Charting Skills in Uncharted Domains: Evaluating How Video Game Competence is Viewed Outside Competitive Desktop Gaming Environments

by

Kaushall Senthil Nathan

A thesis
presented to the University of Waterloo
in fulfillment of the
thesis requirement for the degree of
Master of Applied Science
in
Systems Design Engineering

Waterloo, Ontario, Canada, 2025

Author's Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Statement of Contributions

Kaushall Senthil Nathan was the sole author for Chapters 1, 2, 5, 6, and 7 which were written under the supervision of Dr. Daniel Harley and Dr. Lennart Nacke. Exceptions to sole authorship of material are as follows:

Research Presented in Chapter 3

This chapter consists of work previously written and published in Senthil Nathan et al. [71]. Dr. Daniel Harley and Dr. Lennart Nacke were the primary co-investigators on the study supported by the SSHRC INSIGHT Grant (grant number: 435-2022-0476), NSERC Discovery Grant (grant number: RGPIN-2023-03705), NSERC Discovery Grant (RGPIN-2024-06734), Canadian Foundation for Innovation John R. Evans Leaders Fund (CFI JELF) (grant number: 41844), Mitacs Accelerate Grant (grant number: IT40801), Meta Research Award, Lupina Foundation Postdoctoral Research Fellowship, and the Provost's Program for Interdisciplinary Postdoctoral Scholars at the University of Waterloo.

The research was conducted by Kaushall Senthil Nathan at the University of Waterloo under the supervision of Dr. Daniel Harley and Dr. Lennart Nacke. Dr. Daniel Harley, Dr. Lennart Nacke, Dr. Eugene Kukshinov and Kaushall Senthil Nathan contributed to the study design. Dr. Lennart Nacke contributed to the participant recruitment. Sabrina Sgandurra and Dr. Geneva Smith served as confederates in the experiment and contributed to the materials given to the confederate (which are included in the appendix). Jieun Lee and Derrick Wang contributed to the video coding and the reflexive thematic analysis, and the subsequent write-up of the results portion of these sections. Kaushall Senthil Nathan wrote the draft manuscripts, which all co-authors contributed intellectual input on.

Research Presented in Chapter 4

This research was conducted at the University of Waterloo by Kaushall Senthil Nathan under the supervision of Dr. Daniel Harley and Dr. Lennart Nacke. Kaushall Senthil Nathan designed and conducted the study with consultations from Derrick Wang, Dr. Daniel Harley, and Dr. Lennart Nacke. Derrick Wang also contributed to data analysis. Kaushall Senthil Nathan drafted the manuscript and each author provided intellectual input on manuscript drafts.

As lead author of both chapters, I was responsible for contributing to conceptualizing study design, carrying out data collection and analysis, and drafting and submitting manuscripts. My coauthors provided guidance during each step of the research and provided feedback on draft manuscripts.

Abstract

Player competence heavily shapes multiplayer gameplay experiences, from team success to avoiding frustration, yet existing research focuses predominantly on competitive esports contexts on PC platforms. This lack of research leaves players in understudied domains without a clear understanding of competence. Therefore, I examined the contexts of casual, cooperative games and VR multiplayer games to uncover how competence is conceptualized within them. In study 1, I conducted a mixed-methods experiment with 23 participants playing Overcooked 2 with a competent or incompetent teammate, to examine competence, frustration, and cooperative behaviour. The results of study 1 showed that players evaluated teammate performance comparatively rather than through absolute metrics, and that current frustration and cooperation measures were insufficient in capturing the nuances of player experience. In study 2, I surveyed 111 VR multiplayer gamers to identify novel skill clusters, how skills are adapted from PC to VR, and whether player rank affects the importance of these skills. Findings revealed five new VR-specific skills, highlighted the body's central role in skill adaptation, and found no significant rank-based rating differences. The overarching contribution is in demonstrating that an evaluation of competence drawn from competitive esports is insufficient in describing competence in these domains. Casual, cooperative players judge competence in primarily in relation to their teammates, while VR multiplayer gamers regard physicality and embodied interaction as essential to displaying relevant skills. My thesis puts forward new definitions of competence in casual, cooperative games and VR multiplayer games, as the first step to chart skills in uncharted domains.

Acknowledgements

I would like to first thank my supervisors, Dr. Daniel Harley and Dr. Lennart Nacke, for their support and mentorship that constantly helped me hone my craft and made me a better researcher.

I would also like to thank my readers: Dr. Karen Cochrane and Dr. Cosmin Munteanu, for taking the time to read my work and provide valuable feedback that greatly helped me polish the final version of this thesis.

I am grateful to Derrick Wang and Geneva Smith for their valuable recommendations and feedback throughout the writing of this thesis.

I also want to thank my colleagues at the Games Institute for the welcoming environment and stimulating conversation about games research. It felt like a home away from home.

I thank my family for their unwavering faith in me and support throughout my education. May I always stand on the shoulders of giants.

Dedication

This thesis is dedicated to my mom, Savitha, who always worries about me, my dad, Senthil, who is always proud of me, and my sister, Harshita, who's only half as handsome as me. I love you all more than you will ever know.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

BAQ Brief Aggression Questionnaire 17, 18

NASA TLX NASA Task Load Index 16, 18, 19, 41, 42

Chapter 1

Introduction

Player competence influences multiplayer gameplay experiences, from better performance to increased trust and camaraderie between teammates [52, 28], yet existing research focuses predominantly on competitive esports contexts on PC and console platforms. Therefore, in this thesis, I propose two studies to understand the conceptualization of competence in two under-explored areas: (1) casual cooperative games, and (2) virtual reality (VR) multiplayer games. In this introduction, I begin by describing my motivation for examining competence, the key concept underpinning both studies. Then, I describe the importance of the two areas of focus. Building on these foundations, I present my research questions and outline two distinct studies to answer them, where study 1 is a mixed-methods experiment to understand the relationship between competence and frustration in a casual cooperative game, and study 2 is a survey study to understand how competence is viewed based on skills in VR multiplayer games. Findings of these studies show that the conceptualizations of competence that are prevalent in esports cannot be directly applied to these contexts, as casual cooperative players primarily view competence relationally while VR multiplayer gamers view it physically. Ultimately, I argue that these findings lay the groundwork for future research to refine how competence is defined and measured within these contexts to more accurately capture player needs and player experiences.

1.1 Defining Competence in Video Games

"Git gud, scrub" (meaning 'get good, newbie'). Variations of this sentiment echo through nearly every online multiplayer lobby. Remarks questioning a player's skill (often blunt, sometimes hostile) have become normalized in online gaming spaces [6]. These expressions of frustration are an indicator of how strongly perceptions of competence shape social interactions in multiplayer environments. Given that 1.17 billion gamers played multiplayer games in 2024 [38], understanding and encouraging competence in the player base will increase their enjoyment [52] and contribute to a less frustrating experience for all [4].

An important distinction to make is between skill, competence, and performance. A skill "refers to a player's ability to select, organize, and execute an action, appropriate to a given situation in an effective, consistent and efficient manner" [84]. A competent player can execute most of the skills that are necessary for a given game. Performance is also distinct and refers to the in-game measurable outcomes that are influenced by player action (e.g., the number of enemies killed) [28]. In this thesis, I will define competence as the degree to which the player can exhibit the skills necessary to achieve high performance. For example, if a game requires players to have quick and clear communication about enemy locations to tag them, a player that can communicate quickly and clearly to tag enemies efficiently and increase the chances of success would have "high competence" or be considered "competent". Importantly, high performance can mean different things to different players based on game or context [53]. For this thesis, we also focus on perceived competence, based on the ways that players describe necessary skills and/or the skills that can be visibly observed.

Understanding competence is key for user research in games. This is because having low competence in a game leads to feelings of anger [63, 25], and having an understanding of what skills make up competence in a particular game offers players more targeted training opportunities [46]. As such, evaluating what makes a competent player has been studied in some detail. This ranges from studies interviewing esports players to understand their view of performance [11], to looking into the device inputs that professional and novice players exhibit [43, 68].

However, competence research has predominantly focused on competitive, high-stakes esports contexts played on PCs and console systems [28, 16]. The games in these contexts are competitive (e.g., *League of Legends* [51], *Valorant* [47], and *Counter Strike: Global Offensive* [78]), where players' performance is primarily defined by how well they can beat their opponent. This focus on esports games on PC/console systems neglects several other game types. In this thesis, I explore two distinct areas that are underrepresented in competence research: first, casual games (e.g., *Overcooked 2* and *It Takes Two*, where players must collaborate rather than compete to complete in-game [76, 74]), and second, the experiences of of players using emerging systems like VR. These gaming contexts are increasingly popular. For example, as of November 2025, VR Master League, an emerging VR esports league hosts 11,621 active players across seven different VR multiplayer games [45].

Studying competence in areas beyond esports and beyond PC/console contexts presents an opportunity to help academics and players better understand competence across a variety of game types, streamline training strategies, and ultimately provide greater feelings of enjoyment while reducing feelings of anger and frustration. I propose that examining player competence in casual cooperative games and VR multiplayer games will offer insights that expand and enrich current understandings of competence in gaming. The next two sections further motivate these two areas of study.

1.2 Competence in casual cooperative games

For the purposes of this thesis, I define casual cooperative games as non-competitive games in which players' roles and actions are interdependent and success depends on joint coordination. Popular examples include *Overcooked* and *It Takes Two*, where players must collaborate to complete in-game tasks such as meal preparation and puzzle solving, respectively [76, 74]. One feature of these games is that progression depends on successful performance and that the burden of performance is shared by the teammates. For example, in *Overcooked 2*, players must complete each level to unlock the next. Casual players may not prioritize competence in the sense of high scores or level completion in the same way as professional players, but it still remains relevant in helping players progress and reduce the frustration caused by low mastery [63].

Competence in cooperative play is also dependent on teammate dynamics. Research into competitive games and multiplayer exercise games (exergames) shows that a player's competence has an effect on other players' experience [82, 4, 52]. Previous studies in competitive game contexts have established that increased teammate competence is related to team success and player enjoyment [11, 31, 52]. Conversely, low teammate competence can contribute to feelings of frustration [72, 4]. In cooperative contexts, such as playing an exergame cooperatively, similar performance effects hold true [82]. While useful, these findings may not translate into casual cooperative games given the different operationalizations (e.g., of cooperation) and behavioural frameworks developed for competitive games and exergames [79, 50, 82]. In other words, we do not know whether the effects observed in competitive environments, where poor performance or a lack of cooperation increases frustration, can be applied to casual co-op play. Improved understandings of player competence in casual co-op games would not only support general player performance, but could also be an opportunity to promote benefits of competent play outlined above, such as improved teamwork, reduced frustration, and more enjoyable sessions.

1.3 Competence in VR Multiplayer Games

For the purposes of this thesis, VR multiplayer games are games played with a head mounted display, usually with at least head and hands tracked. Movements are represented in shared virtual spaces as players control an avatar or player character within multiplayer arenas with other simultaneous players. Popular examples of such games include *Population: One* [7] and *Pavlov: VR* [26] . When compared to similar games on PC, VR systems allow for novel actions within games based on the affordances of VR (i.e., a set of possible interactions that leverage the tracked headset and controllers) [81] and opportunities for embodied interaction [21] (i.e., the ways that the player's body and physical space are integrated into gameplay) shaping both the mechanics of interaction and the experiential dimensions of play. For example, compared to similar games on PC or console platforms, VR multiplayer games can be more physically demanding [41] while also allowing new interactions and communication possibilities, similar to those in social VR environments [75].

To the best of my knowledge, the factors that determine competence in multiplayer VR games have not yet been identified. However, there have been efforts to understand skill in VR multiplayer games by adapting what is known about PC and console systems [40, 80, 35]. For example, Korbel et al. [40], interviewed several esports professionals, and suggested that the increased physical demand of VR would play a greater role in VR game competence, mirroring past findings from non-game VR literature [41]. Thus, we see some promise in this line of inquiry. When we look at how competence is defined, we need to look at both skills from existing literature and novel skills that may be specific to VR competence.

Previous studies discussing skills in VR games (e.g., Korbel et al. [40] and Turkay et al. [80]) have primarily focused on the opinions of professional players. Professional players, when compared to non-professional players, play for different goals [50], have a greater amount of play time [48], and often have career outcomes linked with their performance [36]. Even looking more broadly at differences across player ranking, we see that high-ranking players adapt to stress differently than lower ranking players [62]. Therefore, there is also an opportunity to compare VR players of different rankings to better understand how they evaluate the necessary skills for VR multiplayer games.

Another reason to look at the effect of player rank on competence in VR is that our efforts to study VR multiplayer games are broader than our previous gap on casual cooperative games. To put it another way, we are studying players in an entirely new modality rather than another genre of games, which includes both high-ranking and low-ranking players. We do not know whether high-ranking players and low-ranking players value the same skills when defining competence in VR multiplayer games. Therefore, when we examine competence in VR multiplayer games, there is also an opportunity to explore whether high-ranking and low-ranking players share the same valuation of skills.

1.4 Research Goals and Contributions

The overarching research gap that motivates this thesis is that current research on competence focuses primarily on competitive, high-stakes esports contexts, neglecting the understandings of competence for players in other domains. Therefore, the goal of this thesis is to study video game competence in (1) casual cooperative games and (2) VR multiplayer games, two areas that have received little scholarly attention to date. To expand current understandings of competence in games, I propose two studies that examine these contexts.

Study 1

Motivated by gaps outlined in section 1.1 and elaborated in section 2.2, Study 1 examines how players assess teammate competence in casual cooperative games and whether teammate competence influences frustration and cooperation in similar ways to competitive gaming contexts. To address these aims, I ask the following three research questions:

RQ1: How do players evaluate teammate competence in casual cooperative games?

RQ2: How do players experience frustration from teammate performance?

RQ3: How do players behave cooperatively based on teammate performance?

To answer these questions, I investigated teammate competence evaluation and behavioural responses in *Overcooked 2*. With the assistance of members of my lab, I conducted a controlled, between subjects experiment with 23 participants across competent and incompetent teammate conditions. Our mixed-methods study included a questionnaire, behavioural observation, and a post-session reflection. Methodological details and results of the study can be found in chapter 3.

Study 2

Motivated by gaps outlined in section 1.3 and elaborated in section 2.3, study 2 seeks to understand what skills are relevant to understandings of competence in VR multiplayer games, examining novel skills that are exclusively relevant to VR, and skills adapted from existing literature about PC/console games. I propose the following research questions:

RQ4: Which skills adapted from existing PC literature to VR multiplayer games are most valued by professional versus non-professional players?

RQ5: What new skills are identified for VR multiplayer games, if any?

RQ6: How do the affordances and experiences in VR change the understanding and training of existing skills?

To answer these questions, I conducted study 2 in two phases. Phase 1 consisted of a literature-based search where I extracted and synthesized skill clusters from existing literature on competence in PC and console games. Phase 2 consisted of a survey study asking participants the following: what novel skills, if any, they used while playing VR multiplayer games; how important were the skills adapted from existing literature; and how, if at all, did they change when used in VR when compared to PC. We also investigate whether player rank changes the importance of these skills. Methodological details and results of the study can be found in chapter 4.

Contributions

Synthesizing findings across both studies, I contribute three key takeaways:

Takeaway 1: Definitions used in esports research about competence cannot be applied to casual cooperative games and VR multiplayer games.

Our findings show the competence definitions used in esports do not match how players in casual cooperative games and VR multiplayer games think about competence. Casual cooperative gamers viewed competence as relational, by comparing their performance with their teammates to see if they are doing well. VR multiplayer gamers believe that physicality is central to competence, and viewed most skills used in the game as having a physical component, if not being fully physical.

Takeaway 2: Current definitions of frustration and cooperation are not sufficient for casual cooperative games.

Study 1 shows that conflicting results between observational measures and questionnaire measures. The results of the post-session reflection point to the reason being the definitions used in the questionnaire were systems-oriented and did not capture the social aspect of frustration. In other words, participants claimed they were not frustrated by the game or gameplay but they were frustrated *at the confederate*. Furthermore, out of the seven cooperative behaviours studied, only one was found to occur more frequently across conditions. Our post-session reflections suggested that the confederate's communication influenced this, highlighting the need for a nuanced study of cooperation and how it is initiated and maintained in casual cooperative games.

Takeaway 3: Player skills in VR multiplayer games depend on the affordances of the game (e.g., being able to physically reload a weapon) and embodied interactions (e.g., physical dodging, gesturing for coordination).

The results of study 2 show that embodied interactions and the novel affordances of VR shape how skills are displayed and how they are trained. For example, the communication affordances of VR [75] directly contributed to novel skills relating to 'Non-Verbal Communication.' Participants also claimed a greater reliance on the body (i.e., embodied interaction) to handle certain tasks and even trained by developing reflexes to develop greater speed of execution in some tasks (e.g., reloading a weapon more quickly).

I discuss the implications and limitations of these findings in chapter 5 and chapter 6, respectively. I conclude by describing how my results suggest that adapting existing conceptualizations of competence from competitive esports domains into casual cooperative and VR multiplayer games may be insufficient, requiring future research to study and conceptualize how competence changes based on distinct features of the games, genres, platforms, and player dynamics.

Chapter 2

Related Work

In this section, I outline the previous studies that inform the theoretical assumptions of the thesis and motivate the research questions for my two studies.

2.1 The Need to be Competent

The broader importance of competence can be seen in Self-Determination theory, which states that there are three psychological needs: (1) competence, the feeling that you are good at something (i.e., self-efficacy); (2) autonomy, the feeling that only you are in control; and (3) relatedness, the feeling of being connected to others [67]. It has also been used as a motivational model for video games specifically, as research shows that video games can speak to all three needs [64]. Previous research has found that player competence strongly influences multiplayer gameplay experiences, from better performance to increased trust and camaraderie between teammates [52, 28]. Looking at professional players specifically, Musick et al. [52] interviewed 20 esports professionals and found that these players believed their overall performance is tied to executing skills and communicating this quickly and clearly to the team in response to the ever-changing conditions of the fast-paced games they play. In other words, by honing individual competence, they contribute to the team success. Conversely, a lack of competence leads to feelings of frustration and anger. For example, Przybylski et al., [63] conducted a study where they manipulated whether the participant received training for the controls of the game, and found that poor mastery over the game controls (or 'game competence as' they describe it) leads to increased feelings of aggression. Examining VR gameplay, Ferguson et al. [25] conducted a study in which they manipulated the difficulty and violence of a single-player VR game, asking participants to rate their subjective affect after the session. The authors found that participants who found the game more difficult rated feeling a greater affect of aggression. Importantly, this kind of difficulty can be reduced through training, as Lee et al. [46] point out that capturing expert input characteristics allowed coaches to better analyze player's matches and provide more helpful feedback, which led to an increase in player performance. In sum, studying competence in video games offers insights into player motivations and experiences, as well as new training and skill development opportunities.

Current understandings of competence in video games has been predominately shaped by esports research. Several studies have proposed sets of skills that they argue constitute competence in esports. Bányai et al. [16] conducted a systematic review to identify the skills, techniques, and motivations of esports players. They not only summarize key skills put forward by other studies, but also make the distinction between skills needed for successful performance (i.e., just being good) and optimal performance (i.e., being one the best). Bonilla Gorrindo et al. [11] conducted a semi-structured interview with esports clubs in Spain to determine what skills matter the most to them. This approach produced 13 unique skills across both physiological and psychological domains, showcasing how cognitive and physical tasks are involved in gaming. Examining the context directly, Larsen [44] watched 100+ hours of esports events (e.g., *League of Legends*, *Clash Royale*, *CS:GO*, etc.) to understand what constitutes competence, and discussed their understanding with other professional players to refine their findings. This study presented seven strands that describe how players acquire their skills and contribute to a theory of skill in esports. For example, 'Understanding Metagaming' is a skill where players must derived the best strategies from information in the game itself and out of the game (i.e., either online or from other players). Although each of these studies helps to develop a more comprehensive definition of insights into game systems competence, these insights are generated from esports contexts on competitive PC/Console games, leaving open questions about how players in different gaming contexts understand competence.

Differences between high-ranking and low-ranking players offer one example of how context shapes perceptions of competence, as each group evaluates skill and performance through the lens of their distinct experiences and priorities. At the highest levels, we see that professional and non-professional players do not operate with the same resources and pressures. Esports clubs typically have coaches [28], whose main role is to ensure continuous improvement in only the most relevant aspects of the game [69], which would influence what skills they consider important in the game. Additionally, players as part of a club tend to value the relationships and bonds they build to a greater extent than non-club players [50]. Abbott et al. [1], when investigating training methods among professional players, sampled players who had competed in a professional *League of Legends* tournament in the last 2 years and were ranked in the top 0.24% of all players. At this level, players must also consider their career longevity and health challenges associated with esports [36], which would also shape what skills matter most to them. But high-ranking can mean more than just professional players. Poulus et al. [62] created a survey study to identify the link between mental toughness and stress responses in high-ranking players. In this study, participants entered their rank and the authors sorted them into whether they belonged to the upper 40th percentile (i.e. high-ranking) or not, as they believe this is the cutoff where players start playing for achievement rather than purely leisure. The results of this study point to high-ranking players using and valuing similar stress coping strategies to traditional sports players, a connection absent in low-ranking gamers. Regardless of how a high-ranking player is categorized, one trend is clear: high-ranking players are under different pressures and contexts when they perform, and as such value different skills than low-ranking players.

The studies in this section show that competence in video games can influence player experience and can be improved through training, but efforts to understand competence usually stem from competitive PC esports games with professional players. Yet, differences between higher-ranking and lower-ranking players offer a reminder that players may evaluate competence differently based on their own contexts and expectations. Given the focus on esports, PC games, and training for high-ranking players in current research, there is an opportunity to examine how teammate competence is evaluated in other domains. The next sections present two areas that offer open questions about how context shapes understandings of competence: 1) how teammate performance is measured in casual cooperative games; and 2) how the affordances of VR multiplayer games may shape perceptions of skills and competence.

2.2 Measuring Teammate Performance

Teamwork and collaboration are central features of cooperative games, and have been associated with a positive impact on social aspects of players' lives [19, 20, 39], and increased empathy [29]. To analyze these dynamics, Pais et al. [58] introduced a framework to analyze cooperative games, highlighting the many distinctive ways a teammate can help and interact with the player. For example, the game's mechanics may use coupled cooperation, where players take on different tasks that intertwine and typically contribute to a shared outcome, or coincident cooperation, where players are accomplishing the same task together. While these studies show how teamwork and cooperation are understood in cooperative games, little is known about how player competence affects these dynamics in casual contexts. Moreover, teammate roles in casual games introduce additional variables. For example, social contexts can change how players use game mechanics [56], and players may act differently if they are playing with a family versus a stranger [24].

Current research aiming to reduce negative behaviour in games by identifying their causes is also relevant for assessing teammate environments and behaviours in casual games. For example, Shen et al. [72] conducted a longitudinal study of toxicity in *World of Tanks*, a competitive team shooter, and found that high skill disparities, among other factors, can lead to more instances of frustration and toxicity. In a similar vein, McLean et al. [51] found that in *League of Legends*, frustration was most pronounced in the absence of a teammate's expected cooperative behaviour, and that this in turn reduced further cooperation from the player. This research has informed interventions to prevent negative behaviour in games [10, 66]. However, the focus on competitive games overshadows the casual cooperative genre (including games like *Overcooked 2* [76]), whose player base could also benefit from insights into the effect of teammate performance. While there have been studies that focus on the cooperative multiplayer genre, these studies still rely on the competitive aspects of these games. For example, Breuer et al. [14] found that, in a co-located, competitive game played in a casual context, trash-talking had no effect on participants' frustration, which may suggest there are more complex dynamics at play in non-professional contexts.

Another challenge within this context is that there is no clear consensus on how to measure teammate performance in casual cooperative games. Esports research has led efforts to operationalize performance, often to improve training [69]. In a systematic review, Gisbert-Pérez et al. [28] identified two main approaches to understanding performance: as outcomes (e.g., win/loss) or as actions (task or contextual performance). Outcome-based measures, such as rating a streamer's performance after viewing gameplay clips [78], resemble sports-style post-match evaluations [61]. Although this approach can be applied across games, it fails to capture what constitutes good performance during play. Action-based measures include task performance (e.g., kill-death ratio [54]) and contextual performance (e.g., communication, training habits [5]). While combining both forms of action-based measures might appear to have advantages, contextual performance varies widely across genres [53], whereas task performance generalizes more easily (e.g., kill-death ratios in FPS games) and can be adapted to casual cooperative contexts. In short, operationalizing teammate performance is critical for studying its effects on frustration and cooperation, yet current research focuses on competitive games and offers no clear measure for casual cooperative play.

In conclusion, the mechanics and contexts of casual cooperative games emphasize the importance of the teammate in these games. However, operationalizations and the effects of teammate performance have been limited to competitive game contexts. This opens the door to examine how factors like frustration might need to be reconsidered within this context, and how operationalizations of teammate performance may need to change based on the game and the teammate.

2.3 VR Affordances and Player Experience

Affordance theory is a lens through which interactive systems can be evaluated by examining what actions and behaviours are possible within a given environment or interaction context [81]. Through this lens, we see that VR environments allow different affordances than PCs and Consoles. For example, Osborne et al. [57] conducted an autobiographical lab study with 9 participants, examining the affordances of different meeting software in VR (some for leisure like VR chat, others for business like Spatial). They found that VR provided different affordances (e.g., non-verbal communication, see [75] for more details) and interaction possibilities for the meetings (e.g., multiple participants can draw on the board). They also found that leisure meeting software was found more satisfying due to the novel and interesting meeting spaces, when compared to traditional meeting spaces. The opportunity for novel behaviours and actions has also been identified in research on social VR platforms. Maloney and Freeman [49], for instance, reported that users employed VR to "fall asleep together," enabled by embodied interaction and the sense of co-presence in shared virtual spaces. This example illustrates embodied interaction, which theorizes how system use is shaped by physical actions, social contexts, and environmental factors [21]. While these studies demonstrate how VR introduces new affordances and interaction possibilities, they do not address how these affordances influence definitions of competence in VR gaming.

To understand competence in VR multiplayer games, recent research has investigated how skills from PC contexts translate into VR. For example, Korbel et al. [40] and Turkay et al. [80] interviewed esports professionals, asking them how they believed their skills would translate into VR. However, there are also important differences between PC systems and VR systems. For example, Pallavicini et al. [59] conducted a within-subjects experiment where 24 participants played the a single player game on a VR system and a desktop. They found that while performance did not differ greatly across conditions, enjoyment and presence was higher in the VR condition. The authors suggest that VR can elicit greater emotion, affecting player experience.

VR systems also introduce new challenges alongside new interaction possibilities that are not available on PC systems. Korbel et al. [40] and Dużmańska et al. [23] both highlight that simulator sickness would be a key challenge in VR. Korbel et al. [40] also note how the need for more space to use VR (compared to PC) limits its accessibility. Moreover, in their analysis of VR play spaces, Harley & MacArthur [32] describe how a variety of home set-ups and play spaces can also imply a range of impediments and possible dangers, all of which can affect player experience. While social VR spaces offer new forms of communication and interaction as described above, emerging interaction possibilities and player expectations continue to shape how these affordances are designed and used. For example, in their inventory of non-verbal behaviour in Social VR, Tanenbaum et al. [75] describe how many platforms restrict advanced gestures and facial expressions behind complex menu systems, thereby limiting the player's actions and hampering communication. In a gaming context, Turkay et al. [80] interviewed eight members from a local CS:GO esports team after playing a VR shooter, and they believed that the barriers to communication in VR were due to physical distance between teammates, suggesting that the physicality of VR would complicate communication when compared to PC games and would require players to play in novel ways. Each of these challenges may shape how the player adapts and performs in these games.

The unique experiences and affordances of multiplayer VR spaces, such as those in social VR applications, suggest that these characteristics might influence the skills required for competent play in VR multiplayer games. However, to the best of my knowledge, there is no comprehensive list of such skills. This gap presents an opportunity to examine how players interpret competence across VR multiplayer games, considering differences by genre (e.g., cooperative vs. competitive) and player level (e.g., high-ranking vs. low-ranking). Such research can illuminate how VR shapes notions of competence through its affordances, interactions, and challenges.

Chapter 3

Study 1

In the introduction and section 2.1, I have established that low mastery in games can lead to feelings of anger and frustration [63], and the lack of research into competence in casual cooperative games hinders player efforts to get better in these games, motivating **RQ1**. Furthermore, given the difference in the importance of teammate performance in casual cooperative games versus competitive games, we need to investigate whether the teammate's performance has a different effect than what is seen in previous literature (i.e., poor performance causes frustration [72] and low cooperation [51]). This line of inquiry can help us understand the effect of competence training on other players, mirroring the goals of **RQ2** and **RQ3**.

3.1 Methods

To investigate the conceptualization of competence behind teammate performance and its relationship to participants' frustration, I conducted a between-subjects, randomized controlled experiment with two conditions: Competent (C) where the confederate makes no mistakes, and Incompetent (IC) where the confederate makes mistakes. As for the game, I selected *Overcooked 2* because the game's level design necessitated cooperation, and its two-player design reduced the complexity of team dynamics and confounding variables larger team games may have. This game was also selected as it is a game with symmetric ability (i.e., both players have the same abilities), so participants can more easily interpret the confederate's performance. Ethics approval was obtained from a Research Ethics Board at the University of Waterloo (#46330).

Confederate's Behaviour

In an effort to control for teammate performance, I used a confederate in my experimental design to play alongside the participant and manipulate teammate performance appropriately. The performance of the confederate was measured using a task performance metric, i.e., a numerical measure of task completion or accuracy [28]. In other words, the confederate would not make any mistakes in the competent condition (0% percent failure of tasks). In the incompetent condition, the confederate intentionally fails a certain percent of tasks (e.g., they fail every 1-in-4 tasks in the first two levels, and every 2-in-3 tasks in the last two levels.) Pilot testing revealed that an increasing rate of failure in the incompetent condition was more believable in the eyes of the tester. The participant and the confederate could interact with each other in the game and through voice chat. More details on what the tasks were, what counts as a mistake, how the confederates made these mistakes, how the confederate interacted with participant, and how the participants were trained are listed in Appendix A.

Two members (titled 'S' and 'G' here) from my research lab filled this position of the confederate in this experiment. Their contributions, alongside the assistance of all who helped with these studies, are detailed in the Statement of Contributions section .

To ensure experimental validity and to control potential confounds across the two members, the following measures were used:

- Communication was controlled and confederates were given strict guidelines in their reference sheets. (See Appendix A)
- Both members who served as the confederate did so equally in both conditions. S was the confederate for half the competent trials and half the incompetent trials, with G taking the other half of each.
- In order to mimic the setup of an online, cooperative game and to prevent the confederates' differing physical characteristics from biasing the participant in any way and becoming a confound, only a voice chat was used with the confederates using the same codename 'Bri' to introduce themselves.

3.1.1 Measures

Before playing, we collected each participant's age, gender, race, video game types played, hours per week spent playing video games, and whether they preferred challenges while playing video games. They completed all questionnaires electronically via a computer in the experiment room.

Post-Session Reflections

Having participants play with a confederate enables us to inquire about their immediate experience and to examine whether interacting with such teammates replicates findings from the esports literature. Following gameplay, I conducted a 15-minute post-session reflection with each participant. I asked open-ended questions to gauge their views on their teammate's performance, their in-session behaviour, and whether their performance conceptualization aligned with our operationalization post-debriefing. At the end, I told the participants about the confederate and that they were instructed to play a certain way, and I asked them whether this knowledge changed their perspective of their experience.

Frustration and Cooperation

We used several measures of frustration as an attempt to triangulate data collection pertaining to the same construct. Alongside the previously mentioned post-session reflection, we used the NASA Task Load Index (NASA TLX) [34] questionnaire to measure the participant's subjective frustration. The NASA TLX consists of six dimensions: *Mental Workload*, *Physical Demand*, *Temporal Demand*, *Performance*, *Effort*, and *Frustration*. We were mostly interested in *Frustration* because it is most relevant to our research question and because research connecting the remaining constructs to either frustration or cooperation in video games is scant. Despite this, we administered the complete questionnaire, following best practices to maintain experimental validity [15, 42, 60]. We also use observational data. For this, the participant's voice and facial reactions were recorded using a microphone and a webcam, respectively, in conjunction with the gameplay to capture the frequency of frustration and cooperative behaviour. I also included a single channel, in-ear Electroencephalogram (EEG) device manufactured by *IDUN Technologies* to be our physiological measure for frustration, however due to a consistently low signal quality, the data was discarded prior to analysis (more details about the EEG are discussed in Appendix B).

3.1.2 Sample Characteristics

We recruited participants by advertising the study using departmental newsletters and posters distributed to classes held on campus. Any participant between the ages of 18 and

65 was eligible to participate, provided they do not meet any of the following exclusion criteria: (1) have a history of violence or marked persistent excessive anxiety in response to acute mental stress, (2) use an implanted device (such as a pacemaker), (3) have an allergy to silver, and (4) if they have any condition that prevents them from playing a video game. Items (2) and (3) were added according to the EEG's usage guidelines.

Twenty-three participants were recruited for this study (13 self-identified as female, 10 as male). Participants' ages ranged from 20 to 23 years (M=21.39, SD=0.94 years). Fourteen participants self-identified as East Asian, three as Southeast Asian, three as South Asian, three as White, and one as Biracial (East Asian and Southeast Asian). The hours played per week ranged from 0 to 10 (M=4.89, SD=3.63 hours). Participants reported a wide range of games and genres played, ranging from competitive video games like *Call of Duty* to casual games like *Stardew Valley*. All participants reported that they did not know the confederate personally.

I used the Brief Aggression Questionnaire (BAQ) [83] to rule out predispositions to frustration or anger across conditions. Given that I am examining how competence affects a participant's frustration as described in section 2.1, this approach rules out a potential confound across conditions (i.e., one group is more prone to frustration). A Wilcoxon signed-rank test indicated that trait aggression is not significantly different between conditions (W = 52.5, p = 0.422), confirming that it is not a confounding factor in this experiment.

3.1.3 Procedure

In the study room, I presented the participant with the deceptive consent form, reiterated the exclusion criteria, and obtained consent. Then, I asked the participant to fill out the demographics questionnaire. To standardize the study procedure and participant motivation, I told the participant not to repeat any levels and to try to get three stars in all six levels (i.e., a high score). Furthermore, to ensure that the participant would speak to the confederate, we instructed them to act as a leader and discuss strategy with the other player. Following this, I reconfirmed with the participant before starting the video recording and voice call between the participant and the confederate. Finally, I retreated to the observation space with a one-way mirror.

The participants then played through a tutorial and the first six levels of the game. The tutorial was included to ensure that participants new to the game could play. Once they had finished playing through all levels, I returned to the room, terminated the voice call and the recording, and administered the post-experiment questionnaires containing the BAQ and the NASA TLX. Finally, I conducted the one-on-one post-session reflection. The participants were remunerated with $15 CAD upon completion of the study.

3.1.4 Analysis

Quantitative Analysis

I treated the results from the NASA TLX as interval data as has been seen in previous HCI work [9, 65], as opposed to ordinal data which is normally extracted from questionnaires. The limitations of this approach are discussed in the chapter 6. As such, we began with the Shapiro-Wilk test to the normality of our data. As normality assumptions were not met, we used the Wilcoxon signed-rank test.

For the video recordings, we performed a content analysis to identify key behaviours related to our RQs. Specifically, I, with the assistance of a PhD student in my lab, analyzed moments when the participants verbally communicated with the confederate. We independently analyzed the videos based off a code book consisting of items from two relevant sources (*At-Game Frustration* caused by controls and *In-Game Frustration* caused by game mechanics [27]; *Laughing together*, *Worked out strategies*, *Helping each other*, *Global strategies*, *Waited for each other*, *Got in each others' way*, and *Other cooperative behaviour* [70]), while allowing new entries relevant to our RQs to be added. We calculated inter-rater reliability and resolved any conflicts through discussion [22]. I then calculated the total number of times each code was captured for a particular participant (e.g., 'P1' displayed "Laughing together" 20 times) . Following this, I compared the distributions of total number of codes per participant across conditions to see if a behaviour occurred significantly more often in one condition than the other. Inter-rater reliability was acceptable (Initial Cohen's Kappa Coefficient = 0.48), we are aware that with our small sample size, these results may be underpowered. I calculated significance in the same manner as our questionnaire data using the Wilcoxon signed-rank test.

Qualitative Analysis

I transcribed the audio of the post-session reflection using *Otter.ai* [1] with the help of two other members of the lab and corrected any inaccurate transcriptions and removed filler words. To analyze this qualitative data, I employed a reflexive thematic analysis, following the six phase analytical process outlined by Braun and Clarke [12], because it aligned

[1] https://otter.ai

with our interpretive, inductive approach for the data. All three coders brought different experiences to the process, with one coder most familiar with shooters and story games, another familiar with MMOs, and the last coder most familiar with casual, mobile games. We used multiple coders (myself, a PhD student and another master's student from the lab) in this process to bring together multiple perspectives and achieve richer interpretations. First, all three researchers involved in the analysis individually familiarized with the data. With RQ1 and RQ2 in mind, we reviewed all entries reflexively to code responses that understand how participants viewed the confederate's competence, whether they felt frustrated, and due to what. In an iterative process, we inductively coded five participant transcripts (around 20%) at a time to extract information relevant to our research questions, generating descriptive codes (e.g., 'camaraderie reduces frustration'). After each round, the coders discussed to encourage reflexive dialogue rather than reach consensus [13]. Then, we started to collaboratively look for narratives in the codes generated, revising both narratives and codes as our interpretations of the data changed. Following this, we started to consolidate the narratives into themes, maintaining an iterative approach. Next, we compared the themes generated to the original data to see if any stories were missed or if we had misinterpreted something, revising codes and themes where appropriate. At that point, we named the themes based on the narrative present in themes as well as the responses that comprised them, following the iterative process ascribed by RTA. Finally, I began writing the report of the thematic analysis in this study.

3.2 Results

3.2.1 Quantitative Findings

As the assumption of normality was violated, a Wilcoxon signed-rank test was used on the NASA TLX frustration data ($M_C = 25.42$, $SD_C = 23.4$; $M_{IC} = 30$, $SD_{IC} = 23.87$) to find that there was no significant difference between groups ($U = 56$, $p = 0.277$). Consistent with mixed methods practice, the NASA TLX results will be interpreted in conjunction with qualitative findings and behavioural observations.

For the quantitative content analysis, we highlight the notable trends that we observed and discuss them with the other measures used in this study, consistent with mixed-methods practice. Although the average occurrence of *At-Game Frustration* behaviour per participant was low for both conditions ($M_C = 1.667$, $SD_C = 0.188$; $M_{IC} = 4.72$, $SD_{IC} = 0.76$), *In-Game Frustration* behaviours differed vastly across conditions ($M_C = 7.9$, $SD_C = 0.8$; $M_{IC} = 25$, $SD_{IC} = 4.79$). Regarding the cooperative behaviours examined, only

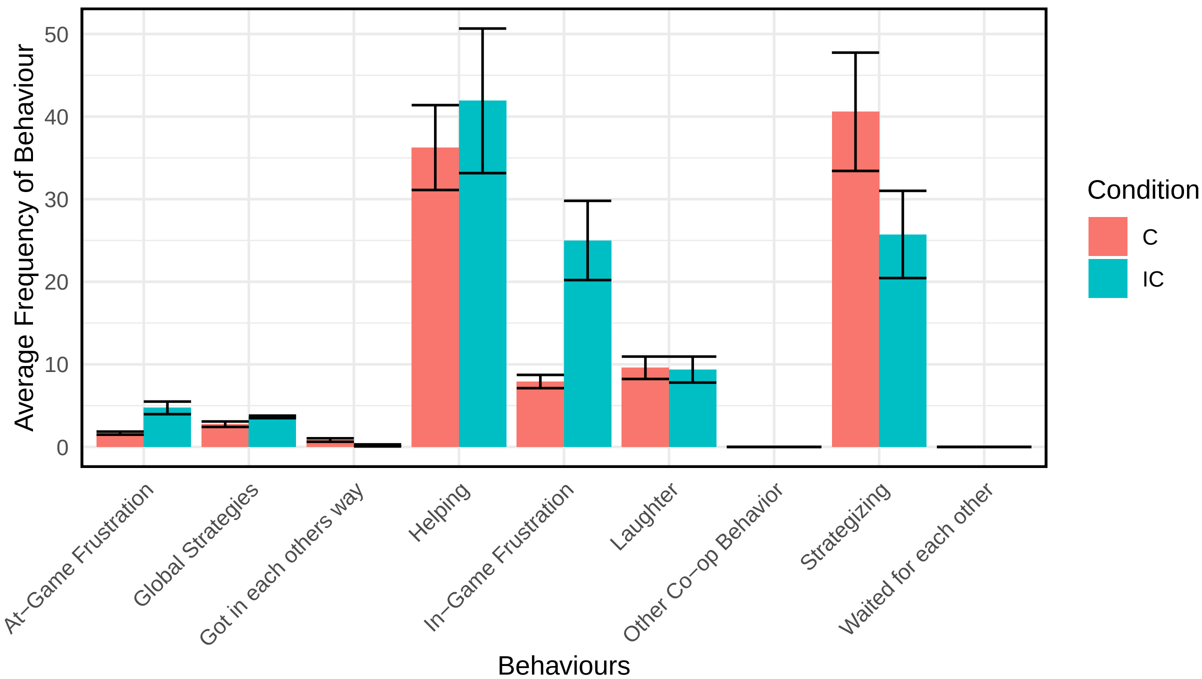


Figure 3.1: Average Frequency of Behaviour across Competent and Incompetent Conditions

Alt text: This figure visualizes the average frequency of our selected behaviour across Competent and Incompetent conditions. It shows that only 'At-Game Frustration', 'In-Game Frustration' and 'Strategizing' were significantly different across conditions.

the average occurrence of *Worked out Strategies* also had a high value and a substantial difference between conditions ($M_C = 40.58$, $SD_C = 7.16$; $M_{IC} = 25.73$, $SD_{IC} = 5.28$). These results are outlined in Figure 3.1, and show two things. First, when frustration is broken down into *At-Game* and *In-Game*, a difference in frequency of *In-Game Frustration* indicates a difference and a potential cause for the frustration that the NASA TLX did not capture. Second, not all aspects of cooperative behaviour in our code book [70] are affected equally by our manipulation of confederate competence, indicating unknown causes influencing the participant's various cooperative behaviour (e.g., a different frequency to strategize across conditions versus roughly equal frequency of laughter across conditions).

3.2.2 Qualitative Findings

We developed two main themes that describe the participants' interpretations of teammate performance and its effects on frustration and/or cooperative behaviour.

Theme 1: Participants evaluate a teammate's performance relative to their own

While esports studies often strive for quantitative measures like task accuracy to evaluate teammate performance [51, 54], our participants' responses suggest that perceived differences between performance mattered most. When asked about the confederate's skill, the participants always compared it with their own skill (e.g., "I was probably playing fairly poorly as well." (**P7**)). These comparisons were not limited to task accuracy. Participants also evaluated themselves in relation to the confederate when describing their perceptions of team behaviour and attitude. As **P19** stated, "I was very calm, and [the confederate was] very calm. We just talked to each other." This illustrates that, regardless of whether it was a task performance measure or a contextual attitude, the participant consistently assessed performance in a relational way. It is important to acknowledge that these conclusions may only apply to casual multiplayer games, as participants considered competitive games different, stating that "one bad player in a team can kind of ruin everybody." (**P20**), supporting the claim that casual cooperative games provide an equal playing field where players contribute towards a collective goal [3]. Thus, we surmise that, in casual cooperative games, teammate performance must be evaluated in relative terms in addition to other quantitative measures to increase external validity.

Theme 2: Frustration and cooperative behaviours are most influenced by the teammate, not the game

Consistent with existing literature in competitive settings [72, 51], participants believed that their overall feeling of frustration during the game stemmed not only from their own performance, but also that of the teammate (the confederate). For example, one participant playing with an incompetent teammate reported that failing to achieve a task performance goal caused their frustration: "the last round we didn't get the three stars. So that was, of course, upsetting" (**P3**). With regards to cooperative behaviour, another participant reported that the responsiveness of the confederate (i.e., high contextual performance) encouraged them to strategize better and mitigate some frustration that arose from playing in the incompetent condition: "we experienced some frustrations as the levels progressed but I think that was smoothed out as we figured out how to work past that." (**P18**). Regarding the effect of the casual game on participants' behaviour, some participants considered the game design as potentially adding to their frustration: "nearing the end as the timer was going down ... it's like a bit more pressure." (**P13**), while others claimed that the game design reduced frustration ("Overcooked is a fun party game, so I'm not stressing out." (**P25**)). Again, participants saw this as different from competitive games, where players "play against an opponent [and] get aggressive [towards their teammates]." (**P1**). Here, even repeated failures did not immediately cause frustration: ("if they keep doing stuff wrong, I may say something" (**P24**)). These results suggest that teammate performance does have an effect on their frustration and cooperative behaviour, while the game itself has no consistent effect across the sample.

3.3 Study 1 Summary of Findings

This study aims to understand how competence is viewed in casual cooperative games, and how the teammate's performance affects the participant. For **RQ1:** "How do players evaluate teammate competence in casual games?", an answer emerges in Theme 1: "Participants evaluate a teammate's performance relative to their own". This data suggests that our participants compared their competence to that of the confederate to determine how well they did. With regards to **RQ2:** "How do players experience frustration from teammate performance?", our observational data shows there is a difference in frustration across conditions, with 'In-Game Frustration' having a bigger difference. Adding explanatory context, the second theme ("Frustration and cooperative behaviours are most influenced by the teammate, not the game") supports the notion that participants are frustrated by the teammate's performance and not the game itself. However, our questionnaire data disagreed, showing no difference across conditions. These findings suggest that the questionnaire is not capturing how participants describe frustration in casual cooperative games. Finally, for **RQ3:** "How do players behave cooperatively based on teammate performance?", our observational data highlights our 'Strategizing Together' differed across conditions. Theme 2 specifically explains this difference with the participants responsiveness being key to strategizing more often. Given that we limited confederate communication in this study, it may explain why cooperative behaviour is so minimal in this study. Implications and limitations are discussed in chapter 5 and chapter 6, respectively.

Chapter 4

Study 2

While not a direct follow up to Study 1, Study 2 examines VR multiplayer games as another site where player competence is understudied. As described in section 2.1, higher ranking players have different priorities than lower ranking players, motivating **RQ4**. Furthermore, section 2.3 shows that other current multiplayer domains like Social VR offer players new forms of embodied actions and communication opportunities based on the unique affordances of VR, motivating **RQ5** and **RQ6**, which examine how players interpret the relevant skills and experiences of VR multiplayer games. Because these research questions require a baseline set of appropriate skills that have not yet been identified in VR contexts, I implemented Study 2 in two phases. Phase 1 involves a literature-based search to identify relevant skills in PC and console games, which I then consolidate into skill clusters that study participants can evaluate and rank for VR contexts. Phase 2 consists of a questionnaire that asks participants to first describe relevant multiplayer skills in VR, then interpret the skill clusters identified in Phase 1 in relation to their VR experiences. By exploring how players interpret the necessary skills for VR multiplayer games, we can better understand skill adaptation in VR, and ultimately inform design and/or training approaches that benefit the broader VR multiplayer community. Ethics approval was obtained from a Research Ethics Board at the University of Waterloo (#47403).

4.1 Phase 1: Literature-Based Skill Extraction

4.1.1 Structured Literature Search

Because there is no comprehensive catalogue of skills for VR multiplayer games, I began by identifying skills in PC and console games that could be relevant for a VR context. This is not without precedent, as past work looking in VR skills has found some analogues of skill applying to both [80, 35], however, a thorough comparison has seldom been attempted. Therefore, in order to capture a non-exhaustive list of relevant video game skills identified in PC and console games, I conducted a structured literature search. In order to gather the papers relevant to my research question, I looked at papers that explicitly mentioned video games, discussed skills that directly contribute to player performance through the following search query: ("Video Games" OR "Esports" OR "Computer Games" OR "Interactive Gaming") AND ("Skills" OR "Skilled" OR "Skill") AND ("Player") AND ("Performance"). After an initial skim of the results, I found a large subset of papers in the medical field not discussing gaming performances but medical interventions, so I added 'NOT ("Medicine" OR "Surgery")' to filter out this large subset of papers. Lastly, I narrowed the search to publications within the last 10 years to gather skills in modern systems and games. The complete query for each database can be found in Appendix C. The search was conducted on August 17, 2025. Academic papers were gathered from 4 major databases in games research and HCI: the ACM library (357 papers), Scopus (321), IEEE (83) and the Web of Science (89), for a total of 850 papers.

After removing duplicates (n=123) and entries without an abstract available (n=60), I screened the abstracts of the remaining papers to identify whether skills for PC and console gamers were discussed. This led to 588 papers being discarded and 79 papers being included for full-text review. The 79 papers are attached in Appendix D. Of the 79 papers selected, I collaborated with another member of the research team to read the papers in detail to catalogue all the skills listed. 44 papers were discarded as they contained no direct mentions of skills for video games. A total of 60 skills were extracted from the remaining articles (n=35). The process is visualized in Figure 4.1.

4.1.2 Affinity Mapping

To consolidate the 60 unique skills identified in the Structured Literature Search, I worked with a PhD student in my lab to cluster them together using affinity mapping on a collaborative digital whiteboard. During the process, conflicts were handled via a discussion

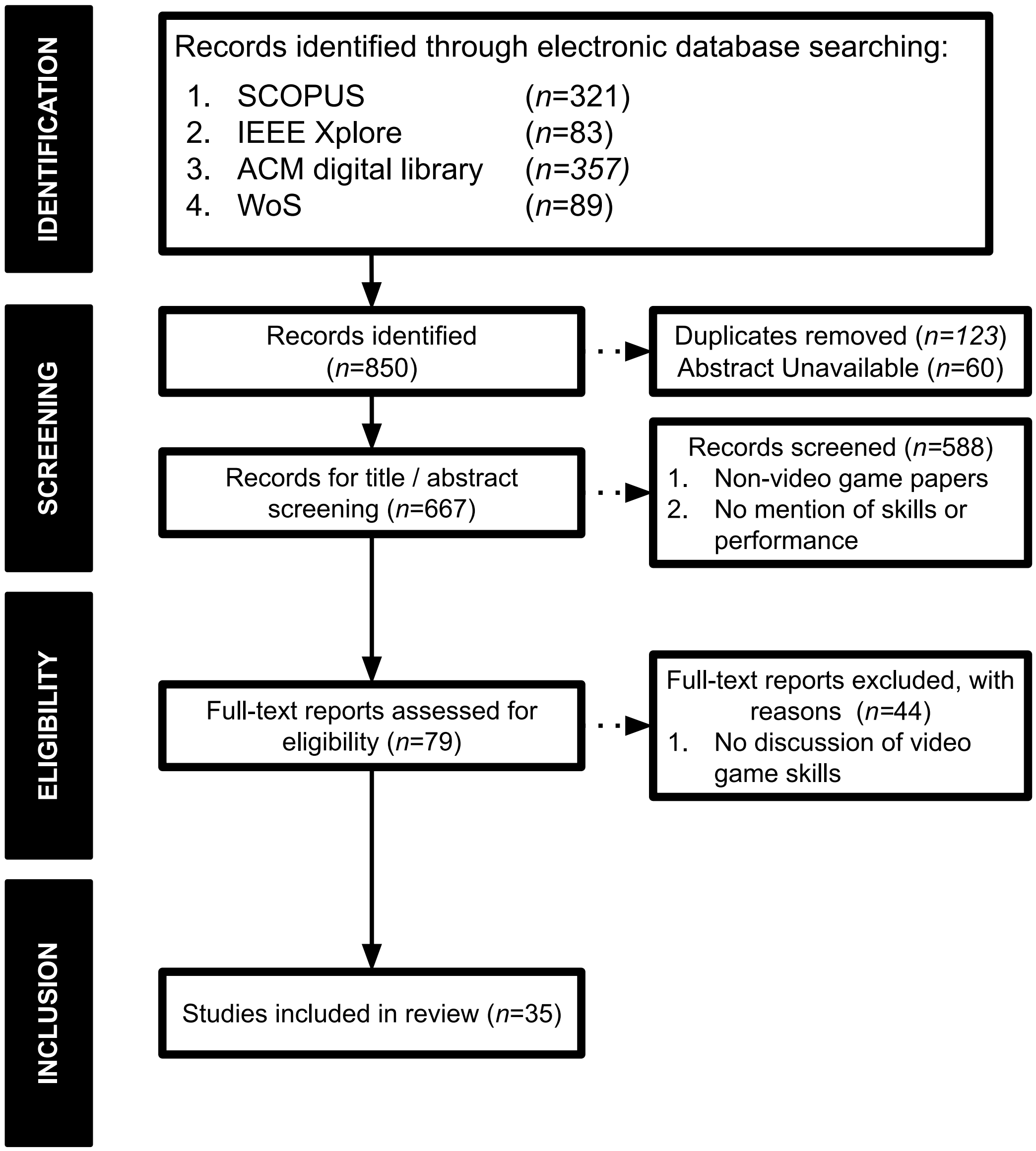


Figure 4.1: Flow diagram of the literature search in this study

Alt Text: This figure shows the total number of papers acquired through the databases and being screened first through their abstract, and then through their content, with papers discarded at each stage for failing to meeting the criteria of relevance.

until consensus was reached. If a consensus couldn't be reached, a third-party (i.e., a supervisor) would have been the tie-breaker, but this didn't happen during our process. We clustered skills based on how similar the processes are in which players use these skills. For example, among the three skills, "Advanced Player Input", "Good Movement in Game", and "Performing under pressure", the first two were grouped together as they were both motor skills while the last one relied on emotional regulation. Next, smaller clusters were titled and merged into bigger clusters following the same logic. This process was then reviewed by a supervisor to ensure the clusters were grounded in the data. The process is displayed in Appendix E. During this process, no skill was deemed too niche or irrelevant such that they had to be discarded. Following this, we synthesized new names and definitions of these skill clusters based on the components skills. Our procedure required that the new names and definitions could accurately capture most of the skills under them, with the understanding that some nuance would be lost in the clustering. For example, while "Maintaining composure" tied well to the cluster name "Emotional Regulation", another skill "Grit" had nuance that couldn't be captured by the cluster name. Thus, eight clusters of skills were created: "Good Use of Game Mechanics", "Reaction Time", "Attentional Skills", "Emotional Regulation", "Team Work", "Device Interaction Skills", "Strategic Thinking", and "Spatial Skills". The definitions for the skills can be found in Table 4.1.

Skills	**Definitions**
Good Use of Game Mechanics	A strong understanding and application of game mechanics.
Reaction Time	Reacting quickly when attention is needed.
Attentional Skills	Keeping track of multiple things at the same time, and dividing attention in real time.
Emotional Regulation	Maintaining composure in a game.
Team Work	Collaborating with teammates.
Device Interaction Skills	Interacting effectively with the device.
Strategic Thinking	Planning the actions. Thinking through different strategies.
Spatial Skills	Having an understanding and being able to make use of Layout/Interactable objects in the 3D environment. Using map knowledge or positioning to gain an advantage or perform multiple functions.

Table 4.1: Skills and their definitions

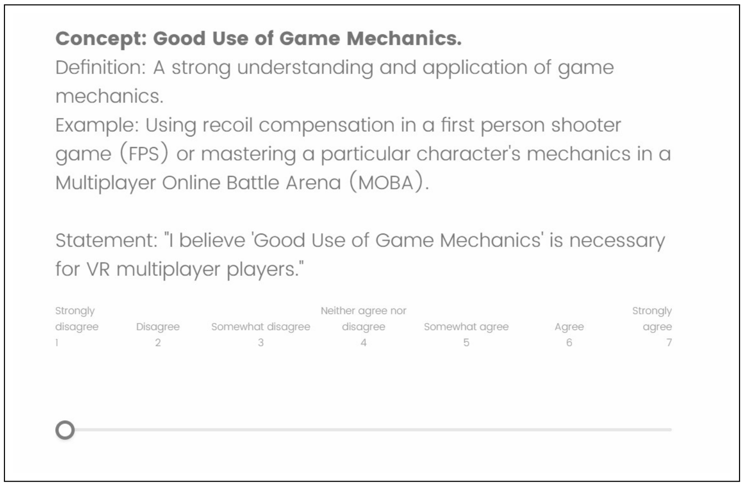


Figure 4.2: The skill cluster's definition, an example, and a statement of agreement as presented to the participant

Alt text: A screenshot of the Qualtrics survey where the concept, the definition of that concept, and an example is displayed. Below that is a statement of agreement, and a slider that ranges from 'Strongly disagree - 1' to 'Strongly Agree - 7', with 7 notches

4.2 Phase 2: Survey Study

4.2.1 Questionnaire

I created a questionnaire to gather participants responses to the importance of the resulting skill clusters in virtual reality multiplayer games. It begins with an open-ended question about what skills the respondents consider important for VR multiplayer games: "Please list the skills you believe are most important to a VR Multiplayer Gamer. For each skill, please include a description (what the skill means to you as a player) and an example (how you've used it or seen it used in a VR multiplayer game)". Then each skill cluster derived from existing literature is presented alongside a definition, an example, and a statement of agreement, such as Figure 4.2. Then a sliding Likert scale is presented asking participants to rate how strongly they agreed or disagreed with the statement, with 7 being strongly agree and 1 being strongly disagree. The UI element used here is a continuous slider that snapped to the integers. The responses will be compared between high-ranking and low-ranking players to see where the importance of these skill clusters converge and/or diverge **(RQ4)**.

Following this, three more questions with open-text boxes are present for each skill cluster:

(i) What is an example of this skill in a VR multiplayer game that you play?

(ii) Is there anything that makes this skill different in VR compared to a desktop or console game? If so, please offer an example.

(iii) Do you train this skill for the VR games that you play? If yes, how do you train? If not, why not?

These questions were used to investigate how the affordances and experiences in VR change the understanding and training of existing skills **(RQ6)**. Attention check questions (i.e. (1) “Please select strongly agree on the scale”, and (2) “Please type 'Yes' in the text box”) were also introduced in this section, and responses that failed this check were discarded. We then asked participants to rank all skill clusters relative to each other. We also asked them if they wanted to inform us about any skills that we had missed that were relevant to the VR Multiplayer experience, (i.e., “Thinking back on your previous responses, are there any other skills you feel are important for playing VR multiplayer games that we haven't talked about yet? If yes, please describe each skill briefly. For each skill, include a definition and an example”.) This question, alongside the first question asking the same, will be used to identify novel skill clusters for VR **(RQ5)**. Lastly, we concluded with the demographics questions, and whether they self-identify as a high-ranking player. Specifically, we used the definition found in Poulus et al. [62], i.e., whether participants believed they ranked in the top 40% of all players. As the paper describes, at this stage they are no longer playing for fun and playing for achievement [62]. This is most useful in a space where tournaments are niche and the player pool is small, like VR multiplayer games. Participants were given 10 CAD in remuneration upon completion. A full copy of the survey is attached in Appendix F.

4.2.2 Sample Characteristics

I recruited participants by advertising the study using an online survey distribution site, *User Interviews*. An a priori power analysis was conducted to determine the minimum sample size needed to detect a medium effect size (d = 0.5) with 80% power at an alpha level of 0.05 for a two-tailed paired-samples t-test. The analysis indicated a minimum required sample size of 134. However, I capped the max sample size at 120 participants due to budgetary constraints. In line with my research goals, the following inclusion criteria was put forward: (1) Participants must be between the age of 18 and 64, and (2) they must have experience with VR multiplayer games. To ensure adherence to the inclusion criteria, a screener questionnaire was employed with the following questions.

1. Have you played a virtual reality (VR) multiplayer game?
2. What VR multiplayer games have you played?
3. For the purposes of the study, an Esports athlete is defined as a player that ranks in the top 40% of all players for that game. Are you an esports athlete?
4. Have you ever competed in a professional VR Esports tournament?

The first and second question were used to filter participants who applied to fill out the survey. 125 participants who applied to fill out the survey were removed as they indicated "No" to the first question, or they wrote down non-VR games (e.g., Fortnite) to the second question. The third and fourth questions were used to categorize participant responses based on how they play, as I wanted a sample of both high-ranking and low-ranking players.

A total of 111 participants completed the survey. 23 submissions were removed as they were either incomplete (n=2), or did not respond correctly to the attention check (n=21), leading our sample total to be 88 participants. In the attention check, the responses that were discarded were ones that either answered anything but 'Strongly Agree' when required (e.g., responding with 'Slightly Agree') or didn't type 'Yes' to open-ended text box (e.g., 'I believe this skill is important to VR.'). 34 participants self identified as high-ranking players, while 54 self-identified as low-ranking players. The sample consisted of a diverse set of participants in terms of age, gender, race, and experience with VR. Participants' ages ranged from 19 to 54 (M=32.19, SD=4.24). The small SD implies that, while the range of ages is large, my sample skewed heavily towards people in their early 30s. 50 (56.81%) participants identified themselves as male, 36 (40.91%) as female, one as non-binary, and one as transgender. With regards to race, 18 participants identified as Black, 44 as White, one as Caribbean, four as East Asian, three as Latine, five as South Asian, two as Southeast Asian, nine as biracial and two preferred not to answer.

4.2.3 Analysis

Quantitative Analysis

For the quantitative analysis, we use an independent samples two-tailed t-test to determine whether there are significant differences in skill ratings between high-ranking and low-ranking players. The data is divided into two groups based on player rank, and we test whether the mean difference between all eight ratings of skills presented across high-ranking and low-ranking players is statistically significant. This was also repeated for our question about rating the skills relatively.

Qualitative Analysis - Affinity Mapping

To catalogue the novel skills that participants provided that form their understanding of competence in VR, I conducted an affinity mapping on a collaborative digital whiteboard to cluster them into skill clusters, following a similar procedure outlined in phase 1. Responses from the open-ended question asking participants about what novel skills do they believe were important in VR were catalogued and organized into sticky notes. Responses containing multiple skills were separated into multiple sticky notes. Given that the first instance of this question was shown before I provided our list of skills from existing literature, I expected some overlap. As such, any skills that would fit into our pre-defined skill clusters were kept separately. The criteria for whether it would be added to our existing skill clusters was whether the skills were similar or differed as the participant described. For example, if the participant stated "Reacting Quickly" and defined it as 'players having to react to something by pressing a button on their controller', then it would be placed under our existing skill clusters. However, if they defined it as 'having the entire body move to avoid something', then it would be placed under a new cluster as it captured a factor that was not included in the existing skill clusters. Next, clusters were titled and merged into bigger clusters where appropriate. This process was then reviewed by another researcher in the group to ensure the clusters were grounded in the data. The process is displayed in Appendix E.

Qualitative Analysis - Reflexive Thematic Analysis

The responses that provided more detail on our pre-defined skill clusters and how they fit into VR were analyzed using a reflective thematic analysis (RTA). I choose this approach to both respectfully and thoughtfully analyze participants' subjective responses, while remaining cognizant of how my role as the researcher affects the interpretation of the data. In this study, I followed the six phase analytical process outlined by Braun and Clarke [12]. First, I familiarized myself with the data while cleaning up the data. I removed entries where participants simply answered "no" or "none". This step resulted in a total of 1957 (out of 2112) valid responses in the form of short sentences. With RQ6 in mind, I reviewed all entries reflexively to code responses that discuss the participants' perception of skills and their importance in VR. The initial coding generated descriptive codes such as "Skill is exclusive to VR" and "the body is the controller". After the initial coding, I revisited the data to ensure all relevant entries have been coded, sometimes changing the codes to better capture the meaning as I understood it. I wanted to improve upon my RTA process done in study 1, so throughout this process, I kept a reflexive journal (like Trainor and Bundon [77]) to document any shifts in my thought processes over time and look back on codes that I interpreted another way at the start of this procedure (see Appendix G). The next step was to generate themes, as in I examined how different codes can be combined to generate an overarching narrative. I made sure that all themes spoke to a coherent and consistent narrative that answered our research question. Next, I compared the themes generated to the original data to see if any stories were missed or if I had misinterpreted something, revising codes and themes where appropriate. At that point, I named the themes based on the narrative present in themes as well as the responses that comprised them, following the iterative process ascribed by RTA. Finally, I began composing the report of the thematic analysis in this thesis.

4.3 Results

4.3.1 Quantitative Findings

Out of the 88 valid responses, we had greater than 30 data points in both high-ranking (n = 34) and low-ranking (n = 54) respondents, normality of the data can be assumed due to the central limit theorem. The t-test was used to compare the responses to importance of each skill cluster across high-ranking and low-ranking. Only 'Attentional Skills' showed a significant result ($t(86)$ = -2.286, p=0.021) across high-ranking (M=5.76, SD=1.08) versus low-ranking players (M=6.26, SD=0.96) players. The complete summary can be found at Table 4.2. When looking at relative ratings (i.e., no two skill clusters could share equal rating), there was no significant differences across any skill (See Table 4.3 for the complete overview). Effect sizes was computed for all t-tests.

Table 4.2: An summary of the t-test results for the skill ratings across High Ranking versus Low Ranking gamers.

	Low-Ranking *M (SD)*	High-Ranking *M (SD)*	t-test *t*	P Value	Cohen's *D*
Good Use Of Game Mechanics	6.14 (0.81)	6.26 (0.83)	-0.65	0.519	-0.143
Attentional Skills	5.76 (1.08)	6.26 (0.96)	-2.29	**0.025***	-0.487
Device Interaction Skills	6.09 (1.22)	6.06 (1.15)	0.13	0.896	0.028
Emotional Regulation	5.44 (1.42)	5.59 (1.33)	-0.48	0.632	-0.104
Reaction Time	6.32 (0.91)	6.44 (0.66)	-0.75	0.453	-0.154
Spatial Skills	6.29 (1.00)	6.00 (1.28)	1.14	0.256	0.265
Strategic Thinking	5.59 (1.27)	6.00 (1.18)	-1.53	0.130	-0.330
Team work	5.96 (1.30)	6.41 (0.96)	-1.86	0.066	-0.380

$^{*}p < .05$, $^{**}\ p < .01$

4.3.2 Qualitative Findings

Novel Skills Identified

Following the procedure outlined in section 4.2.3, we looked at 176 responses from 88 participants, as each participant was asked about novel skills in VR at the beginning and end of the questionnaire. Responses that did not provide any detail about skills or were hard to understand were discarded (e.g., the following statement appears to describe player experience in relation to level design rather than a specific skill: "The [difficulty of] the level. I think it is cool when you accomplish it and move on to a more difficult level"). Our affinity mapping showed us that the skill clusters extracted from previous research resonated with our participants, as many of them reported these pre-existing skills in an open-ended text box question before any of our skill clusters were shown. In addition to this, we also identified several novel skill clusters that deepen our understanding of competence in VR multiplayer games. We also present the overall rationale provided by the participants and a quote that captures the essence of the skill cluster. An important point to note is that we did not separate codes based whether the response was written by a high-ranking and low-ranking player here. A quick overview of these findings is located here: Table 4.4.

Table 4.3: An summary of the t-test results for the relative skill ratings across High Ranking versus Low Ranking gamers.

	Low-Ranking *M (SD)*	High-Ranking *M (SD)*	t-test *t*	P Value	Cohen's *D*
Good Use Of Game Mechanics	3.22 (2.08)	3.38 (2.22)	-0.34	0.736	-0.075
Attentional Skills	4.50 (1.76)	3.79 (1.74)	1.85	0.069	0.404
Device Interaction Skills	4.69 (2.44)	5.09 (2.11)	-0.82	0.414	-0.174
Emotional Regulation	6.02 (1.93)	6.00 (2.19)	0.04	0.968	0.009
Reaction Time	3.39 (1.95)	3.29 (1.70)	0.24	0.810	0.051
Spatial Skills	4.31 (2.55)	5.18 (2.33)	-1.63	0.108	-0.349
Strategic Thinking	5.15 (2.01)	5.03 (2.41)	0.24	0.811	0.055
Team work	4.72 (2.35)	4.24 (2.28)	0.96	0.339	0.209

$^{*}p < .05$, ** $p < .01$

1. **Physical Fitness**

Consisting of stamina (or endurance), flexibility, and acclimatization to VR, participants very clearly identified physical fitness as a key factor in the competence of VR multiplayer games. The flexibility is needed to execute some of the movements VR games demand, and the match lengths require them to keep up this performance for some time, necessitating the need for stamina. Furthermore, being able to tolerate the sensation of motion sickness, especially if the game went on for some time, was cited as a crucial factor in multiplayer games to prevent disappointing the teams. This cluster is best described by the following quote: "It's far more physical than a lot of gamers expect when they first try it and you can be sore after a long gaming session in VR. Also, the ability to crouch very quickly using your body instead of simply hitting a button can be the difference between being shot in the head or the bullet flying over your head" (**P35**).

2. **Suspension of Disbelief**

'Suspension of Disbelief', in this context, refers to the skill of being able to fully immerse yourself in the world, such that the actions taken in the world feel intuitive and are executed without much thought. Participants believed this was necessary to react more quickly and complete tasks more efficiently, by allowing the body to complete tasks intuitively and reduce the mental workload. The quote that captures this is: "I noticed a distinct difference in fun level/performance when I completely suspend my disbelief. When I act like the headset isn't there, and I'm actually IN the game. That little mental shift makes a world of difference in my experience." (**P24**).

3. Real-World Awareness

'Real-World Awareness' refers to the skill of "keen spatial awareness to navigate both worlds" (**P83**). Participants recalled incidents where they or someone playing with them could not effectively perform in the game or hurt themselves due to a lack of awareness of the outside world. They also make it clear that 'Suspension of Disbelief' and 'Real-world Awareness' are not mutually exclusive, as one can feel involved in the world but remain cognizant of the limits in the real world. As an example, "It is very easy to get involved into the game and accidentally harm yourself or others in your vicinity. I will frequently remove the VR to see where I am and if I've moved from where I previously was and to give me an idea of what is around me again to avoid hurting myself accidentally." (**P36**).

4. Adaptability

Adaptability consists of "quickly adjusting to new environments, mechanics, or unexpected player behaviour." (**P38**). As another participant put it, "VR games can be unpredictable, so being able to adjust to new players, controls, or game modes matters." (**P48**). The participants believed there are no fixed strategies or approaches that promise the best results across games, and therefore, participants highlight the importance of being able to switch strategies based on the situations. However, an important caveat is that descriptions of this skill explicitly mention the novelty of VR and the variety of game modes that currently exist, implying that this may change as certain games gain dominance or that VR players don't play favourites. This is best summarized by the following quote: "In VRChat, players jump between wildly different worlds: some are games, others are social spaces. Adapting to new rules and social norms is key to thriving." (**P38**).

5. Non-Verbal Communication

'Non-Verbal Communication' refers to using your body in VR to communicate with teammates. Participants described various instances where different gestures were used to communicate brief messages quickly in key moments, highlighting it as one of the main differentiators of VR versus PC or consoles. An example of is "showing you are patient like throwing your hands up patiently and waiting for your target to get you in gorilla tag, but then slipping away unexpectedly!" (**P60**).

Reflexive Thematic Analysis

Following the procedure outlined in section 4.2.3 titled "Qualitative Analysis - Reflexive Thematic Analysis", I developed two main themes that describe how the participants' be-

Skills	Definitions
Physical Fitness	Being able to execute the range of motion demand, maintaining this level of exertion of long period of time, and training to control simulator sickness.
Suspension of Disbelief	Being able to fully immerse yourself in the world, such that the actions taken in the world feel intuitive and are executed without much thought.
Real-World Awareness	Managing to navigate both the virtual and real world without any interruption.
Adaptability	Being to quickly adjusting to new environments, mechanics, or unexpected player behaviour
Non-Verbal Communication	Using your body in VR to communicate with teammates effectively.

Table 4.4: Skills Identified for VR Multiplayer and their definitions

lieve the affordances and experiences of virtual reality games affect the understanding and training of existing video game skill clusters.

Theme 1: The Body as the Controller

This theme covers responses that discuss how the body shapes how skills are performed in VR multiplayer games. It not only discusses how the body is used in VR games, but also discusses how aspects of gaming (such as communication and attention) are shaped by the involvement of the body. Participants reported that "Your body is a key element [in VR]. Lifting a controller during a tough gaming sequence doesn't do much for a console game but in VR it changes a lot" **(P23)**. In such cases, the player must perform physical actions that would otherwise be as simple as pressing a button or a series of keystrokes. Framing the body as a controller in VR had both positive and negative implications, changing how they played and how they experienced the multiplayer environment. For example, participants believe that non-verbal cues play a greater role in VR communication, and a greater control of body movements was considered important, like "pointing or looking in a certain direction can instantly signal intentions to teammates, which is harder to replicate on a flat screen"**(P41)** and "if you're upset, teammates can sense it right away. On a console, you can just mute yourself, but in VR your reactions feel more visible" **(P27)**.

Secondly, participants believe there is a greater feeling of immersion due to physically performing actions, stating "[The Skill] in VR feels more immersive because you physically act out the plan. For example, coordinating a sneak attack requires crouching, pointing, and moving in sync with teammates, which adds layers that console/PC don't replicate" **(P30)**. However, they also believe there is a loss of precision as "it might be more difficult [to perform] if it relies on motion controls that are harder to be precise on than controllers" **(P52)**. This difficulty could also be tied to an increase in cognitive demand, as participants point to the difficulty in negotiating a variety of physical actions and visual inputs: "in VR I use my whole body to divide attention between sound, movement, and space around me, not just what's on a screen. For example, in Echo VR, I must look over my shoulder physically while also tracking the disc, which is more demanding" **(P65)**.

The implication of this theme is that the body is used more directly and to a greater extent to display skills in VR multiplayer games. This increase in physical demand leads to an increase in both immersion and communication opportunities while also potentially requiring a higher physical and cognitive demand, highlighting the need for a more holistic view of demands for playing in VR games.

Theme 2: Physical Practice for Reflexive Action

This theme covers the common goal of training physical abilities to the point where they occur as reflexes (i.e., almost instinctual) while playing VR games. The theme not only covers why conditioning these skills as reflexes is relevant to VR, but also the different ways players tend to train them. For the participants, the main goal of practising VR skills is to train a range of physical actions so that they can be performed immediately (almost reflexively or automatically) in response to the demands of in-game decisions and actions. One participant stated, "I repeatedly practice quick reloads, precise throwing, and climbing in Population: One to ensure my interactions become instinctive under pressure" **(P41)**. For some participants these physical actions also contributed to their feeling of immersion, and were an option to leverage "intuitive" physical actions. As one participant described, "it feels like you're fully involved. When you're playing a boxing simulator you feel that you're going to get hit and you're intuitively ducking to avoid being hit" **(P36)**.

The methods that participants used to train these reflexive actions varied. Many participants reported using drills in the same type of VR game (e.g. "Yes, I train spatial skills by practising in fast-paced VR games" **(P48)**) or leveraged external guides about the game (e.g., "I just try to uncover instructions and become as knowledgeable as possible" **(P18)**) in order to strengthen their skills. Some participants argue that real-world skills carry over to help build their reflexes (e.g., "I train by continually playing the games but I have buddies that actually go to firing ranges [to train]" **(P72)**). Others claim that "having lots of experience in non-VR games also naturally trains this a little bit and I think it carries over to VR somewhat for sure." **(P70)**, suggesting an agreement with existing literature that claims there is a skill transfer between PC training and VR skill [35].

The main implication of this theme is that as VR games require a wider range of physical demands than their PC counterparts, participants also feel the need to train those skills to the degree that they become automatic. Furthermore, participants also see value in multiple training strategies beyond the game itself, noting strategies that go beyond what is traditionally associated with practice in PC and console gaming. Participants train physical actions across VR, PC, and real-life environments, raising further questions about where and how these skills are best developed.

4.4 Study 2 Summary of Findings

In study 2, I sought to understand what skills, novel and existing, apply to VR multiplayer games, and how the affordances and experiences in VR change the understanding and training of existing skills.

With regards to **RQ4:** "Which skills adapted from existing PC literature to VR multiplayer games are most valued by high-ranking versus low-ranking players?", we see that only 'Attentional Skills' was rated differently between high-ranking and low-ranking players. Theme 1: "The Body as the Controller" provides an explanation for this. The need to physically divide attention (e.g., turning the head while tracking a disc) makes the skill feel more cognitively demanding in VR, and high-ranking player may be more aware of this phenomenon and give it a greater importance.

For **RQ5:** "What new skills are identified for VR multiplayer games, if any?", five new skill clusters relevant to the VR multiplayer experience and are absent in existing PC/Console skill literature were identified. They are 'Physical Fitness', 'Suspension of Disbelief', 'Real-World Awareness', 'Adaptability', and 'Non-Verbal Communication' (See Table 4.4 for details). All the new skill clusters feature the body as a focal point, in one way or another. This nuance is directly explored by Theme 1: "The Body as the Controller", speaking to the greater importance of the body in skills pertinent to VR.

For **RQ6**, "How do the affordances and experiences in VR change the understanding and training of existing skills?", the results of the reflexive thematic analysis speak to this clearly. Both themes highlight the greater importance of the body when playing VR multiplayer games, such as using gestures to communicate instead of voice. Theme 2: "Physical Practice for Reflexive Action" also highlights that when VR players practice, they do so in order to build reflexes to play faster (e.g., they practice the motions so that they can reload a gun faster). This practice may occur in game, or in analogous contexts like real-life gun ranges.

Implications of these findings and limitations of this study are discussed in Chapter 5 and Chapter 6, respectively.

Chapter 5

Discussion

The goal of this thesis is to study competence in games outside the PC/Console esports contexts. Study 1 investigated how definitions of competence change in casual cooperative games, and assessed whether existing findings about the effect of teammate performance on frustration and cooperation from esports research can be replicated in these casual, co-op games. Study 2 aimed to identify the most important skill clusters for competency in VR multiplayer games, what considerations are made by players when adapting skills from PC/console games, as well as studying the role of rank (i.e., professional and casual) in how these skills are valued. Although the two studies investigate separate areas of interest, both offer new insights into player competence. In this section, I bring together the major findings across both of these studies to put forward three main takeaways:

1. Definitions used in esports research about competence cannot be applied to casual cooperative games and VR multiplayer games.

2. Current definitions of frustration and cooperation are not sufficient for casual cooperative games.

3. Player skills in VR multiplayer games depend on the affordances of the game (e.g., being able to physically reload a weapon) and embodied interactions (e.g., physical dodging, gesturing for coordination).

5.1 Identifying Contextual Factors of Player Competence

Takeaway 1: Definitions used in esports research about competence cannot be applied to casual cooperative games and VR multiplayer games.

Synthesizing the findings of the two studies, we can conclude that perceptions of competence are substantially shaped by contextual factors that are not covered by existing esports approaches. These contextual factors of cooperative games and VR multiplayer games can affect player priorities within a given game genre or medium. In study 1, one of the contextual factors for casual cooperative games is that players must cooperate with a teammate to accomplish shared tasks, rather than compete against other players as in competitive games. From our findings, we see that participants tend to conceptualize competence in relative terms rather than the absolute terms seen in competitive games [51, 54], addressing **RQ1**. Specifically, players perceive and interpret their competence relative to their teammate's competence. Study 1's theme 1 ("Participants evaluate a teammate's performance relative to their own") speaks directly to this, suggesting that the quantitative operationalization of teammate competence seen in previous competitive gaming research [51, 11] does not clearly apply to casual cooperative games. Instead, all our participants compared their competence with that of the confederate to determine how well they did. This extended to both task performance and behavioural measures of performance, with one participant claiming that they believed the confederate was competent as they both remained calm. Adding further nuance, in theme 2 ("Frustration and cooperative behaviours are most influenced by the teammate, not the game"), participants reported that this comparison happened during the game rather than an after the fact, with the latter previously used in studies on competitive games [72]. One possible reason can be seen in Wang et al. [82], where participants compared themselves to their teammate to motivate themselves.

In study 2, one of the core contextual factors of VR is the involvement of the whole body to play, offering an obvious contrast to the seated experience of existing esports that relies on input with keyboard and mouse or controller [37]. Looking at the findings for **RQ5** and **RQ6**, we see competence in VR revolves around how the body is used to perform relevant VR multiplayer skills. Consider the new skill clusters identified in study 2: 'Physical Fitness', 'Suspension of Disbelief', 'Real-World Awareness', 'Adaptability', and 'Non-Verbal Communication' (See Table 4.4 for details). The interesting aspect to take note of is that all the new skill clusters identified feature the body as a focal point, in one way or another. Theme 1 of this study ("The body is the controller") offers some explanatory context, with participants highlighting that the body is key in all the actions they perform in VR. While prior research highlights the increased physical demands of VR [41], these findings suggest that physicality is central to our understanding of VR competence rather than just another demand to manage. This is crucial as papers like Korbel et al. [40] and Turkay et al. [80] discuss how skills translate to VR with physicality being an important feature, but the centrality of the skill is not discussed.

With competence being relational in casual cooperative games and physicality being central to our understanding of VR competence, these findings soundly push back on the notion that task-performance views of competence found in esports contexts [28] can apply in our studied contexts. I encourage future researchers to use a bottom-up approach to identify how players in that space regard competence before looking at its effects or developing training regimens. To this end, our findings also serve as a good starting point for future efforts investigating competence in casual cooperative games and VR multiplayer games. I also hope our findings help players focus their training efforts to improve their skills in these areas and enjoy the cooperative and VR games they play (e.g. by focusing on building equal competence in both players for casual cooperative games).

5.2 Understanding Variations in Frustration and Cooperation

Takeaway 2: Current definitions of frustration and cooperation are not sufficient for casual cooperative games.

Building on the previous finding, the relational aspect of competence also changes how frustration and cooperation are viewed in casual cooperative games. In study 1, I sought to answer **(RQ2)**: 'How do players experience frustration from teammate performance'. Applying a mixed methods approach, I included a questionnaire, observational data, and a post-session reflection measure to triangulate the results. When looking at them together, we see two contradictory results: our observational measure reveals there is a significant difference in frustration between the groups while our questionnaire data suggests there is no difference. Using our thematic analysis results, we see participants did report feeling frustrated in study 1's theme 2 ("Frustration and cooperative behaviours are most influenced by the teammate, not the game"), meaning that the difference between the observational and questionnaire data cannot be attributed to memory effects, as the post-session interview happened right after the questionnaire. Therefore, we are inclined to attribute this to the differing definitions in the measures (e.g., the NASA TLX defines the frustration question as “How insecure, discouraged, irritated, stressed and annoyed were you?” [34], while the observational measure proposed by Gilleade and Dix [27] defined *In-Game Frustration* as “that which arises from a failure to know how a challenge is to be completed.” Furthermore, when attempting to divide frustration into ‘At-Game Frustration’ and ‘In-Game Frustration’, as described in Gilleade & Dix [27], we see that the number of instances of ‘At-Game Frustration’ is dwarfed by the number of ’In-Game Frustration’ (See Figure 3.1). This nuance would be lost in studies where there is frequently only one self-reported measure of frustration and that do not consider this distinction [4, 14, 25]. Theme 2 offers an explanation for why ’In-Game Frustration’ behaviour was observed more often. Participants reported that whenever they were frustrated, it was mostly at the other player making things difficult rather than at the game. This also speaks to why the NASA TLX did not capture differences in frustration, as the focus of the question lies on the self rather than what/who caused the frustration.

With regards to cooperation, I used the seven cooperative behaviours put forward by Seif et al. [70]. For **RQ3:** “How do players behave cooperatively based on teammate performance”, our results show that only one cooperative behaviour (i.e., ‘Worked Out Strategies’) was seen significantly more often in the competent condition. Study 1’s theme 2 provides some exploratory context for this, as participants reported that the responsiveness of the confederate (i.e., high contextual performance) encouraged them to strategize better. This seems to align with previous work (e.g., Wang et al. [82]) where more competent players tend to initiate strategic planning. This also explains the low amount of cooperation seen overall in our observational measure, as I instructed the confederates to “act friendly but try to limit banter” (See Appendix A). More broadly, our findings highlight nuances that are not captured in studies where cooperation is simply assumed rather than measured [29] or where it boils down to a simple ‘how often do they help’ [51].

Our findings suggest that while ‘In-Game Frustration’ as described in Gilleade & Dix [27] is a promising start, I recommend building off these constructs to create a measure of frustration and cooperation with a deeper focus on the player relationship between cooperative players. As outlined above, future researchers should give special consideration to how players perceive competence moment-by-moment and what particular difference caused the effect (e.g., Did they stop talking because the teammate displayed poor communication?). This is compounded by the fact that social contexts can change how players use game mechanics [56], and future research can study these social contexts. For example, players may act differently if they are playing with a family versus a stranger [24], but how does this affect their perception of competence.

5.3 Interpreting VR Multiplayer Skills as Embodied Actions

Takeaway 3: Player skills in VR multiplayer games depend on the affordances of the game (e.g., being able to physically reload a weapon) and embodied interactions (e.g., physical dodging, gesturing for coordination).

The first takeaway highlights how physicality affects VR competence. In this section, we see how affordance theory and embodied interaction are key to understanding how player physicality is embedded in the display of these skills. In study 2, to answer **RQ5**, we developed five new skill clusters that are relevant to the VR multiplayer experience and are absent in the existing PC/Console skill literature. All of these skill cluster mirror specific VR affordances and constraints: 'Physical Fitness' addresses the physical demand of VR [41] and managing cybersickness [23], 'Suspension of Disbelief' is connected to immersive possibilities of multiplayer VR experiences [49], 'Real-World Awareness' relates to the considerations about awareness systems in VR [18, 55], and 'Non-Verbal Communication' mirror the inventory of affordances created by Tanenbaum et al. [75]. Therefore, we see that players skills evolve to meet the affordances of a given system, and future research can build off this finding, using insights from affordance theory [81] to better understand VR competence. Furthermore, the introduction of new skills that leverage VR-specific affordances raises the question of how these skills are perceived in relation to existing skills adapted from PC and console platforms, particularly in terms of their relative importance.

Another line of inquiry in study 2 is comparing how high-ranking and low-ranking players differ in rating the importance of skills from existing literature **(RQ4)**. While high-ranking and low ranking players rated all skills highly, my results show that only 'Attentional Skills' was rated significantly differently between high-ranking and low-ranking players. Theme 1 ("The body as the controller") provides an explanation for this. The need to physically divide attention (e.g., turning the head while tracking a disc) makes the skill feel more cognitively demanding in VR, and a high-ranking player may be more aware of this phenomenon and give it a greater importance. One of our novel skills ('Suspension of Disbelief') also supports this notion, with participants saying it was easier to control and have a better grip on the task when they fully immersed themselves in the game. In other words, the body plays a greater role during the cognitive problem-solving task compared to PC/console games. This directly mirrors the concept of embodied interaction [21], where the body and mind are not treated as separate entities but part of a single process. Study 2's theme 2 further adds nuance to this finding, with participants highlighting how training in VR mostly consists of practising the skill until it is conditioned into the body as a reflex. As an example, one participant claimed they had friends who go to firing ranges to practice skills that will be relevant in VR shooting games, leveraging embodied knowledge from real-world parallels and transferring the skills to VR. This also extends a finding by Pallavicini et al. [59] that claims that performance is equal across VR and PC contexts, suggesting that while there are important parallels in performance across PC and VR, the path to get there is very different.

While esports training skills offer a useful starting point to understand relevant skills in VR multiplayer games, this section shows that the novel affordances of and embodied interactions present in VR fundamentally change how a skill is displayed and trained. With this consideration, future studies can use affordance theory and embodied interaction to examine the different game contexts, different game relationships, and player physicality compared to PC systems. Given these physical demands, a future study could examine whether insights from sports psychology (e.g., the physical [30] and mental [73] competencies in a parkour athlete) carry over to the VR context. Another possible direction for future research is to create a comprehensive list of affordances for physical actions in VR multiplayer games, similar to what Tanenbaum et al. [75] do for non-verbal communication affordances in social VR applications. This could then be used to identify what skills are possible and how players interpret or train those particular actions. Rather than our skills-in-games first approach, this approach would examine all skills that are possible in VR, even skills not used in the games thus far. This approach would be most useful for game designers as they can better understand how the affordances directly shape skills, which would allow them to create games that cater to these skills.

5.4 Implications

In both studies, we see that competence definitions used in competitive esports contexts do not carry over to casual cooperative and VR multiplayer contexts. In the same vein, study 1 also identifies shortfalls in current understandings of frustration and cooperation measures. Similarly, study 2 highlights the underlying role of embodied interaction and affordance considerations in VR competence. With these takeaways, we put forward implications for researchers and players.

The first implication is that future researchers should not rely solely on esports conceptualizations of competence to other domains. Instead, there is an opportunity to develop bottom-up approaches that begin with contextual, player-oriented, and affordance-based factors when discussing competence for specific games. For example, conceptualizations of competence may be assessed at the game or genre level before any claims can be made about the effect of performance. Moreover, if understandings of competence do not adequately translate from one domain to another, there may be a need to reassess how training regimens can be applied from one game to another, or from one context to another.

The second implication of our findings is that there is greater support for the explanatory power of Self-Determination theory, affordance theory, and embodied interactions. In study 1, we highlight the relational aspect of competence in casual cooperative games. This finding may be explained by the relatedness need (i.e., people want to feel connected to to others) from Self-determination theory outlined in section 2.1. In study 2, we show the importance of full-body physicality in VR competence, which may be explained through the lens of affordance theory and embodied interactions. This gives future researchers the opportunity to look at how these theoretical considerations may apply more directly.

The third implication of this finding is that measures of frustration and cooperation need to be adapted to their specific context. For example, in study 1, participants responded in the questionnaire that they were not frustrated, but when asked for clarification in the interview, they said that it wasn't the game that had frustrated them but the confederate had. While frustration was not directly explored in study 2, one participant noted that when they are upset in VR, others can tell based on their body language. Therefore, measures of frustration and cooperation need to be adapted and validated for the specific contexts they are studied in. For casual cooperative games, I recommend building off constructs like 'In-Game Frustration' as described in Gilleade & Dix [27] to capture frustration and cooperation as it connects to the teammate. For VR multiplayer, physical expressions of frustration (e.g., fist shaking in frustration) and cooperative behaviour (e.g., high-five to show approval) must be considered.

Chapter 6

Limitations

Both studies had limitations that can be addressed in future studies. In this section, I outline these limitations and suggest future directions to address them.

6.1 Study 1

The small sample and conflicting measurement data of Study 1 made it difficult to conclude anything definitive about **RQ2** and **RQ3**. Future research can expand the sample size with the current methodology to determine whether the difference found by the questionnaire and observational measures has a statistically significant difference, with a pivot to include a comparative measure alongside than an absolute one. As an example, rather than having the confederate playing at 50% task accuracy, future research can obtain a baseline level of performance from the participant (e.g., in the early levels), and at a certain point, the researcher can signal the confederate about the participant's task performance thus far and how the confederate can play better, worse, or equal to the participant. This may help to ensure ecological validity when trying to replicate findings from existing research (e.g., performance to frustration [72]).

Another possible direction in future work attempting a similar study design might include the use of AI agents in *Overcooked 2* controlling confederate performance. I chose to have human confederates so that participants would be more likely to engage as they would in real-life, however, combining existing bots for Overcooked [8] with the confederate talking in real time might lead to greater control of performance and participant engagement. One more limitation of the study is that I did not consider any participant characteristics.

These include different player traits, such as the *Online Gaming Motivation* scale [85] or the participants preference for challenge (which we collected but did not use in the results due to a low sample size), and types of relationships between casual players (e.g., does this trend differ when played with friends/family). Pursuing this direction could help with interventions like the one described in Bongaards et al. [10], as this provides more clarity about what types of teammates best suit our participant in terms of communication styles, goals, etc.

In our methods, we treated data from the NASA TLX as interval data consistent with past HCI research [65, 9]. However, there are shortfalls to this approach as participants may view the distinctions differently. Future research may favour the approach of treating NASA TLX data as ordinal and run the appropriate tests (e.g., skipping the Shapiro-Wilk test and only performing the Mann-Whitney U-Test). Another limitation in study 1 is our use of a single game, *Overcooked 2*. While it meets the criteria described in the introduction, other casual cooperative games can differ in terms of their mechanics. For example, Harris et al. [33] describe multiple ways in which players experiences may be asymmetric or dependence may change. *Overcooked 2* [76] is a game with symmetric ability (i.e., both players have the same abilities) but games like *It Takes Two* [74] have "Asymmetry of Ability - Where one player can do things another player cannot." [33]. Future research should look at the mechanics and affordances of different casual cooperative games and how that affects a player's perceived competence. Furthermore, we know that games and player motivation vary (e.g., a player could play *Valorant* casually or *Overcooked 2* competitively). Therefore, this work can also be expanded into the broader spectrum of different games and player motivations.

6.2 Study 2

6.2.1 Phase 1

In this phase, one limitation was the exclusion of medical papers from our search. Given that our results speak to physical characteristics, including this research could lead to additional skills (e.g., from sports medicine rehabilitation, or VR training applications in these contexts) that could add depth to our data. Another limitation in this phase was not including 'competence' itself in our search. This was a misstep as adding competence would have improved the rigour of our approach. Future research can clarify both these shortfalls by examining the skills put forward across the range of studies that that discuss the relationship between various VR activities and competence.

6.2.2 Phase 2

Our survey study also has important limitations. Firstly, self-reported expertise on such paid platform may be unreliable. Moreover, while screener questions were used to remove participants not suited for the study, we could not verify whether any participant actually played the games they claimed to. Another limitation is caused by the incentive structure of survey sites like *User Interviews*. One possible reason for high failure rate in the attention check is that *User Interview* prioritizes completion rather than the quality of response, so certain participants may have opted to rush through the questionnaire, leading to them failing the attention check. Future research can tackle this limitation by sourcing participants from VR clubs or use other methods to verify their playtime (e.g., metrics in the user's profile). Finally, our sample fell short of the 134 participants indicated by our power analysis, hampering the power of our results. Future research can replicate this study with a higher sample, perhaps even recruiting from a large VR convention or similar to avoid the pitfalls of online survey platforms.

When classifying high and low-ranking players, we used the definition of a high-rank player put forward by Poulus et al. [62], the results for which were obtained via self-report. A natural consequence of that is that participants may overestimate their ability and believe they are in the top 40% of players without evidence to support that. We are also aware that boosting—"a form of cheating whereby high-skilled players access lower-skilled players' accounts for the purpose of increasing the rank of the account for monetary gain"—is also an issue and may influence the ranking on the few VR esports leagues present today [17]. In light of this, two future directions emerge: On one hand, as the VR esports scene evolves, future research can use more concrete rank data to identify top players. Going further, future studies may choose to examine only those who play in tournaments as a career (as seen in Kari & Karhulahti [37]), or explicitly focus on career and health considerations, as seen in Kang et al. [36]. The health considerations are of particular interest, given the physical demands of VR that we have identified. On the other hand, future research can look at the casual cooperative games in VR as we have done in study 1. This research can examine if the findings of study 1 (i.e., competence as relational) apply to VR contexts and how they would change. With regards to our analysis of ratings between high-ranking and low-ranking players, a Bonferroni correction could have been applied to the multiple t-tests conducted in this phase in order to improve the statistical rigour of the analysis. Doing so will correct the inflation of Type 1 errors caused by multiple t-tests and allow researchers to better understand how player rank influences the perception of skill.

Chapter 7

Conclusion

In this thesis, my goal was to investigate how player competence is conceptualized outside competitive PC esports, focusing on the understudied domains of casual cooperative and VR multiplayer games. To achieve this, I conducted two studies aimed at developing a deeper understanding of competence in these contexts. Study 1 examined the conceptualization of competence in casual cooperative games and tested the effect of teammate performance on frustration and cooperation. Study 2 examined the conceptualization of competence in VR multiplayer games, and the effect of player rank on this conceptualization. Findings in study 1 revealed that players in casual cooperative games tend to evaluate competence relative to their teammate rather than in relation to a predefined metric like total number of dishes served by each player. Perceptions of frustration were also shaped by teammate performance: while questionnaire responses suggested low frustration overall, interviews clarified that frustration was directed toward the confederate rather than the game itself. In Study 2, findings underscored the importance of physicality in VR competence, revealing five new skill clusters and participant responses that highlight how required skills and training strategies are shaped by the affordances and embodied interactions that are possible in VR environments.

Future research can build on the overarching takeaways of this work by developing more comprehensive definitions of competence and creating validated measures of frustration and cooperation for diverse game genres. Beyond these broad goals, several specific opportunities arise from the limitations of this thesis. First, studies should replicate and extend Study 1 with larger sample sizes and comparative performance designs to strengthen generalizability. Incorporating measures of individual differences and interpersonal relationships would provide deeper insight into how these factors influence perceptions of competence and frustration. Expanding beyond *Overcooked 2* to include multiple casual cooperative games would ensure findings reflect the diversity of the genre. For VR contexts, future work should address gaps the skill clusters that I identified by including other competence-related research. Additionally, there is a need for more accurate criteria for ranking and/or categorizing VR players, particularly as the VR esports ecosystem evolves. Finally, differentiating between VR game genres and teammate composition will be critical, as each may entail distinct skill demands and competence criteria. Together, these suggestions offer multiple directions for advancing the study of competence across varied gaming environments.

Overall, this research contributes insight into competence in casual cooperative games and VR multiplayer games, emphasizing the need for bottom-up approaches that begin with considerations player needs, experience, and the specific demands of the game and/or platform. Future work should avoid relying solely on esports-based conceptualizations of competence, as measures of frustration, cooperation, and necessary skills must be tailored to their unique contexts. The findings also reinforce the explanatory power of Self-Determination Theory, affordance theory, and embodied interactions, highlighting opportunities to integrate contextual, player-oriented, and affordance-based factors into future models of competence. By doing so, players can better understand and develop their skills, leading to more enjoyable gaming experiences and marking an important step in the quest to chart skills in uncharted domains.

Bibliography

[1] Callum Abbott, Matthew Watson, and Phil Birch. Perceptions of Effective Training Practices in League of Legends: A Qualitative Exploration. *Journal of Electronic Gaming and Esports*, 1(1), October 2022.

[2] Ville Ahonen, Marko Leino, and Tarmo Lipping. Electroencephalography in Evaluating Mental Workload of Gaming. In *2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, pages 845–848, New Jersey, USA, November 2021. IEEE. ISSN: 2694-0604.

[3] In-Chang Baek, Tae-Gwan Ha, Tae-Hwa Park, and Kyung-Joong Kim. Toward Cooperative Level Generation in Multiplayer Games: A User Study in Overcooked! In *2022 IEEE Conference on Games (CoG)*, pages 276–283, New Jersey, USA, August 2022. IEEE. ISSN: 2325-4289.

[4] Nick Ballou and Sebastian Deterding. 'I Just Wanted to Get It Over and Done With': A Grounded Theory of Psychological Need Frustration in Video Games. *Proc. ACM Hum.-Comput. Interact.*, 7(CHI PLAY):382:217–382:236, October 2023.

[5] André C. K. Baumann, Ståle Pallesen, Rune A. Mentzoni, Eirin Kolberg, Vegard Waagbø, Anders Sørensen, and Joakim H. Kristensen. An exploratory qualitative interview study on grassroots esports in sports clubs. *Frontiers in Sports and Active Living*, 6, August 2024.

[6] Nicole A Beres, Julian Frommel, Elizabeth Reid, Regan L Mandryk, and Madison Klarkowski. Don't You Know That You're Toxic: Normalization of Toxicity in Online Gaming. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, pages 1–15, Yokohama Japan, May 2021. ACM.

[7] Inc. BigBox VR. Population: One.

[8] Justin Bishop, Jaylen Burgess, Cooper Ramos, Jade B. Driggs, Tom Williams, Chad C. Tossell, Elizabeth Phillips, Tyler H. Shaw, and Ewart J. de Visser. CHAOPT: A Testbed for Evaluating Human-Autonomy Team Collaboration Using the Video Game Overcooked!2. In *2020 Systems and Information Engineering Design Symposium (SIEDS)*, pages 1–6, April 2020.

[9] Matthew L. Bolton, Elliot Biltekoff, and Laura Humphrey. The Mathematical Meaninglessness of the NASA Task Load Index: A Level of Measurement Analysis. *IEEE Transactions on Human-Machine Systems*, 53(3):590–599, June 2023.

[10] Thom Bongaards, Maurits Adriaanse, and Julian Frommel. Personalized Matchmaking Restrictions for Reduced Exposure to Toxicity: Preliminary Insights from an Interview Study. In *Companion Proceedings of the 2024 Annual Symposium on Computer-Human Interaction in Play*, CHI PLAY Companion '24, pages 31–36, New York, NY, USA, October 2024. Association for Computing Machinery.

[11] Ivan Bonilla Gorrindo, Andrés Chamarro, and Carles Ventura. Psychological skills in esports: Qualitative study of individual and team players. *Aloma: Revista de Psicologia, Ciències de l'Educació i de l'Esport*, 40(1):35–41, May 2022.

[12] Virginia Braun and Victoria Clarke. Reflecting on reflexive thematic analysis. *Qualitative Research in Sport, Exercise and Health*, 11(4):589–597, August 2019.

[13] Virginia Braun and Victoria Clarke. *Thematic Analysis: A Practical Guide*. SAGE Publications, New York, United States, December 2021.

[14] Johannes Breuer, Michael Scharkow, and Thorsten Quandt. Sore losers? A reexamination of the frustration–aggression hypothesis for colocated video game play. *Psychology of Popular Media Culture*, 4(2):126–137, 2015.

[15] Ernesto A. Bustamante and Randall D. Spain. Measurement Invariance of the Nasa TLX. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 52(19):1522–1526, September 2008.

[16] Fanni Bányai, Mark D. Griffiths, Orsolya Király, and Zsolt Demetrovics. The Psychology of Esports: A Systematic Literature Review. *Journal of Gambling Studies*, 35(2):351–365, June 2019.

[17] Eoin Conroy, Magdalena Kowal, Adam J. Toth, and Mark J. Campbell. Boosting: Rank and skill deception in esports. *Entertainment Computing*, 36:100393, January 2021.

[18] Emily Dao, Andreea Muresan, Kasper Hornbæk, and Jarrod Knibbe. Bad Breakdowns, Useful Seams, and Face Slapping: Analysis of VR Fails on YouTube. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, pages 1–14, Yokohama Japan, May 2021. ACM.

[19] Ansgar E. Depping, Regan L. Mandryk, Colby Johanson, Jason T. Bowey, and Shelby C. Thomson. *Trust Me: Social Games are Better than Social Icebreakers at Building Trust*. ACM, 2016.

[20] Igor Dolgov, William J. Graves, Matthew R. Nearents, Jeremy D. Schwark, and C. Brooks Volkman. Effects of cooperative gaming and avatar customization on subsequent spontaneous helping behavior. *Computers in Human Behavior*, 33:49–55, 2014.

[21] Paul Dourish. Embodied interaction: Exploring the foundations of a new approach to hci. *Work*, 1(1):1–16, 1999.

[22] James W Drisko and Tina Maschi. *Content analysis*. Oxford university press, Oxford, United Kingdom, 2016.

[23] Natalia Dużmańska, Paweł Strojny, and Agnieszka Strojny. Can Simulator Sickness Be Avoided? A Review on Temporal Aspects of Simulator Sickness. *Frontiers in Psychology*, 9, November 2018.

[24] Lina Eklund. Family and games: digital game playing in the social context of the family. In *Multiplayer*, pages 162–171. Routledge, 2013.

[25] Christopher J. Ferguson, Anastasiia Gryshyna, Jung Soo Kim, Emma Knowles, Zainab Nadeem, Izabela Cardozo, Carolin Esser, Victoria Trebbi, and Emily Willis. Video games, frustration, violence, and virtual reality: Two studies. *British Journal of Social Psychology*, 61(1):83–99, January 2022.

[26] Vankrupt Games. Pavlov shack.

[27] Kiel M Gilleade and Alan Dix. Using frustration in the design of adaptive videogames. In *Proceedings of the 2004 ACM SIGCHI International Conference on Advances in computer entertainment technology*, ACE '04, pages 228–232, New York, NY, USA, September 2004. Association for Computing Machinery.

[28] Júlia Gisbert-Pérez, Alejo García-Naveira, Manuel Martí-Vilar, and Jorge Acebes-Sánchez. Key structure and processes in esports teams: a systematic review. *Current Psychology*, 43(23):20355–20374, June 2024.

[29] Tobias Greitemeyer. Playing Video Games Cooperatively Increases Empathic Concern. *Social Psychology*, 44(6):408–413, January 2013.

[30] Sidney Grosprêtre and Romuald Lepers. Performance characteristics of Parkour practitioners: Who are the traceurs? *European Journal of Sport Science*, 16(5):526–535, July 2016.

[31] Thorkild Hanghøj and Rune Nielsen. eSports Skills are People Skills. In *"Proceedings of the 12th European Conference on Game Based Learning "*, page 63, Sophia Antipolis, France, October 2019. ACPI.

[32] Daniel Harley and Cayley MacArthur. Sharing Play Spaces: Design Lessons from Reddit Posts Showing Virtual Reality in the Home. In *Proceedings of the 2023 ACM Designing Interactive Systems Conference*, pages 509–522, Pittsburgh PA USA, July 2023. ACM.

[33] John Harris, Mark Hancock, and Stacey D. Scott. Leveraging asymmetries in multiplayer games: Investigating design elements of interdependent play. In *Proceedings of the 2016 Annual Symposium on Computer-Human Interaction in Play*, CHI PLAY '16, page 350–361, New York, NY, USA, 2016. Association for Computing Machinery.

[34] Sandra G Hart and Moffett Field. Nasa-task load index (nasa-tlx); 20 years later. In *Proceedings of the Human Factors and Ergonomics Society 50th Annual Meeting*, pages 904–908, Santa Monica, 2006. SAGE.

[35] Julia M. Juliano and Sook-Lei Liew. Transfer of motor skill between virtual reality viewed using a head-mounted display and conventional screen environments. *Journal of NeuroEngineering and Rehabilitation*, 17(1):48, April 2020.

[36] Jimoon Kang and Seongcheol Kim. Game over too soon: early specialization and short careers in esports. *Frontiers in Psychology*, 16:1585599, May 2025.

[37] Tuomas Kari and Veli-Matti Karhulahti. Do E-Athletes Move?: A Study on Training and Physical Exercise in Elite E-Sports. *International Journal of Gaming and Computer-Mediated Simulations (IJGCMS)*, 8(4):53–66, 2016.

[38] Jasmine Katatikarn. Online gaming statistics and facts: The definitive guide (2024), September 2023.

[39] Mark Keith, Greg Anderson, James Gaskin, and Douglas L. Dean. Team video gaming for team building: Effects on team performance. *AIS Transactions on Human-Computer Interaction*, 10(4):205–231, 2018.

[40] Jakob J. Korbel, Jana E. Riewe, Sophia Elsholz, and Rüdiger Zarnekow. Extended Reality in Esports: Opportunities, Challenges and Future Research Avenues - An Experts' Perspective. *Communication & Sport*, 13(6):1171–1189, December 2025.

[41] Pranav Madhav Kuber and Ehsan Rashedi. Alterations in Physical Demands During Virtual/Augmented Reality-Based Tasks: A Systematic Review. *Annals of Biomedical Engineering*, 51(9):1910–1932, September 2023.

[42] Eugene Kukshinov, Joseph Tu, Kata Szita, Kaushall Senthil Nathan, and Lennart E Nacke. Widespread yet unreliable: A systematic analysis of the use of presence questionnaires. *Interacting with Computers*, 1(1), February 2025.

[43] Andrey Lange, Andrey Somov, Anton Stepanov, and Evgeny Burnaev. Building a Behavioral Profile and Assessing the Skill of Video Game Players. *IEEE Sensors Journal*, 22(1):481–488, January 2022.

[44] Lasse Juel Larsen. The Play of Champions: Toward a Theory of Skill in eSport. *Sport, Ethics and Philosophy*, 16(1):130–152, January 2022.

[45] VR Master League. Vr master league.

[46] Hanbyeol Lee, Seyeon Lee, Rohan Nallapati, Youngjung Uh, and Byungjoo Lee. Characterizing and Quantifying Expert Input Behavior in League of Legends. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*, pages 1–21, Honolulu HI USA, May 2024. ACM.

[47] Anissa Maharani, Virienia Puspita, Raden Arny Aurora, and Nico Wiranito. Understanding Toxicity in Online Gaming: A Focus on Communication-Based Behaviours towards Female Players in Valorant. *Jurnal Syntax Admiration*, 5(5):1559–1567, May 2024.

[48] Laura Maldonado-Murciano, Georgina Guilera, Christian Montag, and Halley M. Pontes. Disordered gaming in esports: Comparing professional and non-professional gamers. *Addictive Behaviors*, 132:107342, September 2022.

[49] Divine Maloney and Guo Freeman. Falling Asleep Together: What Makes Activities in Social Virtual Reality Meaningful to Users. In *Proceedings of the Annual Symposium on Computer-Human Interaction in Play*, pages 510–521, Virtual Event Canada, November 2020. ACM.

[50] Marcel Martončik. e-Sports: Playing just for fun or playing to satisfy life goals? *Computers in Human Behavior*, 48:208–211, July 2015.

[51] Dave McLean, Frank Waddell, and James Ivory. Toxic Teammates or Obscene Opponents? Influences of Cooperation and Competition on Hostility between Teammates and Opponents in an Online Game. *Journal For Virtual Worlds Research*, 13(1), March 2020.

[52] Geoff Musick, Rui Zhang, Nathan J. McNeese, Guo Freeman, and Anurata Prabha Hridi. Leveling Up Teamwork in Esports: Understanding Team Cognition in a Dynamic Virtual Environment. *Proceedings of the ACM on Human-Computer Interaction*, 5(CSCW1):1–30, April 2021.

[53] Eugen Nagorsky and Josef Wiemeyer. The structure of performance and training in esports. *PLOS ONE*, 15(8):e0237584, August 2020.

[54] Francesco Neri, Carmelo Luca Smeralda, Davide Momi, Giulia Sprugnoli, Arianna Menardi, Salvatore Ferrone, Simone Rossi, Alessandro Rossi, Giorgio Di Lorenzo, and Emiliano Santarnecchi. Personalized Adaptive Training Improves Performance at a Professional First-Person Shooter Action Videogame. *Frontiers in Psychology*, 12:598410, June 2021.

[55] Joseph O'Hagan, Julie R. Williamson, Florian Mathis, Mohamed Khamis, and Mark McGill. Re-Evaluating VR User Awareness Needs During Bystander Interactions. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, pages 1–17, Hamburg Germany, April 2023. ACM.

[56] Carl Magnus Olsson, Staffan Björk, and Steve Dahlskog. The conceptual relationship model: understanding patterns and mechanics in game design. In *Digital Games Research Association (DiGRA), Snowbird, Utah, USA (2014)*, pages 1–16. DIGRA, 2014.

[57] Anya Osborne, Sabrina Fielder, Joshua Mcveigh-Schultz, Timothy Lang, Max Kreminski, George Butler, Jialang Victor Li, Diana R. Sanchez, and Katherine Isbister. Being Social in VR Meetings: A Landscape Analysis of Current Tools. In *Proceedings of the 2023 ACM Designing Interactive Systems Conference*, pages 1789–1809, Pittsburgh PA USA, July 2023. ACM.

[58] Pedro Pais, David Gonçalves, Daniel Reis, João Cadete Nunes Godinho, João Filipe Morais, Manuel Piçarra, Pedro Trindade, Dmitry Alexandrovsky, Kathrin Gerling,

João Guerreiro, et al. A living framework for understanding cooperative games. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems*, pages 1–17, 2024.

[59] Federica Pallavicini, Alessandro Pepe, and Maria Eleonora Minissi. Gaming in Virtual Reality: What Changes in Terms of Usability, Emotional Response and Sense of Presence Compared to Non-Immersive Video Games? *Simulation & Gaming*, 50(2):136–159, April 2019.

[60] Sebastian A. C. Perrig, Lena Fanya Aeschbach, Nicolas Scharowski, Nick von Felten, Klaus Opwis, and Florian Brühlmann. Measurement practices in user experience (ux) research: a systematic quantitative literature review. *Frontiers in Computer Science*, 6, March 2024.

[61] Anthony D. Pizzo, Yiran Su, Tobias Scholz, Bradley J. Baker, Juho Hamari, and Leah Ndanga. Esports Scholarship Review: Synthesis, Contributions, and Future Research. *Journal of Sport Management*, 36(3):228–239, May 2022.

[62] Dylan Poulus, Tristan J. Coulter, Michael G. Trotter, and Remco Polman. Stress and Coping in Esports and the Influence of Mental Toughness. *Frontiers in Psychology*, 11, April 2020.

[63] Andrew K. Przybylski, Edward L. Deci, C. Scott Rigby, and Richard M. Ryan. Competence-impeding electronic games and players' aggressive feelings, thoughts, and behaviors. *Journal of Personality and Social Psychology*, 106(3):441–457, 2014.

[64] Andrew K Przybylski, C Scott Rigby, and Richard M Ryan. A motivational model of video game engagement. *Review of general psychology*, 14(2):154–166, 2010.

[65] Anjana Ramkumar, Pieter Jan Stappers, Wiro J. Niessen, Sonja Adebahr, Tanja Schimek-Jasch, Ursula Nestle, and Yu Song. Using GOMS and NASA-TLX to Evaluate Human–Computer Interaction Process in Interactive Segmentation. *International Journal of Human–Computer Interaction*, 33(2):123–134, February 2017.

[66] Elizabeth Reid, Regan L. Mandryk, Nicole A. Beres, Madison Klarkowski, and Julian Frommel. Feeling Good and In Control: In-game Tools to Support Targets of Toxicity. *Proc. ACM Hum.-Comput. Interact.*, 6(CHI PLAY):235:1–235:27, October 2022.

[67] M Ryan Richard and Edward L Deci. Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist*, 55(1):68–78, 2000.

[68] S. Tanvir and T. Shakerin. Player Optimal Positioning Analysis Using FIFA Video Game Data and Classification Models. In *2023 20th International Joint Conference on Computer Science and Software Engineering (JCSSE)*, pages 135–138, July 2023. Journal Abbreviation: 2023 20th International Joint Conference on Computer Science and Software Engineering (JCSSE).

[69] Bader Sabtan, Shi Cao, and Naomi Paul. Current practice and challenges in coaching Esports players: An interview study with league of legends professional team coaches. *Entertainment Computing*, 42:100481, May 2022.

[70] Magy Seif El-Nasr, Bardia Aghabeigi, David Milam, Mona Erfani, Beth Lameman, Hamid Maygoli, and Sang Mah. Understanding and evaluating cooperative games. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 253–262, Atlanta Georgia USA, April 2010. ACM.

[71] Kaushall Senthil Nathan, Jieun Lee, Derrick M. Wang, Geneva M. Smith, Eugene Kukshinov, Daniel Harley, and Lennart E. Nacke. Beyond Competitive Gaming: How Casual Players Evaluate and Respond to Teammate Performance. In *Companion Proceedings of the Annual Symposium on Computer-Human Interaction in Play*, pages 7–14, Pittsburgh USA, October 2025. ACM.

[72] Cuihua Shen, Qiusi Sun, Taeyoung Kim, Grace Wolff, Rabindra Ratan, and Dmitri Williams. Viral vitriol: Predictors and contagion of online toxicity in World of Tanks. *Computers in Human Behavior*, 108:106343, July 2020.

[73] Ben William Strafford, Keith Davids, Jamie Stephen North, and Joseph Antony Stone. Designing Parkour-style training environments for athlete development: insights from experienced Parkour Traceurs. *Qualitative Research in Sport, Exercise and Health*, 13(3):390–406, May 2021.

[74] Hazelight Studios. It takes two, March 2021.

[75] Theresa Jean Tanenbaum, Nazely Hartoonian, and Jeffrey Bryan. "How do I make this thing smile?": An Inventory of Expressive Nonverbal Communication in Commercial Social Virtual Reality Platforms. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, pages 1–13, Honolulu HI USA, April 2020. ACM.

[76] Team17. Overcooked | Cooking Video Game | Team17, 2018.

[77] Lisa R. Trainor and Andrea Bundon. Developing the craft: reflexive accounts of doing reflexive thematic analysis. *Qualitative Research in Sport, Exercise and Health*, 13(5):705–726, September 2021.

[78] Radosław Trepanowski, Samuli Laato, Dariusz Drążkowski, Juho Hamari, and Zuzanna Kopeć. Sexism in esports: How male and female players evaluate each others' performance and agency. *Computers in Human Behavior*, 161:13, 2024.

[79] Michael G. Trotter, Tristan J. Coulter, Paul A. Davis, Dylan R. Poulus, and Remco Polman. Social Support, Self-Regulation, and Psychological Skill Use in E-Athletes. *Frontiers in Psychology*, 12, November 2021.

[80] Selen Turkay, Jessica Formosa, Robert Cuthbert, Sonam Adinolf, and Ross Andrew Brown. Virtual Reality Esports - Understanding Competitive Players' Perceptions of Location Based VR Esports. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, pages 1–15, Yokohama Japan, May 2021. ACM.

[81] Olga Volkoff and Diane M Strong. Affordance theory and how to use it in is research. In *The Routledge companion to management information systems*, pages 232–245. Routledge, 2017.

[82] Derrick M. Wang, Sebastian Cmentowski, Reza Hadi Mogavi, Kaushall Senthil Nathan, Eugene Kukshinov, Joseph Tu, and Lennart E. Nacke. From solo to social: Exploring the dynamics of player cooperation in a co-located cooperative exergame. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems*, CHI '25, page 1–16, New York, NY, USA, April 2025. Association for Computing Machinery.

[83] Gregory D. Webster, C. Nathan DeWall, Richard S. Pond, Timothy Deckman, Peter K. Jonason, Bonnie M. Le, Austin Lee Nichols, Tatiana Orozco Schember, Laura C. Crysel, Benjamin S. Crosier, C. Veronica Smith, E. Layne Paddock, John B. Nezlek, Lee A. Kirkpatrick, Angela D. Bryan, and Renée J. Bator. The brief aggression questionnaire: psychometric and behavioral evidence for an efficient measure of trait aggression. *Aggressive Behavior*, 40(2):120–139, March 2014.

[84] A. Mark Williams, Robert R. Horn, and Nicola J. Hodges. Skill acquisition. In *Science and Soccer*. Routledge, 2 edition, 2003.

[85] Nick Yee, Nicolas Ducheneaut, and Les Nelson. Online gaming motivations scale: development and validation. In *Proceedings of the SIGCHI Conference on Human*

Factors in Computing Systems, CHI '12, page 2803–2806, New York, NY, USA, 2012. Association for Computing Machinery.

APPENDICES

Appendix A

Instructions given to the confederate to control their behaviour and task completion

Task Completion Metric

Above all else, ensure that the conversation is naturalistic.

When the session begins, please introduce yourself with a simple greeting, such as “Hello, my name is [confederate’s name].” Act friendly but try to limit banter.

The PI will navigate to the campaign screen and briefly explain the controls and rules to the participant. They will then explain that they have 30 minutes to complete as many levels as possible with the greatest number of stars. A fake leaderboard will be read aloud to them as well. After which, they will ask them to start the first level.

During the session, you should periodically sound out the task you are doing (e.g., ‘I’m cutting the tomato’), ask what you should do next, and answer any questions the participant may have. Your main goal is to avoid dead silence and make the participant comfortable about talking so keep the previously mentioned comments natural. Some short expressions may arise throughout the course of gameplay, such as ‘Sorry’ and ‘Coming through’, but keep these to a minimum.

For the confederate, the competence level will be measured by the number of ingredients messed up.

Ingredients can be messed up in a lot of ways, but here are some:

- Ingredient is burned
- Ingredient is thrown in the trash
- Ingredient is added to the wrong dish

The PI will re-watch the recordings to count the number of ingredients destroyed. Aim for the correct proportions of mistakes listed below and based on the condition assigned.

When asked if you’ve played before: “Some, yes. Just in the past few weeks.”

If competent,

There must be no mistake made in prepping the dishes from the confederates' side.

If incompetent,

For the tutorial, play competently

For the first two levels, aim for 75% accuracy. In other words, mess up every one in four ingredients you interact with.

Level 1-1

- Drop things in trash
- Serve empty plate
- Serve wrong dish (Make sure all the orders are for the same recipe before serving)

Level 1-2

- Drop things in trash (e.g. “burnt” looking but useable rice)
- Burn rice (i.e. start a fire)
- Serve empty plate
- Serve just seaweed
- Serve just rice
- Serve just fish
- Serve seaweed + rice
- Serve fish + rice
- Serve fish + seaweed

For the next two levels, aim for 50% accuracy. In other words, mess up every one in two ingredients you interact with. If you are responsible for three ingredients in a level, mess up one ingredient when making one dish and then mess up two ingredients when making the next dish.

Level 1-3

- Drop things in trash (e.g. “burnt” looking but useable rice)
- Burn rice (i.e. start a fire)
- Serve empty plate
- Serve just seaweed
- Serve just rice
- Serve just cucumber
- Serve seaweed + rice
- Serve shrimp + rice
- Serve cucumber + rice
- Serve shrimp + cucumber
- Serve shrimp + seaweed
- Serve cucumber + seaweed
- Serve shrimp + cucumber + seaweed

Level 1-4

- Drop things in trash (e.g. “burnt” looking but useable rice)
- Burn rice (i.e. start a fire)
- Serve empty plate
- Serve just seaweed
- Serve just rice
- Serve just cucumber
- Serve just fish
- Serve seaweed + rice
- Serve cucumber + rice
- Serve fish + rice
- Serve seaweed + fish
- Serve seaweed + cucumber
- Serve fish + cucumber
- Serve fish + cucumber + seaweed

For the last two levels, aim for 33% accuracy. In other words, mess up every two in three ingredients you interact with.

Level 1-5

- Drop things in trash close to cutting board (e.g. “burnt” looking but useable pasta)
- Burn pasta (i.e. start a fire)
- Burn tomatoes
- Falling off holding ingredient and/or dish
- Serve empty plate
- Serve just pasta
- Serve just tomatoes

Level 1-6 (Stage 1)

- Drop things in trash close to sink
- Falling off holding ingredient and/or dish
- Serve empty plate
- Serve just tomatoes
- Serve just cucumber
- Serve Cucumber + Lettuce

Level 1-6 (Stage 2)

- Drop things in trash close to sink (e.g. “burnt” looking but useable rice)
- Burn rice (i.e. start a fire)
- Put stuff on the conveyer belt (goes to trash)
- Serve empty plate
- Serve just tomatoes
- Serve just cucumber
- Serve just seaweed
- Serve just rice
- Serve just fish
- Serve Cucumber + Tomato
- Serve seaweed + rice
- Serve fish + rice
- Serve fish + seaweed
- Serve cucumber + rice
- Serve seaweed + cucumber
- Serve fish + cucumber

67

- Serve cucumber + seaweed + fish
- Serve cucumber + rice + fish

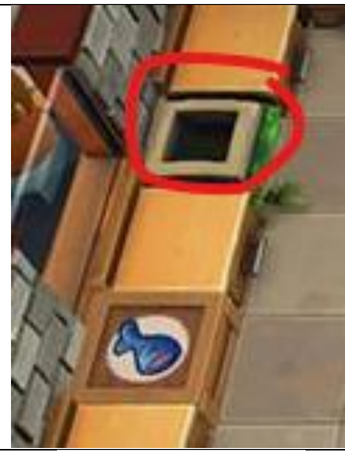
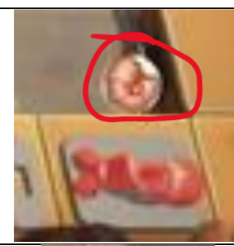
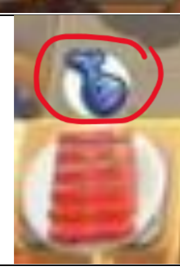
Calibration Pilot

40 Trials on Level 1-6 → 5 trials, then break; repeat until 40 trials

# of Trials	Competent	Incompetent	Done
5	Geneva	Sabrina	X
5	Sabrina	Geneva	X
5	Geneva	Sabrina	X
5	Sabrina	Geneva	X
5	Geneva	Sabrina	X
5	Sabrina	Geneva	X
5	Geneva	Sabrina	X
5	Sabrina	Geneva	X

Level 1-1

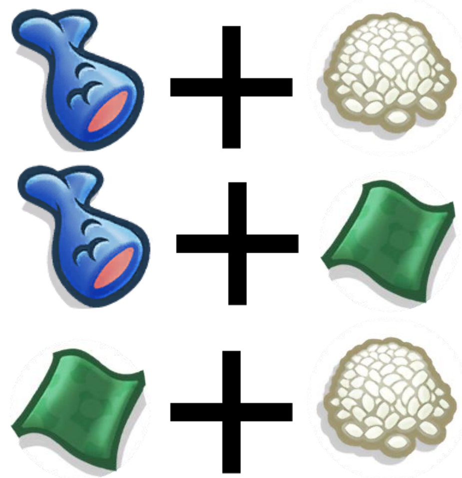
Mess up 1 in 4 tasks (75%)

Drop food in trash		
Serve empty plate		
Serve wrong dish		
		

Level 1-2

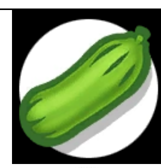
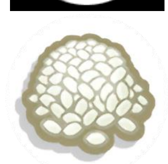
Mess up 1 in 4 tasks (75%)

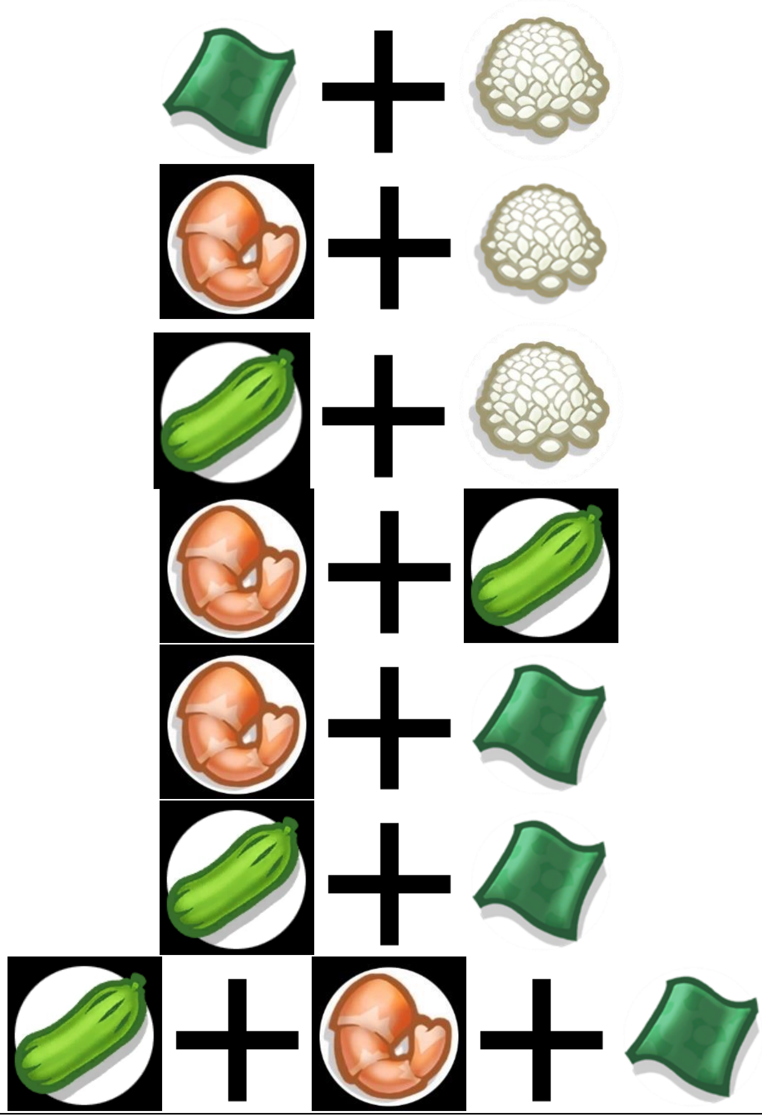
Drop food in trash	
Burn rice (start a fire)	
Serve empty plate	
Serve single ingredients	

Serve incomplete recipes	

Level 1-3

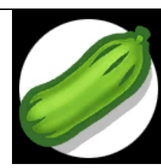
Mess up 2 in 4 tasks (50%)

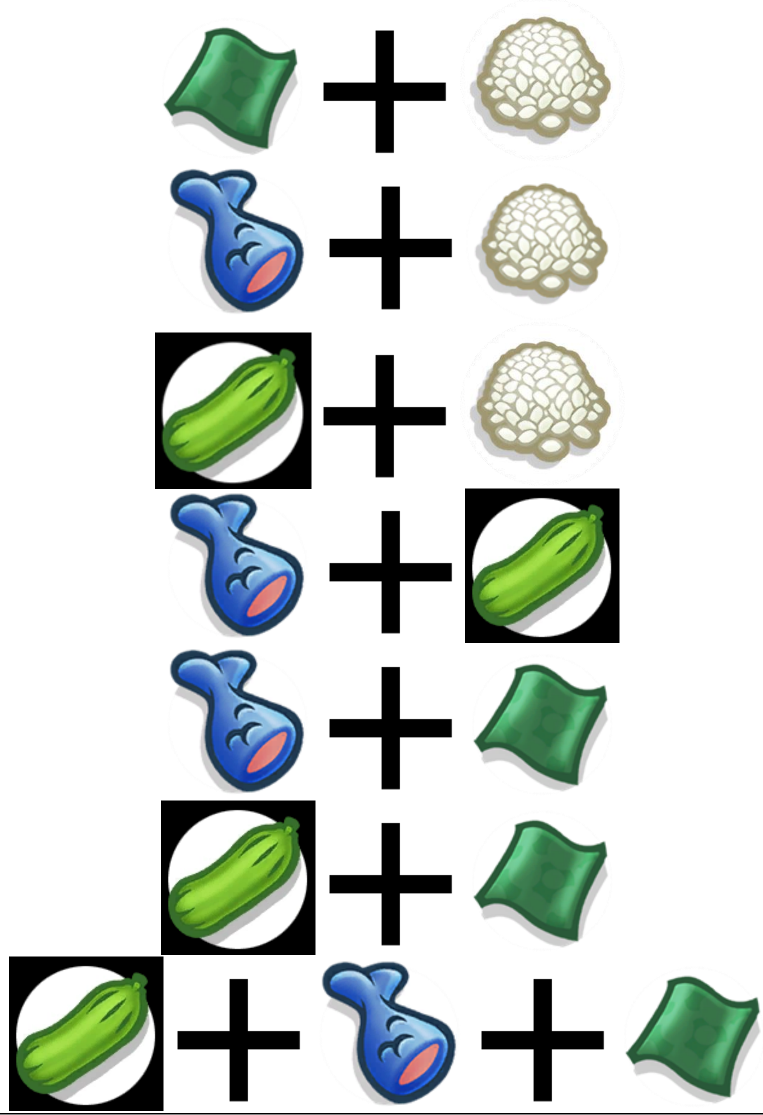
Drop food in trash	
Burn rice (start a fire)	
Serve empty plate	
Serve single ingredients	   

Serve incomplete recipes	

Level 1-4

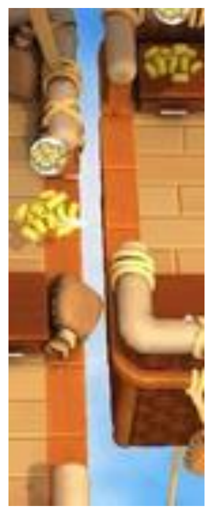
Mess up 2 in 4 tasks (50%)

Drop food in trash	
Burn rice (start a fire)	
Serve empty plate	
Serve single ingredients	   

Serve incomplete recipes	

Level 1-5

Mess up 1 in 3 tasks (33%)

Drop food in trash	
Burn pasta and tomatoes (start a fire)	
Hold food and fall off platform	
Serve empty plate	

Serve single ingredients	 

Level 1-6 Stage 1

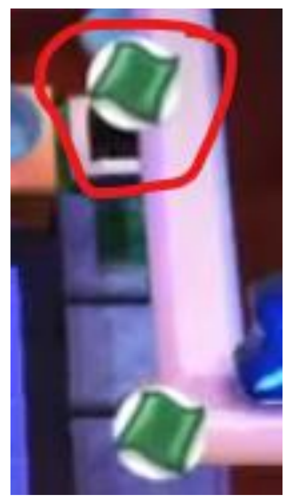
Mess up 1 in 3 tasks (33%)

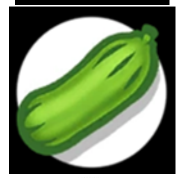
Drop food in trash	
Hold food and fall off platform	
Serve empty plate	

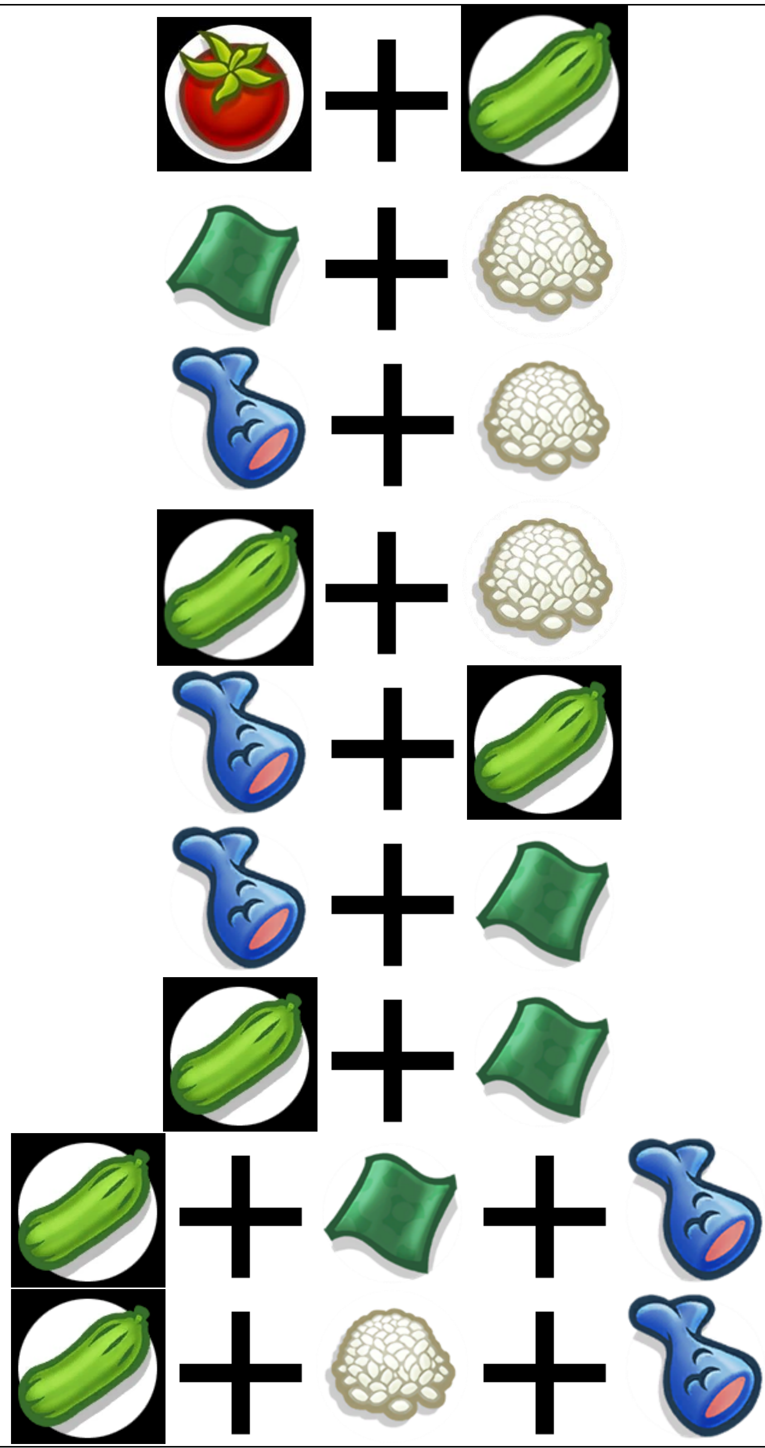
Serve single ingredients	
Serve all but lettuce	

Level 1-6 Stage 2

Mess up 1 in 3 tasks (33%)

Drop food in trash	
Burn rice (start a fire)	
Put food on conveyor belt to trash	 
Serve empty plate	

Serve single ingredients	    

Serve incomplete recipes	

Appendix B

My experience and insights with the EEG

I want to be clear that this section should NOT be treated as a hit-piece against any particular technology or interpreted as my naivety causing a methodological blunder. This was an attempt to use a consumer-grade two-channel EEG device available to the lab to measure a complex cognitive state like frustration. I was asked to test this EEG with the caveat that two electrodes have previously considered to be insufficient for reliable source localization or artifact rejection in such a motion-heavy task. In other words, though we suspected that the tool is not valid for this type of research, we also wanted to check what was possible in terms of signal quality. My intention in this section is catalogue my experience attempting to use a consumer-grade EEG device, how I approached it's implementation, how I tried to address issues as they came up, and what I have learned.

In study 1, I chose a single channel, in-ear Electroencephalogram (EEG) device manufactured by *IDUN Technologies*, given that EEGs have previously been used in video game research [2], to be our physiological measure for frustration. This measure was intended to capture frustration over time. However, it did not perform as expected. We discarded the EEG data as the recordings proved to be highly unstable, with the signal quality, taken at the beginning, of 15 recordings (out of 23) below the manufacturer's standard.

The first point to consider is the design. This design was more non-invasive than bulkier EEGs and even resembled an earphone, thereby allowing a more natural gaming experience. More importantly, this meant that I had to ensure the two electrodes were connected properly to the ear. This device also connected via Bluetooth to a desktop that recorded the readings. I tested whether I could achieved the good signal quality with two members of the lab (both mid 30s, White) and myself (mid 20s, Asian). The manufacturers considered a signal quality of 300 kΩ to be acceptable, so I aimed for that. It was achievable in 5 minutes with both the members of the lab, but I had to wait around 15 minutes for the signal quality to drop to an acceptable level. Speaking to the manufacturers further, they recommended having participants cleaning their ears with a cotton swab, having them sitting still for 5 minutes to let the device calibrate, and to wipe down the electrodes with cleaning alcohol using a cotton swab before and after every use. Following all these instructions, I proceeded with the experiment.

During the experiments, I found that the signal quality recommended by the manufacturers was not met frequently, despite following all the instructions above. Even when the signal quality was considered 'good', there were anomalies in the data, such as spikes or gradual drifts in the baseline signal. When I compared the readings to the recordings of the participant, there was nothing that indicated any significant movement or adjustment of the EEG. On top of this, there were some special cases. I did have one participant who had an ear-piercing and thus, the electrode could not touch the appropriate part of the skin, and the data had to be discarded. After the trials, I stopped the experiment and discussed these findings with the manufacturer. One possible reason they suggested was due to the high number of non-white participants in our sample, as the device was previously tested on a mostly white sample. This could also explain the differences for our in-house testing, where the white members were able to achieve a better signal quality faster. Another possible reason put forward by the manufacturer was due to signal interference from other devices in the area, such as the gaming PC itself. In our experiment, the gaming setup was necessary so this flaw should have been examined much earlier.

The rest of my thesis serves as testament to my ability to conduct research. I hope this section adds to this fact by showcasing how when I used technologies I was unfamiliar with, and navigated challenges by seeking information from the experts whenever possible. For future cases, I would conduct a more thorough testing and research phase before using an unknown technology in my research. Through this effort, I concluded that the EEG we chose was not ideal and that future members of my lab don't need to test this technology in their experiments as well.

Appendix C

The Query Used in each Database for our Structured Literature Review

Database	Query
SCOPUS	Player TITLE-ABS-KEY((“Video Games” OR “Esports” OR “Computer Games” OR “Interactive Gaming”) AND (“Skills” OR “Skilled”) AND (“Player”) AND (“Performance” OR “Training”)) AND NOT TITLE-ABS-KEY(“Medicine” OR “Surgery”) AND PUBYEAR >2014 AND PUBYEAR <2026
IEEE Xplore	((“All Metadata”:“Video Games” OR “All Metadata”:“Esports” OR “All Metadata”:“Computer Games” OR “All Metadata”:“Interactive Gaming”) AND (“All Metadata”:“Skills” OR “All Metadata”:“Skilled”) AND (“All Metadata”:“Player”) AND (“All Metadata”:“Performance” OR “All Metadata”:“Training”)) NOT (“All Metadata”:“Medicine” OR “All Metadata”:“Surgery”) AND (Publication Year:2015:2025)
ACM Digital Library	(Title:(“Video Games” OR “Esports” OR “Computer Games” OR “Interactive Gaming”) OR Abstract:(“Video Games” OR “Esports” OR “Computer Games” OR “Interactive Gaming”)) AND (Title:(Skills OR Skilled) OR Abstract:(Skills OR Skilled)) AND (Title:(Player) OR Abstract:(Player)) AND (Title:(Performance OR Training) OR Abstract:(Performance OR Training)) AND NOT (Title:(Medicine OR Surgery) OR Abstract:(Medicine OR Surgery))
Web of Science	TITLE-ABS-KEY((“Video Games” OR “Esports” OR “Computer Games” OR “Interactive Gaming”) AND (“Skills” OR “Skilled”) AND (“Player”) AND (“Performance” OR “Training”)) AND NOT TITLE-ABS-KEY(“Medicine” OR “Surgery”) AND PUBYEAR >2014 AND PUBYEAR <2026

Table C.1: Table containing the exact search query used in each database

Appendix D

The Papers We Selected For Full Review in Our Structured Literature Search

The sources are arranged and written according to the ACM citation format.

1. R. Arai and T. Ishikawa. 2024. A Research on High Performance Factors in Shooting Tasks of FPS Games. https://doi.org/10.1109/CoG60054.2024.10645567

2. M Aung, Bonometti, A Drachen, P Cowling, A Kokkinakis, C Yoder, A Wade, and IEEE. 2018. Predicting Skill Learning in a Large, Longitudinal MOBA Dataset. 117–124.

3. Farnod Bahrololloomi, Fabio Klonowski, Sebastian Sauer, Robin Horst, and Ralf Dörner. 2023. E-Sports Player Performance Metrics for Predicting the Outcome of League of Legends Matches Considering Player Roles. SN Comput. Sci. 4, 3. https://doi.org/10.1007/s42979-022-01660-6

4. N.A. Beres, M. Klarkowski, and R.L. Mandryk. 2021. Under Pressure: Exploring Choke and Clutch in Competitive Video Games. https://doi.org/10.1145/3474666

5. N. Besombes. 2018. Execution and mindgame in fighting games: Two facets of videomotricity in esports. Movement and Sports Sciences - Science et Motricite 2018-January, 99: 19–34. https://doi.org/10.1051/sm/2018008

6. P.M. Blom, S. Bakkes, and P. Spronck. 2019. Towards multi-modal stress response modelling in competitive league of legends. https://doi.org/10.1109/CIG.2019.8848004

7. I. Bonilla, A. Chamarro, and C. Ventura. 2022. Psychological skills in esports: Qualitative study of individual and team players. Aloma 40, 1: 36–41. https://doi.org/10.51698/aloma.20 41

8. J.W. Bonny, M. Scanlon, and L.M. Castaneda. 2020. Variations in psychological factors and experience-dependent changes in team-based video game performance. Intelligence 80. https://doi.org/10.1016/j.intell.2020.101450

9. D. Buckley, K. Chen, and J. Knowles. 2017. Rapid Skill Capture in a First-Person Shooter. IEEE Transactions on Computational Intelligence and AI in Games 9, 1: 63–75. https://doi.org/10.1109/TCIAIG.2015.2494849

10. C. J. A. Cordova, C. V. A. Villaceran, and C. F. Peña. 2024. Predicting League of Legends Match Outcomes Through Machine Learning Models Using Past Match Player Performance. In 2024 IEEE International Conference on Computing (ICOCO), 522–527. https://doi.org/10.1109/ICOCO62848.2024.10928259

11. C. -Y. Hsieh, J. -H. Liou, and Y. -M. Li. 2024. A Social Recommendation Mechanism for Esports Team up. In 2024 16th IIAI International Congress on Advanced Applied Informatics (IIAI-AAI), 43–48. https://doi.org/10.1109/IIAI-AAI63651.2024.00017

12. L Caroux and ACM. 2016. Low-level visual features of video game interfaces and player expertise. 126–133. https://doi.org/10.1145/3004107.3004114

13. Yinheng Chen, Matthew Aitchison, and Penny Sweetser. 2020. Improving StarCraft II Player League Prediction with Macro-Level Features. In AI 2020: Advances in Artificial Intelligence: 33rd Australasian Joint Conference, AI 2020, Canberra, ACT, Australia, November 29–30, 2020, Proceedings, 256–268. https://doi.org/10.1007/978-3-030-64984-5_20

14. A.F. Cretenoud, A. Barakat, A. Milliet, O.-H. Choung, M. Bertamini, C. Constantin, and M.H. Herzog. 2021. How do visual skills relate to action video game performance? Journal of Vision 21, 7: 1–21. https://doi.org/10.1167/JOV.21.7.10

15. D. Buckley, K. Chen, and J. Knowles. 2017. Rapid Skill Capture in a First-Person Shooter. IEEE Transactions on Computational Intelligence and AI in Games 9, 1: 63–75. https://doi.org/10.1109/TCIAIG.2015.2494849

16. M. De Bois, F. Parmentier, R. Puget, M. Tanti, and J. Peltier. 2025. PandaSkill - Player Performance and Skill Rating in Esports: Application to League of Legends. IEEE Transactions on Games. https://doi.org/10.1109/TG.2025.3581070

17. D. Deng, Y. Zhang, R. Trepanowski, M. Bujić, M. Li, and J. Hamari. 2024. Streaks and Coping: Decoding Player Performance in League of Legends Using Big Data from Top Players' Matches. 50–54. https://doi.org/10.1145/3665463.3678787

18. M. Drew, K.J.M. Bennett, R. Polman, and D.R. Poulus. 2025. Stress and coping in elite esports: A diary study of stress, coping and coping effectiveness. Psychology of Sport and Exercise 80. https://doi.org/10.1016/j.psychsport.2025.102937

19. A. Dupuy, M.J. Campbell, and A.J. Toth. 2025. Differentiating right upper limb movements of esports players who play different game genres. Scientific Reports 15, 1. https://doi.org/10.1038/s41598-025-90949-6

20. C.M. Ford. 2017. Virtuosos on the screen: Playing virtual characters like instruments in competitive Super Smash Bros. Melee. 1935–1948. https://doi.org/10.1145/3025453.3026053

21. S.T. Forlenza. 2023. Using imagined partners to enhance esports performance. Journal of Imagery Research in Sport and Physical Activity 18, 1. https://doi.org/10.1515/jirspa-2022-0022

22. R. Furukado, G. Hagiwara, T. Ito, and H. Isogai. 2020. Comparison of EEG biofeedback and visual search strategies during e-sports play according to skill level. Journal of Human Sport and Exercise 15, Proc4: 1123–1132. https://doi.org/10.14198/jhse.2020.15.Proc4.1

23. J. Gisbert-Pérez, A. García-Naveira, M. Martí-Vilar, and J. Acebes-Sánchez. 2024. Key structure and processes in esports teams: a systematic review. Current Psychology 43, 23: 20355–20374. https://doi.org/10.1007/s12144-024-05858-0

24. N.N. Harischandra, L.A. Jayakody, and T. Madusanka. 2020. Impact of metacognition and age group on contemporary video game interface and gameplay design. 117–123. https://doi.org/10.1109/SCSE49731.2020.9313016

25. D. Himmelstein, Y. Liu, and J.L. Shapiro. 2017. An exploration of mental skills among competitive league of legend players. International Journal of Gaming and Computer-Mediated Simulations 9, 2: 1–21. https://doi.org/10.4018/IJGCMS.2017040101

26. F Hojaji, RE Mcilroy, A Dupuy, G Pedroni, AJ Toth, and MJ Campbell. 2025. Deep learning techniques for identifying KPIs in League of Legends: Win prediction, map

navigation, and vision control. COMPUTERS IN HUMAN BEHAVIOR REPORTS 19. https://doi.org/10.1016/j.chbr.2025.100718

27. T. Iwatsuki, G. Hagiwara, and M.E. Dugan. 2022. Effectively optimizing esports performance through movement science principles. International Journal of Sports Science and Coaching 17, 1: 202–207. https://doi.org/10.1177/17479541211016927

28. S.E. Jenny and T.M. Scholz. 2024. Introduction to esports players. In Routledge Handbook of Esports. 163–166. https://doi.org/10.4324/9781003410591-18

29. I. Jeong, N. Kaneko, R. Takahashi, and K. Nakazawa. 2024. High-skilled first-person shooting game players have specific frontal lobe activity: Power spectrum analysis in an electroencephalogram study. Neuroscience Letters 825. https://doi.org/10.1016/j.neulet.2024.13

30. I. Jeong, D. Kim, N. Kaneko, and K. Nakazawa. 2024. Gaze control ability of League of Legends players in various game situations: Perspectives from solo-ranked match. 1–9. Retrieved from https://www.scopus.com/inward/record.uri?eid=2-s2.0-85191662733&partnerID=40&md5=c18ac755b868fafaae9717caa20cfa0c

31. I. Jeong, K. Kudo, N. Kaneko, and K. Nakazawa. 2024. Esports experts have a wide gaze distribution and short gaze fixation duration: A focus on League of Legends players. PLoS ONE 19, 1 January. https://doi.org/10.1371/journal.pone.0288770

32. N. Khromov, A. Korotin, A. Lange, A. Stepanov, E. Burnaev, and A. Somov. 2019. Esports Athletes and Players: A Comparative Study. IEEE Pervasive Computing 18, 3: 31–39. https://doi.org/10.1109/MPRV.2019.2926247

33. Man-Je Kim, Kyung-Joong Kim, SeungJun Kim, and Anind K. Dey. 2016. Evaluation of StarCraft Artificial Intelligence Competition Bots by Experienced Human Players. In Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems (CHI EA '16), 1915–1921. https://doi.org/10.1145/2851581.2892305

34. E. Kleinman, M.N. Shergadwala, and M. Seif El-Nasr. 2022. Kills, Deaths, and (Computational) Assists: Identifying Opportunities for Computational Support in Esport Learning. https://doi.org/10.1145/3491102.3517654

35. M. Koles and Z. Peter. 2017. “Learn to play, noob!”: The identification of ability profiles for different roles in an online multiplayer video game in order to improve the overal quality of the new player experience. 271–275. https://doi.org/10.1109/CogInfoCom.2016.78

36. A. Lange, A. Somov, A. Stepanov, and E. Burnaev. 2022. Building a Behavioral Profile and Assessing the Skill of Video Game Players. IEEE Sensors Journal 22, 1: 481–488. https://doi.org/10.1109/JSEN.2021.3127083

37. AM Large, B Bediou, S Cekic, Y Hart, D Bavelier, and CS Green. 2019. Cognitive and Behavioral Correlates of Achievement in a Complex Multi-Player Video Game. MEDIA AND COMMUNICATION 7, 4: 198–212. https://doi.org/10.17645/mac.v7i4.2314

38. H Lee, S Lee, R Nallapati, Y Uh, B Lee, and ACM. 2024. Characterizing and Quantifying Expert Input Behavior in League of Legends. https://doi.org/10.1145/3613904.3642588

39. X. Li, L. Huang, B. Li, H. Wang, and C. Han. 2020. Time for a true display of skill: Top players in League of Legends have better executive control. Acta Psychologica 204. https://doi.org/10.1016/j.actpsy.2020.103007

40. Shengmei Liu, Mark Claypool, Bhuvana Devigere, Atsuo Kuwahara, and Jamie Sherman. 2020. "Git Gud!" – Evaluation of Self-Rated Player Skill Compared to Actual Player Performance. In Extended Abstracts of the 2020 Annual Symposium on Computer-Human Interaction in Play (CHI PLAY '20), 306–310. https://doi.org/10.1145/3383668.3

41. M. Aung, V. Bonometti, A. Drachen, P. Cowling, A. V. Kokkinakis, C. Yoder, and A. Wade. 2018. Predicting Skill Learning in a Large, Longitudinal MOBA Dataset. In 2018 IEEE Conference on Computational Intelligence and Games (CIG), 1–7. https://doi.org/10.1109/CIG.2018.8490431

42. E Manci, F Özdalyan, A Gebel, Ç Güdücü, E Günay, SE Jenny, NG Müller, and F Herold. 2025. Listen to the coaches: Practitioners' perspective on the relevance of selected cognitive skills and assessments for esports performance. INTERNATIONAL JOURNAL OF SPORTS SCIENCE & COACHING. https://doi.org/10.1177/17479541251342721

43. E. Marchenko and V. Suschevskiy. 2018. Analysis of players transfers in esports. The case of Dota 2. 255–257. https://doi.org/10.1145/3275116.3275151

44. G. Mendoza. 2019. Online psychological work with esports teams: experiences in Vodafone Giants. Revista de Psicologia Aplicada al Deporte y al Ejercicio Fisico 4, 1. https://doi.org/10.5093/rpadef2019a5

45. S Minami, H Koyama, K Watanabe, N Saijo, and M Kashino. 2024. Prediction of esports competition outcomes using EEG data from expert players. COMPUTERS IN HUMAN BEHAVIOR 160. https://doi.org/10.1016/j.chb.2024.108351

46. N. Mohan, T. Simmons, A. Khedkar, D. Yang, and L. Chukoskie. 2023. Measuring gaze behavior to characterize spatial awareness skill in Rocket League. https://doi.org/10.1109/CoG

47. G. Musick, R. Zhang, N.J. McNeese, G. Freeman, and A.P. Hridi. 2021. Leveling Up Teamwork in Esports: Understanding Team Cognition in a Dynamic Virtual Environment. Proceedings of the ACM on Human-Computer Interaction 5, CSCW1. https://doi.org/10.1145/3449123

48. S. Nagdeote, H. Pendhari, O. Shirsat, R. Lad, and S. Chiwande. 2023. Esports analysis with data science. https://doi.org/10.1063/5.0144108

49. P. M. Blom, S. Bakkes, and P. Spronck. 2019. Towards Multi-modal Stress Response Modelling in Competitive League of Legends. In 2019 IEEE Conference on Games (CoG), 1–4. https://doi.org/10.1109/CIG.2019.8848004

50. E Park, S Lee, A Ham, M Choi, S Kim, B Lee, and ASSOC COMP MACHINERY. 2021. Secrets of Gosu: Understanding Physical Combat Skills of Professional Players in First-Person Shooters. https://doi.org/10.1145/3411764.3445217

51. G.O. Paz, M.C. Freisztav, M.L.B. Gallicchio, and T.A. D'Amelio. 2024. Flow state as a performance measure in Esports. Interdisciplinaria 41, 1: 1–31. https://doi.org/10.16888/interd.2

52. I. Pedraza-Ramirez, L. Musculus, M. Raab, B. Ramaker, and S. Laborde. 2025. Zooming in on Decision Making in Esports: Exploring the Perceptions of Expert Players and Coaches. Sport, Exercise, and Performance Psychology 14, 2: 335–351. https://doi.org/10.1037/spy0000382

53. S. Pioroński and T. Górecki. 2023. Predicting Player Performance in Tactical Games with the Lightgbm Algorithm. 22–27. https://doi.org/10.1109/ICMEW59549.2023.00010

54. M.A. Pluss, A.R. Novak, K.J.M. Bennett, I. McBride, D. Panchuk, A.J. Coutts, and J. Fransen. 2022. Examining the game-specific practice behaviors of professional and semi-professional esports players: A 52-week longitudinal study. Computers in Human Behavior 137. https://doi.org/10.1016/j.chb.2022.107421

55. M.A. Pluss, A.R. Novak, K.J.M. Bennett, D. Panchuk, A.J. Coutts, and J. Fransen. 2023. The reliability and validity of mobalytics proving ground as a perceptual-motor skill assessment for esports. International Journal of Sports Science and Coaching 18, 2: 470–479. https://doi.org/10.1177/17479541221086793

56. G.T. Richard, Z.A. McKinley, and R.W. Ashley. 2018. Collegiate eSports as Learning Ecologies: Investigating Collaborative Learning and Cognition During Competitions. Retrieved from https://www.scopus.com/inward/record.uri?eid=2-s2.0-85162998537&partnerID=40&md5=927548dc6758523a510e7c0e692a8746

57. L. A. L. Rodrigues and J. D. Brancher. 2018. Improving Players' Profiles Clustering from Game Data Through Feature Extraction. In 2018 17th Brazilian Symposium on Computer Games and Digital Entertainment (SBGames), 177–17709. https://doi.org/10.1109/SBGAMES.2018.00029

58. Ryan Rogers, Nicholas David Bowman, and Mary Beth Oliver. 2015. It's not the model that doesn't fit, it's the controller! The role of cognitive skills in understanding the links between natural mapping, performance, and enjoyment of console video games. Comput. Hum. Behav. 49, C: 588–596. https://doi.org/10.1016/j.chb.2015.03.027

59. S. Röhlcke, C. Bäcklund, D.E. Sörman, and B. Jonsson. 2018. Time on task matters most in video game expertise. PLoS ONE 13, 10. https://doi.org/10.1371/journal.pone.0206555

60. M Sanz-Matesanz, GM Gea-García, and LM Martínez-Aranda. 2023. Physical and psychological factors related to PLAYER'S health and performance in esports: A scoping review. COMPUTERS IN HUMAN BEHAVIOR 143. https://doi.org/10.1016/j.chb.2023.1

61. A. Sapienza, H. Peng, and E. Ferrara. 2017. Performance Dynamics and Success in Online Games. In 2017 IEEE International Conference on Data Mining Workshops (ICDMW), 902–909. https://doi.org/10.1109/ICDMW.2017.124

62. D. Sen, R.K. Roy, R. Majumdar, K. Chatterjee, and D. Ganguly. 2022. Prediction of the Final Rank of the Players in PUBG with the Optimal Number of Features. In Lecture Notes in Electrical Engineering. 441–448. https://doi.org/10.1007/978-981-19-1520-8_35

63. V.J. Shute and L. Wang. 2015. Measuring Problem Solving Skills in Portal 2. In E-Learning Systems, Environments and Approaches: Theory and Implementation. 11–24. https://doi.org/10.1007/978-3-319-05825-2_2

64. V Simovic, P Spalevic, D Solesa, D Dubljanin, and IEEE. 2025. From Ratings to Balance: A Review of Glicko's Role in Competitive Gaming Analytics. https://doi.org/10.1109/INFOT

65. A. Smerdov, E. Burnaev, and A. Somov. 2019. eSports Pro-Players Behavior During the Game Events: Statistical Analysis of Data Obtained Using the Smart Chair. In 2019 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted

Computing, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP 1768–1775. https://doi.org/10.1109/SmartWorld-UIC-ATC-SCALCOM-IOP-SCI.2019.00314

66. A. Smerdov, A. Kiskun, R. Shaniiazov, A. Somov, and E. Burnaev. 2019. Understanding Cyber Athletes Behaviour Through a Smart Chair: CS:GO and Monolith Team Scenario. In 2019 IEEE 5th World Forum on Internet of Things (WF-IoT), 973–978. https://doi.org/10.1109/WF-IoT.2019.8767295

67. A Smerdov, A Somov, E Burnaev, and A Stepanov. 2023. AI-enabled prediction of video game player performance using the data from heterogeneous sensors. MULTIMEDIA TOOLS AND APPLICATIONS 82, 7: 11021–11046. https://doi.org/10.1007/s11042-022-13464-0

68. M.J. Smith, P.D.J. Birch, and D. Bright. 2019. Identifying stressors and coping strategies of elite esports competitors. International Journal of Gaming and Computer-Mediated Simulations 11, 2: 22–39. https://doi.org/10.4018/IJGCMS.2019040102

69. M. Suznjevic, M. Matijasevic, and J. Konfic. 2016. Application context based algorithm for player skill evaluation in MOBA games. https://doi.org/10.1109/NetGames.2015.7382993

70. S. Tanvir and T. Shakerin. 2023. Player Optimal Positioning Analysis Using FIFA Video Game Data and Classification Models. In 2023 20th International Joint Conference on Computer Science and Software Engineering (JCSSE), 135–138. https://doi.org/10.1109/JC

71. K. Tharawadeepimuk, A. Nanbancha, and E. Onnom. 2025. CHARACTERIZING PSYCHOLOGICAL STATES IN PROFESSIONAL ATHLETES THROUGH EEG: SEX-BASED DIFFERENCES. EXCLI Journal 24: 1–14. https://doi.org/10.17179/excli2024-7980

72. T.J. Towne, W.R. Boot, and K.A. Ericsson. 2016. Understanding the structure of skill through a detailed analysis of Individuals' performance on the Space Fortress game. Acta Psychologica 169: 27–37. https://doi.org/10.1016/j.actpsy.2016.05.006

73. T Tregel, T Sarpe-Tudoran, PN Müller, and S Göbel. 2021. Analyzing Game-Based Training Methods for Selected Esports Titles in Competitive Gaming. 213–228. https://doi.org/10.1007/978-3-030-88272-3_16

74. M.G. Trotter, E.A.C. Obine, and B.T. Sharpe. 2023. Self-regulation, stress appraisal, and esport action performance. Frontiers in Psychology 14. https://doi.org/10.3389/fpsyg.2023.126

75. P. Varga, T.M. Scholz, and E.T.S. Tan. 2024. Esports player analytics. In Routledge Handbook of Esports. 191–202. https://doi.org/10.4324/9781003410591-21

76. B.B. Velichkovsky, N. Khromov, A. Korotin, E. Burnaev, and A. Somov. 2019. Visual Fixations Duration as an Indicator of Skill Level in eSports. 397–405. https://doi.org/10.1007/978-3-030-29381-9_25

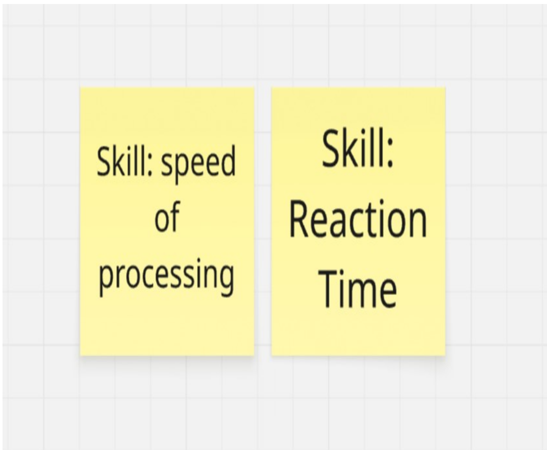
77. A Visti, TN Joelsson, J Smed, and ACM. 2017. Beyond Skill-Based Rating Systems: Analyzing and Evaluating Player Performance. 8–16. https://doi.org/10.1145/3131085.3131096

78. A. Wells, R.E. Mayer, J.L. Plass, and B.D. Homer. 2021. Playing a Video Game and Learning to Think: What's the Connection? Journal of Cognitive Enhancement 5, 4: 459–467. https://doi.org/10.1007/s41465-021-00214-7

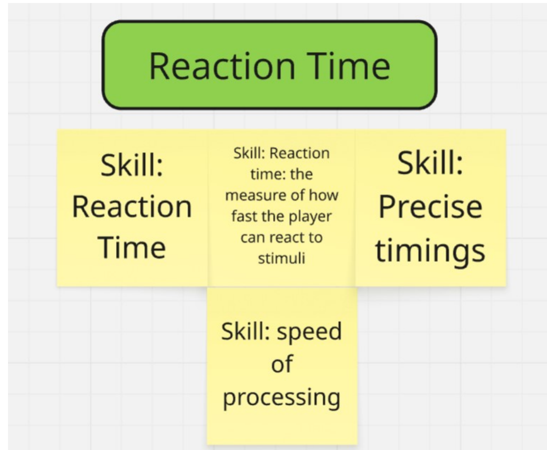
79. Chaoyun Zhang, Kai Wang, Hao Chen, Ge Fan, Yingjie Li, Lifang Wu, and Bingchao Zheng. 2022. QuickSkill: Novice Skill Estimation in Online Multiplayer Games. In Proceedings of the 31st ACM International Conference on Information & Knowledge Management (CIKM '22), 3644–3653. https://doi.org/10.1145/3511808.3557070

Appendix E

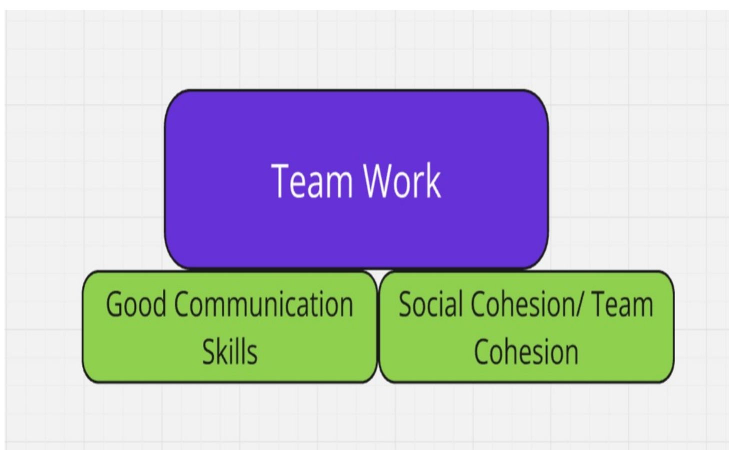
Images of Affinity Mapping being done in both Phase 1 and Phase 2 of Study 2



(a) The skills on individual notes
Alt text: Two post-it notes on the digital board.

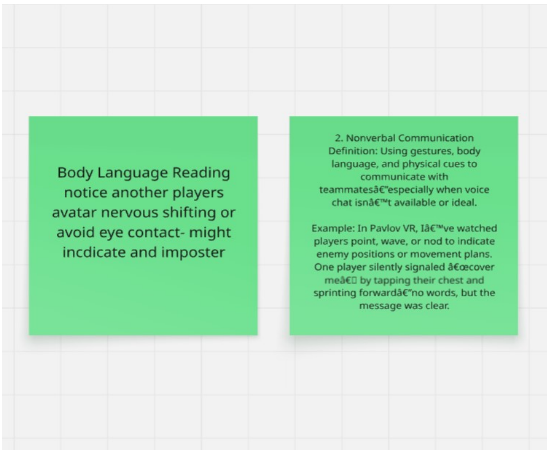


(b) The skills consolidated into small clusters
Alt text: Four post-it notes under a bigger green bar with the name of the cluster

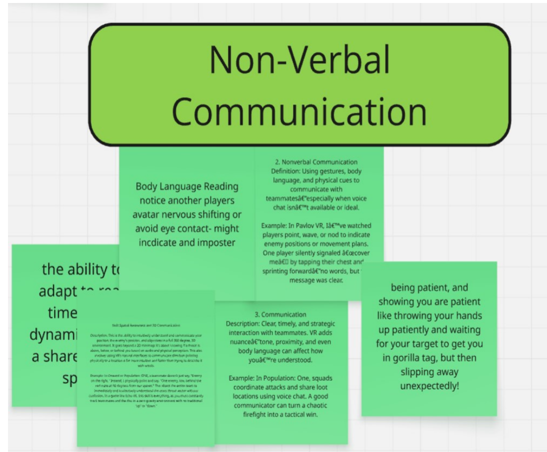


(c) The small clusters consolidated into big clusters
Alt text: Two green bars with the names of the clusters under a bigger purple bar with the name of the cluster of clusters.

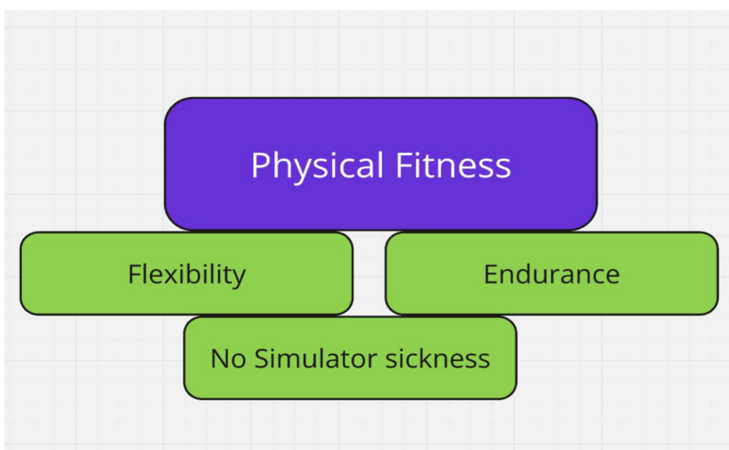
Figure E.1: These images show the process of the affinity mapping being done for Phase 1



(a) The skills on individual notes
Alt text: Two post-it notes on the digital board.



(b) The skills consolidated into small clusters
Alt text: Four post-it notes under a bigger green bar with the name of the cluster



(c) The small clusters consolidated into big clusters
Alt text: Two green bars with the names of the clusters under a bigger purple bar with the name of the cluster of clusters.

Figure E.2: These images show the process of the affinity mapping being done for Phase 2

Appendix F

The Questionnaire Presented to Participants in Study 2

Starter

Please enter your age:

Have you played a VR multiplayer game?

- ○ No
- ○ Yes

What VR multiplayer games have you played? How long have you played each (please note how many weeks or months)?

Open Ended Questions

Please list the skills you believe are most important to a VR Multiplayer Gamer.
For each skill, please include the following:

- A description (what the skill means to you as a player)
- An example (how you've used it or seen it used in a VR multiplayer game)

We would like to know which skills are important to a player in a VR Multiplayer Game. To the that end, we have compiled a list of popular skills for common platforms (e.g. PCs, Consoles, etc.) in the next page.

Skill Block 1

We would like to know which skills are important to a player in a VR Multiplayer Game. Please rate the following statement on a 1 to 7 scale, where 1 is "Strongly disagree" and 7 is "Strongly agree".

Please slide the circle below to choose your rating.

Concept: Good Use of Game Mechanics.

Definition: A strong understanding and application of game mechanics.

Example: Using recoil compensation in a first person shooter game (FPS) or mastering a particular character's mechanics in a Multiplayer Online Battle Arena (MOBA).

Statement: "I believe 'Good Use of Game Mechanics' is necessary for VR multiplayer players."

Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
1	2	3	4	5	6	7

What is an example of this skill in a VR multiplayer game that you play?

Is there anything that makes this skill different in VR compared to a desktop or console game? If so, please offer an example.

Do you train this skill for the VR games that you play? If yes, how do you train? If not, why not?

Skill Block 2

We would like to know which skills are important to a player in a VR Multiplayer Game. Please rate the following statement on a 1 to 7 scale, where 1 is "Strongly disagree" and 7 is "Strongly agree".

Please slide the circle below to choose your rating.

Concept: Reaction Time.
Definition: Reacting quickly when attention is needed.
Example: Aiming and shooting an enemy as soon as they appear in a First Person Shooter.

Statement: "I believe 'Reaction Time' is a necessary skill for VR multiplayer players."

Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
1	2	3	4	5	6	7

What is an example of this skill in a VR multiplayer game that you play?

Is there anything that makes this skill different in VR compared to a desktop or console game? If so, please offer an example.

Do you train this skill for the VR games that you play? If yes, how do you train? If not, why not?

Skill Block 3

We would like to know which skills are important to a player in a VR Multiplayer Game. Please rate the following statement on a 1 to 7 scale, where 1 is "Strongly disagree" and 7 is "Strongly agree".

Please slide the circle below to choose your rating.

Concept: Attentional Skills.
Definition: Keeping track of multiple things at the same time, and dividing attention in real time.
Example: Mentally tracking the cooldowns of your abilities while paying attention to the map.

Statement: "I believe 'Attentional Skills' are necessary for VR multiplayer players."

Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
1	2	3	4	5	6	7

What is an example of this skill in a VR multiplayer game that you play?

Is there anything that makes this skill different in VR compared to a desktop or console game? If so, please offer an example.

Do you train this skill for the VR games that you play? If yes, how do you train? If not, why not?

Feeder Block

We would like to know which skills are important to a player in a VR Multiplayer Game. Please rate the following statement on a 1 to 7 scale, where 1 is "Strongly disagree" and 7 is "Strongly agree".

Please slide the circle below to choose your rating.

Concept: **Paying Attention**
Definition: Reading through the definitions.
Example: Reading what you are reading now.

Please enter "Strongly Agree" for this concept to show that you are paying attention.

Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
1	2	3	4	5	6	7

Please respond with Yes. Answering this question with "Yes" shows that you are paying attention.

Skill Block 4

We would like to know which skills are important to a player in a VR Multiplayer Game. Please rate the following statement on a 1 to 7 scale, where 1 is "Strongly disagree" and 7 is "Strongly agree".

Please slide the circle below to choose your rating.

Concept: Emotional Regulation.
Definition: Maintaining composure in a game.
Example: Not showing malicious anger or sadness when a game doesn't go their way. Remaining calm before a match.

Statement: "I believe 'Emotional Regulation' is a necessary skill for VR multiplayer players."

Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
1	2	3	4	5	6	7

What is an example of this skill in a VR multiplayer game that you play?

Is there anything that makes this skill different in VR compared to a desktop or console game? If so, please offer an example.

Do you train this skill for the VR games that you play? If yes, how do you train? If not, why not?

Skill Block 5

We would like to know which skills are important to a player in a VR Multiplayer Game. Please rate the following statement on a 1 to 7 scale, where 1 is "Strongly disagree" and 7 is "Strongly agree".

Please slide the circle below to choose your rating.

Concept: Team Work.
Definition: Collaborating with teammates.
Example: Developing rapport with teammates. Uses effective communication.

Statement: "I believe 'Team Work' is necessary for VR multiplayer players."

Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
1	2	3	4	5	6	7

What is an example of this skill in a VR multiplayer game that you play?

Is there anything that makes this skill different in VR compared to a desktop or console game? If so, please offer an example.

Do you train this skill for the VR games that you play? If yes, how do you train? If not, why not?

Skill Block 6

We would like to know which skills are important to a player in a VR Multiplayer Game. Please rate the following statement on a 1 to 7 scale, where 1 is "Strongly disagree" and 7 is "Strongly agree".

Please slide the circle below to choose your rating.

Concept: Device Interaction Skills.
Definition: Interacting effectively with the technology used to play the game.
Example: Effective setups alongside good hand-eye coordination.

Statement: "I believe 'Device Interaction Skills' are necessary for VR multiplayer players."

Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
1	2	3	4	5	6	7

What is an example of this skill in a VR multiplayer game that you play?

Is there anything that makes this skill different in VR compared to a desktop or console game? If so, please offer an example.

Do you train this skill for the VR games that you play? If yes, how do you train? If not, why not?

Skill Block 7

We would like to know which skills are important to a player in a VR Multiplayer Game. Please rate the following statement on a 1 to 7 scale, where 1 is "Strongly disagree" and 7 is "Strongly agree".

Please slide the circle below to choose your rating.

Concept: Strategic Thinking.

Definition: Planning the actions. Thinking through different strategies.

Example: Thinking through the steps of a plan, while also accounting for what opponents might do.

Statement: "I believe 'Strategic Thinking' is necessary for VR multiplayer players."

Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
1	2	3	4	5	6	7

What is an example of this skill in a VR multiplayer game that you play?

Is there anything that makes this skill different in VR compared to a desktop or console game? If so, please offer an example.

Do you train this skill for the VR games that you play? If yes, how do you train? If not, why not?

Skill Block 8

We would like to know which skills are important to a player in a VR Multiplayer Game. Please rate the following statement on a 1 to 7 scale, where 1 is "Strongly disagree" and 7 is "Strongly agree".

Please slide the circle below to choose your rating.

Concept: Spatial Skills.
Definition: Having an effective awareness of layout and interactable objects in the 3D environment. Using map knowledge or positioning to gain an advantage or perform multiple functions.
Example: While retreating in a first-person shooter, maintaining your aim on enemy zones while using your knowledge of the map to safely back away.

Statement: "I believe 'Spatial Skills' are necessary for VR multiplayer players."

Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
1	2	3	4	5	6	7

What is an example of this skill in a VR multiplayer game that you play?

Is there anything that makes this skill different in VR compared to a desktop or console game? If so, please offer an example.

Do you train this skill for the VR games that you play? If yes, how do you train? If not, why not?

Ranked Box

Please rank the following skills in terms of their relative importance in VR multiplayer games, with 1 being the most important.

Good Use of Game Mechanics

Reaction Time

Attentional Skills

Emotional Regulation

Team Work

Device Interaction Skills

Strategic Thinking

Spatial Skills

Catch all box

Thinking back on your previous responses, are there any other skills you feel are important for playing VR multiplayer games that we haven't talked about yet? If yes, please describe each skill briefly.

For each skill, include:

- **A definition** (what the skill means to you as a player)

• **An example** (how you've used it or seen it used in a VR multiplayer game)

Demographics

Select all that apply. Please describe your gender:

- [ ] Woman
- [ ] Man
- [ ] Non-binary
- [ ] Transgender
- [ ] Prefer to self describe
- [ ] Prefer not to say

Please select the racial category or categories with which you primarily identify. Select ALL that apply:

- [ ] Black e.g., African, Afro-Caribbean, Black Canadian, Afro-Latine, African American, or other African descent
- [ ] Caribbean e.g., Chinese Caribbean, East Asian Caribbean, South Asian Caribbean
- [ ] East Asian e.g., Chinese, Korean, Japanese, or other East Asian descent
- [ ] Indigenous e.g., First Nations people, Métis or Inuit

- [ ] Latine e.g., Latin American, Hispanic descent
- [ ] Mixed / biracial e.g., Black and another racial identity
- [ ] Middle Eastern e.g., Afghan, Egyptian, Iranian, Lebanese, Turkish, Kurdish, or other Arab or Persian descent
- [ ] South Asian e.g., East Indian, Pakistani, Bangladeshi, Sri Lankan, Indo-Caribbean, or other South Asian descent
- [ ] Southeast Asian e.g., Filipino, Vietnamese, Cambodian, Thai, Malaysian, Indonesian, or other Southeast Asian descent
- [ ] White e.g., British, German, Ukrainian, or other European descent
- [ ] ____________ Another race category (please specify):
- [ ] I prefer not to answer

For the purposes of this study, an Esports athlete is defined as a player that ranks in the top 40% of all players for that game.

Are you an Esports athlete?

- [ ] An esports athlete with consoles/PC games.
- [ ] An esports athlete in VR multiplayer games.
- [ ] Not in the top 40% of all players for the games that they play.

Have you ever competed in a professional VR Esports tournament?

- ○ No
- ○ Yes

Please list the tournaments you have participated in.

Powered by Qualtrics

Appendix G

The Reflexive Journal Used during RTA in Study 2

Session 0 – Oct 24th, 12:53 AM

Testing my process on a response I suspect is entirely written by ChatGPT. (P88)

To my surprise it wasn't. Participant demonstrated good thought, linked back to the games they play, and talked specifically about how VR makes a difference. Honestly, good stuff.

Session 1 – Nov 3rd, 1:38pm

First participant did not provide anything of value. Perhaps our prompts were not asking for enough detail.

Second participant also did not provide enough detail.

P3 provided some more information so good stuff

P4: Got some good codes in but I sensed my background from writing the thesis was enabling me to find some more relevant codes

Will be switching to writing every 5 codes to speed up the process

After P10: Got a lot more good information about how VR skills play out. As I suspected the professional give more detail but some non-pros give good information as well.

After P14: I've developed a flow where the use of the skill in game serves as a primer for their next comment about how VR changes it specifically and how they train it in VR.

Most people seem to be giving good information, and I do my best to look at the codes with a neutral lens. So far example, when a person tells me this skill is not great for VR, I note it down regardless of how strange it sounds to me.

Session 2 Nov 4th, 12:34 pm

I spoke to Dr. Harley regarding my approach, and he reaffirmed my 'themes' rather than buckets approach. With this in mind, I continued to look for the story in the data. This also lead me to skip tagging responses where participants repeated what their rationale multiplate times as it is the same story. I did 5 more responses.

Session 3 Nov 5th, 10:42 am

P22: As I'm reading their responses, it's too brief for me to tell any responses like "Prediction" even with the rest of the entries telling me nothing.

P36: Up until this point, most responses have either been well thought out or simple Yes/No answers but this is strange as they say they don't a VR/nor have regular access to it. Will review as normal however. Edit: They mean they have access to a club VR setup. Maybe an interesting sub group to investigate later.

P38. Skipping this one. So much ChatGPT, I doubt the latent meaning survived. As an example, when asked how the skills translate VR, the entry reads like a tutorial rather than a reflection. Clearly did not answer the question.

P40: Another person who doesn't own their VR headset. Might be an interesting sample to investigate.

I find myself frequently changing the names of the themes to 'fit' better. For example, "VR has a lower floor, but higher ceiling" becauses "The reflexes makes things easier, but precision is harder. "

I'm seeing a story come together

Session 4 Nov 5th, 7:23pm

Finished the remaining pieces of code. There were some cases where I added new codes and had to go back and review some earlier codes. Like deliberate practice versus repletion was a distinction that I didn't see until about P66.

Overall, I'm seeing pieces of a story coming together, but I'll limit guesswork until the clustering.

Session 5 Nov 6th, 1:40pm

I've just finished clustering the codes and the themes are starting to emerge. I've kept an eye out for some blind spots, but otherwise tried to capture the story as faithfully as possible. There were a few places where I had to revisit the codes as I believe I would have named some of them differently to more accurately capture the data. For example, one code I had was called 'VR Exclusive', which was meant to highlight the skill is specific to VR, but upon re-examining it, it felt the story the note was telling was closer to 'PC Skills don't translate to VR' and so I changed it.

Session 6 Nov 8th, 5:44pm

After discussing some potential overlap in the themes with Dr. Harley, I went back to the codes to eliminate any overlapping narratives. This led to two themes that were generated that discussed (1) "The body is the controller" and (2) "Physical Practice for Reflexive Action" I had a suspicion this was caused just by the two questions I had asked, but I saw responses about training and physicality across the two questions, meaning I wasn't just sorting responses by the questions they answered. Furthermore, I changed the wording from embodied cognition to 'reflexes' in the second theme to avoid any baggage that comes with the 'Embodied cognition' term.