Learning Team-Based Esport Games: Success Factors in Learning from Spectating

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n. the dread of finally pursuing a lifelong dream, which requires you to put your true abilities out there to be tested on the open savannah, no longer protected inside the terrarium of hopes and delusions that you start up in kindergarten and kept sealed as long as you could.

- John Koenig

Abstract

Electronic sports (esports) is a fast growing phenomenon in digital games where players compete, in teams or individually, in tournaments or series. Research has recognised spectatorship as a core aspect of esports, motivated among other things by the desire to learn how to play. Yet how to support newer players in learning to play from spectating is little explored.

Over three studies, this thesis therefore aimed to explore how players learn to play team-based esport games, focusing particularly the role and effectiveness of spectatorship. The first study used grounded theory with player interviews to explore learning processes, outcomes, and tools in two team-based esport games. The second study then used a qualitative survey design to identify what players found helpful, useful, or productive about videos and streams for learning to play. The final experimental study tested the hypothesis of a "sweet spot" in learner-teacher skill difference where learners see the greatest improvement in performance.

Overall, spectatorship was found to be an important form of self-regulated learning embedded in esports culture as an informal learning environment. Players deliberately reflect on their learning needs and evaluate available content against them, consuming content that they deem valuable into their learning activities. Helpful features of media highlighted by participants as being helpful for learning are contributory towards these value judgements, including competency, explanations, demonstrations, and relevance, with the most popularly discussed *feature*, competency, being demonstrated as effective for learning. The findings of this thesis also help to set a foundation and a potential path from which esports research can move towards helping make esport games more accessible and enjoyable for newer players.

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Declaration

I declare that the work enclosed within this thesis is original and that I am the sole author. This work has not been presented for any other award at this or any other institution. Any information that has been taken from another source has been properly referenced and attributed. Some of the material this thesis has been published previously in the following conference paper:

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Chapter 1

Introduction

Enjoying any game involves learning how to play it, and how to play it well (Koster, 2004, p.46). When players start a game new to them, they need to learn the goals and actions of the game as well as how the game changes its states over time and actions. In a digital game, players also need to acclimate themselves to the game's controls: mappings between the physical controller and in-game actions. Whilst learning to play is part of the enjoyment, designers note that it is important to help players learn the 'basics' of a game so they can then access and learn to improve at the core gameplay (e.g. Berbece, 2016; Ray, 2010; Wilson, 2017).

When digital games first emerged, players were given instructions either on-screen or on-machine (e.g. on the case of an arcade machine) as to the controls and rules of the game. As games evolved in complexity, the amount of instructions required to play a game pushed designers to develop more complex methods for teaching them. Many modern games now include scripted sections of gameplay for teaching players how to play, commonly known as tutorials, as well as contextual prompts or tips to improve.

Whilst many design patterns for game learning can be carried across most games, how to design for game learning is also game-dependent (White, 2014, p.21-22). Even simple changes, such as the number of players, can produce vast differences in learning outcomes and, by extension, appropriate learning support (Harteveld & Bekebrede, 2011). In single-player player-versus-environment (PVE) games, for instance, designers have a large amount of control over difficulty, challenge, and encounters, allowing them to adjust the obstacles provided to a player to help them learn and, by extension, enjoy the game.

However, in multiplayer player-versus-player (PVP) games, challenge and difficulty is largely dictated by one's opponents, and what players face in what order emerges from player interaction. This makes it difficult for designers to predict when to provide learning support for players without violating fair play, or to afford a predictable sequence of learning supports to be revealed to players. The level of control afforded by singleplayer games and the absence of other people as a confounding factor means that the majority of academic research (e.g. Andersen et al., 2012; Green et al., 2018; Moirn et al., 2020; Shannon et al., 2013; Therrien, 2011) and design practice discourse (e.g. Keren, 2017; Poedenphant & Mikkelsen, 2016; Stout, 2015; Suddaby, 2012; White, 2014) have focused on singleplayer learning support. In comparison, multiplayer games have received less attention.

Electronic sport (esport) games are a popular type of digital multiplayer PVP game which are played professionally in organised competitions by players or teams with sponsors (Hamari & Sjöblom, 2017; *Raising the Stakes: E-Sports and the Professionalization of Computer Gaming*, 2015). Esport games can be split into two categories: team-based esport games, which have two or more teams of players competing against one another; and player-based esport games, which consist of individual players competing against one or more other individual players. They are an increasingly popular spectator sport and, as a result, attract many new players everyday (Newzoo, 2022).

Whilst the complexities of esport games attract spectators, those same complexities may also deter new players, overwhelming them with how much they need to learn. In order to avoid player churn (i.e. players giving up on the game), it is important for game developers and designers to address this issue by utilising effective and enjoyable learning supports. However, since multiplayer game learning is a largely understudied field, developers have very little research to inform their learning support designs. As well as that, esport games, in particular team-based games, also have their own peculiarities that may affect learning support needs (e.g. team communication, how other players will behave) and learning support methods (e.g. spectating, streaming).

The question then becomes: how can research support esports game learning? Whilst research focusing specifically on esports learning and learning support is sparse, games and learning research may provide some insight, if not answers, into some of the ways that players learn and developers can support them.

1.1 Research Motivation

Digital games and learning is a large and growing field of research that can be roughly split into two areas: game-based learning and game learning. *Game-based learning* is a large domain of research mostly concerning itself with the acquisition of external knowledge and skills as a result of playing games (Whitton, 2014). This study of learning through games covers a large variety of domains such as business, engineering, and health (Boyle et al., 2015; Connolly et al., 2012; Plass et al., 2020).

In contrast, the study of *Game learning* focuses on how players learn to play (entertainment) games, as well as how best to support such player learning of the know-how relevant to play a game well. For this, members of the research community and designers in the industry both often draw from psychological literature (e.g. Jones-Rodway & Sun, 2008; Keren, 2017; Ray, 2010; Shannon et al., 2013; Vollmer, 2014; White, 2014). Research in cognitive psychology focused on skill acquisition and expertise has also been looked at for more specific aspects of learning such as how changes in attention and practice affect learning (Boot et al., 2010; Gopher et al., 1989), or quantifying the effect of different practice habits (Huang et al., 2013; Stafford et al., 2017; Stafford & Dewar, 2014). Qualitative research on game learning has found strategies for solving puzzle games (Iacovides, Cox, et al., 2014), strategies for learning fighting games (Huang et al., 2013), and high level overviews of informal learning and involvement in game learning (Iacovides, McAndrew, et al., 2014).

However, most of this game learning literature focuses on single-player or cooperative games. Research on multiplayer and competitive games such as esport games is much sparser. It chiefly revolves around eliciting the competencies professional or expert esports play involves (e.g., Fanfarelli, 2018; Köles & Pèter, 2016; Nagorsky & Wiemeyer, 2020; Roose & Veinott, 2021). How novices learn to play team-based esport games is far less explored with only a few, chiefly theory-testing, experimental studies probing differences between novices and expert learning practices and performance (e.g. Kleinman et al., 2021; Sapienza et al., 2017), or how learning over spectating play on *Twitch* affects subsequent performance (Payne et al., 2017).

In comparison to wider game learning research, team-based esports have seen little to no qualitative research developing a holistic view of how learning actually works, similar to existing work on puzzle games (Iacovides, Cox, et al., 2014) and fighting games (Hung, 2011). Given the marked genre differences of team-based esport games as multiplayer PVP games and dearth of existing best practices for this genre, such a grounded understanding of how current players themselves already do and support their learning would be helpful to identify potentially valuable learning supports for developers.

Specifically, spectating other players via streaming has been documented as a common learning practice in esport games (Payne et al., 2017; Sjöblom et al., 2017), but has not been explored more than assessing whether videos provide better learning compared to no videos (Payne et al., 2017). Spectating other players is thus an important differentiating genre characteristic of game learning in esport games that is poorly understood.

1.2 Thesis and Research Questions

The main question of this thesis then becomes:

> *What are success factors in novice learning of team-based esport games through spectating?*

Based upon the overarching thesis question and the current research, the research questions to be addressed are as follows:

1. How do players learn team-based esports games?
2. What factors are helpful when learning team-based esports games from spectating?
3. How do skill differences between spectator and player affect learning from spectating?

Before delving into spectatorship as a method of learning and learning support, it is important to situate and contextualise this activity within learning of a team-based esports game as a whole. Thus, research question 1 aims to understand where spectating ”fits” within esports game learning. Then, it would be pertinent to look at what players find contributory to the success of learning through spectatorship, which motivates research question 2. Finally, research question

3 is motivated by the results of questions 1 and 2, which suggested that skill and differences between spectator and player were the most important factors for successful learning through spectatorship.

1.3 Research Approach and Methodology

This thesis intends to understand the effectiveness of videos for learning to play team-based esport games. As mentioned earlier, the amount of research concerning how players learn to play esport games, let alone team-based esport games, is scarce. This meant that the first question to ask and explore is how players learn to play team-based esport games and whether learning by watching videos of other players is a significant part of learning to play. From there, if it is a significant aspect of learning, the next questions can focus more on what are the important features of videos that help learning and how effective these features are.

To understand the ways in which players learn to play team-based esports games, it is necessary to examine the experiences of those players as they learn. The first study utilised most of the principles of grounded theory to construct the learning activities players of *Counter-Strike: Global Offensive* (*CS:GO*) (Valve & Hidden Path Entertainment, 2012) and *Dota 2* (Valve, 2013) reported through interviews and is outlined in Chapter 3 (answering RQ1). The results constructed three important aspects of team-based esports learning: learning processes, outcomes, and tools. Out of the four constructed learning processes, *consumption*, including spectatorship, was found to be an important aspect of learning popularly highlighted by participants. The materials and results are available at https://osf.io/hyxqp/.

The next study in this thesis, outlined in Chapter 4 and motivated by the study in Chapter 3, then sets about to answer the question of what makes videos or streams helpful or productive for learning to play team-based esport games (answering RQ2). Since this study has a well-defined subject to explore and seeks only to categorise features of videos and streams, a qualitative study using thematic analysis was carried out. Players of the team-based Multiplayer Online Battle Arena (MOBA) *Dota 2* (Valve, 2013) were given a survey asking them about their experiences with helpful or unhelpful videos and streams for learning to play. This study focused on *Dota 2* due to the availability of participants and the tools provided by the developers of *Dota 2* for creating custom scenarios and accessing highly-detailed match replay data, which may be useful for further research. The results of this thematic analysis constructed 27 *features* and *formats* of media that were helpful for learning. The most frequently coded *feature* contributory to helpful media was the *competency of producer*. The pre-registration, methodology, data, and analysis of this study are available at https://osf.io/9zh2k/.

The third and final study of this thesis, outlined in Chapter 5 and motivated by the key *feature* of *competency of producer* found in Chapter 4, tests the hypothesis that, when learning to Last Hit and Deny in *Dota 2*, there is a "sweet spot" in teacher-learner skill difference where learners, watching teachers through a video, learn the most (answering RQ3). *Dota 2* has a training environment called the last hit trainer where players have three minutes to time their attacks on friendly and enemy AI to land the killing blow. The skill of last hitting (landing the final blow on an enemy minion) and denying (landing the final blow on a friendly minion) are important complex skills that require players to be conscious of attack timings of their character and other characters, the amount of damage their character and other characters can do, and their positioning. The resulting experiment was a between-subject design with a single continuous independent variable (teacher-learner skill difference) and continuous dependent variable (learner performance improvement). Participants were asked to play three rounds of the last hit trainer, reporting their scores, then watch three videos of either amateur, intermediate, or expert players playing the last hit trainer (who were explaining their thoughts whilst playing), and then play three more rounds before answering an open-ended question about their thoughts. Skill difference was found to have a significant weak linear positive relationship to performance change, demonstrating that the better the teacher, the more participants improved after watching them. The pre-registration, methodology, data, and analysis of this study are available at https://osf.io/p6wmu/.

Chapter 6 then outlines and discusses the findings of all studies within this thesis, teasing out key contributions to the fields of game learning, esports game learning, and for developers and content creators within the esports industry.

1.4 Research Ethics Statement

All research was designed and carried out with the express intent of minimising risk to any and all stakeholders involved, within the University of York's ethical guidelines, and with approval of the University of York's Ethics Committee.

All participants involved were 18 years old or older, informed about the study in advance, and gave informed consent prior to participating.

All data, including any personal information when necessary, was stored on password protected Google Drives. Data was anonymised by myself before being made available to any other researchers on the project. After completion of the study, the anonymised data is then made openly available at osf.io as part of the requirements set by the

Intelligent Games and Games Intelligence (IGGI) Centre for Doctoral Training.

1.5 Positionality Statement

Before presenting this thesis, I would like to take a moment of self-reflection and describe my positionality, as guided by Holmes (2020). First, I talk about my perspective as a researcher. Followed by my perspective as an individual outside of research. Finally, I want to talk about my motivations for my research. I will refer back to my positionality the limitations section of Chapter 6, the discussion, to highlight potential blindspots of my research.

I am a PhD student working to attain a PhD in Computer Science at the University of York. I originally came from a post-positivist mindset studying engineering before starting to learn qualitative methodologies and philosophies. Currently, I would argue that my epistemological standpoint is a mix of pragmatism and constructivism. I believe that scientific knowledge is a human construct that does not access some objective truth and that the value of scientific knowledge is dependent on it's ability to model and predict our perceived reality. As a simplification, I see scientific knowledge as a tool whose utility is measured by it's robustness. Therefore, I look at my qualitative work as attempting to capture and reconstruct the constructions others have made to make sense of their experiences. I look at my quantitative work as validating scientific knowledge through measurements of it's ability to model and predict perceived reality. I also prize values of replicability, communism, and public communication in scientific research. I have strived, throughout my work and it's reporting, to communicate my work and findings as clearly as possible such that others may rigorously test and analyse my findings.

I am an English speaking white male from a middle class background in my late 20s. I have played video games from a very young age and they have been influential throughout my life. I currently play and watch a lot of first-person shooter competitive team-based games. However, despite my consumption of games and media, I do not see myself as an insider to these communities. Whilst I feel that I can leverage insight into these games from my experiences, I do not consider myself an insider due to my lack of participation with the wider communities surrounding these games.

I have several motivations that drive my research, both generally and specifically in relation to the topic. Firstly, I want to contribute to the field of games research as I believe games are an important platform in which players create sociocultural artifacts and phenomenon that could be used to better society. This includes both the artifacts and phenomenon themselves and processes that created them. Secondly, I am motivated to research team-based esport games as these are one of my favourite genres of games to play and I wish to understand how people successfully learn them, as I may integrate these findings into my own play. Finally, I wish to use the knowledge gained and generated through my PhD to help further my career in both games research academia and the games industry.

Chapter 2

Background

This section goes over two main fields of research at which this thesis sits at the intersection of; learning and games, and esports. Learning and games discusses research that focuses on learning within the context of a game. I split learning and games into three further subsections; Serious Games and Game-Based Learning, Game Learning, and Game Learning in Industry and Popular Media.

The section on game-based learning gives a high level overview of the current state of research looking at what and how people learn from games. Conversely, the section of game learning is split into two sections; teaching and learning. Teaching looks at how academic and industry literature has developed frameworks, guidelines, or principles for designing learning support in games. Learning looks at how academic literature has explored and tested player learning within the context of singleplayer and multiplayer games. Esports gives a broad perspective on what esports is, the growth of esports, and the culture surrounding it. It then introduces the relevant games discussed in this thesis; *Dota 2* (Valve, 2013) and *Counter-Strike: Global Offensive* (CS:GO) (Valve & Hidden Path Entertainment, 2012). Finally, this chapter discusses the literature surrounding esports learning in the following three subsections: esports expertise, esports learning, and esports tools.

2.1 Learning and Games

Each year, thousands of new digital games are released. Steam is one of the most popular digital games distribution platforms for PC and saw over ten thousand game releases in 2020 (Spy, 2021). These digital games will share features with other games, such as game mechanics, control schemes, atmosphere, and aesthetics, and will form a 'genre' of digital games. A recent popular example of a genre in digital games is the "souls-like" or "soulsborne" genre, named after *FromSoftware's Demon Souls* (FromSoftware, 2009), *Dark Souls* (FromSoftware, 2011, 2014, 2016), and *Bloodborne* (FromSoftware, 2015) games, which involves careful and deliberate combat against difficult enemies, including bosses, with checkpoints that allow players to level up and enemies to respawn.

Despite these similarities shared across genres of digital games, new releases will always differ from other games to differentiate themselves from the rest of the market. It is then inevitable that players starting a new game will come across some aspect of a game that will be novel to them, regardless of how many games they've played previously.

Learning about this new feature will take some time. It may also become a point of frustration for players. If players find aspects of a game too frustrating, then they may give up on the game and stop playing, also known as "rage quitting". Some games and their community embrace these frustrating aspects of play and learning to play. However, designers work hard to carefully balance the difficulty of a game to avoid too much frustration.

As well as designers, games researchers also have an active interest in games and learning. A majority of designers are interested in how players learn to play their games, known as game learning. Research around learning and games has focused more on games that facilitate learning of knowledge and skills external to the game. This is also known as serious games or game-based learning.

2.1.1 Serious Games and Game-Based Learning

Serious games refers to a large genre of games which are designed to help facilitate outcomes beyond entertainment such as knowledge/skill acquisition and behavioural changes. Such games have been used for health, education, citizen science, exercise, therapy, and recruitment (Boyle et al., 2015; Connolly et al., 2012; Plass et al., 2020). As this thesis is concerned with how players learn to play games, in the following, I will focus on games designed for learning, not other serious purposes like behaviour change. This field is commonly called game-based learning. Game-based learning is a large field of research, utilising a variety of competing theories and models, focusing on the acquisition of external knowledge and skills, and mainly concerns itself with the learning outcomes of playing games (Whitton, 2014).

Looking at how people learn with game-based learning, research has found a variety of methods or processes that help players learn external skills. The methods and processes utilised for game-based learning include; modeling (Steinkuehler and Tsaasan, 2020; Steinkuehler and Oh, 2012; Whitton, 2014 p.165-167), apprenticeship or coaching (Steinkuehler and Tsaasan, 2020; Steinkuehler and Oh, 2012; Whitton, 2014 p.45-48; Mayer, 2020), reflection (Whitton, 2014 p.125-127; Mayer, 2020), and contextually situated learning (Gee, 2007 p.105; Whitton, 2014 p.41-45). These often utilise popular constructivist or cognitivist learning theories such as Vygotsky's sociocultural theory of learning (Vygotsky, 1978), cognitive apprenticeship (Collins & Kapur, 2014), Kolb's experiential learning cycle (Kolb, 2014), and Mayer's cognitive theory of multimedia learning (Mayer, 2021).

Game-based learning is also interested in identifying and understanding what learning-supportive qualities are present for differing methods. Cognitivist game-based learning research has identified the following promising features for improving learning: modality, which is the presences of spoken words; personalisation, which is the use of a conversational style of instruction; pretraining, which is the provision of pregrame experiences to familiarise oneself with the game; coaching, which is when others provide advice and explanations; and self-explanation, which is the provision of prompts for learners to explain what they have learnt (Mayer, 2020). Similarly, constructivist game-based learning research has identified features such as learner-interest, collaboration, and relationships of power and status as being important and contributory to learning in game-based learning environments (Steinkuehler & Tsaasan, 2020).

The method of modeling is especially relevant for this thesis since modeling involves teachers demonstrating skills in-action and in-context which is the central role of spectatorship for learning. Two of the promising features of game-based learning found in cognitivist research, modality and personalisation, may be relevant to and could be supported in spectatorship. Constructivist game-based learning factors highlighted above stress the importance of participatory and interactive aspects of spectatorship for learning. They suggest that the interactions between viewers and content creators are at least contributory, if not important, to the efficacy of learning through spectatorship.

The above learning theories, methods and processes, learning- supportive qualities, and potential overlaps with spectatorship may all be reflected in, if not transferable to, game learning. However, there is little research testing these within the context of game learning.

The amount of literature on serious games or game-based learning would require a thesis itself for a comprehensive literature review. As well as a literature review, an analysis of how serious games or game-based learning research can be integrated into game learning would also be an immense undertaking. The aim of this thesis is to understand learning of team-based esport games and so will not delve deeper into the current landscape and findings of serious games and game-based learning literature.

2.1.2 Game Learning

Game learning refers to the process of learning and mastering a game. Research on game learning can span a large range of perspectives including how players learn, what players learn, what players use to learn, and how players learn with others. Game learning also spans a variety of game genres including singleplayer or multiplayer games, cooperative or competitive games, and even serious games (since players still need to learn how to play the game).

Despite the aforementioned importance of supporting new players to a game, game learning literature is sparse, especially in comparison to game-based learning literature. For example, there appears to be no rigorous literature reviews looking at game learning. The literature in this section looks into two different aspects of game learning: how games support players through teaching and how players learn to play games.

Teaching Games

When designing learning support for players, designers have a variety of learning support designs to choose from. Originally, instructions regarding the controls and goals of an arcade game were printed on the arcade machine. As digital games moved from arcades into homes, developers and designers started including different forms of learning support such as instruction manuals, in-game guides, UI overlays that highlighted important information or provided tips, and environments for exploring and experimenting with the action space.

A popular one being the tutorial, consisting of small segments of gameplay dedicated to teaching players specific knowledge or skills about the game. Tutorials have been considered to be particularly important for newer players (Moirn et al., 2020; White, 2014) especially when teaching unconventional and complex games (Andersen et al., 2012). However, they are not solely helpful or important to new players as more experienced players do still consider this help important (Santos et al., 2015). Due to the difference in learning needs between new and experienced players, it has been suggested and found that some games benefit from having context-sensitive tutorials (Andersen et al., 2012; Aytemiz et al., 2018). Despite their perceived importance and effectiveness, tutorials were rated third most preferred out of four types of help (cut-scenes, graphical tips, passing phase, tutorial) (Santos et al., 2015). This indicates that tutorials would benefit from increased research into making them enjoyable for players.

In general, literature suggests that good learning support design requires immediate and corrective feedback (Shannon et al., 2013; White, 2014), unobtrusive just-in-time instruction (Andersen et al., 2012; Aytemiz et al., 2018; Shannon et al., 2013; White, 2014), and scaffolding from cognitive apprenticeship that increases player freedom as they demonstrate more competency (Andersen et al., 2012; Johanson & Mandryk, 2016; Malick et al., 2014; Shannon et al., 2013; White, 2014). Something to take into consideration is that skill improvement increases when players take time between practice, also known as spaced practice intervals (Johanson et al., 2019; Piller et al., 2020). As well as simply pausing the game, providing activities that are similar or dissimilar to the main game can also help improve skill acquisition (Piller et al., 2020).

Developers discuss teaching players how to play games at large developer conferences such as Games Developer Conference (GDC) (Jones-Rodway & Sun, 2008; Keren, 2017; Poedenphant & Mikkelsen, 2016; Vollmer, 2014) or Develop (Wilson, 2017) and developer forums like GamaSutra (Ray, 2010), Game Developer (Stout, 2015), or other developer sites (Pear, 2018). The rationale underpinning developers ideas for designing for game learning tends to be underpinned by experience (e.g., Jones-Rodway & Sun, 2008) or theories of thinking from psychology, some of which are now under contention within psychology (e.g., Ray, 2010 with types of learners; Wilson, 2017 with fast and slow thinking).

Learning Games

When learning games, players utilise a multitude of strategies to help them. "Trial and error" is one such strategy for approaching learning reported by players (Santos et al., 2015) and observed in play (Hung, 2011; Iacovides, Cox, et al., 2014). Trial involves the player performing some action in-game in the hopes that it will lead to progress. Error is then the feedback provided by the game and it's relation to progress. As reported by Iacovides, Cox, et al. (2014), trial and error is framed as an exploratory process with minimal reflection beyond whether the applied action led to progress. Similarly, learning from the game either by "tips" or the aforementioned tutorial has been reported by players (Santos et al., 2015) as well as observed in play (Iacovides, Cox, et al., 2014). The games can provide information to players about how to solve a particular problem, often relevant to the current context, which players then decide whether to follow or not. The exploratory and reflective nature of trial and error, and the structured feedback provided by tips and tutorials, help demonstrate digital games' ability to facilitate cognitive apprenticeship (Collins & Kapur, 2014), primarily the methods of coaching, reflection, and exploration.

In multiplayer games, learning becomes far more collaborative as players then seem to co-construct and share knowledge with each other and with a larger community. Instructing and guiding other players is one behaviour observed in teaching and learning multiplayer games. In multiplayer puzzle games, Iacovides, Cox, et al. (2014) observed a learning strategy they named "Guidance", referring to moments in play where a player either asks for or receives help from another player. This behaviour was similarly noticed by Hung (2011) in a group of four children playing *Super Smash Bros. Melee* (HAL Laboratory, 2001). In an example discussed by Hung, one of the children teaches another by explaining how character movement works in the game (Hung, 2011, p119-121). These kinds of moments were subsequently categorised as "training sessions". Similarly in massively multiplayer (or multi-user) online role-playing games (MMORPGs), Steinekuehler and Oh (2012) demonstrated feedback and scaffolding, two aspects of cognitive apprenticeship involving instruction and guidance were present across three of the MMORPGs they analysed. Looking at *Counter-Strike: Global Offensive* (*CS:GO*), Rusk et al. (2020) explored how an expert player helped to provide instruction and guidance using interaction analysis.

Discussions between players about learnings and the exchange of knowledge has also been observed as a common strategy or technique for learning in multiplayer games. Iacovides, Cox, et al. (2014) refer to this as "Knowledge exchange", observing that players would talk about the games environment and challenges as well as sharing ideas they construct from other strategies (i.e. Trial & error and Experiment). Similarly, Hung talks about how, when discovering new knowledge or information, players then discuss how this impacts the game and how players will approach the game (Hung, 2011, p106-107). Asking players of a broad variety of genres, Santos et al. (2015) found that the use of "information on the internet" was the third commonly used strategy for learning games. However, Santos et al.'s survey sample does not differentiate between singleplayer and multiplayer games. The fact that "information on the internet" was placed third out of four learning strategies, as well as the presence of knowledge exchange in multiplayer learning literature, may be indicative of the reduced need for communal help in singleplayer games. Sometimes, these discussions generate new knowledge. For some games, players work meticulously to break down the underlying logic of games through experimentation, known as theorycrafting (Wenz, 2013). These examples of knowledge exchange and generation further demonstrate the informal nature of learning in these games.

Another multiplayer based strategy for learning is the set up and use of "training/practice sessions" between players. Hung (2011) demonstrates this when players would set up a situation where an expert shows the novice how to play and allows them to try out their learnings. In one example (Hung, 2011, p119-121), the expert sets up a game with just them and the novice to help the novice learn. Rusk et al. (2020) also highlight that, during play, the expert would make reference to some of the teachings they had given to the novice in prior practice sessions. It can be argued that Iacovides, Cox, et al. (2014) also references training/practice sessions through the learning strategy of "Repetition". However, the difference between Hung and Rusk et al., and Iacovides, Cox, et al. is that the purpose of training/practice sessions in the competitive games was to improve proficiency, whereas in the cooperative puzzle game it was to make progress.

One extra aspect of learning to note is the role of prior experience. Gee (2007) uses the system of semiotic domains, the areas or set of activities where signs and symbols (semiotics) are defined by the participants, values, and practices surrounding them, to argue how players transfer knowledge and skills between games:

> *"In the larger semiotic domain of video games, first- and third-person shooter games are a well-defined subdomain. However, such games often have elements that are similar to features found in arcade games, games that involve a good deal of fast hand-eye coordination. Thus, someone who has mastered the domain of arcade games has mastered a precursor domain for shooter games."* (Gee, 2007, p39)

Demonstrating this empirically, Smith et al. (2020) found that longer hours gaming per week, greater gameplay frequency, and a stronger self-identification as a "gamer" were significantly related to faster learning.

2.1.3 Conclusion

The intersection of learning and games is a popular topic of research largely populated by serious games and game-based learning literature. These focus on external learning using games as teaching platforms, simulations, or motivational tools. There is some consensus on the effectiveness of serious games for teaching within all the various perspectives on their usefulness.

However, in both serious games and entertainment games, players need to learn how to interact with the game and what the game's rules and mechanics are. This learning of the game is referred to here as game learning. Both the games industry and academia have a healthy interest in understanding and improving game learning. There is limited research understanding how players learn and how best to teach them.

There is even less clarity on game learning when it comes to team-based esports, competitive digital games where teams of players compete with one another. This matters because both *what* players learn and *how* they learn it likely differs with esports.

2.2 Team-based Esports

Esports refers to sports where the actions of players or teams, the interactions of the rules, and their outcomes are handled by electronic systems (Hamari & Sjöblom, 2017). Esports games span a variety of genres, including first-person shooters (FPS), multiplayer online battle arenas (MOBAs), real-time strategy games (RTS), fighting games, and sports games, with FPS and MOBAs being the most popular genres in 2020 (Newzoo, 2021). All these games feature hierarchies of leagues, ladders, and tournaments organised by the developer/publisher of the game or independent organisations like the ESL, with professional teams that compete for tournament prize money and are usually sponsored by various companies, similar to physical sports (Hamari & Sjöblom, 2017).

Beyond genres, esports can be split into two categories: player-based and team-based esports games. Player-based esport games consist of individual players competing against one or more other individuals. Popular examples of player-based esport games include *Fortnite* (Epic Games, 2017), *Hearthstone* (Blizzard Entertainment, 2014a), *FIFA 2022* (EA Vancouver & EA Romania, 2021), and *Starcraft II: Wings of Liberty* (Blizzard Entertainment, 2010). Team-based esport games consist of multiple players working together in a team against other teams of players. Popular examples of team-based esport games include *Counter-Strike: Global Offensive* (Valve & Hidden Path Entertainment, 2012), *Dota 2* (Valve, 2013), *Overwatch* (Blizzard Entertainment, 2016), and *League of Legends* (Riot Games, 2009).

Due to esports' rapid rise in popularity, size, and revenue (Newzoo, 2022), the very best players can make a living as professional esports athletes, though these careers are notably precarious. Tournaments and competitions are broadcasted through streaming platforms like *YouTube* and *Twitch*, with high-profile events regularly attracting millions of live streaming viewers and thousands of in-person live spectators. Like traditional sports, esports games attract a large base of millions of 'amateur' players, with fuzzy boundaries and many pathways between 'amateur' and 'professional' play. Most esports games are free to play or 'freemium', meaning they can be downloaded and played without an up-front payment, which arguably contributes to their current growth.

Esports' increasing prevelance is largely thanks to it's position as a spectator sport. The interactive nature of *YouTube* and *Twitch*, upon which a majority of esports events are broadcasted on, allows viewers to engage and participate more actively in events with other viewers and the events themselves. Streaming in general has been seen to engender a wide variety of participatory and interactive behaviours between viewers and streamers (Huston et al., 2021; Taylor, 2018). This also leads to viewers watching and engaging with streams for a range of reasons and gratifications (Barney, 2021; Hamari & Sjöblom, 2017; Ma et al., 2021; Sjöblom et al., 2017).

This thesis includes experiments looking at two team-based esports games: *Counter-Strike: Global Offensive* (*CS:GO*) (Valve & Hidden Path Entertainment, 2012), and *Dota 2* (Valve, 2013). Both *CS:GO* and

Dota 2 are two of the most popularly watched (Newzoo, 2022) and played (Steam Charts, 2022a, 2022b) team-based esport games. As well as that, both *CS:GO* and *Dota 2* provide easy access to develop playable content and to replay files, which provide time-series data that record all game objects and variables of a match. Both of these tools make them a fertile space for a variety of research.

2.2.1 *Counter-Strike: Global Offensive* (Valve & Hidden Path Entertainment, 2012)

Counter-Strike: Global Offensive (*CS:GO*) is a competitive team-based multiplayer FPS game released by Valve in 2012 as the fourth game in the Counter-Strike series. *CS:GO* is one of the most popularly played esport games and the most popular FPS game with, at any given time, Steam counts around 600,000 players (Steam Charts, 2022a). It is also one of the most watched, with 215 million hours watched over *Twitch*, *Youtube*, and *Mixer* in 2020, the second most of any esport game (Newzoo, 2021). Whilst it's popularity is ample reason to pay attention to *CS:GO*, it is also a data-rich and malleable platform to research due to accessibility to replay files, gameplay statistics, and it's modding capabilities. All of which are readily used by the community to analyse performances and create new maps and gamemodes.

In *CS:GO*, two teams of five players compete to either defend or attack an objective. A game of competitive *CS:GO* consists of thirty rounds. Each round lasts one minute and fifty five seconds and each team plays one of two sides; terrorists (T) or counter-terrorists (CT). After the first fifteen rounds (i.e. halftime), players switch sides. The aim of each round for the T is to arm and blow a bomb on one of two objectives (i.e. site A and site B) or to kill every player on the CT. The aim of each round for the CT is to either disarm the bomb or to kill

Figure 1: Screenshot of *Counter-Strike: Global Offensive* (Valve & Hidden Path Entertainment, 2012). Taken from Linux Game Network (2020).

every player on the T. The first team to win sixteen rounds wins the game.

CS:GO has a variety of maps for competitive play. All maps have two objectives, a T spawn point, and a CT spawn point. The objectives are placed closer to the defenders, the CT, and there are a wide variety of approaches available to each objective for the attackers, the T. The attackers need to use their grenades, flashbangs, and smokes (i.e. utility) to try and plant a bomb at an objective. Once the bomb is planted, the defenders then need to retake the objective from the T and defuse the bomb. Both planting and defusing the bomb takes time and leaves players vulnerable to being killed.

Players have individual pools of in-game money with which they can buy weapons and equipment at the start of each round. Players gain money by killing opponents, damaging opponents that other teammates kill (i.e. assist), and completing objectives (e.g. planting or defusing the bomb). Players also gain money at the end of each round, but gain considerably more money if they win the round. Each player's pool is reset at half-time.

These player pools are directly closed systems (i.e. players cannot give or steal money) but can be indirectly manipulated. If a player survives a round, all their weapons and equipment are carried over to the next round. However, if a player dies, the player drops their weapon and loses all their equipment next round. Dropped weapons are removed from the game at the end of each round but can then be picked up by teammates or an opponent. This allows players to steal or save weapons, meaning less money will be spent next round. As well as that, players can willfully drop weapons too meaning teams can share their pools of money through weapons.

CS:GO contains thirty six weapons (as of March 2022), ten of which are only available to the CT side, eight of which are only available to the T side, and the rest are available to both sides. Every weapon costs money to buy and their prices are set by the developers. For example, the UMP-45 submachine gun (SMG) costs $1,200 in in-game money and the AWP sniper rifle costs $5,000. These prices can be changed by the developers to incentivise or punish particular tactics or strategies.

The number of weapons, utility, and maps allow for a wide range of tactics and strategies players can learn and utilise. Similar to *Dota 2*, players need to take into account their teammates movement and actions, and their opponents movement and actions.

2.2.2 *Dota 2* (Valve, 2013)

Dota 2 is a competitive multiplayer online battle arena (MOBA) released by Valve in 2013 as the sequel to the mod *Defense of the Ancients* (Eul et al., 2003) for *Warcraft III: Reign of Chaos* (Blizzard Entertainment, 2014b). *Dota 2* is one of the most popular MOBAs and esports games, with approximately 422,260 concurrent players on average in 2021 (Steam

Figure 2: Screenshot of *Dota 2* (Valve, 2013). Taken from Rock Paper Shotgun (2021).

Charts, 2022a) and 198.9 million hours watched over *Twitch*, *Youtube*, and *Mixer* in 2020, the third most of any esport (Newzoo, 2021). Similarly to *CS:GO*, Valve allows players access to replay files, game statistics, and modding capabilities, making it a strong platform for team-based esports research.

Dota 2 is a competitive multiplayer online battle arena (MOBA) where two teams of five players compete to destroy the opponents home base, also known as their ancient. Between each ancient lie three lanes, two jungles, and a river. Each team must utilise various mechanics and tactics associated with the lanes, jungles, and river to acquire gold and experience, which will allow them to become more powerful and destroy their opponents ancient.

Before each game begins, players must choose a hero from a roster of 122 unique heroes (as of March 2022). Players lock-in these heroes for the entire game and cannot change their hero. Every hero has a basic attack which allows them to deal damage to player opponents or non-player characters (NPCs) and can be melee, ranged, or magic in nature. Heroes also have special stats and abilities that differentiate them and allow them to fulfil specific roles. These abilities can have a variety of effects such as stunning opponents, dealing huge amounts of damage, or restoring health for nearby allies. Players need to earn experience to unlock and level up their abilities during a game and can even improve (i.e. buff) their abilities by buying some of the 271 items from the item shop in-game (as of March 2022).

Once in-game, players then need to try and optimise various metrics for their team such as damage output and input, gold intake, and experience whilst minimising similar metrics for their opponent. Players utilise various mechanics and exploits in the lanes, jungles, and river. For example, each team has two barracks per lane in their home base which spawn friendly NPCs, called ”creeps”, that walk down their respective lanes and attack enemies and their towers. When a player makes the final blow, and only then, they get experience and gold for killing the creep (last hitting). However, players may also attack friendly creeps too, meaning if a friendly player gets the last hit on a creep, they can deny the opponent the gold and experience they'd get (denying). By last hitting and denying, players can try and maximise their experience and gold whilst minimising their opponents.

Due to the number of heroes, abilities, items, and mechanics all available on a single map, the amount of tactics or strategies available to a team is immense. Players need to be aware of what their team are doing and planning as well as what the enemy team might be doing and planning in order to play competitively.

2.3 Learning Esports

Esports game learning research focuses on game learning within the context of esports games. This thesis breaks down esports game learning into three sections; learning resources in esports, competencies of esports, and learning processes in esports.

2.3.1 Learning Resources in Esports

Players have access to a wide variety of tools and resources in-game and online to help them learn to play or master their chosen game. These include online forums, videos and streams from content creators, training modes in-game, and tutorials. In this thesis, the tools and resources used by players will be collectively referred to as resources. Similarly to the competencies and processes of learning, the resources players utilise have received little attention in research with regards to learning.

Kow and Young (2013) identified that players of *Starcraft* (Blizzard Entertainment, 1998), a player-based competitive strategy game, learnt by watching streams of players and tournaments. Interviewing 24 professional games, casters, amateur league players, esport news editors, tournament organizers, and community leaders, Kow and Young explored how media technologies were leveraged by the community for learning. As well as utilising streaming platforms, they identified two functions of media technologies to support learning for general learners in public media and expert learners in private media: converting knowledge into symbolic representations for general learners (informational media), and supporting social practices among private groups of experts (socially-oriented media).

Whilst Kow and Young (2013) identified multiple resources and tools for learning esports games, there is little research regarding resources and tools outside of streams and videos for learning. This literature review could not find any further research that looks at different resources for learning esports games and their efficacy beyond spectatorship.

Whilst most research with regards to esports spectatorship looks at the culture of streaming and the experiences of professional players and spectators (e.g., Carter & Egliston, 2018; Lin, 2019; Ruvalcaba et al., 2018; Taylor, 2018), there has been some focus on the learning potential provided by streaming platforms. Sjöblom et al. (2017) examined the relationship between the type of content, the viewer gratifications, and the game genres within the context of *Twitch*. They found a significant relationship between learning to play motives and competitive games as well as learning to play motives and casual games. They suggest that this is because newer players learn by watching casual streams to understand the basics. Whereas more experienced players watch competitive game streams to adopt strategies employed by professional players.

These findings were further explored by Huston et al. (2021) who use the axes of 'skills versus culture' and 'serious vs casual' to plot consumer journeys in esports spectatorship. Through interviews, literature reviews, and researcher grounding in the context of esports spectatorship, they found that serious audiences focusing on skills and casual audiences focusing on skills have different involvements with the esports they watch, provide differing reasons for their consumption of esports, and form different social connections within esports. Serious and skills-based consumers are often highly involved with the game they watch and use esports spectating as a tool for mastering the game, they want to learn professional strategies for their own games, and play and theorycraft with other skills-based consumers. Casual and skills-based consumers either have little involvement in the games or don't play them, watch esports to potentially learn strategies or tips but also to pass time, and only play with friends to socialise mostly or to test learnings. These differences in behaviour show that novices adopt different strategies for learning these games, which may be true for other forms of learning outside consuming esport streams.

Esports spectatorship not only involves the watching of live competitions and tournaments, audiences also have a variety of different content available to them to enjoy as well as utilise to learn. Ma et al. (2021) explored how six "live-streaming types" over four game genres related to ten spectator motives. They found that esports spectatorship was largely motivated by knowledge acquisition, especially for MOBA game genres. They also found that spectators motivated to watch for knowledge acquisition were less likely to watch esports through let's plays (gameplay of people playing in environments outside of tournaments) and talk shows.

Not only do players watch streams in the hopes of learning how to play, players also learn by watching other players. Discussed in further detail in subsection 2.3.3, Learning Processes in Esports, Payne et al. (2017) examined how participants improved in *League of Legends* (Riot Games, 2009) after watching different levelled players. They found that participants all saw a significant improvement in score when watching either a novice or expert player in comparison to the control group.

2.3.2 Competencies of Esports

One aspect of learning and mastery in any domain is the knowledge and skills required. Within this thesis, the knowledge and skills learnt or mastered are referred to as competencies. When learning any complex system, such as a digital game or esport, there are usually a large number of competencies for players to learn and master. This thesis identifies 4 major studiees on competencies and expertise: Fanfarelli (2018) on expert skills; Köles and Pèter (2016) on ability sets in amateur and semi-professional players, Nagorsky and Wiemeyer (2020) on skill relevance with regards to different games, and Larsen (2020) on a theory of skill in esports.

Fanfarelli (2018) analysed 12 interviews of 11 professional *Overwatch* (Blizzard Entertainment, 2016) players to identify important competencies at professional play. The interviews consisted of 11 publicly available interviews and 1 conducted by the author. They identified two themes, each with four subthemes. The first theme is Game Sense which refers to a player's ability to infer information about the current game state and make appropriate decisions in response. It is split into several sub themes: avoiding losing health and dying (survival), the ability to accurately predict what will happen next (anticipation/prediction), relaying only important information at the right time in the right context (communication), and being able to infer the best course of action based on their current knowledge (thoughtfulness).

The second theme is Mechanics and includes the motor skills of the player and their ability to manipulate the game logic. Mechanics is split into the following four subthemes: the ability to aim at and inflict damage on targets (aim), understanding when to appropriately use a character's abilities (ability usage), how to position oneself during a game (movement and positioning), and synchronising all of the above with other members of the team (team-based mechanical synergies).

Fitting into Fanfarelli's findings but focusing on MOBAs, Köles and Pèter (2016) highlight 6 ability sets that emerged from focus groups with semi-professional and amateur players of *League of Legends* (Riot Games, 2009). The ability sets focus more on cognitive and motor skills than any game knowledge or strategic thinking. The 6 ability sets are; motoric precision of executing skill sequences, approximating timings and prospective memory, target identification and task switching, situational awareness, reaction time, and motoric precision of aiming. Situational awareness echoes Fanfarelli's Game Sense theme, although focuses more on the players ability to observe their environment rather than act upon it. Since League of Legends has players control heroes with abilities, Köles and Pèter's execution of skill sequences represents League of Legends equivalent of Fanfarelli's and *Overwatch*'s ability usage subtheme of mechanics. Whilst aiming has been shown to be less important for MOBAs than FPSs, Köles and Pèter have shown that aiming is still important as certain hero abilities in *League of Legends*, and is common in many MOBAs, do require aiming. Some of the key differences between Fanfarelli's findings and Köles and Pèter's is the exclusion of approximating timings, task switching, and reaction time in Fanfarelli's themes and subthemes. This could indicate that these skills are less important for players of Overwatch than for players of League of Legends.

The importance of skills do change over different games and game genres as Nagorsky and Wiemeyer (2020) demonstrated by examining the importance of 19 different competencies over 5 different games as well as analysing the training habits of players. These 19 competencies were constructed by Nagorsky and Wiemeyer based upon a literature review of digital game and sports competencies. Performing a factor analysis on the competencies, they identified six components that explained 62% of variance. The six components are:

Physical competencies (condition): competencies relevant to the player's physical abilities (e.g. strength, endurance).

Sensori-motor or coordinative competencies: competencies relevant to the players ability to accurately receive, hold, and respond to stimuli (e.g. reaction time, accuracy).

Strategic-cognitive competencies: competencies relevant to the player's ability to assess and make decisions from the information they have (e.g. analytical thinking, strategic thinking).

Psychic competencies: the player's personal thoughts, feelings, and motivations towards themselves and the situation (e.g. confidence, personal attitudes).

Social competencies: the player's ability to work with and respond to others (e.g. teamwork, acceptance of critical team feedback).

Media-related competencies: the player's ability to respond to and deal with technical issues(e.g.adapting the game settings).

As well as different games, the importance of skills change for different levels of expertise. Whilst experts may provide targets in competencies for novice players, it is shown that the importance of competencies over varying levels of expertise are not static (Thompson et al., 2013). This indicates that the competencies that make a "good" novice and a "good" expert differ and novices may need to focus on learning and mastering skills different to what experts see as important. Understanding what novices learn is understudied in comparison to experts and requires a greater focus in research (Kirschner & Williams, 2013).

Expert or professional players have mastered relevant and important competencies for the games they compete in. Therefore, they can help provide an overview of all the competencies relevant to all players of a game. A commonly examined aspect of expertise in esports are physical muscle movements and skeletal manipulations known as motor skills, as these have been shown to be a strong delineation between experts and non-experts (Li et al., 2020; Pluss et al., 2020). As well as motor skills, expert players of *Dota 2* have been shown to have different focuses, different scan patterns, and different reflections on performance than novices (Castaneda et al., 2016; Kleinman et al., 2021).

Through personal experiences playing, watching, and discussing esports, Larsen (2020) developed a speculative theory of skill for esport games. Larsen theorises 7 "strands" representing elements of a whole theory of skill. The first being the understanding of game objects (defined as the "building blocks") such as their properties. Larsen also links this kind of skill to theorycrafting, which is the production of knowledge about game objects to help develop optimal strategies for play (Wenz, 2013). The second strand of skill is defined as insights into game systems, where players try to understand how the game and the environment handle interactions between game objects.

The third strand of skill refers to the understanding of the best strategies and game object combinations within the context of the current game object properties and game logic. The fourth strand is called "Yomi", a reference to the japanese word for reading, and is similar to Fanfarelli's Game Sense (2018).

The fifth strand fits into Fanfarelli's Mechanics theme, concerning itself with the ability to carry out game actions through physical application and situated cognition, as well as be able to reflect on immediate outcomes. This also links to cognitive and motor skill research in expert players (Li et al., 2020; Pluss et al., 2020; Toth et al., 2021). The sixth strand discusses a players ability to regulate and control their affective state between engagement and distanced self-awareness.

The final strand focuses on the importance of coherency in teams including social competencies, communication skills, and learning as a team. This theory of skill is very new, requiring further validation. However, it does help lay the foundation for an overview of the relevant competencies for playing and mastering an esport game.

Overall, the main competencies discussed by esports learning literature are: competencies relevant to the physical movement and manipulation of controllers and their relation to in game actions (e.g. motor skills, physical ability); competencies relevant to receiving, filtering, processing, and reacting to stimuli appropriately and quickly (e.g. reaction time, accuracy); competencies relevant to modelling the current game state, the likely future game states, and how best to manipulate the current game state (e.g. game sense, "Yomi"); competencies relevant to socialising with other players appropriately and effectively (e.g. teamwork, communication); and competencies relevant to handling personal affective states (e.g. anger management).

2.3.3 Learning Processes in Esports

Learning is a fluid process that involves different behaviours and methods for absorbing, maintaining, and mastering competencies. Players learn and master games in a diverse range of ways. This is especially true for esport games as the social nature of collaboration and competition both in and out-of-game means players can constantly absorb and disseminate information. The ways that players learn to play are described as learning processes in this thesis. The ways that players learn to play esports games has seen little research.

During a literature review of research based on MOBA games, Mora-Cantallops and Sicilia (2018) found that there was a lack of research around how players learnt to play MOBAs. This also appears to extend outward to other genres of esport games as well. Nagorsky and Wiemeyer (2020) found only two studies on the matter: a survey on how much time expert players spend on physical and non-physical training (Tuomas & Karhulahti, 2016), and a mixed-method study on how amateur and professional *Warcraft III: Reign of Chaos* (Blizzard

Entertainment, 2014b) players train (Adamus, 2015).

Adamus (2015) conducted a survey involving 1,319 *Warcraft III: Reign of Chaos* players of all different levels of play to identify important learning processes in esports. Adamus found six training activities: learning strategies, making appointments with training partners, training particular movements, watching replays of your own games, gathering information about opposing players, and playing against bots, that is AI-controlled opponents.

Games have occasionally served as a test bed for theories of skill acquisition and expertise in cognitive psychology. However, studies in this domain have tackled diffuse phenomena and varied in methodological approach. Seminal work by De Groot (2008) involved process tracing and interview techniques to uncover behaviours that underpin best move selection in expert chess players. Experimental studies of Space Fortress (Donchin, 1989, 1995), a non-commercial game funded by DARPA, have evidenced how differences in attention and practice strategy affect learning over the course of training (e.g. Boot et al., 2010; Gopher et al., 1989).

More recently, researchers have applied computational modelling techniques to decompose skill and investigate move selection in Tetris (Sibert et al., 2016), while observational approaches have quantified the effects of different practice habits in various online games (e.g Huang et al., 2013; Stafford et al., CogSci 2017; Stafford & Dewar, 2014). Taken together, while games have served as task environments to test specific theoretical constructs (e.g., problem solving, attention, practice scheduling), psychologists have yet to fully model performance and learning in any single game (Charness, 2017). A concrete account of how learning unfolds in games, from a psychological perspective, thus remains underdeveloped.

Kleinman et al. (2021)looked at the role of self-regulated learning in esport games, specifically *League of Legends* (Riot Games, 2009) and it's effectiveness for learning across expert, non-expert, and novice players. Self-regulated learning (SRL) is described as a type of learning in which the students decide what and how to learn skills, usually without a teacher. They found that novice players discussed process goals, statements regarding management of opponent and creep positions, significantly more than expert or non-expert players. They also found that the experts and non-experts had significantly more structured routines for their practice than novices. However, they found no significant difference in SRL between skill levels.

Payne et al. (2017) conducted a pre-/post-manipulation laboratory experiment with 350 participants which examined the learning effects of watching other players play. Participant performance was measured by the number of "last hits" players got on minions within the first 10 minutes of the game. Overall, they found that participants significantly improved in performance when given an expert of novice video as help over nothing. However, participants only seemed to benefit from learner-learner interactions with a novice video over just a novice video. Payne et al. demonstrated that one of the activities benefited from learning was to watch other players of varying levels. However, players not only need to learn, but also master skills.

Players may possess knowledge or skills that help improve performance, but in order to successfully and consistently execute these competencies, they need to practice them. Practice refers to the repetition of specific skills in known contexts in order to improve ones efficacy when performing the skill in the future. Toth et al. (2021) demonstrated that practice is beneficial for all skill levels. They found that those who trained, regardless of skill level, significantly improved their rank and skills in comparison. They also found that the amount players improved over the 5-day training protocol was much better for non-gamers (those who had never played *CS:GO* before).

Beyond watching others and practice, there has been some research into how players help one-another. Looking at a vocational school's *CS:GO* team, Rusk et al. (2020) analysed the meaning-making and learning practices of the team through a dialogic approach. Over a period of seven matches and four interviews, they focused on the relationship between the team leader, Martin (mentor), and a novice to the team and game, John (apprentice). Rusk et al. highlight three processes of teaching and guidance that are used by Martin: orienting the apprentice towards previous learning, reminding teammates of the apprentice's position as a novice, and placing the apprentice as an important contributor to the team. This highlights the potential for social learning that team-based esport games can facilitate.

Finally, learning and mastery can be difficult beyond the physical and cognitive requirements. Motivational factors can play a key role in performance improvement, as highlighted by Iwatsuki et al. (2022). With the intention of helping esports research prioritise effective optimisation of esports performance, they emphasize two important motivational factors, from movement science and psychology, which have been shown to enhance an individual's ability to perform physical tasks (motor skills); increased expectancy of the learner for successfully performing physical tasks, and providing control to the learner over their practice in the form of autonomy support.

2.3.4 Conclusion

This thesis splits esports game learning research into three categories: learning resources in esports, competencies in esports, and learning processes in esports. Most learning resource research focuses on the use and efficacy of spectatorship for learning, finding learning to be a large motivation as well as spectatorship being effective for learning in some circumstances. Relevant competencies highlighted in esports game learning research seem to focus on five groups of competencies: physical competencies, cognitive competencies, game sense, social competencies, affective competencies. This is not exhaustive. Finally, a number of learning processes have been raised in esports game learning research, with the main focuses being on practice, modeling, and apprenticeship.

2.4 Conclusion

Games and learning is a large field of research sitting at the intersection of games research and education, spanning the well-developed area of game-based learning, where players learn knowledge and skills external to a game, and the topic of the present thesis, game learning, where players learn knowledge and skills for the game.

Esports game learning is a small subsection of the field of game learning with limited research which can be organised into roughly three topics: learning resources in esports, competencies in esports, and learning processes in esports. Competencies in esports game learning largely looks at the knowledge and skills that expert players possess (e.g., Fanfarelli, 2018; Li et al., 2020; Pluss et al., 2020). Learning processes research in esports game learning highlights different ways that participants learn to play and master games, including watching others (e.g., Adamus, 2015; Payne et al., 2017), playing with others (Frederik Rusk, 2020), and practicing (Toth et al., 2021). Finally, the resources players utilised to learn has been explored by looking at the media technologies players leverage (e.g. *Twitch*) (Kow & Young, 2013; Payne et al., 2017; Robertson et al., 2020; Sjöblom et al., 2017) as well as how games can help players learn (Johanson & Mandryk, 2016).

Due to it's limited research, esports game learning contains many gaps that require further exploration or validation especially with regards to the learning path a player takes when learning a game (Mora-Cantallops & Sicilia, 2018): Firstly, the importance of competencies for playing an esport game changes over expertise level (Thompson et al., 2013). This means that many competencies relevant to experts, which research tends to focus on, may be of limited use to novice players. Secondly, some strong empirical evidence has been gathered on a few learning processes, but does not provide an exhaustive picture of all potential processes. For example, how do players turn knowledge into skills? Thirdly, there are still questions about streaming platforms and how players best learn from them. If players learn equally from novices and experts equally, does that also mean players learn equally from intermediate players? As well as that, what other aspects of spectatorship may be relevant to learning?

The popularity of *CS:GO* and *Dota 2*, the open access availability to gameplay data, and the ability to modify both games for custom gamemodes and maps means there is a wide breadth of potential research opportunities available that are both feasible and important. Due to the aforementioned gaps in competency, process, and resource research for novices, the research question of this thesis focuses primarily on novice players. Novices tend to watch esport games either to learn how to play (Sjöblom et al., 2017) and have been known to benefit from watching other players of all levels (Payne et al., 2017).

However, what makes spectatorship helpful for learning and it's relationship to other learning processes is still an open question. Answering this question could be beneficial for developers and content creators of team-based esport games. Developers would benefit from understanding which methods of learning and teaching are effective for novice players. This can help to avoid player churn which in-turn then provides affective (e.g. more players playing the developers creation) and financial benefits (e.g. longer a player plays, the greater the potential for them to pay for extra content). Content creators would find answers beneficial as they can integrate any effective teaching methods into their content to make it more helpful and, potentially, popular.

Chapter 3

Learning to Play a Team-Based Esports Game: Processes, Tools, Outcomes

3.1 Introduction

Whilst learning to play esport games by watching others is an observed desire (Sjöblom et al., 2017) and a promising method of learning (Payne et al., 2017), it may not be the only or even best way to learn. Many studies have explored different methods or theories of learning in games, but none have looked holistically at all the different methodologies non-professional players incorporate into learning how to play or mastering esport games. The first study of this thesis provides a foundation for future esports learning research to build upon by constructing an overview of how players learn to play esport games, more specifically team-based esport games. This is done with interviews with players of two of the most popular team-based esport games, *Counter-Strike: Global Offensive* (Valve & Hidden Path Entertainment, 2012) and *Dota 2* (Valve, 2013).

This study was approved by the University of York TFTI ethics committee. Participants were not reimbursed. Interview transcripts and *MaxQDA* coding tree are available at https://osf.io/hyxqp/.

3.2 Background

Only four studies could be found to date that looked into the actual learning processes in esport games. Only one of which was an early survey study taking a bottom-up perspective - an early survey identified training foci the esports community considered to be important, such as teamwork, concentration and anticipative thinking, (Adamus, 2015). Looking at processes, Nargorsky and Wiemeyer (2020) developed and tested an integrative model of performance and training across a range of esports games. Toth et al. (2021) found that practice significantly improved performance in *Counter-Strike: Global Offensive* (Valve & Hidden Path Entertainment, 2012) for players of all skills levels. Finally, Kleinman et al. (2021) examined the difference in meta-cognitive processes between skill levels when practicing last hitting in *League of Legends* (Riot Games, 2009). They found that more advanced players would set outcome-oriented goals before play significantly more than novices as well as having significantly more structured routines than novices. In contrast to these top-down approaches, there is limited research using a bottom-up approach to understanding how players learn to play games, let alone how players learn to play esport games.

Using qualitative methods for finding player learning processes has not been widely applied to esport games, meaning there is little knowledge or consensus on what players do to learn an esport game. This gap in research would be beneficial to fill as it can set a foundation from which further empirical research can explore the effectiveness of different strategies, activities, and processes for learning. Since there is no research on all the learning activities involved in learning an esport game, this problem lends itself to an exploratory qualitative methodology that allows the flexible construction and testing of themes and categories. The appropriate methodology for this problem, and one that is said to be lacking in games based research (Salisbury & Cole, 2016), is grounded theory.

Grounded theory is a popular qualitative methodology that focuses on developing theoretical models explaining social activities "grounded" in the reports of those who have experienced them (Ritchie et al., 2013). The reason for using grounded theory in this study is that it is a well-established and robust methodology for developing theories and understandings of sociological phenomena, which is useful for under-developed areas of research (Braun & Clarke, 2013; Ritchie et al., 2013). The defining features of grounded theory set out by Glaser and Strauss (1967) include; the parallel collection and analysis of data, codes and categories based on the data rather than predetermined hypotheses, continuous comparisons of codes and data at every stage, writing memos to elaborate on codes (e.g. finding relationships, gaps, or properties), and testing and evolving theories at each step of collection and analysis.

Since grounded theory first emerged, it has been picked up and developed by many different philosophical frameworks into different schools of grounded theory. The one school utilised as the foundations for this study's methodology is constructivist grounded theory outlined by Kathy Charmaz in *"Constructing Grounded Theory"* (2014). Constructivist grounded theory is motivated by the overarching assertion of constructivism, that scientific knowledge is not discovered or found but constructed by individuals and participants in research. Therefore, constructivist grounded theory incorporates current literature relevant to the question and researchers' prior experiences and knowledge. Due to my involvement in esports and game learning research as well as my prior experiences playing esport games, it seemed vital that my perspective, biases, judgements, and prior experiences also be examined and involved during data collection and analysis. As well as that, since knowledge is constructed both by researchers and participants, constructivist grounded theory is particularly helpful to reconstruct knowledge that participants have constructed themselves such as, in this case, the best methods for learning how to play.

3.3 Experimental Method

The aim of this study is to explore how players learn to play esport games, specifically *Dota 2* (Valve, 2013) and *Counter Strike: Global Offensive* (*CS:GO*) (Valve & Hidden Path Entertainment, 2012). *Dota 2* and *CS:GO* are used as they are two of the most popular games in two of the most popular genres of esport games, multiplayer online battle arenas (MOBAs) and first person shooters (FPSs) respectively (Newzoo, 2021). Whilst this study did not generate theories of learning, it utilised the parallel collection and analysis of data, memoing of codes, theoretical sampling to test codes and memos, and data saturation as outlined in Charmaz's *"Constructing Grounded Theory"* (2014). Themes and sub-themes were found through coding and tested through theoretical sampling, where participants were sampled based upon criteria that were most likely to test and break codes. A framework was developed over multiple interviews which listed the learning processes participants highlighted as well as the tools they used to learn and what they learnt.

Data was gathered through semi-structured interviews conducted by the me. These interviews asked participants to think about their "learning journey" through a game, from the first time they were exposed to the game to their most recent experiences, highlighting key learning moments that stuck out to them. Interviews were used for data collection as they can be easier for participants to provide long and information rich answers in comparison to writing. The use of a semi-structured format allowed me to explore specific interesting events raised by participants dynamically, either to examine spontaneous unique findings in the middle of an interview or to test existing memos and codes. Providing participants with the concept of a "learning journey" allowed them to focus on aspects of learning and mastering a game they found personally important as well as providing them with a structure from which to nurture the recollection of memories, something that can be difficult to do without a prompt or structure (Braun & Clarke, 2013).

At the beginning, participants were sampled randomly with the only criteria being they were 18 years of age or older. When themes and subthemes started to emerge from codes and memos, participants were then sampled based upon criteria that would maximally test these themes. For example, when participants with more hours in-game would discuss the use of videos and streams for learning, participants with fewer hours in-game would then be sampled and the subject of videos and streams would be probed in interviews, either naturally through the interview or at the end if it was not discussed during. This freedom allows for a quicker and more efficient iterative process in the construction and development of themes.

3.3.1 Participants

All participants involved had to be at least 18 years of age and have played some amount of *Dota 2* or *CS:GO*. Participants needed to be at least 18 years old as the PEGI rating for *Dota 2* and *CS:GO* are 12+ and 18+ respectively, as well as ethical reasons of informed consent. Participants were sampled through advertisements on /r/dota2 and

/r/globaloffensive, *Twitter*, and through public and private *Discord* groups dedicated to games, *Dota 2*, or *CS:GO*. Players of all levels of experience were welcomed to participate. Those who registered interest in the study were asked to provide contact details and the number of hours they had played their respective games. This information was kept by and only accessible to me.

During initial interviews, participants were interviewed on a first-come-first-serve basis to generate initial codes. As codes were generated and themes started to emerge, participants were sampled from the pool of interested players based upon what game they played and what amount of experience they had in the interest of challenging and breaking the codes. This process of iterative purposive sampling was carried out until the themes had reached theoretical saturation, such that new data was no longer challenging or breaking the current themes. Whilst grounded theory usually aims to develop a model of some phenomenon through purposive sampling and theoretical saturation, the aim of this study was not to develop a model but to explore what players reported when learning to play.

3.3.2 Materials

Interviews were either conducted online through *Discord* or in person. Online interviews were recorded using *OBS* and in person interviews were recorded using a phone microphone which was restricted from uploading any audio files to any cloud services. Whilst *OBS* recorded video and audio, no input was given to the video. Audio recordings were then listened to and anonymised in *Audacity* by me before being made available to other collaborating researchers. When participants referred to other people by name, the names were replaced with "Friend X" where X is the order in which the friend was mentioned.

Transcription of interviews was done solely by me. After anonymisation, the recordings were uploaded privately to *YouTube* on a University of York Google account to generate a transcription from Google's caption system. The generated transcriptions were downloaded from Google, cleaned of timestamps and formatting, and then formatted by me. The transcribed interviews were then coded using *MaxQDA*.

3.3.3 Procedure

Interviews began by asking participants to provide their name, age, nationality, gender, confirmation of the game they would be discussing, the number of hours of the game they estimate they've played, and an approximation of their skill level either by comparison with the general player-base or with their highest in-game rank.

Interviews, from this point onwards, were fairly unstructured and open ended. The overarching narrative of the interview was to go through the participants' learning journey of their game. Participants were asked to think over the total time they've played and go chronologically over key moments of learning that they can recall. This would span from their first memory of learning to their most recent learning experience. For each key moment that was brought up by participants, these moments were explored further by questions aimed to either elucidate and explore these moments or to test and break emerging themes from the analysis. After a key moment was sufficiently explored, the participant was asked to move onto the next moment, and further questions were then asked.

ID	Age	Gender	Nationality	Game	Total Hours Played
CS1	24	M	NL	*CS:GO*	8
CS2	18	M	UK	*CS:GO*	600
CS3	20	M	FR	*CS:GO*	920
CS4	19	M	NL	*CS:GO*	1500
CS5	20	M	CA	*CS:GO*	1860
CS6	19	M	USA	*CS:GO*	2000
CS7	18	M	UK	*CS:GO*	5500
Do1	20	M	UK	*Dota 2*	30
Do2	22	M	UK	*Dota 2*	1840
Do3	27	M	UK	*Dota 2*	3000
Do4	29	M	GR	*Dota 2*	4000

Table 1: Participant IDs paired with their age, gender, nationality, game, and hours played. CA = Canada, FR = France, GR = Greece, NL = Netherlands, UK = United Kingdom, USA = United States of America.

3.4 Results

A total of 11 players were interviewed, of which 4 played *Dota 2* and 7 played *CS:GO*. Participants ranged in age from 18 to 29 years (M 21.45, SD 3.70). All participants were male, which is an unfortunate outcome from advertising the study through *Reddit*, a primarily male platform (We Are Social et al., 2022),the current demographics of esport games, which is also primarily male (Interpret, 2019), and my own blindspot of the impact of gender on esports participation attributable to my background and privilege. Participants are given in Table 1, with age, gender, nationality, game they were interview on, and hours they have played each game.

Interviews were held between January and June 2019. The average length of an interview was 50 minutes, with 550 minutes of recorded interviews in total. The upper bound for the word count of the transcripts was 10,529 and the lower bound was 2,276 with a mean word count of 6,360. Unfortunately the first half of the interview for Do4 was not recorded. In the second half of the interview, the main points raised by Do4 were then brought up by me when the recording started again and was affirmed by Do4. The full anonymised transcripts of interviews can be found at https://osf.io/hyxqp/.

Three high level categories were constructed, each with subcategories: learning processes, learning tools, and learning outcomes. A summary of constructed categories is given in Figure 3. For each category, I report the number of transcript segments (in the following, 'units') that were coded. I will present each of these categories and sub-categories below, illustrating them with select participant quotes. In quotes, fillers such as "like" and "you know" that do not add to the quotations are removed. Square brackets within quotes are author additions for clarification and parentheses are approximations during transcription. When people are mentioned, their name is changed to *"Friend X"*, where *"X"* is the order in which they were mentioned in the interview.

3.4.1 Learning Processes

Participants indicated that learning to play and improve was a continuous process within and outside of play. This reflects the evolving nature of esports games where players need to continuously learn and improve to continue winning. I identified four learning processes: *identifying* what to learn; *consuming* information through media; *applying* knowledge or skills in new contexts; and *practicing* in familiar contexts. Within each process, a player may learn entirely *incidentally*, *deliberately*, or somewhere in-between.

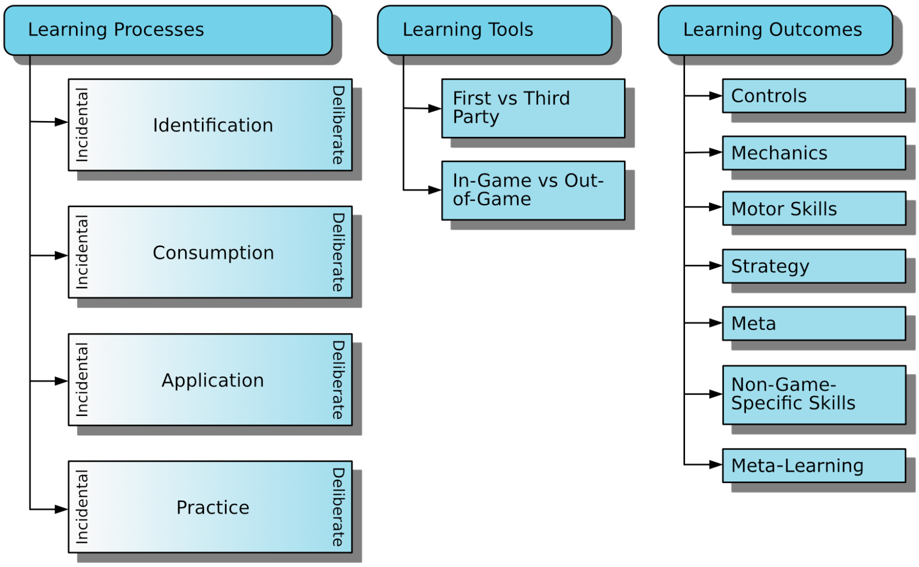


Figure 3: Overview of learning categories and subcategories constructed from player interviews. *Learning Processes* highlight the behaviours described by players when learning and involve some amount of deliberation (whether it be incidental or deliberate). *Learning Tools* divide the kinds of tools players used based upon the author and whether they are located within a game or outside of it. *Learning Outcomes* list the knowledge and skills participants highlighted as trying to learn.

Identification

Participants all spoke about learning to play as a largely self-driven process, an important aspect of which is identifying the knowledge or skills they aim to learn. This process focuses on the meta-knowledge of a player's current knowledge and skills.

Commonly, when starting *CS:GO* or *Dota 2*, participants would use prior experiences as references to identify knowledge and skill gaps. Participants who played *CS:GO* often spoke of similar FPS games such as the *Call of Duty* (e.g. Infinity Ward, 2019) or *Half-Life* (e.g. Valve, 1998, 2004) franchises, while those who played *Dota 2* compared it to other MOBAs or Real-Time Strategy (RTS) games such as leagueoflegends and *Starcraft* (Blizzard Entertainment, 1998, 2010) respectively. These comparison points allowed participants to articulate the knowledge and skill gaps they have within a new game.

> *"I was really used to those games you can run and gun... And in Counter-Strike that's really different, you have to stand still to aim." (CS4)*

When reflecting on previous games, participants started to notice areas that would benefit from improvement or aspects of play that needed to be learnt. These reflections were mainly fuelled by the outcome of matches, but were also discovered by observing the success or failures of another player. These players may have been other players in the same match as them (teammates or opponents), content creators, or professional players. When comparing their team to what they saw with experienced CS:GO teams, CS6 says:

> *"Another thing that I learned a lot was [...] I wasn't talking to my teammates. My teammates (weren't) talking to me. [...] It's very easy to lose that way versus people who do communicate with each other." (CS6)*

Not only did other players provide reference points for a participant's own reflections. They also helped by highlighting things participants needed to learn. Whilst the majority of these moments of highlighting were provided by friends, participants also gave examples involving strangers in the same match, content creators, and professional players.

> *"I think it was [Friend One] again who mentioned [weapon spray]." (CS1)*

> *"Friberg [a famous CS:GO player and streamer] even streamed about it [an aim training map] a long time ago, [...] everybody just suggested use it." (CS7)*

A major moment where participants identified they needed to improve was when their progress stagnated. This tended to prelude looking for information and resources to help players improve, reflecting on what it is they need to improve. Below, both CS7 and Do3 highlight moments of stagnation and a requirement to improve. Do3 discusses a *"pattern"* of *"playing Tidehunter"*. Do3 is indicating that they are playing the same hero, Tidehunter, in the same way every match and that others can then figure out how to counter this playstyle.

> *"I just felt 'okay, if my aim seems to be good it must be something else'." (CS7)*

> *"People will see this pattern with me playing Tidehunter every game. So I need to learn new heroes." (Do3)*

Consumption

This category describes the assimilation and gathering of information relating to game. In contrast to *identification*, which is concerned with knowledge relating to a player's own skills, *consumption* is concerned with skills or knowledge relating to the game itself. When learning to play *CS:GO* or *Dota 2*, players commonly learnt a lot by *consuming* various streams of information concerning a game, either as recommendations by friends and other players (such as teammates and opponents or through forums and websites), or as videos and streams from content creators and professional players/tournaments.

Participants learnt through *consuming* explanations by other players they played with. These included friends or strangers either on the same or opposite team. These explanations arose either when a participant would ask someone to explain something (*"Well I asked in the game chat and somebody explained to me that there's a weapon shop." (CS1)*), or unprompted, other players noticed that participants were not doing something correctly:

> *"Over time, I was told by my friends that certain items have certain bonuses and that you want to build something that deals physical damage if you're playing a physical damage character." (Do1)*

Another information source were materials provided by the developers.Thus, Do1 describes how the classifications and layout of heroes provided by the developers in-game and as online text helped them decide which hero to choose and which they wanted to learn first in *Dota 2*. This also helped them figure out what role the hero commonly plays in the team. For example, Do1 explains how the hero select screen groups heroes into 3 *"sections"* based upon whether they are designed to take a *"ranged"*, *"specialist"* or *"tank"* role:

> *"So you've got the different areas; ranged, specialist, and tank [...] it's like different characters laid out into different sections. That kind of helped a lot in learning what characters go where." (Do1)*

The most common way that people learnt from others was watching content creators, professional players, and professional events. Watching professional players stream on their own personal channels, especially those who would explain what they were doing, was a common and important part of learning to play. As well as that, commentators of professional tournaments would provide contextual information that would be useful for understanding what was happening in a match and why. Says CS7: *"You had someone like friberg who, at that point, was a legend in the best Counter-Strike team ever telling you how to learn something" (CS7)*

Commentators of professional tournaments would provide contextual information that would be useful for understanding what was happening in a match and why: *"The commentators really help talk you through [strategies] [...] and you can actually see what the team does with that little thing in mind." (Do2)*

Notably, watching professional players and content creators was found to be important for learning by participants who had played for longer. Participants who were newer to *CS:GO* and *Dota 2* found watching video tutorials or professional games overwhelming when they first started to learn. CS1 and Do1 both reported having frustrations with learning through this way or actively choosing not to engage with it.

> *"I looked at YouTube. But it's way too much to take in. It's gonna be experience and probably watching content creators more, often watching streamers. I think that's the only way to learn." (CS1)*

> *"I didn't go and watch any videos or anything. And there wasn't much in-game to show how you should play these characters, it was more you pick a character and the game kind of wants you to learn it and if you want to learn more [you're] gonna have to go out to outside sources such as YouTube videos or live streams." (Do1)*

Application

After *identifying* and/or *consuming* new knowledge, participants would then attempt to implement these in-game. This process of *application* can be thought of as putting explicit knowledge into practice. As well as *applying* existing knowledge in situations where it is known to be useful, participants also reported experimenting or exploring with the *application* of existing knowledge and skills in new contexts.

Knowledge implementation was one of the most common forms of applying knowledge and skills amongst players of all skill levels.

CS5 and Do1 discuss their attempts to implement knowledge into their gameplay:

> *"I remember looking up the spray patterns, googling them. And then trying them out in game." (CS5)*

> *"I didn't pull [it] off as well because, obviously, the people I watched were much better but the information was still there and I did try to mimic it in a way." (Do1)*

Participants also highlighted moments where they would either explore or experiment with their existing set of knowledge and skills. This more exploratory side of learning generally was labelled 'trying things out' or 'trial and error'. Within the context of our framework, the *application* of the knowledge or skill can be thought of as the trial and the *identification* through reflection as the error. Participants would have an idea of what scenarios they wanted to try and set up in-game to experiment with ideas. They would also find moments where they would not know what to do. In these moments, participants often spoke about trying out things that either felt good, looked good, or fitted with their previous playstyles. Both Do1 and CS2 describe the process of *applying* knowledge in some new context, receiving feedback, and using that feedback for further improvement:

> *"A lot of the time [...] I'll expect not to do well. But then [...] I'll get a better idea of what order to use things. [...] So it's just trial and error basically." (Do1)*

> *"The more you die somewhere, the more you feel negative about acting in that way. [...] Then, as soon as you start to win, because you walk quieter, it's like a positive confirmation." (CS2)*

Practice

Finally, participants discussed the importance of improving and mastering existing skills and knowledge through practice. *Practice* describes the continued application of existing skills and knowledge in familiar contexts to improve existing them.

A number of examples arose which would be thought of as incidental *practice* but were not identified as *practice* by participants. These included things like playing the same heroes, using the same weapons, playing the same maps, and getting used to the controls. Participants may not have brought up those as learning moments as they may have only thought of this as playing the game. These were coded as examples of *practice*. For example, Do2 and CS4 are both describing behaviours coded as incidental *practice* since they involve continual application to improve:

> *"But I remember playing him quite a lot and it was really just sort of getting better at him and really understanding that hero." (Do2)*

> *"So I'll just go in deathmatch and just pick up the AWP and a pistol and try to hit my shots. Try to get as many kills as I can." (CS4)*

Participants highlighted moments where they would try to set up scenarios in public games or private offline sessions to *practice* a skill. This kind of *practice* tended to overlap with application and identification. Players would try to implement and improve skills they had observed either in their own games or games they watched on videos or streams. They would also *practice* and adapt skills based upon how well they applied them.Do1 discusses setting up situations in-game to *practice* a specific skill: *"It was mostly trying to get myself into situations* *where I have the enemy follow me into these areas and try and learn through experience." (Do1)*

Participants with more hours highlighted the importance of warming up. They would play casual game modes (in which player performance does not affect competitive ranking), before playing competitive game modes. Whilst participants who played *CS:GO* and those who played *Dota 2* both discussed warming up, those who played *CS:GO* tended to stress the importance of warming up more than those who played *Dota 2*. An example of a casual game mode used for practising is the deathmatch in *CS:GO*. The normal game mode in *CS:GO* is a round based mode where players have to defend or attack a site. Deathmatch has no objectives other than to get the most kills within a time limit. This allows players to focus solely on getting kills, which requires good aim accuracy and spray control. CS5 uses deathmatch as an example of a casual game mode to *practice*:

> *"I go into community deathmatches and just practice your aim because a deathmatch won't affect your rank, it won't affect anything. You can just play a little [...] it's practically casual but without planting or something and you just stand there and shoot. And that's how we warm up." (CS5)*

Finally, there are training environments outside of the main gamemode developed by community members that participants (especially those with more hours) would utilise to isolate and improve specific skills. These are discussed further in *Learning Tools* (Section 3.4.2). Aim and recoil training maps in *CS:GO* were brought up by all participants who played *CS:GO*. CS3 discusses these training maps, as well as highlighting their popularity amongst their friends:

> *"I know a lot of people that use workshop maps, so maps made by the community to improve their aim and one of them is called*

aimbotz and basically it's just bots standing and you shoot right, right, left, left and right, left and right." (CS3)

Cross-cutting Dimension: Deliberation

Participants of all levels brought up whether they were deliberately trying to learn something or were learning passively. Whilst participants spoke about whether they were deliberately trying to learn or not, it seemed that the amount of *deliberation* participants put into their learning varied along a spectrum.

Participants, especially those with fewer hours in game, often described behaviours that could be considered to be learning but did not identify them as such. These examples were coded as *incidental* learning. For example, it was common for participants to discuss moments where they would be playing or watching without the intention of learning. Incidental learning seemed to either involve doing things without any intention of learning (e.g. purely for entertainment) or with the hope of learning but without deviating from play to try to learn. CS7 and Do3 both highlight some aspect of *deliberation* involved with learning. CS7 discusses in more detail their thoughts on *deliberation* when consuming esports:

"To be honest, now I watch pro games for a different reason most of the time. I've noticed there are [...] two ways of watching something. Just watching it statically, like not actually engaging with it, just watching it like you'd watch a movie, for instance, or a TV show and you're just tired and you just want to relax. Or there's watching a Counter-Strike game and actively trying to analyze what the teams are doing." (CS7)

"I just played the same heroes again and again and just wasn't really actively learning." (Do3)

Participants with more experience expanded on learning episodes that were more *deliberate*. Examples of this include trying to set up their own scenarios in matches, watching streams or videos of professional players, and using custom maps and modes for practice. Players with more hours in-game seemed to participate in more *deliberate* learning such as analysing professional tournaments, practising skills in private or custom game modes, and warming up before play. For example, Do1 has fewer hours in *Dota 2* than CS7 in *CS:GO* but both engage in some sort of *deliberate* learning:

> *"It was mostly trying to get myself into situations where I can have the enemy follow me into these areas and try and learn through experience." (Do1)*

> *"If there's new things that we want to add, I explain the things and then I show them right in the game. [...] I show them those things that I want us to do and then I respawn them and we all do them. So we dry run. Just practice and repetition." (CS7)*

3.4.2 Learning Tools

Learning tools are defined here as anything participants mentioned using to help them learn to play. Participants utilised a variety of learning tools from a diverse range of sources to help them learn to play. The sub-categories that emerged when exploring learning tools were the creator of the tool (Developer or Third Party) and where the tool is based with respect to the game (In-game and Out-of-game). The most important tools were those used to communicate between players, especially text and voice chats. The learning tools and how they split across these two categories are given in Table 2.

Participants described a variety of tools and systems that developers have included in *CS:GO* and *Dota 2* to help them learn how to play

Tool Author / Environment	**In-Game**	**Out-of-Game**
Developer	Game Modes (e.g. casual, competitive, and private) Training environments Tutorials In-game guides Spectator Modes Match Replays Ping System Text and Voice Chat	
Third-Party/ Community	Custom Game Modes Training Environments Custom Scripts In-game guides	Text and Voice Chat (e.g. Discord, Team Speak) Streaming Services Forums Stat Services

Table 2: The learning tools brought up by participants. Tools are organised in relation to the author of the tool and the environment they are situated within.

the game. One tool that has been included in the game specifically to help players learn to play is the tutorial. However, tutorials were only brought up by one participant. Tutorials are usually played at the start of a learning journey and it may be that participants do not remember playing the tutorials provided. Do2 was the only participant who brought up a tutorial despite both *Dota 2* and *CS:GO* providing tutorials for new players.

> *"[The tutorial] would take you into a premade map that was different from the actual Dota map and it would say 'hey, the creeps are attacking' and 'click here to move and position yourself to shoot them'." (Do2)*

Dota 2 and *CS:GO* allow players to download replays of their games and even games of professional players. Players can follow and watch other players, including opponents, to analyse their movements and behaviours. These tools were commonly used by participants when they had more hours in the game. They would stress their importance to newer players, who would often not listen to the participant's advice. For example: *"One of the things [Friend Two] always suggested for me to do was to download replays of high level players and just watch them. I didn't do that as much as I should have done." (Do3)*

Participants would utilise the spectator tools during play, allowing them to watch their teammates. *Dota 2* has a free camera that is detached from the player's hero and allows them to look anywhere on the map at any point in the game. Players can look at what their teammates are doing but cannot see opponents unless they appear close to a teammate. In *CS:GO*, players who have been killed during a round can watch a teammate from their perspective. Not only was this reported to be a useful learning tool, it was also used as a teaching tool where higher level players could help guide lower level players. CS6 discusses how they used the spectator feature in *CS:GO*:

> *"Whenever you go down you can spectate your teammates. Which is an extremely useful teaching tool. [...] When we would die, we would watch our teammates and you know tell them that 'oh, this angle would probably be better'." (CS6)*

Participants indicated that learning mostly occurred during play within the game modes provided by the developers. Game modes refer to different rulesets players can play with in their games. Participants highlighted the safety of learning in casual game modes. Casual is usually used in contrast to a competitive game mode. In competitive game modes, players are given a public match-making rank (MMR) as a representation of their skill-level. Due to the percieved importance of MMR by players, there is often pressure to perform well in competitive game modes. The performance within and outcome of casual game modes do not affect a players MMR. Therefore, due to the lower cost of losing, participants felt less pressure to perform in the casual modes where their MMR would not be affected. Players also found that casual game modes gave them freedom to play the way they wanted to and allowed them to apply or practice specific knowledge or skills. For example, both Do2 and CS3 talk about learning through casual game modes:

> *"When I was learning the game initially, a lot of it would be through just repetition of playing. I would play unranked matches." (Do2)*

> *"And (Arms Race) was really funny because I was playing each and every weapon of the game so I could learn almost all of them." (CS3)*

Participants brought up community or developer authored information in-game that was helpful for learning and improving. Players of *Dota 2* have access to guides that organise information to let them know how to play specific characters. Whilst the default guides are developer made, participants spoke about how they utilised community made guides. Guides show players what items they should buy for their hero, as highlighted by Do3:

> *"When I first started playing, I would buy those items because they were on the guides." (Do3)*

Participants who played *CS:GO* spoke about training environments developed by community members that allow players to practice specific skills. These environments allow players to set up practice scenarios without the pressure of player opponents. *Dota 2* has a training environment known as the Last Hit Trainer, which was included by Valve. Only Do2 brought up the Last Hit Trainer in interviews. Training environments appear to be commonly used for practising specific motor skills such as aiming and timing. They would also be used for learning and practising where and how to throw the best utility, as illustrated by CS4:

> *"And I also used a map for [utility] [...] That's the second thing I just played all day, except for matchmaking. You can practice everything with that and with almost every map in the game, that's important." (CS4)*

Learning how to play also occurs outside of play and outside of the game. The most popular external tools participants discussed were streaming and video services like YouTube and Twitch. Players can watch professional tournaments, professional players, or content creators either play or teach *CS:GO* and *Dota 2* on these platforms, also referred to as tutorial videos. Participants brought up professional tournaments or players as important, for learning, as discussed by CS6:

> *"Absolutely there was, which is a big thing in the pro scene as well which we picked up on after watching esports teams and other pros play on YouTube and watching their twitch streams they had designated people." (CS6)*

Finally, participants highlighted a strong importance of communication for learning to play by chatting with other players and friends. *CS:GO* and *Dota 2* provide in-game text and voice chat which was often used for learning from or teaching of other players in your match. However, participants tended to utilise third party platforms, such as *Discord*, *Team Speak*, or *Mumble*, for facilitating communication between friends. For examples of in-game and out-of-game communication:

> *"Well I asked in the game chat and somebody explained to me that there's a weapon shop. (CS1)"*

> *"And there's been a couple of times where we've all got in discord and just watched [Friend Four] play." (Do3)*

Another tool for communication that *Dota 2* provides is the ping system. This allows players to place a temporary marker or drawing on the map with some contextual prompt that will notify other teammates. Players can then highlight important information or areas of interest without interrupting conversations over voice. As Do1 notes:

> *"If you're having a conversation with somebody and you don't want to interrupt it to just say 'someone's been missing', you can quickly do a ping to say 'this person's here' or 'this person's missing' or 'there's something's come up' like one of their runes or camps or something." (Do1)*

3.4.3 Learning Outcomes

Learning Outcomes describe the knowledge and skills that players identified, applied, and practised when learning to play games. They are here presented in the order that they usually appeared in participants' learning journeys - from the start until most recently. This does not mean that this is typical of learning experiences in these games. Table 3 highlights the categories of learning outcomes, providing definitions, and examples of skills or knowledge that come under each category.

The first thing participants learnt were the controls. As well as learning what inputs relate to which in-game actions, participants also spoke about "getting used" to the controls. Examples brought up by CS1 and Do2:

> *"I think most of the controls are pretty standard in Counter-Strike, the only big difference is that you don't have a sprint but you have a slow walk instead. And that's something I generally messed up in the beginning quite often." (CS1)*

> *"[The tutorial is] useful in that it gives you a space to get familiar with the input of the game and the controls [...] they were a really good function for that and familiarising yourself with a couple of the heroes so you just get an idea of how this hero interacts with the world." (Do2)*

The next learning outcome mentioned are mechanics: the rules of play and the game logic. Similar to controls, these also need to be internalised through practice. Do1 and CS6 both talk about learning mechanics in their respective games:

> *"I would read through all of [the abilities] because it shows you an outline of what the ability will do. So, if it's a range attack, you*

Categories	Definition	Examples
Controls	The available controller inputs and their relation to in-game actions.	Keyboard for abilities, mouse for aiming
Game Mechanics	The game logic and rules of play.	Win conditions, last hitting, weapons
Motor Skills	Physical movements and reactions and their relation to in-game actions.	Muscle memory, reflexes
Strategies	Manipulating and responding to the game state.	Map knowledge, positioning, utility line-ups, creep management, item shopping
Meta	Knowledge of current best practice with regard to strategy.	Expected and efficient positioning and movement, team composition
Non-Game Specific Skills	Knowledge and skills shared outside of games.	Specialising, leadership, keeping calm, communicating effectively
Meta-Learning Skills	Reflecting on and improving how to learn and improve.	Killing bad habits, utilising practice environments, utilising media more effectively

Table 3: The different categories of learning outcomes found, including definitions and examples that were raised by participants.

> *have the width of the projectile and the range of it. Or, if it's like a range attack, then it will show you the range of it around you. So, looking at that, and then just trying out the abilities." (Do1)*

> *"Because there's a lot of different aspects that I didn't understand were in place, which were smoke grenades, fire grenades, flash grenades, stuff like that. And that was really the first thing where it was like 'oh, I have to take a second and understand what (all) is going on here.'" (CS6)*

Participants next discussed motor skills like reflexes, aiming, and movement. Motor skills were usually *practised* in specialised maps and game modes. Players of *Dota 2* did not often raise these skills, however Do2 does indicate that the need to press the right inputs quickly is an important thing to learn. CS6 also comments that these skills decayed over time when they were not *practised*.

> *"You're just training your muscle memory. In aimbotz, it's a little bit more dependent on your eyes, but it's still muscle memory where you're practicing all these little micro movements." (CS5)*

> *"'They're pressing the button really fast here to pull off this move' and I understand that they're doing it, but to learn that that you can only really learn that through practice." (Do2)*

> *"I say that my skills mechanically as a player declined during year three [...] we would take breaks in between the game month on month off. [...] Definitely mechanically like aiming, jumping, throwing grenades, remembering which spot is which, stuff like that. That definitely fell off." (CS6)*

Participants found that learning how to manipulate the game rules to their advantage and how other players, both teammates and opponents, act, react, and interact with each other was the next focus for learning and improvement. These were commonly described together under strategy. Participants indicated that players require a strong theory of mind of other players and they could utilise that to their advantage. Two participants, both of whom talked about *CS:GO*, referred to this as "game sense". This understanding of how teammates and opponents would react to one's actions also helped participants learn the correct amount of information to communicate. Participants mainly learnt about strategies through watching professional tournaments, professional players, and through their games with other players. Do3 and CS3 highlight strategies below:

> *"It's like 'I died, but they put so many resources into that, and I'm actually about to get more or less everything back out of it by teleporting into the tower and just getting this huge creep wave that's coming at me'." (Do3)*

> *"And this is a really really interesting point. I'm the in-game leader for small team, and so I have to play this chess game with my opponents." (CS3)*

Participants then brought up aspects of competitive play that some would call the meta. Here, meta refers to common knowledge of best practice with regard to strategy. Examples included moving through lanes in particular ways or spending and saving money on items or weapons at particular points. The meta seems to be fuelled by the community, with professional players pioneering new strategies that become popular at lower levels. The meta was referred to by name only by participants who had played *Dota 2* whilst participants who played *CS:GO* would talk about learning outcomes that fit the description of the meta, but do not describe it as the meta. Do2 discusses the prevalence of a meta in esports. CS1 discusses the meta of movements and what you're supposed to do as one of the sides.

> *"There's gonna be a meta that emerges in most of these esports because that's what gives the game their longevity." (Do2)*

> *"I discovered that the terrorists and the counter terrorists have different tactics. The terrorists are supposed to more group up for an objective, while (as) counter terrorists you're supposed to split up." (CS1)*

The previous outcomes all refer to game-specific knowledge and skills. The next set of outcomes are those which I describe as non-game-specific skills. Since *CS:GO* and *Dota 2* are team based games, both require teams to coordinate and work together in order to help out-perform the opposing team. Team communication was important, but understanding when to provide feedback and how to communicate effectively were two examples of other non-game specific skills participants referenced. As CS7 highlights:

> *"I was also taught the basics of team play, so that you can't just go it alone places, you can't just play in pugs and in (faceits) and in matchmaking." (CS7)*

Lastly, participants would reflect on and improve how they learnt their respective game. This is what I refer to as meta-learning. Participants focused on what they did wrong and what they could have improved upon when trying to learn knowledge or skills. Whenever they had learnt the wrong things, they would then need to eliminate 'bad habits'. One issue that participants with more hours in-game noticed when teaching newer players was the tendency of newer players to misidentify the reasons for a given match outcome. For example, players would sometimes incorrectly attribute a success or a failure to unrelated actions. Participants also brought up the importance of sharing and distributing knowledge and found that teaching led to moments of learning. Do3 highlights their meta-learning reflection on what they should've done to improve and Do4 discusses times they've been trying to teach newer players:

> *"One of the things [Friend Two] always suggested for me to do was to download replays of high level players and just watch them. I didn't do that as much as I should have done." (Do3)*

> *"When I was coaching low-level players [...] he said 'Let's do this and put wards in the jungle and we're gonna win.' [...] He didn't have any higher knowledge of his own draft, right? So, he probably won through some random factor then, while he was winning, he put some wards in the jungle and thought that the wards won him the game, where that was (all that) happened." (Do4)*

3.5 Discussion

This study constructed three high-level categories relevant to learning team-based esport games: learning processes, learning tools, and learning outcomes. It also constructed several sub-categories and dimensions within these high-level categories.

3.5.1 Learning Processes

Identification is not a common part of literature around learning of games. This could be due to the focus on single player games which can provide strong scaffolding and learning goals for players. In contrast, esports games usually lack tutorials beyond basic controls and mechanics and leave players to learn the rest on their own. However, Kleinman et al. (2021) examined self-regulated learning (SRL) in another popular MOBA, *League of Legends* (Riot Games, 2009). They observed statistically significant differences in the forethought phase, meaning expert players had structured their practice routines more than novice players. This, along with the discussions of *identification* by participants, indicates a stronger *identification* of practice habits and practice requirements by more advanced players. This study also highlights the importance of self-regulated learning within the context of informal learning environments, like learning team-based esports games.

Overlaps with *identification* as a learning process can be seen in Iacovides et al. *breakdowns* and *breakthroughs* (2011). *Breakdowns* are defined as moments where players reach obstacles that they fail to overcome. There are three kinds of breakdowns: *action breakdowns*, where players are unable to progress through inability to properly use the controls; *understanding breakdowns*, where players do not understand the current objective in-game; and *involvement breakdowns*, where a player's interest in the specific task or game is broken. In contrast, *breakthroughs* are when player's adopt strategies that help them to overcome obstacles found at breakdowns.

Breakdowns and *breakthroughs* have strong overlaps with the learning process of *identification*. All participants discussed moments where they reflected on their own, or other players', behaviours and discover new learning outcomes, changing their own behaviour to learn or master them. These very much reflect *breakthroughs* in their learning journey. As well as that, one particularly important moment in a learning journey was when participants noticed their performance stagnate. These moments demonstrate an *action breakdown*, where participants would face a wall in their performance and progression due to their lack of knowledge or skill. *Understanding breakdowns* could also be seen in participants with fewer hours, where they would not know what they were supposed to do either to play or to improve in their games.

Where the overlap between *identification* and *breakdowns* and *breakthroughs* ends is when participants would receive teachings from others. Specifically, when participants would be taught something they did not know they needed to learn. These learning moments can occur without the presence of a breakdown. For example, CS1 discusses how they were not aware of the difference in tactics between the CT and T sides in *CS:GO*. They did not mention a moment where their progress or proficiency was blocked by some obstacle, but did discuss how this was highlighted by other players during play. This may be due to differences in learning strategies found in and afforded by singleplayer and multiplayer games. In multiplayer games, other players can spectate an individual's performance (thanks to spectating tools) and offer feedback and support (thanks to communication tools). In order for a singleplayer game to provide this level of support it would need to be able to analyse a player's performance in real-time and offer appropriate, tailored feedback. Something that is very difficult to implement.

Consumption appeared to be a large aspect of learning. It has been demonstrated that players watch other players on streaming platforms, such as *Twitch*, to learn how to play (Hamari & Sjöblom, 2017; Huston et al., 2021; Sjöblom et al., 2017; Taylor, 2018) but it is not currently known how much this form of spectatorship contributes to learning. All participants interviewed highlighted these platforms for learning to play at every level of expertise. This highlights the importance of live stream platforms such as *Twitch* and *Youtube* for learning, which are discussed more in the learning tools section.

The discussion of non-competitive game modes and training environments highlights the importance of spaces in which there is little consequence to failure for the *application* of new skills and knowledge (Shannon et al., 2013; White, 2014; Whitton, 2014). In *CS:GO*, players and members of the community have made their own spaces to apply and practice these skills (e.g., aim and recoil maps). Players of *Dota 2* have similar spaces, such as the Last Hit Trainer. In both games, developers have included casual game modes in which player performance does not affect their overall rank.

Findings regarding the role of *practice* in game learning echo seminal work by Ericsson et al. (1996; 1993) on deliberate practice and its centrality for the development of expertise in skilled human activity. Deliberate practice was defined as a structured activity undertaken with the explicit aim of improving performance, often involving tasks which are invented to overcome specific weaknesses. This definition of deliberate practice fits well under the overlap of *practice* and *deliberate* learning constructed in this study. The data demonstrates the existence of community- and developer-made activities created explicitly to enable the practice of specific skills without the distractions present in typical game modes. Whilst results of this study similarly suggest that practice is an important element in the learning of games, the overlap between *practice* and *incidental* learning extends beyond Ericsson's deliberate practice. For example, participants also discussed engineering scenarios in public or offline play to *practice* specific skills, and use of various game modes to prevent skill decay (e.g., deathmatches in *CS:GO*).

Comparing these findings on learning processes to other qualitative game learning research highlights interesting overlaps and divergences. Hung (2011) found three types of play: training, duelling, and regular play. Training sessions are contexts set up specifically for learning, enabling players to engage in *application* or *practice* of skills absent the costs incurred by losing. This kind of behaviour can be facilitated by multiple tools including casual game modes, training environments, and tutorials.

Using breakdowns and breakthroughs as a lens to analyse learning strategies, Iavovides, Cox, et al. (2014) identified five strategies participants adopted when trying to learn single player games (*trial & error*, *experiment*, *repetition*, *stop & think*, and *take the hint*) as well as three strategies specific to cooperative multiplayer games (*knowledge exchange*, *guidance*, and *surrender control or take over*). These strategies integrate well into the learning processes constructed.

Trial & error and *experimentation* was often discussed as a strategy for learning by participants. The main difference between *trial & error* and *experimentation* is that *trial & error* focuses on an open exploration of the action space available to a player, whereas *experimentation* is a directed test of hypotheses formed by *trial & error*. Both these strategies involve reflecting upon in-game outcomes of their actions and re-adjusting their mental models, which fit under *identification*. The open exploration and hypothesis testing aspects of these strategies are categorised as *application*. The use of *trial & error* and *experimentation* in singleplayer puzzle games, multiplayer puzzle games, and team-based esport games suggests a common use of and strong relationship between *application* and *identification* in game learning. Since the action aspects of *trial & error* and *experimentation* are both categorised as *application*, there may be some important differences between these strategies that are not present here because they are either not important within the context of team-based esport games or may be too subtle to differentiate in self-reported data.

Repetition was originally called *practice* by Iacovides et al. before being renamed to include repeating actions in an effort to proceed in a puzzle game, as well as using repetition to gain proficiency. This learning strategy, specifically the repetition of actions to gain proficiency, is categorised under the learning process *practice*. However, the repetition of actions to attempt to make progress is not directly discussed by participants in this study. This may be due to the fundamental difference in what "progress" means in puzzle games and competitive esport games. In puzzle games, progress is the successful completion of a section of gameplay to move forward to the next stage or level of the game. In competitive esport games, progress is more fluid and player driven. Most players will see progression as winning more games, increasing their competitive matchmaking rank (MMR), and improving their proficiency at playing the game. Therefore, repetition of actions to make progress in the context of competitive esport games is synonymous with *practice*, using repetition to improve and master skills and knowledge.

The learning strategy *stop & think* highlights moments in gameplay where players of puzzle games pause for a moment, either by pausing and stopping time in the game or not taking any actions in-game, to reflect on the current game state and how best to make progress. In multiplayer puzzle games, this was observed when one player would stop to observe the other. The reflection aspect of this strategy overlaps with *identification* and similar examples of players watching other players in-game are coded under *consumption*. Similarly to *trial & error* and *rxperimentation*, the presence of *stop & think* it's overlap of *identification* and *consumption* in singleplayer puzzle games, multiplayer puzzle games, and team-based esport games indicate a strong presence as a learning strategy and learning processes in game learning. This overlap also suggests a relationship between the two learning processes and a way in which players move between them. Actively suspending play, by not taking any action in-game, was never mentioned by participants for *identification* or *consumption*. This may be due to the fact that in multiplayer competitive esport games it is undesirable for a player to suspend play, as any time spent idling during a match gives an opportunity for other players or teams gain an advantage. However, when a player dies, they cannot perform any in-game actions until the round ends or until they respawn after a delay. This provides a moment of respite for players to utilise the spectator tools to then *stop & think* about what their teammates are doing.

Take the hint refers to moments when players would be given tips by the game, either explicitly as text or implicitly through the game's design, as to what actions they could or should take to make progress. These clues provided by the game sit under the learning process *consumption*. *Take the hint* also highlights the action of choosing to carry out the suggested action, which then comes under either *application* or *practice*, depending on whether the player has applied the action within the context before. Whilst this does indicate some relationship and movement between *consumption* and *application* and *practice*, the only example of *take the hint* in discussed by participants were the in-game guides in *Dota 2*. Whilst both *CS:GO* and *Dota 2* provide hints or tips during loading screens and in-game, participants never discussed these.

The multiplayer puzzle game learning strategies *knowledge exchange* and *guidance* both involve some amount of *identification*, *consumption*, and *deliberation*. *Knowledge exchange* categorises moments when players discussed in-game obstacles and shared feedback they gained from other strategies. This exchange of information mainly comes under *consumption* as it involves the onboarding of information from a source.

It may also come under *identification* if players were to highlight to another player a learning outcome that the player was not aware of. *Guidance* refers to moments where either one player provides instructions to the other or a player asks the other for help. Not only does this demonstrate the use of *consumption* and *identification* similarly to *knowledge exchange*, it also highlights two different forms of *deliberation* when learning. When players are asking for help, they are making a deliberate effort to learn how to progress or play. In contrast, when someone is telling a player what to do, they may not be deliberately trying to learn but are being taught.

The final strategy involved in making *breakthroughs* in multiplayer puzzle games is to *surrender control/take over*. In contrast to *guidance*, *surrender control/take over* involves a player physically assuming control over another player's character. This strategy is not mentioned by any participants in this study and does not fit into the learning processes constructed. This may be due to two reasons. Firstly, as mentioned by Iacovides et al., this kind of strategy is likely to lead to an *involvement breakdown* as players lose control over their ability to overcome an obstacle. This means that players are unlikely to learn or master the required skills for the action and is not a strategy that involves learning. Secondly, both the in-game and personal goals of puzzle games and competitive games are different. The aim of a puzzle game is to solve the puzzle and progress to the next one. The aim of a competitive game is to win matches by defeating opponents. Whilst there are exceptions (e.g. cheaters, players playing on alternate accounts to play against lower skilled players, paying skilled players to play on another player's account to improve its MMR), winning matches requires players to perform better and improve their proficiencies. Having another person take over a character to win for them defeats the purpose of playing competitive games for many players.

Looking more at learning games in general, Iacovides et al. (2014) developed the *Gaming InvoIvement and Informal Learning* (GIIL) framework to understand the connection between motivation, engagement, and informal learning within digital games. Involvement here refers to the Player Involvement Model (Calleja, 2011) and how motivation and engagement relates to learning in games. The *GIIL* model developed looks at how two different levels of involvement (micro- and macro-) leads to the ways players learn (*through play*, *interacting with others*, or *external resources*) and how what is learnt (at a *game*, *skill*, and/or *personal level*) then feeds back into the player's identity.

Micro- and macro-involvement in games refers to players engagement with the gameplay and their engagement with the larger community and culture respectively. Learning through play is therefore defined as a micro-involved activity. Learning through interacting with others externally and through external resources are defined as macro-involved activities. Whilst Iacovides et al. does state that micro-involved practice may involve interacting with other players, learning through other players is largely, if not entirely, discussed as a macro-involved activity. This positioning of player interaction as a largely external learning process is not replicated in this study. All learning processes outlined often involved interactions in-game where other players would help participants learn how to play or improve. This could be due to the heavy emphasis on communication and coordination with other players in team-based esports games. The learning processes highlighted in this study could be used to further expand the *GIIL*s learning how's with involvement as an extra dimension on top of deliberation.

Finally, the learning processes constructed in this study see interesting parallels with several constructivist learning theories utilised in game-based learning. Cognitive apprenticeship (Collins & Kapur, 2014) is one such theory used in game-based learning (Whitton, 2014, p.45-48) that postulates several different methods for an ideal learning environment (modelling, coaching, scaffolding, articulation, reflection, and exploration). *Identification* can seen as integral parts of the methods of coaching, scaffolding, reflection and application. *Consumption* can be seen as part of modelling. *Application* can be seen as integral to the methods of coaching and exploration. Finally, *Practice* does not appear to be immediately relevant to the methods of cognitive apprenticeship but may be involved in scaffolding and coaching.

More experiential theories of learning, such as Kolb's learning cycle (Kolb, 2014), Gee's probing principle (Gee, 2007, p.105), and Zimmerman's cyclical phase model (Zimmerman, 2000), have been utilised in game-based learning research (Whitton, 2014, p.41-45) and are particularly relevant to the learning processes of *identification*, *application*, and *practice*. At the core of these theories of learning are the experiences people have within the context relevant for learning (e.g. in-game in *Dota 2*) and the reflection on these experiences. The experiences themselves are generated by interacting with the relevant context, either through *applying* or *practicing* knowledge and skills in context, which are then reflected on to *identify* contradictions between reality and the model of reality within the player.

Deliberation, Learning, and Play

Participants also indicated that the level of deliberateness with which one engaged in various learning processes is an important aspect of learning. For instance, CS7 mentioned that how a player approaches learning affects what they learn. More generally, participants of all levels discussed learning behaviours that varied over a spectrum of incidental (e.g. learning by watching a professional match for fun) to deliberate (e.g. practising recoil control in *CS:GO*), although players who were more experienced reported a higher degree of deliberate practice. While I are unclear as to why differences in *deliberation* between novice and experienced players exist, as well as about the precise role of *deliberation* in game learning, I note parallels between our findings on *deliberation* and studies of expertise in sport psychology (e.g. Ward et al., 2007). Whether play and *practice* require structured, deliberate elements for effective learning appears to be an open question in the domain of sport (Baker & Young, 2014), and it is therefore likely to be less clear in the literature on game learning. However, it is evident that both incidental and deliberate types of *practice* contribute to learning.

Participants included many examples of learning moments where they described how they improved by 'just playing'. Some participants even highlighted the importance of performing activities for fun or to improve. These varying levels of 'just playing' gave rise to the cross-cutting dimension of *deliberation*. However, this gives rise to the question of what the role of play is within learning or vice versa, or whether play is separable from learning. Koster (2004, p.46) suggests that games, or more precisely fun in games, is just another word for learning. Therefore, it could be argued that even when aiming to enjoy and wind down when playing games that there is always some passive incidental learning occurring either as application or practice.

However, Hung (2011) separated regular play from training, indicating that there is some play that is not learning. Similarly, Deterding (2016) found that professional esports players would construct differences in meaning and practice between leisurely play and instrumental training or tournament gaming, which they considered to be 'not play' when it was experienced as non-autonomous. Finding this distinction between learning and play was not an aim of this study but the authors note that many of the participants tended to either blur or delineate the two.

3.5.2 Learning Tools

This study highlights a variety of tools players utilised when learning to play. The use of live stream platforms for learning is well documented. Sjöblom et al. (2017) found that two major gratifications people got from using live streaming platforms were information seeking and learning. Looking at how effective learning through *Twitch* or *YouTube* is, Payne et al. (2017) found that participants who received instruction from experts or from novices performed better than those who did not. These live streams and videos set up by Payne et al. were instructional in nature. This study found that whilst some participants highlighted using tutorial videos and streams, many would learn from watching streams that are not aimed to be instructional.

Whilst the Last Hit Trainer in *Dota 2* is only mentioned by two participants, it is seeing increased usage in academic studies. Payne et al. (2017) examined the effectiveness of learning through videos and interacting with other watchers or the teacher in *League of Legends* (Riot Games, 2009). They used the Last Hit Trainer to measure the performance of a single task, last hitting, and to eliminate any distractions of other players or other objectives. Similarly, Kleinman et al. (2021) utilised the same Last Hit Trainers in *League of Legends*, this time to examine the difference of Self-Regulated Learning (SRL) between players of different skill levels. Similar to Payne et al., the use of the Last Hit Trainer allows them to focus on a specific skill without extraneous distractions.

3.5.3 Learning Outcomes

Learning and mastering complex team-based esport games requires knowledge, understanding, and successful execution of a wide variety of learning outcomes. Outcomes that tended to occur earlier in participants' learning journeys, such as controls and mechanics, are common focuses in academic and developer game learning literature (e.g. Keren, 2017; Suddaby, 2012; White, 2014). However, they rarely discuss some of the later learning outcomes (e.g. strategies, meta) or learning outcomes generalise outside of the game (e.g. non-game-specific, meta-learning). This is mainly due to their focus on singleplayer or simpler games where the later learning outcomes are either not relevant (e.g. meta in singleplayer games) or limited thanks to the games simplicity.

Looking at general game learning, Iacovides et al. (2014) developed a list of learning whats from games grouped into the categories of *game level*, *skill level*, and *personal level*. *Game level* outcomes included *controls*, *interface*, *content*, *strategies*, *behaviours of others*, and *games in general*. All of these learning whats either have a one-to-one relationship with the outcomes constructed (*controls* and controls, *content* and mechanics) or are included in one of the outcomes (*strategies* and *behaviour of others* in strategies, *games in general* in non-game-specific skills). However, Iacovides et al. makes a separation between *behaviour of others* and *strategy*, whereas the constructed outcomes of this study group them together under strategy. This may be due to the influence that the behaviour of others has on strategies in team-based esport games, so is regularly discussed as such.

Looking at the *skill level* of learning whats, Iacovides et al. include *psycho-motor*, *cognitive*, *social*, *numeracy*, *literacy*, and *technical skills* under this category. *Psycho-motor* skills map directly onto the motor skill learning outcome. All other *skill level* learning whats do not have a direct mapping onto learning outcomes constructed. *Cognitive*, *social*, and *technical* skills are discussed by some participants at points, but participants did not indicate that they were important or separable to other skills. Under the constructed framework, *cognitive*, *social*, *numeracy*, *literacy*, and *technical* skills could all be grouped under non-game-specific skills. However, the fact that so many of them all fit under one category could mean that further subcategories of non-game-specific learning outcomes could be constructed and explored.

Finally, Iacovides et al. grouped *general knowledge*, *emotional development*, *cultural development*, and *career influence* into the *personal level* of learning whats. Emotions and emotion regulation were commonly spoken about by participants and seen as important for competitive play. These were then coded under non-game-specific learning outcomes since they weren't spoken about significantly by participants with fewer hours. Some participants did discuss how what they learnt was either fed by or fed into other activities such as chess or football, which fits into general knowledge. Similarly to the *skill level* learning whats, the number of categories that fit into non-game-specific learning outcomes indicate that further subcategories could be constructed. The meta-learning outcome constructed here is not present in the learning whats. Whilst it may be argued to be *general knowledge*, it's prevalence in the data indicates it deserves it's own category.

Nagorksy and Wiemeyer (2020) highlighted nineteen competencies that were relevant for Esport games that they grouped into six competencies: *physical*, *sensori-motor/coordinative*, *strategic-cognitive*, *psychic*, *social*, and *media-related*. *Sensori-motor/coordinative* and *strategic-cognitive* competencies align with our learning outcomes of *motor skills* and *strategic skills* respectively. *Physical*, *psychic*, *social*, and *media-related* competencies fit within the learning outcome *non-game-specific skills*. Again, the fact that *non-game specific skills* include four competencies could indicate that either these skills are not that important for early learning of esport games or that *non-game-specific skills* is too broad of a category. It is important to consider that Nagorsky and Wiemeyer were focused on training areas and competencies relevant to higher levels of play in comparison to the focus of this study on a broader range of skill-levels, including newer players. The *physical* competencies (*physical strength*, *endurance*, *speed*, and *agility*) and *technical* competencies (*ability to cope with technical issues* and *adapting the game settings*) outlined by Nagorsky and Wiemeyer were not discussed by any participants in this study. The reason for this could be that these competencies are far more relevant for high-level play than for novices. Similarly, whilst two of the *psychic* competencies (*dealing with pressure* and *personal attitudes*) were discussed in some interviews when discussing emotional regulation, the other two (*confidence* and *motivation*) were also absent from the data.

Another model of skills, competencies, and learning outcomes has been theorised by Larsen (2020) in their "*Theory of Skill in eSport*". They outline seven 'strands' of skills relevant and important to esports. Two of the strands referring to the games objects, properties, rules, relationships between objects (*knowledge of game objects* and *insight into game systems*) map directly onto the game mechanics outcomes. The strand of *ability to execute focuses* on how players interact and interface with the game physically and cognitively as well as reflecting during play. This overlaps with controls, procedural motor, and *non-game-specific* learning outcomes. One strand maps directly onto the meta learning outcome, *understanding meta-gaming*, and also overlaps with strategy. *Emotional discipline* and *team coherency* strands both map onto *non-game-specific* learning outcomes, again highlighting the potential need to further explore and expand *non-game-specific* subcategories. The final strand, *Yomi: reading the opponent*, fits under the outcome of strategy. It mainly refers to the ability of an individual to develop mental models based upon the information available to them in-game, from prior experiences, known about the game and it's systems, and the current meta. This competency has been discussed in popular esports literature and was highlighted by players of *CS:GO* in this study under a specific term, game sense.

Fanfarelli (2018) constructed *game sense* and *mechanics* as two important sets of skills for professional *Overwatch* Blizzard Entertainment, 2016 players. *Mechanics* describes a variety of skills and knowledge surrounding their mechanical ability and the mechanics of the game. *Mechanics* largely match the learning outcomes of motor skills (e.g. *aim* and *movement*) and strategies (e.g. *ability usage* and *positioning*). *Game sense* refers to skills and knowledge relating to the players awareness of the game state. Fanfarelli describes five subthemes that make up game sense; *survival*, *anticipation and prediction*, *communication*, and *thoughtfulness*. As Fanfarelli states, there is no common definition of game sense within academic literature. Yet game sense appears to be a common term within the culture of competitive esports. Participants with more hours in *CS:GO* brought up game sense as a pivotal part of high level play. Based on this study, interviews with experts from Fanfarelli, and *Yomi* as defined and theorised by Larsen, game sense appears to be the player's ability to accurately determine the current game state with the knowledge afforded to them, to accurately predict the future game state based upon the current state of the game, and to act appropriately in order to beat the opposing team based on the prediction of the future state. The prevalence and discussion of this term in our data and popular literature indicates it as an important skill for learning and mastering esport games. Therefore, it would be beneficial to further study the skills this term encompasses and how players improve them.

3.5.4 Learning and Play

It is important to consider the role of play within learning, vice versa or whether play is separable from learning. Many behaviours that participants called 'just playing' seemed to fit into incidental Identification, Application, or Practice processes. Koster (2004 p.46) suggests that games, or more precisely fun in games, is just another word for learning. Therefore, it could be argued that even when aiming to enjoy and wind down when playing games that there is always some passive incidental learning occurring either as Application or Practice.

However, Hung (2011) separated regular play from training, indicating that there is some play that is not learning. Similarly, Deterding (2016) found that professional esports players would construct differences in meaning and practice between leisurely play and instrumental training or tournament gaming, which they considered to be 'not play' when it was experienced as in-autonomous. Finding this distinction between learning and play was not an aim of this study but the authors note that many of the participants tended to either blur or delineate the two.

3.5.5 Limitations

Firstly, the sample size of participants could be considered as small. The exploratory nature and depth of grounded theory means large sample sizes are not always necessary. Experimenting with data saturation and variability, Guest et al. (2006) found that saturation occurred within the first twelve interviews and basic codes emerged as early as six interviews. Therefore it is not unusual for a grounded theory in an understudied area to reach saturation with what could be considered a small sample size.

Secondly, the sample of participants is disappointingly homogeneous with regards to gender. Unfortunately, when sampling through *Reddit* and *Discord* groups, no volunteers came forward who identified as another gender. This may be due to the majority of reddit users and esport players being male Atske, 2021; Interpret, 2019; Newzoo, 2021 and the toxicity faced by non-male esport players Chess, 2017; Madden et al., 2021; Ruvalcaba et al., 2018. This could also be attributable to my naivety on the difficulties integrating into and learning esport games faced by those that don't identify as male. This missing consideration meant I did not purposefully sample for non-male participants, something what would have been appropriate for this study. An ideal distribution would be one that is either more representative of the esports population (Newzoo, 2021) or of the general population. As such, the generalisability of our findings must be tested with a more representative sample.

3.5.6 Future Work

Beyond the suggestions provided for further studies in limitations, three aspects appear to be particularly worthy of future research: the interrelationships, game sense, and deliberation.

Several game and esports learning pieces of literature have shown overlaps between multiple learning processes, tools, and outcomes. These overlaps highlight potential relationships within and without the constructed categories. For example, several strategies reported by Iacovides, Cox, et al. (2014) for overcoming obstacles in puzzle games include multiple learning processes, indicating potential movements or relationships between these learning processes. As well as relationships within categories, there are also potential relationships without categories that have been highlighted by participants, such as *Practising* motor skills using training maps.

The term "game sense" emerged as a particularly important aspect of *CS:GO* mastery that is currently undefined in literature, a sentiment echoed by Fanfarelli (2018) and Larsen (2020). The findings of this study, as well as Fanfarelli's and Larsen's findings, suggest that game sense is the player's ability to determine the current game state, to consider the potential future game states based upon the current state of the game, and to beat the opposing team based on the prediction of the future state. This is not a formal definition and requires theoretical or qualitative research to define.

These findings highlight the importance of *Deliberation* and *Practice* when learning to play, particularly when improving motor skills. However, our understanding of how *Deliberation* and *Practice* affects game learning is limited. The prevalence of community authored tools for practicing skills demonstrates the need for training environments and potential lack of tools provided by developers for supporting *practice*. Developers may benefit from evaluating how well their games provide tools to meet the demand of isolating and practicing specific relevant skills. Researchers investigating learning would benefit from applying grounded theory and similar qualitative approaches as demonstrated here, given the capacity of these methods to uncover rich insights into player behaviour that quantitative approaches may fail to capture (Charmaz, 2014; Corbin & Strauss, 2014; Salisbury & Cole, 2016).

3.6 Conclusion

This study identified the learning processes, tools, and outcomes of players of *Dota 2* and *Counter Strike: Global Offensive*. Four key learning processes were constructed that were common between games and different levels of expertise: *identification* of knowledge and skill gaps, *consumption* of information, *application* of knowledge and skills, and *practising* existing skills. These learning processes show significant overlap with current literature of game learning that hints at how players use and move between processes which would benefit from further study. Different degrees of *deliberation* during learning were observed within every process, ranging from incidental learning to deliberate training, and mapped as a cross-cutting dimension. The importance of *deliberation* and *practice* when learning to play and the prevalence of community made tools for practice highlights an important space for learning team-based esport games. Developers could benefit from evaluating how well their games provide tools to meet these demands.

A variety of tools for learning were found and mapped across two constructed axes: whether the tool was in-game or out-of-game, and whether the tool was developer or third-party made. The most prevalent tools utilised by participants were video and streaming platforms for learning and communication platforms (both in- and out-of-game). Streaming platforms such as *Twitch* have seen increased interest in research, which have found that learning a game is a key motivating factor for watching streams. Not only are videos reported in this study as being an important learning tool, they have also been demonstrated to be effective for helping players improve. However, newer players highlighted some issues with learning from videos and streams. How these tools best support learning are potentially interesting areas for future research and could help developers and content creators better design their learning support for players.

Finally, the learning outcomes constructed from the interviews include controls, game mechanics, motor skills, strategies, meta, non-game-specific skills, and meta-learning. These learning outcomes align with game learning research both in general and with regards to esport games. However, the learning outcome of non-game-specific skills consisted of many categories of learning outcomes identified by other studies, indicating that it is either too general a label or that these skills aren't as important for novice players. Meta-learning has not been highlighted as a learning outcome of games, but there has been some research on games as an informal learning environment and reflective practice in esports. Finally, the term "game sense" was mentioned by multiple participants. This term is popular in esports culture, but has seen little research in comparison. It would be beneficial to develop a definition of "game sense" and how players gain it.

Chapter 4

What Makes Videos Helpful for Learning Esports: Player Perspectives on *Dota 2*

4.1 Introduction

Following the constructed learning processes from the prior chapter, this chapter focuses on one of the learning processes from Chapter 3, *consumption*. The study outlined in this chapter aims to explore and categorise what aspects of videos and streams players find helpful for learning to play team-based esport games using an online survey distributed to players of *Dota 2* (Valve, 2013).

This study was approved by the University of York Computer Science ethics committee. Participants were not reimbursed. This study was pre-registered. Pre-registration, data, and materials used in this study are available at https://osf.io/9zh2k/.

4.2 Background

Consumption highlighted how players would use online media such as videos or streams to gain knowledge about the game and important skills. It's prevalence in the data aligns with research that describes knowledge acquisition and learning to play as significant gratifications for viewers of esport streams (e.g. Hamari & Sjöblom, 2017; Ma et al., 2021; Sjöblom et al., 2017). Live streaming has seen a rapid rise in research, recently focusing on and including streamers and viewers (Harpstead et al., 2019). Not only is *consumption* a popular process, it has also been demonstrated to potentially be an effective one. Payne et al. (2017) examined the performance increase of participants after applying a range of media interventions. They found that participants who had watched a video of an expert or a novice of *League of Legends* (Riot Games, 2009) play between play sessions had a significantly higher performance increase than those who did not watch any video.

Just because videos and streams are shown they can be effective for learning does not mean they are unilaterally effective. Payne et al.'s study provided training videos in which the players in the video verbalised their thoughts and motives through voice. According to Mayer's *Cognitive Theory of Multimedia Learning*, even just the addition of two modalities in media (e.g. visual and auditory) increases learning effectiveness of media (2021). On top of the inclusion of multiple modalities, the content and structure of each modality potentially affects the potential effectiveness for learning. Finally, people are not blank slates that passively receive and process information identically to one another. They bring a wide variety of norms, expectations, and experiences to the information they receive. These also contribute to the relationship between viewer and streamer which add an extra layer of complexity, making it a technically challenging area to study (Harpstead et al., 2019). As such, it is important to consider the features of learning media such as videos and streams that help or hinder learning.

Learning from videos and streams has been demonstrated to be a common and effective method of learning to play esport games. However, what makes these more or less effective for learning esport games is still an open question.

4.3 Experimental Method

The aim of this experiment is to categorise helpful and unhelpful features of streams and videos for learning to play *Dota 2* (Valve, 2013). *Dota 2* is used as it was one of the games utilised in the first study of this thesis and is one of the most popular Multiplayer Online Battle Arena (MOBA) esport games. An open-ended survey was distributed to several forums and groups that were interested in *Dota 2*. At the start of the survey, participants were asked to recall a specific example of a video or stream they found helpful for learning *Dota 2*. They were then asked to discuss what about their example they found helpful. At the end, there is a question asking if participants could recall another example of a helpful video or stream and whether they were willing to discuss it. If they chose to, participants could report up to 10 examples. This would then be repeated but for unhelpful examples of videos or streams for learning *Dota 2*. Finally, participants were given an open-ended question asking if they had any further thoughts they would like to provide.

The results of the survey were coded and analysed using inductive thematic analysis (Braun & Clarke, 2013). I initially immerse myself in the data through in-vivo coding in *MaxQDA*, a qualitative analysis program. These codes are then exported to *Miro*, an online collaborative whiteboard, as post-it notes. Through axial coding, the in-vivo codes are then grouped with similar codes to develop categories. These categories are then grouped to construct a high-level framework for organisation. To test the framework, the data was coded again using the constructed categories. This time, each example and discussion of an example was treated as a single unit. Responses to open-ended questions that were considered to be genuine responses by myself were also treated as units.

When a category was discussed in one of these units, the whole unit was coded as the category. Units were also coded as 'helpful' or "unhelpful" depending on how the example was reported. If any examples were found to include aspects of videos or streams that could not be coded by the constructed categories, then the aspect would be in-vivo coded and taken back to the *Miro* board for further axial coding.

Once the framework and categories represented all relevant aspects of videos and streams for learning *Dota 2*, the relationship of *format* categories with helpful and unhelpful examples were then analysed quantitatively using content analysis. The reason only *formats* are analysed this way is that *features* are complex and their contribution to a video or streams helpfulness exists along one or multiple spectrums (e.g. a video that contains explanations does not make it helpful or unhelpful, the quality of the explanation does). To analyse this relation, proximity analysis was used. Proximity analysis evaluates the co-occurrence of categories/codes in the data. *MaxQDA* was used to count the number of co-occurrences of *format* categories with helpful or unhelpful examples.

4.3.1 Participants

This study required that participants be over the age of 18. Participants were sampled through *Discord* and *Reddit*. *Discord* users were sampled by distributing the survey in private servers dedicated to gaming or *Dota 2* (Valve, 2013). *Reddit* users were sampled by distributing the survey several times on the *Reddit* page /r/Dota2. The original stopping criteria for sampling participants was either when 40 responses were gathered or by December 2021. These stopping criteria were chosen due to time and resource constraints.

4.3.2 Materials

Participants were given a survey to complete through the online survey tool *Qualtrics*. The survey opens by asking players about their playing and watching habits for *Dota 2*, including time played. For the open-ended part, participants are asked to recall examples of videos or streams they watched that they thought were helpful or unhelpful for learning to play *Dota 2*. Specifically, participants were asked to think of an example of a stream or video that they watched to learn or improve and asked three questions about this example: to describe what they watched; what they found about the video or stream that was helpful, useful, or productive; and to elaborate on how the features they found helpful, useful, or productive described in the previous question helped them to learn or improve. Participants were then asked if they would like to recall other examples and elaborate on them with the same set of questions. If they chose not to, they were then asked if they could recall any videos or streams they found unhelpful, useless, or unproductive and would like to report them. Participants were not reimbursed for or incentivised to participate.

For analysis, *MaxQDA* was used to code the data and to analyse co-occurrences of codes. *Miro*, was used to map the in-vivo codes visually and axially code them into categories. All materials used, as well as the collected data, are available at https://osf.io/9zh2k/.

4.4 Results

In total, 204 survey responses with fully consenting participants were recorded. The stopping criteria of 40 was surpassed due to one of the calls for participants on */r/Dota2* gaining a large amount of traction whilst I was not available to monitor the progress of the survey. Responses were collected between 07/06/2021 and 07/07/2021, when the call for participants on /r/Dota2 was noticed to have gained traction and gave 204 responses. The average word count of each survey was 96 words with a standard deviation of 66 words and a total of 19,528 words.

Participants ranged in age from 18 to 43 years (M 25.34, SD 3.74). 189 participants identified as male (92.6%), 11 participants identified as female (5.4%), 3 participants did not wish to provide their gender (1.5%), and 1 participant did not provide an appropriate response (0.5%). The high proportion of males involved is an unfortunate outcome from advertising the study through Reddit, a predominantly male platform (Atske, 2021), and the current demographics of esport games, which is also mainly male (Interpret, 2019; Newzoo, 2021).

The average number of hours participants reported having in *Dota 2* and similar games respectively are 4,968.31 (SD 2,635.34) and 4,018.68 (SD 3,337.09). One participant indicated they had 70,000 hours in *Dota 2*, which is taken to be a misinput as they were the only person to provide anything over 18,000 hours and had entered 7,000 for similar MOBAs. Similarly, another participant indicated they had 100,000 hours in MOBAs outside of *Dota 2*, which is also taken as an input as they were the only person to provide anything over 20,000.

The histograms of the total number of hours of *Dota 2* and other MOBAs played are given in Figures 4. The histograms for the frequency of answers given with regards to participant's weekly stream watching and *Dota 2* playing habits are given in Figures 5a and 5b respectively.

Through thematic analysis, 27 low-level categories were constructed. These are then split into two top-level categories of *features* and *formats* for organisation. *Features* are described here as any aspect of streams, videos, or other media participants referred to. *Formats* are described

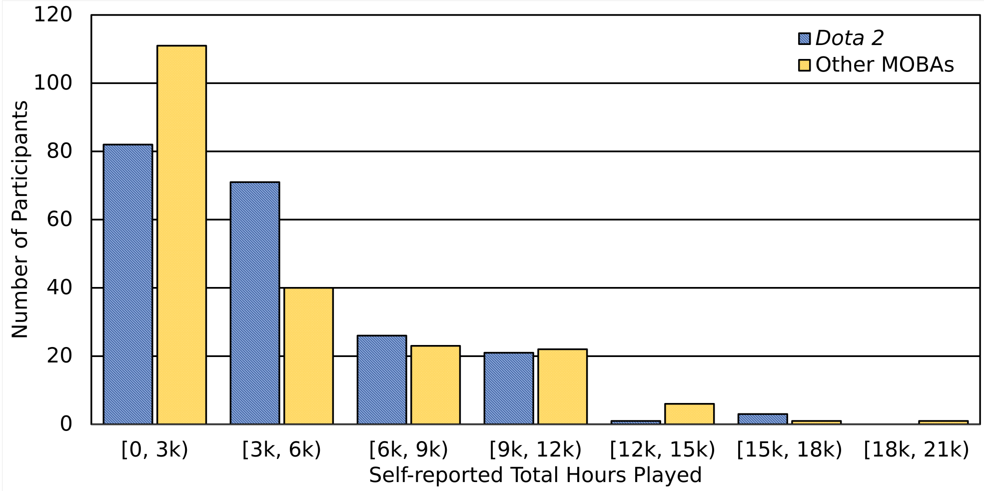


Figure 4: Histogram of the frequency of the total number of hours of *Dota 2* and other MOBAs played as reported by learners.

here as the ways in which streams, videos, or other media is structured or presented. The following terms are used throughout the results:

Media: The medium through which visual and auditory information is provided.

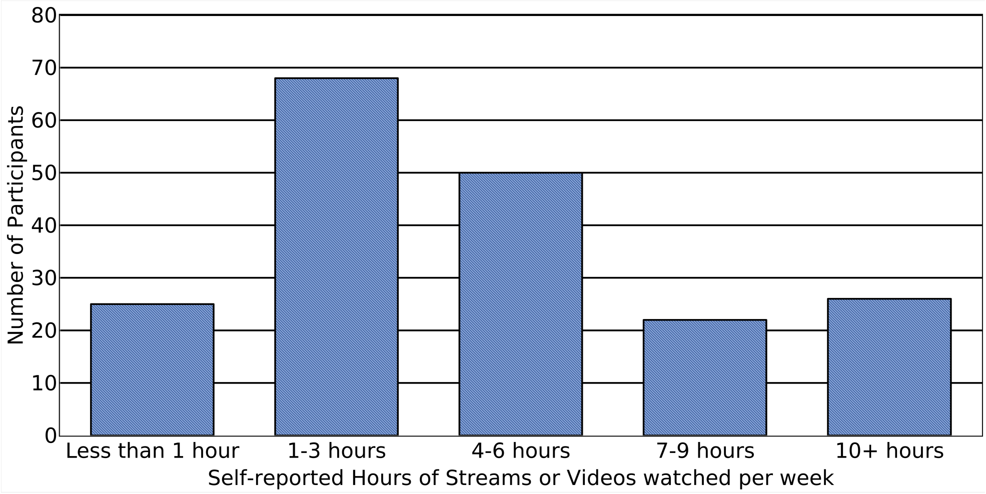
Content: The information provided through the media.

Producer: The individual who presents and produces the content.

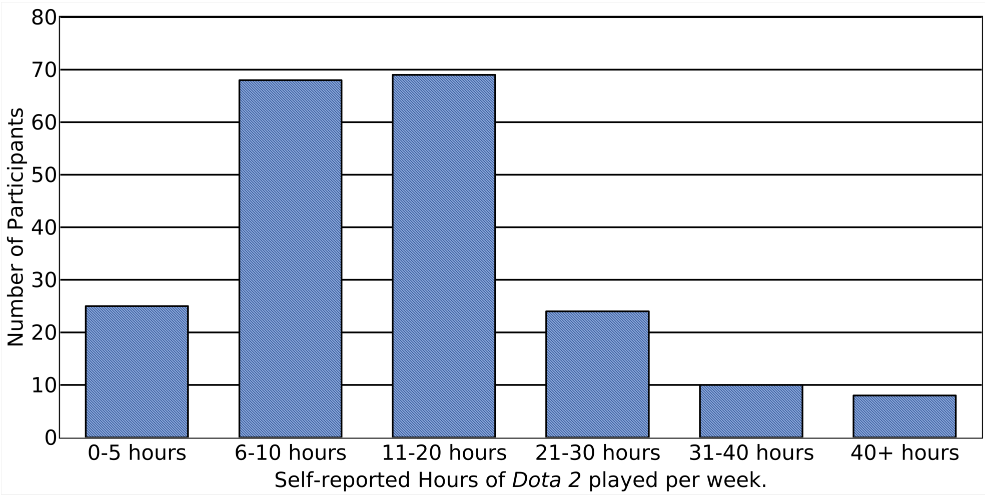
Watcher: The individual who receives the content.

Features are coded as being relevant to one or two of the following subcategories; *media*, *content*, *producer*, *watcher*. *Formats* are coded as being relevant to either *media* or *content*. Each category is introduced with a number that represents the number of units that the category was present in.

Findings are provided with quotations from the survey that help illustrate the category being described. Square brackets are used to either contextualise the quote or to expand any abbreviations (e.g. *"ofc"* to *"of course"*). All *features* and *formats* are quantified by the number of



(a) Hours per week participants reported watching videos or streams per week.



(b) Hours per week participants reported playing *Dota 2* per week.

Figure 5: Histograms of the frequency participants chose each available response in relation to their weekly hours watching streams and videos (5a) and playing *Dota 2* (5b).

units they are present in. Multiple *features* or *formats* can be present in a unit.

4.4.1 Features

Features are described as any aspect of streams, videos, or other media participants referred to. They are split into four categories; *media* *features*, *content features*, *producer features*, and *watcher features*. There were some units where participants either didn't discuss *features* in the context of streams and videos or talked about something other than streams and videos. For example, when asked if there was anything else to add about videos or streams for learning or improving in *Dota 2*, P114 states: *"It's only part of how you learn to play. The other part comes from practice and application"*. This is coded as a unit due to its sincere response about learning from streams and videos, but does not elucidate on any specific *features*. *Features* are described in descending order of the number of units they were present in.

A full list of all 17 *features* are provided in Table 4 with the number of units the *feature* was present in and the mid-level categories they are relevant to. A mid-level category matrix is given in Table 5 that shows how many *features* are shared between categories.

Feature	**Units Present**	**Categories**			
		Media	**Content**	**Producer**	**Watcher**
Competence of producer	119			X	X
Applicability of teachings	99		X		X
Explanation of teachings	75		X		
Teachings in action	59		X		
Relevance of teachings to watcher's skill level	43		X		X

Feature	Units Present	Categories			
		Media	Content	Producer	Watcher
Relevance of teachings to watcher's interests	30		X		X
Easy to understand	29		X	X	
Attentive and receptive watcher disposition	26				X
Provision of tips on what to do	22		X		
Patient and non-judgemental producer disposition	19			X	
Relevance of teachings to current meta	15		X		X
Aimed to help learning	12		X	X	
In-depth detail	12		X		
Trust in the producer's teachings	10			X	X

Feature	Units Present	Categories Media	Content	Producer	Watcher
Shorter lengths	6	X	X		
Ability to control media	4	X			
Ability to interact with the producer and receive feedback	3	X		X	

Table 4: All *features* constructed including the number of units each are present in as well as the high-level categories (*media*, *content*, *producer*, and *watcher*) they are relevant to.

	Media	Content	Producer	Watcher
Media	1			
Content	1	3		
Producer	1	2	1	
Watcher	0	4	2	1

Table 5: Category matrix highlighting the number of *features* relevant to one or two of the high-level categories of *media*, *content*, *producer*, and *watcher*.

Competence of producer (119 units) The most commonly described feature was with regards to the skill level of the producer. *Competence of producer* is categorised as being relevant to the *producer* and the *watcher*, as competence was discussed in relation to the participants own skill-level. For example, P48 discusses a video talking about *"[h]ow good players and pro-players deal with failure and losing game"* and validates how these helped them improve: *"By looking how people who play the game better than me have to deal with the same difficulties, I can learn how they manage to suppress the basic instinct of 'rage'. Even if [they] have a lot of wrath, they manage to win more than lose."*

Professional players were commonly discussed as *producers* of particular interest for learning. Participants often provided examples of videos and streams either with a *"professional player streaming himself playing a public game of dota" (P43)* or *"pro games at competitions" (P15)*. These kinds of videos allowed players to learn via observation: *"Seeing how a high skill player makes decisions and responds to various situations teaches me how to better respond to those situations in my games" (P10)*. The general underlying assumption in most statements referring to professional players seems to be that they are best to learn from as they are, by definition, some of the best players. This aspect of producer competence is discussed further in *trust in the producer's teachings*.

However, some participants indicated that watching professionals or highly-skilled players is not always beneficial, especially for newer players. There were usually one of two arguments that participants used to explain this issue. Firstly, participants stated that it can be difficult to identify what aspects of a professional player's performance is important for competitive play. When discussing watching high-skilled players play matches, P203 states *"it can be difficult to see what they are doing correctly [...] it can be easy to miss what choices ended up being important [or] not"*. This was especially true when content lacked explanations, as discussed by P92: *"Unless the player really explains their decisions [...] the choices they make and why [isn't] implanted in your brain simply by watching them play"*.

The second issue raised was whether the skill-level of the teachings are too high for the watcher to execute or not relevant to their skill bracket. For example, P169 stated they did not watch videos or streams to learn or improve in *Dota 2* and, when asked why, stated *"the tournaments i watch are mostly high skilled players. whenever i try the same thing it doesn't work with my level and my teammates"*. A similar sentiment is expressed by P34: *"If you aren't similar MMR then their decisions are based on what other high MMR players in the game are doing which becomes less useful in your own low MMR games."*

Applicability of teachings (99 units) An important and common *feature* for watchers was their ability to take the learnings and concepts of content and to implement them into their own gameplay. Here coded *applicability of teachings*, this *feature* covers how easy it is for *watchers* to replicate what they learn about and how specific or general the learnings are in their gameplay. This code is categorised under *content* and *watcher*. It is categorised under watcher due to the requirement of the watcher to use *"information to take away and use on my own games" (P114)*.

It is also categorised under *content* because, as discussed in *competence of producer*, the teachings of the content need to be replicable by the watcher. Participants highlighted media that provided "*tips on how to do certain things" (P36)* or discussed *"how to deal with this scenario" (P2)* as helpful, especially for newer players, as they then *"applied them in my own games successfully" (P12)*.nAs well as the replication of tips, many participants highlighted their attempts to mimic high-level players (e.g. *"I watched highlights from a well known Invoker player [...] It inspired me to practice more and try these in my matches." (P24)*).

Generalisability or specificity of the content was often discussed by participants, where *"general information" (P108)* was always brought up in helpful examples. But content covering *"smaller more niche mechanics" (P106)* were sometimes brought up as helpful and other times unhelpful (e.g. *"smaller more niche mechanics that help you get slightly further" (p106)*, *"the scenario is so niche it doesn't translate to any real improvement" (P97)*).

Explanation of teachings (75 units) The next most frequently coded *feature* is the presence of verbal descriptions relating to the what's, how's, and why's of learning outcomes. These justifications and clarifications given by producers helped watchers develop a deeper understanding for decisions and actions that watchers can then take into their own games: *"Helped me understand what to do, and why to do it, which also helps with the when and when not to do it" (P83)*.

Explanations seem to be largely related to the code *easy to understand*, as their presence (or lack of) was often discussed in relation to understanding. For example, when P59 discussed an unhelpful example that provided *"no commentary on choices"*, they then stated that it left them with a *"lack of understanding behind some choices"*. This was a common sentiment expressed by participants, such as P138 who said that it is important to *"understand reasoning behind certain actions"*.

Teachings in action (59 units) Another helpful *feature* was seeing examples of knowledge or skills being used. When *producers* were actively trying to teach and demonstrate teachings, it would be through *"showing examples of concepts through [gameplay]/replays" (P85)*. *Watchers* would be able to see the application of some concept and help them to apply it in their own gameplay.

An example provided by P94 is a *"video on timings to stack creeps"* which *"showed timings and which camps can be double stacked"* which then *"made it easier to double stack camps"*. However, participants also spoke a lot about how they would benefit from just seeing or analysing a skilled player's gameplay. These included *"[seeing] how a much much better player plays" (P149)* and *"[getting] the perspective of a professional player" (P112)* which they would then use to *"more or less mimic the play style"*

(P149) or *"copy and apply to myself (P111)"*.

Relevance of teachings to watcher's skill level (43 units) When discussing unhelpful examples, participants would highlight when teachings of streams or videos were not relevant for the skill levels of themselves and the people they play with. This is categorised under *content* and *watcher* as it depends on whether the teachings of the *content* and the *watcher's* skill level are aligned.

More experienced players would discuss when content was too basic or low-level. P56 provides an unhelpful example of a video that *"just tells basics understandings of heroes"* which, when prompted why it was unhelpful, they then elaborate *"for dota veterans like me its not something new these content provides"*. In contrast, participants who were newer to the game would discuss how they found instructional content catered towards beginners helpful (e.g. *"The [instructional] video was expressly designed to improve the play of lower skilled players such as myself" (P2)*), but found it hard to simply watch high-skill players play. For example, P34 discusses *"streams of high MMR players"* and how *"if you aren't similar MMR then their decisions are based on what other high MMR players in the game are doing which becomes less useful in your own low MMR games"*.

Most unhelpful examples discussed how teachings were too basic or low-level. There was mixed feedback with regards to the skill-levels catered for currently, as some participants highlighted a lack of high-level content (e.g. *"[There] is an overwhelming amount of new player guides for this game, but a surprisingly low amount of intermediate/advanced guides in my opinion." (P180)*), one participant stated that content needed to *"cater more to the lower ranks" (P47)*, and others have commented on how *"It is great that there are guides online for every rank" (P55)*.

Relevance of teachings to watcher's interests (30 units) Another aspect of whether content was relevant to the *watcher* was with regards to the heroes, roles, or playstyles watchers tended to utilise. The relevance to interest is categorised under *content* and *watcher* as, similarly to *relevance of teachings to watcher's skill level*, it depends on whether the teachings of the *content* and the *watcher's* interests are aligned.

Participants would bring up examples of videos or streams that discussed specific heroes and elaborate on it's effectiveness by linking it to how they play. P153 highlights a helpful example of *"replays of characters I want to play"* and states *"it was focused on the character that I wanted to play"* when asked to elaborate on what they found about their example that made it helpful for learning.

Roles and playstyles were also discussed by participants. P149 discusses *"Xcaliburye playing various [heroes] mid"*, where *"mid"* is a role or playstyle where players make the middle lane their point of focus, and says: *"I am a mid player looking to expand hero pool. [It's] useful to see how a much much better player play [...] I can more or less mimic the play style until I develop my own that is more intuitive and fluid once I get a better understanding of the hero after a dozen games or so."*

Easy to understand (29 units) Participants would also highlight the benefits of *"simple"* content, whether it be explanations or tips, for watchers to pick up and follow (e.g. *"Simple explanations for what you can accomplish with said items" (P13)*, *"A simple gameplan you can try and copy" (P63)*) . *"Clear"* was also used a lot by participants in relation to helpful content for learning (e.g. *"Clearly stated concise ideas" (P192)*, *"it was clear on what was done to achieve success" (P153)*). When clarifying further, both *"simple"* and *"clear"* were always used in the context of how easy watchers found it to understand the *content* and *producers*.

These were then grouped under the category of *easy to understand*. This is further categorised under *content* and *producer*. This is because, firstly, participants would highlight how the structure of *content* would help make it more or less understandable. When discussing why a particular video explaining *"support tricks"* were helpful, P135 discusses how it contained *"clearly separated little informational nuggets [and] concepts behind why and when to use these tricks were explained well"*. Secondly, one participant discussed a particularly bad video they watched where the producer *"Couldn't communicate ideas properly. [...] Videos were poorly structured. Might have been a language barrier" (P200)*, highlighting the importance of being able to understand the *producer*.

Attentive and receptive watcher disposition (26 units) Watching videos or streams would be said to yield better learning when watchers *"pay close attention" (P109)* and *"consciously try to think about the decision making the streamer is making" (P125)*. Having this reflective position often occurred when watching *gameplay* or *competition content genres*, discussed further in *media formats* (e.g. *"When I watch a pro player play, especially if it's a hero I want to play, I pay close attention to all their movements and decision making and try to absorb all that information" (P109))*

Whilst taking an active contemplative approach to watching media was always used in examples of helpful media for learning, taking a passive approach and watching media for entertainment purposes appeared to be mixed in it's usefulness. One participant, P83, commented that *"you won't learn anything no matter how educational the content is if you're not actively trying to learn"*. Whilst another participant, P179, when asked why *"Help/Meta guides a few times a week"* were helpful for learning or improving in *Dota 2*, states: *"I use them as background noise while doing other things"*.

Provision of tips on what to do (23 units) Providing explanations of teachings and demonstrating teachings in action appear to help participants understand teachings. What content also does is provide *watchers* with instructions on what actions they should do as well. When elaborating why an example was helpful, P129 states: *"[they're] carefully explaining the player's mistakes - and giving alternatives of what should have the player done instead"*. This category is placed under *content* as these tips are pieces of information provided through the *content*. These recommendations were then often applied by participants in their matches. P24 discusses a helpful example where they found the *"flow of the playstyle for the character and small tips and reasoning"* helpful, further explaining *"it inspired me to practice more and try these in matches"*.

The discussion of tips was often in relation to coaching content genres, discussed more in formats. P58, P59, P97, P129, P133, and P192 all discuss examples of coaching content and highlight that the tips provided helped them improve (e.g. *"Most of video makers are doing coaching, so they know [the] most common mistakes of lower skilled players and can point them out. Also, they provide overall gameplay improvement tips"* (P58)). Interestingly, P83 made a value judgement of explanations of teachings compared to the provision of tips on what to do, saying: *"The good [streams] explain why something was done, vs telling you to do that"*. No other participants made this comparison.

Patient and non-judgemental producer disposition (19 units) Participants would bring up the general attitudes and behaviours of the people starring in and producing content. How *producers* responded towards other players, especially players of a lower level, were seen as important by participants who discussed unhelpful examples of media for learning. For example, *"tilted" (P66)* (an emotional state where your mood negatively affects your performance) and *"dogmatic" (P13) producers* were described as *"disencouraging" (P66)* and *"a setback for players and [enforcing] bad habits" (P13)* respectively.

Toxicity was one of the most commonly used terms when discussing *producers* of unhelpful media for learning. P66 uses the term directly, when discussing why an example of a video was unhelpful for learning they state *"toxicity mostly"*. In contrast, *producers* who had a more helpful disposition would be those whose *"mentality makes [the producer] a good example" (P3)*. Further expanding on how this disposition helped, P3 says *"I became a calmer person after I started to watch [them]"*. As well as that, P161 raised that a non-judgemental producer answering questions helped them learn more about the game: *"He is also quick to answer questions in Twitch chat verbally, and doesn't judge novice questions harshly."*

Relevance of teaching to current meta (15 units) The meta refers to common knowledge of best practice with regard to strategy, including things such as hero choices, item choices, positioning, and timings. The best and optimum practices and strategies in *Dota 2* change frequently as the game is often updated with additions, subtractions, and changes. As such, participants highlighted content they found unhelpful for learning that would either be or become out of date with the current meta. As P196 highlights: *"Patches can change many things within the game. If the streamer or video producer covers information that is no longer relevant to the current patch then it's not very useful information"*. Similarly, although focusing more on the content's potential to be out of date, P2 discusses a video showing a *"current overpowered strategy and how to abuse it"*, stating: *"While this type of video can help me win games in the short term, it does not improve my skill at the game. It also relies on flavor-of-the-month strategies that might not apply at all in a few weeks/months/years"*.

Aimed to help learning (12 units) Participants would discuss one of several different aims the content or producer could have and their relation to the helpfulness of the content. Participants who highlighted content that was *"personality driven" (P25)*, *"for entertainment only" (P97)*, provides a *"quick fix" (P101)*, or *"[focused] on earning ad revenue and* *cinematisation of game clips for views" (P8)* often discussed them within the context of an example that was unhelpful for learning (e.g. *"Streams that are for fun [aren't] [useful] to get better at the game" (P70)*).

These sentiments seem to imply that content aimed to help learning is more helpful for learning than others. This code is categorised under *content* and *producer* as both the structure of the *content* and the desires of the *producer* are spoken about when talking about the content's aims. For example, P25 talks about why they *"feel most content is relatively useless for learning or improving"* by saying *"personality obsession leads to the 'content creator' spending more time on [innocuous] details and rambles, things such as inside jokes or the like, get in the way of legitimately useful content"*.

In-depth detail (12 units) Depth was raised multiple times in relation to the level of detail that content would enter about concepts or examples. Going into depth about teachings was largely seen as helpful, with participants stating an example was more helpful because it was *"More in depth for people with more hours" (P121)*. Similarly, P120 raised that a video *"was unhelpful because it did not go in-depth enough about [a concept]"*, relating to media involving *"players at a lower skill level"*. *In-depth detail* was often discussed in tandem with *explanation of teachings* with participants discussing how helpful it was: *"The streamer broke down the changes in detail and even tried out some of the changes in-game. This helped visualise how much of an effect the update has on the different aspects of the game." (P21)*

Trust in the producer's teachings (10 units) When discussing why given examples were helpful or unhelpful, some participants brought up their trust or distrust in the teachings or *producer*. This *trust in the producer's teachings* is categorised under *content* and *producer* as it is relevant to the information presented and the reputation of the *producer*. The units coded only contain examples where participants explicitly stated their trust, or conversely their lack of trust, in the *producer* they watch (e.g. *"With it being a professional you learn to trust what they do" (P20)*) or where participants discuss the *producer's* accolades and experience when asked why an example was helpful or unhelpful (e.g. *"this guy is top rank but is not in any good team for years" (P73)*, *"Speeed is an Immortal 100+ player so he's in like the top 1% or 0.1% of players in my region (NA) per MMR rank" (P98)*).

However, it seems that there is an implicit trust in the teachings of professional or high-level players. For example, when discussing how they learn from high-skill players, P14 states that *"I think it is important to have a sense of what it looks like when the game is played 'right' [...] The more I watch the more I get a feeling of what is 'wrong' or 'right' when I am playing"*. P14 appears to implicitly trust that what they're observing is the game being played *"right"*.

Shorter Lengths (6 units) When discussing the length of content, participants often emphasised the helpfulness of *"clear, concise" (P82)* explanations and examples (e.g. *"Explained above principles quickly and succinctly" (P25)*). This places *shorter length* into the *content* category. However, *shorter length* is also placed into the media category as some participants discussed how the different *media forms* differed in length. For example, P127 talks about why they don't watch videos or streams for learning *Dota 2* saying *"I have a short attention span to watch streams"*. P161 talks further about the advantages of videos against streams and states: *"I think videos are an amazing source of information, since they are condensed and efficient in presenting concepts and ideas."*

Ability to control media (4 units) Some participants discussed the ability to manipulate aspects of the media to help them focus on what they would like to learn. For example, P15 talks about watching competition videos and states that the *"[a]bility to pause and unwind the video"* was part of what helped them to learn. Another example is the ability in replay files that allow viewers to manipulate the information available to them to either see as much as possible or to limit themselves to a particular player's perspective. P99 talks about watching matches between professionals in *Dota 2*'s replay viewer as a helpful example and states: *"I can use his camera and see the game from his perspective which allows me to see his decision making and mechanics"*.

Ability to interact with the producer and receive feedback (3 units)
Some participants highlighted the benefits of being able to interact with the *producer* and other *watchers* in real-time. Especially on livestream platforms like *Twitch*, audience members can ask questions to the *producer* to have them discuss relevant and important topics for the audience. A helpful example provided by P161 talks about their interaction with the *Twitch* stream *Merlini*: *"He is quick to answer questions in Twitch chat verbally, and doesn't judge novice questions harshly"*.

Features of media relevant to helping players learn to play *Dota 2* are categorised into 4 groups; *media*, *content*, *producer*, and *watcher*. Whilst some *features* are commonly discussed in either positive or negative examples of media for learning (i.e. either being mostly helpful or mostly unhelpful), most *features* have a mixed response from participants as to whether they are helpful or unhelpful. Whilst *features* and their potential relation to learning efficacy of media were the primary focus of this study, the *format* of both the *media* and *content* also emerged as being related to learning efficacy as reported by participants.

4.4.2 Formats

Format refers to how media or content are structured and presented. These are split into two sub-categories; the *media form*, and the *content* *genre*. The full list and explanation of formats is given in Table 6 and the distribution of formats across helpful, unhelpful, and neutral units is given in Figure 6.

Media Forms		
Video	120 units	Recorded and often edited media that is then uploaded to be watched.
Stream	89 units	Broadcasted visual and audio media that is watched live.
Replay	18 units	Files containing time-series information with regards to all events occurring in a game.
Content Genres		
Instructional	77 units	Content that is structured to teach information, skills, or concepts to the watcher.
Gameplay	71 units	Content involving individuals playing a game, potentially including live commentary.
Analysis	38 units	Content involving either one or several individuals discussing events related to the game (e.g. patch notes, competition).
Competitions	22 units	Content covering amateur or professional competitions.
Coaching	17 units	Content involving a highly-skilled player helping a newer player learn to play.
Montage/Clips	14 units	Either a collection of or single highlight of some gameplay.

Content Genres		
Smurfing	10 units	Where the producer plays against players who are in a lower skill bracket than them (using a new "smurf" account that does not reflect the producer's skill level).

Table 6: Full list of media and content formats as well as definitions.

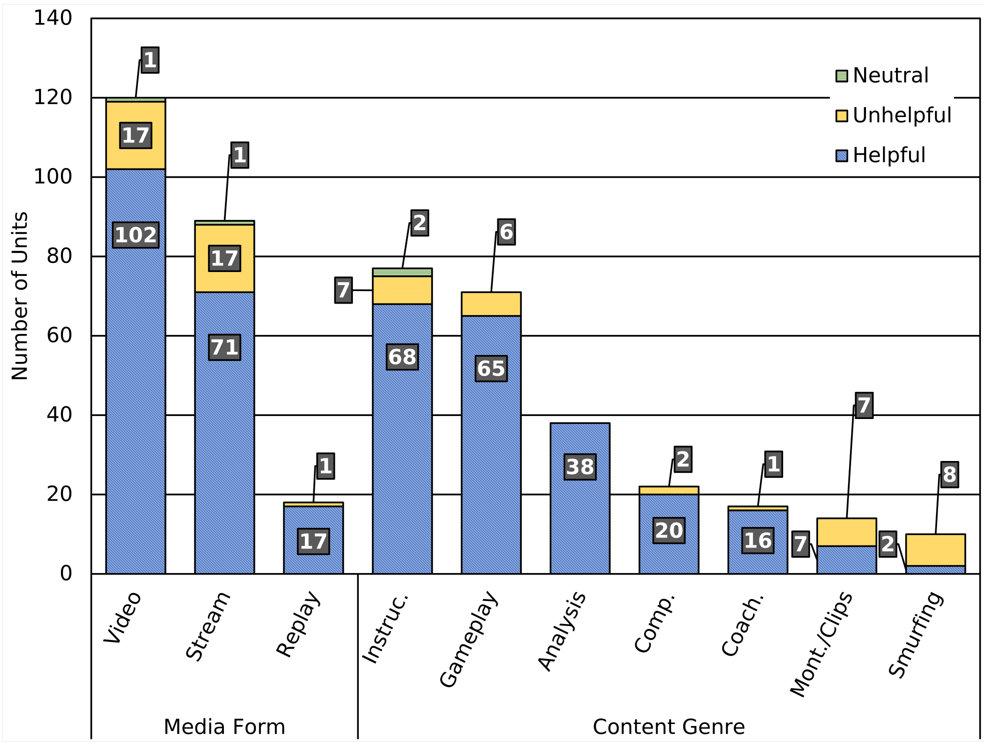


Figure 6: Distribution of co-occurrences of *media formats* with helpful, unhelpful, and neutral units.

Media Form

The two main *media forms* discussed by participants are those asked for in the questions of the survey. *Videos* and *streams* were by far the most popularly discussed *media forms*. However, despite not being included in the questions, multiple examples were raised in which participants discussed how *replays* helped them learn to play. Whilst *media forms* do not have a strong relationship to the perceived efficacy of any media for learning, it seems that certain *forms* appear to be more effective for certain *features* than others. What does appear to have a stronger link to learning efficacy is the various types of *content genres* participants raised.

Content Genre

Participants highlighted 7 ways that content is laid out, here referred to as *content genres*.

Instructional content (77 units) The most commonly raised *content genre* was content structured to help audiences learn and improve their skills in-game. The vast majority of *instructional content* examples were identified as helpful for learning by participants. Due to its educational nature, *instructional content*, in positive examples, often involves *teachings in actions*, *explanation of teachings*, *provision of tips on what to do, aimed to help learning* or any combination of all three (e.g. *"The video was expressly designed to improve the play of lower skilled players such as myself by being easy to understand" (P2)*, *"[It's helpful because] seeing it done and hearing why it's done that way or thought about that way." (P69)*).

Oftentimes, participants discussed how knowing the *"thought process" (P16)* and *"why you make certain decisions" (P29)* would be the reasons that these kinds of videos were helpful. However, the more negative examples provided by participants tended to focus on the fact that what was being shown was difficult to understand. For example, when discussing why "some tutorial" was unhelpful, P189 states: *"[I] could not understand why something should be done"*.

Gameplay content (71 units) This type of content involves just watching someone who has recorded or is streaming themselves just playing a game. When *gameplay content* was raised as being unhelpful or unproductive for learning, the lack, or low amount, of explanations and a poor disposition of the producer were significant factors. For example, when P94 discusses why a stream of a player was unhelpful they state: *"The streamer didn't explain what they were doing, or more importantly why they were doing it. [...] It's hard to understand decisions that good players make - without knowing why people are doing what they are doing, it's hard to learn"*.

When discussing a particularly toxic producer, P29 stated *"Even trying to concentrate on the decisions made and the gameplay instead of other stuff going on, it was extremely difficult to glean any useful information"*. Helpful examples of *gameplay content* often involved the watcher's disposition to understand the gameplay and *"try to analyze why they make some of their decisions and how I can apply that to my own gameplay" (P2)*.

Analysis content (33 units) Some examples were often highlighted as being helpful thanks to the presence of commentary that would break apart what is happening during a game. Examples with this kind of content were often called analysis (e.g. *"Dota 2 is a complicated game, pros analyzing games, picks/bans for me is the best way to enhance my understanding of the game" (P60)*). All examples of *analysis content* were discussed in relation to helpful media for learning.

This *content genre* is heavily linked to *explanation of teachings* as it is a key part of the content. Many of the benefits of *analysis content* come from the presence of explanations. For example, P90 talks about how *"conversation among casters and other professional players"* and *"their analysis on lane matchups, play styles, picks, bans, etc."* then *"gave me a new perspective on how I see and play the game"*. One important thing to note is that a large proportion of examples of analysis content would mention the presence of professional, or highly-skilled, players or casters, individuals who provide commentary during tournaments (e.g. *"[I watched] A high level dissection of macro play by a pro player, focused mainly on map awareness and adaptation in skill builds and item builds" (P82)*).

Competition content (22 units) One of the most important aspects of esports is its positioning as a spectator sport, where audiences watch professional players compete in tournaments or leagues. Media broadcasting *competition content* was not only a form of entertainment for participants, but also a method of learning from the best players of the game (e.g. *"by looking at the pro player or tournament, I can see how the player responds with the opponent hero pick, what hero good to pick against that opponent" (P40)*). One of the main reasons participants found competitions useful for learning was to *"see the game from [the professional player's] perspective which allows me to see his decision making and mechanics" (P99)*.

Whilst seeing *teachings in action* is one of the main *features* that makes competition content helpful for learning, this *content genre* is often found to be more helpful when there are explanations by casters or professionals on the events happening in-game. For example, P157 talks about a helpful example of a large *Dota 2* tournament they watched and how they *"learned mostly from the analysts from the tournament that explained drafting analysis and gameplay analysis"*. This is also an example of a large overlap between *analysis* and *competition content* as examples were raised where producers would analyse footage from a tournament between professional players. However, the helpfulness of competitions for learning also seems to be linked to *relevance of teachings to watchers skill level* and *applicability of teachings*. For example, P169 states: *"the tournaments i watch are mostly high skilled players. whenever i try the same thing it doesn't work with my level and my teammates"*.

Coaching content (17 units) Some participants brought up helpful examples of content where high-skill players would record or stream themselves helping low-skill players learn to play or improve in *Dota 2*. This kind of content was often referred to as coaching since the high-skill players act as a coach to the low-skill players. *Coaching content* was particularly helpful for watchers when the high-skill player had a higher level of competence than the watcher, provided explanations of teachings, and the low-skill player would be at a similar level to the *watcher* such that the teachings were relevant to the *watcher's* skill level.

P15 discusses a helpful example of *"coaching pitched to a beginner level"* and elaborates on why it was helpful by saying *"Having someone who [is] relatively newer to the game to ask questions that would be asked by beginners"*. P140 echoes a similar sentiment saying *"[bananaslammajamma] did a coaching session which gave me a good perspective to compare myself to"*. Coaching sessions were nearly always given as positive examples of media for learning.

Montage/Clip content (14 units) A different *content genre* that was mix- ed in participant's responses was content that consisted of small snippets of gameplay that demonstrated interesting events in either public or professional games. These excerpts of gameplay would be either watched on their own in isolation, here referred to as *clips*, or edited together into a longer video, here referred to as *montages*.

This kind of content appeared equally in helpful examples and unhelpful examples. *Montage/Clip* content was often seen as being made for entertainment, which would then be linked to it's effectiveness for learning. For example, P157 talks about why the clips they watched were unhelpful: *"The intent of the short dota 2 funny clips was [simply] to entertain not to educate in any way"*. Another reason participants said that clips were unhelpful was that they would lack context to the rest of the game: *"The short clips did not show how they performed throughout the entirety of the game or how they leveled their hero as the game progressed" (P180).*

For helpful examples of Montage/Clip content, seeing teachings in action was the main feature mentioned discussing why these examples were helpful (e.g. *"I watched a professional players highlight clips/tips and tricks clips [...] Watching the way they aimed helped me with my aim, even if the video wasn't about that just seeing it almost got me locked in for when I played" (P20)*).

Smurfing content (10 units) Finally, the most negatively regarded *content genre* was when high-skill *producers* would make content of themselves making a new unranked account, with the intention to play against players who are far below them in ability. This was mainly referred to as *"smurfing"*. Participants who saw these videos as unhelpful for learning to play shared the similar sentiment of: *"high rated player is able to consistently put themselves in the best situation against low rated players, and there's nothing to be gained from watching the best case scenario for a match since games very rarely go perfectly" (P44)*. However, a couple of participants found *smurfing content* helpful but did not explain why they found these videos helpful.

Formats of both *media* and *content* displayed some relationships between an example's efficacy for learning as well as some of the *features* highlighted above. The *media formats*, *videos*, *streams*, or *replays*, were not seen as being largely positive or negative for learning or contributory to the efficacy of learning to play. The *content genres* did link more to participants' perceptions of efficacy of learning to play, as well as having individual relationships with different *features*.

4.5 Discussion

This study constructs 27 low-level categories identified as being potentially relevant to stream, videos, and replays efficacy for learning *Dota 2* (Valve, 2013). For organisational purposes, these are then split into the categories of *features* and *formats* as well as further subcategories. In this section, it is found that there appears to be very little literature currently available that explores aspects of media for learning within the context of esport games. This study may be a first of it's kind for this field and provides a potential foundation for future research into novice learning of esport games through media.

4.5.1 Features

Overall, 17 low-level *features* were constructed as being helpful for learning to play *Dota 2*. Each *feature* is then categorised as being relevant to one or two of the following sub-categories: *media*, *content*, *producer*, and *watcher*. *Media* is the medium through which visual and auditory information is provided. *Content* is the information provided through the media. *Producer* is the individual who presents and produces the content. *Watcher* is the individual who receives the content. The full list of the features and the sub-categories they relate to are given in Table 4 and the sub-category matrix is given in Table 5.

Whilst very little literature exists on learning games by watching others, many of these *features* align with findings from cognitivist and constructivist research on game-based learning. One prominent constructivist theory of learning is cognitive apprenticeship. Whilst being based on theories that postulate that knowing is highly linked with doing, cognitive apprenticeship as a family of learning theories prioritises the importance of learning within the relevant context of the learning outcomes (Collins & Kapur, 2014). One important aspect of cognitive apprenticeship is the inclusion of an expert teacher who helps students learn and master skills through a variety of methods including modeling, coaching, scaffolding, articulation, reflection, and exploration. Cognitive apprenticeship focuses on the teacher-student relationship being collaborative, a constant cycle of analysis and feedback. This collaboration can be significantly reduced, in the case of streams, or eliminated entirely, in the case of videos. However, many of the methods highlighted in cognitive apprenticeship are still visible in the features constructed, as discussed below.

Cognitive apprenticeship places a heavy emphasis on the expertise of the teacher. The prevalence of *competency of producer* within examples provided by participants is therefore not surprising. Examples tended to include the accolades or skill-level of the producer, implicitly highlighting the importance of their competency within the context of learning. Interestingly, all examples that highlighted watching lower-skilled producers were raised as being unhelpful for learning. However, *trust in the producer's teaching* appeared to be highly linked to *competency of producer*, something that is not covered in cognitive apprenticeship. This is potentially due to the fact that cognitive apprenticeship was formulated within the context of an environment where the teacher is a central figure to learning and their expertise is assumed by the student, in other words a formal learning environment. In contrast, learning to play team-based esport games requires players to search for and make value judgements on a large number of resources provided by producers and select, for themselves, what they see as valuable. This informal learning environment requires players to place trust in the expertise of the producer and 'correctness' of the teachings. The reason this trust appears to be highly linked to competency could be that the accolades of a producer and their demonstrable proficiency are the best measurements watchers have to judge the value of a producer's teachings.

Returning to cognitive apprenticeship, modeling is one of the methods of teaching provided by cognitive apprenticeship and refers to experts demonstrating how they perform a task as well as providing commentary on how they do it (Collins & Kapur, 2014). Modeling can be seen in the results of this study through the *features explanation of teachings* and *teachings in action*. The fact that these features are two of the most commonly coded indicates the potential importance of modeling in learning from others as well as how videos and streams can help to support learning through cognitive apprenticeship.

Exploration and scaffolding as methods for learning are linked to the *provision of tips on what to do*. In exploration, the teacher aims to foster the development and solving of problems within learners. In scaffolding, the teacher provides support for students during their attempts to perform and master a task. The *provision of tips on what to do* to help them improve lies within both of these methods, but are limited by the inability of the teacher to reflect on individual performances of a watcher and provide further more personal feedback.

Attentive and receptive watcher disposition largely fits under cognitive apprenticeships method of reflection as participants often spoke about comparing what experts were doing, thinking, and saying in relation to their own gameplay. Participants often discussed teachings in action as well as their reflections of producer gameplay as being helpful for providing the perspective of an expert player. The use of self-regulation and reflection within the context of game-based learning is important for learning (Taub et al., 2020) and would therefore not be surprising as being important to game learning as well.

Beyond cognitive apprenticeship, *attentive and receptive watcher disposition* also overlaps with a few other theories and findings in constructivist and cognitive game-based learning research. The experiential learning cycle (Kolb, 2014) is a constructivist learning theory that postulates learning in a relevant context happens in four stages; an experience relevant to learning, a reflection on the experience, a conceptualisation of or adjustment to a constructed mental model, and testing the constructed model through experimentation. The *attentive and receptive watcher disposition* parallels the second stage of the experiential learning cycle, as well as the reflection method in cognitive apprenticeship. This similarly parallels Gee's (2007, p.105) hypothesize stage of his probe/hypothesize/reprobe/rethink process for learning.

Switching to cognitive learning, the *attentive and receptive watcher disposition* can also be seen in the cognitive theory of multimedia learning (Mayer, 2021). One of the three cognitive science principles underlying the cognitive theory of multimedia learning is the active processing principle which states that learning involves active engagement with the information being received as well as purposeful selection, organisation, and integration of information into memory. Not only is this feature seen in the active processing principle, it is also part of fostering generative processing, a goal of multimedia learning where it encourages individuals to take time to make sense of information presented.

The cognitive theory of multimedia learning also provides fifteen learning principles to help improve learning. Many of these principles align with several features constructed in this study. *Shorter lengths* reflects the coherence principle, where instructional multimedia should remove extraneous information, and the signaling principle, where essential information is highlighted. *In-depth detail* appears to stand contrarily to these principles. However, Mayer's principles for improving cognitive learning aim to minimise extraneous processing, cognitive processes used to filter and remove irrelevant information. It could be that what participants identify as *in-depth detail* is important relevant information for learning and improving.

The presence of *teachings in action* and *explanations of teachings*, especially when they are often discussed together, link to the *temporal contiguity principle*, providing narration and graphics (in this case, demonstration) at the same time. They also potentially link to the *multimedia principle* that states words and pictures are better for learning together than words alone, highlighting a strong link between the presence of both explanations and demonstrations to provide better teaching. The multimedia principle *guided discovery*, which indicates that hints should be provided as learners solve problems, can be seen in the *feature* of *provision of tips on what to do*, where *producers* would give *watchers* recommendations on what activities they should do or things they should learn. However, many principles do not appear to be linked or present in the *features* constructed in this study. This may be due to the fact that the cognitive theory of multimedia learning focuses on supporting cognitive processes, which are often unconscious, and so many of the more nuanced principles for learning remain unnoticed, and therefore unreported, by watchers.

Streaming platforms such as *Twitch*, especially as platforms for watching esport games, have seen a large amount of research into the culture surrounding them (e.g. Burroughs & Rama, 2016; Carter & Egliston, 2018; Kriglstein et al., 2020; Taylor, 2018) and the gratifications for audiences (e.g. Barney, 2021; Ma et al., 2021; Sjöblom et al., 2017; Weiss, 2011). Beyond its cultural and social impact, *ability to interact with the producer and receive feedback* has only seen one study exploring its role into learning of team-based esport games. Payne et al. (2017) examined the effectiveness of various forms of spectatorship and interactivity for learning to last hit in the team-based MOBA esport game *League of Legends* (Riot Games, 2009). They asked players to play the last hit trainer several times, provided a variety of interventions and a control, and then asked players to play the last hit trainer again. Their findings suggest that *ability to interact with the producer and receive feedback* does not play a large role in a media's efficacy for learning. The only significant improvement was found comparing the use of videos for learning in comparison to no videos, and that learners discussing a video of a novice with other learners improve more than learners watching the video of a novice alone. This appears to be echoed in the findings of this study as the ability to interact with the producer and receive feedback was the least commonly discussed feature of streams and videos for learning the team-based esport game *Dota 2*.

Both *easy to understand* and *applicability of teachings* are self explanatory in their relationship to learning efficacy of media. If a *watcher* cannot understand the information, skills, or concepts being discussed, then they will not be able to onboard the teachings of the *producer*. As well as that, if a *watcher* cannot transfer the knowledge from a video into their game, either due to the cognitive and physical manipulations being just too difficult for them or contexts not arising where the learnings are applicable, then the knowledge is useless to the *watcher* and may take up cognitive load better suited to other learnings. However, what *features* contribute to *easy to understand* and *applicability of teachings* are not found within the self-reports provided by participants. This may be due to the fundamental limitations of self-reporting and requires further qualitative research.

The features of *ability to control media*, *aimed to help learning*, *relevance to watcher's skill level*, *relevance to watcher's interests*, *relevance to the current* *meta*, and *patient and non-judgemental producer disposition* appear to be less prevalent in learning, game-based learning, and spectatorship research. These all reflect team-based esports unique learning practices that identify it as an informal learning environment, where individuals must find and select appropriate teachers and materials for learning on their own. Gee (2007) discusses a similar concept to informal learning environments known as affinity groups (or affinity spaces) in which individuals of a shared semiotic domain (e.g. team-based esport games, *Dota 2*) form shared ways of *"thinking, acting, interacting, valuing, and believing"* (Gee, 2007, p.27) and players must figure these out on their own to join the group.

Ability to control media, *attentive and receptive watcher disposition*, and all the codes regarding relevancy of content all highlight the active and deliberate role watchers have in seeking out appropriate material for learning. As well as that, *aimed at helping learning* and *patient and non-judgemental producer disposition features* indicate that not all forms of content with regards to their efficacy for learning are equal. The need for content to be aimed at helping *watchers* learn and *producers* to be supportive teachers means simply watching for entertainment or fun is not as effective as watchers seeking out informational and instructional videos. This further supports findings of *Deliberation* given in Chapter 3 and demonstrates that *Deliberation* is helpful when consuming content for learning.

4.5.2 Formats

Out of the three media forms raised in this study, *videos*, *streams*, and *replays*, *streams* are the most popularly researched format in esports spectatorship. This is possibly due to the exciting potential that the extra dimension of interactivity, as well as its live real-time nature, may provide to *watcher* and *producer* experiences. However, for learning, more helpful examples relating to *videos* were highlighted than streams and the feature of *ability to interact with the producer and receive feedback* is the least frequently coded in the data. A small number of participants even discussed that *videos* were better for learning since they managed to distil the information relevant for learning into a shorter time period, further linking *shorter lengths* as a helpful *feature* for learning.

As well as *videos* and *streams*, *replays* were also brought up as a helpful *media form* for learning to play. The *replays* allow *watchers* to manipulate the camera and playback of a match. *Replays* tended to focus on and be mentioned in relation to *ability to control media*, *attentive and receptive watcher disposition*, and *teachings in action* as participants highlighted how they could see a player's perspective and relate it to their own gameplay in as much detail as they require. Most research involving *replays* focuses on data analysis and visualisation such as result prediction (e.g. Johansson & Wikström, 2015; Katona et al., 2019) or analysis of player roles (e.g. Iacovides et al., 2015; Summerville et al., 2016). The findings of this study highlight that *replays* could benefit from more research looking at the efficacy of *replays* for learning.

The resulting *content genres* outlined in this study provide an interesting new opening into team-based esports learning research. The *content genre* of *competition* is well established as being used for learning by audiences (Barney, 2021; Huston et al., 2021; Sjöblom et al., 2017). As a *content genre*, *competition* was mainly spoken in relation to the *features* of *explanations of teachings* and *competence of produce*r as professional analysts and commentators were often mentioned as being helpful for learning. *Competition content* as a method of learning also aligns with cognitive apprenticeship, specifically the method of modeling (Collins & Kapur, 2014), where learners see how experts perform a task.

Gameplay and *instructional content genres* have some research indicating them to be effective at improving audience performance (Payne et al., 2017). *Instructional content* was the most commonly discussed *content genre*, but has seen little research in it's use for game learning. *Instructional content* was highly linked to the *feature applicability of teachings*, indicating that it is most effective when the learners can transfer teachings to their games. Whilst it wasn't a major feature of *instructional content* in the data, *aimed to help learning* is an obvious *feature* of *instructional content* by definition. *Gameplay content* showed more co-occurrences in data with the *feature competence of producer*, potentially highlighting a significant relationship between the performance of the *producer* in *gameplay content* and the helpfulness and effectiveness of the content for learning.

All other content genres (i.e. *analysis*, *coaching*, *smurfing*, *montage/clips*) exhibited even distributions of co-occurrences across a majority of *features*, making it difficult to ascertain any particular *features* that contributed to their helpfulness. *Coaching* as a helpful *content genre* makes sense within the lens of constructivist learning. Coaching as an activity is one of three particular mechanisms for learning within sociocultural game-based learning contexts (Steinkuehler & Tsaasan, 2020) and also a key method for one of the most prominent constructivist theories of learning, cognitive apprenticeship (Collins & Kapur, 2014). The fact that watching the activity of coaching is seen as helpful for learning adds an interesting potential dimension to learning through watching. *Coaching content* is not present in research, despite the links to cognitive apprenticeship and other constructivist theories of learning (Frederik Rusk, 2020).

Most *content genres* were discussed as being helpful. However, *smurfing* was the only *content genre* that was discussed in relation to unhelpful examples for learning. Participants would highlight how this kind of content wasn't aimed to help learning but for entertainment. Similarly, unhelpful examples of *montages/clips* were also given similar reasoning for not being helpful. However, *montages/clips* saw a mixed response as to whether they were helpful or unhelpful for learning. This could be due to the fact that they align to the feature of *shorter lengths* but also stand in opposition to other *features* such as *aimed to help learning*. For content creators and game developers of team-based esport games, the fact that these *content genres* are seen as unhelpful or mixed for learning can help them decide on what kinds of content they want to produce for their audience.

The lack of research into media and content for learning games largely makes sense as learning support for singleplayer or multiplayer cooperative games can be provided interactively through gameplay. However, for competitive multiplayer games, alterations to an individual's gameplay experience to make it easier for them to learn may be seen as unfair or providing them with an advantage. Therefore, most learning support occurs outside the context of competitive play. As such, the field of learning of competitive esport games would benefit from more research into how to provide better learning support for players, in-game as well as outside of competitive play and out-of-game through content platforms such as *YouTube* and *Twitch*. Content creators and game developers of team-based esport games can benefit from this research by analysing the kind of content they want to provide and, if supporting learning, looking at how they can best integrate the helpful *features* constructed in this study.

4.5.3 Limitations

Particular limitations to this study include the distribution of gender in this study's sample, which is unfortunately homogenous. Similar to the study outlined in Chapter 3, the distribution of gender is heavily male. This is likely due to the heavy distribution of males who play esport games (Interpret, 2019; Newzoo, 2021) and who use the social media platform Reddit (Atske, 2021). Why Reddit was used again after a heavily male distribution given in the first study is outlined in the Limitations section of Chapter 6.

This study contains self-reported data. Whilst it is pertinent and important to gather information from individuals who are situated within the relevant context, there are known issues with self-reported information. Social desirability bias means that participants are usually less likely to discuss activities and behaviours that are perceived as violating social norms, both globally and relevant to the community in question (Tourangeau & Yan, 2007). As well as that, participant reports are sensitive to their affective disposition and memory at time of participation (Kihlstrom et al., 1999). Both of these downfalls of self-reported information highlight that there are potentially gaps in these findings that would benefit from further research.

More generally, qualitative studies cannot establish representativeness of findings. The *features* and *formats*, specifically content genres, require further study into how well they characterise important helpful and unhelpful aspects of videos and streams for learning to play *Dota 2*. Such studies could include content analysis of online video content that highlights the presence of *features* or a comparison of *features* found and what players say are helpful for a particular video for learning.

Similarly, qualitative studies cannot conclude the relative relevance and importance of factors constructed in their findings. This study does include a proximity analysis highlighting the co-occurence of *formats* with helpful, unhelpful, and neutral examples, providing insight into the helpfulness of each *format* individually. However, it cannot prove how they rank against one another as being better or worse for learning.

Finally, this study focuses on one particular team-based esport game, *Dota 2*. This is due to its major share in esports spectatorship and player base (Newzoo, 2021, 2022) and to the availability of data at the time of the study. The *features* and *formats* need to be verified for other team-based esport games, both within and without the MOBA genre. As well as that, how *producers* and *watchers* differ in their behaviour between different kinds of esport games needs to be examined. Most studies on spectatorship tend to group esports together as one category or genre, but esport games contain a variety of different genres that may hold subtle differences in how and why members of communities around different games interact with content online.

4.5.4 Future Work

Whilst thematic analysis can provide a good foundation to understand the kinds of behaviours present in social phenomena, the findings presented will benefit from further validation. The kinds of further research from testing and validating these findings are discussed in the Limitations section.

The *content genres* raised show that players participate in many forms of spectatorship rather than just *competitions* or *gameplay*. These *genres* showed varying levels of helpfulness, with regards to the number of helpful and unhelpful examples provided. *Smurfing* was largely seen as unhelpful for learning, and *montages/clips* were controversial in their perceived effectiveness for learning. *Coaching* was almost uniformly positive in participant discussions, especially with lower-skilled participants, and could be an extremely useful *format* for novices. Team-based esports learning would benefit from exploring the learning efficacy of the constructed *content genres* as well as player affections towards them.

Finally, it is interesting to note that competency, despite being the most commonly and positively discussed feature, contains some contradictions in its relationship to media efficacy for learning. Whilst the majority of participants discussed helpful examples of learning from highly-skilled or professional *producers*, a few participants raised issues with learning from these *producers*. Similar to the contradictions and issues raised in Chapter 3 with regards to learning by watching, novice participants found that learning from expert *producers* wasn't helpful or difficult due to the *producers* assumptions of watcher knowledge, the overly high skill-level required for the teachings, or the lack of *relevance to the teachings to the watchers skill level*. Alongside the identification of dispositions, trust, and relevance, both studies indicate that the relationship between competency and learning is complex and requires further examination.

4.6 Conclusions

This chapter highlights the findings of a study asking players of *Dota 2* (Valve, 2013) what they find helpful in media for learning to play, focusing particularly on the parallels with cognitive apprenticeship in general and game-based learning literature as well as the importance of *competence of producer* and *relevance of teachings to watcher's skill level*.

Learning to play team-based esport games through *Consumption* of media, including multimedia such as videos or streams, was found to be the most commonly mentioned learning process identified in Chapter 3. As well as that, watching other players play to improve at an esport has already been demonstrated to be both a desire of the audience and more effective than practising without watching others. These findings motivated the study outlined in this chapter, where players of the team-based multiplayer online battle arena (MOBA) esport game *Dota 2* were asked to discuss helpful and unhelpful examples of media for learning to play. At the end of analysis, 390 examples of media were provided by 204 participants with 27 low-level categories constructed from the data. These categories are split into *features*, aspects of media participants referred to, and *formats*, the ways in which media and content is structured and presented.

Many of the *features* and *formats* exhibited parallels with prevailing constructivist and cognitivist theories of learning in general and game-based learning. For example, *features* such as *competence of producer*, *explanations of teachings*, *teachings in action*, *attentive and receptive watcher disposition*, and *provision of tips on what to do* can be linked to aspects of cognitive apprenticeship such as modeling and scaffolding. However, the findings discussed in this chapter also highlight the potential gaps in cognitive apprenticeship within an informal learning context. Learners need to make decisions about what sources to trust and what teachings to focus on, highlighted by the *features relevance of teachings to watcher's skill level*, *trust in the producer's teachings*, and *aimed to help learning*.

The most commonly highlighted individual feature by participants was the *competency of the producer*, being present in 117 examples. However, while most participants indicated the highly-skilled *producers* were very helpful for learning, and lower-skilled *producers* were not, some participants, mostly those newer to the game, highlighted the difficulties with learning from high-skill *producers* and applying learning to their own games. These conflicting messages run parallel with the difficulties raised by newer players trying to learn through *Consumption* in Chapter 3. It seems the relationship between competency and efficacy for learning appears to be more complex than a linear relationship. Qualitative insights from both studies provided by newer players seem to indicate that there may be some “best” skill-level to learn from relative to one’s own.

Chapter 5

Relative Competency's Role in Learning to Last Hit in *Dota 2*

5.1 Introduction

Chapter 4 demonstrated that the *competency of producer* as a helpful *feature* of videos and streams for learning was the most frequently mentioned or discussed by players of *Dota 2*.The *competency of producer* is interesting as it reflects the focus on an expert teacher or coach in many constructivist theories of learning, but also contradicts some of the issues with learning from watching highlighted by more novice players in the prior two studies. The study outlined in this chapter is motivated by the findings of Chapter 4 and hypothesises that there is a "sweet spot" of learning, or performance change, in relation to the skill difference between the learner and the teacher within the context of the last hit trainer in *Dota 2* (Valve, 2013). The last hit trainer was chosen due to the potential of *Dota 2* as a research platform and the use of last hit trainers in other games and other studies (Kleinman et al., 2021; Payne et al., 2017).

Throughout the previous chapter, the terms *watcher* and *producer* referred to individuals who watched media and produced media respectively. This choice in terminology, rather than terms related to learning (e.g. *learner*, *teacher*), reflects the fact that not all media discussed was watched or produced for learning. In this chapter, the focus is on the use of videos for learning and, as such, the following terms are used throughout:

Learners: Individuals who are watching media to learn how to play.

Teachers: Individuals who are in media that learners watch.

Skill Difference: The difference in ability between the teacher and the learner.

Performance Change: The difference in performance of the learner after spectating a teacher.

This study was approved by the University of York TFTI ethics committee. Participants were reimbursed for their time, being paid £5.63 for 45 minutes at the rate of £7.51/h. This study was pre-registered and it's pre-registration and data are available at https://osf.io/p6wmu/.

5.2 Background

The first study of this thesis found that learning by watching other players (*consumption*) was a core learning process. Whilst many participants spoke of watching players who were more experienced and skilled as being an important part of learning, newer players tended not to watch videos teaching them how to play (i.e. tutorial videos), as these videos would make assumptions about the watchers skill level. Exploring this further, the second study asked players what made videos of others helpful for learning to play. Three important codes emerged that highlighted the importance of relative skill between the watcher, the individual(s) viewing the media, and the producer, the individual(s) creating the media; *competence of producer*, *applicability of teachings*, and *relevance of teachings to watcher's interests* and *skill level*. As such, there appears to be some link between the watcher's competence, the producer's competence, and the difficulty of the teachings. Both the results of the first and second study of this thesis suggest that there may be a zone where optimal learning operates.

Alongside being grounded in the results of the previous studies of this thesis, it is also further supported by a well-established constructivist theory of learning in psychology, Vygotsky's zone of proximal development (ZPD) (Vygotsky, 1978). The ZPD model states there are three 'zones' of competency: things people can do unaided, things people cannot do even with aid, and between these two, things people can do with aid and encouragement by a more knowledgeable other. The latter is called the zone of proximal development because it is where learning can and does best occur.

5.2.1 Vygotsky's Zones of Proximal Development

Developed by Lev Vygotsky throughout the 1920's, eventually collated and translated into English posthumously in *"Mind in Society: The Development of Higher Psychological Processes"* (1978), the constructivist theory of a zone of proximal development (ZPD) is defined as *"the distance between the actual developmental level as determined by independent problem solving and the level of potential development as determined through problem-solving under adult guidance, or in collaboration with more capable peers"* (Vygotsky, 1978, p86). ZPD sits within Vygotsky's sociocultural theory of learning, which describes learning as involving the acquisition and development of values, beliefs, and strategies for problem-solving through collaboration and socialisation with others.

ZPD postulates the existence of three sets of skills; skills that can be completed by a student unaided, skills that cannot be completed by a student unaided but can be completed with guidance from a teacher or expert, and skills that cannot be complete by a student even with the guidance of a teacher or expert. The second set of skills, where

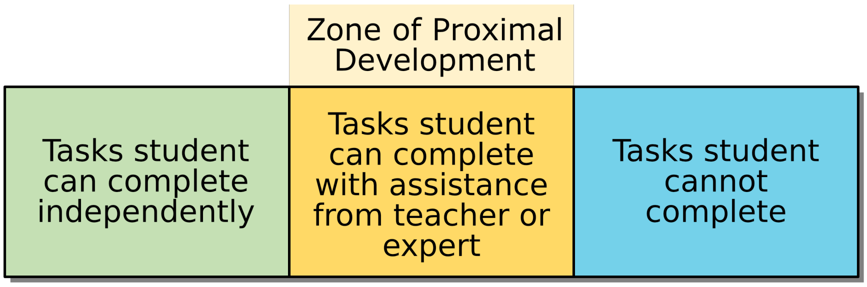


Figure 7: Diagram showing the three zones stipulated by the theory of the zone of proximal development as well the zone of proximal development.

students can complete them with guidance, is the zone of proximal development. A visual representation of the three sets of skills and the zone of proximal development is given in Figure 7. Vygotsky's original proposal focused on students in classrooms and argued against the usage of knowledge-based tests that only assessed the ability of students to recall and communicate information. Since it's first proposal, Vygotsky has become one of the most renowned constructivist psychologists. The zone of proximal development has become a popular cognitivist theory of learning in research (Margolis, 2020), also serving as the basis for further popular cognitivist theories of learning like cognitive apprenticeship (Collins & Kapur, 2014).

The field of game-based learning has explored the use of ZPD in a number of studies, including hypothesising how the different contexts of play and school affect developmental factors (Hakkarainen & Bredikyte, 2008), demonstrating the effect of age in children on learning within the zone of proximal development (Kanevsky, 1994), and the development of principles and frameworks for the design of games for learning utilising the zone of proximal development (Homer et al., 2020; Lecusay, 2015). When it comes to how people learn to play entertainment games, I could not find any prior empirical work exploring ZPD-related hypotheses. Brandse and Tomimatsu (2013) conducted a review of challenge in video game design, equivocating challenge in games to ZPD. Beyond that, there are some articles written by educators, designers, and game enthusiasts that analyse existing games and how their tutorial and onboarding sections teaching players how to play embody ZPD (e.g. Ku, 2018; Navazio, 2020) or look at how to design challenge and difficulty into games using ZPD (Redd, 2012).

Vygotsky's sociocultural theory of learning, including ZPD, as well as the theory of cognitive apprenticeship, which emerged from Vygotsky's sociocultural theory of learning, place high importance on students being able to see skills and tasks performed in context by a teacher or expert. Both theories describe these demonstrations under the term 'modeling', where students can make comparisons of their own ability to use a skill or complete a task against how an expert does. The discussions of previous chapters have highlighted the importance of modeling in learning team-based esport games. The first study of the thesis highlighted the prevalence and potential importance of watching and learning from others when learning how to play. It also demonstrated the potential difficulties newer players find when learning through watching videos and other media.

One issue highlighted by newer players was that these videos and streams often held assumptions on the knowledge of the viewer, knowledge that newer players do not have. This barrier also arose in the second study of this thesis, as the teacher's skill level was a commonly highlighted feature in what made videos helpful. Similarly, some learners highlighted that they would find videos or media frustrating when they could not apply the teachings to their own gameplay, either due to lack of relevance to the learner or lack of skill. Both these findings from the prior two studies suggest that there are difficulties faced by learners (especially novices) due to their competence in relation to the teacher.

Therefore, this study focuses on the skill level of the teacher relative to the learner and hypothesises that there is a skill level difference that produces optimal learning.

5.2.2 Spectatorship in Esports

Esports is not only defined by organised competition, it is also defined by its audiences and spectatorship. Like traditional sports, audiences like to watch esport games live both through streaming services and in-person. From 2019 to 2021, the audience for Esports has grown from 397.8 million to 474.0 million (Newzoo, 2022). People also like to watch other people play games outside the context of organised competitions. The games live streaming audience has also seen a large growth, increasing from 593.2 million people in 2019 to 728.8 million people in 2021 (Newzoo, 2022).

Hamari & Sjöblom (2017) utilises the motivations scale for sports consumption, which includes social interaction, to assess the motivations of watching esports and did not find a significant relationship between esports consumption and socialisation. They instead found that escapism, knowledge acquisition, novelty, and enjoyment of aggression were positively and significantly associated with the amount of esports a participant watched. Ma et al. (2021) explored ten spectator motives and their relationship with six 'live-streaming types' and four game genres. They similarly found that knowledge acquisition, particularly MOBAs, was a key motivation for watching esports. Finally, Huston et al. (2021) further explored how watching esports for learning compared across 'serious' and 'casual' spectators, noting that there were key differences in what each group learnt.

With regards to whether learning this way is actually effective, a study by Payne et al. (2017) found that learning through videos or live streams can significantly improve the watchers ability to perform a skill or task. They recruited a number of novice players to play a last hit trainer in the esport game *League of Legends* (Riot Games, 2009) before and after one of ten interventions. For these ten interventions, they formulated nine hypotheses that would be tested by the results. The only statistically significant results they found were that players would improve after watching a video of either an expert or novice player playing the last hitter, and that participants who watched the video of the novice player play and then discussed the video between themselves after improved more than if they had just watched the video.

Payne et al.'s study gives us some insight into the effectiveness of learning by watching others and even as to whether learning through livestreams is better than learning through video. However, it does not explore whether learning from an expert is better, the same, or worse than learning from a novice. As well as that, it may be that players learn best from players of a similar level and, since the majority of their participants had never played *League of Legends*, the full range of player skill levels was not explored. The following study hopes to explore how learner and teacher relative skill levels affect the performance change of the learner before and after watching the teacher.

5.3 Experimental Method

The hypothesis tested in this study is that there is a peak, or "sweet spot", in the performance change at a particular skill difference. To test this hypothesis, a between-subject single-blind experiment was implemented through an online survey. An online survey was utilised rather than in-person experiments due to the COVID-19 pandemic at the time this experiment was conducted. The video game selected for this experiment was *Dota 2* (Valve, 2013) as it is one of the most popular Multiplayer Online Battle Arena (MOBA) esport games with difficult skills that require practice to master.

5.3.1 Game Context: *Dota 2*

Dota 2 is a MOBA video game developed and produced by Valve. Outside of the main game mode, the developers have provided a variety of smaller game modes that allow players to practice particular skills without distraction. The one utilised for this study is the last hit trainer. The aim of the last hit trainer is to allow players to focus on getting the final hit on small AI controlled characters called "creeps". When players get the final hit on an enemy creep, killing it, they get some amount of experience and gold they can eventually use to level up or buy items respectively. This is known as "last hitting". Players can also get the last hit on friendly creeps to prevent an enemy from collecting experience and gold. This is known as "denying". Last hitting and denying are complex skills, requiring players to juggle information about damage, health, timings, and position.

In the last hit trainer, players are put on a map with a friendly and enemy creep base that spawn creeps in waves every thirty seconds for the three minute duration of the game mode. The creeps then move down a single lane towards the opponents base. On this lane are two towers, one for each team, that attack any opponents within a certain radius. The final scores players get at the end of the last hit trainer are the number of successful last hits, the number of successful denies, and the percentage of successful last hits and denies.

Last hitting is a neatly isolatable skill that the last hit trainer provides automated assessment for. Probably for this reason, last-hitting has seen an increase in usage as an assessment metric in recent research (Kleinman et al., 2021; Payne et al., 2017). It therefore offers the additional benefit of making results comparable across studies.

5.3.2 Present Study

This study asked participants to play six rounds of the *Dota 2* last hit trainer, three rounds before watching three videos of other players playing the last hit trainer, and three rounds after. Throughout this chapter, the three videos watched by participants are referred to as the *intervention*. The people who participated in the study by watching others are referred to as *learners* throughout this chapter. Similarly, the people who play in the gameplay videos are referred to as the *teachers*.

The performance change of the participant is calculated by the following equation:

$$P_{a,b}(X) = \sum_{i=a}^{b} \frac{L_i(X) + D_i(X)}{C} \tag{5.1}$$

$$\Delta P = P_{4,6}(Learner) - P_{1,3}(Learner) \tag{5.2}$$

where ΔP is the performance change, L is the number of last hits, D is the number of denies, and C is the total number of creeps (which is constant as each round of the last hit trainer spawns the same number of creeps). Throughout this chapter, this is referred to interchangeably as the *independent variable* or the *performance change*.

The skill difference between the participants and the people they watched is calculated by the following equation:

$$\Delta S = P_{1,3}(Teacher) - P_{1,3}(Learner) \tag{5.3}$$

where ΔS is the skill difference. Throughout this chapter, this is referred to interchangeably as the *dependent variable* or the *skill difference*.

Once the data is gathered and processed, the skill difference and performance change is analysed using regression analysis. Ordinary least squares (OLS) is utilised to find the value of the coefficients (b_2, b_1, b_0), as well as their significance, of the quadratic equation:

$$\Delta P = b_2 \Delta S^2 + b_1 \Delta S + b_0 \tag{5.4}$$

The findings of this analysis, including how well the data conforms to the assumptions of OLS, is then discussed alongside exploratory quantitative analysis of the last hits and denies as well as exploratory qualitative analysis of open-ended feedback provided by participants at the end.

5.3.3 Manipulation

This experiment consisted of one manipulation. Learners were placed into one of three groups: amateur, intermediate, and expert. The names of these groups indicate the teacher's performance in the videos. For categorising teachers videos, I assume a linear relationship between score and expertise as well as a uniform distribution across scores and expertise level. In the amateur video group, learners would be given 3 videos randomly sampled from a pool of 8 videos where the teacher achieved a score of $P_{1,3}(Teacher) < 0.33$. In the intermediate video group, learners would be given 3 videos randomly sampled from a pool of 8 videos where the teacher achieved a score of $0.33 <= P_{1,3}(Teacher) < 0.66$. In the expert video group, learners would be given 3 videos randomly sampled from a pool of 8 videos where the teacher achieved a score of $P_{1,3}(Teacher) >= 0.66$. The experimental manipulation is summarised in Table 7 and the videos provided are summarised in Table 8.

Group	Videos Percentage Score Range
Amateur	0% - 32%
Intermediate	33% - 65%
Expert	66% - 100%

Table 7: The three groups videos were separated into and the percentage score range for each group.

5.3.4 Measurement

For this experiment, learners were given three open text field boxes per round of the last hit trainer to report their number of last hits, their number of denies, and their last hit and deny percentage. The hypothesis testing only required the last hit and deny percentages, but the number of last hits and denies were gathered for exploratory quantitative analysis to help qualify the results.

In order to verify that the results provided were genuine, learners were asked to provide screenshots of their final score. Due to the volume of learners, not every submission was verified by looking at the presence of screenshots and accuracy of reporting. Instead, 5% of submissions (11 out of 222) were randomly selected for verification. If 20% or more (2 or more) of the samples' data does not match the screenshots or shows spurious screenshots, the rest of the data would be looked over by hand. To make sure that learners had spent sufficient time watching the videos, the questionnaire recorded the time that the page of the first video was opened and the time that the page after the final video was opened. If this time was less than the amount of time it would take to watch the three shortest videos in all categories (in this case, 9 minutes and 40 seconds to watch A60013, I195047, and I230062) then the data was not included in the analysis.

5.3.5 Procedure

Participation in this experiment required the installation of the game *Dota 2*. Potential learners were therefore asked, through *Prolific*, to fill in a short 1-minute questionnaire. This questionnaire asked participants: "Are you interested in playing *Dota 2* for 45 minutes in a future study in which you will be paid £7.51/hour?"; "Do you have *Dota 2* downloaded and installed or would be willing to download and install *Dota 2* before the study on [study date and time]? (You will not be compensated for the time to download and install *Dota 2*)" Participants who responded "Yes" to both questions would then be included and invited to participate in the full study.

Learners were invited to participate in the full study through *Prolific*. After reading the information sheet and filling out the consent form, learners are instructed on how to find the last hit trainer in *Dota 2* and how to select the hero *Juggernaut* on the hero select screen. Learners are told how to deny creeps in *Dota 2* as it requires a specific combination of actions that many newer players are not aware of. This action was also not divulged in any videos.

Learners are then asked to play three rounds of the last hit trainer, reporting their total number of last hits, their total number of denies, their percentage score of last hits and denies, and a screenshot showcasing their results for validation. After playing three rounds, participants asked to watch three videos of teachers playing the last hit trainer in full. Participants are then asked to play three more rounds of the last hit trainer, again reporting the same scores and providing screenshots.

Finally, participants are asked to provide their thoughts on what they "did or did not learn and what was helpful or unhelpful for learning". They were then thanked for their time and asked to click a link back to Prolific to prove they had completed the study and were paid upon validation.

5.3.6 Materials

For this experiment, 28 videos of teachers playing the last hit trainer were gathered. Teachers were recruited through word of mouth, Discord groups, and online forums. They were asked to submit a recording of one round of the last hit trainer. In order to magnify the effect size of the intervention, teachers were asked to talk about what they were doing and what they were thinking during play. Four videos were excluded from the final experiment as they provided little to no talking. In all the recordings, the mouse of the player was visible. Finally, whilst a majority of the videos included audio of the game, several videos only included audio from the teacher talking. However, the spread of videos missing in-game audio were fairly evenly distributed across the three categories and so were included. A summary of the videos are given in Table 8. The videos are also openly available, with audio distortions to protect identities, at https://osf.io/p6wmu/.

Learners were given a questionnaire to complete through the online survey tool *Qualtrics*. The questionnaire consisted of 4 demographic questions, 1 open-ended post study question, and 24 fields in which participants reported and submitted their scores and screenshots. The questionnaire also included instructions on how to access the last hit trainer in *Dota 2*, how to report the final scores of each session, and a reminder before each play session to try to score as many last hits and denies as possible.

Finally, the power analysis and quantitative data analysis was done in Python using the OLS linear model module of the statsmodels package. All materials, as well as the data and python code, are available at https://osf.io/p6wmu/.

Video ID	Group	Last Hits	Denies	Percentage Score	Length (m:ss)
A60013	Amateur	6	0	13	3:16
A80016	Amateur	8	0	16	4:17
A90018	Amateur	9	0	18	3:47
A110022	Amateur	11	0	22	3:22
A130027	Amateur	13	0	27	3:18
A130029	Amateur	12	2	29	4:06
A140029	Amateur	14	0	29	3:17
A150031	Amateur	15	0	31	3:33
I120037	Intermediate	8	10	37	3:22
I145035	Intermediate	5	12	35	3:48
I150033	Intermediate	15	0	31	3:29
I150037	Intermediate	12	6	37	4:58
I195047	Intermediate	16	7	47	3:11
I215054	Intermediate	17	9	54	3:18
I220052	Intermediate	19	6	52	4:31
I230062	Intermediate	16	14	62	3:13
E265075	Expert	17	19	75	3:31
E295079	Expert	21	17	79	3:33
E250066	Expert	18	14	66	4:21
E290077	Expert	21	16	77	3:30
E325089	Expert	22	21	89	3:56
E315085	Expert	22	19	85	3:28
E270070	Expert	20	14	70	3:21
E275077	Expert	18	19	77	3:38

Table 8: Videos gathered for the experiment. Videos were excluded based upon the amount of talking provided during play.

5.3.7 Analysis

Since this study is testing the hypothesis that the performance change can be mapped by a quadratic equation, Ordinary Least Squares (OLS) is employed to find the quadratic equation of best fit. OLS finds the coefficients for a given equation that provides the best fit of the equation to some data by minimising the squares error between the data and the equation. It assumes that the observations are independent, that variance is homogenous, and that the residuals (i.e. the distances between the observations and the equation) are normally distributed. OLS also provides the statistical significance of each coefficient and the equation. OLS was used to find the coefficients of best fit over the generated distributions of data for multiple non-standardized effect sizes and multiple residual errors. This test was then run 200 times for each sample size over a range of samples, residual errors, and non-standardised effect sizes. For a non-standardized effect size and residual error of about 0.1, it was found that a sample size of 220 reached target power of 90%.

When the data had been gathered, the performance change and skill difference is calculated and then mapped. OLS is then used to find the coefficients of a quadratic equation that best fit the data, as well as the p-values of each coefficient and the equation to test the statistical significance of each. How well the data fir the assumptions of OLS was also measured.

5.3.8 Participants

This study required teachers to be over 18 and fluent in English. Teachers were recruited through word of mouth as well as within several Discord communities. An even spread of scores of skill levels was reached without the need for purposive subsampling. 28 videos from 28 different participants were collected. Demographic information was not collected as it was not necessary for any analysis of the results. Four videos were excluded from the main study due to the lack of commentary by participants. This left 24 videos over three groups (eight amatuer videos, eight intermediate videos, and eight expert videos).

Learners must be over 18, have English as their first language, and identify their nationality as British. This criteria was used as a majority of the videos were from individuals with British accents and so would avoid any difficulties understanding what players in the video were saying. Through *Prolific*, researchers can screen participants by various demographics including age, language, and nationality. The first batch of sampling did not pre-screen for whether participants had a copy of *Dota 2* installed, a requirement of the study. After this first batch was gathered, further sampling started with a 1-minute pre-screen questionnaire, which was used to ask participants if they were willing to participate and willing to install *Dota 2* for the study. Participants who responded yes to both questions were then invited to the main part of the study. Participants who had already participated in the study were excluded from participating again.

5.4 Results

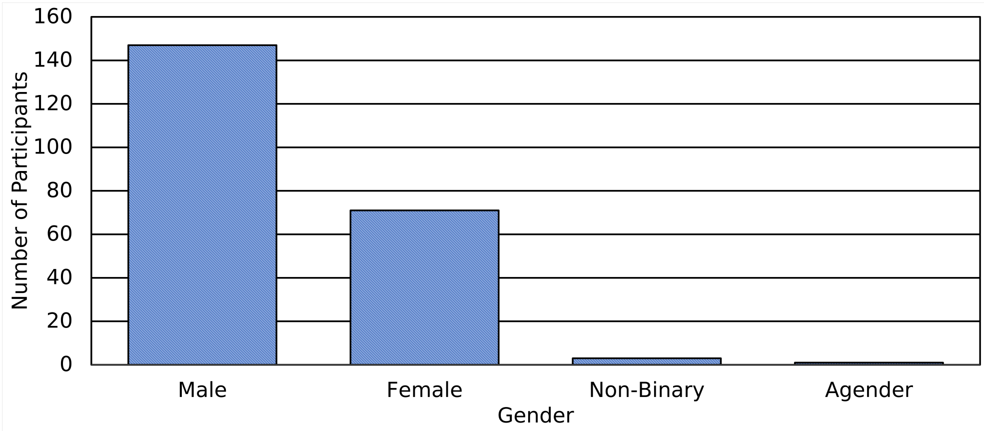
Overall, this study involved 292 participants. 70 responses were removed due to them not meeting the minimal time watching requirement. Out of the remaining 222 responses remaining, 147 participants identified as male (66.2%), 71 as female (32.0%), 3 as non-binary (1.4%), and 1 as agender (0.4%). Participants ranged in age from 18 to 65 years (*M* 30.24, *SD* 9.75). In terms of reported hours of *Dota 2* and Moba's played, each ranged from 0 to 7,750 (*M* 306.74, *SD* 1180.39) hours and

0 to 50000 (*M* 1031.85, *SD* 4573.11) hours respectively. Only two participants recorded hours in excess of 10,000 hours in MOBAs, which would require multiple years of non-stop play to reach these times. These are put down to inaccurate estimations of play-times and are excluded in demographic analysis. The distribution of gender, age, and total self-reported hours of *Dota 2* and other MOBAs played are given in Figures 8a, 8b, and 8c respectively.

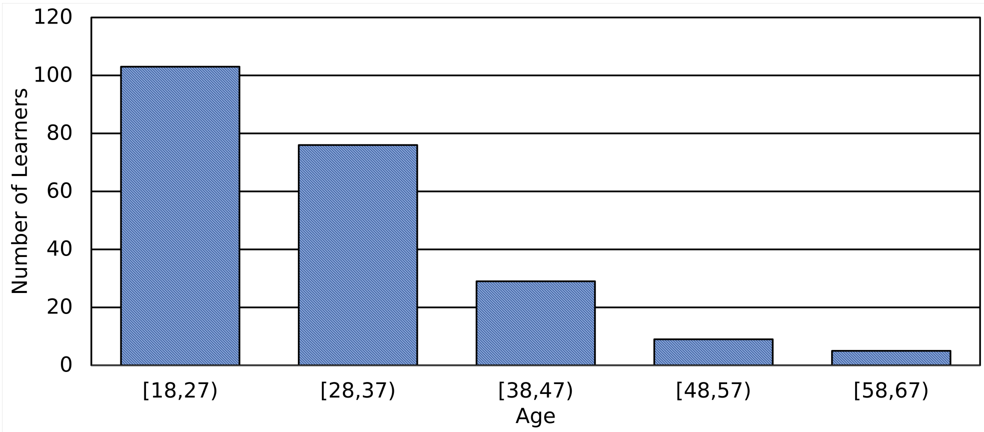
Ordinary Least Squares (OLS) regression indicated that skill difference has a significant influence on the performance change. The F-statistic of the regression model is 15.22 with $p < 0.05$ ($6.50e^{-07}$). However, the T-values of the coefficients for the linear and quadratic components highlight that only the linear relationship has a significant and positive influence. The OLS stipulates that for each 1% increase in the score difference between the teacher and learner, the observer will expect an average positive score change of 9.25%, with a standard error of 2.1%. The adjusted R^2 shows that the model generated by OLS accounts for 11.4% of the variance. Table 9 shows the results of the regression. Figure 10a and 10b both shows the data and the curve of best fit given by OLS, but colour data points by intervention group and self-reported total hours of *Dota 2* respectively.

	Coefficient	**Standard Error**	T **value**	$P > \|T\|$
Intercept	0.0527	0.007	7.975	0.000
ΔS	0.0925	0.021	4.349	0.000
ΔS^2	0.0009	0.044	0.020	0.984

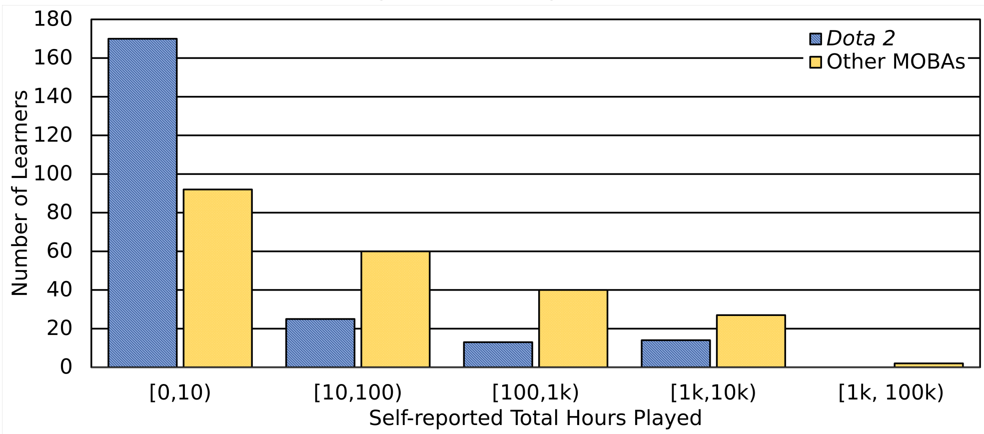
Table 9: OLS regression of the linear and quadratic skill difference. Coefficients and standard errors are given as decimal representations of score percentages.



(a) Distribution of gender among learners.



(b) Histogram of the age of learners.



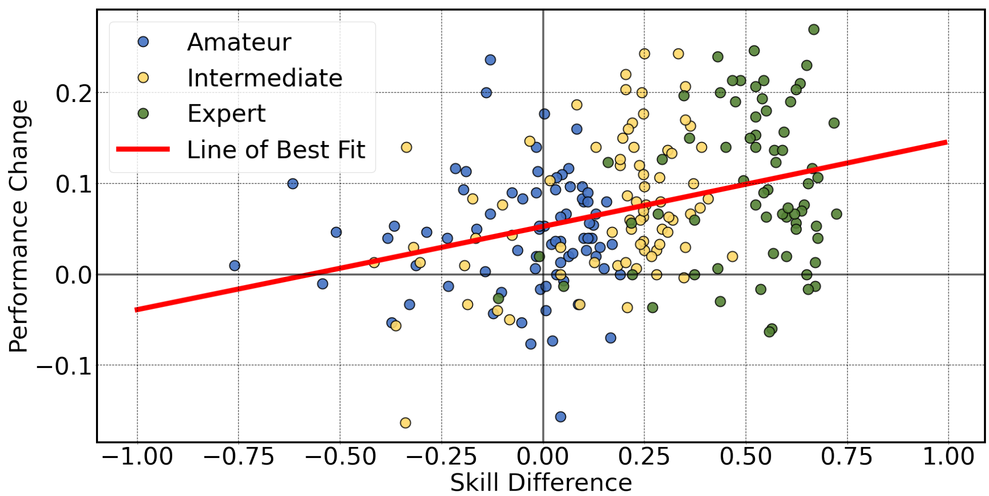
(c) Histogram of the total hours learners reported playing *Dota 2* and other MOBAs in their life.

Figure 8: Demographic data reported by learners including gender (8a), age (8b), and total hours of *Dota 2* and other MOBAs played (8c).

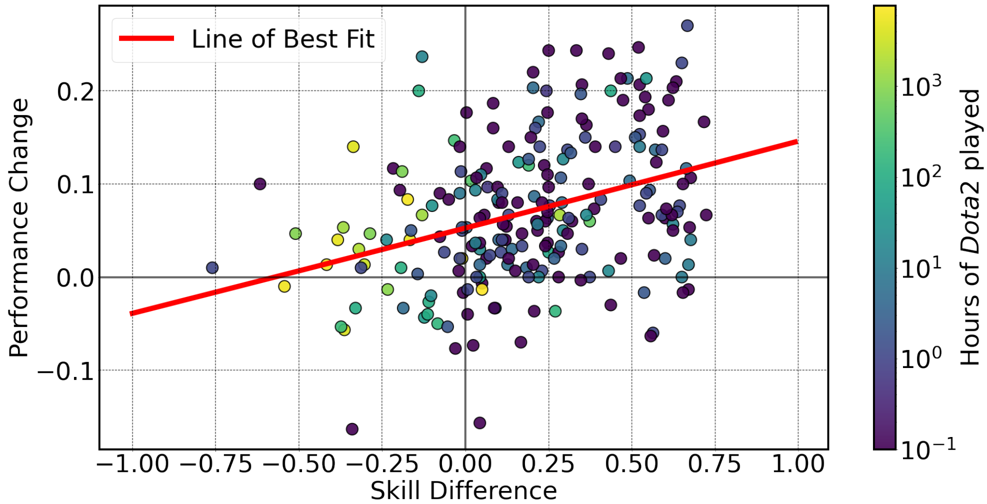
An important assumption underpinning OLS is that of a normally distributed residual error. OLS includes multiple measures to analyse the validity of this assumption in the data. The omnibus of this OLS regression is 0.586 with probability of 0.746 indicating that this assumption may be true. Similarly, a skew of 0.111, a Durbin-Watson of 2.034, and a probability of Jarque-Bera of 0.705 all indicate that the assumption of normally distributed residual error holds true. These values of linearity are mostly satisfactory for the use of a linear model for this data. However, some of these values are also close to the edge of indicating a nonlinear model might be more appropriate. This means that further validation is required using a nonlinear model. The full values for the analysis of how well the data fits a linear regression is given in Table 10.

Secondary Analysis

An exploratory analysis of the number of last hits indicate that there was no significant correlation pre- and post-intervention, unlike denies, which showed a significant positive correlation between pre- and post-



(a) Performance change plotted against skill difference with regression results coloured by intervention group.



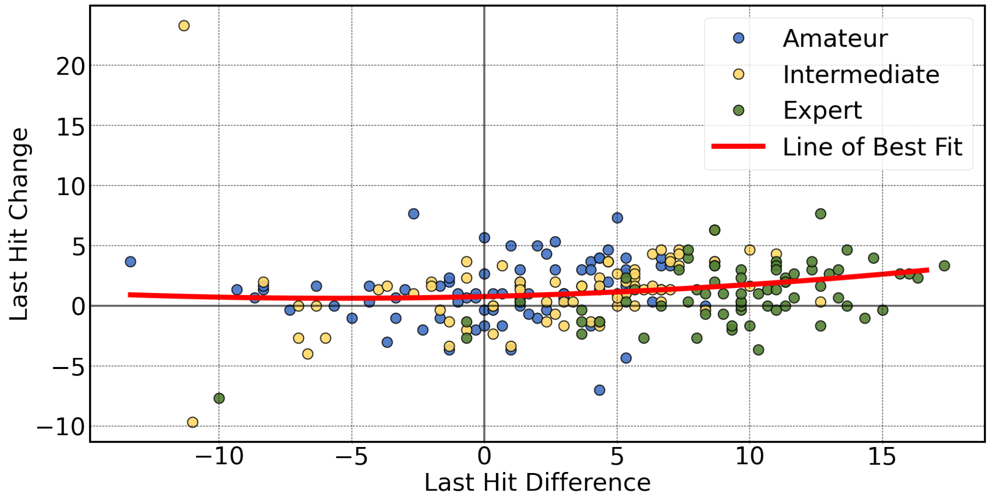
(b) Performance change plotted against skill difference with regression results coloured by self-reported total hours of *Dota 2* played.

Figure 9: Graphs plotting the skill difference against the performance change as well as line of best fit given by OLS. Figure 10a is coloured by intervention group. Figure 10b is coloured by self-reported total hours of *Dota 2* played.

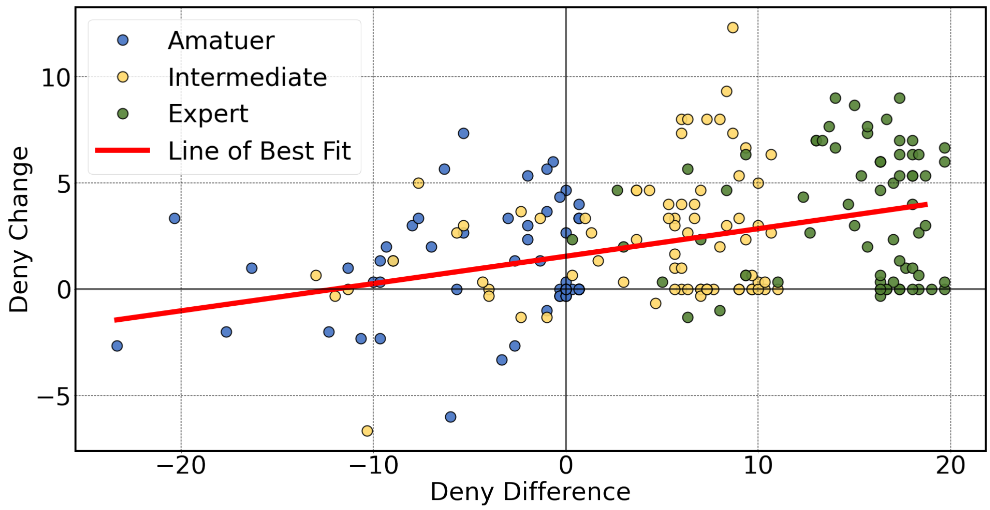
Omnibus	0.586
Prob(Omnibus)	0.746
Skew	0.111
Kurtosis	2.838
Durbin-Watson	2.034
Jarque-Bera	0.698
Prob(JB)	0.705
Condition No.	9.5

Table 10: Values for validating the "goodness" of the OLS model for the given data.

intervention. These are visualised in Figure 10. Whilst it would be possible to split the data into groups of which videos were watched and analyse the pre- and post-intervention score changes, the results are difficult to interpret as they would only provide between 30-45% power (found in the simulatory power analysis for sample size of 60-80 given by splitting the sample of 222 into three).



(a) Last hit difference plotted against last hit change including line of best fit.



(b) Deny difference plotted against deny change including line of best fit.

Figure 10: Graphs plotting last hit and deny skill difference and performance change as well as the results of OLS.

Looking at the open ended responses given by participants, most learners in the amateur group would highlight how unhelpful videos were for learning. For example, learner 7649 was placed in the amateur group, reported having never played *Dota 2* before, and saw in increase in their average post-intervention score, stating: *"The videos were really [helpful]!"*. In contrast, learner 9973 similarly was place in the amateur group, reported having never played *Dota 2* before, and also saw an increase in their average post-intervention score, but stated: *"I found the videos unhelpful as they didn't seem to know what they were doing"*. Learners that reported more hours in the game generally found amateur videos unhelpful. Learner 5759, who reports having 900 hours in *Dota 2*, states about the amateur videos: *"Videos were just 3 people who were unfamiliar with the game getting upset they weren't instantly good. Didn't know the mechanics, provided no useful advice."*

Learners who reported having more hours in *Dota 2* and in MOBAs generally found that intermediate and amateur videos did not help a lot. Even some expert videos weren't helpful for more advanced learners, as learner 7936 states: *"I was trying to apply the concepts mentioned in the videos already - I don't think that watching them taught me anything new"*. Some learners even stated they felt like they had performed worse after watching amateur or even intermediate videos. Learner 1628 states *"I didn't find anything in the videos useful, though they were mildy entertaining/frustrating... I actually think they negatively affected my performance initially"*. Similarly, learner 7520 talks about intermediate videos saying *"after watching the videos, i felt worse"*.

5.5 Discussion

This study aimed to operationalise and test the hypothesis proposed by Vygotsky's Zone of Proximal Development (ZPD) (Vygotsky, 1978) within the context of the complex digital game *Dota 2* (Valve, 2013). Participants were asked to play *Dota 2*'s last hit trainer before and after watching videos of other players playing to compare the score improvement based upon the skill level of the players they watched. Using Ordinary Least Squares (OLS) Regression when comparing the score difference of participant and performer against the participants score improvement, this study found that the quadratic term of the line of best fit has an insignificant influence meaning there is no inflexion point or zone of most improvement. However, the linear term did have a weak positive and significant influence on the score improvement, accounting for 11.4% of the variance. This indicates that the greater the positive difference in score (and by proxy skill) between the teacher and learner, the greater the score improvement of the learner after watching the teacher.

The results of this study apparently disagree with the theory of ZPD, with respect to the apparent skill level of the teacher. This may be due to several different reasons. Firstly, the manipulation may not have been strong enough to identify the zone of proximal development. The range of skill differences between teacher and learner may not be wide enough to identify a quadratic curve. Secondly, this study may not operationalise ZPD. ZPD mainly focuses on the skills being taught. The assumption of this study is that teachers who are slightly better than the learner are teaching skills that are in the ZPD. Based on this assumption, this study then uses the skill difference as a proxy for ZPD. Finally, if the two explanations provided above are unlikely, then the final conclusion of this study would be that ZPD doesn't hold within the context of learning *Dota 2* from watching others. This could then have large ramifications for the applicability of Vygotsky's sociocultural theory of learning (Vygotsky, 1978), if not other theories of learning, to the context of team-based esport games.

Judging the evidence for the three possible explanations of this study's findings, it is likely that this study either does not involve a strong enough manipulation or that it does not operationalise ZPD. Vygotsky's sociocultural theory of learning and ZPD hold significant sway in psychological and pedagogical communities and has become a popular research topic (Margolis, 2020) after being first proposed in

1978. As such, it seems that further research is needed to test ZPD's presence and effectiveness in learning to play team-based esport games.

The presence of a significant relationship between teacher-learner skill difference and learner performance improvement further supports the primary findings of the second study of this thesis, which suggested that the competency of the teacher is an important (or at least perceived to be relevant) feature for learning through videos and streams. The results also seem to disagree with comments provided by more novice players in the first study and second study of this thesis, who stated how they found it difficult to learn from videos made by experts.

Therefore, it seems that the first and second studies of this thesis highlight the importance of the relevance of the subject to the learners skill level and interest. Participants with fewer hours in a team-based esport game would find videos for learning hard to watch as teachers would make assumptions about the viewers knowledge that were incorrect. As well as that, two of the frequently coded features for videos and streams that were helpful for learning was the *relevance of teachings to watcher's skill level* and the *relevance of teachings to watcher's interests*.

It may be that the last hitting and denying is an especially relevant skill for players who are less experienced in *Dota 2* and so found all videos helpful. Further analysis of last hit and deny scores showed that only the deny scores had a positive and statistically significant correlation between teacher-learner score difference and learner score improvement. Since last hits and denies make up the total score, this could indicate that the ability to deny a creep has a far greater impact on the total score improvement than the ability to last hit. Despite the instructions provided by the survey on how to deny, there were comments made by participants that they could not manage to figure out how to do it.

This study is similar to Payne et al.'s (2017) study examining learning effects of watching other players in the MOBA *League of Legends* (Riot Games, 2009). They asked players to play a similar training level that tested players on Last Hits and Denies as well and looked at score differences between pre- and post-intervention. Payne et al. utilised a variety of different interventions that explored how interactivity between learners and performers affected score improvement. Whilst they had asked participants to watch either a novice or expert player, they did not test any hypothesis that compared the difference between participants who had watched a novice player and those who had watched an expert player. They did find that watching either a novice or expert player did cause a significant improvement in score when compared to the control group which largely fits with the findings of this study.

Extrapolating the line of best fit towards the more extreme negative values (where the performer has a score far lower than the watcher) gives negative score improvement (i.e. the watcher gets worse). Not only that, there are examples in data where learners actually performed worse after watching the videos, particularly amateur ones. It was even highlighted by learners with more hours in *Dota 2* who watched amateur videos. One possible explanation could be that learners assumed that the teacher would provide teachings that would help them improve. However, participants did see the scores of those they watched at the end of each video and would often comment about how amateur teachers did the wrong things or didn't help them learn anything. In a future study, it would be interesting to look at how expert players explain these changes in their performance after watching amateur players.

5.5.1 Limitations

Whilst last hitting is a complex skill, it is only a small part within the context of *Dota 2*. In competitive play, players also have to think about the timings and abilities of allies and opponents as well as efficiently distributing the rewards of last hitting and denying to allies who benefit from it most. As well as that, players will level up and gain items that provide various improvements to their character as the game progresses. These then either affect the timings and damages of the abilities they mainly use or provide new abilities to use to last hit and deny. The last hit trainer largely helps players with the technical ability to last hit and deny, but often requires further training in its strategic use. As such, the findings of this study may largely be restricted to the regimented environment of a trainer, the technical ability usage of a skill, or both.

Further feeding into this limitation is the underlying assumption that skills and mastery increase linearly. This was a naive assumption made due to resource constraints. However, skill acquisition and mastery in online games has been demonstrated to have diminishing returns (Stafford & Dewar, 2014). Meaning that as a player's expertise increases, it takes a greater amount of practice to see similar improvements in their skills. It is possible, if not likely, that expertise is not spread evenly over a skill, but logarithmically. It would be pertinent to look at what scores players expect to see from amateur, intermediate, and expert players as well as the distribution of last hitter scores over the general population to test this assumption.

5.5.2 Future Work

This study provides evidence that suggests that a watcher's performance in a skill increases linearly with the skill level of the person they are watching. However, this has only been tested within the context of a specific skill isolated in a training environment, last hitting and denying in the last hit trainer. One reason for this study's findings could be that the manipulation provided is not strong enough. This may be tested in a future study either by increasing the distribution of expertise present in teachers and learners. Equally, it could be tested by looking at a wider range of skills or more complex skills rather than just last hitting and denying. Another reason could be that this study does not operationalise ZPD, at least not directly. In order to test ZPD, by looking at skills, within the context of a team-based esport game, a future study would categorise important skills for a particular game and ask players of a similar level to learn these skills either on their own or with a teacher and measure the performance change of each skill depending on the presence of a teacher.

The linear relationship between skill difference and performance improvement implies that there may be a point where the producer's skill level is so much less than the watcher that the watcher performs worse after watching. This was even highlighted by one participant in the open-ended question at the end of the experiment. The idea of someone performing worse after watching someone else play, even someone significantly lower in skill than them, seems counterintuitive to common models of skill and mastery as being cumulative, degrading over time without practice. It would be pertinent to explore if this extrapolation does work by testing a variety of skills in-game with highly-skilled or professional players. Can watching players who are significantly worse than you negatively impact your ability to play a game? And what might be the contributing factors?

Exploratory quantitative analysis found a similar linear relationship to the score improvement for denies, but not for last hits. This implies that denies, and the ability to deny, are having a larger impact on the resulting score improvement than last hits, and ability to last hit, are. Whilst the current evidence seems to suggest the increased importance of denies over last hits, it must be further validated by another study that performs an ANOVA over the last hits, denies, and total score improvements either over the existing data (if power is reached) or over newly generated data.

5.6 Conclusion

This study aimed to examine the idea of a “sweet spot” for learning *Dota 2* (Valve, 2013) from watching others through regression analysis. The hypothesis, that there is a certain learner-teacher skill difference that produces the most improvement, stems from two sources: the previous findings of the two prior studies in this thesis, and the theory of Zones of Proximal Development (ZPD) (Vygotsky, 1978). Participants were asked to play the Last Hit Trainer in *Dota 2*, a small training environment that tested the skills of last hitting and denying, before and after watching other players of varying levels also play the Last Hit Trainer The score improvements of 222 participants were measured against the difference in scores of participants against the people they watched. Using Ordinary Least Squares (OLS) regression analysis to find the quadratic line of best fit, it was found that there was a statistically significant correlation for the linear coefficient, but not for the quadratic coefficient. The line of best fit was also statistically significant, indicating that there is a positive linear correlation between the learner-teacher skill difference and the skill improvement of the learner.

The linear correlation between teacher-learner skill difference and learner improvement further validates the findings of the previous study that indicated the competency of the teacher was an important factor in videos or streams for learning. However, it does contradict some of the concerns given by some participants in both the first and second study of this thesis, who highlighted the difficulty with learning from experts and its relevance to their skill level. This relationship also compliments work on spectatorship which shows that the use of any video for learning is better than none at all. However, exploratory analysis indicated that teacher-learner last hit difference and learner last hit improvement were not significantly correlated. But deny scores were. This relationship to the score improvement needs to be explored further as participants highlighted that they did not understand how to deny, despite the experimental procedure informing them how to.

Chapter 6

Discussion

This thesis aimed to explore the role of spectatorship in how novices learn to play team-based esports games. Through qualitative player interviews, I first identified general learning processes, tools, and outcomes. Further qualitative survey research then identified aspects of media that made them helpful for learning a particular team-based esport game, *Dota 2* (Valve, 2013). Here, players identified the relative competency as the most important factor for learning. The final study of this thesis therefore experimentally tested the effect that competency of a producer relative to the watcher has on the watcher's performance after watching a producer.

Whilst the first two studies indicate that newer players benefit learning from players closer to their skill-level, the final study's findings suggest that players learn best from highly-skilled players. This overarching finding makes empirical and theoretical contributions to team-based esports learning research, especially for novice players. The individual findings of each study also provide starting points for future research into team-based esports learning and the use of media for learning in games. As well as contributions to research, the findings also provide practical implications for developers and content producers looking to create content to help players learn to play.

The discussion of this thesis looks at each of the research questions outlined in the Introduction where it highlights the findings of the relevant studies, discusses key contributions, and outlines future work. The answers to the thesis question, including the contributions of this thesis as a whole, are then examined. Finally, the discussion ends by raising potential limitations of the methods and findings presented in this thesis.

6.1 Research Question 1: How do players learn team-based esports games?

Whilst game learning research has taken similar qualitative approaches to understanding how players learn to play e.g., puzzle games (Iacovides, Cox, et al., 2014) or fighting games (Hung, 2011), there has been no similar bottom-up research tracing the learning processes of team-based esports games. In response, the study reported in Chapter 3 identifies learning processes, tools, and outcomes observed in common learning team-based esports games.

Spectatorship plays an important, if not a pivotal, role in learning of team-based esports games. Players of both *Dota 2* (Valve, 2013) and *Counter-Strike: Global Offensive* (*CS:GO*) (Valve & Hidden Path Entertainment, 2012) discussed a number of examples of learning moments where observing other players played a significant role in learning something new. So much so that it was the most frequently mentioned learning process raised by the first study.

Watching other players plays a large part in learning team-based esport games, often discussed within the context of watching professional players' gameplay or by observing other players in-game. This learning process was coded under *consumption*. Whilst research on spectatorship has found knowledge acquisition an important motivation (Hamari & Sjöblom, 2017; Ma et al., 2021; Sjöblom et al., 2017) as well as being effective for learning (Payne et al., 2017), Chapter 3 demonstrates it's important role in learning team-based esport games. Within game-based learning, *consumption* finds parallels in constructivist learning theories that include some form of modeling, where teachers demonstrate skills in-action within relevant contexts (Steinkuehler & Tsaasan, 2020; Whitton, 2014). Despite it's importance, what makes *consumption* and spectatorship effective for esports learning has not been explored - something that would be a pertinent next step for esports learning and spectatorship research.

Spectatorship also helps players recognise new knowledge or skills they have not yet acquired or mastered, described by the learning process *identification*. Research on learning behaviours and processes similar to *identification*, including the process of reflection, in esport games is limited to work demonstrating differences in self-regulated learning between experts and non-experts (Kleinman et al., 2021). Kleinman et al. (2021) found that experts and non-experts set up different aims in for practice as well as structured their practice differently. The choosing of aims for practice and the constructed definition of *identification* reflects aspects of the three following experientially focused constructivist theories of learning: Kolb's experiential learning cycle (Kolb, 2014), Gee's probing principle (Gee, 2007, p.105), and Zimmerman's cyclical phase model of self-regulated learning - some of which have seen adoption in game-based learning (Whitton, 2014, p.41-45). These findings emphasise importance of self-identifying what one does and doesn't know and what one needs to know, which exemplifies the context of team-based esport games as an informal learning environment, where learners must find and make value judgements of information and instruction. Esports learning research would benefit from focusing on how players navigate such a large informal learning environment, potentially using the lens of self-regulated learning.

These concepts highlighted in *identification* and assimilated through *consumption* are then put into play for the first time through *application*.

As a learning process and method, *application* involves a variety of strategies (e.g. trial and error, experimentation, exploration) which have been observed in singleplayer and multiplayer puzzle games (Iacovides, Cox, et al., 2014). Finding such strategies in two contrasting game genres suggest that *application* as a learning process may be important to a wide variety of games. This learning process finds parallels with ”experience” steps in constructivist theories of learning that focus on experience (e.g. Gee, 2007; Kolb, 2014). Examining how players take learnings from *consumption* and *identification*, and observing how they *apply* them to their gameplay, would be a pertinent step for research.

Players can then embed learnings through *practice* in-game. *Practice* has been demonstrated within the contexts of other games such as fighting games (Hung, 2011) and puzzle games (Iacovides, Cox, et al., 2014). However, puzzle game *practice*, or *repetition* as it’s defined by Iacoivdes et al. (2014), focuses on the repetition of a specific action within the context of solving an individual puzzle. Within the context of esport games, *practice* focuses more on the repeition of general skills to then be applied within multiple competitive contexts. *Practice* also echoes seminal psychological research on *deliberative practice* (Ericsson et al., 1993) as well as research in sports psychology (Ward et al., 2007). However, the cross-cutting dimension of *deliberation* constructed in this thesis suggests that *practice* consists of more than *deliberative practice*. For example, participants discussed times when playing that they would not highlight or recognise as *practice* but involved activities that aligned to the constructed definition of *practice*.

Chapter 3 also constructs a list of learning outcomes relevant to novice learning of team-based esport games. These outcomes reflected many competencies hilighted by other esports research. However, some deviations were noticed, such as a lack of reference to *controls* in other research, or large numbers of competencies raised all fitting under the single learning outcome of *non-game specific skills*. Since most research focuses on expert players, these discrepancies potentially highlight that the relevance of competencies changes over skill level as well as which competencies are more relevant to novices. The fact that *controls* are present with novice learners and many *non-game specific skills* are not suggest that it is important for developers to focus on simpler game specific skills for newer players and more general non-game specific skills for more expert players.

Finally, dimensions of learning tools were constructed, reflecting the tools position in- or out-of-game and whether the tool was produced by the developers of the game or by another party. The main contribution of these findings is to highlight the myriad of tools players of team-based esport games and to direct future research towards the more promising tools, such as training environments and spectatorship platforms.

The findings outlined in Chapter 3 can help players further understand their learning habits and allow them to reflect on the methods of learning they find helpful and productive. They can also help developers of esport games identify aspects of their games that they could improve support for. *Identification*, reflection, and self-regulated learning also suggest that developers could provide learning support for new players of esport games by, potentially adaptively, highlighting important learnings through tips or recommendation systems. Developers could help support *consumption* as a learning activity by either producing and recommending their own instructional video or stream content or by recommending existing content to players. The presence of *practice* and it's links to training modes indicate that these environments would be useful for developers to implement for a wide variety of learning outcomes. These results could also be integrated into design frameworks for developers to adopt, such as the Accessible Player Experience (Beeston et al., 2018) framework that helps developers identify and design solutions for concerns around accessibility.

Chapter 3 highlights that, throughout a player's learning journey of a team-based esport game,learning by spectatorship plays a constant role in the growth and development of a player's abilities and skills in game. Regardless of whether the intention of watching other players was for learning or entertainment, it was highlighted by participants that they were always opportunities to learn.

6.2 Research Question 2: What factors are helpful when learning team-based esports games from spectating?

There are a variety of factors that players highlight as being contributory to the helpfulness of videos and streams for learning. Any aspect of streams, videos, or other media participants referred to were categorised under *features*. Overall, 17 *features* were constructed which were then categorised as being relevant to one or two of the following sub-categories: *media*, *content*, *producer*, *watcher*. *Features* of media more frequently being described as helpful include: *competence of producer*; *applicability of teachings*; *explanation of teachings*; *teachings in action*, where viewers can see teachings being used within the appropriate context; and *relevance of teachings to watcher's skill level*, where the teachings provided by the content creator are relevant to the contexts the viewers typically engage with (e.g. playing against lower-skill players). The prevalence of these *features* in responses further demonstrate esports game learning as an informal learning environment as players have to make value judgements of media based on the producer and relevance of teachings, which are often assumed in formal learning environments.

Many constructed *features* contain parallels with cognitivist principles and findings for multimedia learning. Mayer (Mayer, 2020) identifies several promising aspects of multimedia learning contributory to better learning that parallel some of the *features*, such as: *attentive and receptive watcher disposition* and the cognitive science principle *active processing*, which states learning involves active engagement; *short length* and the *coherence* principle, which states multimedia should remove extraneous information; and *explanation of teachings* and the promising feature of *modality*, which states that words presented in spoken form tend to provide better learning gains.

As well as *features*, the different ways content of media was structured and presented was also discussed by participants, labeled as *formats*. *Content genre* focuses on the ways that the content of media is structured an presented. Seven *content genres* were constructed (*instructional content*, *gameplay content*, *competition content*, *analysis content*, *coaching content*, *montage/clips content*, and *smurfing content*), of which *instructional content*, where producers make content that is structured to highlight and teach skills or concepts, was mentioned as the most helpful. This is because many of the helpful *features* constructed were inherently present in *instructional content*, such as: *explanation of teachings*, *teachings in action*, *provision of tips on what to do*, and *aimed to help learning*. Interestingly, *coaching content* provides a potential new dimension to the coaching method of learning highlighted by cognitive apprenticeship (Collins & Kapur, 2014) and utilised for game-based learning (Whitton, 2014). Coaching in cognitive apprenticeship considers the learner as a participant in the activity, but the findings outlined also highlight the benefit for learners who are observing the activity.

The findings of Chapter 4, discussed here, help to further demonstrate spectatorship as a pivotal learning practice for esports game learning. The *features* and *formats* constructed show strong potential parallels with theories of learning utilised by game-based learning research, indicating they could be relevant and should be looked at in more detail. For example, how much do promising cognitivist features of games in game-based learning (Mayer, 2020) affect learning through spectatorship? In what ways could the method of coaching in cognitive apprenticeship (Collins & Kapur, 2014) be relevant to watching *coaching content*?

These findings are also relevant to developers and content creators for esport games that are interested in supporting learning. There is little to no research or media currently that helps producers of videos and streams identify what aspects of their content are helpful for supporting learning of esports games. The *features* and *content genres* highlighted as being helpful by participants can be integrated into stream and videos produced by developers or content creators for supporting learning of esports games. Developers could integrate the *features* and *content genres* into videos and streams they produce, that they then present or recommend in-game, to help novice players learn to play. Content creators can benefit similarly from the *features* and *content genres* highlighted as they can integrate these into content they make for supporting learning. The resulting content output would then be more helpful and potentially more popular with viewers.

What participants found most important in spectatorship for learning is the teaching of replicable and relevant skills from trusted expert players who discuss reasonings behind their teachings.

6.3 Research Question 3: How do skill differences between spectator and player affect learning from spectating?

Newer players of team-based esport games in both the first and second study of this thesis highlighted some difficulties with learning from highly-skilled players. These insights provided part of the reasoning behind testing the hypothesis of a "sweet spot" in competency difference between the producer and watcher, and the performance increase of the watcher. These insights also seem to align partially with the pedagogical theory of zone of proximal development (ZPD) (Vygotsky, 1978) which stipulate that there is a zone of learning where individuals can perform and learn tasks with the aid of a teacher.

However, the resulting regression analysis does not support the presence of a point or zone of optimal improvement, but a positive linear correlation between skill difference and performance change. This contradiction between the hypothesis and the results could be due to several different reasons: the manipulation may not be strong enough to identify the zone of proximal development, the study design may not operationalise ZPD, or ZPD does not hold within the context of learning *Dota 2* by watching others. Since Vygotsky's sociocultural theory of learning (Vygotsky, 1978), and ZPD as one of it's resultant theories, is a highly researched and popularly cited constructivist theory of learning (Margolis, 2020), it is highly likely that this study either does not involve a strong enough manipulation or that it does not successfully operationalise ZPD. As such, it seems pertinent to the field of esports learning research that, in order to integrate commonly used theories of learning used in game-based learning such as ZPD (Whitton, 2014 p.55-

56) and cognitive apprenticeship (Whitton, 2014 p.45-48; Steinkuehler and Tsaasan, 2020), more research utilising different methods of operationalising theories of learning needs to be conducted within the context of esport games.

Further extrapolation of the findings, some examples in the data, and some reports by participants suggest a point in teacher-learner skill difference where the performance change becomes negative. This indicates that if a learner watches a teacher who is sufficiently lower in skill, that the learner's performance will be negatively impacted by watching the teacher.

6.4 Thesis Question: What are success factors in novice learning of team-based esport games through spectating?

Throughout this thesis, various methods of research and inquiry are taken to understand the role of spectatorship in learning and what makes it a successful method of esports game learning. Beyond the direct findings and contributions each individually makes, there are some shared contributions across all studies that provide implications for theory and practice of esports learning.

The findings of this thesis highlight an interesting dimension to self-regulated learning and informal learning environments that has not been directly looked at. The learning process *identification* constructed in Chapter 3 focuses on players reflecting on previous experiences and performances and discovering what knowledge and skills they currently do not possess or require. This reflective process parallels self-regulated learning (SRL), where students systematically orient self-generated thoughts, feelings, and behaviours towards the attainment of personal goals (Zimmerman, 1990).

The use of SRL has already been demonstrated in players of differing levels in esports when *identifying* what outcomes to focus on and how to structure *practice* (Kleinman et al., 2021). SRL is also a constructivist theory of learning within the context of informal learning environments, where students are not guided by a central authoritative teacher or curriculum but by their own values and judgements of available information and teachers. The overlap of *identification* with SRL is not surprising due to the fact that learning esports games is largely an informal learning environment, since players do not follow a curriculum or listen to a teacher of esports games.

The *features* constructed from player reflections on helpful video and streams for learning also highlights esport learning as an informal learning environment. Several of the *features* included value judgements viewers make about media's efficacy for learning, such as: *applicability of teachings*, as viewers either may struggle to implement teachings into practice or find that teachings are not relevant to common contexts they find themselves in; *relevance of teachings to watcher's skill level*, as viewers need to make sure that what is being taught will work for them; *trust in the producer's teachings*, as viewers need to make judgements about whether the producer is genuinely trying to help and providing useful advice; and *aimed to help learning*, as there is a lot of content online that is geared towards other gratifications such as entertainment.

The construction of *identification* as an important informal learning process, the presence of self-regulated learning within the context of esports, and the need to make value judgements about resources for *consumption* show that spectatorship is a self-regulated learning activity, linking it strongly with *identification*, embedded in the informal learning environment of esports game learning. This is an interesting finding and contribution to the field of esports game learning. Constructivist learning theories that place experience and reflection central to learning (Kolb's experiential learning cycle (Kolb, 2014), Gee's probing principle (Gee, 2007, p.105), Zimmerman's cyclical phase model (Zimmerman, 2000)) and are used within game-based learning (Steinkuehler & Tsaasan, 2020; Whitton, 2014) focus on the *application* and *practice* of knowledge and skills to generate experiences. This thesis, therefore, posits that spectatorship is a popular self-regulated learning activity, alongside *application* and *practice*, in which players strategically choose videos and streams they think will lead to more successful learning.

Alongside spectatorship's role as a self-regulated learning activity, this thesis also looked closely at one of the potential success factors highlighted throughout. In Chapters 3 and 4, participants highlighted the importance of competency of teachers when learning to play. These teachers could be friends, other players in-game, and content creators over videos and streams. Focusing on spectatorship, Chapter 4 found the *competency of producer*, the person in the video or stream, as being the most frequently discussed helpful *feature* of media for learning. More experienced players would often discuss how important it was to utilise gameplay and replays of high-skill players for learning to improve.

However, some contradictions were raised, especially by players who had fewer hours in-game or were lower-skill. They would talk about difficulties they had with learning from media presented and produced by highly-skilled players. In Chapter 3, participants with fewer hours in *Dota 2* and *CS:GO* reported how these videos and streams would assume knowledge and skills they didn't have access to. They would recognise the importance of learning from these platforms and would be told by more experienced players to use them. However, they often disclosed that they didn't watch videos and streams as much as they *"should"* have. In Chapter 4, the *feature* of *relevance to watcher's skill level*, constructed through participant responses, echoed similar sentiments of newer or lower-skill players finding difficulties learning from videos and streams due to skill differences. These sentiments, taken together, suggest that the relationship between teacher-learner skill difference and performance change is either complex or non-linear.

These sentiments seem to mirror the constructivist theory Vygotsky's zone of proximal development (ZPD) (Vygotsky, 1978), which posits a zone of proximal development where optimal learning occurs. The zone of proximal development is collection of skills that a learner can only do with assistance from a teacher or domain expert. Whilst ZPD focuses the difficulty of and ability to perform skills, the sentiments provided by novice players highlighted above echo the idea of an optimal zone of development but in relation to the teacher-learner skill difference.

Chapter 5 outlines the experiment performed to test the presence of a zone of optimal development for teacher-learner skill difference. Through regression analysis of 222 participants performance change in *Dota 2*'s last hit trainer from watching other players, the study found a significant weak linear relationship between skill difference and performance change. No peak or zone of proximal development was found. These results run contrary to the sentiments raised by novice players when discussing *consumption*. This contradiction may demonstrate how what participants report and what actually occurs in action can be different and even contradictory. Or this may be due to the limitations of the first few studies, such as sensitivity bias and the sensitivity of self-reports to participant mood, and the final study, such as too weak a manipulation or not properly operationalising ZPD.

This thesis demonstrates the importance of *identification*, *consumption*, and spectatorship for learning team-based esport games, particularly *CS:GO* and *Dota 2*, and contextualises these activities as being self-regulated within an informal learning environment. These findings can be utilised by developers of these games to provide tools that support these activities. For *identification*, developers may benefit from providing tips that highlight, perhaps contextually, important knowledge and skills relevant for learning how to play. *Overwatch* (Blizzard Entertainment, 2016) already provides contextual prompts that appear in-game, when certain criteria are met, that help players *identify* potential solutions to difficulties they face. Similarly, since *identification* and *consumption* are so highly linked, players would also benefit from receiving recommendations of streams or videos to watch to help them learn to play. Developers could provide these recommendations, or media directly, in-game.

In addition to esports and game learning, this thesis also contributes to informal learning environment research and to formal learning environments that are turning towards videos, streams, and video conference platforms. Thanks to video's increasing pervasive presence in life, some of it due to the Coronavirus (COVID-19) pandemic, asynchronous and synchronous media for learning is becoming more popular. For example, both prior to and during the COVID-19 pandemic, universities have increasingly adopted asynchronous learning management systems and synchronous video meeting platforms for delivering materials and providing lectures (Camilleri & Camilleri, 2021). Another example is the increasing popularity of *YouTube* videos for learning musical instruments, even before COVID-19 (Marone & Rodriguez, 2019). The findings of this thesis demonstrate the potential importance of videos for learning, as well as what makes them helpful. Focusing on informal learning environments, this thesis also highlights that learners form and impose value judgements on the media for learning available to them in order to decide what works and what doesn't.

Outside of the individual contributions each study makes, the combination of findings provide two key contributions: spectatorship is a popular self-regulated learning activity, within the team-based esports *CS:GO* and *Dota 2* if not generally, in which players strategically choose videos and streams they think will lead to more successful learning; and, despite sentiments to the contrary, players of all levels in *Dota 2* learn best from the most expert players within the context of the last hit trainer.

6.5 Limitations

This thesis relies on the self-reported behaviours and attitudes of players who play team-based esport games, in particular *Dota 2* (Valve, 2013) and *Counter-Strike: Global Offensive* (*CS:GO*)
(Valve & Hidden Path Entertainment, 2012). Players have hours of experience learning, mastering, and playing these games and can provide the best insight into the habits and practices surrounding them. However, there are several potential limitations inherent to self-reported behaviour. Firstly, participants are often less likely to report behaviours and activities that are perceived as 'taboo' or violate some existing social norms, known as social desirability bias (Tourangeau & Yan, 2007).

Whilst social desirability bias is largely associated with more taboo subjects such as alcohol consumption, gambling habits, and sexual activity, a large part of online gaming culture is steeped in identity formation and groups of practice (**gee2007:learning**). As such, there can be a 'threat of disclosure', where participants feel threatened by the potential negative consequences that arise from divulging habits and activities that go against the communal norms. Whilst this concern is rather minor, to alleviate this concern participants were assured that their data would be kept securely and confidentially, only being available to the primary author without anonymisation.

Secondly, self-reports are sensitive to a participant's disposition and memory at the time of participation (Kihlstrom et al., 1999). Memories are not simply a recollection of data, but uses and is influenced by the prompts of the context surrounding an individual. There may be potentially important memories that are not reported due to the inability of the participant to recall them. Questions for both studies were structured in a manner to help recollection by compartmentalising recall with examples or through chronologically ordered events. Future studies could avoid issues of recall by embedding observations within practice either through live ethnography or contextual enquiry.

The studies outlined only look at two team-based esports learning games, *Counter-Strike: Global Offensive* (*CS:GO*) and *Dota 2*, with the majority of studies focusing solely on *Dota 2*. Whilst these two games represent two of the most popular games in two of the most popular genres of esports, the findings from this thesis may not generalise to all team-based esports games, let alone esports games, and requires further research in this regard. Future work to test how these results generalise may use an inductive approach, where research would observe or ask players of esport games how they learn them, or a deductive approach, where research could either attempt to operationalise the findings of this thesis and test them within other esport games or ask players whether the findings of this thesis accurately represent their phenomenological experiences with learning esport games.

An unintended consequence of the dependence on players of these games, as well as the platforms used to sample participants, is the uneven distribution of demographic data compared to the rest of the population. The studies described in Chapter 4 and Chapter 5 have a heavily male bias, 100% and 92.6%, respectively, likely due to a male bias in esports (Interpret, 2019) and a male bias on the main platform for sampling, *Reddit* (We Are Social et al., 2022). Further qualitative research should be conducted to explore any differences in learning a team-based esport game. The final study of this thesis outlined in Chapter 5 provided a closer distribution of gender in comparison to the general populace. This is likely due to the use of the sampling platform *Prolific* in comparison to the use of *Reddit*. Whilst there are no statistics available measuring the distribution of age across players of esport games, in comparison to the general population of video games globally, the distribution of ages sampled in all studies tended to be younger on average as well as more focused on a younger audience (ISFE, 2021).

However, this does not excuse the use of Reddit as a sampling platform again after having a heavily male bias previously. This stems from my personal biases and blind spots of my background and gender privilege. There was a naive assumption that, because the first study included only a handful of participants, the second study would provide a better demographic distribution due to it's larger sample size. This poor representation for those who do not identify as male is disappointing and would be one of the first things I would like to be addressed in any future work.

None of the studies outlined in this thesis involved individuals under the age of 18, or at least individuals who stated they were not under the age of 18. This was purposefully done for ethical reasons. Children do make a considerable proportion of players of video games and may often play games that are not intended for their age rating (e.g.

Dota 2 is PEGI 12+ and *CS:GO* is PEGI 18+). The results outlined in this thesis should not be applied to children without further exploration of learning in team-based esport games for individuals under the age of 18. As well as age, these studies also focus on english speaking individuals and do not make efforts to diversely sample for other demographics such as ethnicity and socioeconomic status. Therefore, the generalisability of these findings are limited to english speaking 18+ individuals and may not be relevant to some ethnic and socioeconomic groups. Future work would benefit from testing the results of this thesis over a wide variety of demographics.

Finally, there are limitations created by my positionality within this research.

My demographic background reflects that of the core demographic playing and spectating team-based esport games. As well as that, the vast majority of participants within this research are also members of that core demographic. As such, there are at least some phenomenological blind spots that this research may be missing. One such blind spot is the exposure and adverse affects of toxicity within these contexts. I have had some experiences of toxicity, but these are very likely mild in comparison to the levels of toxicity faced by other demographics, such as those identifying as different genders (Madden et al., 2021). I feel this provides a limited and potentially overly positive portrayal of esports games.

As mentioned previously, my background has formed blind spots with regards to the unfortunate impacts of gender in esports and gaming communities. For example, women are faced with the need to conform to male norms on *Twitch* to avoid exclusion and so participate in a culture that devalues their gender (Olsson, 2018). As well as from the communities surrounding them, female gamers also face social and cultural pressures from games themselves as game designs rarely cater to women's wants and even include desings that are harmful to women (Lopez-Fernandez et al., 2019). This is without the consideration of non-binary, genderfluid, and other identities outside the gender binarism, something that even HCI has seen limited discussions and research on (Kirschner & Williams, 2019). Whilst I was aware of some of these issues, I was not conscious of the barriers to participation and pressures for conformity faced by those who do not identify as male. Reflecting on this thesis has helped me to appreciate the gravity of these issues and I hope that any future work, mine or others, takes these into careful consideration throughout experimental design and execution.

As mentioned in my positionality statement, I do not feel I am an insider within the team-based esports community. However, due to my considerable amount of time spent playing these games, my own experiences of these games and learning them are likely to bias reports by participants that align to my own experiences. Nearly all of the findings of Chapter 3 align to my experiences of learning team-based esport games. The only aspect of these findings that did not align to my experience was *meta-learning* as a learning outcome. I have only had limited experience using videos and streams for learning, so I have not felt that the findings of Chapters 4 or 5 have confirmed or contradicted my sentiments. I have tried to minimise this alignment bias by asking various colleagues and supervisors to look over my work and to provide thoughts and feedback from differing perspectives, including those who are not well-acquainted with these games and communities.

My motivations have also generated potential blind spots and biases within my work. My motivations espousing the importance of games research and advancing my career in games research or the industry, as well as my involvement with the genre of game being studied, exposes me to positivity bias, where one will tend to stress findings favouring a topic and either minimise or ignore findings deemed harmful to a topic. This can be seen in the previously mentioned perspective of this research, that of members of the core audience. I have attempted to alleviate any positivity bias by constantly taking moments to self-reflect upon my work, thoughts, and feelings and to relay them to colleagues and supervisors throughout my PhD. As well as that, I have attempted to align with my research value of replicability and communism by providing open access to my data, analysis, and findings.

Chapter 7

Conclusion

Esports research has spent considerable time looking into the culture of spectatorship and the practices of experts. Whilst research has demonstrated that a key motivation of spectatorship is knowledge acquisition and that novice and expert esport players differ in their learning needs, little no work has been done to explore and understand how novices use esports spectatorship for learning. The research presented in this thesis provides qualitative and quantitative insights into the role and effectiveness of spectatorship for novice players learning to play team-based esport games. Esports spectatorship is not just a form of entertainment, it is an interactive sociocultural form of integration into an esports community situated in complex learning practice it itself perpetuates and shapes. As well as that, this thesis posits that spectatorship is a popular self-regulated learning activity, alongside *application* and *practice*, in which players strategically choose videos and streams they think will lead to more successful learning.

This thesis provides several contributions to the fields of game and esports learning. Firstly, it helps lay a foundation for esports game learning by identifying learning processes, tools, and outcomes players of team-based esport games see as relevant to learning. One key learning process, *consumption*, situates spectatorship as an important and integral learning activity for learning to play team-based esports games, specifically *CS:GO* and *Dota 2*. Secondly, this thesis highlights helpful features and formats of media for learning to play esport games through spectatorship. These findings demonstrate that spectatorship is a self-regulated learning activity, where players must make value judgements about which media to integrate into their learnings and which to ignore. Finally, it demonstrates the relevance and efficacy of one of the previously highlighted features in learning to play, further validating these features as benefiting from further validation and adoption.

Learning by spectating manifests many features of cognitive apprenticeship and self-regulated learning, namely that spectatorship supports and parallels the learning method of modeling, where learners watch experts or teachers performing teachings in-action, and that, when watching to learn how to play, spectators make constant judgements about which media to trust and integrate into their learning practices. Most self-regulated learning theories focus on the experiential aspect of informal learning environments, where students choose the activities and experiences they participate in to maximise their success in learning. This thesis highlights another important experience beyond *application* and *practice*, *consumption* and spectatorship where students leverage and decide what materials they should utilise and integrate into their learning activities.

Developers of team-based esport games should support *identification* and *consumption* as learning processes more, due to their pivotal role in informal learning environment that is esport games learning. They could support *identification* by highlighting important skills and knowledge, perhaps contextually, that players would benefit from learning about. In addition to that, developers could provide recommendations of videos or streams for players to watch for learning. Beyond these primary findings, developers would also benefit from including more training environments that players can use to experiment or *apply* knowledge and skills as well as for *practice*. Finally, the *features* and *content genres* constructed as being helpful for learning in streams and videos can be utilised by content creators to produce better content for learning team-based esport games, or specifically *Dota 2*, by integrating the *features* and structuring the content to one of the more helpful *content genres*.

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