or bridging gaps between non-technical and technical language.

Client Prioritization (P) = 9

Clients highly value clear and precise communication because it directly influences project success.

Miscommunication can lead to costly rework or delays; hence, this task is one of the most critical from the client's perspective.

Conduct technical research to identify effective solutions, best practices, and appropriate technologies to inform the development process.

R = 4 (Mostly Paid Work)

Technical research is vital for determining the best approach to meeting client requirements. Although it involves preparatory work and often additional effort at the worker's end, most of this research directly informs the development process and contributes to the final deliverable, making it predominantly paid work.

Frequency (F) = 7

Research is project-specific and occurs throughout the planning and design phases. It is a daily recurring task, it is an integral part of every project, especially when new technologies or innovative solutions are needed.

Duration (D) = 7

Technical research can be highly variable ranging from a few focused hours for standard gigs to days for highly specialized or novel solutions. In most cases, a substantial portion of the early project phase is dedicated to this activity.

Complexity (C) = 8

The task requires deep technical understanding, critical evaluation of emerging trends, and the ability to synthesize different sources of information. It also often involves risk assessment and weighing trade-offs, making it one of the most intellectually demanding aspects of the worka developer might do.

Client Prioritization (P) = 7

Clients rely on the developer's expertise to select robust and future-proof solutions. The outcome of this research directly affects the quality, performance, and scalability of the final product, which is highly valued by clients.

Develop and maintain code to meet specific client requirements related to custom software and web applications.

R = 5 (Fully Paid Work)

Writing and maintaining code is the core production activity for developers. Nearly all time spent coding directly contributes to the client's deliverable, making this activity entirely revenue generating and fully billable.

Frequency (F) = 9

Coding or using user interface tools that help with coding is the core of a freelance developer's workload and occurs almost continuously during a project. Even when not writing new code, significant time is devoted to refactoring and maintaining existing codebases.

Duration (D) = 10

Development is extremely time-intensive. Depending on project scope, developers may spend the majority of their workday coding, testing, and iterating over multiple iterations to ensure quality and functionality.

Complexity (C) = 9

This task involves solving complex technical problems, recalling coding knowledge, integrating multiple systems, and ensuring that the code adheres to best practices and client specifications. The cognitive load is high as developers must consider performance, security, maintainability, and scalability.

Client Prioritization (P) = 7

Although the deliverable is the product and not the code itself, clients place the high importance on its quality and robustness. A well-implemented solution is directly tied to project success, making this task paramount.

Optimize websites, content management systems (e.g., WordPress, Drupal), and applications for performance, speed, security, and reliability as needed or per client request.

R = 5 (Fully Paid Work)

Optimization tasks directly impact the quality and functionality of the client's digital assets. These improvements are a key part of the deliverable and are fully revenue generating, so they are entirely billable.

Frequency (F) = 7

Optimization tasks occur during initial development and continue as part of routine maintenance or

client-driven updates. While not as constant as coding, they are frequent enough to be a regular part of a developer's workflow.

Duration (D) = 7

Optimization involves profiling code, identifying bottlenecks, and implementing improvements. Although some optimizations are quick fixes, others (especially security enhancements or scalability improvements) may require extensive testing and iterative refinement.

Complexity (C) = 8

This task demands a detailed technical understanding of system performance metrics, network behavior, and modern security protocols. Developers must often balance trade-offs between speed and security, making the task intellectually challenging and complex.

Client Prioritization (P) = 8

Clients expect their applications to perform well under load and be secure. Optimization directly impacts user experience and reliability and therefore is highly prioritized by clients.

Document code and technical processes to ensure quality and maintainability.

R = 5 (Fully Paid Work)

Proper documentation is critical for ensuring long-term maintainability and quality of software. Documentation, if required, is typically included as part of the deliverable, making it predominantly a paid work effort.

Frequency (F) = 5

Documentation is often created during and after development. Although not a daily task, it is essential for each project, especially in collaborative or long-term maintenance contexts when documentation is a part of a gig contract.

Duration (D) = 6

Effective documentation requires a significant time investment. Developers must write clear, concise explanations, often revisiting and updating documents as the code evolves, which can take hours per project.

Complexity (C) = 7

Producing high-quality documentation involves not only technical writing skills but also an

understanding of the underlying code and architectural decisions. Balancing comprehensiveness with clarity requires significant cognitive effort.

Client Prioritization (P) = 8

While end clients may not read the documentation, it is critical for the ongoing maintainability and scalability of the solution. For clients who rely on long-term support or further development, well-documented code is highly valuable.

Troubleshoot and resolve technical issues in existing systems and codebases, including debugging and addressing production challenges.

R = 5 (Fully Paid Work)

Troubleshooting and debugging are essential for resolving issues and ensuring smooth operation of the software. Often the job itself is this troubleshooting.

Frequency (F) = 7

Troubleshooting is a recurrent task and often the entirety of a gig and as larger projects scale or enter maintenance phases. Developers are often hired particularly to encounter bugs or performance issues that must be addressed promptly.

Duration (D) = 7

Debugging can be time-consuming, requiring hours to isolate and fix a single issue, particularly in complex systems. The overall duration is moderate-to-high, depending on the severity and number of issues.

Complexity (C) = 9

This task involves deep technical analysis, creative problem solving, and sometimes even rethinking parts of the architecture. The complexity is very high, as issues may be intertwined with the core functionality of the system and freelancers are often hired when other troubleshooting options are exhausted.

Client Prioritization (P) = 9

Production issues directly affect the usability and reliability of the client's product. Rapid and effective troubleshooting is critical to maintain client trust and operational continuity, making it one of the highest-priority tasks.

Provide ongoing maintenance, updates, and improvements to ensure long-term viability and scalability of the project.

R = 5 (Fully Paid Work)

Ongoing maintenance is often part of a long-term service agreement, directly impacting on the performance and scalability of the system.

Frequency (F) = 4

Maintenance is an ongoing process that is typically scheduled periodically (e.g., weekly, monthly) or as new issues emerge. While it does not demand daily attention, it is recurrent enough to warrant a moderate frequency rating as it impacts the continuity of client-freelancer relationship

Duration (D) = 5

Maintenance and updates can be extensive, particularly for complex systems. They often require thorough testing and multiple iterations to implement improvements without disrupting existing functionalities, resulting in a medium duration score.

Complexity (C) = 6

The task involves evaluating system performance, integrating new features, and ensuring backward compatibility. The balance between innovation and stability adds a moderate-to-high level of complexity.

Client Prioritization (P) = 7

Clients expect their products to remain current and operational. Ongoing maintenance directly contributes to long-term satisfaction, though it may be less visible than new development, it is still highly prioritized for ensuring system longevity.

Proactively search for and apply to new work opportunities by developing and submitting tailored proposals on freelance platforms and negotiating contracts, project terms, and rates with clients.

R = 1 (Unpaid Work)

Seeking new work, developing and submitting proposals on platforms, interviewing and negotiating terms with potential clients, are essential for long-term work availability but do not directly contribute to current client deliverables. These efforts are entirely overhead and, therefore, fully unpaid.

Frequency (F) =8

The highly competitive platform work economy requires freelance developers to routinely apply to a number of jobs, often staying up late to quickly apply for new opportunities and overcome time zone differences. This task is very frequent in almost all freelance platform work occupations. Since freelancers continuously scan platforms for new opportunities to maintain a steady work pipeline, the frequency score is high.

Duration (D) = 5

While an individual proposal might not take an extensive amount of time to prepare, the cumulative time spent on job searches, tailoring multiple proposals, and engaging in negotiations can be substantial. Freelancers often invest several hours each day in this activity, which justifies a moderate duration score.

Complexity (C) = 7

The cognitive demands are moderately high, as it involves some market research and tailoring one's pitch to a competitive environment. While crafting effective proposals requires an understanding of the client's needs and persuasive writing, and strategic pricing , the overall cognitive load is moderate compared to coding and troubleshooting.

Client Prioritization (P) = 2

This task is entirely self-directed. Existing clients do not see this work, and it does not impact ongoing projects, which keeps its client prioritization very low.

Manage administrative tasks such as invoicing, bookkeeping, and scheduling to sustain smooth business operations.

R = 1 (Unpaid Work)

Administrative tasks are necessary for running a freelance business efficiently; however, they do not produce client deliverables and are therefore fully considered unpaid work.

Frequency (F) = 2

Administrative tasks are typically performed once per small project, such as marking a work as completed billing, and sharing transcribed files with the client after a project is completed or updating hours worked on a platform. Additionally, many platforms automate a significant portion of these

functions. As a result, these tasks do not occur on a daily basis but rather as one-off events at the end of each project, leading to a low frequency score.

Duration (D) = 3 The time required to complete administrative tasks is generally short compared to core transcription activities. When performed through platforms, tasks such as logging hours and payment processing relatively quick, especially when much of the work is automated by freelance platforms. Therefore, the duration score is low.

Complexity (C) = 2 Managing administrative tasks involves basic data entry and routine scheduling functions. These tasks are straightforward and do not require specialized skills or intensive cognitive effort, particularly when automation tools are used. Hence, the complexity is rated low.

Client Prioritization (P) = 2 Since these functions support internal business operations and are not directly visible to clients, they are assigned a low client prioritization score despite their importance to overall business continuity.

Maintain and update an online portfolio and professional profile by regularly showcasing recent work samples, client testimonials, and case studies to attract potential clients.

R = 1 (Unpaid Work)

Updating the portfolio and professional profile is important for attracting new business; however, it does not generate immediate revenue. The time invested in this task is fully considered overhead in this analysis.

Frequency (F) = 3
Updates are done intermittently (e.g., after major projects or after acquiring new skills), rather than as a continuous daily task, which justifies a low frequency score.

Duration (D) = 2
The act of updating platform profiles and personal portfolios, uploading new content, revising bios, or refreshing case studies, is usually a quick process compared to technical work.

Complexity (C) = 4
Although technically simple, effective portfolio management requires strategic branding and curation of work samples, demanding a moderate level of decision-making and creative insight.

Client Prioritization (P) = 8

A strong online profile is often the first point of contact with prospective clients. Its quality and currency directly impact hiring decisions, making it a high priority for client acquisition.

Dedicate scheduled time for continuous professional development to keep skills and knowledge current.

R = 1 (Unpaid Work)

Continuous professional development is essential for staying competitive and to finish many of the projects that require learning new tools, but it does not result in immediate income. Thus, the time spent on learning and upgrading skills is fully categorized as unpaid work.

Frequency (F) = 7 unpaid professional development is a very frequent activity among freelance developers that may feel learning new skills is important to keep up with the changing market trends. This is an activity that might not be limited to a particular job but to overcome overall precarity and nature of available work. Its frequency is high, reflecting the need for continuous improvement and constant engagement.

Duration (D) = 8 While individual training sessions or self-study periods might last a few hours, cumulatively over a month, the time investment can be significant. This justifies a moderate-to-high duration score.

Complexity (C) = 9 Learning new tools or mastering advanced subject matter demands a high degree of cognitive engagement in technical occupations. Developers must often adapt to rapidly evolving technologies or delve into entirely new specialized content areas to find their niche, which requires a sophisticated level of learning and unlearning, thus a high complexity rating.

Client Prioritization (P) = 3 Although the benefits of professional development manifest in improved service quality, the learning process itself is not directly visible to clients. Hence, while it is crucial for long-term success, it is assigned a low client prioritization.

Glossary

Ajira Digital	A Government-run Kenyan program that trains youth for online freelancing and links them to clients.
Algorithmic Management	The system of rules and controls through which platforms deploy algorithms to match tasks, monitor performance, set pay, and allocate reputational scores, thereby structuring who works, on what terms, and for how much.
Algorithmic Matching	The automated assignment of workers to tasks that best fit their profile or past metrics. It can align gigs with skills, but it also reinforces platform control over the labour process.
Autonomy Paradox	The tension whereby platforms (or AI tools) promise freedom from rigid schedules yet simultaneously intensify surveillance and competition, so the very technologies that grant flexibility can undermine genuine autonomy.
Automation (AI-Driven)	Full transfer of a human task to a machine or an AI system when the task is highly modular, richly documented, and low in contextual complexity.
Capability Approach (CA)	A framework developed by Amartya Sen and others that measures well-being by the expansion of individuals' genuine opportunities and substantive freedoms to achieve valued functionings (the things a person manages to do or be), rather than by resources or utility alone. From a normative perspective, it evaluates social arrangements (such as labour markets) by asking whether they expand people's real freedoms to pursue the lives they have reason to value, rather than merely providing goods or eliciting satisfaction.
Capability Multiplier	A condition that amplifies several capabilities simultaneously. In the thesis, temporal autonomy is demonstrated to enhance workers' ability to achieve family, learning, and income-earning goals, particularly in contexts where external support systems are limited.
Capability for Voice	In the context of work, the capability for voice denotes a worker's process freedom to influence the rules and conditions of their work. It refers to each worker's substantive freedom to express preferences and have them considered in decision-making at all levels. This notion is related to but distinct from collective bargaining. True voice requires that any collective structures expand individual participation rather than simply substituting one imposed set of outcomes for another.

Capability for Work	In Sen's capabilities framework, the capability for work is the substantive freedom to choose, refuse, and shape one's work in ways one has reason to value. It reframes job quality from a checklist of entitlements to an appraisal of real freedom. For example, not just what a worker earns, but whether they have the genuine option to turn down degrading work. Achieving this capability rests on certain conditions, such as sufficient available opportunities, supportive conversion factors to turn resources into outcomes, and a viable exit option to avoid being trapped in valueless work, all of which enable a worker to pursue work on their own terms.
Conversion Factors	Personal, social, and environmental conditions that determine how well a person can transform resources or opportunities into real freedoms and outcomes (e.g., skills, gender norms, or access to reliable internet).
Crowd Work / Microwork	A particular type of platform work that includes mass-distributed micro-tasks (e.g., data labelling) that platforms parcel out to large numbers of workers, typically at piece rates and with minimal client contact
Decent Work	A concept introduced by the International Labour Organization (ILO) to describe work that meets fundamental criteria of quality. In summary, decent work is productive, delivering a fair income, ensuring workplace safety and social protection for workers and their families, and offering better prospects for personal development and social inclusion. It also entails freedom for individuals to voice their concerns, organize with others, and participate in decisions that affect their lives, as well as equality of opportunity and treatment for all workers.
Decent Work Agenda (DWA)	ILO's global initiative aims to promote the implementation of decent work principles. The Decent Work Agenda is based on four main objectives: (1) promoting fundamental rights at work, including protecting workers' dignity, equality, and safe working conditions; (2) generating employment and income opportunities, such as creating quality jobs and ensuring equal opportunities; (3) expanding social protection; and (4) fostering social dialogue for continual improvements in working conditions. This agenda presents access to decent work as a key element of inclusive development and social justice. It highlights that achieving decent work involves more than just fulfilling economic needs; it also involves fostering dignity, fairness, and employee voice in the workplace. DWA is formally included in the United Nations Sustainable Development Goal 8, which advocates for decent work for all.
Decision Complexity under	Task metric that gauges the breadth of information and risk trade-offs a worker must juggle when outcomes are uncertain.

Uncertainty (DCU)	
Digitalization (of Work)	The process through which work and employment are transformed by digital technology. In the context of this thesis, the digitalization of work has a dual nature. On the one hand, the expansion of internet connectivity and digital tools can potentially increase service-sector employment in developing regions. On the other hand, work enabled by digitalization is often temporary or freelance, exhibiting a precarious quality with declining employment security and new forms of marginalization for workers in those regions.
Disruption (Labour Market Disruption)	In this research, disruption refers to any drastic departure from the established status quo in the world of work. It denotes an overall transformation in how tasks are configured and executed, affecting both the nature of work and the compensation of workers.
Enabling-Obsolescence Paradox	I coined this phrase to describe how AI tools initially help freelancers by automating tedious, unpaid tasks, yet the same helpful automation support accelerates the dehumanization of work and paves the way for replacing paid labour.
Enhancement (AI Task-Level)	AI support that augments, rather than substitutes, human effort. IT materializes when tasks are moderately structured yet still benefit from human judgment
Fairwork Project	Research initiative that benchmarks digital labour platforms against principles of fair pay, conditions, contracts, management and representation.
Focused Thematic Analysis	Streamlined qualitative coding that begins with pre-set categories but remains open to emergent themes.
Functionings	A concept widely used in Capability Approach literature. It denotes actual "doings and beings", the entitlements that people achieve (for example, earning a living, caring for family).
Global South	A term used to denote the economically developing regions of the world, historically characterized by lower incomes and often by colonial legacies, in contrast to the wealthier industrialized nations of the Global North. In this thesis, the *Global South* highlights contexts where workers face distinct socio-economic conditions and development challenges.

Informational Basis of Judgment in Justice (IBJJ)	Sen's term for the specific kinds of information considered relevant when judging people's situations or making distributive decisions.
Indirect Network Effects	Two-sided platform market dynamic in which the value to one user group rises as the opposite group grows (e.g., more clients result in more attractiveness for freelancers).
Livelihood	In development studies, *livelihood* is an encompassing term for how people make a living, including the means and strategies they use and the context in which these are pursued. Chambers and Conway (1992) famously defined a livelihood as the capabilities, assets, and activities needed to make a decent living and reach one's potential. This definition emphasizes that a person's livelihood depends not just on income or a single job, but on a combination of resources (e.g., skills, social networks, savings), and it is influenced by external factors such as social norms, policies, and institutions.
Livelihood Sustainability	In this research, a livelihood is considered sustainable if it can cope with and recover from stresses and shocks, maintain or enhance its capabilities and assets, and not compromise the well-being and choices of the worker, both in the present and in the future. This concept combines economic stability with personal fulfillment and resilience, aligning the quality of work with long-term development and well-being.
Meaningful Work	Work that people experience as significant and fulfilling to themselves, beyond just earning an income. While *decent work* asks whether a job meets basic social and economic standards, *meaningful work* asks whether workers find their job psychologically or existentially rewarding. It focuses on the lived experience of work, examining how individuals derive purpose, identity, or dignity from their daily activities. This thesis views meaningful work as an intrinsic component of a sustainable livelihood, noting that a job's meaning often stems from factors such as autonomy, personal growth, or social contribution, rather than solely from the task content itself.
Multi-Sided Market (Platform)	A digital marketplace or a platform that brings together distinct user groups (clients and freelancers) and sets rules such as pricing, reputation and visibility that govern interactions.

Negative Freedom	Freedom from interference, harassment or abuse (as distinct from freedom to act).
Online Labour Index (OLI)	An Online indicator tracking global supply and demand on major online work platforms.
Opportunity Freedom	The range of valuable job alternatives realistically open to a person.
Platform Economy	The economic system is emerging around digital platforms that mediate work, such as freelancing marketplaces. The platform economy is essentially the ecosystem of online labour platforms connecting work seekers with work providers for short-term tasks.
Platformization of Work	The reorganization of work into platform-mediated, task-based arrangements. The platformization of work transforms how labour is organized by deconstructing traditional jobs into discrete tasks that can be contracted out via digital platforms. Platformization transforms roles that were once stable jobs into a series of on-demand tasks, with profound implications for worker security, identity, and rights.
Platform Work	Also referred to in this thesis as digital labour, gig work, or online freelancing. I use these terms interchangeably to refer to short- and medium-term tasks typically performed online. Platform work is work mediated by digital platforms where individuals undertake gigs or assignments, such as software development, graphic design, writing, data entry, transcription, virtual assistance, or customer service, on a freelance or piecework basis for clients who may be anywhere in the world. Such work is usually remote and contract-based.
Precarious Work (Precarity)	Forms of employment characterized by insecurity, uncertainty, and a lack of protections. Precarious work often involves short-term or informal engagements with little guarantee of steady earnings or job stability. In the platform economy, work is frequently described as precarious because workers are dislocated from stable organizational contexts and re-embedded within a system of intense competition and precarity.
Process Freedom	The substantive freedom to influence the rules and decisions that shape one's work (e.g., dispute resolution, contract terms). A deficit here is highlighted where platforms offer access but little voice.

Rating Systems / Reputational Capital	Platform-based feedback mechanisms that rank workers and heavily influence their access to tasks and earnings.
Resilience (Livelihood)	The capacity of a worker or livelihood to absorb shocks (market, health, technological) and still maintain or improve well-being.
Silicon Savannah	Informal name for a Nairobi-area tech ecosystem and BPO hub.
Social and Interactive Complexity (SIC)	Task-characteristic indicator that captures relational and communicative demands, used in the AI disruption scoring rubric.
Social Capital	The network-based resource of value that individuals and groups derive from their social relationships. Social capital is commonly viewed as a resource that contributes to individual and collective growth. Having robust social networks can make it easier to cooperate, access opportunities, or get support. In contrast, a deficit of social capital can leave people isolated and economically vulnerable (lacking connections for jobs, advice, or aid).
Substitution (AI Task-Level)	The partial replacement of human effort by AI when tasks are sufficiently structured but still require some oversight; scored separately from automation in the thesis model.
Sustainable Livelihoods Approach (SLA) / Sustainable Livelihoods Framework (SLF)	A holistic approach to understanding and improving how people make a living, originally developed in the field of development studies. The sustainable livelihoods approach looks at individuals' livelihoods in terms of the full range of assets they have (e.g. human, social, financial, natural, and physical capital), the vulnerabilities they face (e.g. economic shocks, social norms), and the structures and processes (e.g. institutions, policies, cultural practices) that shape their options. It emphasizes that livelihood choices and outcomes are influenced by people's access to resources and their ability to withstand stresses.

Task Modularity & Granularity (TMG)	An indicator of how neatly a task can be decomposed into independent sub-tasks; high TMG favours AI automation but can also enable rapid outsourcing.
Temporal Autonomy	Control over when and for how long one works; Kenyan freelancers value this flexibility as a cornerstone of livelihood strategy and work–life quality.
Time Poverty	A chronic shortage of discretionary time caused by long hours, commuting, or care duties or other responsibilities.
Unpaid Work (Platform)	All overhead activities performed by platform workers, such as bidding, profile upkeep, learning, and negotiation, which are essential for securing work, yet generate no immediate revenue.
Valuable Exit Option	The genuine ability to refuse or leave unsatisfactory work without undue hardship (e.g., because one has portable skills or unemployment protection). A cornerstone of the capability for work.
Vulnerability	In this thesis, vulnerability refers to the structural exposure of workers to forces that jeopardize their livelihood opportunities. A vulnerable worker is one who is at risk of harm from changes in the labour market or economy, for example, facing wage cuts or job losses due to factors beyond their control (such as shifts in demand, policy changes, or technological disruption). The conceptualization of vulnerability in this context focuses on adverse economic outcomes. It highlights how certain workers (especially those in precarious or unsupported positions) are more susceptible to negative shocks. For platform workers, vulnerability may mean lacking a financial cushion or alternative job options in the event that platform income dries up or competition drives down earnings.