Essays on Mobile Banking Adoption

by

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The following served on the Examining Committee for this thesis. The decision of the Examining Committee is by majority vote.

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Author's Declaration

I hereby declare that I am the sole author of this 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.

Abstract

Mobile banking (m-banking) has transformed financial services by enabling seamless access. This dissertation examines psychological factors, mental health, device type, and m-banking adoption in Canada through three studies. The first study conducts a systematic literature review on intrinsic factors in m-banking adoption, categorizing influences into psychological, personal, perceptive, and social dimensions. Using text-mining and statistical techniques on 143 studies, it highlights overlooked trends and promotes diversified research approaches. The second study analyzes mental health's association with m-banking adoption in Canada, integrating into it moderating effects of relationship satisfaction, smartphone dependency, and social media usage. Using fixed-effect logistic regression on Canadian Internet Usage Survey data, it finds that better mental health correlates with lower adoption rates, while social media users and smartphone-dependent individuals show higher adoption tendencies. The third study compares smartphone and smart wearable users in m-banking adoption. Analyzing 18,000 survey records with logistic regression, it finds perceived trust is more crucial for smartphone users, while wearable users prioritize time-saving. Demographics relate to m-banking adoption differently across devices, emphasizing the need for tailored financial strategies. This dissertation bridges academic and industry perspectives, advancing technology adoption models and offering insights for financial institutions. By integrating psychological and behavioral aspects, it lays a foundation for more user-friendly banking applications. Addressing research gaps, it explores current adoption trends and the role of emotional states in shaping mobile banking behaviors, particularly within the Canadian context.

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I would like to express my deepest gratitude to my supervisor, Dr. Stanko Dimitrov, for helping me become a better writer and a stronger researcher. His belief in me and his encouragement have meant more than words can convey. A heartfelt thank you to my co-supervisor, Dr. Brian Cozzarain, for his kindness, and unwavering encouragement throughout this journey. His understanding and support provided a much-needed sense of stability and reassurance. I am also incredibly grateful to my committee members for their invaluable feedback and time. A special thanks to Dr. Mikko Packalen, whose insightful contributions during my comprehensive exam reshaped the direction of this work in a profound way. To Dr. Rob Duimering, for providing detailed feedback and allotting time to discuss improvements further. To all the other committee members, thank you for your thoughtful and important comments, for reading both my dissertation and comprehensive exam document, and for helping refine my research through your feedback.

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To my biggest supporters – my family – words are not enough. To my mother, who, despite living 8.5 hours away on a different continent, has been there for me every single day. She has heard my worries, seen my shed tears and has worried for me every single day – but through it all, supported, trusted and encouraged me to go on. To my brother, my rock, for his constant reminders that I could do this, my personal cheerleader and coach. Without him, I would not be where I am today. To my dad, who has been in heaven for 13 years, I have talked to you often, and I hope you are looking down and feeling proud. To all the dear people I have lost over the years, and to all the friends I didn't get to see along the way – I am grateful for your presence in my life. And finally, to myself. For pushing through, working hard, and never giving up. This journey has been sometimes lonely and undoubtedly challenging, but I am better because of it.

Generative AI/LLMs for copy editing

For the purposes of editing this manuscript, I used a Large Language Model (chatgpt.com — models GPT3.5 and later GPT4 and GPT4o, free plans). The exact prompt used was as follows:

> *Read the following text and improve it by doing the following:*
>
> 1. *Make the writing I give you 60% shorter.*
> 2. *Do not remove or add any information.*
> 3. *Do not remove latex code anywhere.*
> 4. *Use simple language so that it's very clear and easy to understand but be formal.*
> 5. *If you think moving things around in the writing makes it flow better, do so.*
> 6. *Make sure the writing is at an undergraduate level, formal and concise. Be very very clear everywhere. Nothing should require much thinking to be understood.*

Remember this prompt for every paragraph I give you unless otherwise specified. Here is the text: ...

I first wrote entire papers – which were quite long. This tool was used to make sure my papers fit journals' maximum page limit, correct grammatical mistakes and avoid overly complicated and long sentences, and ensure good flow of ideas to make the reading as easy as possible. This prompt was used paragraph-by-paragraph. I then read the generated output and made necessary changes before adding them to my writing. Copies of previous versions of writings were saved.

After considering valuable feedback from committee members, to aid with the editing of the manuscript, several LLMs were used. First, I compiled all the comments from committee members previous to defense session, during and afterwards into a large word document, cleaned the comments manually and added action plans for each comment in my own words. This file was then given to ChatGPT 4-o mini to summarize and format with a simple prompt (*Read the comments and my notes on actionable to do and come up with a chronological list of tasks, formatted in a way that is easy to follow*). Then, the formatted file was given to Gemini 2.5 Pro (https://gemini.google.com/app) with the following prompt:

> *Given my dissertation (file attached) and the comments you've read (another file*

attached), can you clarify these comments to me with actionable ideas on how to tackle these and what exactly each point means:

1. *Clarify logic and theoretical basis for the hypotheses.*
2. *Link observed results to theoretical findings in the literature, and consider alternative explanations for your results (e.g. construct validity).*
3. *Defend lack of competing hypotheses (e.g. null and alternative hypothesis) and bring some elements of discussion section to hypothesis to make them directional (do not rerun analyses)*
4. *Articulate clearly throughout the dissertation whether the results are supportive of causal effects and why or why not - are they causal or indicative?*

Next, I went through the response generated by Gemini for clarifications as well as to expand on ideas. A file on this including my exact prompts used was shared with the committee members which will be added to the appendix of this file for full transparency in the use of artificial intelligence. Lastly, do tackle the changes, few other LLMs and AI-based applications were used as well as Scopus and Web of Science. Additionally, Perplexity (perplexity.ai) was used to conduct literature search to support or to challenge ideas. No AI system was used for generating text or writing tasks from scratch or to write outlines. All the writing in the dissertation was written by me, and only edited/enhanced by artificial intelligence. The reason for this strict no-use of AI in generating text is due to the non-negligible risk of hallucination.

Dedication

To my world — ***Mom***, ***Makan*** & the one in my heart, ***Dad***.

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List of Abbreviations

AB Alberta 95

ADHD Attention Deficit Hyperactivity Disorder 109

AET Affective Events Theory 81

AFFCT Affective 24

AI Artificial Intelligence 137

ANOVA Analysis of Variance 5

ASTI Adaptive Structuration Theory for Individuals 50

ATTD Attitude 24

BC British Columbia 95

BDM Bass Diffusion Model 21

BHVINTNT Behavioral Intentions 24

BLF Beliefs 24

BRT Behavioral Reasoning Theory 49

CAT Cognitive Appraisal Theory 24

CFA Confirmatory Factor Analysis 48

CIUS Canadian Internet Usage Survey 87

COG Cognitive 24

CRT Conservation of Resources Theory 81

DCT Digital Cohort Theory 49

DIG_LIT Digital Literacy 21

DM DeLone and McLean Model 49

DOI Diffusion of Innovation 48

ECM Expectation Confirmation Model 50

EFA Exploratory Factor Analysis 48

EFEX Effort Expectancy 21

ELM Elaborate Likelihood Model 48, 49

ENJY Enjoyment 24

FAMSAT Familial Relationship Satisfaction 88

FOMO Fear of Missing Out 77

FRISAT Friendship Satisfaction 88

GST Gender Schema Theory 49

HCD Hofstede Cultural Dimension 50

HDI Human Development Index 61

HED_MOTIV Hedonic Motivation 23

ICC Intra-Cluster Correlations 104

ICT Information Communication Technology 107

IDF inverse domain frequency 30

INNOV Innovativeness 21

INTNT Intentions 24

IOT Internet of Things 162

IQR interquartile range 46

IS Information Systems 68

KNOW Knowledge 21

LDA Latent Dirichlet Allocation 5

LIFE Life Style 21

LLM Large Language Models 66

LOC_SPECIFIC Limitations due to study being location specific 54

LOR log odds ratios 97

LR Likelihood Ratio 94

MAT Mental Accounting Theory 72

MB Manitoba 95

MBANK Mobile banking 132

MH Mental Health 6

NB New Brunswick 95

NFC near field communication 115

NL Newfoundland and Labrador 95

NLP Natural Language Processing 61

NO_CAUSAL limitations due to not assessing causality 54

NO_LONG Limitations due to not doing a longitudinal study 54

NS Nova Scotia 95

NS.Factors non-significant factors 40

ON Ontario 95

OR odds ratios 97

OS Operating System 117

OSL Optimum Stimulation Level 49

PA Path Analysis 48

PBHV_CTRL Perceived Behavioral Control 20

PC Personal Computers 116

PEEX Performance Expectancy 21

PEOU Perceived Ease of Use 20

PHON User Does not use a Smart Wearable Device (Only Smartphone) 135

PICOC Population, Intervention, Comparison, Outcome, Context 26

PIT Perceived Interactivity Theory 49

PLS-SEM Partial Least Squares 38

PRISK Perceived Risk 20

PSEC Perceived Security 123

PU Perceived Usefulness 20

QC Quebec 95

RS Relationship Satisfaction 6

SAMPLE Limitations due to the sample not being representative 54

SBJ_NRM Subjective Norms 22

SCGT Social Cognitive Theory 22

SCT Social Contagion Theory 23, 50, 169

SD Smartphone Dependency 6

SEM Structural Equation Modeling 38

SIT Social Influence Theory 48, 169

SK Saskatchewan 95

SLR Systematic Literature Review 2

SNS Social Networking/Social Media 6

SOC_PRSR Social Pressures 22

SOCINF Social Influence 22

SPT Social Practice Theory 48

SRT Social Role Theory 163

TAM Technology Acceptance Model 2

TCV Theory of Consumption Values 49

TF term frequency 30

TF-IDF Term Frequency-Inverse Document Frequency 30

TRA Theory of Reasoned Action 22

TRST Trust 24

TTF Task Technology Fit 49

UG Uses and Gratification Theory 24

UTAUT Unified Theory of Acceptance and Use of Technology 2

UX User Experience 109

WEAR User Uses a Smart Wearable Device (In addition to Smartphone) 135

WOM Word of Mouth 23

Chapter 1

Introduction

The proliferation of Mobile banking, referred to in this manuscript as m-banking, has transformed financial services, enabling consumers to conduct transactions conveniently through mobile devices. Mobile banking is the use of mobile device – a portable, handheld computer – to conduct banking tasks [455]. Despite the advantages, m-banking adoption rates vary significantly. Adoption is the early stage usage or uptake of a technology. This is the most important stage before consumers become long-term users [149]. This dissertation aims to bridge critical gaps in understanding how different factors (according to literature trends and through novel contributions) and device-specific attributes shape m-banking adoption. The central research question addressed in this dissertation is: "What are the factors that are important in understanding mobile banking adoption decisions across different user segments?"

The current chapter is a holistic introduction to the dissertation. To answer the main research question, I conducted three distinct yet interconnected studies. In the introduction (current chapter) and the conclusion (Chapter 5), I use the first-person singular voice to describe the research process and methodologies undertaken. However, within each chapter, the first-person plural pronoun is used to reflect a more conventional academic tone and to acknowledge the collaborative nature of the work(s). Each chapter will be discussed shortly, but to introduce the chapters, I will include the name of each in chronological order followed by a brief one-sentence summary:

1. **The Inner Workings of Mobile Banking Adoption: A Systematic Literature Review of**

Intrinsic Factors – A Systematic Literature Review (SLR) of a specific group of adoption factors defined for the first time in this study as "intrinsic factors" (more on this in Chapter 2).

2. **The Relationship Between Mental Health and Mobile Banking Adoption: Evidence from Canada** – An analysis of the impact of mental health and related psychological factors on m-banking adoption.
3. **The Device Divide: Unpacking Mobile Banking Adoption Differences for Smartphones and Smart Wearable Devices** – An investigation into the role of device type (smartphone vs. smart wearable) in shaping adoption behaviors.

This dissertation makes several contributions to the field of technology adoption and financial services research.

Theoretical Contributions

1. My research extends the understanding of factors in m-banking adoption by providing a useful categorization in two levels.
2. My research is the first to look at mental health and its related concepts in m-banking adoption, integrating mental health considerations into behavioral technology models.
3. My research is the first to consider device differences in a comparative setting in m-banking, specifically looking at smartphone and smart wearable devices. The results show that Perceived Trust, Perceived Security, and Time-saving advantage of m-banking are associated with m-banking adoption in distinct ways for smartphone users compared to smart wearable users. Therefore, I argue that even established theoretical frameworks such as the Unified Theory of Acceptance and Use of Technology (UTAUT) [530] and Technology Acceptance Model (TAM) [124] could be improved by integrating device specific measures.

Methodological and Practical Contributions

1. I use text-mining techniques to extract topics and classify articles in a systematic literature review study, providing a structured approach for future research.

2. I conduct a comparative study, the first of its kind, between different devices and the difference in m-banking adoption between the two. For Practical Contributions, the insights from this dissertation help financial institutions as well as researchers on many frontiers.
3. The results of Chapter 2 could be used as a reference for future scholars to conduct more directed research by finding context-specific theories, factors and methodologies.
4. I highlight various gaps in the literature and offer suggestions for future researchers.
5. My categorization of adoption factors helps clarify these latent ideas, improving understanding for both practitioners and researchers.
6. The results from Chapter 3 show that Social Media is one of the best platforms for marketing for banks.
7. From the same study, I highlight the various ways banks could promote and engage consumers with various mental health concerns.
8. From the results of Chapter 4, I offer actionable strategies for financial institutions to tailor their mobile banking services based on device-specific adoption behaviors.

By synthesizing psychological, empirical, and device-specific perspectives, this dissertation provides a comprehensive examination of mobile banking adoption, paving the way for future advancements in financial technology research. The following sections provide a brief introduction for each chapter/study. Please note that since studies are written as research papers, each starts with an introduction. To minimize redundancy, this chapter presents each study as a conceptual pitch where I emphasize the motivation behind each study (future chapters), the rationale for its inclusion and undertaking, the research question it addresses, and a high-level overview of its findings. The goal is to set the stage and justify the necessity of each study without replicating the full introductions found in their respective chapters. That said, some overlap may still occur despite efforts to streamline this part. Additionally, note that the introduction for the first study is longer and more in depth because I introduce several new concepts.

1.1 The Inner Workings of Mobile Banking Adoption: A Systematic Literature Review of Intrinsic Factors

Despite extensive research on m-banking adoption, a clear framework categorizing user-specific influences is still missing. After investigating the m-banking adoption literature, I found that uniform definitions for factors[1] influencing m-banking adoption was lacking. Furthermore, existing research tends to rely heavily on a limited set of factors and theoretical frameworks. While this is not inherently problematic, it raises the question of whether alternative theoretical foundations or methodologies might offer valuable insights that are currently being overlooked. This motivated my decision to conduct a systematic literature review (SLR) to identify under-utilized theories with potential relevance. An SLR study is particularly valuable in this context because it enables a comprehensive, structured mapping of existing research, helping to uncover conceptual gaps and highlight opportunities for theoretical exploration [43].

To address the problem of lack of uniform definitions, I categorized adoption factors based on context and impact. This way, using group/category membership help identify similarities between factors. Thus making definitions more cohesive. Several studies support the idea that categorization helps in defining and understanding concepts more easily [419, 1, 203]. Research suggests that categorization plays a crucial role in defining concepts, moving from a classical view (fixed definitions) to a probabilistic view where categorization helps in making sense of concepts based on shared characteristics [327]. Categorization enables more effective organization and processing of information which are essential for learning new concepts [570].

I adopt a broad approach to classifying factors, focusing on two key dimensions of decision-making based on how they relate to the user: Intrinsic and Extrinsic. In the context of m-banking adoption, *intrinsic* factors discuss how individuals evaluate an m-banking application[2] internally — based on perceptions, goals, pressure felt from other people's judgment, and emotions. *Extrinsic* factors, on the other hand, refer to the apps' measurable features, such as performance and func-

[1] The words *factor* and *construct* are used interchangeably throughout most of m-banking adoption literature with no significant distinction between them [373].

[2] Often shortened to "app".

tionality. In Chapter 2, I detail this process from the choice of words to presenting justification on why this methodology is useful in addressing the lack of uniform definitions for factors across the literature. Since extrinsic factors are easy to quantify and experienced similarly across the board, they are also straightforward to study. Thus, I focus on intrinsic factors. Because intrinsic factors relate to so many different inner processes (mentioned above), I further categorize them into four main groups:

- **Perceptive**, which are based on perceptions.
- **Personal**, which are based on individual motivations and traits.
- **Social**, which are based on the impact of others on the decision-maker.
- **Psychological**, which are based on various cognitive, emotional and mental processes.

A comprehensive discussion on this categorization is presented in Chapter 2 Section 2.2.2 – based on how individuals make decisions, i.e., the decision maker is first presented with a cue or trigger which they perceive, they interpret the trigger using simple mental shortcuts which are different among individuals due to differences in personality and experiences, and sometimes go through more deliberate thinking to arrive at the decision but sometimes are overcome by affects (moods and emotions) or pressure from other people. This categorization of intrinsic factors into four sub-categories provides a useful context-specific grouping. Additionally, I include text-mining in this SLR study which adds more value than a traditional SLR would. This is because by using text mining, I am able to find trends and pattern across a much larger sample size (143 papers vs the median number of papers included in Engineering SLR studies which is 57 [546]) and validate my findings using statistical tests.

Scientific articles gathered are given themes using text mining techniques – specifically, Latent Dirichlet Allocation (LDA) for Topic Modeling. Some of these themes match my sub-categorization, as well. I also extend prior SLR studies by using statistical techniques – specifically, Analysis of Variance (ANOVA) – to mathematically validate my findings. My results provide a strong empirical foundation for future researchers to do context-focused investigation. The **outcome** of this study is to help enhance the understanding of intrinsic factors, highlight underutilized methodologies, and identify research gaps. Additionally, I highlight the dominance of certain theoretical models while advocating for greater exploration of under-studied theories

and methods. My findings show notable geographical and study-design biases, particularly longitudinal research in developed nations. For practitioners and policymakers, I recommend designing emotionally engaging apps, ensuring transparent risk communication, and educating users on safe practices. These steps enhance m-banking adoption and effectiveness.

1.2 The Relationship Between Mental Health and Mobile Banking Adoption: Evidence from Canada

Following the work of the previous study, I focus on intrinsic factors. One of the factors I found to be under-explored in the literature was mental health. Psychological factors are comparatively less-studied across the m-banking literature [529, 580, 509]. I verified this further doing a quick preliminary search on Web-of-Science. Using the following search query returned 1,067 studies with no filters set on the results:

```
("mobile banking" OR "mbanking" OR "m-banking") AND ("adoption")
```

When changing the search query to find studies specifically on psychological factors, the total number of studies returned were 157, which is about 14% of the total. The new search query was:

```
("mobile banking" OR "mbanking" OR "m-banking") AND
("adoption") AND ("affective" OR "psychological" OR "affect based" OR
"affect-based" OR "emotional" OR "cognitive" OR "mental" OR "personal")
```

Using the same search queries in Scopus, 753 results were returned for the first, and 101 in the second search (13.4%). It is clear that only a small portion of the literature in m-banking adoption is focused on psychological factors. In this study, I investigate the direct and moderated relationship of Mental Health (MH) with m-banking adoption. Moderators are extracted from theories in technology adoption or from literature related to mental health: Relationship Satisfaction (RS), Smartphone Dependency (SD), and Social Networking/Social Media (SNS). I use a fixed effect logistic regression model grouped based on Canadian provinces following the cluster sampling design of my dataset. The **results** show that mental health significantly and negatively correlate with m-banking adoption: better mental health outcomes were associated with lower likelihood of m-banking adoption. I do not find sufficient evidence for the moderating effects.

1.3 The Device Divide: Unpacking Mobile Banking Adoption Differences for Smartphones and Smart Wearable Devices

Moving on from focusing only on smartphones, I decided to do a comparative study considering newer devices used in m-banking. One of the findings of my SLR study from Section 1.1 was that few comparative studies exist in general, and studies that focus on various tools used for m-banking are increasingly important. Addressing this gap is the main motivation for the last study. In this chapter, I examine the nuances of m-banking adoption decisions across two mobile devices: smartphones and smart wearable devices. I investigate the association of the following factors with mobile banking adoption: perceived trust, perceived security, time saving, and demographic variables. Demographic factors are important as numerous studies identify these (e.g., age, gender, income, and education) as key factors in m-banking adoption decisions [96, 305]. I include detail discussions on why each of the other factors are considered in this model.

The **results** from this chapter are device-specific insights. This study also refines existing technology adoption models. Additionally, to the best of my knowledge, this is the first study to compare behavioral differences between smartphone and smart wearable users in the context of m-banking. I found that perceived trust is more important among smartphone users, while wearable users prioritize time efficiency. Users perceive smartphones as more secure. Demographic factors such as age, education, and gender exhibit different associations with m-banking adoption based on device type as well.

Chapter 2

Literature Review

The Inner Workings of Mobile Banking Adoption: A Systematic Literature Review of Intrinsic Factors

2.1 Introduction

Mobile banking (m-banking) has gained popularity due to its convenience and the increasing use of smartphones [170, 478]. This service revolutionizes traditional banking by allowing users to perform transactions and manage accounts from their mobile devices. The COVID-19 pandemic has introduced new factor into m-banking adoption research, particularly individual differences in technology-related anxiety [384] and health-related anxiety [138]. These factors underscore the need to examine influences pertaining to individuals [65, 452, 176]. Despite numerous studies examining demographic, social, and individual characteristics, the existing literature lacks a systematic framework for effectively categorizing adoption factors [346].

Marikyan *et al* [317] show that effects of adoption factors vary by context. They advise researchers to choose models and factors according to the specific context of their study. However, to the best of our knowledge, no study has clearly contextualized theories and factors of technology adoption. This dissertation fills this gap in the literature in two ways. First, we categorize adoption

factors based on context. Second, we conduct a systematic literature review to provide insights on the state of research aligned with the categorization established in the first step.

This study is the first to categorize technology adoption factors, specifically m-banking adoption, into distinct groups. First, we classify the factors into two dimensions: *Intrinsic* and *Extrinsic*, based on whether they originate internally or externally to the decision-maker. Next, we focus on intrinsic factors, further categorizing various intrinsic factors according to context. Intrinsic factors involve perceptions, internal evaluations, beliefs, and emotions. Extrinsic factors relate to measurable features of technologies like app performance and functionality. For instance, while an app's login time may be objectively measured as s seconds (where s is a small numeric value), some users may find s to be *fast* while others perceive it as *slow*. Thus, the login time itself is an extrinsic factor (objective and measured in seconds), but the perception of its speed is intrinsic (mostly subjective, depending on consumers' definitions of fast and slow). We categorize intrinsic factors into further sub-categories, grouping similar factors that are related to an overarching idea together. By doing this, we contribute to the literature in three main ways:

1. **Clarification of Meaning**: Many intrinsic factors lack cohesive definitions across the literature [346]. Categorizing factors into separate clusters helps researchers understand the core ideas behind factors.
2. **Focused Research**: Our framework allows researchers to narrow their focus to relevant factors. Tailored categorizations provide guidance on appropriate theories that capture underlying behaviors and factors for specific contexts or themes. We believe using this categorization, researchers will be able to produce focused and effective studies more efficiently.
3. **Highlighting Overlooked Patterns**: As per our results and previous literature reviews [472], certain theories and factors dominate the literature, often overshadowing the effects of others. Clustering studies by sub-categories uncovers neglected factors and their behaviors, offering fresh insights for future research.

Additionally, there are few systematic literature review studies in m-banking adoption [232, 317]. We extend these studies by employing Latent Dirichlet Allocation to group scientific papers into topics (called themes), some of which align with our sub-categories of factors. From this, we

identify patterns and trends and analyze them using statistical tools. The main objective is to serve as a reference, helping technology adoption researchers identify relevant methods, theories, and factors to strengthen their work. By synthesizing recent studies, we highlight limitations, gaps, and emerging trends in the literature with a focus on intrinsic factors for each sub-category. We identify and summarize nearly all intrinsic factors cited in recent years, providing a valuable starting point for other researchers.

The remainder of this paper is organized as follows: Section 2.2 introduces intrinsic factors in m-banking adoption and our categorization in detail. Section 2.3 outlines the SLR methodology and data collection process. Section 2.4 presents the dataset (collection of scientific papers) and some exploratory analysis. Section 2.5 provides statistical analysis for results and data exploration. Section 2.6 is a detail discussion of the findings, as well as recommendations for future researchers and practitioners. Section 4.7 concludes the paper.

2.2 Categorization of Intrinsic Factors

Technology adoption hinges on various factors. Among these, intrinsic factors play a pivotal role. Due to the complexity and overlapping nature of adoption factors, a precise categorization has been lacking in prior research. This section explains why this study is needed by pointing out the complications created by conceptual ambiguity of adoption factors. By organizing these factors into categories, we offer a clearer and more useful framework. Our argument is that this categorization addresses a key gap in the literature. We also break down intrinsic factors into sub-categories with examples from m-banking research. Our goal is to provide a framework that can be used by researchers in future studies.

2.2.1 Rationale for a Structured Conceptual Framework

Technology adoption studies rely heavily on latent factors/constructs [373]. Latent factors are abstract concepts like trust, perceived usefulness, attitude, social influence, security, or ease of use. These factors cannot be directly and uniformly observed or measured. They are crucial to

understanding user behavior, but there is a fundamental issue: the definitions, interpretations, and measurements of these factors vary significantly across studies. This goes beyond the technology adoption literature and appears in many social sciences that study human behavior [320]. We will use *trust* as an illustrative example for each of the concerns we bring up. This is to clarify exactly how various inconsistencies show up across the literature and why they need to be addressed. It is important to emphasize that this is just one of many such factors; similar inconsistencies are evident across other factors throughout the literature.

1. Construct Validity and Consistency

The first problem with the lack of clear and consistent definitions is that it causes confusion and inconsistencies. Many factors in technology adoption literature may have different dimensionalities [315]. Factor dimensionality is sometimes treated inconsistently across studies. In some cases, these dimensions appear to be subjectively defined; in others, they are context-dependent. As stated before, we use examples of how these inconsistencies appear in the literature using Trust[1]. Trust is used in different ways depending on what it is referring to: trust in the technology (e.g., mobile banking app), trust in the provider (e.g., the company developing the app or the bank behind it), trust in the device (e.g., smartphone).

In their study on Airbnb, Mao *et al* [315] identify two types of Trust: Trust-in-Hosts and Trust-in-Platform. We discuss this study to illustrate one example of how Trust is operationalized as a multi-dimensional construct. Trust-in-Hosts (also called personal Trust) is a consumer's belief and willingness to rely on a host to meet their obligations. This is shaped by four main factors: 1) experience-based Trust from direct past interactions with hosts, 2) calculative-based Trust based on rational cost-benefit analysis (e.g., the host has more to lose by being dishonest), 3) Cognition-based Trust formed from indirect signals like reviews, and 4) personality-based Trust, which reflects a person's general tendency to trust others based on their traits and life experience. Trust-in-Platform, or institutional Trust, is the belief that the platform (e.g., Airbnb) has proper systems in place to ensure smooth transactions. It is shaped by four main factors: 1) perceived

[1]Whenever Trust is capitalized mid-sentence it is to emphasize that it is the factor (or model variable) and not the notion of trust in general.

security, i.e., the safety of payment methods, 2) perceived privacy, the belief that personal data is protected, 3) perceived website quality, the assessment of the site's design, features, and usability, and 4) social presence, a sense of human connection, such as through host profiles or photos.

Now we present a second operationalization of Trust based on a different dimensionality from the study by Choudrie *et al* [108]. The authors define Trust with three dimensions: 1) ability, i.e., the provider's perceived competence to perform tasks, 2) integrity, i.e., keeping promises and avoiding deception, and 3) benevolence, i.e., showing concern for the consumer's interests. Choudrie *et al* also note that Trust develops over time, distinguishing between initial Trust (before use) and continuance Trust (built through experience). Together, these examples show how the same concept – Trust – is portrayed differently in technology adoption studies. Table 2.1 includes several other instances of how Trust is defined across other articles. While all approaches to conceptualizing and operationalizing trust are valid within their contexts, they reflect fundamentally different emphases, thereby creating confusion in conceptual alignment across studies. This inconsistency justifies the need for a more clearly articulated and contextually grounded definition of trust, and as we pointed out, most other adoption factors.

Table 2.1. Example Definitions for Trust Across the Literature

Author/Reference	Year	Definition (exact quote from papers)
Nguyen et al. [358]	2024	Trust is the belief that enables users to engage in m-banking service voluntarily, while considering its susceptible mutual features.
Jafri et al. [232]	2024	Trust measures customers' confidence in banks to provide adequate services competently and with integrity. Trust is categorized into cognition-based, personality-based, institutional-based, calculative-based, and experience-based.
Iqbal et al. [382]	2023	Trust is defined as the perceived credibility and benevolence of a target of Trust.
Kumar et al. [274]	2023	(Perceived) Trust refers to the feeling of confidence and assurance about using mobile banking.
Hanafizadeh et al. [199]	2014	(Perceived) Trust is an individual's belief to use mobile banking services willingly.
Gefen et al. [177]	2003	Trust is the trustor's willingness to engage in a risky behavior.
Mayer et al. [322]	1995	Trust reflects a willingness to be in a state of vulnerability based on the positive expectation toward another party's future behaviour.

2. Measurement and Operationalization

The second issue with unclear definitions is the mismatch between what researchers intend to measure and what their tools/items actually capture. We continue with our focus on Trust as an example factor. A survey may aim to assess Trust, but end up measuring distrust instead. Distrust involves active suspicion (i.e., not just low Trust), which reduces construct validity [190]. Measures that ask about suspicion or perceived wrongdoing by institutions are measuring how much individuals do not trust those entities, not how much they positively trust them [190]. Another facet of trust is mistrust, which is often defined as unease or suspicion toward groups (e.g., "all providers" or "the healthcare system") [404].

Mistrust reflects beliefs that institutions may fail or cause harm. Survey items that highlight doubt, suspicion, or discomfort likely measure mistrust, not trust [404]. Wang *et al.* show how trust-oriented questions may unintentionally reflect mistrust, such as: "Do you think most people would take advantage of you if they could, or try to be fair?" [541]. This frames the issue negatively, highlighting suspicion. Other examples show how focusing on selfishness, indifference, or lack of safety ends up measuring mistrust [541]. These examples demonstrate how mistrust carries distinct emotional and cognitive implications compared to the absence of trust, which is often neutral. Researchers sometimes conflate mistrust with the absence of trust, leading to conceptual ambiguities.

3. Comparisons

The last problem with lack of clear and consistent definitions is the difficulty in comparing studies and results. We continue with our focus on Trust. If different studies define and measure Trust differently, then meta-analyses become unreliable, theory development becomes fragmented and practical recommendations become weak. Furthermore, it becomes increasingly difficult to build on top of previous theories if a context drift requires shift in the definition of a factor.

Given the discussion thus far, we content that it is important to address this shortcoming. To do this, we take inspiration from ideas in linguistics such as Distributional Semantics and Prototype Theory. Distributional semantics is at the heart of semantic analysis, which is the study of the

meanings and similarity of words in terms of their meanings [489]. It underlies techniques like topic modeling (more on this in Section 2.4.1) for language processing tasks. In computational linguistics, distributional semantics posits that words appearing in similar contexts have similar meaning, i.e., "you shall know a word by the company it keeps" [419].

Prototype theory suggests that a concept is represented by its average category example [1]. In other words, this theory suggests that categories are formed around prototypical examples and meanings are understood based on similarity to central (ideal) members, although category boundaries are sometimes fuzzy [1]. That is, it may be the case that there is no clear line where a category starts or ends, items can partially belong to a category and there are words that represent categories better (more typically) than others. For example, if the category is *bird* – a sparrow is a typical (i.e., prototypical) bird but a penguin, while still a bird, is not as perfect a fit.

Drawing on these two linguistic approaches, we argue that categorizing words and identifying their membership in semantic groups enhances conceptual clarity and strengthens our understanding of their meanings. However, we also acknowledge that such categorization is not without its limitation as often times, category boundaries are difficult to enforce and many words, depending on context, may belong to more than one category. We do our best to address this issue by considering the top three categories for each word and avoiding multi-category memberships. The following sections outline the methodology used for this task and provide evidence supporting its value and validity.

2.2.2 A Novel Categorization of Technology Adoption Factors

Having outlined the issues caused by inconsistent definitions, we now discuss how this study addresses them, and why the proposed method is effective. In an attempt to offer a solution to the lack of uniform definitions, we introduce a novel categorization of adoption factors. Depending on how a factor relates to the decision maker, we categorized adoption factors into two categories: Intrinsic and Extrinsic. *Intrinsic* factors are internal stimuli that influence the individual's decision. These are thoughts, beliefs, feelings/emotions, perceptions, and personal differences such as goals and taste. *Extrinsic* factors are external, objective, and measurable elements that influence

individual decisions such as app features or design attributes (e.g., font face or theme color). While their existence (e.g., a specific color's hexadecimal value) is fixed and consistent, individuals may interpret or react to them differently. For instance, the same color scheme may evoke different feelings depending on the user's taste.

A clear and contextually relevant example of this distinction involves the time it takes a user to log into a mobile app. Suppose multiple timers are used to measure login duration using identical start and stop signals, on the same devices with uniform software and storage conditions. If all users input their credentials correctly and face no device-related issues, each timer should yield the same objective login time. This duration – from pressing the login button to accessing the account – is a consistent app feature that can be measured precisely (typically in seconds or milliseconds [360]). It falls under standard performance thresholds for mobile apps and is an example of an external factor based on our definition. However, individual users may *perceive* this identical login time differently. That is, the same s seconds of time could be thought of as fast or slow depending on expectations, perceptions, personal goals and personality traits of different users. Therefore, the perceived login time (or speed) is an intrinsic and subjective experience shaped by user-specific interpretations.

It is important to briefly address the rationale behind the use of the terms intrinsic and extrinsic in this study. In marketing research, product attributes that shape consumer perceptions and decisions are commonly categorized as either intrinsic or extrinsic [213]. Intrinsic attributes refer to inherent product characteristics such as taste, texture, design, or color that cannot be altered without changing the product's nature [168]. In contrast, extrinsic attributes include elements like brand name, price, packaging, or advertising – features external to the product itself and modifiable without altering the product [213].

Similar to marketing, motivation literature also uses the terms intrinsic and extrinsic for different types of motivation driving a behavior. Intrinsic motivation comes from within the individual, not from the outside world. This motivation involves the individual engaging in an activity for its own sake, due to interest, curiosity, enjoyment or satisfaction [136]. On the other hand, extrinsic motivation involves seeking rewards or avoiding punishments, arising from external

factors separate from the activity itself [361]. While the terminology adopted in this dissertation draws a parallel to these concepts, it also meaningfully diverges from them. Therefore, the use of the terms extrinsic and intrinsic is both appropriate and justified.

In this work, the focus shifts from the properties of a product (e.g., a mobile banking app) to the consumer. Instead of asking how product features influence consumers, we explore how consumers interpret and assess the same features differently. Unlike motivation studies that ask why people behave a certain way, we look at how consumers evaluate key factors already known to shape m-banking adoption. In this sense, our use of intrinsic refers not to a feature of the product but to an internally generated, subjective interpretation by the individual based on a feature. This inversion of the marketing framework highlights a key theme in this dissertation: adoption behavior is not only shaped by the technology itself, but also by how users internally experience and interpret it, even when the external conditions remain constant.

Categorizing factors in this way will help clarify meanings. There is sufficient evidence that shows grouping related or ambiguous concepts help derive more consistent and uniform definitions. Research suggests that categorization plays a crucial role in defining concepts, moving from a classical view (i.e., fixed definitions) to a probabilistic view where categorization helps in making sense of concepts based on shared characteristics [327]. Furthermore, categorization enables more effective organization and processing of information which are essential for learning new concepts [570].

The importance of categorization is also observed in various lexical semantic techniques, which are strategies and concept-representations for dealing with ambiguous or multi-meaning words. For example, the idea of Polysemy relates to words with multiple related meanings[2]. Scholars treat these as continuous variations within a semantic space. That is, words are thought of as vectors (or points) in a coordinate space of meaning. This vector-space model allows for the grouping of words based on contextual similarity, aligning with distributional semantics, which posits that words appearing in similar contexts tend to share meanings [203].

[2]The word "bank" is an example of polysemy where bank has multiple meaning: a) a financial institute (noun) and b) the side of a river (noun).

Since extrinsic factors are easy to quantify and experienced similarly across the board, they are also straightforward to study. Thus, we focused on the more interesting group: intrinsic factors. To begin the discussion on intrinsic factors, we first offer a holistic look into human decision making. We do this because decisions (e.g., m-banking adoption) unfold as layered psychological processes, each shaped by distinct perceptual, personal, social, and psychological dimensions that mirror our proposed categorization. Human decision making is a complex, multi-step process that engages both intuitive and deliberate cognitive mechanisms.

Decision-making starts with an initial trigger – when the individual perceives a stimulus, whether an external event or an internal thought [245]. The key word here is *perception*. Perception as the start of the decision-making process is one of the building blocks of behavioral intent (i.e., intention to carry out a behavior). For example, when individuals are considering whether to adopt m-banking, their perceptions of security of the app, its trustworthiness, ease of use, and utility act as initial cognitive filters in the decision-making process. Given this, we believe at least some of the factors in the technology adoption literature ought to reflect how perceptions change decisions.

Almost immediately, this initial trigger is evaluated by the person through heuristics. These are simple, efficient rules or mental shortcuts that allow individuals to make decisions quickly without excessive cognitive effort [518]. However, these heuristics, which impact the decision, vary significantly between individuals as a result of cognitive ability [457, 549, 230], personality differences [549, 479], different thinking styles [129, 475], gender [549, 503], and previous experience [62, 550]. Such traits are endogenous to the individual (i.e., not easily changed by outside influences) and tend to persist over time [482]. These factors capture the variability in adoption decisions that stem from who the user is, rather than what they perceive or feel in a particular context. Therefore, a second group of factors are needed that pertain to these individual (i.e., personal) characteristics.

The next steps in decision making are more deliberate, involving what Kahneman calls System 2 thinking – slow, effortful and logical thinking that involves evaluating evidence, consulting

rules, norms, comparing alternatives and imagining outcomes [245]. At this stage, two distinct forces come into play: psychological/affective processes [502] and social influences [572]. Psychological factors such as emotions [501, 118], attitudes [182, 80], cognitive evaluations [479], and mental health [140] are factors that influence and govern how the individual interprets, weighs, and integrates information [375]. Therefore, we argue for the existence of such factors that are separate from perceptions (as they are precursors to perceptions) and beyond just personal differences. These factors are tied to the individual's mental and emotional state, often shaped by past experiences but operating independently of immediate social input [258].

In parallel, Social influences are the impact of other people like family, friends, peers, societal expectations, and norms on the individual which may affect their decision-making processes [28, 55, 292]. While the psychological dimension focuses on internal cognition and affect, the social dimension captures how external social environments shape choices by influencing the inner monologues of individuals [141, 167]. Social influence, peer pressure, and the perceived expectations of others often serve as benchmarks or constraints that individuals consult during decision-making. These are conceptually distinct from perceptions or personal traits because they emerge from interpersonal dynamics, not from within the individual. Thus, separating Psychological and Social categories allows us to distinguish between internally generated processes of deliberation and externally motivated pressures or cues. This distinction not only mirrors the dual nature of System 2 thinking – internal reasoning vs. external validation [245] – but also enhances conceptual clarity when organizing the multifaceted drivers of decision-making.

Our discussion of this framework justifies the categorization of intrinsic factors in such a way to align with different layers of the decision-making process. Namely, these stages pertain to *perceptions*, *personal* traits, *social* aspects and *psychological* dimensions. It is important to note that the stages of decision making described here are not always chronological. Emotions can influence decisions before memory, knowledge and logic are even involved in the process. Reasoning can override feelings later. These stages often interact, not replace each other. Which is also reflected in how factors from each category interact within conceptual models of technology adoption. Effective exploration of m-banking adoption requires a nuanced understanding of these inner processes – what we have called intrinsic factors – that drive user decision-making,

ultimately leading to the behavior of adopting an m-banking app.

We clearly demonstrated that categorizing factors is effective. We take this a step further and break down intrinsic factors into four sub-categories:

- **Perceptive**, which are based on beliefs and perceptions.
- **Personal**, which are based on individual motivations and traits.
- **Social**, which are based on the impact of others on the decision-maker.
- **Psychological**, which are based on based on cognitive, emotional and mental processes.

Each sub-category matches one of the dimensions of the human decision-making process described above. Therefore, we believe our categorization is acceptable and not random.

It is both conceptually useful and appropriate to categorize intrinsic factors as such, aligning with established theories and empirical models in behavioral and technology adoption research. Research into m-banking adoption frequently extends traditional technology acceptance models by incorporating a broader spectrum of influences [30]. While models like the Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology primarily focus on aspects such as perceived usefulness and perceived ease of use, a more holistic understanding necessitates integrating emotional, social, and individual dispositional factors. This multi-faceted approach recognizes that consumer decisions are influenced by a combination of rational evaluations, personal predispositions, social pressures, and emotional responses [523]. Here, we will discuss each category to provide examples and theoretical basis for each group.

2.2.3 Perception-based Factors

This category refers to an individual's interpretations, capturing how users perceive an aspect of a technology. Perceptions are opinions shaped by available information [111]. They are immediate sensory experiences that may not necessarily align with beliefs, as they can be influenced by external stimuli and cognitive biases [467]. It is rare for different individuals to perceive something identically [68]. Since people process information differently, perceptions vary widely, making them difficult to measure [84]. Perceptions are influenced by education [113], experiences [163],

and even surroundings.

Technology Acceptance Model (TAM) is the foundational theory at the heart of perception-based factors. Two examples of perception-based factors are Perceived Ease of Use (PEOU) and Perceived Usefulness (PU), central to TAM [124]. TAM posits that an individual's intention to use a technology is determined by the technology's perceived usefulness (i.e., "will using the system enhance my performance?"), and perceived ease of use of the technology (i.e., "how much effort is required to use this system?") [124]. The Theory of Planned Behavior (TPB) includes Perceived Behavioral Control (PBHV_CTRL) to account for external factors affecting behavior [14]. However, it reflects an individual's perception of control, not the actual influence of these factors. In other words, perceived behavioral control is how much control an individual *thinks* they have on a behavior.

Adding to this, several other perception-based factors and models were introduced. Rooted in consumer behaviour literature, Perceived Risk (PRISK) is a crucial factor, defined as the combination of uncertainty and seriousness of potential negative outcomes [109]. This encompasses financial, security, privacy, and performance risks [383]. Perceptions of risk are major barriers to m-banking adoption [325, 386, 452, 573, 553, 496, 330], particularly concerns over security and privacy [509]. Risk perceptions strongly shape user opinions on m-banking [347, 559] – often by triggering emotions like fear and anxiety [104, 384, 432].

Consumers evaluate technology based on their expectation of value. Values may be utilitarian (i.e., functional benefits like convenience or economic gain) or hedonic (i.e., enjoyment and fun) – all of which are the perceived value of the technology [383]. These factors directly shape an individual's attitude towards a technology and their subsequent behavioral intention to adopt it. A higher perception of usefulness, ease of use, behavioral control and value, alongside a lower perception of risk generally leads to a stronger intention to adopt. This group is easily identifiable as many of these factors have "*perceived*" in their names, forming the Perception-based category. PRISK, PU and PEOU are some of the examples of perception-based factors in the technology adoption, and specifically, m-banking adoption literature.

2.2.4 Individual (Personal) Factors

Individual factors arise from individual characteristics and preferences, personal experiences, tolerances, goals, and motivations. Some individuals adopt m-banking for convenience, while others do so out of necessity, highlighting different motivations. Personal differences are often overlooked in adoption studies [384]. The goal of this research is to help researchers integrate these factors into their models. We categorize factors that relate to personal values, goals, motivations, and experiences as Personal. Self-Determination Theory addresses the impact of intrinsic motivation and personal autonomy on technology use [414, 421]. Studies on individual differences show that variables like age, gender, education, and prior experience directly influence readiness to adopt m-banking [411]. Personal factors dictate both the likelihood and speed of adoption [109].

The Bass Diffusion Model (BDM), which considers social circles/networks and effects of mass media on technology adoption, classifies individuals as Innovators or Imitators [59]. Innovators are those driven by their Innovativeness (INNOV), while imitators are influenced by Social Pressures (discussed in Section 2.2.5). Innovativeness, i.e., how much a person values innovations, is a personal characteristic shaped by age, education, culture, and values [398]. The Five-Factor Model of Personality underscore personality's influence on individual responses to new technology [63]. In the UTAUT, Performance Expectancy (PEEX) and Effort Expectancy (EFEX) explain adoption behavior [528]. Performance Expectancy reflects expected performance benefits, while Effort Expectancy represents how much effort the user expects the technology requires of them.

Users are more likely to adopt a technology if they expect greater performance enhancement and lower efforts required for adoption and use. These expectations vary by user motivations and goals, therefore they are categorized as personal factors. Other examples of personal factors are Life Style (LIFE), Knowledge (KNOW) and Digital Literacy (DIG_LIT). Personal factors influence an individual's initial receptiveness, confidence, and continued engagement with m-banking. They can directly influence adoption intention and behaviour, and also moderate the impact of other factors, reflecting individual differences in how technology is embraced.

2.2.5 Social Factors

Social factors involve external influences from others, i.e., peers, family, culture and broader social structures, which shape internal behaviors and beliefs [226, 465]. Although seemingly external in origin, these factors are classified as intrinsic. This is because rather than explicit external coercion, social factors drive internal behaviors. From BDM, it was observed that imitators are motivated by Social Pressures (SOC_PRSR). Social Pressures are outside pressures that lead to feelings of missing out or the desire to maintain credibility within social groups. These feelings in turn drive consumers to adopt technologies, emphasizing the influence of social circles on adoption decisions [59].

One of the main factors from UTAUT influencing users' opinions and decisions on technology adoption is Social Influence (SOCINF) [530, 240, 371, 267]. Social influence is a fundamental concept in psychology and technology adoption research, broadly defined as the degree to which an individual thinks that important others believe they should use a new system or technology [530]. This stems from pressures exerted by one's social community in terms of adopting an innovation [384]. Social influence encompasses the individual's internalization of their reference group's subjective culture and specific interpersonal agreements. Social influence is a core construct in prominent technology acceptance theories, including Theory of Reasoned Action (TRA), TPB and UTAUT. It is often used interchangeably with the term Subjective Norms (SBJ_NRM). The Theory of Reasoned Action explains behavior as intention-driven, shaped by attitudes and subjective norm [158]. Subjective Norms are societal "truths" collectively agreed upon [16].

To clarify why social factors are categorized as intrinsic, we explore how the impact of social influences operate through several psychological mechanisms. Kelman [256] proposes three processes for behavior and attitude change: Compliance, Identification, and Internalization. Compliance occurs when individuals accept the opinions of others to gain favorable benefits or avoid risk [22]. Identification involves maintaining desired relationships by aligning with the opinions of others [256]. Internalization is the strongest form, where individuals accept others's opinions both publicly and privately. Social Cognitive Theory (SCGT) highlights that social assistance, rules, open communication, and various social knowledge sources are integral to cognitive processes. Social interactions, even in early childhood, are crucial in shaping an individual's disposition to

trust [264].

Social Contagion Theory (SCT) explains how beliefs, knowledge, attitudes, emotions, and behaviours spread and are accepted through interpersonal processes and social networks [336]. People tend to seek similar experiences from their closest networks before making decisions. This contagion can occur physically or online and leads to behavioural changes. Social factors have become especially critical due to the influence of social media. These factors play a significant role in m-banking adoption, particularly in communities where collective norms, such as familial or communal expectations, drive technology adoption [145]. The sharing of experiences and recommendations among peers significantly impacts perceptions and intentions towards technology adoption. This informal communication – known as Word of Mouth (WOM) – can be particularly powerful [447]. Consumers often rely on their social networks to reduce anxiety and uncertainty associated with adopting new technologies [384]. To distinguish these factors, we consider any factor that inherently captures the effects of other people on adoption decisions to be social.

2.2.6 Psychological Factors

Psychological factors, the most complex subgroup, include beliefs, attitudes, emotions, and intentions, reflecting deep cognitive and affective processes. Psychological factors include emotional mechanisms like trust, anxiety, and enjoyment. Cognitive–affective theories reveal that emotions such as anxiety or trust mediate and moderate technology adoption [95, 421]. Research confirms that psychological needs (autonomy, competence, relatedness) and emotional resonance (enjoyment, technology anxiety) significantly affect intention to use and adoption [414, 63]. Individuals strive for harmony between their beliefs, attitudes, and intended behaviors to avoid dissonance [246].

Psychological factors maintain and reinforce the ongoing engagement with m-banking apps by influencing the quality of the user experience. Emotions are recognized as fundamental drivers of consumer behaviour and innovation adoption [523]. Positive Emotions such as enjoyment, fun, pleasure, and Hedonic Motivation (HED_MOTIV) – which refer to the non-instrumental, experiential, and affective values derived from using a service – foster interest, desire and action

leading to adoption. On the other hand, negative emotions including anxiety (e.g., technology anxiety), discomfort, frustration, and fear (e.g., fear of fraud, data privacy concerns, fear of missing out) can act as significant barriers or inhibitors to technology adoption [6].

The Cognitive Appraisal Theory (CAT) suggests that emotions arise from an individual's evaluations of events or thoughts, influencing their behaviours and intentions [303]. Attitude (ATTD) is a key driver of behavior in TRA [158]. It is shaped by psychological mechanisms, such as cognitive evaluations of risks and benefits, emotional responses to perceptions, and motivational drivers like optimism or anxiety [515]. Ajzen defines attitude as "a disposition to respond favorably or unfavorably towards some psychological object" [16]. Attitude encompasses evaluative judgments, Beliefs (BLF) represent cognitive structures, and Intentions (INTNT) reflect motivational states – all fundamental psychological elements that are subtly different from one another in the literature of psychology [406]. The Theory of Planned Behavior (TPB) focuses on Behavioral Intentions (BHVINTNT), shaped by attitudes toward expected outcomes and subjective evaluations of risks and benefits [15]. These factors link rational thought with emotional experiences, representing a spectrum of emotional responses.

The concept of cognitive absorption – a state of intense focus – encompasses dimensions like Enjoyment (ENJY), demonstrating how deep psychological engagement with technology can influence beliefs and intentions [10]. The Uses and Gratification Theory (UG) explains how individuals adopt technology to fulfill five needs: cognitive needs, affective needs, personal integrative needs, social integrative needs, and tension-free needs [73, 251]. These drive technology adoption and use. For example, using technology for knowledge satisfies Cognitive (COG) needs, while emotional fulfillment meets Affective (AFFCT) needs. According to UG, self-esteem is a personal integrative need, which blends cognition and emotion [251]. Since these three needs involve psychological aspects, they and their related factors are categorized as psychological. Psychological traits influence risk behavior [201], making both risk-aversion and risk-seeking behaviors psychological concepts as well. A closely related psychological factor to risk is Trust (TRST). Having more trust reduces perceived risks in m-banking, leading to adoption [325, 573, 162, 25].

To close our discussion of intrinsic factors, we address a key consideration. We separated

beliefs and perceptions into different subgroups for two key reasons. First, while beliefs and perceptions interact, they are distinct concepts with different definitions, roles, and processes. Beliefs are cognitive representations shaped by personal experiences and social influences, while perceptions are immediate interpretations of sensory input [441]. Beliefs can influence perception, often leading to motivated reasoning, where individuals interpret information to fit pre-existing opinions [417]. Second, the use of *perceived* as a pre-fix in factor names in the literature makes perception-based factors easy to identify. Categorizing beliefs and perceptions separately allows us to analyze trends within each group. Table 2.2 presents a comprehensive list of intrinsic factors and their categorization.

Table 2.2. Categorization of Intrinsic Factors (from the current study's main literature)

FACTOR	ABBR.	FACTOR	ABBR.	FACTOR	ABBR.	FACTOR	ABBR.
				PERCEPTION			
Perceived Risk	PRSK	Perceived Usefulness	PU	Perceived Ease of Use	PEOU	Perceived Credibility	PCRED
Perceived Value	PVAL	Perceived Security	PSEC	Perceived Quality	PQUAL	Perceived Behavioral Control	PBHV_CTRL
Perceived Privacy	PPRIV	Perceived Deterrent	PDET	Perceived Convenience	PCONV	Perceived Usability	PUSBL
Perceived Trust	PTRST	Perceived Relative Advantage	PREL_ADV	Perceived Compatibility	PCOMPAT	Perceived Cost	PCOST
Perceived Intelligence	PINTLJ	Perceived Enjoyment	PENJY	Perceived Privacy Concerns	PPRIV_CN	Perceived Benefits	PBENEF
Perceived Ease of Use of ATMs	PEOU_ATM	Perceived Aesthetics	PAEST				
				PERSONAL			
Compatibility	COMPAT	Innovativeness	INNOV	Personal Factors	PRSN	Knowledge	KNOW
Digital Literacy	DIG_LIT	Task Technology Fit	TTF	Functional Value	FUN_VAL	Emotional Value	EMO_VAL
Epistemic Value	EPI_VAL	Monetary Value	MON_VAL	Quality Value	QUAL_VAL	Utilitarian Value	UTIL_VAL
Hedonic Values	HED_VAL	Social Value	SOC_VAL	Private Employment	PVT_EMP	Digital Capability	DIG_CABL
Self-employment	SEMP	(User) Experience: Usability	EXP_USE	(User) Experience: Credibility	EXP_CRED	Lifestyle Compatibility	LIFE_COMPAT
Religiosity	RELIGIS	Utilitarian Expectation	UTILEX	Lifestyle	LIFE	Lifestyle Fit	LIFE_FIT
Value Barriers	VAL_BAR	Expectations	EXPECT	Performance Expectancy	PEEX	Effort Expectancy	EFEX
Age	AGE	Gender	SEX	Education	EDU	Income	INCOME
Habit	HABT	Pragmatic	PRGMT	Personality	PERSNT	Financial Literacy	FIN_LIT
				SOCIAL			
Normative Belief(s)	NORM_BLF	Word of Mouth	WOM	Social Influence	SOCINF	Customer Interaction	CUS_INT
Interaction	INTRAC	Recommendation	RECOM	Subjective Norms	SBJ_NRM	Social Factors	SOC_FAC
Social Interactions on Platforms	SOC_INT_PLT	Social Isolation	SOC_ISO	Herd Behaviors	HERD	Coercive Pressure	COE_PRSR
Normative Pressure	NORM_PRSR	Mimetic Pressure	MIM_PRSR	CSR Social Responsibility	CSR_SOC_RES	CSR Environmental Responsibility	CSR_ENV
CSR Economical Responsibility	CSR_ECON	Social Norms	SOC_NRM	Human-Human interactions	HH_INT	Collectivist Cultural Practices	COLCUL
Social Media Influence	SNSINF	Family Influence	FAM_INF	Culture	CLTR		
				PSYCHOLOGICAL FACTORS			
(Computer) Self-efficacy	SELF	Self-congruence	SELF_CONG	(Technology) Anxiety	ANXIETY	Attitude	ATTD
Trust	TRST	Satisfaction	SATIS	Hedonic Motivation	HED_MOTIV	Resistance to Change	RESIST_CHNG
Optimism	OPTIM	Decision Discomfort	DIS_COMF	Insecurity	INSEC	Cognitive Resistance	COG_RESIST
Self-image congruence	SIM_CONG	Empathy	EMPATH	Attitude towards ATMs	ATTD_ATM	Covid-19 Psychological Distress	DIST_COVID
Benevolence	BENV	(User) Awareness	AWAR	Risk Aversion	RISK_AVRS	Enjoyment	ENJY
Cognitive	COG	Agreeableness	AGRBNS	Consciousnesses	CONSCN	Openness to new experiences	OPEN
Decision Comfort	DEC_COMF	Loyalty	LOYAL	Obedience	OBED	Interdependency	INTER_DEP
Novelty Seeking	NEW_SEEK	Online Self-image	ONSIM	Technological Stress	TECH_STRSS	Behavioral Intention	BHV_INTNT
Intention	INTNT	Confidence	CONFDNC	Post adoption Trust	POST_TRST	Green Concerns	GREEN_CN

2.3 Search Methodology and Data Collection

This section includes the details of the SLR methodology. The components in the main research question map to the Population, Intervention, Comparison, Outcome, Context (PICOC) framework [331]. The **population (P)** are potential or new users of m-banking (adopters). **Interventions (I)** are Intrinsic factors impacting m-banking adoption. **Comparisons (C)** are between different sub-categories of Intrinsic factors in the literature. The **Outcome (O)** is better understanding of Intrinsic factors in m-banking adoption, and the **Context (C)** is m-banking apps. This breakdown guides the search, data collection, and extraction processes.

2.3.1 Search Strategy

Search keywords are defined in accordance with the above PICOC components. The two main parts of the research question are: "Mobile banking Adoption" and "Intrinsic factors". To ensure a broad and inclusive literature search, we used synonyms and specific factors identified in Section 2.2.

Table 2.3. Keyword and synonyms for components of main research question

Main Keyword (phrase) for search	Synonym(s)
Mobile banking Adoption	
"Mobile banking"	mbanking, m-banking, "smartphone banking"
Adoption	acceptance, uptake, "usage intention", "use intention"
Intrinsic Factors	
Intrinsic	internal, affective, subjective, individual, social, personal, perception, perceptual, emotional, psychological, mood, mental, cognitive
Factors	constructs, attributes

Table 2.3 lists all the synonyms associated with each phrase in the main research question. The search query is used in Web–of–science, as it offers thorough filtering capabilities and data extraction flexibility. Web–of–science facilitates obtaining BibTEX information for large quantities

of results (up to 1,000). The search query is a mix and match of synonyms introduced in Table 2.3 and boolean operators (AND, OR) and is as follows:

("Mobile banking" OR "m-banking" OR "mbanking" OR "smartphone banking") **AND** ("adoption" OR "acceptance" OR "uptake" OR "usage intention" OR "use intention") **AND** ("internal factors" OR "subjective factors" OR "individual factors" OR "social factors" OR "personal factors" OR "perception factors" OR "perceptual factors" OR "emotional factors" OR "psychological factors" OR "mood factors" OR "mental factors" OR "cognitive factors" OR "internal constructs" OR "subjective constructs" OR "individual constructs" OR "social constructs" OR "personal constructs" OR "perception constructs" OR "perceptual constructs" OR "emotional constructs" OR "psychological constructs" OR "mood constructs" OR "mental constructs" OR "cognitive constructs" OR "internal attributes" OR "subjective attributes" OR "individual attributes" OR "social attributes" OR "personal attributes" OR "perception attributes" OR "perceptual attributes" OR "emotional attributes" OR "psychological attributes" OR "mood attributes" OR "mental attributes" OR "cognitive attributes" OR "affective factors" OR "affective constructs" OR "affective attributes" OR "trust" OR "social influence" OR "satisfaction" OR "perceived risk" OR "risk" OR "compatibility" OR "habit" OR "culture" OR "attitude" OR "convenience" OR "perceived security" OR "word of mouth" OR "anxiety")

The search query is applied to titles, abstracts and keywords (*topics* on WOS). The initial result without filtering the search returned 250 articles.

2.3.2 Inclusion and Exclusion Criteria

In order to find suitable literature, we establish multiple inclusion and exclusion criteria which are as follows: (1) **Include** only recent studies (2018 – 2024), (2) **Exclude** manuscripts not in English and (3) **Exclude** conference papers, theses and dissertations. Filtering in web–of–science ensures criteria compliance. The process yielded the following: From 250 papers, 168 remained (published after 2018), with 166 in English. After removing conference papers, theses, and

dissertations, 162 remained. BibTEX data was imported into Zotero (version 6.0.37), which retrieved files for all but 39 papers. These were manually obtained, except one, which was discarded.

All papers were read for relevance and quality, resulting in several articles being removed from the collection. The largest exclusions were irrelevant topics (e.g., digital service failure, social networks, artificial intelligence, internet of things, and cryptocurrencies) and studies on internet/e-banking instead of m-banking. Since m-banking requires mobile devices, studies not using these devices were also excluded. Papers outside the specified time frame, conference papers, and those unrelated to intrinsic factors were also removed. After quality assessment, 143 papers were retained as the final dataset.

2.4 Data Analysis

In this section, we present the dataset of 143 studies from the systematic search in Section 2.3. Key information is extracted from each paper manually, described in detail in Table 2.4, which is saved in a comma separated value file. Topic modeling identifies themes, and a rule-based algorithm assigns papers to the best-fitting theme, verified through manual classification by the author. **Python** (version 3.9) is used for all text analysis while **R** (version 4.2.2) is used for visualizations (`ggplot2`) and statistical analysis. For a snapshot of the dataset, refer to Appendix A.4.

Table 2.4. Description of Extracted Information from Database

Feature Description	Column[1]	Data Type	Information on Values
Unique ID	ID	string	143 unique values[2]
Paper Title	Title	string	143 unique values
Year of publication	Year	integer	value between 2018 – 2024
Country[3]	AffiliationCountry	string	42 unique values
Factors of influence	F1 – F9	string	233 unique factors
Theme of factors	F_THEME1 – F_THEME9	string	9 unique values
Contested Factors	FNS1 – FNS4	string	31 unique factors
Percent Significant†	Score_Sig	integer	values 0 – 1
Percent Not Significant†	Score_NOT_Sig	integer	values 0 – 1
Keywords	Keywords	string	400 unique combinations
Paper Abstract	Abstract	string	copy of abstract
Type of Research	ResearchType	string	15 unique values
Sample Size	SampleSize	integer	value between 26 – 25,000
Method of Analysis	METHOD1 – METHOD4	string	40 unique values
Foundational Theory	THEORY1 – THEORY4	string	42 unique values
Limitations of study	LIMIT1 – LIMIT3	string	15 unique values
Technology of study	Tech	string	8 unique values
Theme(s) Assigned Manually	Man_Theme	string	8 unique themes
Theme(s) Assigned Rule-based	Algo_Theme	string	8 unique themes

Notes:

1: Column name in a Microsoft Excel file.

2: ID's are values from P2_01 to P2_143.

3: Country research was conducted in or the author's affiliated country.

†: These values are calculated and saved in a separate database (pivoted on F1 – F9 and FNS1 – FNS4)

2.4.1 Topic Modeling

Text data is analyzed to identify patterns and themes across the collection of articles. The first step is to extract text from files using `PyMuPDF` (version 1.24.3). All the text is then cleaned following standard practices in text analysis: everything is converted to lowercase, and special characters,

extra spaces, and stop words are removed using `NLTK`[3] [69]. The sample code for the function written to do this pre-processing is available in Appendix A.1. Since all articles are collected in a single Python dictionary, we refer to them as corpus, i.e., a structured collection of texts. Next, the corpus is broken into uni-grams and bi-grams (single words and word pairs). This is a standard text analysis method called tokenizing where a large body of text is broken into smaller units. A token is any item such as a single word, pairs of words, phrases and even sentences and so on.

To find the topics across the corpus, we first find the most important tokens using Term Frequency-Inverse Document Frequency (TF-IDF) [425] via `gensim.models.tfidfmodel`. TF-IDF is a numerical method that measures the importance of a token within a document relative to the corpus. Mathematically, the TF-IDF algorithm finds the inverse domain frequency (IDF) and term frequency (TF) of tokens to compute their corresponding TF-IDF values. The TF-IDF value is in turn used to assign weight or importance to the word in text analysis [276]. The mathematical formula to calculate TF-IDF for token t in document d is as follows:

$$TF(t,\mathbf{d}) = \frac{\text{count of } t \text{ in } \mathbf{d}}{\text{number of tokens in document } \mathbf{d}}$$

$$\begin{aligned} DF(t) &= \text{number of documents containing token } t \\ IDF(t,D) &= log(\frac{|D|}{DF(t)}) \\ TF-IDF(t,\mathbf{d}) &= TF(t,\mathbf{d}) \times IDF(t) \end{aligned} \tag{2.1}$$

Where $|D|$ is the total number of documents in corpus D, $TF(t,\mathbf{d})$ calculates the frequency of a single token t across a document $\mathbf{d}$, $DF(t)$ is the document frequency for a token t, and $IDF(t,D)$ calculates how frequent a word is across the entire corpus D. We then find the latent topics across the corpus using Latent Dirichlet Allocation via (LDA) via `gensim.models.ldamodel.LdaModel` from `Gensim` (version 4.1.2). LDA treats documents as mixtures of latent topics represented by word distributions [71].

In LDA, a topic refers to a set of tokens that frequently occur together. The algorithm takes two

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main inputs: the corpus and the number of topics to be identified within that corpus. A token represents the smallest unit of data, defined as an element from a vocabulary indexed by $1,...,V$. Tokens are expressed as unit-basis vectors, where one component is equal to one and all others are zero. Specifically, using superscripts to indicate components, the vth token in the vocabulary is expressed as a V-dimensional vector $\mathbf{t}$ such that $t^v = 1$ and $t^u = 0$ for $u \neq v$. A document is made up of a sequence of N tokens, denoted by $\mathbf{t} = (t_1,...,t_N)$, with t_n being the nth token in the sequence. A corpus consists of M documents and is represented as $D = \{\mathbf{d}_1,...,\mathbf{d}_M\}$.

Latent Dirichlet Allocation is a generative probabilistic model of the entire corpus. LDA models the generative process for each document $\mathbf{d}$ in a corpus D as follows: First, Choose $\theta \sim \text{Dir}(\alpha)$ (Dirichlet distribution). Then, for each t_n in $(t_1,...,t_N)$, choose topic $z_n \sim \text{Multinomial}(\theta)$ and a token t_n from $p(t_n \mid z_n, \beta)$. The basic LDA model makes a few simplifying assumptions. First, it assumes that the number of topics, k, is known and fixed. Second, the probabilities of tokens are defined by a $k \times V$ matrix β where each element $\beta_{ij} = p(t^j = 1 \mid z^i = 1)$. Lastly, we define a $(k-1)$-simplex as a set of all k-dimensional vectors $\theta = (\theta_1,...,\theta_k)$ such that $\theta_i \geq 0$ for every component and $\sum_{i=1}^{k} \theta_i = 1$. A k-dimensional Dirichlet random variable θ can take values in the $(k-1)$-simplex and has the following probability density:

$$p(\theta \mid \alpha) = \frac{\Gamma(\sum_{i=1}^{k} \alpha_i)}{\prod_{i=1}^{k} \Gamma(\alpha_i)} \theta_1^{\alpha_1 - 1} ... \theta_k^{\alpha_k - 1} \tag{2.2}$$

where $\alpha = (\alpha_1,...,\alpha_k)$ is a k-vector with components $\alpha_i > 0$, and $\Gamma(x)$ is the Gamma function. The joint distribution of a topic mixture θ, a set of N topics $\mathbf{z}$, and a set of N tokens $\mathbf{t}$ is given by:

$$p(\theta, \mathbf{z}, \mathbf{t} \mid \alpha, \beta) = p(\theta \mid \alpha) \prod_{n=1}^{N} p(z_n \mid \theta) p(t_n \mid z_n, \beta) \tag{2.3}$$

where $p(z_n \mid \theta)$ is simply θ_i for i such that $z_n^i = 1$, i.e., topic z_n is assigned to this token. Integrating over θ and summing over z, we obtain the marginal distribution of a document:

$$p(\mathbf{t} \mid \alpha, \beta) = \int p(\theta \mid \alpha) \left(\prod_{n=1}^{N} \sum_{z_n} p(z_n \mid \theta) p(t_n \mid z_n, \beta) \right) d\theta \tag{2.4}$$

This is to remove the hidden variables (the latent topic distribution θ and the topic assignments $\mathbf{z}$) to compute the likelihood of observing the document itself. Finally, we take the product of the marginal probabilities of documents to obtain the probability of a corpus:

$$p(D \mid \alpha, \beta) = \prod_{d=1}^{M} \int p(\theta_d \mid \alpha) \left(\prod_{n=1}^{N_d} \sum_{z_{dn}} p(z_{dn} \mid \theta_d) p(t_{dn} \mid z_{dn}, \beta) \right) d\theta_d \tag{2.5}$$

This corpus probability (i.e., probability that the corpus is observed under this particular latent topic structure with parameters α, β) is what is maximized when fitting the model [388]. Model fitting and optimization is to learn the best topics and document-topic distributions to explain the data. As previously mentioned, one of the assumptions of LDA is that the number of topics k is known. To run the algorithm in Python, `Gensim`'s LDA function requires this number as an input from the modeler. To decide on how many topics are suitable, we start with our knowledge of the literature. From technology adoption literature, certain topics appear more often than others, some of which align with our sub-categories of intrinsic factors:

1. **Demographic** studies focus on age, education, and gender of users.
2. **Individual Consumer Behavior** studies investigate personal differences, values, and tastes in shaping adoption decisions.
3. **App Functionality/Characteristics** studies mostly focus on the app's performance, and operational features.
4. **Adoption Drivers** studies analyze motivators for adoption, i.e., factors that result in adoption.
5. **Adoption Barriers** studies look at deterrents to adoption, i.e., factors that drive users away.
6. **Cultural** studies are specifically about country or culture differences and how they impact adoption.
7. **Social** studies consider the influence of others' opinions and expectations on adoption decisions.

Some of these topics may overlap: for example, almost all other topics could also be either drivers of or barriers to adoption. Furthermore, some domain-specific topics may have been missed [516]. Therefore, 7 topics may either be too many or too few topics to consider. To pick the best number of topics, we consider models with 5 to 15 topics ($k \in [5, 15]$ where k is the number

of topics) across uni-grams and bi-grams, training 22 models in total. We believe these topic numbers adequately capture the various themes across the related literature and further break down of topics (i.e., more than 15 topics) provides no benefits. This is because the larger the number of topics, the more likely it is for the algorithm to just categorize words as their own topics.

The point of topic modeling is to group documents together under the same category for easier comparisons. To avoid confusion with the intrinsic factor categories, we refer to the document categories as "themes" from this point forward. Rather than comparing 143 unique and specific studies, we group them together based on context (i.e., theme) to find patterns. We compare the 22 different models and choose the best value for number of topics based on the highest coherence value. In topic modeling, coherence measures model correctness, and higher coherence values show better model performance [333]. The best number of topics is $k = 8$ using bi-grams as is seen in Figure 2.1.

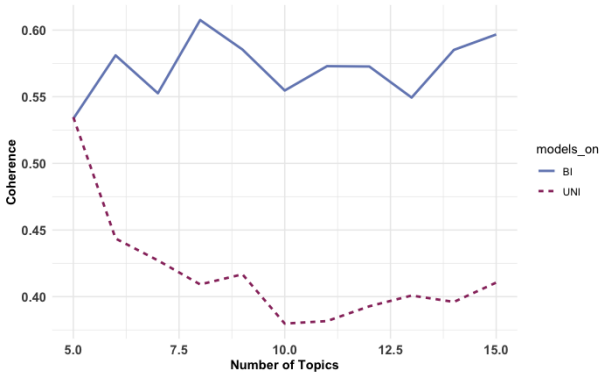


Figure 2.1. Coherence scores for topic models with $k \in [5, 15]$ for uni–grams and bi–grams

The result of topic modeling are depicted in Table 2.5. Tokens include single words, bi-grams, and phrases (n-grams, $n \geq 3$). The underlying context and idea of these tokens are used to decide their group. Tokens related to perception indicate Perceptive theme. Tokens linked to cognition, emotions, or the mind (e.g., belief, attitude, behavior) are Psychological. Individual characteristics fall under the Personal theme. Demographic tokens cover age, gender, income, and education, while Cultural tokens relate to specific countries, regions, religions, or cultures. External tokens are those that are universally experienced (extrinsic factors). Market tokens refer to technologies

(e.g., devices), and Social tokens reflect interpersonal influences. Unclassified or vague tokens are classified as Generic.

Table 2.5 lists topics with stop words and punctuation added for readability. The topic modeling algorithm groups related tokens, but topics may contain diverse tokens with varying contribution weights (numeric values in [ ]). Contribution weight typically refers to how strongly a token is associated with the given topic. It is a measure of the token's probability within the topic distribution [72]. Since topic modeling is a mixed-membership model [427], tokens can belong to multiple topics. From Table 2.5, the main themes are: *Perceptive*, *Psychological*, *Market*, *Demographic*, *Social*, *Personal*, *Cultural*, *External* and *Generic*. Generic tokens are excluded for lack of specificity and potential to overshadow meaningful themes. External tokens are also not considered for theme classification, as the focus here is on intrinsic factors. The LDA Python code can be found in Appendix A.2.

Table 2.5. Topic Modeling results – The theme with the highest contribution weight is chosen as the topic

No.	Bi-gram Memberships	Themes Representation[1]
1	Perceived usefulness (Perceptive)[.045], Ease (of) use (External)[.040], Perceived ease (of use) (Perceptive)[.025], Subject norms (Social)[.017], Use perceived (Perceptive)[.016], Intent toward (Psychological)[.13], Customer intention (Psychological)[.11], Positive effect (Generic)[.008], Effect perceived (Perceptive)[.004]	**Perceptive [.09]**, External, Psychological [.024], Social, Personal, Generic
2	Intention (to) adopt (Psychological)[.038], Behavioural intent (Psychological)[.035], Social influence (Social)[.027], Facilitating conditions (External)[.026], Behavioral intent (Psychological)[.025], Performance expectancy (Personal)[.024], Effort expectancy (Personal)[.023], Factors affecting (Generic)[.014], Expected social (Social, Personal)[.007], Expected effort (Personal)[.007]	**Personal [.129]**, Psychological [.098], Social [.03], External, Generic
3	Payment system (Market)[.052], Customer satisfaction (Psychological)[.028], Factors influencing (Generic)[.012], Positive influence (Generic)[.011], Social network (Social)[.009], Perceived trust (Perceptive)[.007], Consumer use (Generic)[.006], Empirical evidence (Generic)[.006], Information technology (Generic)[.005]	**Market [.052]**, Generic [.04], Psychological, Social, Perceptive
4	Older adult (Demographic)[.018], Male female (Demographic)[.008], Also found (Generic)[.006], Customer perception (Perceptive)[.005], Use new (Generic)[.004], Impact perceived (Perceptive)[.004], Task characteristics (External)[.003], Gender male (Demographic)[.003], Also show (Generic)[.003], Level (of) education (Demographic)[.003]	**Demographic [.032]**, Generic [.012], Perceptive [.009], External
5	Consumer behavior (Psychological)[.010], High level (Generic)[.005], Consumer trust (Psychological)[.005], Creative common (Generic)[.005], Influence consumers (Generic)[.004], Satisfaction (and) trust (Psychological)[.004], Prior studies (Generic)[.004], Better understand (Generic)[.003], Trust and attitude (Psychological)[.003]	**Psychological [.022]**, Generic [.021]
6	Develop countries (Cultural)[.035], Dependent variable (Generic)[.009], Independent variable (Generic)[.007], Consumer intention (Psychological)[.006], Social cognitive (Social)[.005], Customer adoption (Generic)[.004], Internet user (Market)[.004], Social pressure (Social)[.004], Country perspective (Cultural)[.003], Recent studies (Generic)[.003]	**Cultural [.038]**, Generic [.023], Social [.009], Personal, Market
7	Intent (to) use (Psychological)[.062], Social media (Social)[.027], Use (of) service (Generic)[.022], Social influence (Social)[.013], Previous studies (Generic)[.013], Trust intent (Psychological)[.008], Customer experience (Personal)[.006]	**Social [.040]**, Psychological [0.07], Generic [.035], Method [.012], Personal
8	Covid-19 pandemic (External)[.015], Attitude intention (Psychological)[.006], Trust customers (Psychological)[.005], Service offer (External)[.005], Many studies (Generic)[.005], User experience (Personal)[.004]	**External [.020]**, Psychological [.011], Personal, Generic

Notes: 1: Weights are added for groups that are repeated multiple times. Weights for groups with 1 member are not repeated.

2.4.2 Theme Assignment

Each paper is assigned 1 to 3 themes by the author based on themes from Section 2.4.1. A rule-based text mining approach using TF-IDF verifies these assignments by counting token occurrences and impact to assign up to 3 themes per paper. This assignment method is valid, as keyword frequency is widely used by search engines and databases for ranking relevance [114]. Similar approaches, like keyword density analysis, are used for optimizing search results as well [473]. The way this algorithm works is as follows: First, a Python dictionary including all the factors across the corpus is fed into the algorithm for learning. Each theme is a key in the dictionary, and each key's value is a list containing all the identified factors from the literature that belong to it. For example, the key-value pair for Perceptive theme is: `"perceptive": list(set(["perceived`

```
benevolence","perceived risk","perceived financial cost","perceived ease of
use","perceived value",
"perceived interactivity","perceived usefulness",...])).
```

The algorithm goes through each article and counts the number of times each factor appears in the article, aggregating the number of appearances to each theme category's score. That is, each article is given a series of weights for each of the 7 possible themes. The themes corresponding to the top 3 largest values for the weights are the top 3 themes assigned to the paper. A portion of the code for the class of object that generates token frequencies is available in Appendix A.3. Since themes overlap due to the mixed-membership nature of the task, assigning multiple themes is acceptable. Algorithm results are compared with author-assigned themes, and final themes are determined by the order of weights given to themes (in descending order).

If both algorithm and author have assigned the same theme, this is chosen as the main theme (e.g., third row in Table 2.6). If there are more than one theme that match between author and algorithm, the theme with the highest weight is assigned to the paper (e.g., first row). If there are no matching themes between author's opinion and the algorithm, we review the paper again and decide on the theme according to all the options (e.g., last row). If more than one match is found but the orders do not match, the author's first match is chosen (e.g., second row). The analysis shows a 90.2% agreement between manual and rule-based assignments. Only 14 paper out 143 had no matching themes.

2.4.3 Exploratory Data Analysis: Overview of Literature

In the following sections, we explore the dataset holistically and then delve deeper into some of the more important features. The dataset consists of 143 articles published between 2018 and 2024. A large variation in sample sizes is observed. One study uses a sample size of $25,000$ electronic payment consumers across Japan [301], while a second study uses $21,526$ m-banking app reviews from Google Play Store as their primary dataset [86], contributing to the large standard deviation. Not considering the outliers, studies (on average) have a sample size of 451 ($\pm$330), median of 384 with the smallest sample size pertaining to an SLR study with 26 articles [232]. On average,

Table 2.6. Examples of Manual and Rule-based Theme Assignments and final decision making

Reference	Paper Title	Man_Theme[1]	Algo_Theme[2]	Final Theme	Reason for Choosing Theme
[209]	Examining Consumers' Adoption of Smart Wearable Payments	Market, Personal, Psychological	Market, Personal	Market	Smart wearable devices (market)
[302]	A Comparative Study of Trust in Mobile Banking: An Analysis of U.S. and Thai Customers	Cultural, Psychological	Psychological, Cultural, Demographic	Cultural	Study where cultures are directly compared.
[329]	An Empirical Examination of The Moderating Role of Age and Gender in Consumer Mobile Banking Use: A Cross-national, Quantitative Study	Demographic	Demographic, Psychological, Personal	Demographic	Age and Gender are the main variables.
[22]	Exploring The Antecedents of Internalization, Identification and Compliance Social Influence for Mobile Banking Adoption	Social, Psychological	Social, Psychological	Social	Social Influence is one of the major themes discussed in the paper.
[249]	Consumption Values and Mobile Banking Services: Understanding the Urban-rural Dichotoour In a Developing Econoour	Demographic, Personal	Psychological, Market, Perceptive	Demographic[3]	Urban-rural comparative study is demographic.

Notes: 1: Theme assigned manually 2: Theme assigned according to rule-based algorithm 3: No match

studies find five influential factors and the majority do not find any factors insignificant.

India dominates geographically with 11 studies, followed by Malaysia (7), and China, England, Pakistan, and Thailand (5 each). Ghana and Saudi Arabia contribute 4 studies each (3% of the dataset). Most studies are Quantitative (80), followed by Empirical (27), Qualitative (7), and Comparative (5). Between $2018-2024$, only 5 literature review studies were conducted in this domain and just one meta-analysis [231]. Of the 143 studies, 100 focus only on m-banking, 18 on cashless payments, 4 on electronic or mobile wallets (e.g., Apple Pay), and a few on niche technologies like Hybrid payment systems [260].

The continuous refinement of theoretical models has been pivotal in the literature. By looking at the theoretical foundations of the articles in the dataset, we aim to identify the dominant models and theories. From the 143 articles, only 27 (about 19%) do not use an underlying theory as the foundation of their study. The remaining studies employ at least one theory, applying or expanding these theories in various contexts. This has broadened the scope of m–banking literature. To accommodate the changing landscape of m–banking adoption, it is necessary to note the evolution of theories.

TAM stands out as the most predominant theory in the literature, serving as the foundational framework in nearly 40% of the studies. Table 2.7 shows the distribution of the frequency with

Table 2.7. Summary of Theories Used in Studies in our Database

Value Name	Abbr.[1]	n[2]	Value Name	Abbr.	n
Technology Acceptance Model	TAM	53	Unified Theory of Acceptance and Use of Technology	UTAUT	23
Extended UTAUT	UTAUT2	23	Diffusion of Innovation	DOI	9
Theory of Planned Behaviour	TPB	7	D&M IS Success Model	DM	4
Service Quality Model	SRVQUAL	3	Elaborate Likelihood Model	ELM	2
Meta UTAUT	mUTAUT	2	Social Contaigeon Theory	SCT	2
Expectation Confirmation Model	ECM	2	Stimulus-Organism-Response	SOR	2
Theory of Consumption Value	TCV	2	Theory of Reasoned Action	TRA	2
Affect Referral Heuristic Theory	ARHT	1	Adaptive Structuration Theory for Individuals	ASTI	1
Affordance Theory	AT	1	Behavioral Reasoning Theory	BRT	1
Consumer Brand Egagement Model	CBEM	1	Digital Cohort Theory	DCT	1
Decomposed Theory of Planned Behavior	DTPB	1	Gender Schema Theory	GST	1
Hofstede Cultural Dimension	HCD	1	Institutional Theory	INST	1
Innovation Resistance Theory	IRT	1	Optimum Stimutation Level	OSL	1
Perceived Interactivity Theory	PIT	1	Religiosity-Intention Model	RIM	1
Signaling Theory	SIG	1	Social Influence Theory	SIT	1
Technological Readiness	TECHRD	1	Trust Theory	TT	1
Task Technology Fit	TTF	1	Uses & Gratification Theory	UG	1
Corporate Social Responsibility	CSR	1			

Notes: 1: Abbreviation 2: Frequency of Occurrence in Database.

which theories of technology adoption have been used in the studies. The majority of the theories appear only once, indicating untapped potential for future research. TAM, UTAUT, and UTAUT2 dominate, covering 70% of the literature, indicating both their popularity and a potential over-reliance. ANOVA results confirm a significant difference in theory usage across studies (MSSR[4] $= 120.8,\ F = 3.632,\ p < .001$), justifying further investigation.

Table 2.8 depicts the frequency of methods applied across the literature. Structural Equation Modeling (SEM) and its Partial Least Squares (PLS-SEM) variant dominate methodologies, comprising 65% of all methods in the database. Most methods appear only once, suggesting opportunities for innovative approaches and new insights. ANOVA confirms significant differences in method usage (MSSR$= 192.8,\ F = 3.824,\ p < .001$), warranting further analysis. Challenges faced by authors are grouped based on similarity, as shown in Table 2.9.

[4]Mean Sum of Squared Residuals.

Table 2.8. Summary of Methods Used in Studies across Database

Value Name	Abbr.[1]	n[2]	Value Name	Abbr.	n
Structural Equation Modeling	SEM	63	Partial Least Squares SEM	PLS-SEM	29
Regression	Regression	7	Confirmatory Factor Analysis	CFA	6
Thematic Analysis	TA	6	Partial Least Squares	PLS	4
Systematic Literature Review	SLR	4	Multiple Regression	MUL-REG	3
Correlation Analysis	Correlation	2	Exploratory Factor Analysis	EFA	2
Hierarchical Regression	HIR-REG	2	Multigroup Analysis	MUGRP	2
Ordinal Regression	ORD-REG	2	Review	Review	2
Binary Logistic Regression	B-Logit	1	Factor Analysis	FA	1
Financial Ratios Analysis	FRA	1	Instrumental Variable	IV	1
Fuzzy Set Qualitative Comparative Analysis	fsQCA	1	Linear Regression	LIN-REG	1
Latent Drichelet Allocation	LDA	1	Logistic Regression	Logit	1
Longitudinal Analysis	LONG	1	Mediation Analysis	MEDI	1
Meta-analysis	Meta	1	Moderation Analysis	MODE	1
Multigroup SEM	Multi-SEM	1	Neural Networks	NN	1
Path Analysis	PA	1	Principal Component Analysis	PCA	1
Fuzzy BWM	Fuzzy BWM	1	Fuzzy TOPSIS	Fuzzy TOPSIS	1
Interview	Interview	1	Smart PLS	Smart PLS	1
Survey Analysis	Survey Analysis	1	Variance Analysis	ANOVA	1
Case Study	CASE	1			

Notes: 1: Abbreviation 2: Frequency of Occurrence in Database.

Unlike theories and methods, challenges are more evenly distributed, though two categories stand out significantly. The most common challenge is limited generalizability due to a focus on specific countries. Future research should address this by expanding geographical scopes beyond single regions. Sample-related challenges are also prominent, such as studies restricted to university students. Broader, more representative samples are recommended. The third major limitation is the lack of longitudinal studies, as they are costly and time-consuming. Innovative data collection methods could mitigate these challenges. Methodological issues, including studying causal relationships, measurements, and certain statistical tests are the least cited, suggesting that data access, not methods, is the primary challenge researchers face in this domain. ANOVA confirms significant differences in cited limitations (MSSR$= 96.9,\ F = 8.84,\ p < .001$), justifying further investigation.

The dataset contains 233 unique factors. On average, factors are found to be significant 95%

Table 2.9. Summary of Limitations Cited in Studies across Database

Value Name	Description	n[1]
LOC_SPECIFIC	Results are location-specific, therefore not generalizable.	47
SAMPLE	Sampling issues such as unrepresentative samples like only students, only urban, etc.	40
NO_LONG	Not a longitudinal study.	26
LIMIT_SCOPE	Study has limited scope such as only one banking app.	14
SAMPLE_SIZE	Small sample size.	12
QUESTION	Study is based on Questionnaire results/limitations of the questionnaire.	10
INCOMP_FAC	Not all factors are considered.	9
NO_MOD	No Moderation Analysis is carried out.	6
BIAS	Possibility of Respondant Bias.	5
ISLAMICBANKS	Only relevant to Islamic Banking, i.e., not generalizable.	3
LIMIT_METHOD	Method of analysis could be improved.	3
NO_CAUSAL	No causal relationships are explored.	2
CROSS_CULT	Not cross-cultural, i.e., cultural differences not accounted for.	1
LIMIT_MEASURE	Measures in the analysis (such as definitions) may not be generalizable	1
TTEST	Using t-test may be prone to errors.	1

Notes: 1: Frequency of Occurrence in Database.

of the time (median 100%) with a standard deviation of 18%. Perceived Usefulness appears most frequently (53 times). On average, each factor appears 3.28 times, with a standard deviation of 7.23 and a median of just once. The first two quintiles (25% and 50%) contain factors appearing only once (153 factors), while the 75th percentile includes factors appearing twice. There are 48 factors which appear more than twice in the fourth quintile. The top 10 factors are: Perceived Usefulness (53), Perceived Ease of Use (49), Trust (49), Social Influence (38), Performance Expectancy (30), Facilitating Conditions (29), Effort Expectancy (26), Perceived Risk (26), Security (17), and Attitude (15). Most of these are foundational to TAM and UTAUT, the most utilized theories across the literature. ANOVA confirms significant differences in factor frequency (MSSR= 86.72, $F = 3.373$, $p < .001$).

The dataset includes 31 unique non-significant factors (NS.Factors). These are adoption factors that were found to be insignificant in determining adoption behavior at times. On average,

factors are found to be non-significant only 5% of the time (median 0%) with a standard deviation of 18%. The high standard deviation shows that some factors are appearing as non-significant a lot more than others. ANOVA results confirm no statistical difference in how often these factors appear as non-significant (MSSR$= 2.671,\ F = 1.249,\ p = 0.262$). Individually, they may not provide insights, but we investigate whether patterns exist where typically significant factors become non-significant. Could external influences be masking their effect? Is a specific theory, method or inclusion of a certain other factor consistently rendering a factors non-significant? If so, why is that the case? These are the questions we will try to answer in Section 2.5.

2.5 Statistical Analysis of Patterns in Literature

In this section, we explore interactions between the following properties: themes, theories, methodologies, limitations, factors, and non-significant factors and discuss the following relationships:

1. Are there notable differences in the distribution of paper groups across years? (e.g., did certain groups dominate or appear exclusively in specific years?)
2. Are paper groups significantly associated with specific technologies?
3. Are there significant differences in sample sizes across paper groups?
4. Do research types vary significantly among different paper groups?
5. Are there significant differences in methods used across paper groups?
6. Are the significant factors identified in studies notably different among paper groups?
7. Are the non-significant factors identified in studies notably different among paper groups?

2.5.1 Themes

Figure 2.2 shows the distribution of themes across the years which shows the lowest diversity in 2018, an uptick in psychological and market studies in more recent years but a downward trend in perceptive, cultural and social studies. The distribution of themes across the database is: Psychological (47), Market (25), Perceptive (18), Cultural (15), Demographic (15), Social (14), and Personal (9). ANOVA confirms significant differences between themes

($MSSR = 82.9,\ F = 15.05,\ p < .001$).

Had extrinsic factors been included in this study, the results would differ, with extrinsic studies dominating: Extrinsic (41), Psychological (40), Market (16), Demographic (15), Cultural (13), Perceptive (7), Social (6), and Personal (5). Extrinsic themes dominate because they are easier to study and quantify, reflecting the literature's focus. Despite the targeted search for intrinsic studies, they remain scarce, highlighting the importance of the paper in addressing this gap.

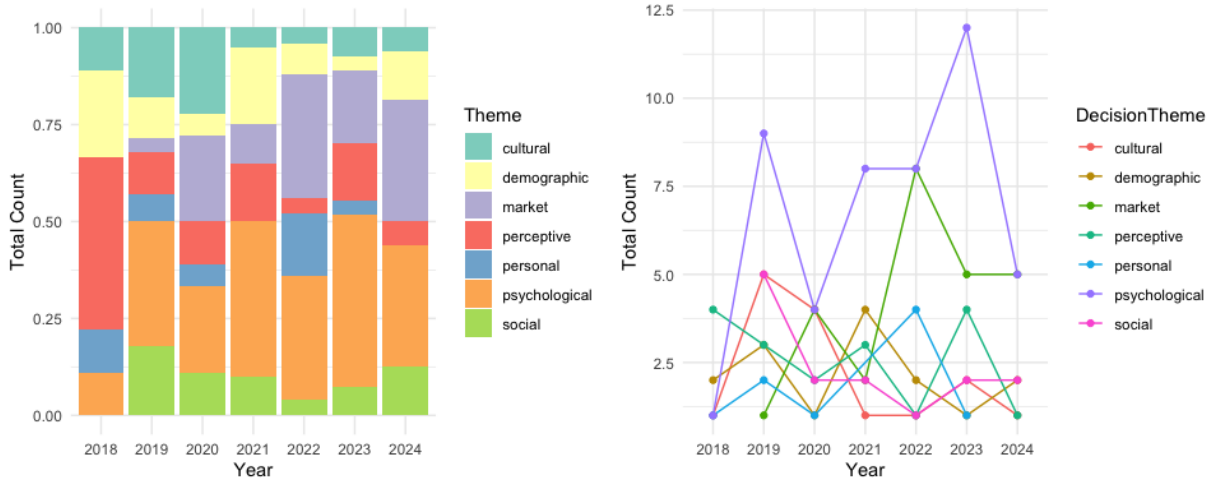


Figure 2.2. Distribution of themes of papers across the years

Psychological themes emerge as the most notable. Studies related to various associated technologies to m-banking (e.g., mobile payments, mobile wallets, and Fintech in banks) are mostly categorized under *Market* themes, reflecting the growing diversity of m-banking services, including use of smartwatches and m-wallets. *Perceptive* themes follow, unsurprisingly, given the prominence of perceptive factors in TAM. Demographic and cultural studies are equally represented, followed by social studies. Personal studies remain the least explored, aligning with our earlier observation in Section 4.1 that few studies focus on personal differences. Table 2.10 presents statistical test results for independence between variables and themes to analyze the 7 aforementioned relationships.

Sample sizes are binned according to quintile information (setting aside null values and outlier studies with large sample sizes). Any study that does not state their sample size is grouped separately as "*NotStated*" (total of 40 studies). The statistical analysis ignores this group (results are still the same with this group considered). The sample size quintile information for the available groups is as follows: first quintile $26 \leq SQ1 \leq 252$ with 26 studies, second quintile $253 \leq SQ2 < 384$ with 28 studies, third quintile $384 \leq SQ3 \leq 504$ with 23 studies, and finally, 26 studies in the fourth quintile $505 \leq SQ4 \leq 25,000$. Statistical test of independence (χ^2 test) is used to test whether groups of variables are related to themes, the results of which are summarized in Table 2.10.

Table 2.10. Results of χ^2 test of independence between **Themes** and other variables

Variable	χ^2	df	p-value
Year	44.414	36	0.159
Tech	102.59	48	0.002**
SampleSizeBin	8.6582	18	0.967
ResearchType	127.06	90	0.006**
Theories	251.84	252	0.491
Methods	272.02	240	0.076
Limits	89.327	84	0.325
Factors	1461.4	1386	0.078
NS.Factors	207.87	180	0.076

Notes: $^{***}: p < 0.001; ^{**}: p < 0.01; ^{*}: p < 0.05$

There are no significant differences in theme distribution across years, sample sizes, theories, methodologies, limitations, factors, or non-significant factors. However, there are relations between specific technologies and research types with paper's theme. To explore these relationships, we visualize the connection between themes, technologies, and research types in Figure 2.3. As expected, Market studies cover the broadest range of technologies. This is because studies on variations of m-banking, such as m-wallets and smart wearables fall under the Market category, influencing the theme distribution across technologies. To confirm that this effect is driven by Market studies, we exclude them and rerun the above test. The new results show no significant

difference between theme and technology ($\chi^2_{df=20} = 19.629,\ p = 0.481$), confirming that Market studies account for the observed significance.

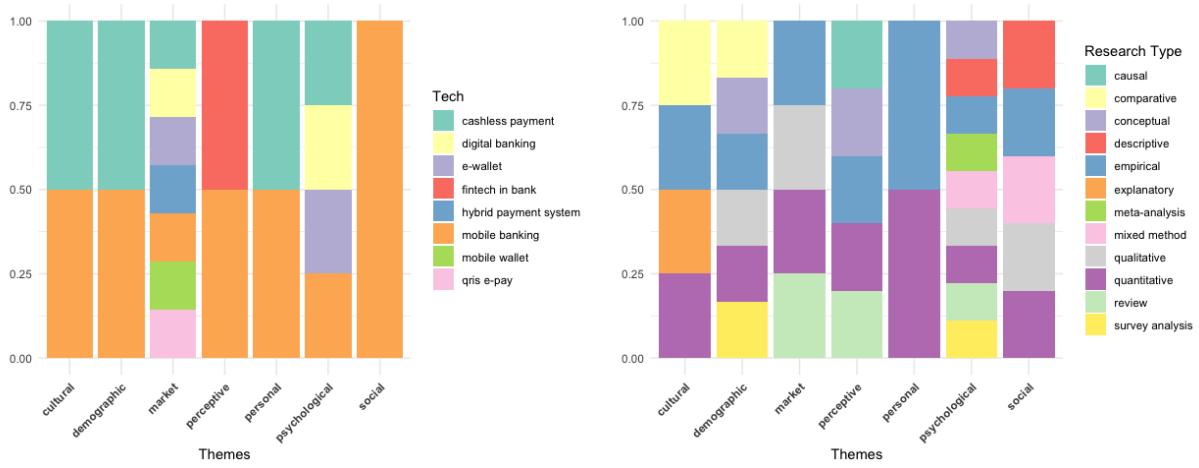


Figure 2.3. Distribution of Technologies (left) and Research Methods (right) across Themes

Patterns between research types and themes are less distinct. Market and Personal studies show the least research type diversity, while Psychological studies exhibit the most, likely due to their prevalence in the dataset. Comparative research appears only in Cultural and Demographic studies. Future research could explore comparisons between devices, social groups, and personal traits. There are 233 unique factors across the data. Standard visualization and tabular methods fail to effectively communicate key insights for such a large number of variables. In Section 2.4.2, factors were grouped into categories. These same categories are used instead of single factors as factor membership across sub-categories. A significant relationship exists between factor sub-categories and paper themes ($\chi^2_{df=36} = 139.26,\ p < .001$), as is shown in Figure 2.4.

Market studies contain the most diverse set of factors influencing m-banking, likely due to device differences. This suggests that variations of the same technology (e.g., m-wallets, m-payment devices) introduce different influencing factors. A comparative study between devices could provide valuable insights. Market-specific factors appear only in Social and Perceptive themes (aside from Market itself). This suggests that Social and Perceptive studies are the only studies that are considering device differences. Therefore, future research should expand the

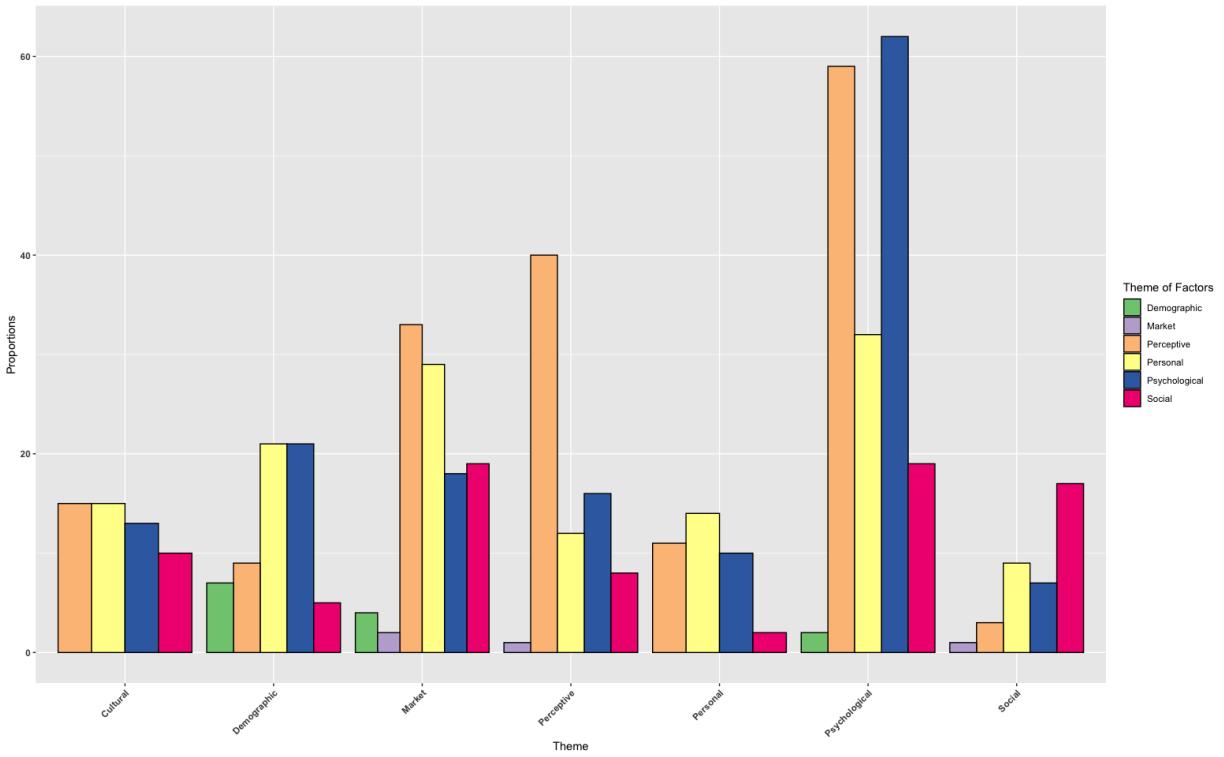


Figure 2.4. Distribution of Factors' sub-categories across themes

understanding of device differences in m-banking adoption by conducting thematically different studies.

Cultural and Personal themes have the least diverse factor sets. Within Cultural studies, personal and perceptive factors dominate, indicating that cultural influences shape individual perceptions (opinions) and values (personal factors). In personal studies, social factors are overshadowed by others, suggesting that individual preferences take precedence over group opinions. Most studies on individual differences do not consider societal influences, signaling an unexplored area for future research. Although no significant relationship exists between factors and themes, it is still useful to look at some patterns.

Figure 2.5's left panel shows that most themes have a high median significant score. The median for all themes is close to 1.0, meaning most factors are frequently significant, at least

relative to their total occurrences. Variation exists, but it's minor. Some themes (e.g., market, cultural and demographic) have slightly lower median than others. The interquartile range (IQR) is small, indicating that most factor scores are clustered near the top. Some data points fall below 0.5, suggesting a few factors appear non-significant more so than they are significant. These outliers might indicate less relevant factors for certain themes. Since most medians are high and IQR's are similar, no theme strongly dominates in terms of factor scores.

Market studies might have slightly lower scores than others, indicating device and technology specific factors may be needed. The outliers (`Score_Sig` ≤ 0.5) and the related theme they appeared as an outlier in are: Age (Psychological), Education (Market), Triability (Social), Hedonic and Social Value (Perceptive), and Age, Education and Social Value (Demographic). The reason for these outliers are: 1) these factors either do not appear frequently in those themes, or 2) they do appear, but they are not frequently found to be significant. For example, we expected age and education to appear in many Demographic studies. Therefore, it is surprising that these factors have low scores. This indicates that age and education are either not frequently used in Demographic studies or they are frequently found to be non-significant variables in m-banking adoption.

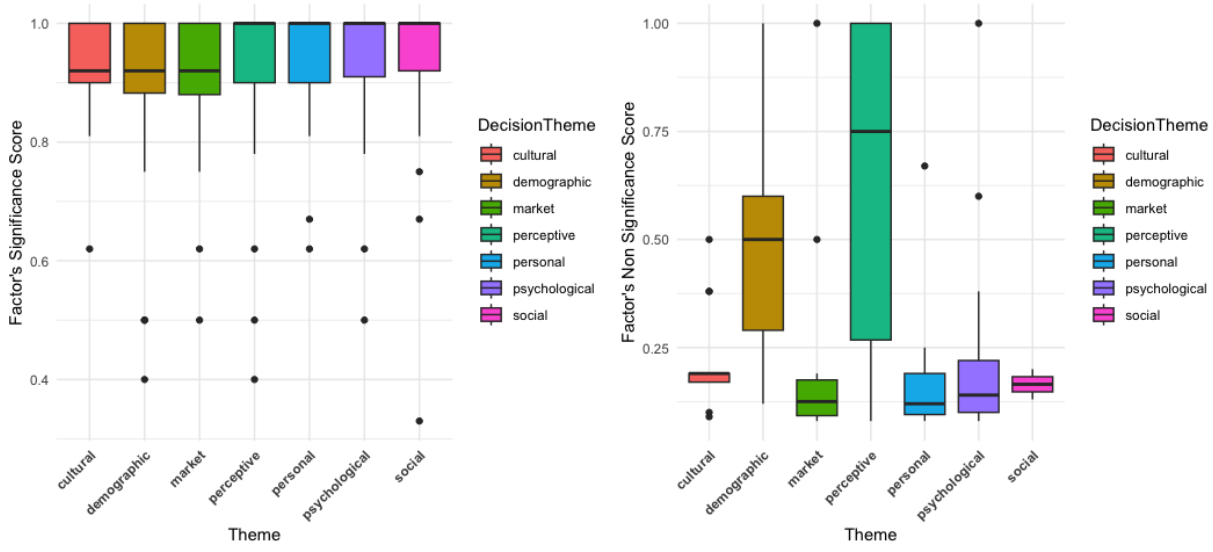


Figure 2.5. Box plot for outlier detection – (left) Distribution of factor's significance scores across different Themes, (right) Distribution of factor's non-significance scores across different Themes

The right panel in Figure 2.5 visualizes how non-significant factor scores (i.e., factors that were not statistically significant in the studies) vary across different themes. Perceptive has the widest range of non-significant scores, with a high median (around 0.75). Demographic also has a relatively high median, meaning many factors in demographic-related studies were found to be non-significant. Some themes (e.g., Perceptive and Demographic) show high variability in non-significant factor scores, while some report very low variability.

The presence of outliers suggests that certain studies had unusually high numbers of non-significant factors. The outliers are factors with non-significant scores of higher than 0.5 (appearing more than half of their total frequency as non-significant). These are: Social Value, Conditional Value, Triability (Demographic), Perceived Usefulness of ATM devices, Search Convenience and Evaluation Convenience (Perceptive), Social Value and Hedonic Experience (Psychological), Triability (Personal) and Convenience barriers (Market).

An interesting observation is social values being an outlier in demographic studies for both significance and non-significane score. This is because of the study of Karjaluoto *et al* [249] where they found that social values did not influence trust in m-banking directly. However, social value is a significant moderator between functional value and intention to m-bank. Other insights from this analysis are: Perceptive studies may either not be reliable or may be useful to frameworks to assess the significance of factors in. Since another reason for low scores of factors are due to them not appearing as frequently across the literature, we also highlight several of these overlooked factors across themes. Identifying these gaps can provide valuable insights for future research and broaden the understanding of m-banking adoption.

Cultural studies predominantly rely on UTAUT and TAM as foundational theories. However, some factors remain under-explored in these studies: Collective Culturalism [260], Competence [302], Economics issues [366], Lifestyle Fit [97], Loyalty [260], and Normative Beliefs [302]. In Psychological studies, overlooked factors include Anxiety [429], Behavioral Control [53], Cognitive Resistance [433], Decision Comfort [385], and Discomfort [433], Enjoyment [127], Empathy [252], No branch visits [200], Covid-19 related psychological distress [294], and green

concerns [495]. Demographic studies neglect Accessibility [110], Digital Divide [110], Resistance to change [40], Cognitive Decline, Digital Capabilities, and Social Isolation [342].

Across Perceptive studies, rarely studied factors include: Perceived Relative Advantage [36], Perceived compatibility [36], Perceived costs [464], Perceived privacy [50], and Perceived value [379]. In Social studies, less-explored factors are: Family Influence [349], Social media influence [349], Social interactions on platforms [22], Compatibility [21], and Cost-saving [220]. Market studies have seldom considered the following factors: Alternatives to the technology [61], Brand Image [219], Brand Engagement [250], Health [116], Education [372], Environment [225], Financial Literacy, Herd behavior, and Risk aversion [301]. Finally, Personal studies often overlook Agreeableness of individual [11], Technological Awareness [485], Digital Literacy [350], Openness to new experiences [11], and Perceived Security [352].

2.5.2 Foundational Theories

Recent studies integrate multiple theoretical frameworks to analyze m-banking adoption [236, 156, 147, 347]. Post-pandemic research highlights shifts in technology integration into daily life, expanding m-banking literature [390]. Recognizing this evolution, we examine the theoretical developments in the literature. Theory distribution remains consistent across years, technology, research type, and sample sizes. However, significant relationships exist between theories and methods, limitations, factors, and non-significant factors (Table 2.11). For methods, SEM and PLS-SEM dominate across the board. Setting aside these two methodologies and the most prominent theories (TAM and UTAUT), clearer patterns emerge. Older theories, such as Diffusion of Innovation (DOI) (abbreviated by either DIT or DOI) [59], Theory of Planned Behavior (TPB) [15], Theory of Reasoned Action (TRA) [158], and Technological Readiness [381] commonly use Confirmatory Factor Analysis (CFA), Exploratory Factor Analysis (EFA), and Path Analysis (PA).

More modern theories employ diverse techniques. Elaborate Likelihood Model (ELM) incorporates Mediation and Moderation Analysis [447]. Ordinal Regression is used with TAM2 [137]. Thematic Analysis is applied to Affordance Theory [350], Social Practice Theory (SPT) [350, 349], and Social Influence Theory (SIT) [22]. For limitations, we exclude TAM, UTAUT

Table 2.11. Results of X^2 test of independence between **Theories** across other variables

Variable	X^2	df	p-value
Year	262.92	252	0.305
Tech	309.21	294	0.260
SampleSizeBin	112.35	108	0.368
ResearchType	421.38	630	0.999
Methods	315.09	168	$< .001^{***}$
Limits	133.81	78	$< .001^{***}$
Factors	1745.5	1134	$< .001^{***}$
NS.Factors	247.63	162	$< .001^{***}$

Notes: $^{***}: p < 0.001; ^{**}: p < 0.01; ^{*}: p < 0.05$

and two outlier limitations: t-test and limit scope (captured in Islamic banking). We find the following notable patterns as shown in Figure 2.6: Task Technology Fit (TTF), TPB and Digital Cohort Theory (DCT) appear to not integrate moderation analysis. The DeLone and McLean Model (DM) of Information Systems Success is restricted in applicable methodologies (only SEM has been used [51, 176, 181]).

TPB, TTF, and UTAUT2 studies often cite the limitation of not considering additional factors, which could indicate additional factors do not integrate well with these models. Methodological biases in data gathering and measurement appear in studies using Meta-UTAUT [29], Trust Theory [29], and TPB [166]. Sample size limitations affect studies based on Optimum Stimulation Level (OSL)[47], Perceived Interactivity Theory (PIT) [561], SERVQUAL model [252], Theory of Consumption Values (TCV) [249], and UTAUT2 [197]. Islamic banking (scope) limitations were cited in studies using Religiosity-Intention model [487] and UTAUT2 [382, 426].

Analyzing factor sub-categories reveals distinct patterns. Demographic factors appear only in TPB [272], TAM, Gender Schema Theory (GST) [13], ELM [233], and Behavioral Reasoning Theory (BRT) [13], primarily appearing in TAM (5), DOI (3), and ELM (2). Market factors are exclusive to TAM [231], TPB [231], and UTAUT2 [92]. Social factors are most frequent in TAM (23), UTAUT2 (16), UTAUT (14), and TPB (7), while least frequent in UG [220], Technological

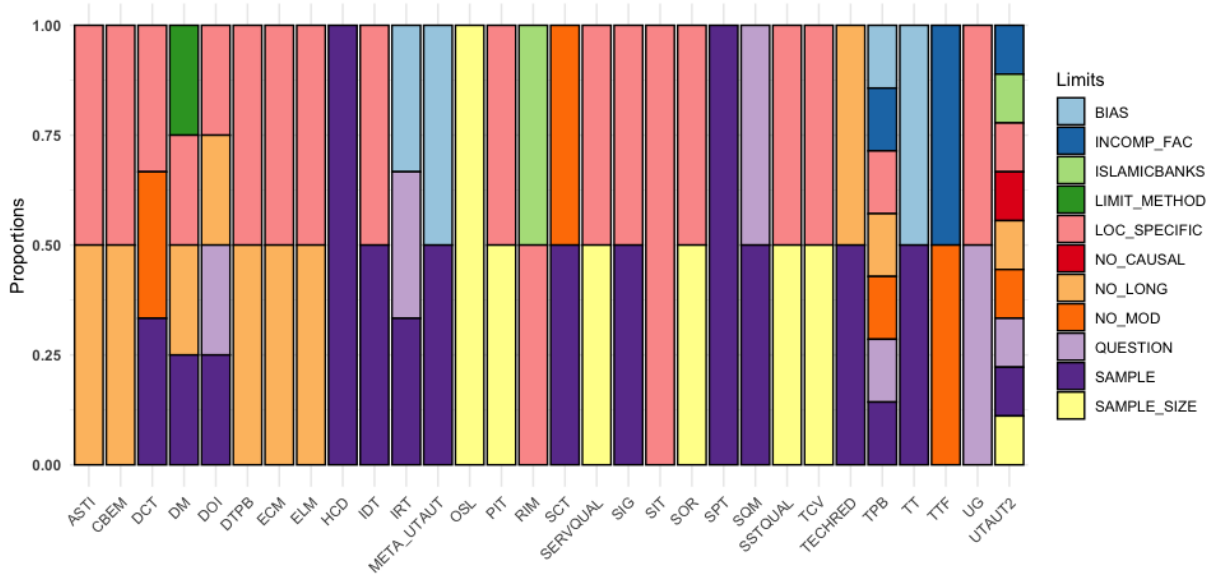


Figure 2.6. Proportion of Limitations across various theories in the database (Outlier removal: Theories do not include TAM and UTAUT, while limitations do not include T-test and limits in scope)

Readiness [433], TAM2 [137], PIT [354], and OSL [47]. Personal factors appear most in UTAUT2 (47), UTAUT (33), TAM (27), and five instances of DOI, UTAUT, and TCV, but least in TTF [50], TRA [97], Hofstede Cultural Dimension (HCD) [302], DCT [450].

Psychological factors dominate TAM (47), UTAUT2 (28), and UTAUT (24), followed by DOI (10), TRA (9), SCT (8), TPB (7), Trust Theory (6), and Expectation Confirmation Model (ECM) (5). They appear least frequently in SERVQUAL [252], Signaling Theory [508], TCV [249], Trust Theory [29], HCD [302], Institutional Theory [3], and PIT [561]. Perceptive factors are least used in OSL [47], TCV [379], TAM2 [137], institutional theory [3], DM [181], Adaptive Structuration Theory for Individuals (ASTI) [359], and DCT [450], but most in TAM (117), UTAUT (27), TPB (13), UTAUT2 (11), and DOI (6).

Some of the rarely used theories and their key factors are as follows: BRT with attitude, intention, and gender [13], Signaling Theory with performance, satisfaction, and system quality [508], TAM2 with credibility, perceived usefulness, and social influence [137]. DCT with emo-

tional experiences, perceived ease of use, pragmatism, and satisfaction [450], and ELM with age, argument quality (for Google reviews), consistency, privacy/security concerns, gender, trust, and valence (Google reviews) [233, 447]. Figure 2.7 (tree map) shows UTAUT2 and UTAUT frequently lead to non-significant results. TPB often finds demographic factors (age, income, education) insignificant as adoption predictors.

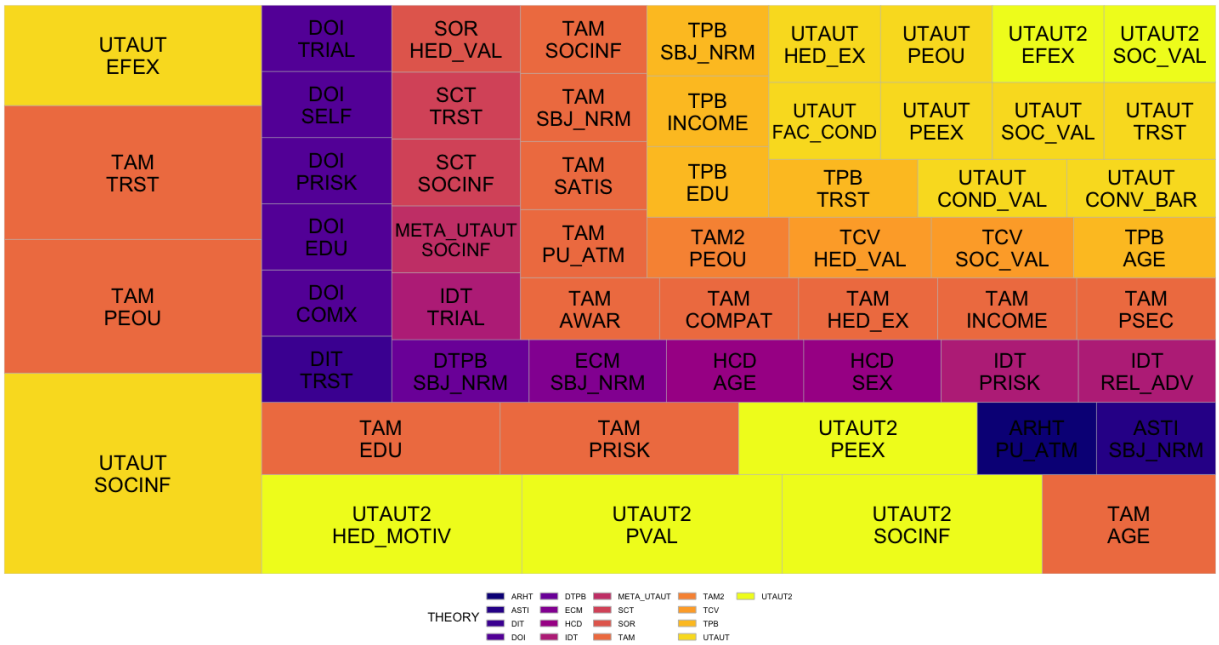


Figure 2.7. TreeMap of Non-significant Factors Across Theories in the Literature

2.5.3 Methodologies

Method distribution across years, non significant factors, themes and theories shows no significant differences. However, specific methods are strongly linked to certain technologies, sample sizes, research types, limits and factors. Figure 2.8 highlights how some methodologies are exclusive to certain technologies, while others, like PLS-SEM, have broader applications. Surprisingly, SEM, despite its popularity, has not been applied to technologies like m-wallets. Certain methods also align with specific research types, as shown in Figure 2.9. Regression emerges as the most diverse

method after SEM, used as widely as PLS-SEM. This suggests regression is highly adaptable across research types. However, specialized methods remain valuable. Some, like Interviews for Qualitative studies, provide depth and precision despite their narrower scope. Versatile methods offer broad applicability, while specialized tools address specific research needs.

Table 2.12. Results of X^2 test of independence between **Methods** across other variables

Variable	X^2	df	p-value
Year	233.32	240	0.609
Tech	402.72	320	$< .001^{***}$
SampleSizeBin	87.174	87	0.475
ResearchType	889.59	600	$< .001^{***}$
Limits	415.58	336	0.002^{**}
Factors	9315	8931	0.002^{**}
NS.Factors	263.24	330	0.997

Notes: $^{***}: p < 0.001; ^{**}: p < 0.01; ^{*}: p < 0.05$

Significant differences exist in sample sizes across methodologies. Text mining (including LDA), Random Forest, Instrumental Variables, and Logistic regression are applied to the largest datasets, emphasizing the capability of Machine Learning algorithms in handling large-scale data efficiently. Considering limitations of studies across methodologies, we note: Bias in samples cause challenges for PLS, SEM, CFA, Multi group SEM, and Ordinal Regression. Meta-analysis and SLRs often cite failure to include all relevant factors as a limitation. Thematic analysis is primarily constrained by sample size limitations, as text analysis techniques often require large datasets. A significant relationship exists between factors and methodologies, with rarely used methods offering unique insights. For example, fsQCA identifies life compatibility, PEOU, and trust as factors impacting smart wearable payment adoption [207].

Instrumental Variable analysis highlights financial literacy, herd behavior, and risk aversion [301]. Multigroup analysis finds attitude, intention, and gender to be significant indicators of technology adoption [13]. Mediation analysis reveals consistency, valence, and word-of-mouth volume (e.g., number of reviews) as key factors in m-banking adoption [447]. Demographic

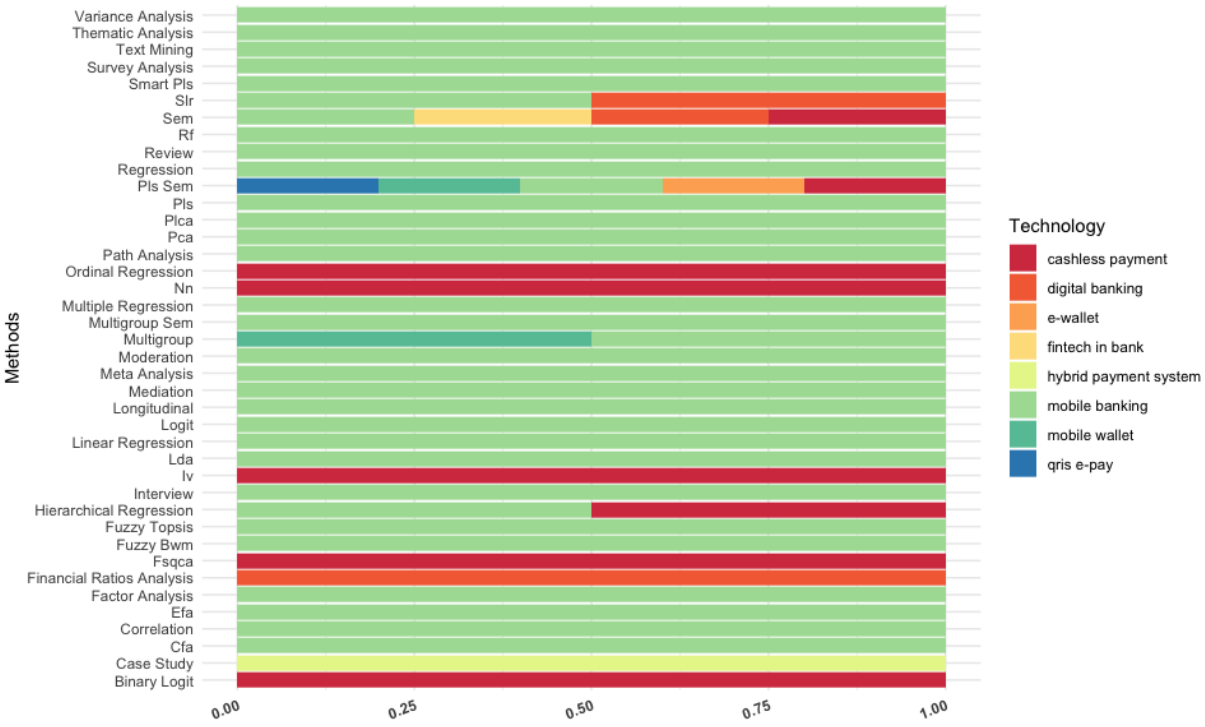


Figure 2.8. Distribution of Methods across Technologies in the literature.

factors frequently appear in regression models (binary, hierarchical, etc.). Market factors are strictly analyzed using SEM and PLS. Different methodologies uncover new or overlooked factors. We urge researchers to expand method selection for deeper exploration.

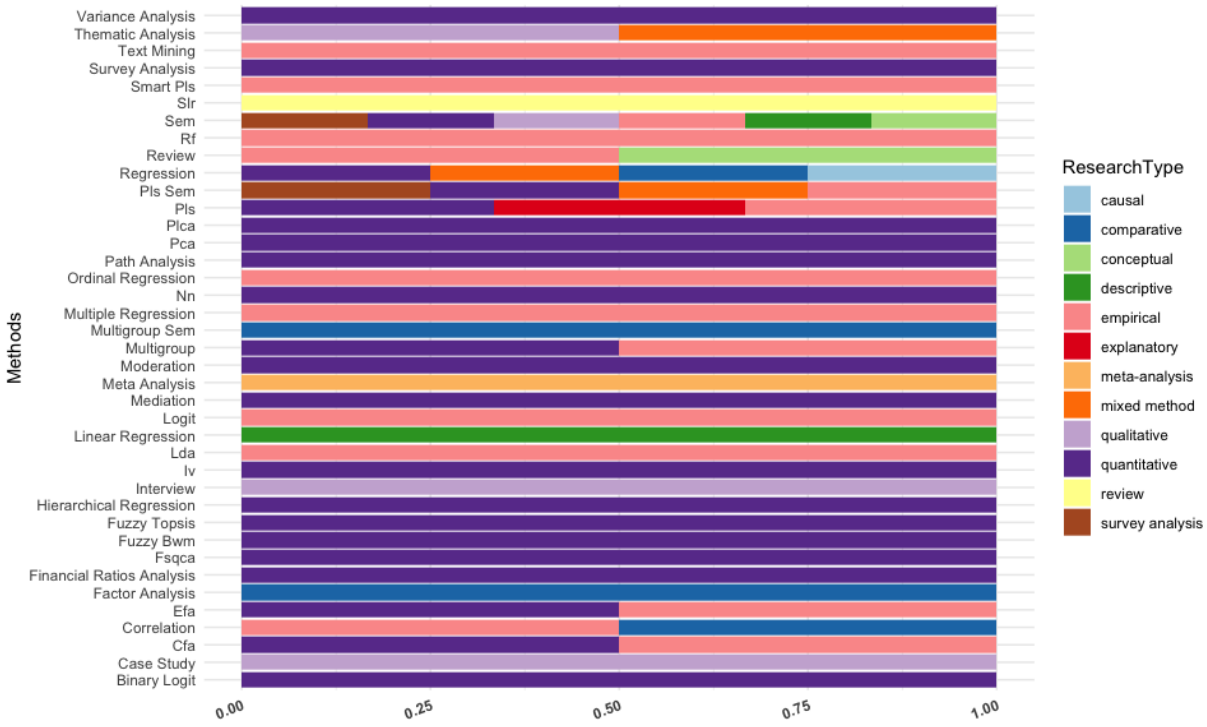


Figure 2.9. Distribution of Methods across Research Types in the literature.

2.5.4 Limitations

There is no statistical evidence for a significant relationship between limitations and years, technologies, sample sizes, factors, non-significant factors and theories. However, the type of research is related to limitations. For brevity, the results that have been previously discussed are not repeated. Figure 2.10 depicts the distribution of research types across the limitations. As expected, the most cited limitations, i.e., Limitations due to study being location specific (LOC_SPECIFIC) and Limitations due to the sample not being representative (SAMPLE) show the most diversity. The majority of survey studies cite a lack of causality analysis as their limit (limitations due to not assessing causality (NO_CAUSAL)). On the other hand, Causal studies cite not using longitudinal data (Limitations due to not doing a longitudinal study (NO_LONG)) and being location specific as the limitations. The largest share of location specific limitations is in fact for Causal and Descriptive studies whereas meta-analysis studies do not have this limitation.

Table 2.13. Results of X^2 test of independence between **Limits** across other variables

Variable	X^2	df	p-value
Year	90.311	84	0.299
Tech	112.27	98	0.154
SampleSizeBin	48.103	39	0.151
ResearchType	249.46	196	0.006**
Factors	2077.5	2506	0.999
NS.Factors	120.79	180	0.999

Notes: $^{***}: p < 0.001; ^{**}: p < 0.01; ^{*}: p < 0.05$

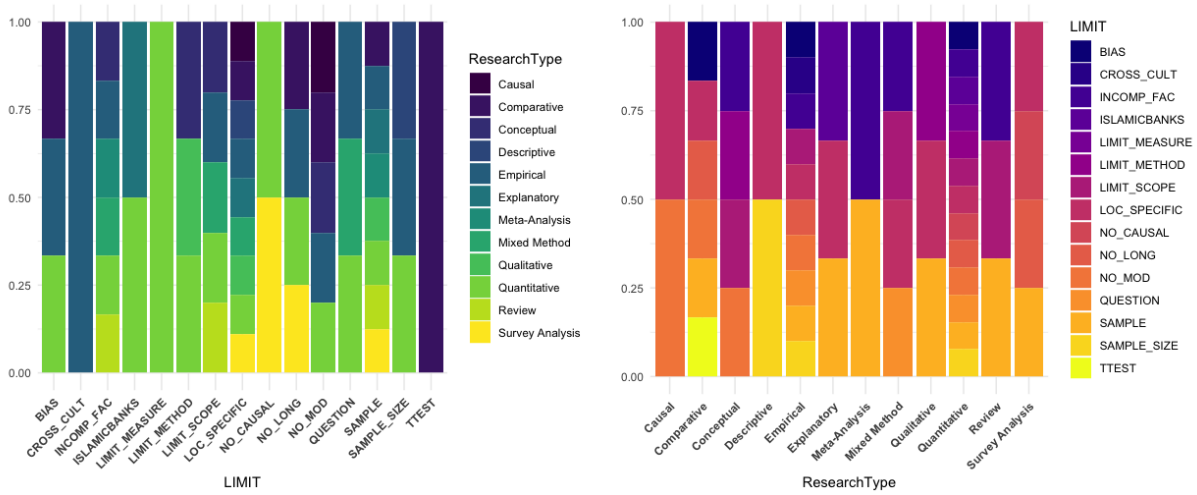


Figure 2.10. Distribution of Limits across Research Types in the literature (Left panel depicts groupings on Limits, Panel on right is grouped on ResearchType.).

2.5.5 Significant Factors

The most important variable in this literature analysis is the factors that influence m-banking adoption. Table 2.14 depicts the most frequent factors across the database. Since factors are the

building blocks of theories, it is no surprise that the top factors are those of the top theoretical frameworks: TAM, UTAUT and UTAUT2. Only 48 factors (21.5% of the total) are found significant for more than three times. This shows an unbalanced emphasis on certain factors. Future research should move away from proving the already verified impact of TAM, UTAUT, UTAUT2 factors and investigate new and less-frequently explored factors in various contexts. It is important to not that those less-frequently significant factors are appearing as non-significant. Rather, this unbalance exists because not many studies include them to begin with. Therefore, we believe future research should aim to either study the well-established factors from theories such as TAM, UTAUT and UTAUT2 in new settings or utilize less-frequently used methodologies and theories to obtain new insights and explore new factors.

Table 2.14. Top Factors (more than 3 times found significant)

Factor	n[1]	Factor	n	Factor	n
PU	53	PEOU	49	TRST	49
SOCINF	38	PEEX	30	FAC_COND	29
EFEX	26	PRISK	26	SEC	17
ATTD	15	HABT	15	HED_MOTIV	15
INNOV	13	SERV_QUAL	10	COMPAT	9
CONV	9	PTRST	9	SATIS	9
PRICE	7	PRIV	7	RISK	7
SBJ_NRM	7	EOU	6	PSEC	6
SYS_QUAL	6	AWAR	5	FIN_LIT	5
PVAL	5	SEX	5	SELF	4
ACCBILITY	3	AGE	3	BHV_INTNT	3
CLTR	3	COMPTNC	3	CRED	3
EMO_VAL	3	INCOME	3	INFO_QUAL	3
INTNT	3	INTNT_USE	3	PPRIV	3
REL_ADV	3	RELIGIS	3	RELY	3
RESIST_CHNG	3	TASK_CHAR	3	USBL	3

Notes: 1: Frequency of appearance in the database.

So far, significant differences were observed across distribution of theories and methods for factors, but no difference in the distribution of factors across the years, technology, research types and limits. There are some interesting differences among sample sizes (although not significant due to the large number of studies having not cited their sample sizes). The one significant relationship we explore here is with non-significant factors. Recall that larger sample-size studies lack market as well as cultural and demographic factors, highlighting challenges in conducting this type of research. That is, studies that focus on demographics, cultures and markets which have a large sample size. Given that small sample sizes were a top-cited limitation, larger samples are needed to address gaps. However, studying some aspects of m-banking adoption on a large scale remains difficult.

Table 2.15. Results of χ^2 test of independence between **Factors** across other variables

Variable	χ^2	df	p-value
Year	1373.7	1386	0.587
Tech	1862.6	1848	0.400
SampleSizeBin	521.24	519	0.464
ResearchType	2681.9	3465	0.999
NS.Factors	2569	2,280	$< .001^{***}$

Notes: $^{***}: p < 0.001; ^{**}: p < 0.01; ^{*}: p < 0.05$

Psychological factors require detailed tools like surveys, interviews, or psychometric tests. Scaling these for large samples demands significant time, labor, and funding – all of which are often limited in academic research. Online data sources such as app reviews and online surveys could help expand reach, but large-scale psychological data collection raises ethical concerns regarding privacy, security, and oversight, discouraging researchers. Market factors are easier to quantify and analyze due to their objective nature, streamlining data collection. Emerging trends like m-banking via smart wearable devices are opportunities for future research. As smartwatches and other wearables and m-wallets grow in use, large-scale studies are needed to explore adoption across different devices and services.

Sample diversity remains a major obstacle and is the second most common challenge researchers

face. Large samples span multiple contexts, making it hard to capture nuances without adding methodological complexity. Standardizing cultural measurement tools is resource-intensive since cultural constructs are context-dependent. Demographic data is easier to collect but often studied in isolation, ignoring interactions with cultural or social factors. For example, income's impact on m-banking adoption may vary based on cultural traditions, such as Islamic banking practices [35]. Based on Figure 2.11, all Market factors are found in studies with sample sizes in the second quintile ($253 \leq SQ2 < 384$). No Market and Demographic factors are available withing studies with datasets smaller than 100. Demographic factors appeared the most prominently across studies with either $100-500$ or with $500-1,000$.

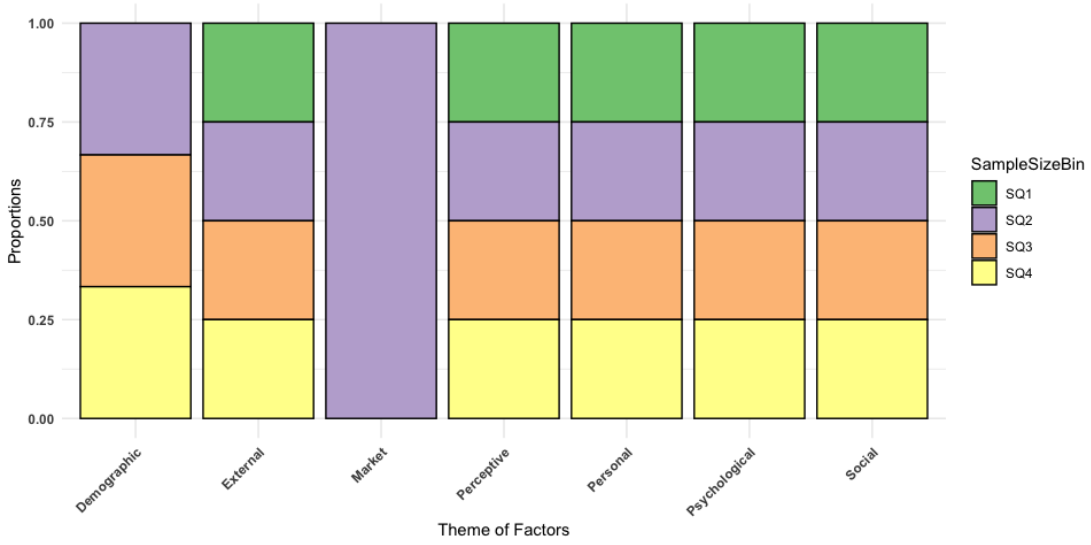


Figure 2.11. Sample size distribution across themes of factors

2.5.6 Non-significant Factors

There is a significant relationship between non-significant and significant factors ($\chi^2_{df=2280} = 2569, p < .001$) and a significant relationship with theories which was discussed in Section 2.5.2. Calculating the proportion of times a factor is deemed non–significant to number of times it is found to be significant; we assert that all the top non-significant factors are predominantly

significant (all ratios are less than 50%). To identify patterns, we analyze studies with both non-significant and significant factors. The contingency Table 2.16 shows the frequency with which factors have appeared in the same studies as significant when another factor was non-significant. The number in () for the non-significant factor in the first and 4th column of Table 2.16 is the total number of times the factor has appeared as non-significant in the database.

Table 2.16. Factors that are significant vs Factors that are non-significant

NS.Factor[1]	Factor(s)[2]	n[3]	NS.Factor	Factor(s)	n
SOCINF (44)	PEEX	7 (16%)	AWAR (**7**)	DIGLIT, INNOV, PEOU, PRISK, PU, RESIST_CHNG, SBJ_NRM	1 (14%)
	EFEX	5 (11%)	COMPAT (**7**)	DIGLIT, INNOV, PEOU, PRISK, PU, RESIST_CHNG, SBJ_NRM	1 (14%)
	FAC_COND, TRST	4 (9%)	COND_VAL (**5**)	BHV_INTNT, EFEX, EMO_VAL, FUN_VAL, PEEX, EFEX, FAC_COND, IMG_BAR, PEEX, RISK_BAR, SOCINF, VAL_BAR	1 (20%)
	HABT, HED_MOTIV, PEOU, PSEC, SELF	2 (5%)	EVAL_CONV (**5**)	ACC_CONV, BEN_CONV, CONV, POS_CONV, TRSN_CONV	1 (20%)
	ATTD , BHV_INTNT , EMO_VAL , FUN_VAL , INTNT_USE , LIFE_COMPAT , PCOST , PPRIV, PRICE , PTRST , PVAL , SEC	1 (2%)	COMX (**4**)	COMPAT, PRISK, REL_ADV, TRST	1 (25%)
TRST (**19**)	PEOU	4 (21%)	AGE (**20**)	COMPETNC, PEOU, PU	2 (10%)
	PU	3 (16%)		BENV, CLTR, HLTH_EFF, INCOME, NORM_BLF, PRIV, PRV_EXP, PTRST, PVT_EMP, REL_ADV, SEC, SEMP, SEX, TRST	1 (5%)
	ATTD, OBSRV, PCOMPAT, PCOST, PSEC, PTRST, SBJ_NRM, SEC, SELF, SOCINF	1 (5%)	EDU (**14**)	PEOU, PU, SEX	2 (14%)
				AGE, ATTD, BENV, COMPETNC, INCOME, INTNT, PRIV, SEC	1 (7%)
EFEX (**14**)	SOCINF	3 (21%)	FAC_COND (**22**)	TRST	3 (14%)
	FAC_COND, PEEX	2 (14%)		PEEX, PEOU, SOCINF	2 (9%)
	ANXIETY, HED_MOTIV, PTRST, RECOM, RISK, RWRD, SEC	1 (7%)		ANXIETY, EFEX, FAC_COND, HABT, HED_MOTIV, INNOV, LIFE_COMPAT, PRISK, PU, RECOM, RISK, RWRD, SEC	1 (5%)
PEOU (**17**)	PU	3 (18%)	HED_MOTIV (**16**)	PEEX	3 (19%)
	PEOU, PTRST, SOCINF	2 (12%)		EFEX, FAC_COND, HABT, TRST	2 (13%)
	COMPAT, CONV, CRED, FAC_COND, INNOV, PRISK, PSEC, P_AEST	1 (6%)		PPRIV, PRICE, PRISK, PSEC, SOCINF	1 (6%)
SOC_VAL (**14**)	EMO_VAL	3 (21%)	PVAL (**16**)	PEEX	3 (19%)
	EFEX, FUN_VAL	2 (14%)		EFEX, FAC_COND, HABT, TRST	2 (13%)
	BHV_INTNT, EPI_VAL, MON_VAL, PEEX, QUAL_VAL, SOC_VAL, TRST	1 (7%)		PPRIV, PRICE, PRISK, PSEC, SOCINF	1 (6%)
PEEX (**13**)	TRST	2 (15%)	SBJ_NRM (**11**)	PU, TRST	2 (18%)
	EFEX, EMO_VAL, FAC_COND, HABT, MON_VAL, PEEX, PPRIV, PRICE, PSEC, QUAL_VAL, SOCINF	1 (7%)		ATTD, PBHV_CTRL, PEOU, PRISK, SATIS, SBJ_NRM, SELF	1 (9%)
PRISK (**25**)	COMX, INNOV, PEOU, PU, REL_ADV	2 (8%)	TRIAL (**9**)	COMPAT	2 (22%)
	ATTD, AWAR, BRD_IMG, COMPAT, GOV_SUP, HLTH_EFF, INCOME, INTNT, OBSRV, PTRST, PVT_EMP, RELIGIS, SEMP, SOCINF, TRST	1 (4%)		AWAR, COMX, OBSRV, PRISK, RELIGIS, REL_ADV, TRST	1 (11%)
HED_EX (**5**)	BHV_CTRL, HABT, PPRIV_CN, SEC, UTILEX	1 (20%)	HED_VAL (**5**)	EPI_VAL, HED_VAL, PVAL, SOC_VAL, UTIL_VAL	1 (20%)
INCOME (**7**)	BENV, COMPETNC, PEOU, PRIV, PU, SEC, SEX	1 (14%)	PSEC (**2**)	PEOU, PU	1 (50%)
PU_ATM (**5**)	ATTD, ATTD_ATM, PEOU, PEOU_ATM, PU	1 (20%)	REL_ADV (**5**)	AWAR, COMPAT, COMX, OBSRV, RELIGIS	1 (20%)
RISK (**5**)	EFEX, HABT, HED_MOTIV, PEEX, TRST	1 (20%)	SATIS (**2**)	PEOU, PU	1 (50%)
SELF (**4**)	COMX, INNOV, REL_ADV, SOCINF	1 (25%)	SEX (**5**)	CLTR, COMPETNC, NORM_BLF, PRV_EXP, TRST	1 (20%)
SRCH_CONV (**5**)	ACC_CONV, BEN_CONV, CONV, POS_CONV, TRSN_CONV	1 (20%)			

Notes: The number in () for the non-significant factors is the total number of times the factor has appeared as non-significant in the database.
1: Non-significant 2: Significant factor(s) in the same study 3: Frequency of occurrence (together) across the database (percent)

The table indicates that social influence (SOCINF) is non-significant in 44 cases, suggesting that users rely more on performance expectations (PEEX) rather than social factors when deciding to adopt m-banking. In seven of these cases, PEEX appears as a significant factor, reinforcing the idea that users prioritize tangible benefits over external opinions. This insight is valuable

for practitioners – if forced to choose between enhancing usability or increasing social influence strategies (e.g., word-of-mouth marketing), improving the app's functional benefits would likely be more impactful. Trust (TRST) appears to be counteracted by perceptions of ease of use (PEOU) and usefulness (PU). This implies that if an app is perceived as intuitive and beneficial, users may not feel the need to place significant trust in the bank or developers. This could be due to the inherent reliability of widely used banking technologies, making trust a secondary concern when usability and utility are assured.

For effort expectancy (EFEX), SOCINF is frequently observed as significant. This suggests that if peers actively endorse the app or if a user feels socially pressured to adopt it, the perceived effort required for adoption becomes less relevant. In other words, even if an m-banking app is difficult to use, strong social recommendations can override concerns about usability. A notable pattern emerges between emotional values (EMO_VAL) and social values (SOC_VAL) – when emotional factors are significant, social values tend to be non-significant. This indicates a tendency for individuals to prioritize personal emotional benefits over broader social acceptance when making adoption decisions. The relationship between PEEX and hedonic motivation (HED_MOTIV) suggests that when strong performance improvements are present, enjoyment factors become irrelevant. This makes sense, as m-banking apps are primarily functional tools rather than entertainment platforms – users prioritize efficiency and reliability over enjoyment.

Additionally, trust and PU together appear to reduce the importance of social norms (SBJ_NRM). This suggests that once users believe an app is trustworthy and beneficial, they are less likely to be influenced by societal expectations or external pressures. Another key observation is that compatibility (COMPAT) seems to reduce the need for trialability (TRIAL). If an app is inherently compatible with a user's needs and lifestyle, they are likely to adopt it immediately without requiring a trial period. Finally, for other observed relationships, the number of non-significant cases is relatively small, making it difficult to draw firm conclusions. However, the overall trends suggest that users prioritize functional efficiency, trust, and personal relevance over social and hedonic factors when adopting m-banking.

2.6 Discussion

In this section, theoretical and practical implications of the findings are discussed and recommendations for both researchers and practitioners are provided. This review focuses on intrinsic factors in m-banking adoption, highlighting the lack of systematic literature reviews in studies from $2018-2024$. Addressing this gap is a key goal here. Qualitative research in this field is growing, with thematic analysis increasing due to better qualitative data access and Natural Language Processing (NLP) advancements. Studies typically analyze survey data from $250-500$ participants but often face sample size limitations and rely on cross-sectional rather than longitudinal designs. Research is geographically biased toward developing countries, where most studies originate from. According to the Human Development Index (HDI), fewer than 10% of countries in the dataset are developed nations [522], highlighting a research gap in the developed world. While developing nations offer higher growth potential and unique challenges, more studies in developed countries are needed.

Geographical limitations also arise from studies focusing on individual countries, reducing generalizability. Differences in findings stem from both national and developmental contexts. Cultural factors further influence adoption, as people prefer technologies aligned with their values and norms [534]. A meta-analysis could help address these geographical limitations. Intrinsic factors are shaped by cultural influences in several ways. Within the same culture, *Social Influence* is typically stronger [296]. Cultural values and social environments also impact *Trust* in brands [261]. When most people in a cultural group adopt a technology, *Social Pressure* reinforces *Habitual* behavior, leading to different adoption decisions.

Shared familiarity with certain technologies within a culture strengthens the role of *Attitude* and *Habit* in adoption [471]. Religiosity, as explained in the Religiosity–Intention Model, also significantly affects m-banking adoption [487, 12], underscoring cultural differences. The findings highlight the crucial role of cultural factors in m-banking adoption and the need to integrate them into future research. To improve generalizability in country-specific studies, we propose categorizing scenarios by cultural or developmental classifications. That is, incorporate and highlight the specific cultural aspects of the study's participants as key information.

The findings reveal significant insights into intrinsic dimensions of m-banking adoption. The results identify two niche frameworks, Digital Cohort Theory and Signaling Theory, which emphasize satisfaction as a key factor. This shows that underutilized theories reveal overlooked influences, and need to be explored. Psychological factors such as trust, anxiety, and cognitive barriers have a profound impact on user adoption behaviors. The integration of psychological factors such as optimism and satisfaction is increasingly recognized as critical to improving user experiences. Assessing the cultural and demographic aspects of studies in tandem with factors, the results highlight how perceptions of risk and privacy concerns remain major barriers to adoption, but particularly in regions with low digital literacy. Based on the results and prior studies, a list of recommendations for future research is available in Table 2.17.

Most studies rely on TAM and UTAUT, despite evidence that alternative theories also capture m-banking adoption complexities. Similar conclusions appear in a systematic review on trust and risk in m-banking [232]. One suggestion is to explore alternative frameworks or combine models to address adoption behavior complexity. This review finds that trust is commonly studied within UTAUT and UTAUT2, which better incorporate social and psychological dimensions than TAM. This may be because UTAUT includes Social Influence and Facilitating Conditions, both linked to trust. A future meta-analysis could examine how trust integrates differently into TAM and UTAUT, providing deeper insights into its role in m-banking adoption. That is, future research should set out to answer whether there is a specific other factor(s) that result in Trust working well in UTAUT's structure but less so in other frameworks?

Although Social, Perceptive, and Personal studies are less common in the literature, they are highly cited, reflecting their influence and growing importance. A recommendation here is that future researchers focus on these aspects to leverage their emerging relevance. Certain significant factors appear infrequently, often representing new research areas. Future studies should explore these factors in greater depth to expand knowledge and uncover new insights (refer to Sections 2.5.5 and 2.5.1 for detailed lists of factors across themes). Few studies simultaneously address *Perceived Risk* and *Perceived Trust*. A suggestion here is to integrate both in future research to examine their interactions, as these are well-studied in other fields [119]. Additionally, these interactions should

be studied across diverse demographic, cultural, social, theoretical, and methodological contexts to provide a broader understanding.

A major limitation in studying m-banking adoption is the sampling methods, particularly small sample sizes and limited demographic diversity. Additionally, the reliance on cross-sectional data reduces the generalizability of findings. A recommendation is that future research employ longitudinal studies with larger, demographically representative samples spanning broader regions where feasible. However, we acknowledge that in university settings, financial and time constraints may make such studies impractical [90]. This review also highlights a significant lack of focus on developed countries in recent years. This disparity underscores the need for more research on m-banking adoption in these regions, especially given the behavioral changes caused by the COVID–19 pandemic. A recommendation is to conduct more studies in developed nations to address this gap.

This discussion is concluded by offering actionable recommendations for banks and financial institutions to enhance m-banking adoption. For **Researchers**, investigating the interplay of psychological factors in adoption behaviors is recommended. Additionally, researchers should use less-utilized theories that incorporate newer factors, and expand cross-cultural studies to compare intrinsic motivators across diverse markets. **Financial Institutions and Banks** should facilitate an investment involving banks and developers jointly should perhaps focus on introducing features that cater to emotional engagement, such as gamified interfaces or reward systems. Additionally, banks should enhance perceived Trust and address perceived risks of m-banking. Perceived Trust and Risk are critical factors in m-banking adoption.

Banks should prioritize transparent communication about security and privacy measures in their apps. Transparency in explaining security protocols and privacy policies fosters trust, as trust reduces the need for guarantees and positions the business as reliable [263], increasing consumer engagement. According to Olsina and Lew [369], several product features significantly impact users' perceived trust in m-banking apps: *Functional Quality*, the app reliably delivers the promised functionalities. *Performance Efficiency*, the app uses resources efficiently, such as completing tasks within an acceptable time. *Usability*, the app is user-friendly, with attributes like

being easy to understand, learn, and operate, while minimizing errors and ensuring attractiveness and accessibility. *Reliability*, the app functions as intended, is consistently operational, and is accessible when needed. *Security*, the app protects users through error prevention, authorized access, and safeguards against malicious attacks. *Information Quality*, the app provides accurate, credible, and relevant information that meets user expectations. While not exhaustive, these features are critical for building and enhancing users' perceived trust in m-banking apps.

Banks should design apps for performance improvement, not to appeal to the masses. To address factors such as social influence, banks should leverage word of mouth and use customers' reviews and testimonials to their advantage. However, the results show that Performance Expectancy quite often renders social influence non–significant. Consumers seem to care more about the performance enhancement they would gain from m-banking adoption than other people's opinions and their enjoyment of the app. For practitioners, this means that if they must choose between enhancing the practical benefits of their app, launching campaigns to facilitate social influence or making the apps more engaging, focusing on tangible improvements that enhance users' performance is likely to be more beneficial. Consequently, by focusing on designing apps that improve users' lives and performance, banks are likely to have satisfied costumers who are more inclined to spread positive word of mouth [493]. To supplement the usefulness of their applications and enhance the ease of use, banks should add easy financial management, budgeting tools and personalized financial advice to their applications.

2.7 Conclusion

This study systematically reviews intrinsic factors influencing mobile banking (m-banking) adoption. It identifies key trends, discusses their implications, and provides recommendations for future research and financial institutions. The contributions include a structured framework categorizing adoption factors and identifying significant trends. Text mining is used to assign overarching themes to papers. The results highlight trends in research type, limitations, methodologies, theoretical models, and significant factors. The literature shows strong geographical and methodological biases, emphasizing the need for representative, longitudinal studies in developed nations.

Technology Acceptance Model dominates the field, making its two core constructs the most frequently cited adoption factors. While risk and trust appear often on their own, few studies examine both together or explore their interactions. Financial institutions can use the results of this study to improve m-banking adoption. Trust can be strengthened through clear communication, social proof, and a focus on tangible benefits. Policymakers should promote digital literacy and enforce strong privacy standards to encourage adoption. App developers should optimize usability and integrate emotionally engaging features to meet diverse user needs.

Future research should examine the relationship between trust and perceived risk across different demographics and cultures to develop more comprehensive adoption models. Under-explored factors, advanced analytical methods, and longitudinal studies with representative samples should also be prioritized. Additionally, emerging technologies like Smart wearable devices, Artificial Intelligence and Cryptocurrency should be explored for their potential to address drivers and barriers in m-banking adoption. Addressing these gaps will improve the robustness and generalizability of findings while uncovering neglected or emerging aspects.

This study has limitations in scope and text mining sensitivity. First, this study only includes papers published from $2018 - 2024$, which limits the scope in terms of time frame. Second, it relies on several similar words for the search query, potentially overlooking alternative terminology. This may have limited the scope of the literature found. Third, for theme classification, no word embeddings were used due to time and hardware restrictions. Additionally, theme

assignments were finalized through manual review, which becomes impractical as the dataset grows. Alternative sensitivity analysis methods could further refine results. For future research, implementing the following suggestions may address the above limitations:

1. To address the first limitation, expand the time frame of the study to include studies from the earliest roll outs of mobile banking applications to better capture the changes in trends.
2. Use tools to search for similar keywords across the literature to expand the search query.
3. Additionally, to address the second limitation, word embeddings from natural language processing could prove useful. However, these tools might add unnecessary information which could over-complicate things and misdirect query search.
4. For the third limitation, various word embeddings could be implemented and tested such as Google's Word2vec [334] or Hugging Face's BERT model [134].

Lastly, Large Language Models (LLM) can be used to streamline the process for extracting information from a much larger database of articles. This would give researchers to target larger time frames and include more studies. Not doing so does not invalidate the results of the current study. At the time of this endeavor[5], the only commercially available Large Language Model was OpenAI's ChatGPT version $3-3.5$, which would not allow for undertaking of a task of this size. Despite of their potential usefulness in this aspect, it is important to consider their drawbacks as well.

LLMs are prone to hallucination – they can generate factually incorrect or unsupported content – and therefore methods to fact-check and verify their processing are necessary [512, 241]. Which begs the question of whether using LLMs would truly improve this and similar work. However, this is still an interesting and worthwhile avenue to explore as the next step to systematic literature review processes especially when they include text and natural language processing. Nevertheless, the structured framework developed in this work could serve as valuable training data to fine-tune LLMs, potentially improving their domain-specific reliability and enabling more accurate, scalable literature analyses in the future.

[5]The majority of this work was done in 2021–2023, with a revision to include papers from 2024 in late 2024.

Table 2.17. Recommendations and open questions for future research to address

Reference	Recommendation
Author[1], [232]	Future studies should explore less commonly used theories as foundations, such as SCT and SDL.
Author	Future studies should examine whether trust appears significantly less often in TAM-based models than in UTAUT-based models. This will determine if trust fits better in certain models.
Author	Future studies should consider both *perceived risk* and *trust* in their models, simultaneously.
Author	Future studies should examine emerging technologies like mobile wallets and smart wearable payment devices. Only 16 studies (11%) in the current literature focus on these, all published after 2020: 2020 (3), 2021 (2), 2022 (6), 2023 (2), and 2024 (3).
Author	Future research should explore new and less-studied factors by using novel theories, interdisciplinary approaches, new settings, and innovative methodologies. Existing studies confirm the influence of factors from TAM, UTAUT, DOI, and their extensions.
Author	Future research should explore using Machine Learning (ML) techniques for analysis of larger sample sizes. ML is able to work with large datasets, which is one of the top limitations in the literature (both obtaining and their analysis).
Author	Future research should should focus on developed countries. There is a large gap between studies conducted in developing and developed countries.
Author	Future meta-analysis research should be conducted to address geographical limitations of studies.
Author	Future research should consider developmental status of countries and the cultural aspects at play.
Author	Future research should expand methodological selections. Research is largely dominated by SEM and PLS-SEM and relies on established approaches.
Author	Future research should explore new technologies such as blockchains, smart wearable devices and contactless payment options.
Author	Future research should conduct comparative studies between device types' influence on m-banking adoption.
Author	Future research should consider cultural influences on individuals in studies.
Author	Future research should explore differences in adoption trends between devices, social groups, and personal traits.
Author, [317]	Future research should explore alternative frameworks or combining models to address adoption behavior's complexity.
[571, 461, 294]	Future studies should examine how COVID-19 has permanently impacted m-banking usage. Has the shift to m-banking because of the pandemic led to lasting changes in digital habits?
[509, 461, 452, 433, 426, 382]	Future studies should focus more on Demographic, Cultural and Social factors related to m-banking.
[385, 560, 433, 447, 294]	Future studies should investigate less–frequently examined factors such as anxiety, benevolence, cognitive resistance, and more.
[4, 281, 452, 433, 150, 466, 558, 237, 447]	Future studies need to employ longitudinal studies with sufficiently large and demographically representative samples.

Notes: 1: Author recommendations based on findings of the current study.

Chapter 3

Mental Health

The Relationship Between Mental Health and Mobile Banking Adoption: Evidence from Canada

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3.1 Introduction

Mobile technologies such as smartphones are exceptionally popular nowadays, making up a higher portion of internet access devices than personal computers and laptops combined [478]. Smartphone ownership is projected to increase almost 31% between 2024 and 2029 globally [476]. Mobile banking (m-banking) is the use of a smartphone to do banking tasks such as payment of bills, viewing account balance, and transferring funds. Our goal is to examine the association between mental health and m-banking adoption and other factors that might moderate this association. The notion of *"adoption"* appears in various forms throughout the Information Systems (IS) literature, such as technology adoption. Adopting technology is not merely a singular

choice but it involves a series of phases over an extended period of time [133]. In this study, adoption is the recent or new use of m-banking (more specifically, a time period of three months).

One reason for m-banking's popularity is convenience [237]. In–person visits to a bank pose multiple challenges such as: queues, commute time and costs, potential system shutdowns, and many others. Banking via a smartphone, a daily companion for most, resolves these challenges. The perpetual accessibility of smartphones contrasts with the restrictions imposed by brick–and–mortar banks, offering users access beyond business hours and other constraints. Despite the potential benefits of m-banking, not all m-banking apps achieve success in user uptake. The m-banking adoption literature has examined a multitude of factors related to the uptake of m-banking [27, 20, 52, 122, 313, 204, 545, 367, 444, 435, 343, 267, 520, 496, 253], but has less frequently studied psychological and emotional constructs that are predictive of consumers' decision about adopting m-banking [155, 176, 25, 234, 363].

Emotions have been shown to predict consumers' technology adoption decisions [332, 381]. However, to the best of our knowledge, the literature has only focused on emotions that arise due to technology adoption, such as apprehension and anxiety about a new technology [70], which is different from pre–existing anxiety that is unrelated to technology; satisfaction and joy gained from use of a new technology [176], which is not the same as being content with life in general regardless of the existence of a technology; and the notion of trust [25, 234, 363] which is the measure of how safe the consumer deems the products from a certain brand to be, and how willing they are to invest money to purchase a brand's products or services. Thus, we see that *pre–existing emotional states* and *emotions due to technology adoption* are different. Our study aims to address the lack of research on emotions existing before the adoption of a technology and their relationship with the adoption decision in the specific area of m-banking.

Mental Health (MH) is elected to replicate the (pre–adoption) emotional state of individuals, independent of technology adoption. Mental health is influenced by a combination of internal factors, such as emotions and mood, and external factors, including relationships, and environment [191]. Therefore, to develop a comprehensive understanding of mental health, we introduce other variables to our model that we believe might moderate mental health's association with m-banking

and are relevant in the context of our study. We use literature to identify these variables: Relationship Satisfaction (RS), Smartphone Dependency (SD) and Social Media/Networking Sites use (SNS). Relationship satisfaction is considered in this study in accordance with Sociometer theory, which states that a person's well–being depends fundamentally on their sense of belonging or acceptance from others [526].

Our emphasis on mobile technology sets us apart from other (non–mobile) technology adoption studies. This indicates the importance of considering the device type that is being studied in all aspects of the adoption. Specifically because device differences matter in mobile technology adoption [117]. Therefore, we consider two smartphone specific constructs which we verify (using the literature) impact mental health to be included in our study: Smartphone Dependency and Social Media use [1]. In short, in this study, we ask and seek answers to the following questions:

1. Does consumers' mental health state prior to adoption of m-banking increase or decrease their m-banking adoption likelihood?
2. Does relationship satisfaction change how consumers' mental health prior to adoption of m-banking is associated with their m-banking adoption decision?
3. Does smartphone dependency change how consumers' mental health prior to adoption of m-banking is associated with their m-banking adoption decision?
4. Does social media use change how consumers' mental health prior to adoption of m-banking is associated with their m-banking adoption decision?

Mobile banking has the potential to positively impact society, thus making it a worthwhile topic to investigate. Financial institutions, and banks specifically, may use the results of our study to efficiently plan, strategize, develop, and promote their m-banking products. Consequently, consumers gain access to better m-banking apps tailored to accommodate their preferences and constraints. The main research question of our study is: is there an association between the state of consumers' mental health and m-banking adoption? Controlling for the moderating effects of relationship satisfaction, smartphone dependency and social media use as well as demographic information such as age, income and education helps identify associations between mental health and m-banking adoption that are not confounded with pre–existing individual variations in mental

[1] See discussion in section 3.2.

health.

The remainder of the paper proceeds as follows: Section 3.2 combines the review of related literature and development of our hypotheses. Section 3.3 is concerned with introducing the study's main source of data. Section 3.4 presents the study's modeling and analytical methods. In section 3.5, we discuss the results of our model(s) in detail and offer theoretical and managerial insights. Lastly, the paper concludes in section 3.6.

3.2 Related Work and Hypotheses Development

The discourse surrounding affective constructs in technology adoption traces back to seminal works such as Diffusion of Innovation [410] and the Theory of Reasoned Action [16] in the 1960s. Despite the rich literature, a notable gap persists regarding the exploration of individuals' attitudes towards adoption of new technologies that are explained by their psychological/mental state. Our main goal is to address this gap. We consider individuals' mental health as an indicator of their susceptibility to various mental states (emotions, moods, etc.). Unlike many other technology adoption studies, we do not base our discussion on a single technology adoption theoretical framework. This is because our study is the first to incorporate mental health and other related variables in technology adoption. Our results could be used to enhance our understanding of how mental health relates to technology adoption and potentially lead to developing more comprehensive models (read discussions in section 3.5.5). In this section, we will develop our main hypotheses and justify the choice of each variable using various literature.

First, we introduce the foundation for our hypothesis development. Testing an entire population is impractical and costly. Therefore, statistical hypothesis testing uses samples and allows for possible inference errors [539]. This makes it vital to clarify hypothesis testing terms. Rejecting a hypothesis discredits it, but failing to reject it does not prove the hypothesis or rule out other explanations. Hence, data only yield definitive conclusions when a hypothesis is rejected. To minimize error, researchers often frame hypotheses so that rejecting them supports claims [539]. Our hypothesis testing framework revolves around the null hypothesis (H_0), i.e., the specific hypothesis under test [539]. Rejection of the null hypothesis leads to consideration of

the alternative hypothesis (H_a). The alternative hypothesis represents the key theoretical claim, and the null hypothesis typically negates it. We either reject the null hypothesis in favor of the alternative hypothesis or fail to reject it due to insufficient evidence.

Initially, all hypotheses were framed as null to test for statistical relationships. Following committee feedback, we were asked to revise some into directional hypotheses that align with theory and literature. However, as our study is the first to consider mental health in m-banking adoption, we rarely find precedent for directionality. Furthermore, at times, we find contradictory results across the literature, revealing conflicting theoretical expectations. As a result, some of the alternative hypotheses are non-directional because there is no clear basis for directional predictions. The null hypotheses are kept non-directional to preserve uniform language across the writing.

3.2.1 Mental Health (MH)

In this section, we set the stage for the development of our main hypothesis on mental health. We discuss the study that prompted us to look closer into psychological states. Their unexpected result suggests that pre-existing emotional/psychological states can fundamentally alter how users make technology adoption decisions. This study's findings serve as our main motivation for deciding to address psychological states. Our secondary motivation is based on the results of our first study in this dissertation (Chapter 2) in which we highlighted the lack of focus on certain psychological factors in the m-banking adoption literature. We then discuss why and how we connect psychological states to mental health. Following this, we introduce our underlying framework for defining mental health and justify why it is a good proxy for psychological states. We focus on technology adoption literature to build an understanding of how psychological states influence decision making. Lastly, we use this understanding as the logic behind our first hypothesis and finish the discussion by developing the hypothesis.

A pivotal study by Park *et al* investigated the effects of anxiety on mobile payment (m-pay) adoption, using the Mental Accounting Theory (MAT) framework [384]. According to MAT, individuals engage in a cognitive evaluation process wherein they assess potential economic outcomes, weighing benefits, risks, and uncertainties before making decisions [504]. Surprisingly, Park *et*

al found that anxiety positively influenced the perceived benefits of m-pay, thereby increasing adoption likelihood. These results are in stark contradiction to established norms in the area of technology adoption when anxiety is concerned [528].

We expect anxiety around a technology to be associated with a decrease in its adoption [222]. Park *et al* attributed their surprising outcome to variations in the intensity of anxiety among individuals, a factor they had not accounted for in their study. This counterintuitive result suggests that emotional states, and varying levels of proneness to anxiety, may systematically distort how users mentally evaluate technology options. The results from Park *et al* [384] prompted us to incorporate a measure of susceptibility to various psychological responses and subsequent behavioral choices within the realm of technology adoption. This highlights the importance of considering mental health differences in individuals.

While the study of Park *et al* focuses specifically on anxiety, it raises a broader question: how do pre-existing emotional and psychological conditions alter the mental accounting process described in MAT? Since anxiety is just one form of emotional arousal, it is reasonable to hypothesize that a broader psychological construct (i.e., overall mental health) may also influence technology adoption behaviors. Mental health is a better construct as it captures emotional susceptibility and baseline emotional states. Mental health is not just a synonym for emotions, but a precursor that influences how and which emotions arise [37, 323]. We now define mental health and show that it captures emotional susceptibility and emotional states.

The dual model of mental health, as described by Keyes, posits that mental health and mental illness are not opposite ends of a single continuum but rather exist on separate continua [257]. Keyes' dual model of mental health challenges the common idea that mental health is just the absence of mental illness. Mental illness is when individuals are suffering from psychiatric conditions [438]. The dual model of mental health provides a framework for understanding how overall mental health can influence behaviors, including technology adoption [257]. It emphasizes that mental health is not merely the absence of mental illness but a complete state involving emotional, psychological, and social well-being.

Emotions are the results of neuro-biological activity in the brain [228]. They are temporary states of being, often reflections of thoughts and circumstances, i.e, emotions are short-term responses to stimuli [151]. Moods are longer lasting affective states, different from emotions and unrelated to any immediate triggering stimulus [356]. Therefore, we believe that an overarching concept is needed to consider all such mental states. Mental health is the underlying condition influencing emotional and mood reactivity. Here, we provide substantial evidence for this, thereby justifying the use of mental health as a proxy for pre-existing affective states and susceptibility to emotions/moods.

Mental health is a valid measure of affective states and susceptibility to emotions as it is the precursor to emotions felt by individuals. Being sad (sadness as the emotion) is different from being depressed (depression is a mental illness), but a depressed individual is more likely to *be* sad; i.e., sadness is a symptom of a mental health problem [340]. Keyes defines emotional well-being as a cluster of symptoms that include positive affect (e.g., cheerfulness, satisfaction, and being full of life) and life satisfaction [257]. These affective states are central to the operationalization of mental health, indicating that mental health is inherently tied to the emotions individuals experience.

Individuals with high mental health are filled with positive emotions and function well psychologically and socially [257, 38]. Conversely, those with low mental health experience emptiness and stagnation, which parallels negative emotional states such as hopelessness or despair. This suggests that mental health sets the stage for the types of emotions individuals are likely to feel [324, 257]. Therefore, mental health is an appropriate measure of individuals' mental state because it controls and predicts people's emotional reactions to stimuli and is the precursor to emotional susceptibility [328, 54, 89, 257, 356].

We now discuss how mental health may relate to technology adoption. Mental health is a predictor of functioning [257]. Individuals with high levels of mental health exhibit superior psychosocial functioning, including better emotional health, fewer limitations in daily activities, and higher productivity [257]. These traits may positively influence technology adoption behaviors, as these individuals are better equipped to adapt to change and cope with adversity and may be

more open to engaging with new technologies. This adaptability and resilience are critical for technology adoption, as it often involves overcoming initial challenges and learning curves [494].

Conversely, those with low levels of mental health are associated with significant psychosocial impairments, including poor emotional health, higher limitations in daily activities, and reduced productivity. These impairments could hinder technology adoption behaviors, as these individuals may struggle with the cognitive and emotional demands of learning and using new technologies. Furthermore, overall mental health influences behaviors. Emotional well-being (e.g., satisfaction and positive affect) and positive functioning (e.g., purpose in life, environmental mastery) impact an individual's willingness and ability to adopt new technologies [494].

We now examine the current state of m-banking and broader technology adoption literature to understand how psychological states have been integrated into this discussion. Since no existing studies have directly investigated mental health in this context, we draw on related psychological constructs to inform and guide the development of our hypothesis. Recently, there has been an increase in incorporation of psychological dimensions into the investigation of technology adoption through the study of affective constructs [468, 270].

Thus far, the focus has been on post–consumption positive and negative mental states (positive and negative emotions), for example feeling happy (positive emotion/mental state) as a result of using a new technology [65, 408]. In many consumer research studies the main focus is on loyalty and continued use, thus only the consequences of an emotional response to an experience (use of an app or service) are considered and not how certain emotions arise and what their antecedents are [308]. Emotions arise due to various stimuli and impact individuals' decision on performing a behavior such as technology adoption [403].

An example of a positive emotion (positive mental state) that encourages further use of an application would be: Offering discounts and gifts to consumers makes them feel special and important, thus appreciative towards the business [221]. Mobile banking users who feel appreciative are more likely to continue to use m-banking apps [307]. On the other hand, certain stimuli that result in negative emotions such as anger and frustration, are negative mental states that hinder

m-banking use [396]. An example of such negative emotions arising is adding too many features to an m-banking app which could confuse users, cause accidental misuse, and many other issues. Lyu *et al* argues that the addition of non–core features to m-banking apps leads to "user fatigue", which they show negatively impacts m-banking use [307]. These examples showed how stimuli (gifts, discounts, too many features) cause emotions (appreciation, anger and frustration) that impacts technology use.

Most studies that have explored technology use due to pre–existing emotions and emotional susceptibility have focused on negative usage such as addictive internet use [266, 143, 42]. Liu *et al* shows that Alexithymia (the inability to recognize emotions) and proneness to boredom positively correlate with an addiction to reading fiction novels online [297]. However, no such studies exist in the m-banking domain that discuss the relationship between susceptibility to emotions and pre–existing emotions (not caused by m-banking app use) with m-banking adoption. To fill this gap in knowledge in the m-banking literature, we consider mental health as a proxy to show both the susceptibility to emotions and represent the pre–existing emotional (mental) state of consumers.

We have shown that mental health is a good proxy for pre-existing emotions and a measure of susceptibility to these states. Mental health affects how individuals respond to environmental stimuli, regulate emotions, and make decisions under uncertainty [37, 323] Product adoption literature has confirmed that pre–existing mood biases user attitude and perception associated with a product [120, 540]. To formulate our hypothesis as a directional hypothesis, we consult the available literature on the relationship between pre-existing mood and technology adoption. Here, we note several contradictory findings across the literature that contribute to our formulation of the first alternative hypothesis as a non-directional hypothesis.

Studies show that pre-existing mood and affect bias user attitudes and perceptions [120] and these biases carry over to digital contexts [384]. Myers *et al* showed that individuals with poor mental health (i.e., negative mood) are more critical and have less positive evaluations of brands compared to people with better mental health (i.e., positive mood) [345]. Low, less positive or negative evaluations of a brand are directly correlated with lower adoption and use [395, 152].

Negative affect can directly inhibit action and negatively impact self-efficacy in learning new technology, which may hinder technology adoption [39]. Technology anxiety is identified as a significant antecedent of intention to adopt mobile payment services [523]. Anxiety has a negative and significant effect on the intention to use said technology [222, 433]. In short, these studies support a positive correlation between mental health and technology adoption.

Some studies find a significant negative effect between anxiety and e-banking adoption, while other studies report no relationship between the two [6]. This is an example of a contradiction in the literature. The second contradiction is the change in the direction of the relationship we noted previously. Namely, high anxiety, when combined with strong hope, can actually boost new product adoption, as both are future-oriented and goal-focused emotions [524]. Anticipated sadness, a negative emotion (low mental health score), related to product deprivation can positively influence adoption intentions [523]. These are examples supporting a negative correlation between mental health and technology adoption.

Sadness at other times has a significant negative relationship with the intention to adopt new technology [178]. It is generally said that positive affect positively influences usage intentions, encouraging users to adopt the technology. Conversely, negative affect inhibits usage intentions, potentially deterring adoption. However, users often experience both positive and negative affect simultaneously when evaluating a technology [537]. The presence of mixed emotions implies that technology adoption decisions are more complex than models that consider only positive or negative feelings. Hence, our consideration of mental health is not only valid, but strengthens our understanding of m-banking adoption decisions too.

Depending on how it is framed, fear may be a barrier to or an antecedent of technology adoption. For instance, general fear of or aversion to technology can lead to a reluctance to adopting new technologies [179]. However, Fear of Missing Out (FOMO) is positively linked to adoption of new technology as users are constantly worried about missing out on experiences [171]. As demonstrated, different emotions can influence technology adoption decisions in varied ways. More complex still, combinations of emotions may produce entirely new effects, and individuals

often experience both positive and negative emotions when evaluating a technology [537]. Even the same emotion can have divergent outcomes depending on its context (e.g., fear of technology versus fear of missing out). Thus, it is overly simplistic to assume that positive/negative emotions consistently lead to/deter from technology adoption.

Given the conflicting perspectives discussed thus far, we refrain from stating a directional alternative hypothesis. Our inaugural alternative hypothesis is that there exists an association between mental health outcomes and m-banking adoption. The formulation of our hypotheses closely follows the convention used by Cozzarin and Dimitrov [117]. Our null and alternative hypothesis are as follows:

H1$_0$ The probability of m-banking adoption is independent of an individual's mental health.

H1$_a$ The probability of m-banking adoption depends on an individual's mental health.

3.2.2 Moderators of mental health's association with m-banking

Many factors, both internal (e.g., biological, hereditary, and emotional) and external (e.g., a global pandemic), are known to influence mental health [525]. In this study, we focus on three variables that are either well-established in the mental health literature or highly relevant in the context of smartphone-mediated technology adoption. These are: Relationship Satisfaction (RS), Smartphone Dependency (SD), and Social Networking Site (SNS) usage.

We include relationship satisfaction because research across multiple disciplines has consistently shown its strong correlation with mental health [186, 499, 311]. Satisfying interpersonal relationships can buffer stress, improve emotional regulation, and are often used as indicators of mental well-being. Including relationship satisfaction allows us to capture the role of social support and interpersonal dynamics in moderating the relationship between mental health and technology adoption. In addition, we consider two smartphone-specific constructs: Smartphone Dependency (SD) and Social Networking/Media Site (SNS) usage. The rationale for selecting these two variables is both theoretical and empirical.

Smartphone dependency refers to habitual or compulsive smartphone use and is linked with poorer mental health outcomes such as anxiety, sleep disorders, and depression [399]. Social media usage, while enabling social connection, has also been associated with psychological distress, social comparison, and reduced well-being [31]. These two variables are particularly important in the context of mobile technology (i.e., m-banking), as they reflect the broader behavioral patterns associated with smartphone usage. We include smartphone-specific constructs that are also linked to mental health, as the type of device used for digital activities can influence how people adopt mobile technologies [117].

No prior research has directly investigated how mental health and mobile banking adoption correlate, nor how other factors such as relationship satisfaction, smartphone dependency, or social media usage usage might interact with this relation. This presents a conceptual gap and a methodological challenge. Without precedent, we cannot formulate strong directional alternative hypotheses regarding how these variables might moderate the relationship between mental health and m-banking adoption. Therefore, some of our alternative hypotheses will not be directional. If we find no evidence supporting a directional hypothesis, we posit that a factor moderates the relationship between m-banking and mental health – potentially strengthening, weakening, or altering its direction – without specifying how. We offer a detailed explanation of each construct, describing what it is, how it connects to mental health, and why we expect it to have a moderating effect. This forms the basis for our hypotheses.

Relationship Satisfaction (RS)

The association between relationship satisfaction and mental health has been extensively studied in the psychological literature [418, 165, 227]. Humans are intrinsically social creatures, thus, it is not surprising that loneliness impacts the mental health of people regardless of their age and overall health [393, 189]. Loneliness is the lack of a social support systems; in our context, manifesting as dissatisfaction with one's relationships. Loneliness negatively impacts mental health, i.e., the lonelier a person feels the worse their mental health is going to be [393, 189]. Many studies have explored the impact of social support on mental health in various contexts.

Even though it is argued that having almost any social relationship is considered to be better than none at all [186], not all social relationships have positive impacts on mental health.

Supportive social relationships, which we conceptualize as high relationship satisfaction, improve mental health [186, 470]. On the other hand, dysfunctional or maladaptive relationships or unsupportive social circles significantly impair psychological well–being, leading to increased stress, depression, and anxiety [521]. Research has consistently shown that negative social interactions undermine mental health by exacerbating feelings of loneliness and lowering self–esteem [121, 492, 353]. Therefore, social relationships have the ability to either support or harm mental health of individuals based on their quality. Hence, we use relationship satisfaction to include both qualities (i.e., good and bad social relationships) in our study. Next, we focus on how relationship satisfaction may moderate mental health's association with technology adoption.

Relationship satisfaction may moderate the association between mental health and decision-related constructs such as technology adoption. The logic and empirical support for this moderating effect derive from several areas. Individuals with high relationship satisfaction tend to have stronger emotional support systems, which can buffer the negative effects of poor mental health. This support enhances resilience and helps regulate emotions during decision-making, such as whether to adopt a new technology, making these individuals less likely to act impulsively or avoidantly under stress [248]. Conversely, low relationship satisfaction may leave individuals more vulnerable to the cognitive and emotional challenges associated with poor mental health, potentially leading to maladaptive choices or reluctance to engage with new tools like m-banking [112].

Research also shows that relationship satisfaction can lessen the impact of anxiety, depression, and distress on daily behaviors and coping strategies [376]. Furthermore, satisfaction with the relational aspect of digital therapeutic alliance (e.g., with an app or online therapist) has been shown to boost engagement and outcomes even when initial mental health or technological skepticism is high [160, 278]. This suggests that relational satisfaction, whether offline or online, may strengthen a person's willingness and ability to adopt and sustain use of mobile platforms.

Empirical evidence additionally strengths our position. A study among state park travelers found that variables like emotional well-being, mental health, and life satisfaction all interconnect to shape behavioral intentions, with relational factors moderating these correlations [463]. This underscores the role of relationship satisfaction in either buffering or amplifying the association of mental health with behaviors. Other research corroborates that relationship satisfaction plays a protective role in moderating how mental health and perceived stress translate into performance, engagement, and acceptance of innovations [575]. From a theoretical perspective, the Affective Events Theory (AET) and the Conservation of Resources Theory (CRT) suggest that satisfaction acts as a mediating or moderating factor, determining whether daily stresses or positive/negative mental health states result in productivity and adaptive behaviors, such as technology adoption or informed decision-making [244].

The Affective Events Theory (AET) can support the argument that relationship satisfaction moderates or mediates the relationship between mental health and m-banking adoption by framing interpersonal relationships as sources of affective events that influence emotional well-being and, in turn, behavior. According to AET, both positive and negative events trigger emotional responses that influence individuals' attitudes and behaviors [244]. High relationship satisfaction can buffer negative emotions or enhance positive ones, thereby moderating how mental health translates into behavior. For example, a person with poor mental health but high relationship satisfaction might experience more emotional support and stability, which could reduce avoidance behaviors and promote technology use as a manageable tool. Conversely, low relationship satisfaction might amplify emotional distress, making individuals less likely to engage with new technologies.

The Conservation of Resources Theory (CRT) posits that individuals strive to obtain, retain, and protect resources such as time, emotional stability, and supportive relationships. Stress arises when these resources are threatened or lost, or when investment in them does not yield sufficient return. Using CRT, we argue that relationship satisfaction functions as a resource that may moderate the relationship between mental health and m-banking adoption. Relationship satisfaction can buffer resource depletion associated with poor mental health. Individuals with high relationship satisfaction have access to emotional support, which preserves or replenishes psychological resources. This support can reduce the cognitive and emotional strain associated

with using new technologies. Thus, even if someone has poor mental health (a depleted resource state), high relationship satisfaction can moderate the effect, enabling technology adoption by offering emotional reinforcement, stability, or decision support.

Drawing from our discussion so far and the extensive body of research exploring various social determinants linked to mental health, we posit that relationship satisfaction is an important factor influencing mental health. We have evidence suggesting that relationship satisfaction may act as a buffer between mental health and technology adoption. Our null and alternative hypothesis are as follows:

H2$_0$ Relationship satisfaction does not moderate the association between mental health and m-banking adoption.

H2$_a$ Relationship satisfaction moderates the association between mental health and m-banking adoption, such that the association is weaker in those with higher relationship satisfaction.

Smartphone Dependence (SD)

This factor is a measure of smartphone usage. To clarify what we mean by smartphone dependence, we first look at various ways the same idea has been introduced in the literature. Smartphone addiction typically correlates with extensive use of smartphones [564], which is one way the literature has conceptualized smartphone dependence (excessive usage). This excessive smartphone use is connected to increased risks of depression and anxiety [460]. Excessive use of smartphones impact physical and psychological health in various way. For example, in a study by Shoukat [460] it was found that teenagers use their smartphones the most at night which leads to sleep deprivation, subsequently contributing to physical and mental health issues, including increased anxiety.

Numerous other studies have thoroughly explored the impact of smartphone addiction or excessive use on mental health [454, 34, 535]. High levels of anxiety is one of the most frequently cited mental health outcome of high smartphone dependence across the literature [312, 460, 399]. Especially in the recent years and with the impact of the COVID–19 pandemic on people's smartphone

usage, we deem the addition of this construct to our study essential. Chopdar *et al* [390] argues that COVID-19–related phobia has reshaped people's smartphone usage patterns. Constant and frequent exposure to pandemic–related news negatively affect mental health of individuals. In turn, the heightened anxiety, fear, and concerns about COVID–19 exacerbate smartphone addiction.

The study by Chopdar *et al* is similar to our study in that their goal is to investigate the impact of excessive smartphone usage on online shopping adoption (an effect they prove significant). Because online shopping is a different form of technology adoption than m-banking [19], it is unclear whether the factors that influence online shopping are transferable to our study. Therefore, it is important to consider studies such as Chopdar *et al* with the aim of investigating the significance of factors in various technology adoption settings.

We conceptualize smartphone dependency as a measure of frequency of use of smartphones (the more frequently, the higher dependency). Studies show that problematic smartphone use is associated with greater emotional and cognitive fatigue, stress, anxiety, depression, and even social anxiety, especially when smartphone engagement is compulsive or unregulated [484, 491]. For individuals with poor mental health, excessively checking their smartphones may worsen their symptoms, leading to greater vulnerability and indecision, or maladaptive technology adoption patterns, such as compulsively downloading apps or impulsively engaging with technology platforms [469]. Excessive use of smartphones can lead to cognitive overload (related to mental health) and decision fatigue, thereby it may hinder technology adoption [491].

Literature highlights that excessive smartphone use is both a consequence and a cause of mental health deterioration, and it can intensify (i.e., moderate) the relationship between mental health challenges and subsequent decision-related behaviors [484]. For example, people with anxiety or depression may be more drawn to frequent smartphone checking, which in turn increases cognitive load and distractibility, impeding thoughtful engagement with technology [300]. Those with poorer mental health may use smartphones as a coping mechanism, leading to problematic use that makes them more susceptible to technological stress and decision fatigue [484].

This dynamic has been observed in studies of digital technology addiction among adolescents and

young adults, where high smartphone use was significantly correlated with mental and emotional health problems and hindered positive technology adoption or engagement [459, 262]. Excessive smartphone use can moderate how mental health influences openness to new technologies, willingness to try or engaging with new apps: those with high smartphone usage and poor mental health may be less receptive to technology that is designed to help or may use technology in ways that do not benefit them [60, 218, 531].

Thus far, we have provided evidence supporting the existence of a relationship between smartphone dependency and mental health, however, it remains unclear whether this relationship alters mental health's association with m-banking adoption. Based on our discussion, we expect that excessive smartphone use may amplify the correlation between mental health and m-banking. Our null and alternative hypothesis as follows:

H3$_0$ Smartphone dependency does not moderate the association between mental health and m-banking adoption.

H3$_a$ Smartphone dependency moderates the association between mental health and m-banking adoption, such that the association is stronger in those with higher smartphone dependency.

Social Networking/Social Media Use (SNS)

The m-banking literature has thus far been unable to establish a direct and unequivocal relationship between social media use and m-banking. Most studies in the literature consider social media as a means of communication between banks and consumers. Social media is the most popular platform for m-banking advertisement which directly relate to m-banking adoption [447, 449]. Most studies argue that social media platforms are beneficial to banks by providing easy access to communication channels with consumers especially to advertise for m-banking [449, 212]. However, there have been studies that offer contradictory findings which suggest social media can have negative impacts on m-banking adoption [348].

Naeem and Ozuem interview bank personnel and managers, who offer insights into how social media negatively influences customers: *negative reviews*. Social media provides easy access for people to anonymously share feedback and opinions. Anonymity impacts consumers' emotional expressions and rating behavior in the context of online reviews, where people are more likely to express negative emotions and give lower ratings [131]. Negative reviews are deemed more helpful [416] and more persuasive [101] across the board. Therefore, potential adopters are more likely to be impacted by reading negative comments and sentiments from others, dissuading them from adopting m-banking.

In addition to the direct relationship between social media use and m-banking, we also consider its relationship with mental health. It seems that the most natural deduction is that social media use leads to worsening of mental health due to various factors such as exposure to unrealistic and unattainable standards and comparisons [380]. While that is true, and many other studies have also ascertained as much [412, 255, 387, 31], there have also been studies that discover and illustrate the opposite. The caveat is that it is not always clear whether social media use is associated with better or worsened mental health outcomes.

Some studies suggest that social media use alleviates loneliness leading to better mental health outcomes [500], while others show that spending more time on social media is associated with higher levels of loneliness leading to worsening of mental health [75]. Studies show that passive or negatively appraised use of social media, especially in individuals prone to anxiety or depression, can intensify symptoms, leading to poorer decision quality or maladaptive technology engagement [146]. Conversely, more positive engagement or supportive online communities may buffer adverse effects and support better decision outcomes [488].

When individuals experience positive interactions or beneficial content, the negative link between social media use and (low) mental health weakens or reverses [146, 488]. These contradictory findings mean that we are not able to develop a directional alternative hypothesis on how social media relates to mental health, let alone its subsequent relationship with m-banking adoption. We also note that age and developmental stage significantly moderate how social media influences mental health outcomes [146]. We account for this by including demographic variables in our

model.

Compulsive or information-overloaded social media use can moderate the link between mental health and behaviors like technology adoption [491]. This is a major problem among youth, where social media fatigue is associated with emotional stress and reduced well-being, affecting everyday choices and openness to new technologies [319]. Social media use may moderate the relationship between mental health and technology adoption. However, we argue that this moderation's direction is contingent on several contextual factors, including usage patterns, content exposure, and individual differences in user characteristics.

Drawing on theories of social comparison and social support, we note that social media can act as both a stressor and a buffer in relation to mental well-being, which in turn changes technology engagement decisions. For example, individuals with poor mental health may engage with social media differently – some may experience heightened social anxiety and negative affect from passive browsing, while others may find emotional support and informational resources that promote proactive behavior, such as adopting mobile banking technologies [556, 389, 581, 66].

Therefore, social media use and mental health are not uniform. Our discussion thus far shows the relationship between social media use and mental health. However, the contradictory findings aforementioned stop us from confidently proposing a directional alternative hypothesis. Therefore, our null and alternative hypothesis are:

H4$_0$ Social media use does not moderate the association between mental health and m-banking adoption.

H4$_a$ Social media use moderates the association between mental health and m-banking adoption.

3.3 Data Analysis and Measurements

The dataset used in this study is the Canadian Internet Usage Survey (CIUS), conducted from November 3^{rd}, 2020 to March 3^{rd}, 2021 across Canada [87]. The dataset includes various question on the impact of COVID–19 pandemic on the lives of Canadians and thus effectively reflects the changes brought about due to the pandemic. Given this timeline of data collection, it is important that we acknowledge that our results may be influenced by unaccounted factors such as the ongoing pandemic at the time, which could have impacted participants' responses. This is because the pandemic may have had adverse effects on mental health [554] as well as forcing people to use digital platforms due to various lockdown measures in place [269].

Questions from CIUS are used as model variables. First, we make sure to consider only the subset of participants in the dataset that use a smartphone to connect to the internet. CIUS includes a question on the internet access device: "What device do you use to access the Internet? A smartphone." We use this question to select only those individuals that use a smartphone device, regardless of whether they use other devices or not. The outcome variable is question `UI_Q050D` on CIUS relating to online banking, which measures m-banking after the selection of smartphone users. The question is: "During the past three months, which of the following online activities have you done over the Internet? Conducted m-banking.".

The use of *adoption* is appropriate since the question for m-banking considers a three month long time period. As previously discussed in section 3.1, adoption is a repeated action and not a single point in time. Mobile banking is a binary variable as the responses to this question are Yes (1) for having used m-banking in the last 3 months, and No (0) otherwise. Mental health (`MH`) is measured by the following question on CIUS: "In general, how is your mental health?". The answer choices are: 5 = Excellent, 4 = Very Good, 3 = Good, 2 = Fair and 1 = Poor. We note that while this measurement is simplistic, it aligns with our operationalization of mental health based on Keye's dual model of mental health. As discussed in Section 3.2.1, the dual model of mental health says that mental health and mental illness are not two ends of the same line. Instead, they are two separate concepts that may exist at the same time.

Based on the dual model of mental health, a person can have no mental illness but still feel unhappy, unmotivated, or disconnected. In other words, they may not be mentally healthy (low scores on MH). On the other hand, someone with a diagnosed mental illness (like anxiety or depression) can still experience positive emotions, strong relationships, and a sense of purpose, which are signs of good mental health. This distinction is important because it changes how we think about well-being. In the context of m-banking, this matters because someone with poor mental health is not necessarily clinically ill. We use Keye's dual model of mental health to operationalize MH in a way that goes beyond just mental illnesses, and encapsulate emotions as well. Still, we acknowledge that this measurement is not without its issues and limitations. We will discuss this in the limitations of our study by the end of the chapter.

For relationship satisfaction (RS), we use two questions from the survey: Question TS_Q010A and TS_Q010B: "In general, on a scale from 1 to 5 (where 1 means completely dissatisfied and 5 means completely satisfied), how satisfied are you with the relationships you have with *friends*/*Relatives or Family members, excluding those you live with*?". Answers to the former are scores on Friendship Satisfaction (FRISAT) while answers to the latter are scores on Familial Relationship Satisfaction (FAMSAT), with both having values of $1-5$. Regarding Smartphone Dependency (SD), it is important to recognize that smartphone addiction is described in scholarly works as the compulsive use of smartphone devices [85, 513].

Additionally, we built our hypothesis on the excessive and frequent use of smartphones. To measure SD, we use the following question from CIUS: "In a typical day, how often do you check your smartphone?". The answer choices are: 6 = at least every 5 minutes, 5 = at least every 15 minutes, 4 = at least every 30 minutes, 3 = once every hour, 2 = once/few times a day, and 1 = less than one time per day. While this question does not directly measure excessive smartphone usage, the literature supports the notion that compulsive and frequent checking of smartphone is strongly correlated with high smartphone dependency and excessive use [91, 293, 148, 287].

Social media use (SNS) is measured using the following question: "During the past three months, which of the following activities have you done over the internet? Used Social Networking websites/apps.". The answers are Yes (1) indicating use of social media, and No (0) otherwise.

The data used in this study comes from a secondary source, i.e., the authors were not involved in the survey's design or data collection. Consequently, our measurement of social media use is constrained as we lack information on usage patterns or the specific content users engaged with. Despite this limitation, our analysis in Section 3.2.2 centered on the presence or absence of social media use, rather than the quality or type of usage. While a more nuanced measure incorporating content type and usage behaviors would have enabled deeper insights, we argue that our findings remain valuable and meaningful given the scope of the available data. We summarize the study variables in Table 3.1 by depicting the number of observations for each answer choices of each variable.

Before discussing Table 3.1, it is useful to gain an understanding of the m-banking landscape in Canada. According to Statista Consumer Insights [477], the distribution of banking methods among Canadian bank account holders in 2019 was as follows: 65% primarily conducted banking online via PC or laptops, 53% used mobile devices for m-banking, 48% of Canadians banked in–person, 12% used telephone banking, and 3% utilized other methods. By the last quarter of 2023, these preferences have shifted to the following: 60% of Canadians now primarily use m-banking, 51% use PC or laptops to conduct online banking, 42% bank in–person, 14% rely on telephone banking and 3% use other methods. This underscores a transition in Canadians' primary banking method from online to m-banking within the last few years. Fig 3.1 reflects the changes in banking methods used by Canadians over the years.

The results according to Table 3.1 align with the notion that more Canadian bank account holders use m-banking than not. We observe that $8,965$ Canadians in this survey have used m-banking in the past three months (are m-banking adopters) compared to $1,423$ who have not. In Table 3.2, the mean and standard deviation for each of the variables are depicted. Here, we see that m-banking (a binary variable with values of 0 and 1 for non-m-bankers and m-bankers) has a mean of 0.87, which is close to 1. This means that most individuals in the dataset are m-bankers. Most participants have high scores for `MH`, `FAMSAT` and `FRISAT`; indicating overall positive well-being. The majority of respondents use `SNS` while only a small minority have high `SD` scores.

Table 3.1. Summary of study variables from the CIUS dataset

Variable	# of obs.	Variable	# of obs.
Mobile banking adoption		Social Media Use (SNS)	
1: m-banking adopter	8,965	1: social media user	8,129
0: otherwise	1,423	0: otherwise	2,259
Age Group (AGE)		Smartphone Dependent (SD)	
1: 15–24 years old	620	6: every 5 minutes	219
2: 25–34 years old	1,443	5: every 15 minutes	2,729
3: 35–44 years old	2,016	4: every 30 minutes	2,834
4: 45–54 years old	1,833	3: every hour	2,564
5: 55–64 years old	2,377	2: once or twice	1,494
6: 65+ years old	2,099	1: less than once a day	548
Income Quintile (INC)		Friendship Satisfaction (FRISAT)	
1: <=$44,119	1,647	5: completely satisfied	5,247
2: $44,120 - $75,321	2,119	4: satisfied	3,316
3: $75,322 - $109,431	2,178	3: neutral	1,373
4: $109,432 - $162,799	2,320	2: dissatisfied	298
5: >=$162,800	2,124	1: completely dissatisfied	154
Mental Health (mental health)		Family Relation Satisfaction (FAMSAT)	
5: excellent	2,231	5: completely satisfied	5,280
4: very good	3,540	4: satisfied	3,255
3: good	3,101	3: neutral	1,341
2: fair	1,215	2: dissatisfied	348
1: poor	301	1: completely dissatisfied	164
Education Level (EDU)		Immigration Status (IMM)	
1: high school diploma	2,729	1: Immigrant	1,297
2: some college credits	3,894	0: Non–immigrant	9,091
3: university degree	3,765	Employment Status (EMP)	
Family Type (FAM)		1: Employed	6,610
1: with children < 18	2,939	0: Unemployed	3,778
2: without children < 18	5,014	Gender (SEX)	
3: single person	2,143	1: Female	5,454
4: other	292	0: Male	4,934

To understand the relationship between model variables, the correlation matrix (Fig. 3.2) is examined. Most of the study's variables are significantly correlated with one another with the strongest positive correlation exhibiting between `FAMSAT` and `FRISAT` and the strongest negative correlation between `SD`/`SNS` and `AGE`. People who are highly satisfied in their familial relationships are also highly satisfied in their friendships (the reverse is also true). Additionally, older adults are less dependent on their smartphones and are more likely to not use `SNS`. We add several demographic measures from the data to our models as control variables. According to Fig. 3.2, `FAMSAT` and `FRISAT` are highly correlated. Including highly correlated independent variables in

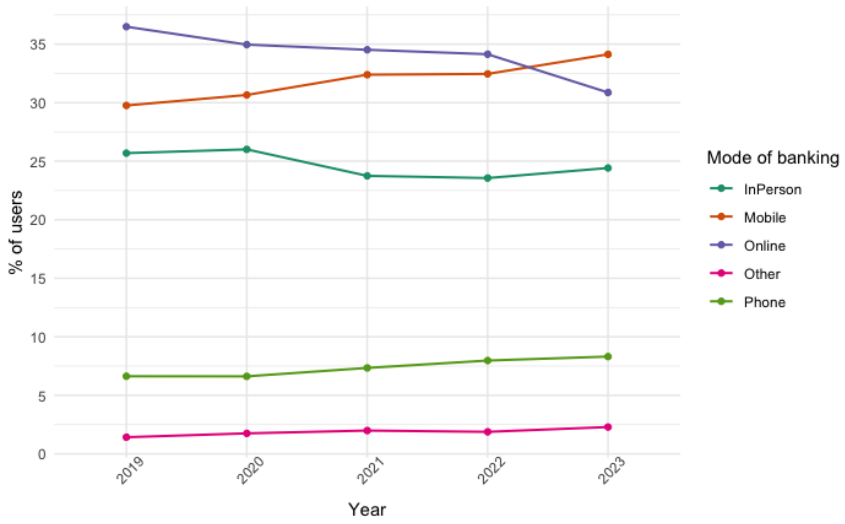


Figure 3.1. Canadian banking methods changes over the years (data from Statista Consumer Insights [477])

Table 3.2. Descriptive Summary Statistics of main model variables

Variable	Abbreviation	Description	Mean	SD
Mobile banking adoption	m-banking	Adopter (1), otherwise (0)	0.87	0.34
Age Group	AGE	age groups (15 and over)	3.98	1.52
Income Quintile	INC	Income quintile according to 2019–2020	3.10	1.37
Education	EDU	Highest level of education obtained	2.10	0.78
Family Type	FAM	Household/family type[1]	1.98	0.78
Immigration Status	IMM	Immigrant (1), otherwise (0)	0.12	0.33
Employment Status	EMP	Employed (1), otherwise (0)	0.64	0.48
Gender	SEX	Female (1), Male (0)	0.53	0.50
Friendship Satisfaction	FRISAT	how satisfied are you with friend relationships?[2]	4.28	0.90
Family Relation Satisfaction	FAMSAT	how satisfied are you with family relationships?[3]	4.27	0.92
Mental Health	MH	In general, how is your mental health?	3.60	1.04
Social Media Use	SNS	user (1), otherwise (0)	0.79	0.41
Smartphone Dependency	SD	Frequency of checking smartphone (/day)[4]	4.39	1.22

Notes: 1: household with children under 18 (1), household without children $<$ 18 (2), single person household (3), other household types (4)

2: On a scale of 1 (completely dissatisfied) to 5 (completely satisfied) how satisfied are you with the relationships with the following people in your life? Friends.

3: On a scale of 1 (completely dissatisfied) to 5 (completely satisfied) how satisfied are you with the relationships with the following people in your life? Family/Relatives.

4: every 5 minutes (6), every 15 minutes (5), every 30 minutes (4), every hour (3), once or twice (2), less than once a day (1).

a model causes multicollinearity issues. `FAMSAT` and `FRISAT` measure similar ideas relating to relationship satisfaction, where the only difference is the type of relationship.

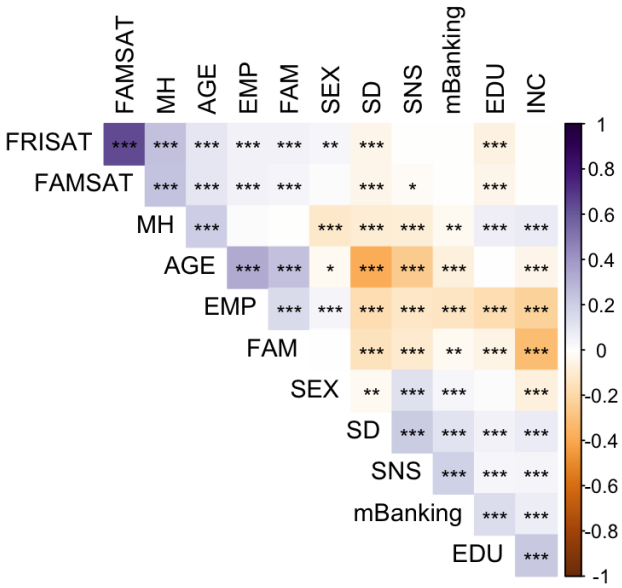


Figure 3.2. Correlation Matrix (p–values: *p<.1; **p<.05; ***p<.01)
Empty cells indicate non–significant correlation

Combining both variables into a single composite variable is strongly recommended rather than omitting either or both from the model [188]. Thus, we add the values of `FAMSAT` and `FRISAT` together and present this summation in a new variable called Relationship Satisfaction (`RS`). Recall that `FAMSAT` and `FRISAT` take values of $1-5$ where a 1 indicates extreme dissatisfaction with the relationship and 5 extreme satisfaction. Following this, `RS` ranges from $2-10$, where higher `RS` indicates higher relationship satisfaction. We test the validity of `RS` as the first step of our analysis, explained in detail in the next section.

3.4 Methodology and Model

We use logistic regression to test the hypotheses introduced in section 3.2. To decide on the exact model to fit the data, we follow three sequential steps: First, following the discussion on the composite variable `RS` from the previous section, to ensure that `RS` captures the essential information and the shared variance from `FAMSAT` and `FRISAT`, we run two versions of the same standard logistic regression model. The result of this step is a decision between having `FAMSAT`

and FRISAT in the model or having RS in the model. Next, we choose a best approach to modeling from three different logistic regression models: standard logistic regression, and two versions of a mixed effect logistic regression model: fixed and random effect models.

From this analysis, we obtain the most optimal modeling approach, resulting in a singular, superior logistic regression model. In the last step, we run the best model with and without interaction terms to test the hypotheses. The results from the model without interactions and with interaction in tandem are used to test **H1**, while the results from the modeling with interactions are used for testing **H2, H3, H4**: The interaction term between MH and RS informs our decision on **H2**, the interaction term between MH and SD is used to test **H3**, and the interaction term between MH and SNS aids with the decision on **H4**. Before discussing the methodology in detail, we briefly note that considering MH, RS and SD as numeric variables instead of categorical does not produce unreliable results. This is because we are not interested in predictions nor accuracy of the model, but simply testing hypotheses regarding associations of variables [184].

3.4.1 Variable Selection

The study's outcome variable, m-banking adoption, is binary and presented as $\mathbf{Y} \in \{0,1\}$ where 1 indicates m-banking adoption (m-banking use within the last 3 months), and 0 otherwise. In the previous section, we explained the reason for considering a composite variable (RS). To validate the robustness of our approach using RS (instead of FAMSAT and FRISAT), we built two models: First, a model with RS as one of the independent variables and no FAMSAT and FRISAT. We name this model *M_RS* for easier reference later. Second, a model with FAMSAT and FRISAT as two of the independent variables (and no RS), named *M_FSAT* for reference. For comparisons, we only consider the standard logistic regression model. For simplicity, we only use the M_RS model's mathematical formula for the remainder of this section. The mathematical representation of the M_RS model is as follows [2]:

$$\ln \frac{P(\mathbf{Y}=1)}{1-P(\mathrm{Y}=1)} = \beta_0 + \beta_1\,\mathtt{MH} + \beta_2\,\mathtt{SD} + \beta_3\,\mathscr{D}_{\mathtt{SNS}_0} + \beta_4\,\mathtt{AGE} + \beta_5\,\mathscr{D}_{\mathtt{SEX}_1} \tag{3.1}$$

[2]Full equation of M_FSAT is available in the Appendix B.2, eq B.1

$$+ \beta_6 \mathscr{D}_{\texttt{EMP}_0} + \beta_7 \texttt{EDU} + \beta_8 \texttt{INC} + \beta_9 \mathscr{D}_{\texttt{FAM}_1} + \beta_{10} \mathscr{D}_{\texttt{FAM}_3}$$
$$+ \beta_{11} \mathscr{D}_{\texttt{FAM}_4} + \beta_{12} \mathscr{D}_{\texttt{IMM}_1} + \beta_{13} \texttt{RS} + \varepsilon$$

Where the β's are regression coefficients (in log odds) of the independent variables, ε is the error term, and $\mathscr{D}$ is the dummy variable generated for categorical variables. $\mathscr{D}_{IV_t}$ is the dummy variable for independent variable IV where the level is t, for example, $\mathscr{D}_{\texttt{SNS}_0}$ is the dummy variable of $\texttt{SNS} = 0$. We verify the robustness of using RS as opposed to FAMSAT and FRISAT by comparing M_RS (eq 3.1) and M_FSAT (eq B.1) using the Likelihood Ratio (LR) test [357]. The LR test compares the fit of these models to test the null hypothesis that the two models are the same. If the LR test shows a significant difference between the two models, we consider the fixed effects model to be a better model as it captures more information about the outcome variable by considering groupings.

3.4.2 Modeling Approach

Based on an initial exploratory data analysis, detailed in the appendix (Tables B.1 and B.2), we observe provincial variations in m-banking adoption across Canada. A visualization of the differences between provinces in terms of probability of m-banking adoption in Fig. 3.3 shows overlap for mental health scores across the provinces for the most part with the exception of NL. Additionally but separately, we see variations in provinces' m-banking adoption behavior (Fig. B.1 in the appendix). This stems from the sampling methodology employed by Statistics Canada, which organizes data by provincial clusters [87].

We do not rely solely on visualizations for inference; nevertheless, we think it is crucial to incorporate the observed variation into our modeling approach to at least test for whether these variations are significant. We do this by comparing three distinct modeling approaches: one that discards both variations (standard logistic regression model), one that includes the province on m-banking variation (fixed effect logistic regression model) and one that includes that province variations in the relationship between mental health and m-banking (random effect logistic regression model).

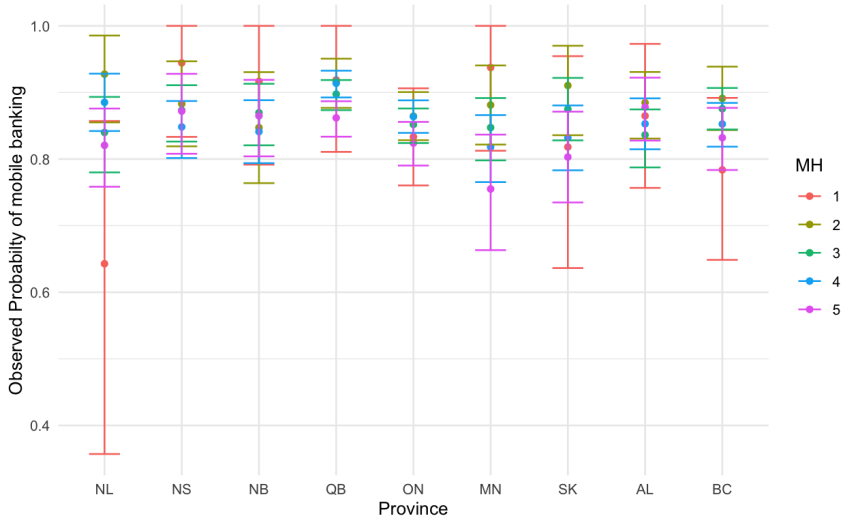


Figure 3.3. Probability of m-banking across different provinces

In the first model, we hypothesize that there is no significant inter–provincial variation in the relationship of any model variables with m-banking adoption. Consequently, this model does not account for provincial differences, assuming uniformity across all variables (standard logistic regression presented in eq 3.1). The second model posits that provincial variations directly influence m-banking adoption, but do not interact with other variables. This model is a mixed effect logistic regression with fixed effects for all independent variables and a random effect term only for the intercept. We mathematically formulate this model as follows:

$$\begin{aligned}\ln\frac{P(\mathbf{Y}=1)}{1-P(\mathrm{Y}=1)} = {} & \gamma_{0,j}+u_{0,j}+\beta_1\,\mathtt{MH}+\beta_2\,\mathtt{SD}+\beta_3\,\mathscr{D}_{\mathtt{SNS}_0}+\beta_4\,\mathtt{AGE}+\beta_5\,\mathscr{D}_{\mathtt{SEX}_1} \\ & +\beta_6\,\mathscr{D}_{\mathtt{EMP}_0}+\beta_7\,\mathtt{EDU}+\beta_8\,\mathtt{INC}+\beta_9\,\mathscr{D}_{\mathtt{FAM}_1}+\beta_{10}\,\mathscr{D}_{\mathtt{FAM}_3} \\ & +\beta_{11}\,\mathscr{D}_{\mathtt{FAM}_4}+\beta_{12}\,\mathscr{D}_{\mathtt{IMM}_1}+\beta_{13}\,\mathtt{RS}+\varepsilon\end{aligned} \tag{3.2}$$

Where index j is for the provinces in the data: Alberta (AB), British Columbia (BC), Manitoba (MB), New Brunswick (NB), Newfoundland and Labrador (NL), Nova Scotia (NS), Ontario (ON), Quebec (QC) and Saskatchewan (SK). In eq 3.2, the intercept coefficient in eq 3.1 is replaced by the following: $\gamma_{0,j}+u_{0,j}$ and that is the only difference between the two models. The constant $\gamma_{0,j}$ is the fixed effect component, and $u_{0,j}$ is the random effect where $u \sim \mathrm{N}(0,\sigma^2)$ and is estimated

differently for each of the provinces.

The third model assumes significant inter–provincial differences in both the coefficient of independent variables on m-banking adoption and the differences in m-banking adoption itself. Again, we treat province as a grouping variable with substantial variation impacting both the decisions surrounding m-banking adoption and the influence of independent variables on it. Similar to the fixed effect model, we utilize a mixed effect logistic regression, but add a random effect term to independent variables and the intercept. We use a similar notation to eq 3.2 and construct the following for the last modeling approach:

$$\begin{aligned}\ln \frac{P(\mathbf{Y}=1)}{1-P(\mathrm{Y}=1)} = {} & \gamma_{0,0}+u_{0,j}+(\gamma_{1,0}+u_{1,j})\,\mathtt{MH}+(\gamma_{2,0}+u_{2,j})\,\mathtt{SD}+(\gamma_{3,0}+u_{3,j})\,\mathscr{D}_{\mathtt{SNS}_0} \\ & +(\gamma_{4,0}+u_{4,j})\,\mathtt{AGE}+(\gamma_{5,0}+u_{5,j})\,\mathscr{D}_{\mathtt{SEX}_1}+(\gamma_{6,0}+u_{6,j})\,\mathscr{D}_{\mathtt{EMP}_0} \\ & +(\gamma_{7,0}+u_{7,j})\,\mathtt{EDU}+(\gamma_{8,0}+u_{8,j})\,\mathtt{INC}+(\gamma_{9,0}+u_{9,j})\,\mathscr{D}_{\mathtt{FAM}_1} \\ & +(\gamma_{10,0}+u_{10,j})\,\mathscr{D}_{\mathtt{FAM}_3}+(\gamma_{11,0}+u_{11,j})\,\mathscr{D}_{\mathtt{FAM}_4} \\ & +(\gamma_{12,0}+u_{12,j})\,\mathscr{D}_{\mathtt{IMM}_1}+(\gamma_{13,0}+u_{13,j})\,\mathtt{RS}+\varepsilon\end{aligned} \tag{3.3}$$

The intercept term in eq 3.3 includes the fixed component of all independent variables, indicated by $\gamma_{i,j}$ for the ith independent variable and jth province. The coefficient estimates dependent on the grouping variable (province) where $u_{i,j}$ is the random effect of independent variable i on m-banking adoption for province j. To decide on the best model, we first compare model of eq 3.2 with eq 3.1 using the LR test introduced previously. If the result from LR test shows a significant difference between the two models, we consider the fixed effects model to be a better model as it captures more information about the outcome variable by considering coefficient of province (as a grouping variable) on m-banking adoption.

Next, to decide whether the addition of random effects to independent variables (eq 3.3) improves upon the fixed model, we use the Hausman test [206]. We test the following null hypothesis using Hausman: adding random effects to the fixed model is beneficial. The Hausman null hypothesis states that unique errors (individual effects) are not correlated with independent variables. For

both the Hausman and LR test, we report the χ^2 statistic. Under the null hypothesis, estimates are the same, therefore the test is based on the following contrast vector [187]:

$$H = [\mathbf{B}_{fix} - \mathbf{B}_{ran}]'[\mathbf{V}(\mathbf{B}_{ran}) - \mathbf{V}(\mathbf{B}_{fix})]^{-1}[\mathbf{B}_{fix} - \mathbf{B}_{ran}] \sim \chi^2_k$$

Where k is the number of independent variables in the model, $\mathbf{B}_{fix}$ is the matrix of coefficients in the fixed model, $\mathbf{B}_{ran}$ is the matrix of coefficients in the random model, and $\mathbf{V}$ is the variance–covariance matrix.

3.4.3 Hypothesis Testing

By this point in the analysis, we have chosen a best model to fit the data. What is left is to run the model and analyze the results. The goal is to test the study hypotheses discussed in section 3.2. To do so, we run the best model twice. The results of both runs are depicted in Table 3.4. First, we run the best model as is, with no interaction terms to test **H1**: the association between mental health and m-banking adoption. Second, we add the interaction terms: MH $\times$ RS, MH $\times$ SD and MH $\times$ SNS. Each interaction term provides the necessary information for our hypothesis testing.

By analyzing the coefficient estimate of MH $\times$ RS, we test **H2**: whether the correlation between MH and m-banking adoption is moderated by RS. Using the coefficient estimate of MH $\times$ SD we test **H3**: whether the correlation between MH and m-banking adoption is moderated by SD. Lastly, the interaction term coefficient estimate for MH $\times$ SNS is used to test **H4**: whether the correlation between MH and m-banking adoption is moderated by SNS. The addition of interaction terms are to assess the change in the relationship between MH and m-banking adoption (log likelihood) across different values of RS, SD and SNS.

3.5 Results and Discussion

In this section, we discuss the results of our analysis. All values reported in Tables are log odds ratios (LOR). For easier communication, understanding and interpretation, we also represent odds ratios (OR) in text, which are simply e^{LOR}. It is important to note that this study utilizes

a cross-sectional research design and a secondary dataset. Therefore, the analysis can identify associations between variables but cannot establish causal relationships. Furthermore, our results are perhaps influenced by other factors not directly measured or considered, such as the ongoing pandemic.

The language used in the interpretation of the results will reflect the correlational nature (by strongly avoiding causal interpretations). Additionally, we are cautious not to interpret our results as generalized statements due to several limitations previously discussed in Section 3.3. Moreover, while our models include several control variables, these variables may not fully capture the nuanced characteristics of individuals in the population. It is possible that the observed results are driven by unmeasured factors that have not been considered. Therefore, we are cautious in interpreting the results which are based on what this particular data provides us.

3.5.1 Model Selection

Following the discussion from section 3.4, we present the results of model comparison for both LR and Hausman tests for various tasks in Table 3.3. M_FSAT includes both FRISAT and FAMSAT while model M_RS includes only RS. According to the LR test's result, RS captures the same information as FRISAT and FAMSAT. Thus its use in the model as a substitute is warranted. The results indicate that the fixed model (eq 3.2) is preferred over standard logistic regression and random effects model (eq 3.3). Thus, the best model is M_FIX (eq 3.2) which will be referred to as the study's model from here onward. Adding the interaction terms for hypotheses testing, the model with interaction terms is as follows:

$$\begin{aligned}\ln\frac{P(\mathbf{Y}=1)}{1-P(\mathrm{Y}=1)} = {} & \gamma_{0,j} + u_{0,j} + \beta_1\,\mathtt{MH} + \beta_2\,\mathtt{SD} + \beta_3\,\mathscr{D}_{\mathtt{SNS}_0} + \beta_4\,\mathtt{AGE} + \beta_5\,\mathscr{D}_{\mathtt{SEX}_1} \\ & + \beta_6\,\mathscr{D}_{\mathtt{EMP}_0} + \beta_7\,\mathtt{EDU} + \beta_8\,\mathtt{INC} + \beta_9\,\mathscr{D}_{\mathtt{FAM}_1} \\ & + \beta_{10}\,\mathscr{D}_{\mathtt{FAM}_3} + \beta_{11}\,\mathscr{D}_{\mathtt{FAM}_4} + \beta_{12}\,\mathscr{D}_{\mathtt{IMM}_1} + \beta_{13}\,\mathtt{RS} \\ & + \beta_{14}\,\mathtt{RS}\times\mathtt{MH} + \beta_{15}\,\mathtt{SD}\times\mathtt{MH} + \beta_{16}\,\mathscr{D}_{\mathtt{SNS}_0}\times\mathtt{MH} + \varepsilon\end{aligned} \tag{3.4}$$

Table 3.3. Model Comparisons using LR test and Hausman test

Model(s)	Description	χ^2_{LR}	Pr($>\chi^2_{LR}$)	χ^2_H	Pr($>\chi^2_H$)
M_FSAT (eq. 3.1)	Standard Model with FRISAT & FAMSAT	0.055	0.815	—	—
M_RS (eq. 3.1)	Standard Model with RS ✓				
M_RS (eq. 3.1)	Standard Model with RS	22.549	$< .001^{***}$	—	—
M_FIX (eq. 3.2)	Mixed (Fixed) Effects Model ✓				
M_RAN (eq. 3.3)	Mixed (Random) Effects Model	—	—	−0.054	$< .001^{***}$
M_FIX (eq. 3.2)	Mixed (Fixed) Effects Model ✓				
Notes:	*p<.1; **p<.05; ***p<.01	✓indicates the model is preferred.			

3.5.2 Fixed Effects Logistic Regression

Table 3.4 depicts the results of fixed effect logistic regression modeling to test our hypotheses. We run the model once without including any interaction terms (mathematical formulation in eq 3.2), and once including the following interaction terms: MH × RS, MH × SD and MH × SNS (mathematical formula eq 3.4). Starting with the results for the without interaction term model, we observe that a 1 scale point increase in scores of MH (towards better mental health outcomes) is associated with statistically significant lower log odds of m-banking adoption (-0.083, OR $= 0.920$).

This corresponds to an 8% decrease in likelihood of m-banking adoption for people with better mental health. In $\mathbf{H1}_0$, we hypothesized that MH is not correlated with (log odds of) m-banking adoption. Based on the results, we reject $\mathbf{H1}_0$. According to the data, individuals with better mental health are less likely to adopt m-banking.

Table 3.4. Fixed effects Logistic Regression Results — outcome variable: *m-banking(yes/no)* to test Hypotheses **H1** (w/o interaction), **H2** (MH×RS), **H3** (MH×SD) and **H4** (MH×SNS)

Variable	Description	Model	
		w/o interaction	including interaction
		Coeff./s.e.	Coeff./s.e.
_cons	intercept	2.592^{***}	2.592^{***}
		(0.086)	(0.086)
MH	Mental Health	-0.083^{***}	-0.121^{***}
		(0.031)	(0.038)
SD	Smartphone Dependency	0.182^{***}	0.181^{***}
		(0.028)	(0.028)
SNS	Indicator Variable (IV) = 1 if non user	-0.969^{***}	-0.985^{***}
		(0.066)	(0.066)
RS	Relationship Satisfaction	0.025	0.025
		(0.018)	(0.019)
AGE	Age Group	0.025	0.026
		(0.024)	(0.025)
SEX	IV = 1 if Male	-0.110^{*}	-0.109^{*}
		(0.061)	(0.061)
EMP	IV = 1 if Unemployed	-0.566^{***}	-0.566^{***}
		(0.065)	(0.065)
EDU	Highest Education obtained	0.495^{***}	0.495^{***}
		(0.040)	(0.040)
FAM	IV = 1 if FAM= with children < 18	-0.219^{***}	-0.217^{***}
		(0.082)	(0.082)
FAM	IV = 1 if FAM= single household	−0.057	−0.056
		(0.081)	(0.081)
FAM	IV = 1 if FAM= other	0.040	0.038
		(0.194)	(0.194)
IMM	IV = 1 if immigrant	-0.245^{**}	-0.242^{**}

Continued on next page →

Variable	Description	Model	
		w/o interaction	including interaction
		Coeff./s.e.	Coeff./s.e.
		(0.095)	(0.095)
INC	Income	0.044*	0.043*
		(0.025)	(0.025)
RS × MH			0.001
			(0.016)
SD × MH			0.017
			(0.024)
SNS × MH	IV= 1 if non-user		0.122*
			(0.063)
Group Level Effects			
σ(intercept)		0.148	0.148
95% confidence interval		[0.081, 0.279]	[0.081, 0.279]
logLik		−3790.1	−3788.2
BIC		7718	7742
Notes:	*p<.1; **p<.05; ***p<.01		

We see a significant increase in log odds of m-banking adoption with a one unique increase in SD (OR = 1.200). This corresponds to a 20% increase in likelihood of m-banking adoption for a 1 point increase in smartphone dependence scores. Those with a higher smartphone dependence have higher likelihood of m-banking adoption.

With SNS, we observe that non users are statistically significantly less likely (OR = 0.380) to adopt m-banking. This means that non social media users are just over 6% less likely compared to SNS users to adopt m-banking. RS has a negligible, positive and non–significant relationship with m-banking adoption (OR = 1.025, $p = 0.182$), which aligns with our expectations based on Fig. 3.2, where we saw a non–significant correlation between RS and m-banking adoption ($r = -0.01$, $p = 0.364$). Age has a similar non significant ($p = 0.307$) relationship with m-banking adoption to RS. Men are less likely than women to adopt m-banking, but this difference is

non–significant (OR $= 0.895$, $p = 0.071$).

Individuals who are unemployed are significantly less likely than those who have jobs to adopt m-banking (OR $= 0.568$). In other words, those without jobs are 43% less likely to adopt m-banking compared to those who are employed. Interestingly, income is slightly positively (log odds of 0.044) and non–significantly related to m-banking adoption (OR $= 1.045$, $p = 0.079$). For family types, the reference level is FAM $= 2$, which corresponds to families without children under 18. Individuals from families with children (under the age of 18, FAM $= 1$) are statistically significantly less likely to adopt m-banking (OR $= 0.803$) compared to those without children. However, the difference between single households (FAM $= 3$) and other household types (FAM $= 4$) with families without children is non–significant.

Considering the family types, it appears that children under 18 are a dividing factor in m-banking adoption. Both singles and families with children are less likely to adopt m-banking compared to FAM $= 2$ (family without a child under 18), while other household types (FAM $= 4$) are more likely to adopt m-banking compared to FAM $= 2$ [3]. One reason for the significant difference between FAM $= 1$ and FAM $= 2$ might be due to the fact that the respondents in the FAM $= 1$ group are in fact the children between $15-18$ years old, as CIUS is administered to persons over the age of 15. When we consider the interaction between MH and RS in model 6, we observe no changes to the model performance. The interaction term of MH and RS has no significant association with m-banking adoption (OR $= 1.000$, $p = 0.993$).

In $\mathbf{H2}_0$, we hypothesized that RS does not moderate the link between MH and (log odds of) m-banking adoption. Based on the results of the addition of the interaction between RS and MH, we observe that a unit increase in mental health outcome behaves the same regardless of the level of RS (log odds of RS $\times$ MH $= 0.001$, $p = 0.975$). Since there is no significant difference in MH's relationship with m-banking adoption we fail to reject $\mathbf{H2}_0$. In $\mathbf{H3}_0$, we hypothesized that SD does not moderate the link between MH and (log odds of) m-banking adoption.

When considering the interaction between SD and MH, we observe a larger correlation com-

[3] StatsCan offers no further explanation or examples on what exactly constitutes "other household type".

pared to the MH's interaction with RS (log odds of SD $\times$ MH $= 0.017$) but this coefficient is not significant ($p = 0.487$). Therefore, we do not have sufficient evidence to reject $\mathbf{H3}_0$. Lastly, we consider the interaction of SNS and MH. Since SNS is a binary variable (0: does not use social media, 1: uses social media), the interaction term at each level will have the same absolute value with a different sign. That is, for non social media users, the correlation between mental health and m-banking is stronger (log odds $= 0.122$) than for social media users.

The interaction term for SNS and MH is positive for non SNS users (OR $= 1.130$), but not statistically significant at the 5% level ($p = 0.053$). The change in the log odds of mental health from -0.083 to -0.121 between the two models (OR $= 0.920$ to OR $= 0.886$) is mostly due to the SNS $\times$ MH interaction term ($0.122 > 0.017 > 0.001$). However, we are not interested in the significance of this difference, because there is no change in the direction of the relationship (sign remains negative from one model to the next). Additionally, this difference is merely 4% (0.038 in log odds).

In the model without interactions, a 1 point increase in mental health scores is associated with an 8% decrease in likelihood of m-banking adoption (log odds $= -0.083$). Considering the interactions, a 1 point increase in mental health scores is associated with 12% decrease in likelihood of m-banking adoption, a stronger negative relationship. Compared to SNS users, non SNS users are less likely to adopt m-banking (log odds $= -0.985$, OR $= 0.374$). In other words, the likelihood of m-banking adoption is expected to significantly decrease by about 60% for non social media users (compared to users) holding all else constant.

Compared to those that do not use social media, SNS users are statistically significantly more likely to adopt m-banking (log odds $= 0.985$, OR $= 2.677$). That is, the probability of an SNS user also adopting m-banking is 0.728 or a 73% chance of a social media user adopting m-banking. For $\mathbf{H4}_0$, we hypothesized that SNS does not moderate the link between MH and (log odds of) m-banking adoption. That is, regardless of whether or not an individual uses SNS, mental health's association with m-banking adoption remains the same. Based on the results of the regression analysis, we do not have sufficient evidence to reject $\mathbf{H4}_0$.

3.5.3 Average Marginal Effects

According to our model, the average log odds of m-banking adoption across Canada is 2.59, i.e, people across the country are more inclined to adopt m-banking than not. However, only less than 1% of the variance in m-banking adoption is explained at the group level (Intra-Cluster Correlations (ICC) = 0.007). The standard deviations reported at the group level in Table 3.4 indicate the deviations in logistic regression slopes for the particular variable across groups. In our model, this is only the intercept variation, which is the variation between provinces in terms of m-banking adoption likelihood. Numerical analysis from Table 3.4 shows that there is a statistically significant difference between the provinces in terms of m-banking adoption as the confidence interval for standard deviation of intercept (m-banking) at the group level does not include zero (0.081 to 0.279). Thus, we calculate the average marginal effect of all the independent variable in our model according to the grouping to better understand m-banking adoption.

Table 3.5 depicts the marginal effects of model variables across provinces on m-banking. Marginal effect is the change in log odds of m-banking that is expected for when an individual matching the attribute is added to the population. For example, an individual identifying as male, regardless of which province they live in, will on average have 0.012 lower log odds of adopting m-banking than women (this is not statistically significant, $p = 0.079$). Summarizing the statistically significant marginal effects we have: On average, those with better mental health outcomes are less likely to adopt m-banking.

Those who have higher smartphone dependence are more likely to adopt m-banking, while non social media users are less likely than `SNS` users to adopt m-banking. Having higher levels of education is associated with higher likelihood of m-banking adoption. Compared to those without children, households with children are less likely to adopt m-banking. Unemployed (compared to employed), and non–immigrants (compared to immigrants) are all, on average, less likely to adopt m-banking.

Table 3.5. Average Marginal Effects for Mixed Effects Logistic Regression

Variable	Margin	S.E.	z	Pr(z)	95% CI
MH	−0.009	0.003	−2.570	0.010	[−0.015, −0.002]
RS	0.003	0.002	1.325	0.185	[−0.001, 0.007]
SD	0.020	0.003	6.365	0.000	[0.014, 0.026]
SNS (ref: 1) = 0	−0.127	0.011	−12.002	0.000	[−0.147, −0.106]
AGE	0.003	0.003	1.083	0.279	[−0.002, 0.008]
EDU	0.054	0.005	11.552	0.000	[0.045, 0.063]
EMP (ref: 1) = 0	−0.064	0.008	−8.109	0.000	[−0.080, −0.049]
FAM (ref: 2) = 1	−0.024	0.009	−2.565	0.010	[−0.043, −0.006]
FAM (ref: 2) = 3	−0.006	0.009	−0.673	0.501	[−0.023, 0.011]
FAM (ref: 2) = 4	0.004	0.020	0.200	0.841	[−0.035, 0.043]
IMM (ref: 0) = 1	−0.028	0.012	−2.394	0.017	[−0.050, −0.005]
INC	0.005	0.003	1.747	0.081	[−0.001, 0.010]
SEX (ref: F) =M	−0.012	0.007	−1.759	0.079	[−0.025, 0.001]

3.5.4 Discussions and Limitations

The results of our hypothesis testing are summarized in text and in Table 3.6. In general, mental health scores are significantly correlated with m-banking adoption likelihood. According to our data we observe that those with better mental health outcomes are less likely to adopt m-banking apps. We failed to find sufficient evidence in our dataset to show that relationship satisfaction, smartphone dependency and social media use moderate the link between mental health and m-banking adoption outcome. That is, mental health's relationship with m-banking adoption remains consistent across different levels of relationship satisfaction, smartphone dependency and social media use.

We acknowledge that our findings should be interpreted with caution, as methodological limitations and contextual factors may offer alternative explanations for the observed associations. Specifically, the following may have influenced our results:

1. **Construct Validity and Measurement Error:** As previously noted, the CIUS 2020 dataset is a secondary data source not tailored to the specific goals of our study. Several variables

rely on single-item proxies – for example, mental health is used as a stand-in for pre-existing emotional states and affective susceptibility, while smartphone dependency is approximated by the frequency of checking one's device in a day. While we have sufficiently addressed (using the literature) that these variables are fair proxies, we also acknowledge the limitation of using them. For example, our measure of smartphone dependency may conflate brief, habitual actions (like checking notifications) with more sustained usage patterns.

The use of proxies may introduce systematic bias as well. For instance, someone who checks their phone frequently might do so briefly (e.g., glancing at notifications), which does not reflect actual dependency or problematic use. This misalignment may distort the relationship between smartphone dependency, mental health and m-banking adoption. Similarly, a single-item measure of mental health might not distinguish between chronic low mental health and temporary emotional discomfort, potentially overstating or understating its influence on m-banking adoption. Lastly, all measures are based on self-reported survey responses, which are subject to bias and misinterpretations. Such measurement issues may have contributed to the results as well, creating spurious correlations or masking true moderating effects.

2. **Confounding Variables and External Context:** Another plausible explanation for our findings is the influence of unmeasured confounding factors – most notably, the COVID-19 pandemic. The dataset was collected during a period of significant social disruption, which could have simultaneously impacted individuals' mental health and their likelihood of adopting m-banking. Heightened psychological distress due to isolation and health concerns may have increased emotional vulnerability. Additionally, the lockdown during the pandemic may have forced individuals to adopt m-banking. In situations of forced adoption of technology, users may experience discomfort, anxiety, and frustration, which may negatively influence users' adoption behavior and mental health outcomes alike [152]. This could falsely inflate/deflate the observed association between mental health and m-banking adoption, making the pandemic a possible underlying cause of the relationship we report.

Table 3.6. Summary of Hypotheses Testing Results

Hypothesis	Hypothesis Statement	Result
$\mathbf{H1}_0$	The probability of m-banking adoption is independent of an individual's mental health state.	Reject
$\mathbf{H2}_0$	Relationship satisfaction does not moderate the association between mental health and m-banking adoption.	×
$\mathbf{H3}_0$	Smartphone dependency does not moderate the association between mental health and m-banking adoption.	×
$\mathbf{H4}_0$	Social media use does not moderate the association between mental health and m-banking adoption.	×

Notes: ×: Cannot Reject

Despite the limitations of our study, we find evidence from various disciplines that support our results. According to the Information Communication Technology (ICT) literature, digital divide (sometimes called digital inequality) is one of the major issues of the information technology era [422]. This is the gap in digital literacy due to unequal access to technology, information and resources such as education for use of technology [565]. Technology adoption is moderated by information literacy and digital skills [565], and digital literacy is an important factor in m-banking adoption [519]. Our results align with some components of digital divide. We highlight this connection to show support for our findings. Education is proven to be a key socioeconomic factor of innovation adoption in general [565]. In addition to relating to digital divide, education is also related to financial literacy [536], thereby strengthening its importance in studying m-banking.

In the realm of ICT, research has shown that immigrants are more likely to adopt and use new technologies driven by their need to communicate with friends and family back home [9, 64, 8]. Unemployment is significantly associated with a higher likelihood of being un–banked [185]. Hence, it's understandable that unemployed individuals exhibit lower m-banking adoption likelihood, given their higher likelihood of lacking bank accounts in the first place. Older adults are more likely to not use social media [543] and less likely to be dependent on smartphones; However, smartphone dependency is an issue among older adults as well [555]. Many previous studies have investigated the relationship between age, mental health, digital divide and technology adoption [341, 377, 161].

Older people have better mental health outcomes compared to younger people [115], but many researchers are hesitant to claim this is a significant relationship because older adults are more likely to under–report mental health problems [306]. Additionally, age is another indicators of digital divide [474], which might explain why non social media users (who are more likely to be older) are less likely to adopt m-banking while those who are more dependent on their smartphones (who are more likely to be younger) are more likely to adopt m-banking. There could be various reasons for the significant difference in m-banking adoption likelihood we observe between households with and without children.

One explanation is that individuals from households with children under 18 are less likely to adopt m-banking due to security concerns. Parents may be cautious about using an m-banking application because their children have access to their devices. Another reason might be the existence of joint bank accounts or more complex financial arrangements such as mortgage payments and setting up accounts for children for future which would require in-person visits to banks. Next, we discuss the implications of these results in theory and practice.

3.5.5 Managerial and Theoretical Insights

Here, we offer several recommendations to banks and managers according to our results. These practical suggestions would hopefully result in increased accessibility of products as well as increased productivity of users. This will improve consumers' satisfaction related to m-banking products. First, we address the implication of our first hypothesis result, where our data shows that those with poor mental health outcomes are more likely to adopt m-banking. We re-iterate that based on the dual model of mental health, mental health and mental illness are separate but highly related notions.

Despite being conceptually distinct, it is useful to consider the various mental health challenges that contribute to poor mental health outcomes such as sadness, low mood, and languishing [257]. This is because these emotional states directly influence user behavior, risk perception, and technology preferences as we will outline in this section. Understanding these underlying

psychological dynamics enables us to derive both theoretical and managerial insights from our findings. From a theoretical standpoint, these results support models that emphasize the role of emotional states in technology adoption. From a managerial perspective, they suggest practical strategies for designing digital banking tools that accommodate users with varying emotional and psychological needs.

While our main result may seem surprising, we find that it is indeed supported by various studies in psychology. Certain mental health challenges prompt individuals to seek m-banking as opposed to traditional in–person banking to avoid various undesirable outcomes, depending on the specific cases. To clarify this, we focus on three mental health challenges: social anxiety, Attention Deficit Hyperactivity Disorder (ADHD) and general anxiety disorder. We consider social anxiety as an example to show how our **H1** result is supported by literature. Those with social anxiety prefer neutral, distant or anonymous relationships with businesses [130, 285]. A smartphone application such as m-banking fits all of these criteria. Socially anxious individuals are apprehensive about interacting with strangers or have a fear of verbal interactions with strangers [434, 314, 79].

A smartphone app that replaces the need to interact with people becomes an alternative that people with various anxiety types (social, general, and others) gravitate towards and benefit from [401]. These support the idea that those with social anxiety – who experience higher instances of low mood (low mental health scores [400]) – are more likely to adopt m-banking apps. However, social anxiety is just one example of mental health challenges. There are various other underlying mental health challenges that would yield similar results. This result has significant implications for banks. By using our results, banks expand their consumer base. One way to do so is by targeted advertising campaigns or the integration of tailored strategies within m-banking applications.

By demonstrating that banks are aware of the challenges facing those with mental health conditions, banks stand to enhance consumer engagement and trust. An important aspect of technology adoption is the User Experience (UX) paradigm [216]. Hence, it becomes imperative for banks to enhance their applications, ensuring optimal UX for users across the board, but especially those with specific mental health challenges. These enhancements do not need to be elaborate; rather,

simple feature implementations that signal banks' awareness of the struggles these individuals face can be efficacious.

We offer two practical examples of such feature implementations: Individuals with ADHD face challenges with understanding bank statements, banking protocols, evaluating financial problems and overall financial competence [56]. Designing applications that are specifically tailored to accommodate the needs of individuals with ADHD, while simultaneously benefiting a broader user base is one way that banks could use our study's results. Drawing from expert recommendations, applications that incorporate clear and easily understandable educational resources, timely reminders, and minimalist design elements to reduce distractions are best suited for those with ADHD [532]. A user-friendly app conducive to concentration and task completion enhances the experience for individuals with ADHD, making them more likely to become long term users. Another example feature to implement is regarding stress-induced decision-making tendencies which are exacerbated in individuals with high levels of anxiety such as those with general anxiety disorder.

Financial decisions are highly stressful [548], therefore features that are included to stop stress-based reactive decisions are likely to be useful to everyone, but in particular to those with a proneness to anxiety. These individuals tend to make risky decisions at times of heightened stress [407]. Banks could implement a protection feature in their app with this knowledge in mind, advertising this to consumers. This protection could be by way of adding a pop-up box message that asks the user for confirmation of a transaction twice before finalizing the transaction.

Such a (protection) step where an action is delayed helps reduce the influence of anxiety and negative affects on decisions [424], directly benefiting the consumers. By implementing these strategies, banks show support and understanding for consumers that face such challenges on a daily basis. Businesses that support individuals with mental health problems can expect greater costumer satisfaction in return [443, 318, 271, 211]. Knowing what to advertise and to whom makes advertisement campaigns more effective, and cheaper to plan for and run.

We now move on to other results of the study. We showed that social media use is associ-

ated with m-banking adoption, but does not moderate the relationship between mental health and m-banking adoption. Specifically, we found social median users (compared to those who do not use social media) are more likely to adopt m-banking. This result offers valuable insights to banks. Using social media as a primary advertisement platform will reach those individuals who are shown to be more likely to adopt m-banking. Therefore, social media marketing is an excellent avenue of investment if banks want to attract new m-banking costumers.

We showed how several demographic factors affect m-banking adoption: More educated individuals, those without children and immigrants are more likely to adopt m-banking. Neither of the results regarding education and immigration are surprising, as they aligns with the consensus from the ICT literature. For family types, more studies need to be conducted to specify the exact reason for the differences. However, security concerns are a major contributing factor to decisions against adoption of m-banking (more on this later), therefore justifying the results for families with young children. Banks and financial institutions are able to use these results to understand the demographic that is more likely to become m-banking adopters, simplifying and focusing their advertisement strategies.

We now discuss the theoretical contributions of our study. Our study's finding can be interpreted through the lens of the Theory of Planned Behavior (TPB), which posits that an individual's intention to perform a behavior is shaped by three core components: attitude toward the behavior, subjective norms, and perceived behavioral control [14]. As mentioned before, for individuals with social anxiety or other mental health challenges, traditional banking environments may present psychological barriers such as fear of judgment, stress from face-to-face interactions, or general discomfort in social settings [401]. These barriers reduce their perceived control over performing in-person banking. Mobile banking, by contrast, minimizes social interaction, offers greater privacy, and allows users to engage at their own pace. This digital format can enhance the individual's perceived behavioral control by removing the situational pressures associated with physical banking. As a result, those with poorer mental health may perceive m-banking as a more manageable and accessible alternative, thereby increasing their intention to adopt it.

We contribute to the literature by showing how mental health relates to m-banking adoption,

thus improving our understanding of users' mobile banking adoption decisions. We demonstrated how social media use and smartphone dependency directly correlate with m-banking adoption, but failed to show significant moderating effects on mental health's and m-banking adoption's correlation. We did not find sufficient evidence on the relationship between relationship satisfaction and m-banking nor a moderating effect on mental health and m-banking's correlation.

Our results help researchers better understand why some affective constructs (anxiety, joy, etc) are important in technology adoption, specifically, m-banking. Theoreticians may use our discussions and results to develop models that incorporate mental well-being in the discussions of technology adoption to capture consumer decision-making more accurately and potentially developing new theories and models. The results of this study can be extended to other technologies and theories, however, some adjustments are required. To extend the results of this study, two major considerations are needed:

Firstly, it should be noted that financial decisions are stressful decision-making processes [153]. Disability and mental illness play important roles in financial health [202]. As such, studying behavioral and affective factors that relate to attitude and well-being are important in the context of technologies related to finance such as in our study (m-banking). Studying mental health, which is a proxy encompassing various affective constructs, in relation to financial technology is important and necessary. We clarify why this is the case.

Mobile banking adoption is a behavioral decision paradigm [192, 429]. Behavior changes influence (behavioral) decision–making [453, 321]. Mental health factors are integrated into many behavioral change models [280, 195, 175, 77]. This is because mental health conditions significantly impact an individual's mood and emotions [208]. In turn, these changes in mood(s) and emotional state(s) influence people's behavior [229]. Implementing this logic, we conclude that as a behavioral decision, m-banking is related to behavior changes. Moreover, mental health is closely related and indicative of behavior changes. Therefore, there is a clear relationship (mediated by behavior changes) between mental health and m-banking adoption. Behavior change is a broad term that might encompass anything having to do with behaviors that influence mental well-being of an individual, such as social media use. Previous studies have confirmed the association of

mental health conditions and consumer behavior [338, 82]. This discussion highlights the importance of considering mental health of the users in relation to m-banking and strengthens our results.

The second consideration for extending this study is about the risks associated with the specific technology. The majority of the risks associated with m-banking apps are related to security [164]. One of the most important factors in not using mobile technologies (especially those related to finances) is attributed to anxiety, often presented as security concerns [309, 193, 169, 7, 237, 26, 288, 277, 123]. Technologies that deal with sensitive information such as finances are more likely to induce anxiety due to security concerns. This is part of why our study is focused on m-banking and an affective construct such as mental health (which inherently includes anxiety and proneness to anxiety on an individual-level). Social Media Usage is another factor that is included in our study which relates to both security concerns and mental health [144, 172].

All in all, we content that while this study can be extended to understand other mobile technology adoption problems, one needs to carefully consider all dimensions of the specific application (technology). Other studies about technologies that have similar aspects such as anxiety and security concerns, might be able to extend the results of this study.

3.6 Conclusion

This study investigates the relationship between users' mental health and adoption of m-banking. Additionally, we explore the potential moderating influences of other constructs on this association. Drawing on foundational Information Systems theories, we select key variables for our model, including affective constructs related to social well-being (relationship satisfaction) and smartphone use patterns, particularly smartphone dependency and social media use. Hypotheses corresponding to these variables were tested using logistic regression models. Our findings show a significant association between mental health and m-banking adoption. However, we found that social media use, smartphone dependency and relationship satisfaction do not moderate the above mentioned relationship. These findings suggest implications for banks and managers to prioritize consumers' mental health in application design, advertising, and promotional strategies, as well

as underscore the importance of considering customers' demographics and backgrounds.

This study offers several noteworthy contributions to existing literature. Firstly, it pioneers the investigation of mental health in the context of m-banking adoption. Secondly, it examines various variables related to mental health and its implications for m-banking adoption, thereby enhancing our understanding of this phenomenon. Financial institutions can leverage these findings to target demographics more inclined towards m-banking adoption in their promotional endeavors and optimize their m-banking application and advertising strategies accordingly. Consumers benefit from improved m-banking apps tailored to their constraints and preferences.

Our study is limited in several ways. First, the construct validity of our primary variable is a concern. The dataset used is based on the results of the Canadian Internet Usage Survey. In this dataset, a single self-reported item is used to measure mental health, where the distinction between answer choices like is ambiguous and lacks clinical validation. The scale used in the CIUS lacks a clear midpoint, potentially leading to ambiguity in participants' responses. Our results may therefore be an artifact of this measurement rather than a true underlying relationship. Future research endeavors should employ more robust measurement tools, such as tailored questionnaires designed to assess mental health accurately, thereby strengthening analytical outcomes.

Second, this survey was collected between November 2020 and March 2021, during a critical phase of the COVID-19 pandemic in Canada. This event is a major confounding variable; it simultaneously exacerbated psychological distress in the population and dramatically increased the need for remote, contactless technologies like m-banking. Therefore, the correlation we observe might be spurious, with the pandemic being the unobserved cause of both variables. Due to the rapid changes especially in the context of technology adoption in the post COVID–19 word, we recommend future researchers use data that captures the behavior in the post–Covid world to better represent the current state of m-banking adoption. Lastly, our dataset captures only Canadian m-banking users' behaviors. Due to this geographical limitation, our results may not be generalizable to other countries that are significantly different from Canada. These limitations underscore the need for future research using validated, multi-item psychological scales and longitudinal data from a post-pandemic period.

Chapter 4

The Device Divide

The Device Divide: Unpacking Mobile Banking Adoption Differences for Smartphones and Smart Wearable Devices

4.1 Introduction

The global financial services industry has been transformed by mobile banking (m-banking). As mobile devices become essential, m-banking has grown rapidly as a convenient option. The COVID-19 pandemic accelerated this trend, with consumers relying on smartphones for contactless banking [517]. By 2024, m-banking became Canada's most popular banking method [477]. Smartwatches have gained importance in m-banking, offering contactless banking options [173]. Since COVID-19, adoption of smart wearable devices like smartwatches has steadily increased [94], creating both opportunities and challenges for m-banking providers. Their small size, accessibility, and integration with other tech could reshape consumer interaction with financial services. Therefore, understanding user behavior with these devices is essential.

Contactless payments such as using credit cards for online purchases and near field communication (NFC) payments for offline purchases, reduce the discomfort of spending money, known as the pain of payment [402, 78]. Smartwatch-enabled contactless payments have particularly

low perceived pain of payment, which significantly encourages overspending [78]. Despite their convenience, smartwatches face challenges like small screens, which can be harder to use [574], security risks (e.g., theft, accidental swipes, or impersonation during authentication) [483], and limited capabilities like short battery life [420].

There is little research on how device choice relates to m-banking adoption, defined as early-stage usage (e.g., first three months). A search in Scopus and Web of Science found no studies comparing smartphones and smart wearables in this context. Even beyond m-banking, comparative studies on these devices are scarce. Only two relevant studies in the past five years were found: Van Til *et al* [527] compared mobile apps and wearable health monitors for bipolar disorder, while Stopher *et al* [481] examined smartphone apps versus GPS loggers. Device choice influences technology use and behavior. Cozzarin and Dimitrov [117] found that perceived risks differ between Personal Computers (PC) and mobile devices in online shopping. Users who perceive higher risks are less likely to shop online. While PC users slightly reduce purchases due to risk, mobile users show a sharper decline, showing higher sensitivity to risks [117]. This highlights security risks are a greater barrier in m-commerce than PC-based e-commerce. We aim to apply a similar comparative study in terms of m-banking adoption between smartphone and smart wearable users.

This research is significant for both theory and practice. Understanding how device type relates to adoption helps financial institutions improve user experiences and engagement. We analyze survey data with over $10,000$ records using a logistic regression model. Our hypotheses, grounded in literature, examine how device type changes the association of perceived trust, perceived security, time-saving (benefits), and demographic factors like age, education, income, and gender with m-banking adoption. Unlike previous studies with small sample sizes under $1,000$, our research offers statistically significant insights into m-banking behaviors across diverse demographics and two major mobile device types.

The remainder of this paper is structured as follows: Section 4.2 outlines the basis for model building and hypothesis development. Section 4.3 introduces the dataset and user profiles for smartphone and smart wearable users. Section 4.4 details our modeling approach. Section 4.5

presents the model results across different scenarios. Section 4.6 discusses the findings and their implications. Finally, Section 4.7 concludes the paper.

4.2 Hypothesis Development

The device used to access a service determines technology adoption decisions [440, 74]. Our study examines how mobile devices relate to m-banking adoption, focusing on pocket-sized devices with Operating System (OS) specific m-banking apps: smartphones and smart wearable devices. Five Canadian banks' m-banking app information was manually gathered using iOS App Store to see their compatibility with different devices. The choice of the banks was straightforward: these were the first five apps that appeared when searching iOS app store for "banking". We observed that all five m-banking apps were Apple watch compatible and even included screenshots of the app on the watch. Detailed app features are available in the Appendix C, Tables C.1 and C.2.

The literature on m-banking primarily focuses on smartphones, identifying various factors in consumers' adoption decisions. Smart wearable devices are gaining attention in healthcare and mobile payments, however, to the best of our knowledge, no studies compare their use to smartphones in m-banking. This study is the first to address this gap. Given the limited research specific to wearable devices, we often derive insights by drawing on technology adoption studies from other fields, such as healthcare. Most factors influencing adoption in other areas also apply to m-banking, provided they are not context-specific [235, 58].

In this section, we consult the technology adoption literature (at times from other fields but mainly focusing on m-banking adoption) to construct a conceptual model of m-banking adoption. To do this, we choose 3 main factors often cited as significant in relation to m-banking adoption: *Perceived Trust*, *Perceived Security*, and *Time-saving Benefits*. Additionally, we include discussions on demographic variables such as *Age*, *Gender*, *Education* and *Income*. These variables control for individual-level differences as well as serve as important factors that are often included in technology adoption models. For each factor in the model, we first present a discussion defining the scope of the factor in the literature. By doing this, we lay the foundation to introduce the data and our measurements later in Section 4.3.

Next, we expand our discussion by including theoretical frameworks that include each of the factors. This clarifies the way theory explains how these factors interact with technology adoption decisions and as a result, what we expect to see in our model outcome. Lastly, we formulate assertions concerning the populations of smartphone users and smartwearable users related to each factor. These conjectures are our statistical hypotheses. Before we start our discussion on each factor, we set the stage for the hypothesis development.

Without examining the entire population (i.e., a task often deemed impossible or too expensive and impractical), it is not possible to discern the validity (i.e., truth or falsity) of a statistical hypothesis [539]. Therefore, any hypothesis testing procedure must account for the risk of making an incorrect inference. In statistics, the terminology surrounding hypothesis testing is critical and warrants clarification. Rejecting a hypothesis typically serves to effectively discredit it. Conversely, failing to reject a hypothesis does not confirm its validity or eliminate alternative explanations. Thus, data only yield a definitive conclusion when a hypothesis is actively rejected.

The way a hypothesis is formally stated often reflects concerns about minimizing the likelihood of error. When researchers aim to substantiate a claim, they often frame it so that rejecting the hypothesis would support their position [539]. In our context, to argue that one demographic group is more likely to adopt m-banking than another, the hypothesis tested would posit no difference between the groups' behaviors. Rejection of this hypothesis would then lend support to the claim that a difference exists. The framework for hypothesis testing is built around the concept of the null hypothesis, denoted as H_0, which refers to the specific hypothesis being tested [539].

If the null hypothesis is rejected, this leads to the consideration of an alternative hypothesis (often denoted as H_1 or H_a). Understanding the distinct roles of the null hypothesis and the alternative hypothesis is essential for grasping the foundational principles of hypothesis testing. Typically, H_a expresses the core question or theoretical claim being evaluated, making its formulation a critical step. Conversely, H_0 is structured to oppose or negate H_a, often serving as its logical complement. Analysis reaches one of two possible conclusions: either we reject the null hypothesis in support of the alternative hypothesis based on sufficient evidence, or we fail

to reject the null hypothesis due to a lack of compelling evidence. It is important to note that the conclusion is never a direct or literal acceptance of H_0. Instead, the null hypothesis often represents the current state of understanding or the "status quo," while the alternative hypothesis suggests a novel idea or proposition. Thus, failing to reject H_0 is the appropriate conclusion when evidence does not adequately support the alternative.

Initially, all hypotheses were framed as null hypotheses to test for the existence of any statistical relationship. In the revised draft of this dissertation and as per comments from committee, some have been reformulated as directional hypotheses (e.g., "X is greater than Y") to better align with theoretical expectations. However, to keep a consistent flow in language used, the null hypotheses remain directionless. This does not present any inconsistencies because if the alternative hypothesis is that "X is greater than Y", then the null hypothesis of "X is equal to Y" is a logical complement.

We note that not all alternative hypotheses are directional. Due to the limited number of studies on smart wearable devices particularly in the realm of financial services, in cases where no clear precedent or evidence existed, we framed the hypotheses as differences without specifying a direction (e.g., "X differs from Y"). This approach ensures that the hypotheses align with existing knowledge where available, while remaining cautious and unbiased where it is not. In the discussions of results, we avoid using language that insinuates accepting a hypothesis.

4.2.1 Perceived Trust

Trust in technology adoption literature refers to the user's willingness to be vulnerable to the actions of a technological system or those who design, operate, and maintain it [480]. In the context of m-banking, trust is the user's confidence in a bank's honesty and service quality [362]. In this way, trust is rooted in the actual qualities or proven reliability of the technology – such as system performance, security, and accuracy [480]. Trust may also be influenced by the user's prior experiences, reputation of the technology provider, or institutional assurances [24].

In the technology adoption literature, notions of trust are often discussed in terms of perceived

trust. We consider trust and perceived trust as separate constructs. Perceived trust is the subjective belief or impression that users form about a technological system's trustworthiness, regardless of whether that trust is objectively warranted [568]. That is, perceived trust is an individual's perception or judgment, not necessarily aligned with the actual trustworthiness of the system. This measure is often recorded using self-reported surveys or questionnaires assessing how much a user believes they can rely on or feel comfortable with a system [57, 335]. This aligns with the available data in our project and our measurement, discussed in Section 4.3.

Similar to trust, perceived trust is also strongly influenced by interface design, branding, transparency, and communication [335]. However, unlike with trust, personal biases, even in the absence of direct proof of reliability also influence perceived trust [335]. Many technology adoption models focus on perceived trust because what matters for adoption is how trustworthy users think a technology is – not just how trustworthy it actually is [374]. Particularly in financial technology adoption literature, perceived trust is noted as a significant predictor of adoption intention, even when objective evidence of trustworthiness is limited [568].

Defining perceived trust is inherently complex as it encompasses multiple dimensions and levels and can relate to perceived trust in the technology, the vendor, the brand, or even the broader environment [177]. Perceived trust is often conceptualized as belief in both the provider (institution) and the technology itself [268, 264]. Scholars in Information Systems and Psychology have long debated whether perceived trust refers to a stable disposition, a context-specific perception, or a dynamic state that evolves over time [326]. In the context of m-banking, perceived trust may refer to perceptions of trust in the institution offering the service (e.g., a bank), the technology platform itself (e.g., the app or operating system), or even the device through which the service is accessed (e.g., smartphone vs. smart wearable device).

This conceptual ambiguity makes perceived trust a challenging construct to define and measure consistently. To avoid conflating multiple forms of trust, we adopt a more focused approach here. Specifically, we define perceived trust as the user's perceived trust in the financial institution that provides the m-banking service, i.e., the bank. This operationalization aligns with how perceived trust is typically measured in the literature as well [507, 264, 430, 106]. This way of

measuring perceived trust ensures consistency across device types. The reason this is important is because measuring perceived trust in smartphones versus perceived trust in smartwatches would reflect differences in devices themselves.

By focusing on perceived trust in the institution, we can more meaningfully explore whether different user groups perceive the same source of trust differently. This would reveal insights into user behavior or device influence. Since both smartphone and smart wearable users interact with the same institutional entity (i.e., the bank), isolating institutional trust allows us to attribute any observed differences in adoption behavior to characteristics of the device type that are shaping these perceptions, rather than the object itself. By holding the source of trust constant, we aim to examine whether the relationship between perceived institutional trust and m-banking adoption is different depending on the device through which users access the service. In essence, the question becomes: is perceived trust associated differently with m-banking usage depending on whether the user accesses it through a smartphone or a smart wearable?

To develop the first hypothesis based on perceived trust, we look at the literature and assess the theoretical structure of previous studies. Various studies in technology adoption literature have established perceived trust (and/or trust) as pivotal factors influencing consumer decisions [98, 302, 573]. In m-banking adoption where users entrust sensitive financial information to digital platforms, the importance of perceived trust becomes even more critical [397, 61, 174, 344, 498]. From a theoretical perspective, several technology adoption theories have integrated measure of trust into their conceptual models.

Many studies extend the original Technology Acceptance Model (TAM) to include trust as an additional factor for explaining technology adoption, especially in contexts like digital banking, mobile payment services, and e-commerce [30, 106]. In such studies, it is shown that perceived trust positively influences attitude toward using the system, which then affects the behavioral intention to adopt it [81, 23]. Perceived trust is also modeled as having a direct relationship with intention to use and sometimes with actual usage, separate from perceived usefulness and perceived ease of use of a system [275]. Perceived trust is also integrated into TAM as a moderator between behavioral intention and actual use, i.e., higher perceived trust strengthens the

link between intention and actual adoption or as a mediator between perceived ease of use and adoption behavior [125].

Another important theory that has been extended with the notion of trust is the Unified Theory of Acceptance and Use of Technology (UTAUT) [30, 507, 194, 557]. Alalwan *et al.* demonstrated that including a trust component significantly improved the predictive accuracy of the UTAUT2 model for behavioral intention [25]. Initial Trust Model (ITM) is specifically designed around the concept of trust in technology adoption [448, 2, 298]. Similar to TAM and UTAUT, the Theory of Planned Behavior (TPB) has been extended with perceived trust as a factor [557]. Perceived trust emerges as a key factor influencing adoption decisions in studies on wearable devices as well [29, 61, 98, 142, 207, 214, 304, 397].

As we've shown here, it is widely acknowledged that perceived trust is a crucial factor influencing technology adoption, especially in uncertain and risky environments like financial transactions and emerging technologies. Therefore, both theoretically and empirically, perceived trust is an important factor in technology adoption. Despite its importance, however, no previous research has looked at whether perceived trust (in institutions) is associated differently with m-banking adoption for smartphone users and smart wearable users.

As this study is the first to directly compare smartphone and smart wearable devices in the context of m-banking, there is currently no existing research to guide a directional hypothesis. However, based on the discussion thus far, we hypothesize that because the user groups are fundamentally different and the devices themselves serve distinct functions, the way individuals perceive trust also differs between the two groups of smartphone and smart wearable users. It's important to clarify that we are not comparing the same individuals using two different devices. These are two entirely separate subsets of the population.

Smartphone users rely on their devices as primary tools for sensitive tasks. Smartphones store more personal data (e.g., photo gallery) and are used for conducting secure transactions with more built-in controls [132]. In contrast, smart wearables are typically secondary devices used for convenience, carrying less personal data but potentially more vulnerable to accidental information

leakage (e.g., theft or loss). These differences highlight that the devices are not just functionally distinct, but they reflect different user needs and behaviors too. Still, we do not claim to know exactly how these distinctions shape the relationship between perceived trust and m-banking adoption. What we argue is that, given the clear contrast between both the devices and the users, it is reasonable to expect that their perceptions of trust and how this perception correlates with m-banking adoption may also be distinct.

Therefore, our first alternative hypothesis is that the association between perceived trust and m-banking adoption differs between smartphone and smart wearable users. The formulation of our non-directional null hypotheses closely follows the convention used by Cozzarin and Dimitrov [117]. As discussed in Section 4.2, we will primarily focus on the null formulation of a hypothesis. Our null and alternative hypothesis on perceived trust are as follows:

H1$_0$ The association between perceived trust and the probability of adopting m-banking does not differ between smartphone and smart wearable users.

H1$_a$ The association between perceived trust and the probability of adopting m-banking differs between smartphone and smart wearable users.

4.2.2 Perceived Security

Having concerns about an app's security remains one of the most frequently reported barriers to m-banking adoption [7, 26, 194]. Security threats such as malware and phishing attacks lower the Perceived Security (PSEC) of services, deterring users from adopting m-banking platforms [123]. Security vulnerabilities exacerbate these concerns, impacting adoption [237]. Data handling and storage are important aspects of the overall security of the app perceived by users which impact service adoption [169, 237]. Perceptions of security are shaped not only by app features but also by user characteristics and experiences. Studies have highlighted that technical literacy and awareness shape how secure users perceive m-banking systems to be [273, 288].

Perceptions of security for a mobile banking app are shaped by a combination of technolog-

ical features, user experience, psychological factors, and external influences. The most influential aspect shaping users' trust is the perceived strength of the app's security features, such as encryption, two-factor authentication, and regular security updates [45]. Users' perception of data security is directly linked to their adoption decisions [551]. An aspect of security features of apps that is often overlooked is their ease of use. Complex security processes that are difficult to navigate may actually deter users from adoption [490]. Transparent and timely communication on app updates and potential threats positive shape perceptions of app's overall security [551].

Peer opinions expressed via reviews on app stores, social media, and word of mouth can heavily affect perceptions as well [365]. Similarly, news and media reports about attacks, vulnerabilities and breaches associated with the app or the bank may damage perceptions of security [44]. Apps perceived to provide users with meaningful control over their privacy settings that clearly inform users about how their data is handled, foster greater Perceived Security [18]. Factors such as education level, age, and prior experience with digital technology affect perceived security [490]. Our inclusion of demographic variables will control for this relationship in the model. Perceived security in terms of its risk is not only a barrier but also a critical determinant in technology acceptance models and theories.

Technology Acceptance Model (TAM) and its extensions have been widely used to integrate perceived security to understand behavioral intentions of technology adoptoin [462]. Technology Readiness and Acceptance Model (TRAM) incorporates *insecurity* as an inhibitory factor of technology readiness, which includes skepticism about technology's performance. This insecurity is closely related to perceived security concerns [265]. The Unified Theories of Acceptance and Use of Technology (UTAUT) model is another well-verified theoretical framework in technology adoption context that is often extended to incorporate security-related constructs like perceived security to investigate customer behavioural intentions [384, 259, 368].

The UTAUT model has also been used in studies examining technology adoption, where emotion-related factors, including deterrence emotions like anxiety and fear (which can be triggered by perceived threats and a lack of control over consequences) are considered in relation to effort expectancy and social influence, thereby impacting behavioural intention [6]. This implicitly links

to security concerns as a source of threat. Perceived security risks are frequently cited as one of the factors influencing smartphone m-banking adoption [61, 98, 174, 397, 561, 394, 495].

For smart wearable devices, perceived security is similarly shown to influence adoption decisions [142, 352, 207]. Security perceptions vary by individual and user groups [437]. However, devices and apps may also have varying features that address security aspects differently [462]. Smartphones typically offer more control over security settings like authentication, which allows smartphone users to be more proactive in addressing risks [32]. In contrast, wearable users worry less about security often due to device limitations [283]. Even when linked to smartphones, wearable devices' security largely depends on the primary device, limiting their independent protection [566].

These differences in the capabilities of devices lead us to believe that there are differences in which users in the two different groups' perceived security is associated with m-banking adoption. Since our discussion points to lower importance and emphasis put on security by smart wearable users, we hypothesize that the same should be observed in our dataset. Thus, our alternative hypothesis is that the association between perceived security and m-banking is weaker in smart wearable users than it is for smartphone users. Our null and alternative hypothesis on perceived security are as follows:

H2$_0$. The association between perceived security and the probability of adopting m-banking does not differ between smartphone and smart wearable users.

H2$_a$. The association between perceived security and m-banking adoption is weaker for smart wearable users than for smartphone users.

4.2.3 Time-saving Benefits

The literature on mobile banking adoption consistently identifies time-saving as a critical factor influencing people's decisions to adopt m-banking [86]. Many studies frame time-saving under the broader concept of convenience, efficiency and the removal of spatial and temporal constraints

[109, 100, 264]. Convenience and time-efficient aspects of m-banking highlight how users see this tool as a way to conduct transactions faster and at any time or location [511, 445, 510]. This reduction in time spent and as a result, in effort, is often among the reasons for adoption of m-banking [86]. Users prioritize features that allow them to avoid visiting bank branches or waiting in queues in order to save time [579].

While not exactly presented as time-saving, convenience is often equated with time-saving in the context of technology adoption. Many technology platforms and digital services are adopted precisely because they save users time. For instance, platform-based business models in sectors like banking, e-commerce, and logistics are designed to reduce transaction steps, automate processes, and deliver faster outcomes [428, 48]. This time-saving is consistently identified as a core competitive advantage of these platforms; it enhances user experience and is a decisive factor in adoption decisions [431].

Major technology adoption frameworks, such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), routinely include factors relating to convenience [205]. In TAM, both constructs of perceived usefulness and perceived ease of use include considerations around convenience and time-saving [431]. Technologies that allow users to accomplish more in less time are seen as more convenient and are more rapidly accepted by users. Mobile banking services are widely preferred due to their ability to provide around-the-clock access, eliminate the need for physical branch visits, and allow transactions to be completed quickly and easily [431].

In various studies, performance expectancy (an element of UTAUT) is operationalized as how helpful, quick, and task-efficient users find m-banking [180, 273, 5]. Performance expectancy reflects the improved efficiency and convenience derived from using mobile payment, which inherently includes time-saving [433]. Effort expectancy, another UTAUT factor, also relates to the ease of learning and skillfully using m-banking, implying less time and effort expended [109]. The relative advantage factor in Innovation Diffusion Theory (IDT) directly accounts for time-saving benefits of technology [445].

Mobile banking's ability to offer services regardless of time and place or being free from temporal and spatial restrictions provides a clear advantage over traditional banking, thereby accelerating its adoption [282]. Within the Decomposed Theory of Planned Behaviour (DTPB) framework, time-saving is often an underlying component of attitude towards usage of technology. The benefits that align with an individual's lifestyle and improve performance, including time efficiency, contribute to a positive attitude towards m-banking [439].

The importance of time-saving is not limited to any specific geography or group either. Research spanning different global contexts (e.g., Uganda, Bangladesh, India, Nepal) finds that convenience in terms of access and time-saving has a significant positive effect on adoption intentions [279]. Studies note that this factor is particularly crucial in developing countries, where banking infrastructure may be limited, amplifying the appeal of services that save time [451]. While perceived security and perceived trust are also influential, literature shows that time-saving – especially the ability to bank without space and time limitations – is often what initially attracts users and maintains active engagement with m-banking services [291, 579]. For this reason, we include time-saving in our model.

The literature on wearable device adoption consistently integrates time-saving as a significant factor influencing people's decisions to use these devices. Hence, wearable devices are seen as time-saving tools. In this setting, time-saving is often framed within broader factors like convenience or efficiency as well. Most studies apply technology adoption models like the TAM or UTAUT, highlighting time-saving as a key motivator in adoption [497, 210]. For wearables, features like real-time data delivery, automated tracking, and streamlined notifications are seen as improving convenience and reducing time demands compared to manual or less integrated alternatives [247, 207]. In healthcare, wearables are valued for providing real-time monitoring and alerts, enabling faster responses and minimizing the need for frequent clinic visits or manual checks [207, 533, 41].

Studies show that wearables gain adoption by allowing users to save time in everyday health and fitness tracking, payment processing, and even managing chronic conditions [210, 207, 93]. Features like automatic data syncing, reminders, or accessing quick insights require less user

input and facilitate seamless integration into routines with wearable devices [93]. For groups such as older adults, time efficiency like automating reminders or simplifying data sharing and information access is a reported facilitator of adoption [337]. The literature lays out models in which the value added by the device, including saved time and effort, determines whether it is integrated into daily life [337].

Value-added is the consumer's belief in the benefits of using a new technology, and it is one of the key factors of both smartphone and smart wearable m-banking and technology adoption [174, 61, 505, 214, 135, 552]. While not directly equivalent to m-banking, we posit that the same time-saving features valued in healthcare settings and generally across wearable-device adoption may also appeal to potential m-banking adopters. We are not claiming equivalence; we are positing a plausible transfer of value perception from one domain (healthcare and device adoption) to another (m-banking adoption) based on shared functionality (convenience and time-saving).

Device features, software, and hardware may highlight unique advantages to users: A wearable device may highlight m-banking convenience and speed, while a smartphone offers both convenience and advanced features for complex tasks. Since wearable devices are designed for maximum on-the-go convenience [289], we believe they may yield even stronger effects in terms of the benefits of time-saving through their use for m-banking adoption. This prompts us to inquire whether the distinctions between smartphones and smart wearables are associated with different perceptions of time-saving benefits in m-banking adoption. Since the primary attribute often attached to smart wearables is of convinience, we hypothesize that the time-saving benefits are more pronounced for smart wearable users. Therefore, our null and alternative hypothesis on time-saving are as follows:

H3$_0$. The association between time-saving benefits and the probability of adopting m-banking does not differ between smartphone and smart wearable users.

H3$_a$. The association between time-saving benefits and m-banking adoption is stronger for smart wearable users than for smartphone users.

4.2.4 Demographic Variables

To finalize our conceptual model, we add important demographic variables. In many studies, demographic factors are important in technology adoption models. We include the following demographic variables based on their heavy presence across literature: *education* [149, 370, 83, 440], *age* [239, 370, 409, 420, 440, 442, 569], *income* [442, 440, 370, 83], and *gender* [149, 370, 442]. Our study is the first to consider the differences between smartphone and smart wearable users in m-banking adoption literature. However, to formulate hypotheses that better align with theoretical expectations, we consider the broader literature on the differences in the use of smartphone and smart wearable devices and how they differ by age, sex, education and income.

Age

Smartphone ownership is nearly universal across adult age groups, but wearable device usage decreases with increasing age [446, 542]. Younger adults are more likely to adopt both smartphones and smart wearables, while older adults are less likely to own or consistently use smart wearables [93, 337]. That is, younger individuals are more likely to own smart wearable devices than older individuals. However, this does not necessarily translate to younger people also using smart wearable devices more frequently as an m-banking tool as ownership does not guarantee usage (for m-banking or otherwise).

Younger individuals are more open to using smart wearables for financial tasks due to greater overall tech engagement [351, 456]. Studies have shown that generation Z (i.e., those born approximately between the late 90s and early 2010s) are more open to adopting digital financial products such as electronic wallets and wearable financial devices [415]. This is driven by their familiarity, motivation and self-efficacy in digital environments [423]. Therefore, we hypothesize that younger people are more likely to adopt m-banking through smart wearables than older individuals, relative to smartphones. Our null and alternative hypotheses based on age are:

H4.1$_0$ There is no difference in the association between age and the probability of adopting m-banking across smartphone and smart wearable users.

H4.1$_a$ The association between age and the probability of m-banking adoption varies by device type, with younger individuals more likely to adopt m-banking via smart wearables than older individuals, relative to smartphones.

Gender

Women are more likely to own and use wearable devices than men. In a study of over $1,300$ individuals, women had notably higher wearable ownership rates compared to their male counterparts [446, 351]. Additionally, women with a higher technology literacy and socioeconomic status are more willing to adopt smartwatches whereas for men, its adoption is related to health needs [128]. Women also put slightly more emphasis on convenience compared to men in Fintech services [243]. Alternatively, women are more concerned about operational and technical issues (e.g., data security and reliability) in Fintech and they have more concerns about data sharing compared to men [243, 93].

Larger proportion of men use multiple Fintech services compared to women, who prefer using a single type of Fintech service [243]. Furthermore, men generally perceive online business activities as less risky than women [282]. Older female adults tend to be more cautious and conservative when interacting with digital products [295]. Women are more likely to express greater concern for the risk of using online services and experience more anxiety than men [183]. All in all, these are opposing views that make it difficult to propose a directional alternative hypothesis. However, there are reasons for us to believe that there may be differences between men and women in terms and m-banking via the two devices (smartphone vs smart wearable). Our null and alternative hypothesis for gender are:

H4.2$_0$ The association between gender and the probability of adopting m-banking does not differ between smartphone and smart wearable users.

H4.2$_a$ The association between gender and the probability of adopting m-banking differs between smartphone and smart wearable users.

Education

More educated adults also display greater openness to sharing device-generated data and engaging in digital health studies [446]. Individuals with greater educational attainment tend to possess better digital literacy, higher income, and greater technological proficiency, all of which facilitate technology adoption [391]. Literature on Fintech more broadly suggests that digital financial engagement rises with educational level, implicating a greater propensity to experiment with or uptake of novel channels like smart wearables [139].

While wearables generally require more digital skills and a willingness to invest in new technology, smartphone m-banking is now mainstream even among lower education groups, especially in regions with expanding mobile internet access [391]. This could imply that higher education might differentiate smart wearable more sharply than smartphone users [339]. Therefore, we expect individuals with a higher education to have a higher probability of m-banking through smart wearable devices than smartphones compared to those with lower levels of education. Our null and alternative hypothesis for education are:

H4.3$_0$ The association between education and the probability of adopting m-banking does not differ between smartphone and smart wearable users.

H4.3$_a$ The association between education and m-banking adoption differs by device type, such that individuals with higher levels of education are more likely to adopt m-banking through smart wearable devices (relative to smartphones) than those with lower levels of education.

Income

Household income is a strong predictor of smart wearable adoption [446]. Wealthier individuals are more likely to own smart wearables than those with lower incomes [93]. Surveys consistently identify a digital divide where younger, wealthier, and more educated adults adopt wearables at higher rates than older, poorer, and less educated groups [446]. Furthermore, research on smart wearable payment adoption acknowledges that such devices are still positioned as technological *luxuries* and tend to have higher uptake among consumers with higher disposable incomes, since

acquiring and maintaining a smart wearable device is costlier than owning a smartphone [210].

This contrasts with smartphone-based m-banking, which has seen wide diffusion across income levels due to cheaper handsets and broad mobile internet access, whereas smart wearables remain concentrated among higher-income users who can afford both devices [210]. Therefore, we expect individuals with a higher level of income to have a higher probability of m-banking through smart wearable devices than smartphones compared to those with lower levels of income. Our null and alternative hypothesis for income are:

H4.4$_0$ The association between income and the probability of adopting m-banking does not differ between smartphone and smart wearable users.

H4.4$_a$ The association between income and m-banking adoption differs by device type, such that individuals with higher levels of income are more likely to adopt m-banking through smart wearable devices (relative to smartphones) than individuals with lower levels of income.

4.3 Data and Measurements

This study uses the Canadian Internet Usage Survey (CIUS), conducted from December 2, 2022, to April 5, 2023 [88], with 25,118 records. CIUS questions serve as model variables, detailed in Table 4.2. The outcome variable is Mobile banking (MBANK) (Yes: 1, No: 0). In our study, we consider the CIUS question regarding participants' trust in banks as our measure of perceived trust. As discussed in Section 4.2.1, we argued that measuring perceived trust in institutions is a stronger choice for our analysis rather than measurements on device-specific trust. There are several reasons for this.

First, measuring perceived trust in banks ensures the variable is the same for both groups of smartphone-only and smart wearable users. This consistency across groups makes any observed difference more likely to reflect differences in user perception or interaction style, rather than differences in the object of trust. Second, this focus on the institution is imperative to m-banking. This is because in m-banking, users are ultimately trusting the institution to handle sensitive

data and not the hardware (device) itself. Device-specific trust introduces confounding variables like brand loyalty, operating system design, or device user experience. Third, measuring device-specific trust would result in our testing whether people trust different devices differently, which is obvious and less insightful. Our hypothesis is framed around whether the same perceived trust construct functions differently across user groups. Having two conceptually distinct variables (device-specific trust) would violate the basis of a direct comparison.

To operationalize perceived security, we follow standard approaches from the literature that combine various measures in a single construct using confirmatory factor analysis [157, 578]. Protective measures assure consumers of their security in the absence of physical services [99]. As previously discussed in Section 4.2.2, having control over security features which the user is able to turn on/off form the perception of security. We select protective measures that relate to security, and define perceived security in accordance with the literature's definition. Previous studies have defined perceived security as "consumers' perception of the degree of protection against various threats" [563]. These protections are available to users through technical measures which provide integrity (data is not accessible to third party without permission), confidentiality (data is only seen by authorized individuals), authentication (certain operations are only possible after identification), and non-repudiation ("procedures that prevent entities from denying they had carried out a certain operation") [159].

The technical aspects are measured in our study using questions from CIUS that address whether users have restricted access to various forms of personal data (`SP_010A to SP_010D`). For authentication, various identity verification measures are used from CIUS (`SP_020A to SP_010E`). Similar to Flavian *et al* [159], non-repudiation is measured by the already included measures above that take into consideration the overall safety of the app from log-in to access from third-party. Additionally, the government of Canada requires all banks to keep records of transactions [154]. Therefore a receipt of activities is available to users at all times. Our confirmatory factor analysis results in Table 4.1 show that our measurement is statistically significant ($p < .001$) and valid with acceptable fit (CF $= 0.97$, Cronbach's $\alpha = 0.810$). The minimum `PSEC` score is -1.530 indicating lowest perceived security. First quintile is -0.707, the median is 0.103 (mean is 0.000), and the third quintile is 0.778. The maximum `PSEC` score is 1.302, highest perceived security.

Table 4.1. Confirmatory Factor Analysis Results for Measurement of *Perceived Security*

Construct	Estimate	Std.Err	z-value	P(> |z|)	Std.lv	Std.all
Perceived Security						
SEC_RES_LOC	0.274	0.004	74.861	0.000	0.274	0.581
SEC_RES_DAT	0.300	0.004	82.428	0.000	0.300	0.627
SEC_ACC_WEBSEC	0.281	0.004	70.897	0.000	0.281	0.564
SEC_ACC_CHNGPR	0.336	0.004	88.679	0.000	0.336	0.673
SECOPT_QS	0.258	0.004	65.258	0.000	0.258	0.523
SECOPT_PL	0.219	0.004	58.760	0.000	0.219	0.466
SECOPT_2FA	0.275	0.003	81.371	0.000	0.275	0.620
SECOPT_BIO	0.221	0.004	58.219	0.000	0.221	0.462
SECOPT_PAS	0.217	0.004	55.881	0.000	0.217	0.446
Covariances						
SEC_RES_LOC ∼ SEC_RES_DAT	0.059	0.001	40.627	0.000	0.059	0.414
SECOPT_QS ∼ SECOPT_2FA	0.026	0.001	19.955	0.000	0.026	0.181
SECOPT_BIO ∼ SECOPT_PAS	0.033	0.002	21.891	0.000	0.033	0.180
SEC_ACC_WEBSEC ∼ SEC_ACC_CHNGPR	0.020	0.002	13.119	0.000	0.020	0.131
SECOPT_QS ∼ SECOPT_PL	0.021	0.001	14.773	0.000	0.021	0.119

Notes: Comparative Fit Index (CFI): 0.969, Tucker-Lewis Index (TLI): 0.949, Root Mean Squared Error of Approximation (RMSEA): 0.057
Standardized Root Mean Square Residual (SRMR): 0.034

Higher values of PSEC correlate to users perceiving stronger security. This shifts the focus to users and their device's capabilities (having the feature to mitigate threats), which play a major role in security [238]. To measure time-saving, we consider whether using m-banking (the online activity of the current study) has saved users time. Time-saving aspect of m-banking has been shown to significantly influence its adoption [86]. We acknowledge that this is a self-reported survey measure, shaped by each user's own interpretation of time-saving. However, by incorporating demographic variables into our conceptual model, we account for variations across user groups, making this approach acceptable.

The CIUS question regarding online banking does not specify whether online banking is different from m-banking. Therefore, in order for MBANK to be specifically m-banking, we only keep users that have isSmartPhone $= 1$, i.e., smartphone users. Thus, we remove $4,982$ records from the

dataset and are left with 20,136 records. Additionally, all OTH (−1) values of model variables are dropped, leaving the cleaned dataset with 18,552 records. USR_TYP determines the type of user. Records where "isSmartWear = 1" are smart wearable users, identified as User Uses a Smart Wearable Device (In addition to Smartphone) (WEAR). Otherwise, they are considered User Does not use a Smart Wearable Device (Only Smartphone) (PHON) (isSmartWear = 0), which are only smartphone users.

Table 4.2. Overview of CIUS2022 Variables – Model Variables

CIUS	Abbrv.[1]	Question	Answers
		DEMOGRAPHIC VARIABLES	
PROVINCE	PRVNC	Information derived using postal codes	Newfoundland and Labrador (NL), Prince Edward Island (PEI), Nova Scotia (NS), New Brunswick (NB), Quebec (QC), Ontario (ON), Manitoba (MB), Saskatchewan (SK), Alberta (AB), British Columbia (BC)
AGE_GRP	AGE		15 to 24 years old (1), 25 to 34 years old (2), 35 to 44 years old (3), 45 to 54 years old (4), 55 to 64 years old (5), 65+ years old (6)
GENDER	SEX		Male (0), Female (1)
EDU	EDU	Highest certificate earned	High school or less (1), Some post-secondary & certificate(s) (2), University degree (3), OTH[2] (−1)
HINCQUIN	INCOME	Census family income quintile	Q1: ≤ $42,256 (1), Q2: $42,257 – $72,366 (2), Q3: $72,367 – $107,480 (3), Q4: $107,481 – $163,750 (4), Q5: > $163,750 (5), OTH (−1)
		DEVICE ACCESS VARIABLES	
During the past three months, what devices did you use to access the Internet?			
DV_010A	isSmartPhone	Smartphone	Yes (1), No (0), OTH (−1)
DV_Q010G	isSmartWear	Internet-connected Smart Wearable	Yes (1), No (0), OTH (−1)
		ONLINE ACTIVITIES VARIABLES	
During the past three months, which of the following activities have you done over the Internet?			
UI_050D	MBANK[3]	Conducted online banking	Yes (1), No (0), OTH (−1)
		EFFECTS OF ONLINE ACTIVITIES	
During the past twelve months, did your use of online activities have any of the following effects?			
UI_110E	EFF_TIME	Save you time	Yes (1), No (0), OTH (−1)
		SECURITY VARIABLES	
Have you carried out any of the following to manage access to your personal data over the Internet during the past twelve months?			

Continued on next page →

CIUS	Abbrv.[1]	Question	Answers
SP_010A	SEC_RES_LOC	Restricted or refused access to your geographical location	Yes (1), No (0), OTH (−1)
SP_010B	SEC_RES_DAT	Refused allowing the use of personal data for advertising purposes	Yes (1), No (0), OTH (−1)
SP_010C	SEC_ACC_WEBSEC	Checked that the website where you provided personal data was secure	Yes (1), No (0), OTH (−1)
SP_010D	SEC_ACC_CHNGPRV	Changed the privacy settings on accounts or apps	Yes (1), No (0), OTH (−1)
During the past twelve months, did you enable any of the following optional security features to verify your identity when accessing accounts or applications over the internet?			
SP_020A	SECOPT_QS	Answers to personalized security questions	Yes (1), No (0), OTH (−1)
SP_020B	SECOPT_PL	Partner login	Yes (1), No (0), OTH (−1)
SP_020C	SECOPT_2FA	Two-factor authentication or two-step verification	Yes (1), No (0), OTH (−1)
SP_020D	SECOPT_BIO	Biometric security features for online functions	Yes (1), No (0), OTH (−1)
SP_020E	SECOPT_PAS	Password manager program	Yes (1), No (0), OTH (−1)
TRUST VARIABLES			
In general, to what extent do you trust the following technologies/organizations with your personal information?			
SP_040B	TRST_BANK	Banking or other financial institutions	Cannot be trusted at all (1), Can rarely be trusted (2), Neutral (3), Can mostly be trusted (4), Can be trusted completely (5), OTH (−1)
AUTHOR ADDED VARIABLES			
This variable is added to label the records based on the type of device they use.			
—	USR_TYP	What is the user type based on values of isSmartWear	PHON, WEAR
This variable is added to measure perceived security.			
—	PSEC	Based on Yes (1) answers to the security questions SP_010A, SP_010B, SP_010C, SP_010D, SP_020A, SP_020B, SP_020C, SP_020D, and SP_020E	Values from −1.530 (lowest perceived security) – 1.302 (highest perceived security)

Notes: 1: Abbreviated Variable Name 2: Valid Skip, Don't Know, Refusal, Not Stated 3: Outcome Variable

According to the summary statistics for model variables in Table 4.3, we observe that most users are not WEAR users (median = 0). There is a large variation in the time-saving benefits of m-banking. Most users perceive banks as trustworthy. The average perception of security is slightly lower than the median. Among WEAR users, 169 have not m–banked in the past three months, while 2,995 have. For PHON users, 2,214 have not m–banked in the past three months, compared to 13,174 who have. Using a χ^2 test of independence, we confirm that these numbers are statistically significantly difference ($\chi^2_{df=1} = 191.04,\ p < .001$).

Having confirmed this difference, we examine whether our hypotheses explain these variations in the following sections. Here, we provide a descriptive overview of the two user groups in our analysis: individuals who use only a smartphone for m-banking (PHON users), and those who use both a smartphone and a smart wearable device (WEAR users). These two groups do not overlap as we are separating them using a single variable's value (`isSmartWear`). This comparison helps illustrate the distinct characteristics of each group before diving into the main analysis.

The majority of PHON users are m-banking adopters. The largest age group is $45-54$ year olds, most are female, and many have some post-secondary education. Most have no children, and fall into the 3rd income quintile. Most set up security questions and two-factor authentication but rarely use partner login, biometrics, or password managers. They feel neutral about trusting wearable devices, and have low trust in Artificial Intelligence (AI) and social media, but view banks and the government as highly trustworthy. Few phone users invest in bonds or cryptocurrencies. They use credit cards for online payments.

Table 4.3. Summary Statistics of Model Variables

Variable	Description	Mean	SD	Median	Min - Max
`isSmartWear`	Binary Variable: Yes (1), No (0)	0.17	0.38	0.00	0.00 – 1.00
`AGE`	Factor Variable: 15-24 – 6: 65+	4.12	1.50	4.00	1.00 – 6.00
`SEX`	Binary Variable: 0 (Male), 1 (Female)	0.52	0.50	1.00	0.00 – 1.00
`EDU`	Factor Variable: 1 (High School), 2 (Some post-secondary), 3 (University degree)	2.15	0.79	2.00	1.00 – 3.00
`INCOME`	Factor Variable: 1 (Q1) – 5 (Q5)	3.23	1.35	3.00	1.00 – 5.00
`EFF_TIME`	Binary Variable: Yes (1), No (0)	0.51	0.50	1.00	0.00 – 1.00
`TRST_BANK`	Factor Variable: 1 – 5	3.71	0.96	4.00	1.00 – 5.00
`PSEC`	Numeric, values from -2 to 2	0.00	0.88	0.10	-1.53 to $+1.30$

Notes: Results are based on $n = 18,552$ records

Similarly, the majority of WEAR users are m–bankers, but they are younger than PHON users. Wear users are predominantly female, and have some post-secondary education. They typically do not have children and fall into the 4th income quintile, indicating higher wealth than PHON users (explained by owning an additional device). Compared to PHON users, they engage more

with social media and streaming TV shows and movies. WEAR users' security practices are more advanced. They use security questions, partner logins, two-factor authentication, biometrics, and password managers, unlike PHON users, who mostly rely on security questions and two-factor authentication.

WEAR users have higher trust in technology while maintaining a neutral stance toward AI and slightly higher trust in social media compared to PHON users. Similar to PHON uses, WEAR users' trust in the government and banks remains high. WEAR users do not invest in bonds but almost half of them invest in cryptocurrencies. They demonstrate greater knowledge of technology specifically AI compared to PHON users, recognizing AI's use in most domains. They also have a more positive attitude toward online payments and virtual wallets compared to PHON users, who often avoid them.

4.4 Method and Modeling

In Section 4.3, we demonstrated significant difference between PHON and WEAR users in terms of m-banking. In this section, we develop a model to test our hypotheses outlined in Section 4.2. The model examines factors and the differences between PHON and WEAR users. Since our outcome variable is binary, we apply a logistic regression model. Before finalizing the model, we evaluate whether province-based differences should be included using a mixed effect model, given that the CIUS 2022 dataset is clustered by provinces in the sampling stage. Visualizing m-banking adoption across provinces and user types in Figure 4.1, we observe no overall geographical variation with only one exception for Manitoba. This exception is not large enough to impact our analysis.

To confirm this mathematically, we compare a mixed effect logistic regression model (grouped by province) with the standard logistic regression model using a Likelihood Ratio (LR) test [357]. The test results indicate no improvement in model performance with the mixed effect model ($\chi^2 = 1.241, p = 0.265$). Thus, we use a regular logistic regression model with robust standard errors calculated based on province clusters to account for heteroscedasticity and intra-cluster correlations. We run our model on 3 separate datasets: the full dataset, the PHON users sub-set

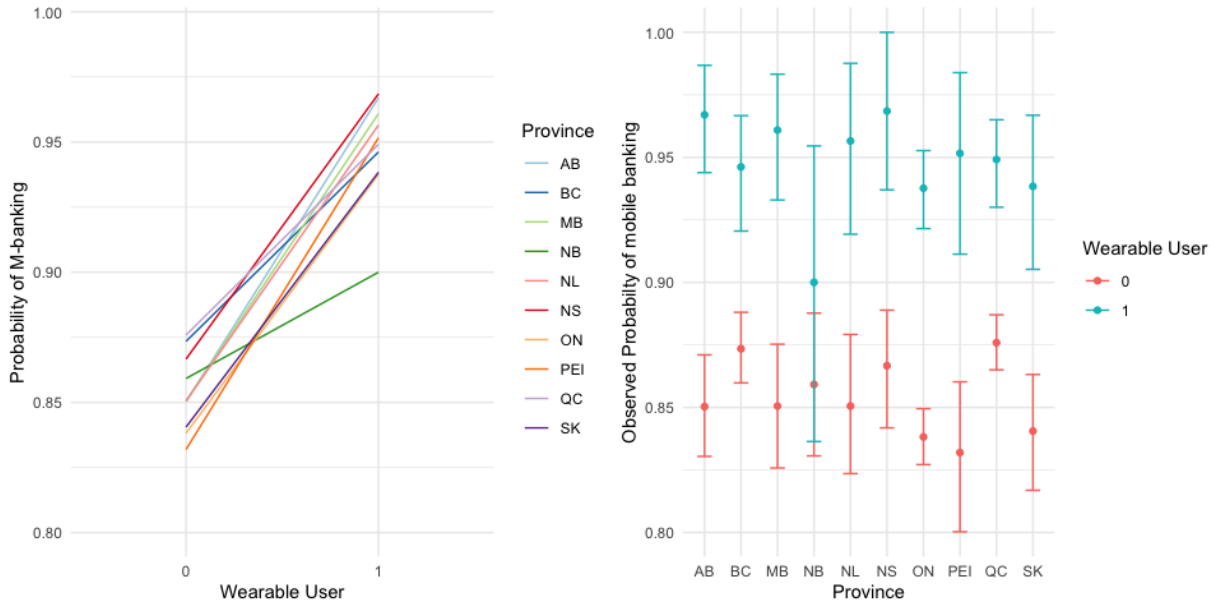


Figure 4.1. Differences in m-banking based on device types across Canadian Provinces

(i.e., dataset filtered on `isSmartWear` $==0$), and the WEAR users sub-set (i.e., dataset filtered on `isSmartWear` $==1$). The model equation is as follows:

$$
\begin{aligned}
&logit(\texttt{MBANK}) = \\
&\quad \beta_0 + \beta_1\,\texttt{AGE}_1 + \beta_2\,\texttt{AGE}_3 + \beta_3\,\texttt{AGE}_4 + \beta_4\,\texttt{AGE}_5 + \beta_5\,\texttt{AGE}_6 + \\
&\quad \beta_6\,\texttt{SEX}_F + \beta_7\,\texttt{EDU}_2 + \beta_8\,\texttt{EDU}_3 + \beta_9\,\texttt{INCOME}_2 + \beta_{10}\,\texttt{INCOME}_3 + \\
&\quad \beta_{11}\,\texttt{INCOME}_4 + \beta_{12}\,\texttt{INCOME}_5 + \beta_{13}\,\texttt{EFF_TIME} + \beta_{14}\,\texttt{TRST_BANK}_1 + \\
&\quad \beta_{15}\,\texttt{TRST_BANK}_2 + \beta_{16}\,\texttt{TRST_BANK}_3 + \beta_{17}\,\texttt{TRST_BANK}_4 + \beta_{18}\,\texttt{PSEC} + \varepsilon
\end{aligned}
\tag{4.1}
$$

To avoid multicollinearity, $\texttt{AGE}_2$ (reference for age group), $\texttt{SEX}_M$ (reference for gender), $\texttt{EDU}_1$ (reference for education), $\texttt{INCOME}_1$ (reference for income quintile), and $\texttt{TRST_BANK}_5$ (reference for perceived trust in bank) are not included in the model. To discuss our hypotheses, we use the Wald test [538]. The null hypothesis is that model coefficients are equal, i.e., $H_0: \quad \beta_{\textbf{PHON},\texttt{V}_l} = \beta_{\textbf{WEAR},\texttt{V}_l}$, where $\beta_{\textbf{PHON},\texttt{V}_l}$ is the coefficient for variable `V` at level l in the PHON-only model and $\beta_{\textbf{WEAR},\texttt{V}_l}$ is the coefficient for `V` at level l in the WEAR-only model. Rejecting this hypothesis for `V` means the coefficient of `V` is significantly different between PHON

and WEAR users, i.e., the association between V and m-banking (log) likelihood is different.

Perceived trust and perceived security are closely connected [325, 386]. This makes it essential to examine both in technology adoption studies. Higher perceived trust reduces security concerns, as users perceive less risk with the technology and similarly perceiving an app to be more secure rises perceived trust in the app [452, 573, 553, 496, 330]. This relationship between perceived trust and perceived security rises multicollinearity concerns. In our model, while there is a statistically significant correlation between perceived trust and perceived security ($r = 0.085$, $p < .001$), this correlation is quite small (less than 1%). Therefore, including both in the model will not cause multicollinearity issues (all variance inflation factors are less than 3).

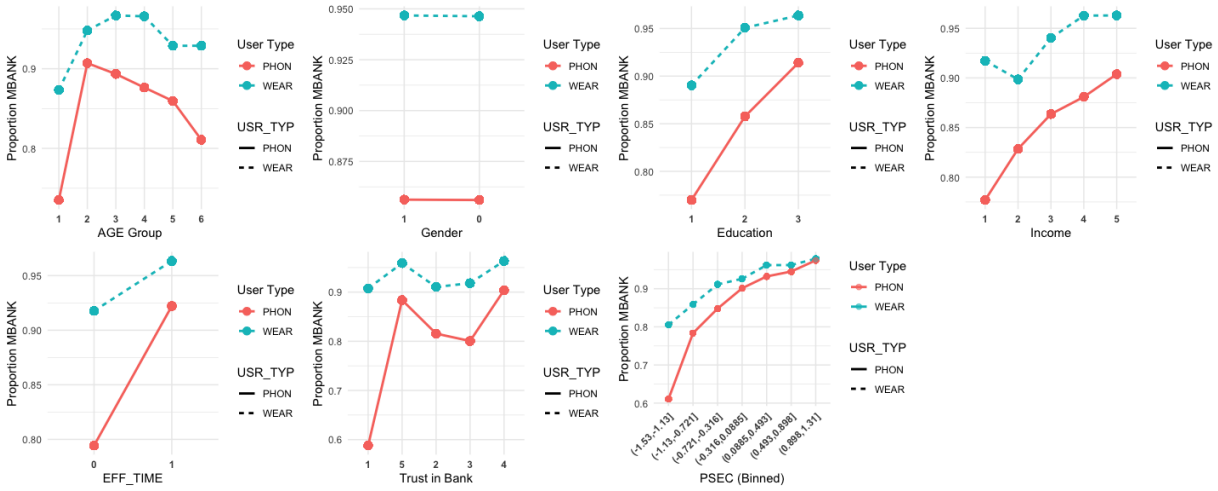


Figure 4.2. Mobile banking probability of PHON and WEAR users across model variables

We visualize the changes in probability of m-banking adoption for WEAR and PHON users for each model variable in Figure 4.2. WEAR users (blue dotted line) generally have a higher likelihood of m-banking. PHON users show a sharp increase in adoption between ages $15-24$ and $25-34$, while WEAR users see a smaller rise. As PHON users age, m-banking declines, whereas WEAR users adopt slightly more. There does not seem to be any difference between genders in terms of m-banking, however between the two device types, WEAR users are more likely to adopt m-banking. Higher education is positively correlated with m-banking adoption,

especially for PHON users.

Income correlates positively with m-banking for both groups, despite a slight dip from $Q1$ to $Q2$ for WEAR users. Time-saving is associated with higher m-banking probabilities, with a sharper increase for PHON users, but stronger difference in WEAR users (reaching almost 100% probability of m-banking in this group). Perceived trust in banks is generally positively associated with m-banking adoption, though the relationship is volatile for PHON users and weak for WEAR users. Lastly, past a certain PSEC score, both groups show similar m-banking behavior, but prior to this, incremental changes in perceived security are differently related to m-banking adoption. We next discuss the results of our modeling on the three separate datasets.

4.5 Results

The results of the logistic regression for the full dataset, as well as comparative models trained on PHON and WEAR data, are available in Table 4.4. All models are statistically significant, confirming the reliability of our analysis. We choose the second youngest group (AGE$= 2,\ 25-34$ year olds) as the baseline age group to ensure more meaningful comparisons and interpretations of results as the youngest age group includes individuals who may still be in high school (minors younger than 19). For perceived trust in bank, the baseline is set as the highest trust level perceived. This way, our results are interpreted as comparisons with those that perceive banks to be completely trustworthy, i.e., they have full trust in banks.

Initially, we review what the numbers mean in terms of odds ratio, i.e., the odds of adopting m-banking to not adopting it. Next, we discuss the implications of the numerical results. For full data, individuals aged $15-24$ are 64% less likely to m-bank compared to the baseline (OR$= 0.363,\ p < .001$). The results show that individuals aged $35-44$ are slightly but not significantly more likely to m-bank than the baseline (OR$= 1.025$, $p = 0.812$). Middle-aged and older adults, i.e., those aged $45-54$ years (OR$= 0.970$, $p = 0.818$), $55-64$ years (OR$= 0.910$, $p = 0.570$), and those over 65 years old (OR$= 0.794$, $p = 0.067$) are less likely to m-bank compared to baseline, but these differences are not statistically significant.

In general, women are significantly more likely to adopt m-banking compared to men (OR= 1.116, $p = 0.001$). Higher education levels are positively associated with m-banking adoption. University-educated individuals have a higher likelihood of m-banking (OR= 1.602, $p < .001$) compared to those with some college credits (OR= 1.382, $p < .001$). Each increase in income quintile is correlated with increases in the likelihood of m-banking, with individuals in $Q5$ (highest earners) being 80% more likely to m-bank than those in $Q1$ (lowest earners). Saving time due to m-banking is associated with a 76% (OR= 1.759, $p < .001$) higher likelihood to m-banking adoption. The most significant factor is the perceived trust in banks.

Each incremental decrease in trust perceptions compared to baseline (full trust in banks) is associated with higher likelihood of m–banking, all statistically significant, except for level `TRST_BANK`= 4 (i.e., "banks can mostly be trusted"). This means that those that perceive banks as mostly trustworthy are not likely to m–bank any differently from those that fully trust banks (OR= 0.894, $p = 0.356$). Individuals who perceive banks as not trustworthy (i.e., `TRST_BANK`= 1 or "cannot be trusted at all") are 76% (OR= 0.236, $p < .001$) less likely to adopt m-banking. Finally, higher perceived security is associated with significantly higher probability of m–banking (OR= 2.537, $p < .001$).

Table 4.4. Results of Logistic Regression Model (eq 4.1.) – Robust Standard Errors, Clustered on Province

	Description	Full Data β/(SE)	PHON-only β/(SE)	WEAR-only β/(SE)
`AGE=1`	15–24 year olds	-1.015^{***}	-1.124^{***}	-0.250
	ref†: `AGE=2` (25–34 years)	(0.052)	(0.110)	(0.247)
`AGE=3`	35–44 year olds	0.024	-0.056	0.517^{**}
	ref: `AGE=2` (25–34 years)	(0.102)	(0.116)	(0.158)
`AGE=4`	45–54 year olds	-0.030	-0.117	0.998
	ref: `AGE=2` (25–34 years)	(0.133)	(0.176)	(0.515)
`AGE=5`	55–64 year olds	-0.095	-0.128	0.158
	ref: `AGE=2` (25–34 years)	(0.167)	(0.195)	(0.299)
`AGE=6`	65+ year olds	-0.230	-0.289	0.391

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	Description	Full Data β/(SE)	PHON-only β/(SE)	WEAR-only β/(SE)
	ref: AGE=2 (25–34 years)	(0.126)	(0.152)	(0.353)
SEX=1	Female	0.110^{**}	0.086^{***}	0.164
	ref: SEX=0 (Male)	(0.034)	(0.023)	(0.272)
EDU=2	Some post-secondary/certificate	0.323^{***}	0.250^{***}	1.020^{***}
	ref: EDU=1 (Highschool Diploma)	(0.074)	(0.052)	(0.289)
EDU=3	University degree	0.471^{***}	0.420^{***}	0.937^{***}
	ref: EDU=1 (Highschool Diploma)	(0.024)	(0.029)	(0.225)
INCOME=2	Q2: $42,257 - $72,366	0.149^{*}	0.203^{*}	-0.515
	ref: INCOME=1 (Q1: $\leq \$42,256$)	(0.072)	(0.094)	(0.352)
INCOME=3	Q3: $72,367 - $107,480	0.204^{*}	0.212^{*}	-0.030
	ref: INCOME=1 (Q1: $\leq \$42,256$)	(0.086)	(0.103)	(0.278)
INCOME=4	Q4: $107,481 - $163,750	0.428^{***}	0.417^{***}	0.187
	ref: INCOME=1 (Q1: $\leq \$42,256$)	(0.117)	(0.120)	(0.415)
INCOME=5	Q5: > $163,750	0.589^{***}	0.598^{***}	0.161
	ref: INCOME=1 (Q1: $\leq \$42,256$)	(0.101)	(0.145)	(0.436)
EFF_TIME=1	Yes (Saved time)	0.565^{***}	0.539^{***}	0.694^{*}
	ref: EFF_TIME=0 (No)	(0.048)	(0.044)	(0.327)
TRST_BANK=1	Banks cannot be trusted at all	-1.442^{***}	-1.532^{***}	-0.000
	ref: TRST_BANK=5 (Banks can be trusted completely)	(0.177)	(0.168)	(0.591)
TRST_BANK=2	Banks can rarely be trusted	-0.692^{***}	-0.674^{***}	-0.657^{***}
	ref: TRST_BANK=5 (Banks can be trusted completely)	(0.173)	(0.184)	(0.188)
TRST_BANK=3	Neutral	-0.675^{***}	-0.726^{***}	-0.285
	ref: TRST_BANK=5 (Banks can be trusted completely)	(0.126)	(0.116)	(0.193)
TRST_BANK=4	Banks can mostly be trusted	-0.112	-0.163	0.312
	ref: TRST_BANK=5 (Banks can be trusted completely)	(0.121)	(0.094)	(0.400)
PSEC	Perceived Security (continuous)	0.931^{***}	0.943^{***}	0.697^{***}
		(0.047)	(0.039)	(0.087)
Intercept		1.835^{***}	1.949^{***}	1.227^{**}
		(0.160)	(0.198)	(0.390)

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Description	Full Data β/(SE)	PHON-only β/(SE)	WEAR-only β/(SE)
Num. obs.	18,552	15,388	3,164
Model Fit ($\chi^2_{df=18}$)	205.06***	205.83***	18.83***
Pseudo-R^2	0.253	0.253	0.152

Notes: *p<.5; **p<.01; ***p<.001 †: Reference Level

Next, we review the results of the PHON-only model. Significant differences in m-banking likelihood are observed only for the $15-24$ year olds, who are significantly less likely than $25-34$ year-olds to m-bank. In PHON users, $35-44$ year olds are also less likely (non-significant, OR $= 0.945$, $p = 0.632$) to m-bank than the baseline. This shows that the significant difference we observed in the Full Data model was likely due to WEAR users. Similar to the Full Data model, women are slightly more likely to m-bank (OR$= 1.090$, $p < .001$). Higher education levels are significantly associated with increased m-banking likelihood for PHON users, consistent with the Full Data model.

Each incremental increase in income quintile is associated with significant increases in m–banking likelihood, with $Q5$ users being 82% more likely to m-bank than $Q1$ users (OR$= 1.819$, $p < .001$). Time saved using smartphones for m–banking is also associated with higher m-banking adoption likelihood (OR$= 1.714$, $p < .001$). Having low perceived trust (OR$= 0.216$, $p < .001$), little perceived trust (OR$= 0.510$, $p < .001$) and neutral perceived trust (OR$= 0.484$, $p < .001$) in banks are all associated with significantly lower m–banking adoption likelihood. However, believing banks can mostly be trusted does not significantly differ from full trust in terms of m–banking adoption (OR$= 0.852$, $p = 0.084$). Finally, higher perceived security is associated with significantly higher m–banking likelihood (OR$= 2.569$, $p < .001$).

When focusing on WEAR users, distinct patterns emerge. Individuals aged $15-24$ are less likely to m-bank compared to the baseline group, but this difference is not significant (OR$= 0.779$, $p = 0.311$). In contrast, $35-44$ year-olds are significantly more likely to m-bank (OR$= 1.677$, $p = 0.001$), a reversal of the PHON-only model and in alignment with the Full Data model's direction (though significant here). For WEAR users, $45-54$ year-olds are more likely to m-bank

(OR= 2.714, $p = 0.052$), but not significantly. This differs from both previous models in direction.

There is no significant difference between $55-64$ years (OR= 1.172, $p = 0.597$) and 65+ year olds (OR= 1.478, $p = 0.268$) and the baseline age group. Gender differences are not significant for WEAR users (OR= 1.178, $p = 0.547$). Higher education is positively associated with m-banking likelihood. However, university graduates (OR= 2.552, $p < .001$) are slightly less likely to m-bank compared to those with some college credits or certificates (OR= 2.773, $p < .001$) relative to high school graduates. These results reveal notable differences in age, gender, and education patterns specific to WEAR users, highlighting distinctions from PHON users and the Full Data model.

Interesting patterns emerge when analyzing income levels for WEAR users. Those in the second (OR= 0.598, $p = 0.143$) and third (OR= 0.970, $p = 0.913$) income quintile are less likely to m-bank compared to $Q1$. However, neither of these relationships are significant. No significant differences exist for the other income brackets ($Q4$: OR= 1.205, $p = 0.652$; $Q5$: OR= 1.174, $p = 0.712$). Benefits of time-saving are correlated with 100% higher m–banking likelihood for WEAR users (OR= 2.003, $p < .001$), indicating that convenience and speed are crucial factors. The relationship between perceived trust in banks and m–banking likelihood varies for WEAR users.

Users with the lowest perceived trust are slightly but non-significantly less likely to m–bank (OR = 1.000, $p = 0.999$). Users who believe banks can rarely be trusted are significantly less likely to m–bank than those with full trust in banks (OR = 0.518, $p < .001$). Having neutral perceptions of trust (OR = 0.752, $p = 0.140$) and believing banks can mostly be trusted (OR = 1.366, $p = 0.435$) are not significantly different from full trust. Lastly, better perceived security is significantly associated with higher m–banking likelihood for WEAR users (OR= 2.007, $p < .001$). These results highlight complex interactions between income and perceived trust among WEAR users, emphasizing their unique adoption patterns.

4.5.1 Results of Hypothesis Testing

To discuss our hypotheses, we analyze statistical differences in coefficients across models, based on results in Table 4.5. We consider the null formulation for all of our hypothesis. In the event that we find sufficient evidence to reject the null hypothesis, we state this as having evidence against the null hypothesis in favor of the alternative hypothesis. Otherwise, we do not have sufficient evidence to reject the null hypothesis. The Full and PHON models show similar results, which is expected as the PHON model represents the full dataset excluding users with `isSmartWear` $= 1$, which were in the minority. This exclusion does not lead to significant differences in coefficients. Our decisions are based on the last column of Table 4.5, which compares coefficients directly between PHON and WEAR models.

In $\mathbf{H1}_0$, we hypothesized that the probability of m-banking adoption is independent of individuals' perceived trust across WEAR and PHON users. From the results of our model, we observed that perceived trust in banks was not consistently associated with m-banking adoption for WEAR users, unlike for PHON users and the Full Data model. Specifically, while higher trust generally aligned with greater adoption likelihood among PHON users, this pattern was not evident among WEAR users. The Wald test further indicates that the trust coefficients differ significantly between the two groups at all levels except when `TRST_BANK`$= 2$ ("Banks can rarely be trusted"). As a result, we reject the null hypothesis of **H1** in favor of the alternative hypothesis. That is, we have sufficient evidence that shows the association between perceived trust and the probability of adopting m-banking is different between smartphone and smart wearable users. Particularly, we observe that perceived trust in banks is strongly related to m-banking adoption for PHON users but not for WEAR users.

It is important to interpret these finding cautiously. Our study relies on a cross-sectional dataset and observational modeling, and we cannot claim that device type *causes* differences in how perceived trust relates to m-banking behavior. This limitation reflects endogeneity concerns, where unobserved confounding variables or self-selection (measurement) may bias results [46]. This is true for all subsequent discussions and analysis as well, but for brevity, we avoid repetition. The observed differences may reflect broader variations in the types of users within each group, rather than an effect of the device itself. We detailed few of the differences between the profiles of PHON

and WEAR users in our dataset in Section 4.3. Furthermore, it may be that the difference we observe here stems from other characteristics not available in the dataset or not captured in our model.

We selected consumers' perception of trust in banks because it is device-agnostic. Perceived trust (in banks) is conceptually unrelated to the type of device a person uses. In other words, a person's level of trust in financial institutions should, in theory, be a more stable belief – formed through prior experiences, social influences, or institutional factors – not something that varies based on whether the individual access banking through a smartphone or a smart wearable device [290]. We refrain from interpreting this result as a difference *caused* or *driven* by the devices, but rather, a difference in the way in which the two user groups of PHON and WEAR perceive trust in banks. Thus, while the difference in the perceived trust coefficient is statistically significant, it should be viewed as a descriptive difference between two user populations, not as evidence of a device-driven effect. Potential reasons for this difference between user groups are explored in Section 4.6.

In $\mathbf{H2}_0$, we hypothesized that the probability of m-banking adoption is independent of individual's perceived security of the app regardless of the device. The results in Table 4.5 show a significant difference in how the odds of m-banking depend on perceived security for PHON and WEAR users. While higher perceived security is associated with increased m-banking adoption likelihood for both user groups, we see that the relationship is significantly stronger for PHON users. Based on this and the results of Wald test, we have evidence to reject the null hypothesis formulation of **H2** in favor of the alternative hypothesis. That is, our results show that the association between perceived security and m-banking adoption is weaker for smart wearable users than for smartphone users. Similar to our discussion on perceived trust, we do not claim that this observed significant different is caused by device differences.

We observed that for PHON users, higher time-saving were associated with significantly higher likelihood of m-banking adoption. Similarly, WEAR users showed a significant likelihood of m-banking, and the relationship between time-saving and m-banking adoption was even stronger for this group. The Wald test results confirm that the difference between the two groups is statistically significant. Thus, we reject the null formulation of hypothesis **H3** in favor of the alternative

Table 4.5. Statistical comparison of coefficients based on Wald test

Variable	$(\beta_{FULL} = \beta_{PHON})$		$(\beta_{FULL} = \beta_{WEAR})$		$(\beta_{PHON} = \beta_{WEAR})$	
	z	P> $\|z\|$	z	P> $\|z\|$	z	P> $\|z\|$
AGE == 1 (ref==2)	1.485	0.137	-10.352^{***}	$< .001$	-5.625^{***}	$< .001$
AGE == 3 (ref==2)	0.555	0.579	-3.413^{**}	0.001	-3.48^{**}	0.001
AGE == 4 (ref==2)	0.460	0.646	-5.480^{***}	$< .001$	-4.488^{***}	$< .001$
AGE == 5 (ref==2)	0.142	0.887	-1.072	0.284	-1.038	0.299
AGE == 6 (ref==2)	0.330	0.742	-3.488^{***}	$< .001$	-3.159^{**}	0.002
SEX == 1 (ref==0)	0.493	0.622	-1.138	0.255	-2.363^{*}	0.018
EDU == 3 (ref==1)	0.698	0.485	-6.641^{***}	$< .001$	-10.406^{***}	$< .001$
EDU == 2 (ref==1)	1.500	0.134	-13.742^{***}	$< .001$	-12.788^{***}	$< .001$
INCOME == 2 (ref==1)	-0.525	0.600	6.484^{***}	$< .001$	5.403^{***}	$< .001$
INCOME == 3 (ref==1)	-0.069	0.945	1.932	0.053	1.658	0.097
INCOME == 4 (ref==1)	0.071	0.943	1.456	0.145	1.351	0.177
INCOME == 5 (ref==1)	-0.063	0.950	3.013^{**}	0.003	2.13^{*}	0.033
EFF_TIME == 1 (ref==0)	0.382	0.702	-1.923	0.054	-2.489^{*}	0.013
TRST_BANK==1 (ref==5)	0.361	0.718	-5.769^{***}	$< .001$	-6.453^{***}	$< .001$
TRST_BANK==2 (ref==5)	-0.071	0.943	-0.141	0.888	-0.065	0.948
TRST_BANK==3 (ref==5)	0.287	0.774	-2.181^{*}	0.029	-2.682^{**}	0.007
TRST_BANK==4 (ref==5)	0.301	0.763	-2.475^{*}	0.013	-3.559^{***}	$< .001$
PSEC	-0.19	0.849	3.546^{***}	$< .001$	4.524^{***}	$< .001$

Notes: *p<.05; **p<.01; ***p<.001

hypothesis. That is, the association between time-saving benefits and m-banking adoption is stronger for smart wearable users than for smartphone users.

The ability to save time is a key factor in m-banking adoption, and this relationship is even more pronounced for WEAR users. This finding aligns with expectations and our observations in Section 4.4, as wearable devices are often more convenient for on-the-go usage and enable faster interactions compared to smartphones. We re-iterate that this is not the effect of using a wearable device, but rather a significantly stronger association between time-saving and m-banking adoption for WEAR users.

The coefficients for age are significantly different between PHON and WEAR users across all age groups except for those aged $55-64$. In $\mathbf{H4.1}_0$, we hypothesized that there are no differences between various age groups across smartphone and smart wearable users in terms of m-banking adoption. For both user types, it seems that younger people are less likely to adopt m-banking. However, the difference is less negative and not significant for WEAR users, suggesting younger individuals are relatively more represented in the WEAR group compared to PHON.

While the coefficient for younger WEAR users is not significantly different from other groups, the stronger negative association for the PHON users suggests that younger individuals are relatively more inclined toward m-banking via wearables than older individuals. Therefore, we have sufficient evidence against the null formulation of hypothesis **H4.1** in favor of the alternative hypothesis. That is, our dataset shows that younger individuals are more likely to adopt m-banking through smart wearable devices than older individuals.

In $\mathbf{H4.2}_0$, we hypothesized that the association between gender and the probability of m-banking does not defer based on device. However, we observed a significant gender difference in m-banking adoption across devices. Women are slightly more likely to m–bank in both groups, but female smart wearable users are much more likely to m–bank than female smartphone users. While women are significantly more likely to adopt m-banking in PHON users, this relationship does not carry over to WEAR users. The difference in coefficients across device types is statistically significant. Therefore, our results provide evidence to reject $\mathbf{H4.2}_0$ in favor of the alternative hypothesis. The gender gap in m-banking is more pronounced for PHON users than WEAR users.

In $\mathbf{H4.3}_0$, we hypothesized that the association between education and the probability of adopting m-banking does not differ between smartphone and smart wearable user. Our results indicate that the relationship between education and m-banking adoption is significantly different for PHON and WEAR users. Furthermore, we see that in both groups, more education (compared to high school diploma) is associated with higher m-banking likelihood, but this is much stronger for WEAR users. Therefore, we have evidence to reject the null formulation of **H4.3** in favor of the

alternative formulation. That is, our results show that individuals with higher levels of education are more likely to adopt m-banking through smart wearable devices (relative to smartphones) than those with lower levels of education.

In $\mathbf{H4.4}_0$, we hypothesized that the association between income and the probability of adopting m-banking does not differ between smartphone and smart wearable users. Among PHON users, higher income is significantly associated with greater m-banking adoption, aligning with our prior expectations. In contrast, this pattern does not hold for WEAR users. Surprisingly, individuals in the second and third income quartiles ($Q2$ and $Q3$) are less likely to adopt m-banking compared to those in the lowest quartile ($Q1$). One possible explanation is that many $Q1$ individuals in the WEAR group are younger users or students, who may be more tech-savvy or open to wearable adoption despite lower income.

This finding highlights an important divergence in the relationship between income and m-banking across device types and warrants deeper investigation in future studies. The downward trend for $Q2$ and $Q3$ in the WEAR group directly contradicts both the positive association seen in PHON users and the our assumed link between higher income and greater m-banking adoption in WEAR users. Wald tests show significant differences between PHON and WEAR groups in $Q4$ and $Q5$ but in the opposite direction of our current alternative hypothesis. Thus, we can reject the null formulation of **H4.4** but we do not have evidence in favor of the alternative hypothesis. The data shows that higher income is more strongly associated with m-banking adoption among smartphone users, not wearable users.

We acknowledge that due to the limitations of a secondary data, the chances of confounding effects (that are not considered) are high. Therefore, this surprising outcome may be due to other factors not accounted for and not differences in the user groups of the two devices. Additionally, it may be that the smart wearable devices that the individuals in our dataset own are not suitable for m-banking in particular (e.g., Virtual Reality gaming headsets or sleep tracking rings). We suggest future research consider collecting data through a survey and specifically design the questions such that the devices are certain to have m-banking capabilities (e.g., smart watch).

4.6 Discussion

For clarity, we structure the discussion as follows: First, for each hypothesis (linked to a model variable), we examine the insights provided by each model and compare differences between device groups. Next, we compile all results in Table 4.6. Lastly, we conclude by discussing the theoretical and practical implications of our findings. It is important to note that this study utilizes a cross-sectional research design and a secondary dataset. Therefore, the analysis can identify associations between variables but cannot establish causal relationships. The language used in the interpretation of the results will reflect this correlational nature and we strongly avoid causal interpretations.

Table 4.6. Summary of Findings

Observation	Based on
H1. Perceived Trust (in banks)	
The probability of m-banking[1] varies with individuals' perceived trust in banks, and this relationship differs between smartphone users and smart wearable users.	**H1**
Having less trust in banks is associated with lower likelihood of m-banking.	Full Data
Smartphone users with lower trust (none, little and neutral trust) in banks are less likely to m–bank than those who have full trust in banks.	PHON-only
Perceived trust in banks is not related to m-banking for wearable[2] users.	WEAR-only
H2. Perceived Security	
The probability of m-banking varies with individuals' perceived security in apps, and this relationship differs between smartphone users and wearable users.	**H2**
Higher perceived security is associated with higher m-banking.	Full Data
For wearable users, higher perceived security is associated with higher m-banking.	WEAR-only
For smartphone users, higher perceived security is associated with higher m-banking. This relationship is stronger in this group than in wearable users.	PHON-only
H3. Time-saving	
The probability of m-banking varies with individuals' perceptions of time-saving benefits, and this relationship differs between smartphone users and wearable users.	**H3**
Having previously saved time due to m-banking is associated with higher m-banking likelihood.	Full Data
Smartphone users who have saved time by m-banking are 71% more likely to m–bank.	PHON-only

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Observation	Based on
Wearable users who have saved time by m-banking are 100% more likely to m–bank.	WEAR-only
H4.1. Age	
Younger individuals are more likely to m-bank through smart wearable devices relative to smartphones, compared to older individuals.	**H4.1.**
In general, $15-24$ year olds are less likely to m-bank than $25-34$ year olds.	Full Data
Smartphone users aged $15-24$ are less likely to m-bank than $25-34$ year olds.	PHON-only
Smartphone users aged $35+$ are not significantly different from $25-34$ year olds in terms of m-banking.	PHON-only
Wearable users aged $35-54$ are more likely to m-bank than $25-34$ year olds.	WEAR-only
Smartphone users aged $15-24$ and $55+$ are not significantly different from $25-34$ year olds in terms of m-banking.	WEAR-only
H4.2. Gender	
Women are more likely to m-bank through smartphone devices relative to smart wearable devices, compared to men.	**H4.2**
In general, women are more likely than men to m-bank.	Full Data
Female smartphone users are more likely to m-bank than their male counterparts.	PHON-only
There is no statistically significant difference between male and female wearable users in m-banking.	WEAR-only
Women prefer smartphones over wearable devices for m-banking.	
H4.3. Education	
Individuals with higher levels of education have a higher probability of m-banking through smart wearable devices relative to smartphones, compared to those with lower levels of education.	**H4.3**
Having higher education is associated with higher m-banking adoption.	Full Data
Compared to high school educated, smartphone users with more education are more likely to m–bank.	PHON-only
Compared to high school educated, wearable users with more education are more likely to m–bank. This relationship is stronger in WEAR users than PHON users.	WEAR-only
H4.4. Income	
Income is significantly associated with m-banking adoption among smartphone users, but not among wearable users.	**H4.4**
In general, individuals in the upper quintile income brackets are more likely to m–bank.	Full Data
Smartphone users in the upper quintile income brackets are more likely to m–bank.	PHON-only
Among wearable users, income is not significantly associated with m-banking adoption. None of the income coefficients reach statistical significance.	WEAR-only

Continued on next page →

Observation	Based on
The association between income and m-banking adoption does not significantly differ between smartphone and wearable users for $Q2$ and $Q3$ (vs. $Q1$).	Wald test
The association between income and m-banking adoption is significantly stronger for smartphone users than wearable users for $Q4$ and $Q5$ (vs. $Q1$)	Wald test

Notes: 1: For brevity, we refer to m-banking adoption as m-banking.

2: For brevity, we refer to smart wearable users as wearable users.

4.6.1 Discussion on Perceived Trust

Perceived trust is a dynamic factor existing along a continuum. Users may initially be uncertain or skeptical of a new technology. However, through repeated and positive interactions with the new technology, users may gradually develop trust in the system, thereby, having higher perceptions of trust in the technology [326]. Another intricate aspect of perceived trust is in the way in which we discuss mis-trust, distrust and not trusting something. That is, no trust is not synonymous with mistrust or distrust. A lack of trust or low perceptions of trust implies an absence of confidence. On the other hand, mistrust (or distrust) implies active doubt or suspicion [49]. It is important to clarify that in our context, based on the wording used by CIUS questionnaire available in Table 4.2, we only consider lack of trust and low perceptions of trust.

Given the multifaceted nature of trust, researchers often isolate specific dimensions (such as institutional trust) to improve construct validity and ensure analytic clarity [264]. Accordingly, our methodological decision to focus on trust in the institution behind the m-banking app aligns with standard practice and is appropriate for our analysis. This focus also fits our hypothesis, which posits no difference between users of different devices (smart wearable devices and smartphones) in the association between perceived trust in banks and m-banking adoption. While this approach is justified, we recognize that excluding trust in the devices themselves may overlook additional factors that influence adoption.

Prior research suggests that perceived trust can also be shaped by the characteristics of the

device, which may directly affect perceptions of technological trustworthiness and, in turn, user behavior [486]. Furthermore, perceived trust in the provider and perceived trust in the technology often interact in ways that jointly influence adoption decisions [486]. Therefore, we suggest future research to include measures on device-specific trust as well to strengthen this analysis. We now interpret our results, focusing on how the relationship between perceived trust and m-banking adoption differs between PHON and WEAR user groups.

Our analysis showed that for both groups, perceived trust is associated with m-banking, which aligns with the literature [382, 304]. In general, higher trust in banks increases m-banking adoption [29, 207]. Studies frequently find that perceived trust plays a pivotal role in users' intention to adopt and use smartphone-based technologies (including apps, mobile commerce, and mobile payments) [514]. Perceived trust is a major predictor for e-wallet (smartphone-based Fintech) adoption, often surpassing factors like ease of use or perceived utility [198]. Perceived trust also mediates acceptance in contexts where personal or financial data are exchanged via smartphones, such as in mobile apps [514, 107].

Studies on perceived trust and wearables are rare. However, research into other smart internet-connected devices (like voice-based devices) underscores that trust in both manufacturers and the technology itself strongly affect adoption [378]. In health-related wearables, perceived trust is often linked to the reliability and perceived accuracy of health or fitness data, as well as assurances regarding personal data privacy. Concerns about data misuse or inadequate protection can present significant barriers to widespread adoption, especially in health-related wearables. For smartphones, perceived trust is often tied to the platform (in our context, this is the iOS or Android operating systems), app quality, and familiarity, given their role in daily life and frequency of use [224, 514, 198].

For wearables, perceived trust may hinge more on the integrity of sensitive personal data, the transparency of data use policies, and the transparency of sensor-based feedback [378]. The perceived complexity and novelty of wearables may lead users to seek more robust assurances about privacy and security than with smartphones, which are now considered essential and familiar devices for most users [378, 310]. Perceived trust relates to m-banking adoption differently for

PHON and WEAR users. Among PHON users, low or neutral perceptions of trust (in banks) is linked to lower adoption, but high perception of trust doesn't significantly boost it.

For WEAR users, only those who rarely perceive banks as trustworthy are less likely to adopt; all other perceived trust levels show no difference. This suggests that while lower perception of trust is associated with lower m-banking likelihood for PHON users, perceived trust levels are not associated with WEAR users' adoption decisions. Smart wearables usually serve as convenient add-ons to smartphones, not primary tools for banking. This suggests WEAR users' perceived trust may relate more to their device than to banks. Group demographics may also explain differences in trust patterns: as noted in Section 4.3, WEAR users are generally younger, more tech-savvy, and more open to risk. These traits may shape how they assess trust. Perceived trust in technology also connects to security, i.e., features like encryption, authentication, and regulatory compliance [462]. Since these vary by device, they may help explain the distinct perceived trust patterns seen among WEAR users. Future research should explore whether WEAR users prioritize device trust over institutional trust.

4.6.2 Discussion on Perceived Security

Our results show that perceived security is associated with m-banking adoption for both PHON and WEAR users, but the relationship is stronger for PHON users. Smartphones and smart wearable devices may evoke different security perceptions due to inherent hardware and software differences. This may reflect how users view smartphones as more secure and capable for sensitive tasks compared to smart wearable devices, which are seen as secondary tools. Smartphones' more advanced hardware, stronger security protocols, and role as primary devices may contribute to their perceived robustness [567]. Smart wearables, by contrast, are often used for quick interactions and may be perceived as less secure due to small screens, limited input, and simpler protections [103, 576].

Our results align with existing literature [355]. Smartphones are more advanced in both hardware and software [436] and are often perceived as more secure [217]. On the other hand, wearable devices are perceived as less secure because of limited processing power and simple security

mechanism [103]. For example, smart wearable devices such as smartwatches have smaller screens that make some security measures such as PIN and pattern locks harder to use [576]. Additionally, smart wearable devices' constant accessibility may create a false sense of security. As extensions of smartphones worn on the body, users may underestimate their ability to capture sensitive data that could potentially expose them to security risks [196].

While various studies have investigated the link between perceptions of security and technology adoption – with a heavier focus on smartphones – direct comparative studies addressing differences across device types are rare [458]. Perceived security significantly increases user willingness to adopt smartphone-based services [413]. Smartphone users in both the U.S. and Korea rate security as the most influential factor in their frequency of mobile payment use, above cost or convenience [458, 413, 577]. Older adults may experience more barriers to smartphone adoption if they perceive a high threat of cyberattacks or low device security [392]. For this group, the perception of cyber risk is a significant factor discouraging adoption. Among low-income groups, fear of inadequate security limits both device adoption and uptake of wearable-based services [254]. Our inclusion of demographic factors (age and income) controls for such nuances.

Security concerns also shape the use of specific security features (e.g., antivirus apps, biometric locks) [242]. Some users discontinue using security tools due to misunderstandings about their effectiveness or fears of reduced device performance [33]. Our measure of perceived security included various such features. The literature on wearable device adoption points toward security and privacy concerns being barriers to adoption, especially for health-related wearables which collect sensitive personal data [254]. Users are often apprehensive about how data is shared and stored, which may slow adoption compared to more established devices like smartphones. However, most available studies combine privacy and security, making it difficult to isolate pure security perceptions apart from privacy alone. Our narrow focus on security alone helps to address this gap.

While security matters for both device types, users perceive risks differently [33, 105]. When considering smartphones, users' adoption tends to focus on risks of financial loss or data theft via mobile payments, m-banking apps, or unsecure networks [458, 413, 242]. For wearable devices, on the other hand, adoption barriers are often tied to the risk of highly personal data (e.g., health,

biometric data) being misused, hacked, or inadequately protected [102, 506, 506]. We believe this difference partly explains the patterns seen in our results. However, since we rely on secondary data, we cannot examine this further. Future work could address this with direct survey questions targeting device-specific security perceptions.

4.6.3 Discussion on time-saving

Time-saving, facilitated by using m-banking, plays a significant role in m-banking adoption for both PHON and WEAR users, though the strength of its relationship with m-banking is different between these groups. That is, the association between time-saving benefits and m-banking adoption is stronger for WEAR users than for PHON users. This aligns with the design and use of wearable devices, which prioritize convenience and speed, making them ideal for quick, on-the-go interactions [544]. Smart wearable devices are designed for quick, seamless interactions, which makes them particularly effective for time-saving tasks like approving transactions, paying using NFC or checking notifications. This usability advantage enhances the perception of time efficiency.

Several studies show that perceived time-saving benefits are strongly associated with smartphone adoption [17]. In transit, smartphone apps reduce wait times and improve planning, which is linked to higher adoption and satisfaction [67]. In retail, smartphones are favored for saving time compared to traditional shopping, making time-saving a key predictor [223]. This aligns with the Diffusion of Innovation (DOI or DIT) theory, where relative advantage (e.g., time-saving) supports positive adoption attitudes [562]. Wearable device studies highlight health monitoring, data accessibility, and convenience, but rarely isolate time-saving as a main adoption factor. While perceived usefulness and ease of use matter for wearables, time-saving receives little focus in user surveys or models. Direct device comparisons in terms of time-saving remains underexplored in the literature, making it a great opportunity for future studies.

4.6.4 Discussion on Demographic Variables

Across most age groups, device type shapes distinct adoption behaviors, reflecting differences in user preferences, device functionality, and usage contexts. For PHON users, age relates to

m-banking adoption in a consistent, predictable pattern. In contrast, WEAR users display a more dynamic relationship between age and m-banking adoption. Some possible explanations for variations observed in the data could be tested in future studies: Certain age groups (such as $35-54$ year olds) may have more established digital habits, especially compared to younger adults who may still be exploring financial tools. Additionally, this age group may have more stable income, so they may be more likely to require m-banking services. Another explanation could be that younger adults in the $25-34$ year old age group may prefer even newer Fintech technologies (e.g., Venmo, PayPal, Cash Apps, Cryptocurrency) instead of more traditional m-banking solutions. Even users aged 65 and older show higher m-banking adoption (though non-significant), suggesting that WEAR users in older age groups than baseline are more tech-savvy, early adopters or value the convenience of smart wearable devices for financial transactions.

The association between gender and m-banking adoption differs for PHON and WEAR users. While female PHON users are significantly more likely to adopt m-banking, this difference disappears for WEAR users. This is despite the fact that more women use smart wearable devices than men [299]. Based on our data, women seem to actively choose smartphones over smart wearable devices for m-banking. This slight gender preference may reflect broader trends, such as women's growing engagement with mobile services for managing finances or women's hesitation towards more risky options. Women are more loss and risk averse than men [215, 126]. Therefore, this difference may stem from women's greater emphasis on safety, leading them to prefer more secure options, such as smartphones. Additionally, women's concerns with aesthetics, privacy and practicality may lead them to be more selective of choosing wearables for financial tasks [316].

Education plays a significant role in m-banking adoption. Higher education levels are generally associated with increased m-banking adoption across both device types, but the magnitude and patterns vary. For PHON users, higher education consistently correlates with greater m-banking adoption. University graduates are slightly more likely to adopt m-banking than those with some college education. This aligns with the literature which posits that higher education enhances comfort and familiarity with technology, leading to greater adoption of secure and multi-functional devices like smartphones for managing finances [397, 442]. For WEAR users, this association is even stronger. This is also supported by the literature [207]. Although in our

analysis we noted that WEAR users with some college education or certificates are slightly more likely to m–bank compared to university graduates, this difference is not statistically significant ($\text{OR} = 1.02,\ p = 0.940$). The difference may simply reflect the demographics of smart wearable users who are younger, tech-savvy individuals who are currently in college or early in their careers who are more likely to own these devices. The preference for wearables among younger, less formally educated users could also stem from lifestyle factors, where convenience and integration with health or fitness apps play a bigger role than the need for detailed financial management.

Lastly, we observed that higher income for PHON users is associated with increased m-banking likelihood. Users in the highest income quintile ($Q5$) are particularly likely to m–bank, reflecting their greater access to financial resources and comfort with technology. This result strengthens the findings of literature [442]. PHON users in the second quintile ($Q2$) are significantly more likely to m–bank than those in the lowest quintile ($Q1$). This could indicate that smartphones are seen as essential, versatile devices for financial management, even for users with relatively moderate income. For WEAR users, however, higher income is not significantly correlated with m-banking adoption.

The relationship between income and m-banking is less straightforward for WEAR users. While higher-income users ($Q4$ and $Q5$) adopt m-banking at higher rates, these differences were not significant. Those in $Q2$ and $Q3$ are less likely to m-bank compared to $Q1$ users, although, these differences are also not significant. Based on our data, the association between income and m-banking adoption significantly differed in two income groups between PHON and WEAR users (the highest earners). It seems that high earning smartphone users (relative to smart wear users) are more likely to m-bank. This may be explained by demographic differences of users, which may represent a niche group: younger, tech-savvy individuals who own smart wearable devices but do not yet rely on them for banking. This group may serve as a transitional demographic: they have both the means to adoption and the technological know-how.

4.6.5 Theoretical Insights

Our findings contribute to technology adoption theories, particularly regarding how perceived trust, perceived security, time-saving, and demographic factors are associated with m-banking adoption for smartphone and smart wearable users. Perceived trust emerged as a key factor influencing m-banking adoption. For smartphone users, perceived trust was strongly associated with m-banking adoption more so than for WEAR users. The significant association of perceived trust in the institution and m-banking for smartphone users aligns with the Unified Theory of Acceptance and Use of Technology (UTAUT), which emphasizes barrier to adoption which can be mediated through enhanced trust [528].

For smart wearable users, the relationship between trust and adoption was not straightforward. Surprisingly, having low perceived trust was not significantly different from having full trust in terms of its relationship with m-banking adoption. Those with low perceived trust in banks were less likely to m-bank than those with full trust, while slightly lower trust than full did not relate to significant adoption. This finding challenges traditional adoption models by highlighting the unique role of smart wearable devices. While our results indicate trust is less critical for smart wearable users, an alternative explanation lies in the measurement of our perceived trust construct.

The survey question concerns trust in financial institutions generally, not trust related to a specific device. It is possible that for smartwear users, trust in the technology manufacturer (e.g., Apple or Google) is more important than institutional trust, a dimension our data does not capture. In short, the difference we observe may be attributed to the fact that smart wearable users may prioritize trust in their smart wearable device over institutional trust. Additionally, smartphones are often the primary device for a wide range of sensitive transactions, whereas smart wearables often serve as convenient, supplementary extensions. Because the scope of risk is greater on the primary device, institutional trust is likely to be a more critical factor in mitigating that risk for smartphone users. In contrast, for quick transactions on a wearable, convenience may outweigh the need for high institutional trust. Our results extend previous understandings by emphasizing the interaction between perceived trust in banks and device-specific perceptions, suggesting that perception of trust plays a more nuanced role for emerging technologies like smart wearable devices in Fintech.

Our findings suggest that classical technology adoption models such as UTAUT may require refinement to better capture device contexts. Institutional trust does not translate the same across different devices. Therefore, technology adoption models should include perceived trust in a way that these expected device nuances are accounted for. Currently, this is not addressed in most frequently used models, which assume uniform trust mechanisms regardless of device when addressing mobile or online banking. Future models might benefit from distinguishing between device-specific influence of trust. Our results also highlight that depending on how the device is being used (and how central it is to the users' technological ecosystem), perceptions of trust may differ significantly. In a way, device creates a segmentation in trust perceptions. This opens the door to theoretical development and improvement, especially in expanding TAM/UTAUT to include device-specific moderating factors that influence user adoption behavior differently across technologies.

Perceived security is significantly associated with m-banking adoption, with a stronger relationship for smartphone users. Smartphones are perceived as secure, versatile devices. Aligning with UTAUT and its extensions, perceived security is one of the drivers of technology adoption [529]. Smartphone users, more reliant on their devices for diverse financial tasks, demonstrate higher adoption rates and perceive their devices as more secure. For smart wearable users, perceived security also positively correlates with m-banking adoption but to a lesser extent. This reflects smart wearables devices' complementary role, where users may rely on smartphones for more sensitive tasks. Users may also not consider smart wearable's security as most of the security options related to m-banking apps are taken care of through smartphone apps. The findings suggest that the device's perceived security and primary versus supplementary role may mediate the relationship between perceived security and adoption, extending UTAUT by accounting for device-specific roles.

Our findings refine the UTAUT framework by emphasizing the importance of device context in moderating the relationship between perceived security and adoption. While perceived security is a known enabler of adoption in UTAUT, our results indicate that this relationship is not uniform across device types. In other words, perceptions of security and their importance in predicting users' m-banking adoption depends on the device the user is using. Particularly, we believe this

may be due to the primary and supplementary nature of the devices such as smartphones and smart wearable devices. This suggests the need to model perceived security as a context-sensitive construct that is influenced by the device being used. Additionally, based on our previous discussions, a large part of this difference is due to the device-dependent security perceptions. For smart wearable users, the reliance on smartphones for actual authentication and risk mitigation reduces the perceived role of the wearable in handling sensitive data.

We may think of this as a delegation of responsibility to the primary device. In an Internet of Things (IOT) ecosystems, such as using IOT devices and smartphones in home automation, smartphones often act as local hubs where they delegate control commands to other devices [547]. Users often rely on the primary hub device that manages access, authorizes transactions and enforces security settings for other devices. This device is the anchor managing the ecosystem, and often perceived as the device that is the most secure (or is able to carry out most security measures) [547]. This intra-ecosystem transfer of control and security responsibilities is largely overlooked in existing technology adoption models. Future theoretical work should explicitly account for this delegation effect, especially in multi-device environments like those involving smart wearables and smartphones, where the perception of security and control may be device-specific.

Our results showed that the association between time-saving benefits and m-banking adoption is stronger for smart wearable users than for smartphone users. This aligns with smart wearables' design for quick, seamless interactions. We view time-saving as a value added for users, similar to much of the literature especially in terms of smart wearable devices where convenience is an important feature. Our results are supported by Diffusion of Innovations theory [59], where relative advantage (e.g., time-saving benefit) drives adoption. For smart wearable users, time-saving represents a key relative advantage, reinforcing the device's role as a convenient, on-the-go tool. Smartphone users also value time-saving, but to a lesser degree. Smartphones' multi-functionality makes them well-suited for time-intensive tasks, but this broader scope may dilute the perceived benefits of time-saving for m-banking specifically. These findings highlight how time-saving benefits (similar to relative advantage) interact with device type and relate to m-banking adoption, offering a refined perspective in adoption theories.

As stated, our results support and refine the DOI theory, where relative advantage is a central predictor of adoption. Time-saving benefit of technology adoption is a relative advantage [284]. Our contribution is showing that the strength of the association between time-saving and m-banking adoption varies significantly by device type. This nuance is currently not explored in DOI-based studies. For smartphones, time-saving is just one of many benefits, possibly diluted by the device's multifunctionality. In contrast, for smart wearables, the ability to save time is core to the device's design, making it a much stronger driver for this type of device. Our result suggests that relative advantage, depending on context, should not be treated as device-agnostic. Therefore, specific design features that may amplify certain advantages need to be considered.

Our data showcased how younger individuals are more likely to adopt m-banking through smart wearable devices (relative to smartphones) than older individuals. Within each group, we observed interesting patterns as well. Smartphone users demonstrate a steady decline in adoption with age, consistent with the Digital Divide Theory, where older individuals face greater barriers to technology adoption [422, 565, 474]. Smart wearable users, in contrast, show increasing adoption rates with age, reflecting their technological savvy and preference for convenient, multifunctional devices. These results suggest that smart wearable devices appeal to a distinct demographic that values convenience, health and speed. The association between gender and the probability of adopting m-banking differs between smartphone and smart wearable users. For smartphone users, women were more likely to m-bank than men. For smart wearable device uses, there were no significant differences between men and women in terms of m-banking. These results highlight how women may prefer smartphones for m-banking over smart wearable devices. This aligns with Social Role Theory (SRT) as well as aligning with discussions on women's risk behaviors. SRT posits that women are more likely to adopt technologies that support multitasking and accessibility [405, 292].

Education correlates positively with m-banking adoption for both group, with a stronger tie in smart wearable users. These findings align with digital divide [422, 565, 536]. The association between income levels and the probability of adopting m-banking differs between smartphone and smart wearable users. For smartphone users, m-banking adoption increases steadily with income, reflecting broader access to technology and financial resources, supported by research on financial

inclusion and vulnerability [536, 442, 536]. For smart wearable users, the relationship is less consistent, with unique behaviors in lower income groups suggesting that smart wearable devices attract niche demographics prioritizing lifestyle integration over financial utility. These results contribute to adoption theories by emphasizing the interplay between socioeconomic factors and device-specific perceptions.

4.6.6 Managerial Insights

Our findings provide actionable insights for banks and financial institutions to tailor their m-banking strategies for different user segments, focusing on device-specific preferences, perceived trust, perceived security, time-saving, and demographic factors. Perceived trust plays a critical role in m-banking adoption. However, our observed results based on the data shows that its association with m-banking adoption varies by device type. Banks and financial institutions should enhance perceived trust through transparent communication for smartphone users who are highly influenced by it [462]. Additionally, banks and financial institutions should focus on partnerships with smart wearable manufacturers and software developers to improve security measures and risks within these devices and apps such as accidental triggers, access to unlocked screen, small user interface design, and more.

For example, a user is able to trigger Apply Pay by double tapping the side button without inputting their PIN number or verifying their identity [1]. This brings up the top card in user's Apple wallet on Apple smart watches, which can be quickly swiped if an NFC device is nearby. Although the wearer would get a notification of a transaction, this is not a sufficient security measure in place. Financial institutions should build perceived trust incrementally by providing transparent communication about data privacy, fraud prevention measures, and account security to reassure hesitant users. They should Focus on smart wearable users differently: Perceived trust is less critical for smart wearable users, who may rely on their perceived trust in their devices. Financial institutions should appeal to these users by improving security of these devices to the level of smartphones. Highlight convenience, innovation and device-specific security measures rather than overemphasizing (perceived) institutional trust.

[1] This is true for the version of Apple Pay at the time of this writing.

Perceptions of security are enhanced through various measures [286]. Financial institutions should leverage security features to drive adoption, but do not make it overly complicated. Making the already existing security features more seamless and easy to set up so that all users are able to use these features would enhance adoption across both devices. While security threats exist, many users are simply unaware of the measures available to protect themselves against these [364]. Institutions should provide education, such as offering free in-person aid to educate users about security features on both smartphones and smart wearable devices, targeting older or less tech-savvy segments to reduce apprehension. Additionally, security features should be easily implementable and users need to be made aware of their existence.

Time-saving is a significant motivator for m-banking adoption, particularly for smart wearable users who value convenience. Banks should focus on designing streamlined experiences, developing smartwatch apps optimized for quick transactions similar to smartphone apps such as approving payments, checking balances, and receiving alerts. Additionally, banks should market convenient features. Highlight features like contactless payments, quick transfers, and pre-filled forms to demonstrate how m-banking saves time for on-the-go users.

Banks and financial institutions should customize their strategies for different demographic segments. Demographics such as age, gender, education, and income significantly influence m-banking adoption. Financial institutions should target younger users with smart wearable devices to encourage m-banking adoption. Younger, tech-savvy users often own smart wearable devices and value their integration capabilities. Tailor promotional campaigns to emphasize innovation, security and ease of use for this group. Engage older users with smartphones as these users rely on smartphones for financial tasks. Provide step-by-step tutorials and in-app support to build confidence in using m-banking. Address gender preferences as women who use smartphones are more likely to adopt m-banking. This insight also helps market researchers know the likely demographics for each device group. Lastly, focus on moderate-income groups with smartphones to promote m-banking as a cost-effective and essential tool for managing finances.

4.7 Conclusion

This study highlights the nuanced factors associated with mobile banking adoption across smartphones and smart wearable devices. Smartphones serve as versatile tools with higher mobile banking adoption influenced by perceived trust, perceived security, and demographic factors such as income and education. Conversely, smart wearable devices attract users prioritizing convenience and efficiency, with less emphasis on perceived trust and income. Our results underscore the importance of tailoring mobile banking strategies to device-specific user needs. Financial institutions should enhance smartphone applications by strengthening trust-building mechanisms, such as robust security features and user-friendly interfaces. For smart wearables, optimizing time-efficient functionalities and seamless integration with other devices is critical.

Our findings not only contribute to the literature on technology adoption but also offer actionable insights for improving mobile banking adoption, thereby advancing financial inclusion and user satisfaction across diverse demographic profiles. Future research should explore the role of evolving technologies and cross-device interactions in shaping mobile banking behaviors. Our findings refine existing technology adoption theories by incorporating device-specific contexts. They extend Technology Acceptance Model and Unified Theory of Acceptance and Use of Technology by highlighting how perceived trust, perceived security, and time-saving benefits interact with device type to shape adoption behaviors.

The results also underscore the importance of demographic and socioeconomic factors, suggesting that smart wearable and smartphones fulfill distinct roles in users' device ecosystems. This work contributes to a deeper understanding of how emerging technologies like smart wearable influence the dynamics of technology adoption, offering actionable insights for researchers and practitioners. By leveraging these insights, banks and financial institutions can refine their mobile banking strategies, ensuring they cater to the diverse needs of smartphone and wearable users. Tailored approaches to trust, security, convenience, and demographic preferences will enhance adoption and foster long-term engagement with mobile banking services.

Our research is limited in few ways. Most of the limitations stem from the secondary nature of

our dataset. As a result of this, some of our model variables may be inflated. More specifically, we were limited in the following measures: First, we did not have access to questions on device measures of (perceived) trust for both smartphones and smart wearable devices. We suggest future studies further investigate the nuances in perceived trust by asking whether smart wearable and smartphone users prioritize trust in their device over institutional trust (i.e., trust in banks). Next, the time-saving benefit of using mobile banking could be inflated by other measures as the specific question used for this measurement does not specify whether the time that is saved is a direct result of using a mobile banking app. Future studies should directly measure the time-saving that is the result of using mobile banking adoption. For future studies, we suggest looking into why women prefer to use smartphones for mobile banking rather than smart wearable devices, despite being more likely to use smart wearable devices in general.

Chapter 5

Concluding The Dissertation

In this chapter, I will conclude the dissertation by discussing each individual chapter's purpose, what was done and what the results were. Next, I go over some of the limitations and challenges faced in this dissertation and offer suggestions and ideas for future work to address these limitations and move the research paradigm ahead.

5.1 Conclusion

The integration of technology into the banking sector has introduced challenges and opportunities, with mobile banking (m-banking) adoption becoming one of the areas of interest. In this dissertation I set out to unravel the blueprint of m-banking adoption. Overall, this dissertation contributes to the m-banking literature in many ways. From a theoretical perspective, my contribution is refining existing models through the integration of intrinsic factors, mental health considerations, and device-specific measures. Methodologically, the use of text-mining techniques in literature reviews and comparative studies on device-specific adoption patterns further strengthen the analytical side of m-banking research.

From a practical point of view, my findings have important implications for banks, financial institutions, application developers, and policymakers. The categorization of intrinsic factors

contributes significantly to the literature of technology adoption, beyond m-banking adoption. This framework provides a reference for researchers to discover related factors, theories, methodologies, and challenges. This work provides a comprehensive exploration of m-banking adoption, systematically examining intrinsic factors – a novel way to look at a certain group of inwardly processed factors – as well as studying mental health's relationship with m-banking adoption, and device-specific influences that shape user behavior in this area. This was done through the following three interconnected studies.

5.1.1 Study 1 – Chapter 2

Researchers have identified various factors that influence consumers' m-banking adoption decision. Many of these factors are latent, i.e., not directly measurable or observable. For this reason, there is a lack of uniform definition for many of these factors across the literature. In the study of **Chapter** 2 – titled "*The Inner Workings of Mobile Banking Adoption - A Systematic Literature Review of Intrinsic Factors*" – I set out to address the shortcomings of the literature in offering specific and clear definitions and categorizations. Doing this provided a clear categorized framework that researchers can use as a reference to produce context-specific and focused studies in the future.

I revealed significant gaps in existing literature such as a lack of focus on various theoretical frameworks (e.g., SCT and SIT), lack of insight on multiple factors particularly related to psychological aspects such as anxiety, cognitive resistance and enjoyment, lack of studies where both trust and perceived risks are considered simultaneously, lack of studies examining newer mobile devices that have been introduced into existing m-banking ecosystems such as smartwatches, and lack of certain study methods such as cultural and comparative.

The findings emphasize that existing research is heavily concentrated on certain theoretical models such as Technology Acceptance Model and Unified Theory of Acceptance and Use of Technology. One of the most challenging aspects of research in this area, according to my findings, is data. That is, many studies either had small or unrepresentative samples or were challenged due to biased samples. With the exception of one study [76], the literature significantly lacks longitudinal research. Furthermore, comparative studies, cultural studies, and studies done regarding

m-banking behavior in the developed world are in the minority.

5.1.2 Study 2 – Chapter 3

My second study was motivated by the first study where the results of my systematic literature review showed a significant gap: very few studies investigated psychological and cognitive related constructs such as anxiety in the m-banking adoption literature. However, the main motivation for this study came from the results of Park *et al*'s investigation of anxiety in mobile payments [384]. Their results were in contrast with what was expected, i.e., anxiety lowers adoption of m-pay (they found evidence of the opposite). One belief is that that not considering differences in how people experience anxiety (personal level) is the reason for observing such results. Therefore, I set out to test this assumption, but extending it to encompass many different emotional paradigms.

In **Chapter** 3, the relationship between Mental Health and mobile banking adoption was analyzed. Mental health was used as a proxy measure for emotions, and sufficient justification was provided for this measurement. This study explored the relationship between mental health and mobile banking adoption in Canada, considering moderating factors such as relationship satisfaction, smartphone dependency, and social media use. My findings revealed that individuals with better mental health are less likely to adopt m-banking, challenging the assumption that digital financial services cater to all consumers equally.

A deep dive into the literature strengthened my results by providing context and explanations (e.g., individuals with Social Anxiety often prefer to do business without face-to-face interactions). My results showed that while social media use and smartphone dependency were positively related to m-banking adoption, they did not significantly moderate the association between mental health and m-banking adoption. The results also showed that relationship satisfaction did not correlate with m-banking adoption and it had no moderating effect on mental health. Financial institutions can benefit from the results of this study. The results encourage targeted advertising, mental health-aware marketing and social media-driven engagement.

5.1.3 Study 3 – Chapter 4

The third study was also motivated by the results of the first study. Particularly, I decided to address two things: lack of focus on comparative studies and lack of focus on studies on newer mobile banking-capable devices. In **Chapter** 4, "The Device Divide - Unpacking Mobile Banking Adoption for Smartphones and Wearables", I provide a comparative analysis of mobile banking adoption between smartphone and smart wearable device users, highlighting distinct behavioral and demographic factors. The results showed that perceived trust significantly correlates with m-banking adoption for smartphone users, but it did not have the same relationship with m-banking for smart wearable users.

Smart wearable users prioritized time efficiency (i.e., using their device to do m-banking saved them time) more than smartphone users did. My results showed that users perceived smartphones as the more secure device. Perceived security was more pronounced among smartphone users – possibly due to greater awareness and control over security settings. Demographic variables such as age, education, and gender are also significant in m-banking adoption. This study is the first to offer a comparative analysis of m-banking adoption across different device types, providing valuable insights into optimizing user experiences.

Next, I will discuss the limitations of the studies. To do this, I will first point out the limitations for each chapter corresponding to one study (Chapter 2 – Chapter 4). Then, I will offer some suggestions that are either ideas to address the limitations mentioned for each study or suggestions for future work based on the results of each study.

Limitations

The following are the limitations of my dissertation. These are discussed separately for each study/chapter. For Chapter 2, *The Inner Workings of Mobile Banking Adoption: A Systematic Literature Review of Intrinsic Factors*, I faced the following limitations:

1. **Scope - limited years considered** Only papers published in 2018 – 2024 are included in this systematic literature review.
2. **Search** To do my literature search, I used various synonymous words for the main word to expand the search. However, other potential terminology beyond this might exist that might have been missed.
3. **No Word Embeddings** Due to time and hardware limitations, large word embeddings could not be used in text analysis. Word embeddings would have strengthened my text analysis results.
4. **Manual Decision Making** I decided on the theme of each paper by reading papers, considering the factors, keywords, and titles. This was possible for 143 papers, but as this number grows, this becomes inefficient.
5. **Sample Size Not Reported** Over 28% of the articles in the literature gathered did not specify the exact number of samples in their studies. This limited my analysis as I had to discard these studies for the statistical analysis and visualizations that were related to sample sizes.
6. **Large Sample Size Variance** Another limitation due to sample sizes was the large variance between studies' sample sizes. This caused problems for binning the samples as the sample sizes were spread too far.

For Chapter 3, *The Relationship Between Mental Health and Mobile Banking Adoption: Evidence from Canada*, I faced the following limitations:

1. **Secondary Dataset** The dataset used for this study was secondary, meaning, at no point in the data collection were the authors involved with the questionnaire design and data collection and even before this with sampling. Therefore, we use caution in interpreting results as this secondary nature of the data poses threats to our measurements and construct validity.

2. **Canadian-specific Data** The dataset used was specific to Canada, limiting generalizability to other countries that are not similar to Canada.
3. **Measurement** The measurement scale used by CIUS was not aligned with standard Psychological measurements of mental health. The scale used in the CIUS lacks a clear midpoint as well as meaningful/descriptive answer choices (e.g., *what exactly is the difference between "excellent" and "very good"?*), potentially leading to ambiguity in participants' responses.
4. **COVID-19 Effects** The CIUS dataset for this study was collected during the COVID-19 pandemic. Despite including questions about COVID-19, none were related to mobile banking. Therefore, I was not able to discuss COVID-19's impact on m-banking. Furthermore, the relationships observed in the dataset may stem from the impact of COVID-19 at the time (as a confounding variable not considered in the study).

For Chapter 4, *The Device Divide: Unpacking Mobile Banking Adoption Differences for Smartphones and Smart Wearable Devices*, I faced the following limitations:

1. **Secondary Dataset** The dataset used for this study was secondary, meaning, at no point in the data collection were the authors involved with the questionnaire design and data collection and even before this with sampling. Therefore, we use caution in interpreting results as this secondary nature of the data poses threats to our measurements and construct validity.
2. **Canadian-specific Data** The dataset used was specific to Canada, limiting generalizability to other countries that are not similar to Canada.
3. **Measurement** CIUS did not have a specific measurement for Perceived Security of devices. Therefore, a latent variable had to be defined and included. Direct measurements would have provided much stronger insights.
4. **Lack of Smart Wearable Device Studies** Because the literature on m-banking use through smart wearables is lacking, I had to look into the uptake of smart wearables in other areas of research such as in healthcare and fitness. For the most part, this is not a problem – but there may have been factors that are context specific that were either added or missed because of this.
5. **Smart Wearables as Extensions of Smartphones** There may be compound effects in the measures of smart wearable-perceived security because these devices are often extensions

of smartphones. That is, they do not work as standalone devices. Therefore, their security is highly dependent on smartphones. There is no clear separation between security questions referring to smartphones or smart wearables, specifically. This is because all users have to be smartphone users. I had to assume that the answers when data was filtered on `isSmartWear`$== 1$ (smart wearable user) were not about smartphones, and data was filtered on `isSmartWear`$== 0$ (smartphone user), they were about smartphone security.

6. **No smartphone-specific Trust Question** There were no direct questions on trust in smartphones. Therefore, trust in devices as measures were not added to the model.
7. **Time-saving may not be directly a result of m-banking** Based on how the question is presented in the survey and since other tasks could have been involved for time-saving effect (the question is not specifically about m-banking, refer to Table 4.2), there may be unaccounted factors mediating time-saving's relationship with m-banking – which are not considered here.
8. **Smart Wearable instead of Smartwatch** Lastly, the question on CIUS is specifically regarding smart wearable devices which could also include fitness trackers and Virtual Reality devices – many of which are not compatible with m-banking, at least not at the time of this writing.

Next, I will offer some recommendations for future research. These may either address the limitations of each study or are future work suggestions based on the results of each study.

Suggestions for Future Work

To address the limitations of the first study, I suggest the following be done:

1. **Expand Publication Time** Expanding the time frame of the study to include studies from the earlier roll outs of mobile banking applications to recent times could better capture the changes and trends in the literature. However, I acknowledge that this may be a very large dataset. Perhaps Large Language Models (LLMs) could be used to automate some of the work in the future.
2. **Use Large Language Models to Expand Time Frame** LLMs can be used to streamline the process for extracting information from a much larger database of articles published in a larger time frame. However, this has its own challenges. LLMs are prone to hallucination, i.e., they can generate factually incorrect or unsupported content. Therefore, steps need to be taken to ensure the extracted information is correct while also ensuring that using LLMs is expediting the process.
3. **Fine-tuning LLMs** The results of this study can be used to fine-tune LLMs for similar future tasks.
4. **Better Search** To expand the search query, use tools (such as word embeddings from natural language processing, LLMs or scientific databases) to search for similar keywords across the literature. However, these tools might add unnecessary information which could over-complicate the task and misdirect search.
5. **Implement Word Embeddings** If resources and machine power allow, various word embedding such as Google's Word2vec or Hugging Face's BERT model could be used to strengthen the text analysis tasks.
6. **Sensitivity Analysis** A suggestion for manual theme classification could be to allocate the task between more experts to minimize the load on one person. Another suggestion is to use Artificial Intelligence based models to choose between themes.
7. **Missing Samples** Researchers and journals should be more transparent in communicating their study designs. For immediate solutions, several methods to handle missing data could be used: replace with mean or median (in this case, it was not possible due to large variation), use machine learning techniques and other features of the data to predict sample sizes (ambiguous accuracy), or contacting the corresponding author of the studies.

8. **Large Variations in Sample Size** One way to improve upon this issue is to normalize or use other standardization techniques. However, this does not mitigate the issue of missing data.

Additionally, based on the results of this study, the following are some recommendations for future research:

1. **Explore New Theories** TAM and UTAUT account for almost 70% of the theoretical foundations of the studies in the literature. Perhaps it is time to move away from these theories, as their effectiveness has been showcased numerous times. The majority of the other theories cited in my first study appear only once, indicating untapped potential for future research.
2. **Compare Cultures and Countries** The most common challenge is limited generalizability due to a focus on specific countries. Doing more comparative research between cultures and countries could potentially provide new insights that would not be found when focusing on just one culture/country.
3. **Use Online Surveys** Sample-related challenges are prominent across the literature, such as being restricted to university students. Various websites could be used to reach a global audience with a more diverse background.
4. **New Technologies** With the addition of NFC payments and smartwatch and mobile wallets, mobile banking is moving towards implementing even newer methodologies of doing banking. Future research should compare and understand these various technologies. Other emerging and evolving technologies are Blockchain based applications and Artificial Intelligence such as chatbot customer service agents.
5. **Finding New Factors** Various factors are mentioned throughout my first study, which have only been considered by one or two studies. These factors should be studied further in different settings and models.
6. **Meta-analysis** Within the years $2018 - 2024$, only 1 meta-analysis study was published in the area of mobile banking. A future meta-analysis could examine how trust integrates differently into TAM and UTAUT, providing deeper insights into its role in m-banking adoption.
7. **Integrate Trust and Perceived Risk** Few studies simultaneously address Perceived Risk

and Perceived Trust. A suggestion here is to integrate both in future research to examine their interactions. These interactions should be studied across diverse demographic, cultural, social, theoretical, and methodological contexts to provide a broader understanding.

8. **Sample Size** Small sample sizes hurt some of the studies in the literature. Using online survey tools could potentially remedy this, and open up the potential to use more advanced analytical tools such as machine learning.
9. **Developed Countries** This review also highlights a significant lack of focus on developed countries in recent years. This disparity underscores the need for more research on m-banking adoption in these regions, especially given the behavioral changes caused by the COVID–19 pandemic.
10. **Why is a factor better suited for some models?** Future studies should examine whether certain factors (that are not the core building blocks of a model) appear significantly less/more often in some models.
11. **COVID-19** Future studies should examine how COVID-19 has permanently impacted m-banking usage. Has the shift to m-banking because of the pandemic led to lasting changes in digital habits? A comparative study of before and after the COVID-19 pandemic could provide answers to this question.
12. **Emotions and Cognition** Future studies should investigate less–frequently examined factors such as anxiety, benevolence, cognitive resistance, and more.

To address the limitations of the second study, I suggest the following be done:

1. **Comparative Analysis between Canada and US** A future study could use US-based data as well as Canadian based data to compare the two countries as they share similar cultures.
2. **Use better measurements for Mental Health** Use Psychologically backed measurements of mental health from the Psychology literature to design questionnaires that measure mental health.
3. **Comparative Analysis of before and after COVID-19** Conduct a comparative analysis, similar to my third study, of use m-banking adoption behavior before COVID-19 and after COVID-19.
4. **Specific and Targeted Data** Design surveys to collect data using direct questions that measure what is needed for conceptual models.

To address the limitations of the third study, I suggest the following be done:

1. **Comparative Analysis between Canada and US** A future study could use US-based data as well as Canadian based data to compare the two countries as they share similar cultures.
2. **Specific Question on Perceptions of Security** Design questionnaires that specifically measure perceived security.
3. **Smart Wearable Device M-banking** Conduct studies focusing on the uptake of smart wearables such as smartwatches for m-banking.
4. **Measure Perceived Security for Each Device** Design a questionnaire that measures perceived security for each device type separately.
5. **Measure Trust in Devices** Design a questionnaire that measures Trust in specific device types as well as trust in banks and application developers.
6. **Measure Time-saving as a result of m-banking** Design a questionnaire that measures time-saving as a direct result of m-banking or use of a device or consider confounding effects and other variables that may be impacting time-saving's effect on m-banking adoption.
7. **Smartwatch** Since smartwatches are the most accessible and widespread wearables, consider designing a questionnaire that is specifically about smartwatch use rather than the larger group of smart wearable devices.
8. **Specific and Targeted Data** Design surveys to collect data using direct questions that measure what is needed for conceptual models.

Additionally, based on the results of this study, the following are some recommendations for future research:

1. **App Specific Features** A suggestion for future research is to consider combining Extrinsic (e.g., app specific features) and Intrinsic factors in a model and do comparative analysis between devices.
2. **Age and Digital Habits** Test whether certain age groups have more established digital habits, therefore are less likely to use new technologies.
3. **Age and Financial Needs** Study the financial needs of different age groups and demographics to see if associations exist between certain m-banking requirements and demographic profiles.

4. **Age and New Fintech** Investigate whether younger individuals are more likely to use other financial services such as money sharing apps (Venmo, PayPal, Cash Apps) or Cryptocurrencies than traditional banking extended to m-banking.
5. **Cross-Device Interactions** Study whether implementation of multi-device solutions (that involve more than one device) is beneficial for m-banking adoption.
6. **Trust in banks or Trust in device** Study whether users' trust in the bank (organization) is more or less important than trust in their devices for m-banking adoption, and how does this differ between smartphone and smart wearable users.
7. **Why do Women prefer smartphones to smart wearables for banking?** Investigate possible reasons such as risk-preferences, accessibility, multi-tasking capability and other features of devices to answer this question.

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APPENDICES

The following sections are additional information that were mostly out of the scope of the work. For Chapter 2, Appendix A is added to include Python code written by me for the Rule-based algorithm and topic modeling discussed in Sections 2.4.2 and 2.4.1, respectively. Additionally, a screenshot of the dataset is included so that readers can better see the data that was used in this study. For Chapter 3, Appendix B is added to include differences in Mental Health outcomes across provinces using a contingency table where mobile banking adoption is shown as well as a break down of the marginal effects of Mental Health on mobile banking for each province. Variations (random effect of province from the model) in m-banking adoption is visualized in a simple graph and a formula for when two variables enter the model is also added. For Chapter 4, Appendix C is added which includes manual information from iOS App Store for examples of some apps.

Appendix A

Code For Chapter 2

A.1 Code for Data Cleaning

The following is one of the functions I wrote in Python to clean the dataset. Each article's pdf file is read is read and the text is extracted and added to a Python dictionary where the key is the unique ID from Table 2.4. Therefore, the `preprocess_Dict(dct)` function takes in as input an entire dictionary, and cleans each entry (an entire article), and updating the dictionary.

```
def preprocess_Dict(dct):
    for k, v in dct.items():
        # if the value is in a list format
        if isinstance(v, list):
            processed_list = []
            for item in v:
                item = item.lower() # convert to lower case
                item = re.sub(r'http\S+|www\S+|@\S+', '', item) # remove
                ↪ links
                item = re.sub(r'(?<=\w)-(?=\w)', ' ', item) # remove
                ↪ hyphens
```

```
            item = re.sub(r'[^a-z0-9\s\n]', '', item) # keep
             ↪ alphanumerics
            item = re.sub(r'\s+', ' ', item).strip() # remove
             ↪ whitespace
            item = re.sub(r'\d+', '', item).strip() # remove digits
            item = " ".join([word for word in item.split() if word not
             ↪ in stop_words]) # remove stop words
            item = " ".join([lemmatizer.lemmatize(word,
             ↪ get_wordnet_pos(word)) for word in item.split()]) #
             ↪ lemming
            item = " ".join([stemmer.stem(word) for word in
             ↪ item.split()])
            processed_list.append(item) # keep stems
        dct[k] = " ".join(processed_list) # add list items together,
         ↪ and update dictionary
    else:
    # entire document in a single string (not a list)
        v = v.lower()
        v = re.sub(r'http\S+|www\S+|@\S+', '', v)
        v = re.sub(r'(?<=\w)-(?=\w)', ' ', v)
        v = re.sub(r'[^a-z0-9\s\n]', '', v)
        v = re.sub(r'\s+', ' ', v).strip()
        v = re.sub(r'\d+', '', v).strip()
        v = " ".join([word for word in v.split() if word not in
         ↪ stop_words])
        v = " ".join([lemmatizer.lemmatize(word,
         ↪ get_wordnet_pos(word)) for word in v.split()])
        v = " ".join([stemmer.stem(word) for word in v.split()])
        dct[k] = v
return dct
```

A.2 Implementation of Latent Dirichlet Allocation

The following are Python functions written for topic modeling. Function `build_lda_model` is the implementation of LDA algorithm. Function `train_models` trains 11 separate models each with a different value for number of topic, saving the models in a list. Function `calculate_coherence` calculates coherence for a model. Function `build_model_comparison_table` builds a table for easy comparison of models trained on uni-grams and bi-grams with various topic numbers. Function `pick_best_model` takes in the best number of topics which I found from `build_model_comparison_table` and picks the model with the best coherence score. For 22 models (uni-grams and bi-grams are 2, and each has 11 models in it with topic numbers from 5 to 15, for a total of 22 models) this is not necessary as a simple look up suffices. However, the function is written for the sake of scalability.

```
def build_lda_model(n_topic, corpus_, dictionary_):
    lda_model = gensim.models.ldamodel.LdaModel(corpus = corpus_,
                                                num_topics = n_topic,
                                                id2word = dictionary_,
                                                random_state = 100,
                                                update_every = 1,
                                                chunksize = 1000,
                                                passes = 10,
                                                alpha = 'auto',
                                                per_word_topics = True)
    return lda_model

def train_models(corpus_, dictionary_):
    list_to_hold_models = []
    topic_n_to_try = [5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15]

    for i in range(len(topic_n_to_try)):
```

```
        list_to_hold_models.insert(i, build_lda_model(topic_n_to_try[i],
        ↪  corpus_, dictionary_))

    return list_to_hold_models

def calculate_coherence(model, text, dictionary_):
    coherence_model_lda = CoherenceModel(model = model, texts = text,
    ↪  dictionary = dictionary_, coherence='c_v')
    coherence_lda = coherence_model_lda.get_coherence()

    return coherence_lda

def build_model_comparison_table(list_of_models, corpus_, dictionary_,
↪  data):
    tracker = 5 # to make sure I do not go above the required topic
    ↪  numbers
    models_coherence = []
    models_topics = [5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15]

    for model in list_of_models:
        models_coherence.append(calculate_coherence(model, data,
        ↪  dictionary_))
        tracker += 1 # increment tracker by 1

    if tracker == 10: # when done, show this message.
        print("Successfully generated model comparison table.")

    models_df = pd.DataFrame({
        'Num_Topics': models_topics,
        'Coherence': models_coherence})
```

```
    return models_df

def pick_best_model(num, m):
    """
    Model inputs are:
        num = best number of topics found according to
        ↪ build_model_comparison_table
        m = list of models
    """
    model_index = num - 5 # since number of topics starts at 5
    model_index = int(model_index) # making sure it is an integer value

    best_model = m[model_index]

    return best_model
```

A.3 Theme Assignment Code

To assign theme, I wrote a custom class, `CustomTfidfVectorizerUpdateClass`. A Large Language Model (`chatgpt.com`) was used to aid with fine-tuning the class, specifically for memory management (`csr_matrix`) and writing the method to determine themes as well as allowing multiple themes. This class extends `TfidfVectorizer` from `sklearn.feature_extraction.text`, adding new functionality to classify documents into themes based on TF-IDF scores. It creates a TF-IDF vectorizer using a predefined vocabulary. The vocabulary is a python dictionary of factors identified across articles, which I manually extracted from the papers. It normalizes term frequencies to avoid bias toward long documents. Then, it assigns themes to each document based on TF-IDF scores. `theme_of_words` is a dictionary where each key is a theme (e.g., "Psychology", "Personal", etc) and each value is a list of factors related to that theme.

The vocabulary for TF-IDF is built from all words in `theme_of_words`. `self.threshold` is a hyper parameter to determine whether a document belongs to multiple themes. The `build_analyzer()` method calls the original TF-IDF analyzer but wraps it in a lambda function, which allows further customization later if needed. The `fit_transform()` method calls the original `TfidfVectorizer.fit_transform()` method to create the TF-IDF matrix `X`. Then, it computes maximum word frequencies for each document using `_compute_max_frequencies()`, which is stored in `self.max_frequencies`. The `transform()` method just converts the original TF-IDF to a custom *augmented* term frequency:

$$augmented_tf = 0.5 + 0.5 \times \frac{\text{term frequency in document}}{\text{max term frequency in document}}$$

This scales term frequency values to avoid bias toward long documents. The resulting matrix is returned as a sparse matrix using `csr_matrix` to save memory. The `determine_themes()` method transforms documents into the TF-IDF matrix `X` and maps words to their index. It then calculates theme scores for each document: Each theme is scored based on the sum of TF-IDF values of its associated words. Themes are filtered based on the threshold: If a theme's score is greater than or equal to threshold $\times$ max_score, it is assigned to the document. Lastly, `_compute_max_frequencies()` method computes the highest word frequency per document.

```
from scipy.sparse import csr_matrix # compressed sparse row matrix for
 ↪  memory efficiency

class CustomTfidfVectorizerUpdateClass(TfidfVectorizer):
    def __init__(self, theme_of_words, threshold=0.8, **kwargs):
        # Generate vocabulary from theme_of_words
        vocabulary = list(set(word for words in theme_of_words.values()
         ↪  for word in words))
        super().__init__(vocabulary=vocabulary, **kwargs)
        self.threshold = threshold  # Threshold for determining multiple
         ↪  themes
```

```
        self.theme_of_words = theme_of_words  # Store theme_of_words for
        ↪ later use

    def build_analyzer(self):
        analyzer = super().build_analyzer()
        return lambda doc: [w for w in analyzer(doc)]

    def fit(self, raw_documents, y=None):
        self.fit_transform(raw_documents, y)
        return self

    def fit_transform(self, raw_documents, y=None):
        X = super().fit_transform(raw_documents, y)
        self.max_frequencies = self._compute_max_frequencies(X,
        ↪ raw_documents)
        return X

    def transform(self, raw_documents):
        X = super().transform(raw_documents)

        # Calculate augmented term frequency
        max_frequencies = self.max_frequencies
        max_frequencies[max_frequencies == 0] = 1  # Avoid division by
        ↪ zero
        augmented_tf = 0.5 + 0.5 * (X.toarray() / max_frequencies[:,
        ↪ None])

        return csr_matrix(augmented_tf)

    def determine_themes(self, documents_dict):
        """
```

```
    Determines the themes for each document based on TF-IDF scores.
    A paper can have multiple themes if the scores are within the
    ↪ threshold.

    :param documents_dict: Dictionary of documents (keys: IDs, values:
    ↪ text)
    :return: Dictionary where keys are document IDs and values are
    ↪ lists of themes
    """
    document_ids = list(documents_dict.keys())
    raw_documents = list(documents_dict.values())

    X = self.transform(raw_documents).toarray()
    feature_name_to_index = {name: i for i, name in
    ↪ enumerate(self.get_feature_names_out())}

    theme_scores = {}
    for doc_index, doc_vector in enumerate(X):
        doc_id = document_ids[doc_index]
        # Calculate scores for each theme
        scores = {
            theme: sum(doc_vector[feature_name_to_index[word]]
                       for word in keywords if word in
                       ↪ feature_name_to_index)
            for theme, keywords in self.theme_of_words.items()
        }
        max_score = max(scores.values()) if scores else 0

        # Determine themes within the threshold
        selected_themes = [
            theme for theme, score in scores.items()
```

```
                if score >= self.threshold * max_score
            ]
            theme_scores[doc_id] = selected_themes

        return theme_scores

    def _compute_max_frequencies(self, X, raw_documents):
        max_frequencies = np.zeros(X.shape[0])
        for i, doc in enumerate(raw_documents):
            term_freq = {}
            for term in doc.split():
                if term in term_freq:
                    term_freq[term] += 1
                else:
                    term_freq[term] = 1
            max_frequencies[i] = max(term_freq.values())
        return max_frequencies
```

Then, from this class, I create a custom vectorizer `vectorizer_keys2`. Create the TF-IDF matrix `tfidf_matrix2`, calculate the theme weights for each papers based on the frequency of the words in each theme `theme_weights2` and finally extract the top 3 themes picked for each paper `top_3_themes_for_papers`.

```
# theme_of_words_cleaned is the pre-processed version of theme_of_words.
# generate a class object
vectorizer_keys2 = CustomTfidfVectorizerUpdateClass(theme_of_words =
↪  theme_of_words_cleaned, threshold = 0.75) # non embeddings

# generate the term frequency matrix
```

```
tfidf_matrix2 = vectorizer_keys2.fit_transform(papers_cleaned.values()) #
 ↪  papers_cleaned is the dictionary of all articles, cleaned

# convert to dataframe
tfidf_df2 = pd.DataFrame(tfidf_matrix2.toarray(),
 ↪  index=papers_cleaned.keys(),
 ↪  columns=vectorizer_keys2.get_feature_names_out())

# each word becomes a key and gets a single theme assigned to it
theme_of_words_flip = {word: theme for theme, words in
 ↪  theme_of_words_cleaned.items() for word in words}

# generate an empty dataframe called theme_weights2 the same size as
 ↪  tfidf_df2
theme_weights2 = pd.DataFrame(0, index=tfidf_df2.index,
 ↪  columns=theme_of_words_cleaned.keys())

# for each word - look up its corresponding theme, and calculate the
 ↪  weight for the theme
for word, theme in theme_of_words_flip.items():
    if word in tfidf_df2.columns:
        theme_weights2[theme] += tfidf_df2[word]


for _, row in df2.iterrows():
    paper_id = row['ID']
    for word in vectorizer_keys2.get_feature_names_out():
        if word in tfidf_df2.columns:
            theme = theme_of_words_flip.get(word, None) # find the theme
             ↪  of the word
            if theme: # if it exists, update paper's theme
```

```
                theme_weights2.at[paper_id, theme] +=
                ↪  tfidf_df2.at[paper_id, word] * 5 # times 5 is only to
                ↪  make the weights larger for visualization (scaled)


# find the 1 maximum weight as the main theme of the paper
top_3_themes_for_papers = {
    paper_id: theme_weights2.loc[paper_id]
    .sort_values(ascending=False)[:3]  # grab the top 3 weights
    .index.tolist()
    for paper_id in theme_weights2.index
}
```

A.4 A Snapshot of the dataset

Figure A.1 is a screenshot of R markdown result for a glimpse at the dataset. This is an Excel file with the left most section representing the columns: CiteKey is the Zotero citation key for BibTEX ID is a unique identifier for each paper, Algo_Theme is the rule based theme decided by algorithm, DecisionTheme is the final theme, Man_Theme is the manual theme I decided, Math is whether or not my opinion matched the algorithm, Title is the paper title, Year is the year of publication, PublicationTitle is the journal name, Creators is a list of authors, Publisher is the name of publisher, AffiliationCountry is either the first author's country or the country the study was conducted in, K1 – K10 are keywords which is a combination of author provided keywords from the metadata from Web of Science, and keywords I extracted from papers, F1 – F9 are the factors which were found significant in explaining m-banking adoption, F1_THEME – F9_THEME are each factor's theme, FNS1 – FNS4 are non-significant factors, ResearchType is the type of research the paper uses, SampleSize is the size of the sample studied, METHOD1 – METHOD4 are methods used in the paper for analysis, Tech is the specific type of m-banking technology studied, THEORY1 – THEORY4 are theories used for the foundation of study models,

LIMIT1 – LIMIT3 are three of the limitations the authors of the papers mentioned, Abstract is a copy of the paper abstract and SampleSizeBin is the updated binning information of sample size.



Figure A.1. A screenshot of the dataset from R with columns, types and few values visible

Appendix B

Appendix For Chapter 3

B.1 Differences across provinces as clusters of sampling

Here, we include a contingency table as well as a table of marginal effects for each province. In Table B.1, we see the proportion of m–banking adopters vs non adopters in each province as well as in each province based on their mental health score.

Table B.1. Mobile banking based on the distribution of mental health scores across the provinces

Variable	# obs. m–banking		Mental Health	# obs. m–banking	
Group (code)	=No	=Yes	(MH)	=No	=Yes
			MH= 1	5	9

Continued on next page →

Newfoundland and Labrador (10)	84	503

Variable	# obs. m–banking		Mental Health	# obs. m–banking	
Group (code)	=No	=Yes	(MH)	=No	=Yes
			MH= 2	5	64
			MH= 3	24	126
			MH= 4	24	185
			MH= 5	26	119
Nova Scotia (12)	94	613	MH= 1	1	17
			MH= 2	11	83
			MH= 3	27	186
			MH= 4	39	218
			MH= 5	16	109
New Brunswick (13)	94	567	MH= 1	2	22

Continued on next page →

Variable	# obs.	m–banking	Mental Health	# obs.	m–banking
Group (code)	=No	=Yes	(MH)	=No	=Yes
			MH= 2	11	61
			MH= 3	24	160
			MH= 4	37	196
			MH= 5	20	128
			MH= 1	3	34
			MH= 2	17	186
Quebec (24)	244	2,108	MH= 3	68	596
			MH= 4	73	774
			MH= 5	83	518
			MH= 1	16	80

Continued on next page →

Ontario (35)	378	2,152

Variable	# obs. m–banking		Mental Health	# obs. m–banking	
Group (code)	=No	=Yes	(MH)	=No	=Yes
			MH= 2	45	287
			MH= 3	117	673
			MH= 4	106	672
			MH= 5	94	440
Manitoba (46)	106	521	MH= 1	1	15
			MH= 2	12	89
			MH= 3	31	172
			MH= 4	38	171
			MH= 5	24	74
Saskatchewan (47)	98	541	MH= 1	4	18

Continued on next page →

Variable	# obs. m–banking		Mental Health	# obs. m–banking	
Group (code)	=No	=Yes	(MH)	=No	=Yes
			MH= 2	6	61
			MH= 3	24	168
			MH= 4	38	188
			MH= 5	26	106
Alberta (48)	139	835	MH= 1	5	32
			MH= 2	15	115
			MH= 3	47	240
			MH= 4	50	290
			MH= 5	22	158
British Columbia (59)	186	1,125	MH= 1	8	29

Continued on next page →

Variable	# obs. m–banking		Mental Health	# obs. m–banking	
Group (code)	=No	=Yes	(MH)	=No	=Yes
			MH= 2	16	131
			MH= 3	52	366
			MH= 4	65	376
			MH= 5	45	223

In Table B.2, we see the marginal effect of each MH score across the provinces. This data confirms the validity of not considering a random effect for MH based on groupings (province). In other words, the effect of MH on m–banking does not vary significantly across provinces. Therefore, it is not useful to consider a random effect model.

Table B.2. Marginal Effects of Mental Health on m–banking across different provinces

Mental Health (MH)	Predicted Marginal Effect	95% confidence Interval
Newfoundland and Labrador		
MH = 1	0.88	[0.86, 0.90]

Continued on next page →

Mental Health (MH)	Predicted Marginal Effect	95% confidence Interval
MH = 2	0.87	[0.86, 0.89]
MH = 3	0.86	[0.85, 0.88]
MH = 4	0.85	[0.84, 0.87]
MH = 5	0.84	[0.83, 0.86]
Nova Scotia		
MH = 1	0.88	[0.86, 0.90]
MH = 2	0.88	[0.86, 0.89]
MH = 3	0.87	[0.85, 0.88]
MH = 4	0.86	[0.84, 0.87]
MH = 5	0.85	[0.83, 0.86]
New Brunswick		
MH = 1	0.88	[0.86, 0.90]
MH = 2	0.87	[0.86, 0.89]
MH = 3	0.86	[0.85, 0.88]
MH = 4	0.85	[0.84, 0.87]
MH = 5	0.84	[0.83, 0.86]
Quebec		
MH = 1	0.91	[0.89, 0.92]

Continued on next page →

Mental Health (MH)	Predicted Marginal Effect	95% confidence Interval
MH = 2	0.90	[0.89, 0.91]
MH = 3	0.89	[0.88, 0.91]
MH = 4	0.89	[0.88, 0.90]
MH = 5	0.88	[0.87, 0.89]
Ontario		
MH = 1	0.87	[0.85, 0.89]
MH = 2	0.86	[0.84, 0.88]
MH = 3	0.85	[0.84, 0.87]
MH = 4	0.84	[0.83, 0.86]
MH = 5	0.83	[0.81, 0.85]
Manitoba		
MH = 1	0.87	[0.85, 0.89]
MH = 2	0.86	[0.85, 0.88]
MH = 3	0.85	[0.84, 0.87]
MH = 4	0.84	[0.83, 0.86]
MH = 5	0.83	[0.81, 0.85]
Saskatchewan		
MH = 1	0.88	[0.86, 0.90]

Continued on next page →

Mental Health (MH)	Predicted Marginal Effect	95% confidence Interval
MH = 2	0.87	[0.85, 0.89]
MH = 3	0.86	[0.85, 0.87]
MH = 4	0.85	[0.84, 0.87]
MH = 5	0.84	[0.82, 0.86]
Alberta		
MH = 1	0.88	[0.86, 0.90]
MH = 2	0.87	[0.86, 0.89]
MH = 3	0.87	[0.85, 0.88]
MH = 4	0.86	[0.84, 0.87]
MH = 5	0.85	[0.83, 0.86]
British Columbia		
MH = 1	0.89	[0.87, 0.91]
MH = 2	0.88	[0.86, 0.90]
MH = 3	0.87	[0.86, 0.88]
MH = 4	0.86	[0.85, 0.88]
MH = 5	0.85	[0.84, 0.87]

To get an overall understanding of which provinces contribute the most to the variation in m–banking adoption, we visualize the random effects of province on m–banking in Fig. B.1. Nova

Scotia, Quebec, Ontario, Manitoba and British Columbia have the highest variations in m–banking adoption. This can be useful for policy makers and researchers who are interested in demographic as well as geographic differences in m–banking adoption. For example, one might want to understand why it is that m–banking across NS and AB is almost uniform but very volatile across QC. One reason might be social class differences, with provinces such as QC and BC having a larger gap between the upper and the lower classes.

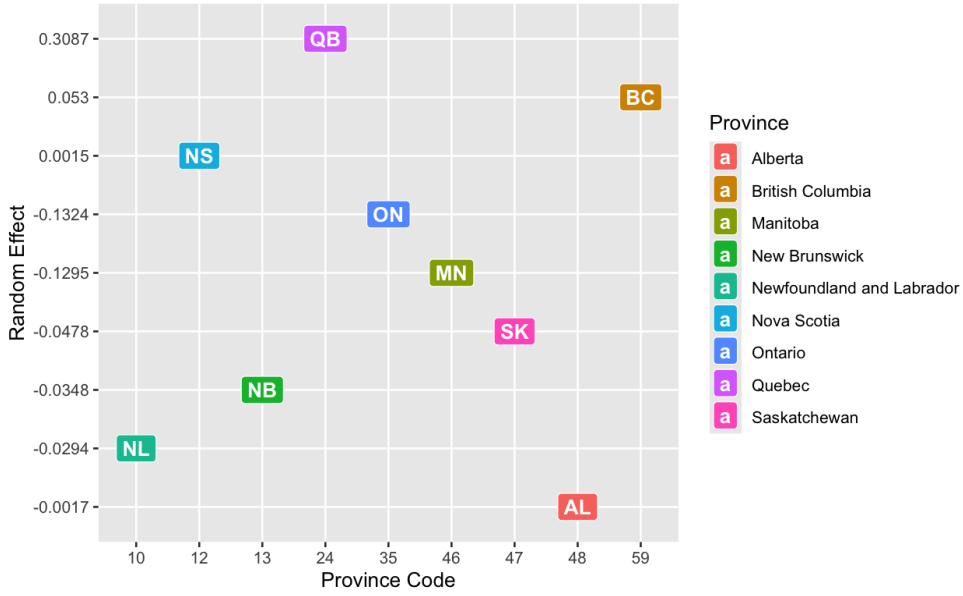


Figure B.1. Variation in m–banking adoption attributed to each province

B.2 Mathematical Formula for M_FSAT

In model M_FSAT, instead of RS we have two variables: FAMSAT and FRISAT. The mathematical formulation is as follows:

$$\ln \frac{P(\mathbf{Y}=1)}{1-P(\mathrm{Y}=1)} = \beta_0 + \beta_1 \text{ MH} + \beta_2 \text{ SD} + \beta_3 \mathscr{D}_{SNS_0} + \beta_4 \text{ AGE} + \beta_5 \mathscr{D}_{SEX_1} \tag{B.1}$$

$$+\beta_6\ \mathscr{D}_{EMP_0}\ +\ \beta_7\ \text{EDU}+\ \beta_8\ \text{INC}\ +\ \beta_9\ \mathscr{D}_{FAM_1}+\ \beta_{10}\ \mathscr{D}_{FAM_3}$$

$$+\beta_{11}\ \mathscr{D}_{FAM_4}\ +\ \beta_{12}\ \mathscr{D}_{IMM_1}+\ \beta_{13}\ \text{FAMSAT}+\beta_{14}\ \text{FRISAT}+\ \varepsilon$$

Appendix C

Appendix For Chapter 4

C.1 Summary Information of Mobile Banking Apps on iOS and Google Play Store

Select Canadian mobile banking apps on the iOS App Store platform were chosen for demonstration purposes. I simply chose the first five mobile banking apps that were listed when searching for "banking" on the iOS App Store. The apps were Canadian Imperial Bank of Commerce (CIBC), Toronto-Dominion (TD), Royal Bank of Canada (RBC), Bank Of Montreal (BMO) and Scotiabank.

Table C.1. Mobile Banking Apps on iOS App Store - Summary Statistics (Categorical Variables)

Variable	Type	Values	Variable	Type	Values
date_collection	Datetime	2024-10-29	developer	str	VV[1]
appname	str	VV	language	list of str	['EN', 'FR'][2]
category	str	Finance	headline	str	VV
size	float	124.5 – 583.7[3]	theme_color	str	app icon colors
device_compatible	list of str	device[4]	name_in_icon	binary	1: Yes, 0: No
most_frequent_stars	int	1 – 5	second_most_frequent_stars	int	1 – 5
chart_rank	int	3 – 10	avg_rating	float	1 – 5
third_most_frequent_stars	int	1 – 5	num_ratings	int	21K – 761.5K
update_info	Datetime	VV	version	str	VV
age_min	int	4	price	str	'free'
data_gathered	list of str	VV	summary	str	app provided summary
num_pictures_iphone	int	4 – 10	apple_watch	boolean	1: Yes, 0: No
num_pictures_ipad	int	3 – 10	apple_wallet	boolean	1: Yes, 0: No
num_pictures_watch	int	0 – 4	url	str	Link to app download page
Bank	str	VV	weighted_average[5]	float	88.2K – 3.6M

Notes:

1: Various Values

2: TD bank supports Simplified and Traditional Chinese, additionally.

3: Summary Statistics of Numerical Values Available in Table C.2.

4: 'iphone', 'ipad', 'apple watch'

5: avg_rating $\times$ num_ratings

Note that these apps provide information on mobile wallet (Apple Wallet) and smart watch (Apple watch) compatibility on the main app's download page. For a visual representation, consider the following images which are screenshots of the iOS App Store web-page of one mobile banking app. For copyright and privacy reasons, identifying information are redacted in the images.

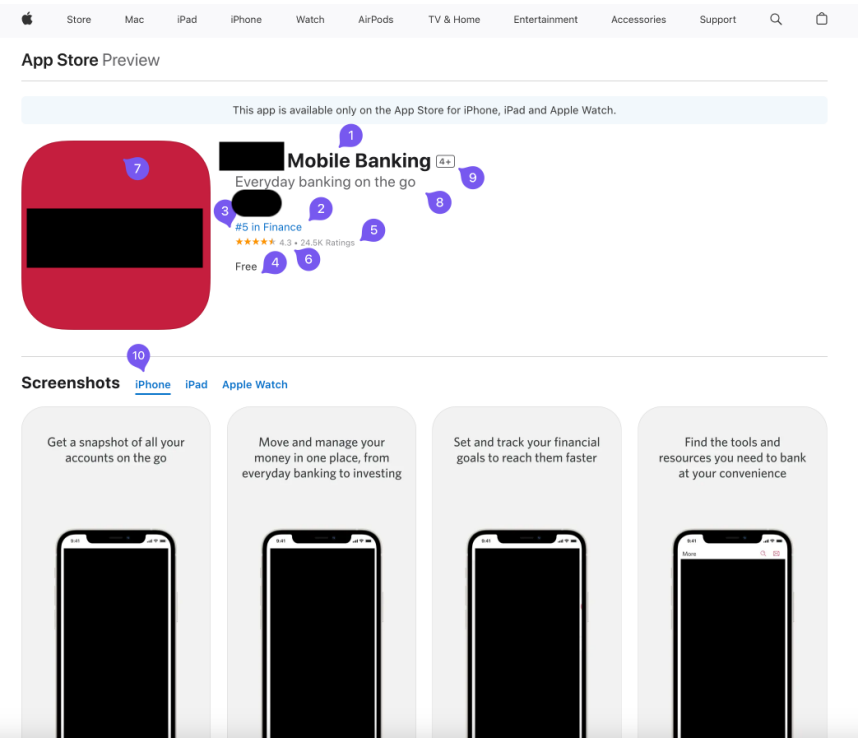


Figure C.1. Screenshot of Mobile Banking App on iOS App Store - Part 1

In Figure C.1, (1) is the full name of the mobile banking app. (2) is the category of the app (Finance). (3) is the ranking of the app in the chart for that specific category (#5 here). (4) is the price of the app, which is free. (5) is the number of ratings ($24,500$ here). (6) is the average rating of the app (4.3 here). (7) is the color theme for the icon, which is red here. (8) is the headline for the app, which is "*Everyday banking on the go*" here. (9) is the minimum age this app is suitable for, which is 4 years and above. (10) is the screenshots of the app on different devices: iPhone (Smartphone), iPad (Tablet) and the Apple Watch (Smartwatch).

In Figure C.2, we (1) shows the number of screenshots for iPad and (2) the number on Apple Watch. The picture is taken when Apple Watch tab is selected – the screenshots visible are on the apple watch device. (3) is the version history of the app (current version here is 10.59.4). (4) is the summary provided by the developer introducing the app. Some more information is extracted from the summary as well.

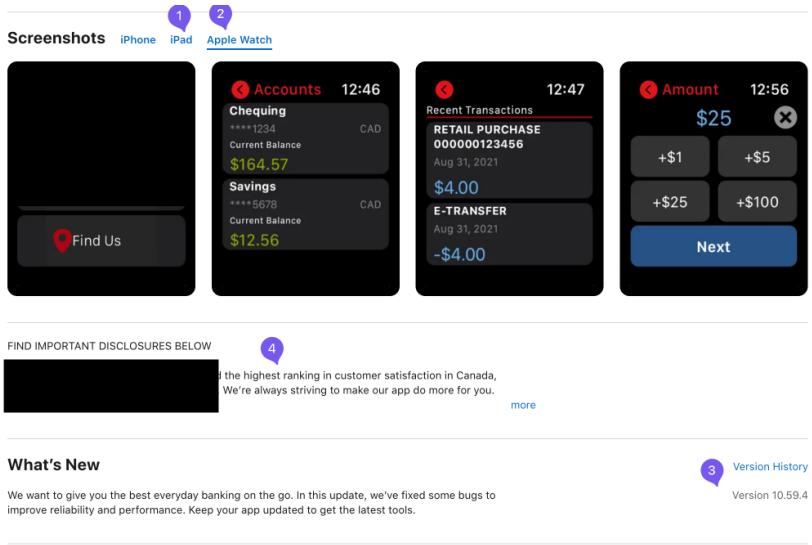


Figure C.2. Screenshot of Mobile Banking App on iOS App Store - Part 2

Lastly, in Figure C.3, we have: (1) is the information on which devices and particular operating system version is required and compatible with this app (iPhone, iPad, iPod touch and Apple Watch in this case), (2) is the size of the application on the mobile device's storage (142 MB here), and (3) is the list of languages supported within the app. Lastly, the red box shows Apple Wallet support where cards and this mobile banking app may be used within the apple wallet.

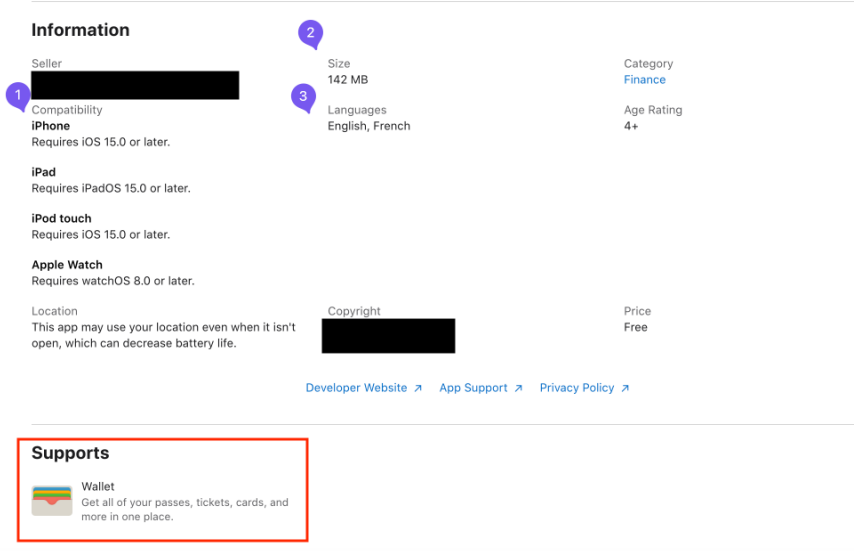


Figure C.3. Screenshot of Mobile Banking App on iOS App Store - Part 3

Table C.2 shows the summary statistics information across the 5 apps that were selected.

Table C.2. Mobile Banking Apps Summary Statistics (iOS) - Numeric Variables

Variable	Description	Mean	SD	Median	Min - Max	Skew
chart_rank	Rank in Finance Apps	5.8	2.77	5	3 - 10	0.44
avg_rating	Rating Out of 5	4.56	0.23	4.6	4.2 - 4.8	−0.5
num_ratings	Total Rankings	236,380	301,349.16	111,300	21,000 - 761,500	0.94
weighted_average	avg_rating × num_ratings	1,107,670	1,421,030.07	511,980	88,200 - 3,579,050	0.93
age_min	Minimum Age Appropriate	4	0	4	4 - 4	NaN
num_pictures_iphone	Screenshots of the iPhone App	8	2.45	8	4 - 10	−0.65
num_pictures_ipad	Screenshots of the iPad App	6.2	3.56	5	3 - 10	0.19
num_pictures_watch	Screenshots of the Apple Watch App	3	1.73	4	0 - 4	−0.92
size	App Size in MB	274.10	190.69	193.3	124.6 - 583.7	0.68
most_frequent_stars	Most Frequent Ratings	5	0	5	5 - 5	NaN
second_most_frequent_stars	2nd Most Frequent Ratings	4	0	4	4 - 4	NaN
third_most_frequent_stars	3rd Most Frequent Ratings	1.8	1.1	1	1 - 3	0.29

Glossary

ADHD Attention Deficit Hyperactivity Disorder is a neurodevelopmental disorder characterized by inattention, hyperactivity, and impulsivity that interfere with daily functioning. 110

adoption A recent or new use (uptake) of mobile banking. 1

affective constructs Technology adoption factors that are related to emotions and mental states. 71

Affective Events Theory (AET) Affective Events Theory (AET), proposed by Weiss and Cropanzano in 1996, is a framework that explains how workplace events influence employees' emotions, attitudes, and behaviors. It suggests that the work context creates conditions for daily micro-events, categorized as daily hassles (stressful and annoying occurrences) and daily uplifts (positive and pleasurable experiences). These events trigger affective reactions, such as emotions, which subsequently impact work-related attitudes (e.g., job satisfaction) and behaviors (e.g., performance). It emphasizes the importance of understanding how situational factors and emotional experiences shape employees' overall work experience. 81

affective needs Human needs related to emotions and feelings. 24

Affordance Theory Describes how objects or environments offer possibilities for action based on their properties and the abilities of the user. 48

Airbnb Airbnb is an online platform that allows property owners, or hosts, to rent accommodations to individuals. 11

Alexithymia Alexithymia is a psychological condition characterized by difficulty in identifying, expressing, and processing emotions. Individuals with alexithymia often struggle with emotional awareness, social interactions, and distinguishing between physical and emotional sensations. 76

alternative hypothesis The hypothesis that represents the question to be answered or the theory to be tested. 72, 118

Alternatives to the technology What are the alternatives to the technology at hand and how good are they? 48

application A program designed for a device with specific software and hardware, such as a smartphone. 4

Attitude A disposition to respond favorably or unfavorably towards some psychological object. 24

authentication The process of verifying a user's identity to grant access to a system, typically using credentials such as passwords, biometrics, or multi-factor authentication. 125

Brand Engagement The emotional and behavioral connection that customers develop with a brand. 48

Brand Image How a brand or business is viewed by consumers based on their personal beliefs and experiences in addition to others' beliefs and experiences. 48

BRT Behavioral Reasoning Theory is a decision-making model stating that reasons for and against behaviors influence attitudes and intentions, explaining why individuals adopt or resist specific actions. 50

CFA Confirmatory Factor Analysis is a statistical technique used to test whether a set of observed variables aligns with a predefined latent factor structure. 52

cognitive absorption A state of deep cognitive engagement in which an individual experiences intense concentration, a distorted perception of time, diminished self-awareness, and intrinsic enjoyment during an activity, thereby facilitating optimal interaction with the task environment. 24

Cognitive Decline Refers to any form of deterioration be it physical or mental in a person's cognitive health and well-being. 48

cognitive needs Human needs related to cognition and mental capacity. 24

Cognitive Resistance An individual's reluctance to accepting new information, ideas, or changes due to pre-existing beliefs, biases, or mental discomfort. 47

coherence An accuracy measure for topic modeling. The higher the coherence, the better the algorithm has performed. 33

Collective Culturalism A cultural orientation in which individuals prioritize the goals, values, and well-being of the group – such as family, community, or society – over personal interests. 47

Comparative Type of research that compares two different settings, groups, methods, or any other concept. 37

Compatibility How well does the new technology fit the user according to their values and goals. 48

Competence How competent is the bank or business responsible for the creation of the m-banking app at what they do. 47

Conservation of Resources Theory (CRT) The Conservation of Resources (COR) Theory, developed by Hobfoll in 1989, is a psychological framework that explains how individuals manage stress and resources. It posits that people strive to acquire, maintain, and protect valuable resources, such as time, energy, social support, and mental health. Stress occurs when these resources are threatened, lost, or insufficient to meet demands. The theory also suggests that individuals with greater resources are less vulnerable to resource loss and more

capable of resource gain. For example, positive mental health can act as a resource that helps individuals cope with daily hassles and enhances their ability to adapt to challenges. 81

corpus A corpus is a structured collection of texts. 30

Covid-19 related psychological distress Psychological distress due to or following Covid-19 pandemic, which forced people into do banking tasks remotely. 47

Cultural tokens Words or phrases related to cultural aspects such as country, religion and cultures. 33

DCT Digital Cohort Theory suggests that individuals who grow up during the same technological era share similar digital behaviors, preferences, and competencies. 50

Demographic tokens Words or phrases related to demographic information such as age, gender and income. 33

Digital Divide A phenomenon in the communication and information technology field related to the differences between groups of individuals in how they use and interact and live with technology. 48

Distributional Semantics In computational and cognitive linguistics, this approach assumes that words that appear in similar contexts tend to have similar meanings. 13

DM DeLone and McLean Model is a framework that evaluates the success of information systems based on six interrelated dimensions: system quality, information quality, service quality, use, user satisfaction, and net benefits. 50

DOI Diffusion of Innovation technology adoption theory that explains how new ideas, products, or technologies spread within a society over time. 49

Effort Expectancy How much effort does the user expect the new technology requires to learn and use. 21

Empirical Type of research that collects data through direct observations or experimentation. 37

Extrinsic Factors that are external to the users, and usually objective. 4, 14

Facilitating Conditions Certain conducts put in place by a business to help consumers. 40

fear of missing out Is the feeling that others are having rewarding or exciting experiences without you. It often includes a desire to stay constantly connected to what others are doing, especially on social media, and can lead to anxiety, dissatisfaction, or the urge to participate in activities just to avoid being left out. In psychological terms, FOMO reflects a combination of social comparison, perceived exclusion, and a fear of regret. It's linked to lower well-being and higher engagement with digital platforms, where users frequently check for updates to avoid missing something important or fun. 78

Five-Factor Model of Personality The five-factor model (FFM) of personality, also known as the Big Five, is a widely accepted taxonomy of personality traits. It proposes that personality can be described using five broad dimensions: Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism, often remembered by the acronym OCEAN. 21

fsQCA Fuzzy-Set Qualitative Comparative Analysis. A case-based methodology that uses set theory and Boolean algebra to analyze complex causality, identifying combinations of conditions that lead to an outcome. 52

general anxiety Generalized anxiety disorder is an anxiety disorder characterized by excessive, uncontrollable, and often irrational worry about events or activities. 109

GPS loggers Devices that record location data over time using Global Positioning System (GPS) technology, typically used for tracking movement, navigation, or geospatial analysis. 116

green concerns Personal worries regarding the environment and the impact of business practices on it. 47

Hausman test The Hausman test is a statistical test used to determine whether fixed effects or random effects models are more appropriate in panel data analysis. 96

HCD Hofstede Cultural Dimension is a framework for understanding cultural differences based on six dimensions: power distance, individualism vs. collectivism, masculinity vs. femininity, uncertainty avoidance, long-term vs. short-term orientation, and indulgence vs. restraint. 50

heteroscedasticity A statistical condition where the variability of a dependent variable differs across levels of an independent variable, often violating the assumption of constant variance in regression analysis. 138

heuristics Heuristics are efficient cognitive processes, conscious or unconscious, that ignore part of the information. 17

Imitators People who do not value innovation and only adopt technologies when the majority of others do. 21

Innovativeness A measure of how much a person values innovations or is innovative. 21

Innovators People who value innovation and want to try new technologies first. 21

Institutional Theory Explains how social structures, norms, and regulations influence organizational behavior, emphasizing isomorphism (mimetic, coercive, and normative pressures) in shaping institutional practices. 50

Instrumental Variables A statistical method used in causal inference to address endogeneity, where an external variable (instrument) is used to isolate the independent effect of a predictor on an outcome. 52

intra-cluster correlations A measure of similarity among observations within the same cluster, indicating the degree to which data points in a group resemble each other more than those in different groups. 138

Intrinsic Factors that are internal to the users, and usually subjective. 4, 14

IOT The Internet of Things (IoT) refers to a vast network of physical objects, or "things," that are embedded with sensors, software, and other technologies, enabling them to connect and exchange data with other devices and systems over the internet.

162

IQR A measure of statistical dispersion that represents the range between the first quartile (Q1, 25th percentile) and the third quartile (Q3, 75th percentile). 46

Large Language Model A Large Language Model (LLM) is an AI system trained on massive text datasets to understand and generate human-like language. It predicts the next word in a sequence based on context, allowing it to perform tasks like summarizing, translating, or answering questions. 66

Latent An unobserved variable or construct. 10

lexical semantic techniques Lexical semantic techniques involve analyzing the meanings of individual words and their relationships within a language. This includes examining how words are used in different contexts, how their meanings change over time, and how they relate to each other in a semantic network. 16

Logistic regression A supervised classification method based on probabilistic outcomes of belonging to a class. 52

LR The Likelihood Ratio Test (LRT) is a statistical test used to compare the goodness-of-fit between two nested models. It evaluates whether a more complex model significantly improves fit over a simpler model by comparing their likelihood functions. The test statistic follows a chi-square distribution, with degrees of freedom equal to the difference in model parameters. 94

Machine Learning A field of study where computer algorithms are fed raw input data and output knowledge and insights. 52

Market tokens Words or phrases related to devices and various technologies in the market of mobile banking such as smartphones or smartwatches. 33

mental illness When individuals are suffering from psychiatric conditions. 73

mixed-membership model A probabilistic framework in which each observation is represented as a combination of multiple latent classes or groups. 34

Mobile banking the use of a mobile device to conduct banking tasks. 1

mobile devices Any portable personal device, e.g., Smartphone, Laptop, Tablet, Smart wearable device. 1

mobile wallets Digital applications that store payment information, allowing users to make electronic transactions via smartphones. 37

multicollinearity Multicollinearity in statistics refers to a situation in a regression model where independent variables are highly correlated with each other. This can lead to unstable and unreliable coefficient estimates, making it difficult to interpret the individual impact of each predictor. 91, 139

NFC Contactless transactions using Near Field Communication (NFC) technology, allowing secure payments by tapping a smartphone or card on a compatible terminal. 157

No branch visits The fact that no in-person branch visit is required when using m-banking. 47

non-repudiation Procedures that prevent entities from denying they had carried out a certain operation. 133

Normative Beliefs An individual's perceptions of social norms and expectations regarding a particular behavior. 47

null hypothesis Any statistical hypothesis we wish to test. 71, 118

Ordinal Regression A statistical technique that predicts the behavior of ordinal variables in which orders matter. 48

OSL Optimum Stimulation Level is a psychological theory suggesting that individuals seek an ideal level of stimulation, influencing their behavior in areas such as novelty-seeking, risk-taking, and consumer choices. 50

pain of payment The psychological discomfort or negative emotional response experienced when making a payment, influenced by factors such as payment method, timing, and perceived loss of money. 115

partner login A secure authentication system that grants business partners or affiliated users access to restricted resources, platforms, or services. 137

Perceived compatibility An individual's belief that a new technology fits their values and life, and is compatible with them. 48

Perceived privacy An individual's belief about the safety of themselves, their data and their assets from third party malicious attacks or illegal access to account and information. 48

Perceived Relative Advantage An individual's belief that a new technology, product, or innovation is superior to existing alternatives. 48

Perceived Security Consumers' perception of the degree of protection against various threats. 124

Perceived value An individual's belief about the benefits of m-banking. 48

Perception-based A sub-category of intrinsic factors where all member adoption factors have the word "perception" in them. 20

Perceptions Opinions shaped by available information. 19

Performance Expectancy How much does the user expect the new technology to improve their performance. 21

Personal A sub-category of intrinsic factors where all member adoption factors relate to personal motivations, goals and traits. 21

personal integrative needs Human needs related to sense of self. 24

PIT Perceived Interactivity Theory explains how users perceive the level of control, responsiveness, and two-way communication in digital environments, affecting engagement and satisfaction. 50

Polysemy When a single word has multiple but related meanings. 16

Prototype Theory In cognitive linguistics, instead of relying on strict definitions, this theory suggests that categories are formed around prototypical examples, and meanings are understood based on similarity to these central members. 13

Psychological Factors that capture mental, cognitive and emotional related ideas. 23

psychometric tests Standardized assessments that measure psychological attributes such as intelligence, personality, attitudes, or abilities, ensuring reliability and validity. 57

Qualitative Type of research that employs non-numeric data such as interviews. 37

Quantitative Type of research that employs numerical data and statistical methods. 37

Random Forest An ensemble supervised machine learning method which combines several decisions trees used for classification tasks. 52

Religiosity The degree of an individual's commitment to religious beliefs, practices, and values, often studied in its impact on behavior, ethics, and decision-making. 61

Religiosity-Intention model Examines how religiosity influences behavioral intentions, particularly in consumer behavior and ethical decision-making. 49

Resistance to change An apprehension, usually due to psychological reasons, to changing environments, habits and behaviors. 48

Risk aversion A measure of how likely a person is to avoid taking risks. 48

SERVQUAL model A framework for measuring service quality based on five dimensions: tangibles, reliability, responsiveness, assurance, and empathy, commonly used in customer satisfaction research. 49

Signaling Theory Describes how one party (the sender) conveys credible information to another party (the receiver) to reduce uncertainty, commonly used in economics, marketing, and job markets. 50

smart wearable Electronic devices worn on the body that integrate sensors and connectivity to track health, activity, or enhance user interactions, such as smartwatches, fitness trackers, and augmented reality glasses. 117

smartphones Mobile devices that combine cellular communication with advanced computing capabilities, featuring touchscreens, internet access, and various applications for productivity, entertainment, and communication. 117

Social Factors that capture the impact of other people on adoption decisions. 22

social anxiety Social anxiety is a psychological condition characterized by an intense fear of social situations, leading to avoidance behavior and distress. It involves excessive worry about being judged, embarrassed, or negatively evaluated by others. 109

social integrative needs Human needs related to sense of community. 24

Social interactions on platforms Involves any form of business-to-consumer interaction such as replying to reviews, responding to comments on social media pages and engaging with consumers for content and marketing. 48

Social Pressures Outside forces from other familiar individuals that influence a person. 22

SRT A psychological theory that explains gender differences in behavior as a result of societal expectations and culturally assigned roles rather than inherent biological factors. 163

Subjective Norms Societal truths collectively agreed upon. 22

TCV Theory of Consumption Values proposes that consumer choices are driven by five key values: functional, social, emotional, epistemic, and conditional values, influencing purchasing decisions. 50

Technological Awareness An individual's or organization's understanding, knowledge, and familiarity with a particular technology, including its existence, features, benefits, risks, and potential uses. 48

Technological Readiness A theory explaining individual's or organization's willingness and ability to adopt and effectively use new technologies. 48

Technology Acceptance Model A theoretical framework for technology adoption where users make choices based on how easy and useful they perceive a new technology to be. 19

technology-related anxiety The anxiety, stress or fear people feel when using or learning new technology. 8

tension-free needs Human needs related to rest and rejuvenation. 24

text-mining Analytical tools to gather information from text data. 5

TF-IDF A machine learning method to find the most important tokens (words or combinations of words such as phrases) across a corpus. 35

Thematic Analysis A qualitative research method used to identify, analyze, and interpret patterns (themes) within textual data. 48

Theory of Planned Behavior A theoretical framework where users make decisions based on how much control they believe they have over a particular task. 20

Theory of Reasoned Action A psychological model that explains how attitudes and social norms influence an individual's intentions, which in turn affect their behavior. 22

therapeutic alliance A digital mental health relational agent (or therapeutic alliance) is a software program, often using AI, designed to build and maintain a therapeutic relationship with users, aiming to support their mental well-being through personalized interactions. 80

token An item in a text dataset such as a single word, pairs of words, phrases and even sentences and so on. 30

tokenizing A text analysis technique where large texts are broken into tokens. 30

Topic Modeling An unsupervised machine learning technique used to identify hidden topics within a collection of texts by clustering words that frequently appear together. 5

Topic modeling A machine learning task which extracts potential topics discussed within a dataset consisting of document(s). 28

Trust Theory Examines how trust is formed, maintained, and impacts relationships between individuals, organizations, or systems. 49

TTF A model that evaluates how well a technology supports the requirements of a specific task, influencing user performance and adoption. 49

UG A theoretical framework related to mass communication and media which posits adoption and usage of technology is related to satisfying 5 categories of needs. 24

Unified Theory of Acceptance and Use of Technology A theoretical framework for technology adoption where people adopt technologies based on how much performance benefit they gain, what their social circle think, how difficult they think the technology is to use, facilitating services the technology offers and habits. 19

UX User Experience refers to a user's overall interaction with a product, system, or service, encompassing usability, accessibility, design, and emotional response. A good UX ensures efficiency, satisfaction, and ease of use. 109

variance inflation factors A metric that quantifies the degree of multicollinearity in a regression model, with higher values indicating stronger correlations between independent variables. 140

virtual wallets Digital platforms or applications that store payment information securely, enabling users to make electronic transactions without physical cards or cash. 138

Wald test A statistical test used to assess the significance of individual coefficients in a regression model by evaluating whether they are significantly different from zero. 139

word embeddings Word embedding is a technique in natural language processing (NLP) that represents words as dense numerical vectors in a continuous vector space. It captures semantic relationships between words based on their contextual usage, allowing similar words to have closer vector representations. 65

Zotero A citation manager application with the ability to fetch pdf files of scientific articles. 28