SHOSHANNAH TEKOFSKY

YOU ARE WHO YOU PLAY YOU ARE

YOU ARE WHO YOU PLAY YOU ARE

Modelling Player Traits from Video Game Behavior

Proefschrift ter verkrijging van de graad van doctor aan Tilburg University op gezag van de rector magnificus, prof.dr. E.H.L. Aarts, in het openbaar te verdedigen ten overstaan van een door het college voor promoties aangewezen commissie in de aula van de Universiteit op maandag 19 juni 2017 om 16.00 uur door Shoshannah Tekofsky, geboren te Wapenveld.

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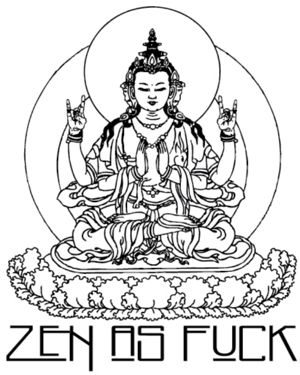

This image was included as core inspiration for the author. It was first encountered during my time at MIT. It serves as a reminder to strive for a balance between inner peace and inner strength.

PREFACE

Video games have it all. That epiphany came to me a decade ago, and it led me to devote my working career to gaming. It constituted a realisation that video games offer a platform to express myriad professional, societal, and personal ambitions. The road has led me from my early years as a video game tester to this moment where I present my doctoral dissertation as a video game researcher. None of this would have been possible without the support of many wonderful people.

First of all, I would like to thank my promoters, Pieter Spronck and Eric Postma, for their unfailing support and guidance through my PhD trajectory. The same gratitude extends to Jaap van den Herik and Aske Plaat for ushering me into the PhD track. Additionally, I am grateful to all my colleagues at TiCC who have made these last few years an unforgettable experience.

Secondly, I would like to thank Tal Achituv and Kevin Slavin for making my time at the MIT Media Lab possible. I met many wonderful and inspirational people there, and will carry that experience in my heart forever.

Thirdly, I would like to thank my partner, my family, and my friends for all the talks, the advice, and votes of confidence. I have been blessed with many amazing people in my life. They were there with me to bemoan the bad times and celebrate the good times.

Lastly, I would like to write an extra thank you for both of my parents. My father has always been there to offer unconditional support and acceptance. When I was little, he was the one who would go out of his way to find video games for me to play. When I was all grown up, he was the one who did not blink an eye when I declared I was going to make a career out of video games. My mother was initially more skeptical. She has been an example to me in critical thinking, perseverance, hard work, and a kick-ass attitude. She always made time for me, and let me talk through anything till there was nothing left to say. Together my parents supported my interests and ambitions from a young age, while stimulating me to keep improving all the way. Thank you.

ABSTRACT

Problem Statement. *To what extent are a player's real-life traits related to their play style in video games?*

The problem statement was answered by homing in on three parts: personality, age, and gaming motivation. Personality is found to not significantly relate to play style among a sample of 13,000 players of the First Person Shooter Battlefield 3. In contrast, age is found to be strongly related to play style in both a cross-sectional and longitudinal analysis of the same sample. Older players play more slowly and perform worse at the game. Everyone improves over time, with older players increasing their speed of play more quickly than younger players. Lastly, gaming motivation is explored outside the player base of Battlefield 3. It is connected to play style through both a behavioral and a cognitive model. The behavioral model is the Directed Action Model that proposes that game behavior can be related to motivations by looking at the directions of the player's actions in terms of being any combination of player-, goal-, and/or fantasy-directed. The cognitive model is the GAMR model which combines existing surveys into one validated survey positing 13 motivational factors. The model is shown to significantly relate to game genre preference, personality, and demographic traits in a sample of 3000 players of World of Warcraft, League of Legends, Battlefield: Hardline, and Battlefield 4.

Overall, the relationship between real-life traits and play style in video games is found to vary per trait. Traits that can be directly related to game performance (age) or game design elements (motivation) show clear and intuitive relationships with play style, while a trait such as personality displays no clear link to play style. For future work, we see strong potential implementing the insights on age in game design, and further developing and validating the motivational models presented in this dissertation.

PUBLICATIONS

The following is a list of the publications that the author contributed to during her doctoral research. They are the basis of the current dissertation.

Tekofsky, S., Miller, P., Spronck, P., & Slavin, K. The Effect of Gender, Native English Speaking, and Age on Game Genre Preference and Gaming Motivations. In *Proceedings of the 8th International Conference on Intelligent Technologies for Interactive Entertainment (INTETAIN)*. EAI, 2016.

Tekofsky, S., Spronck, P., Goudbeek, M., Plaat, A. , & Van den Herik, J. Past Our Prime: A Study of Age and Play Style Development in Battlefield 3. *Transactions on Computational Intelligence and AI in Games*. IEEE, 2015.

Bialas, M., Tekofsky, S., & Spronck, P. Cultural Influences on Play Style. In *Proceedings of the International Conference on Computational Intelligence and Games (CIG)*. IEEE, 2014.

Tekofsky, S., Spronck, P., Goudbeek, M., & Broersen, J. M. Towards a Player Age Model. In *Proceedings of the International Conference on Artificial Intelligence and Interactive Digital Entertainment (AIIDE)*. AAAI, 2013.

Tekofsky, S., Spronck, P., Plaat, A., Van den Herik, J., & Broersen, J. Play Style: Showing Your Age. In *Proceedings of the International Conference on Computational Intelligence in Games (CIG)*. IEEE, 2013.

Tekofsky, S., Spronck, P., Plaat, A., Van den Herik, J., & Broersen, J. Psyops: Personality Assessment Through Gaming Behavior. In *Proceedings of the International Conference on the Foundations of Digital Games (FDG)*. SASDG, 2013.

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1 INTRODUCTION

Video games have become a major force in our lives. They are now a tool to connect, to learn, and to explore. Games are created to show the horrors of war [1], teach programming [63], or improve attention [37]. Yet the most remarkable thing is that the games that seem the most frivolous and potentially damaging to the human psyche, might be the most useful and rewarding. Research by Green and Bavelier [29, 37, 38, 39] has shown that First Person Shooters offer the highest gains in spatial cognition and visual attention found so far. On the other hand, the greatest social and management skill gains have been found in the purportedly addictive MMORPG genre with games such as World of Warcraft [90]. With all of that said, what makes video games such a uniquely appealing and powerful force in attracting and influencing our minds?

1.1 AN EXPERIENCE LIKE NO OTHER

Video games are *interactive entertainment media*. Neither interactive media, nor entertainment media are unique, but the combination of the two is particular to video games. Interactive media like the internet and the telephone offer tools for mass communication and engagement with information, while entertainment media like books and film offer experiences that entertain or enrich our minds. Video games merge the two media, shadowing and surpassing books and film in particular. Books describe a story and world, allowing the reader to imagine the presented fiction. TV and film show a story and world, allowing the viewer to see and hear the presented fiction. Video games go a step further. They are the closest that fiction can come to reality. They model a story and world, allowing the player to *interact* with the fiction.

It should be noted that, when a player interacts with a game, information flows two ways: The game presents a fictional world and narrative to the player, and the player responds by inputting actions into the game. The game reacts in turn by updating the game world and narrative, and presents the update back to the player. The mutual feedback loop between player and game is what constitutes *interaction*.

Though such interaction is unique for (mass) media, it is not unique for games. Here we define "games" as proposed by Juul [47]. According to his *Classic Game Model*, a game consists of six features that can occur in any medium. Video games are unique in that they bring these features into a digital space. The features he proposes are as follows.

1. *Rules* - Games are rule-based, unlike pure "play" [45].
2. *Variable, Quantifiable Outcomes* - Games have variable, quantifiable outcomes that are (partially) influenced by the player.
3. *Value Assigned to Possible Outcomes* - The aforementioned outcomes have values assigned to them such as positive versus negative in the case of winning versus losing.
4. *Player Effort* - The player needs to exert effort to influence the aforementioned outcomes. This is also more commonly referred to as "challenge".
5. *Player Attached to Outcome* - The aforementioned outcomes have affective consequences for the player (e.g. the player is "happy" if he wins and "unhappy" when he loses).
6. *Negotiable Consequences* - The game would be playable both with or without real-life[1] consequences.

The introduction of games into the digital medium has widened the scope of possible rules (1), outcomes (2, 3, 5) and forms of player effort (4) that can be integrated in games. At the same time, the digital component of video games allows us to log and analyse all player actions and their outcomes. The player actions are embodied by the *Player Effort* feature, and encompass the actions of the player as he endeavours

1 Throughout this manuscript, the term 'real-life' is intended to refer to the realm outside video games. It is not intended to imply that video games are somehow 'less real' than other experiences.

to surmount the challenges in the game to gain the outcome(s) he desires. Challenges can come in the form of progression, survival, or creation, but all offer a sense of mastery [67] as challenges are met and surmounted. The player increases his mastery of the game through resource gathering, knowledge building, and skill development. In other words, the player moves through a process of *learning* by building a mental *model* of how the game world works [33]. The model is used to predict and improve the outcome of his game actions, which increases his success in the game. A better model (greater mastery) leads to more desirable outcomes for the player. This natural form of learning is part of our mental machinery as humans. However, the more interesting question is if video games can reciprocate that process. Can a game build a model of the player and learn how to make itself more challenging, immersive, or interesting for each individual player?

1.2 PLAYER MODELING

When a game builds a model of a player, this is referred to as *player modeling*. The practice of player modeling has spawned a whole field of scientific inquiry. Currently, the term *player modeling* lacks a clear definition with different academic authors providing different definitions [72]. We adhere to a general definition that player modeling *is a field of AI that focuses on understanding and predicting the characteristics of a player*. Just like a player can come to model the game world in detail by experimenting and probing through different interactions, the game can do the same with the player.

Yannakakis et al. [92] offer a broad taxonomy to understand the different approaches to player modeling (Figure 1). Their core distinction is between model-based (top-down) and model-free (bottom-up) approaches. Model-based approaches result in the theory-driven models that are common in psychology and the social sciences in general. A model of the player is proposed a priori, and statistical tests are employed to determine the validity of the model. Conversely, model-free approaches result in data-driven models that are common in computer science and the exact sciences in general. Various computational

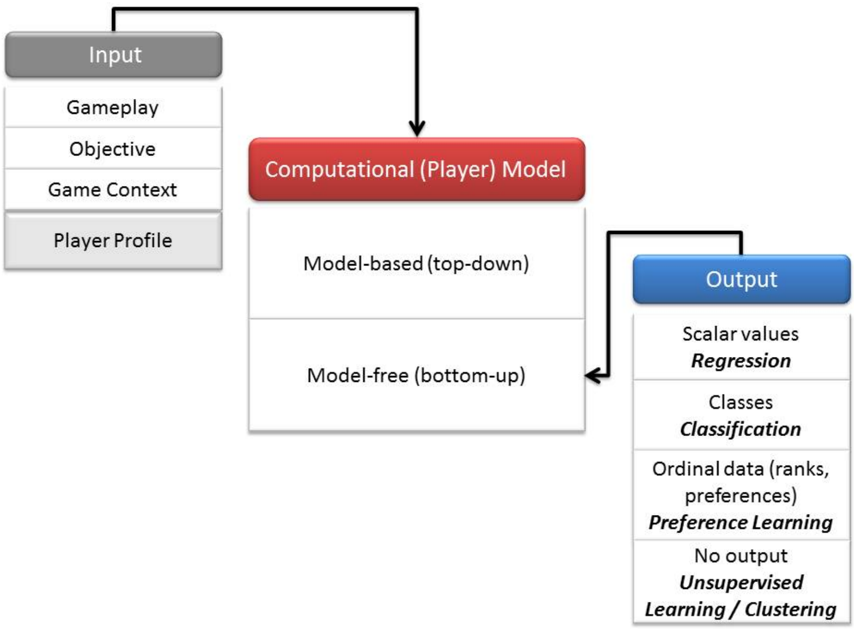

Figure 1: Core Components of Player Modeling According to Yannakakis et al. [92]

techniques (e.g. classifiers, regression models, etc.) are used to determine the most accurate model for the given data.

Both model-based and model-free approaches have their strengths and weaknessses. The model-based approach delivers meaningful models that can be logically interpreted, but often fails to find support for its models or leverage the full scope of the available data. The model-free approach commonly finds a player model that fits the given data, but is prone to integrating meaningless data or overrepresenting spurious results. Yanakakis et al. [92] point out that most player modeling endeavors are a *hybrid* of the model-based and model-free approaches. The work presented in this dissertation can also be classified as a hybrid approach. Section 1.6 will expand more on our particular approach to developing player models.

1.3 STATE OF THE ART

The input modalities of Yanakakis et al.'s taxonomy of player modeling lends itself well to structuring an overview of the state of the art in player modeling research. The input modalities are *gameplay*, *objective*, *game context*, and *player profile* (see Figure 1). We highlight prominent research using each modality as its main input.

First, gameplay input refers to using the player's actions in the game to infer information about the player. The main assumption with this input type is that game actions reliably map to the target information. It is common practice for game developers to model play time (player retention) based on gameplay behavior. For instance, Weber et al. [87] apply this approach to Madden NFL 11 where they find a connection between knowledge of game controls and player retention. Additionally, more sophisticated player models are developed to adjust the difficulty of a game based on the player's performance. Such difficulty scaling can be achieved by a static decrease of the challenges the player encounters (e.g. the speed of enemy units [55]) or by a dynamic update to the game content by generating challenges that play into the particular strengths and weaknesses of the player (e.g. dynamic track evolution in a racing game [79]).

Secondly, objective input refers to integrating physiological measurements of a player into the player model. Physiological measurements can include anything from direct body sensor data (e.g. heart rate, galvanic skin response) to recordings of emotional expressions. The objective inputs do not naturally arise from regular gameplay and must be actively acquired by the experimenter outside the confines of the game. They are considered the most reliable measure of player states such as enjoyment and arousal, as they consist entirely of "honest signals". For instance, Mandryk and Atkins [54] modeled the arousal and valence of players playing NHL 2003 using their physiological inputs. Using fuzzy logic modeling they could accurately predict player enjoyment of the game based on these objective inputs.

Thirdly, game context input refers to integrating the state of the game in a player model. A player model using gameplay or objective inputs will most often also need to integrate game context inputs to allow for meaningful interpretation of the players actions (gameplay) and/or physical state (objective). Drachen et al. [24] show a strong example of the importance of integrating game context in player models. They employed emergent self-organizing maps to determine four types of players based on a combination of gameplay and game context inputs for the game Tomb Raider: Underworld.

Lastly, Yanakakis et al. [92] consider player profile input a class apart from the other inputs. In the literature, it has even spawned its own subfield of player modeling referred to as "player profiling". Player profile input and player profiling both refer to determining any static information (traits) about the player that is not directly linked to the playing of the game, such as age, personality, or gender. On the one hand, game data may be used to derive traits[2] of the player, while on the other hand, the traits of the player can be used as control variables in the player models aimed at determining game-related variables such as enjoyment or engagement.

What traits of the player may be modeled from game data is an unbounded question related to the larger mystery of how much of our identity is actually expressed in the way we interact with video games. Though demographic [2] and psychometric surveys [15] of the player population are common, this data is rarely brought into the realm of player modeling. Specifically, demographic data is most often listed to describe a sample, but rarely included in the player model. In contrast, psychometric data has enjoyed attention from researchers from various angles. Specifically, Lankveld et al. [82, 83, 84] started preliminary explorations of how personality might be expressed in video games. Their work on Fallout 3 and Neverwinter Night (both role-playing games) initially focussed on the link between gameplay and the Extraversion dimension of the Big Five, but found more evidence for a connection between gameplay and the Agreeableness, Neuroticism, and Openness dimensions. Additionally, there is a strong move-

2 Note that our use of the term 'trait' does not relate to its meaning within the field of Trait Theory in psychology. It is a matter of discussion if 'trait' is the correct term in the context of player modeling. However, competing terms such as 'feature', 'characteristic', and 'attribute' likewise introduce ambiguity. To avoid confusion of terminology in the course of this manuscript, we set out to use the term 'trait' to specifically indicate any information about the player that is static throughout his/her engagement with a particular video game. We recognize that this is not the commonly used definition of the term 'trait' within the field of psychology.

ment focused on creating player typologies based on self-report of gameplay patterns or preferences. For example, the Bartle types [9], Yee's motivational types [95], and BrainHex [56] all ask the player to describe their gameplay actions and preferences in order to create a psychological preference profile for gaming. In essence they define a set of motivational traits (i.e., traits that define what you find motivating). Though such typologies commonly rely on player self-report of gameplay behavior, they should per definition also lend themselves to using gameplay data as a direct input.

1.4 PROBLEM STATEMENT

Overall, video games have become the largest entertainment industry, providing trackable behavior data on a diverse, representative majority of the population. Currently, the wealth of information in that new data source goes largely untapped as we are still discovering what game data might tell us about players and how the data might be utilised.

Player modeling is the research field where such knowledge and understanding is generated. It is a research field that is largely still in its infancy. A thorough research of the player traits that can be determined from game behavior offers a strong momentum forward for the research field as it deepens our general understanding of how players behave in game worlds, and can be used to tweak and optimize player models focussed on other modalities than player profile inputs. Therefore, our research is aimed at exploring what real-life traits of players can be modelled from their video game behavior. As such, our problem statement is as follows:

Problem Statement. *To what extent are a player's real-life traits related to their play style in video games?*

The following section details how the problem statement is tackled in the course of three research questions. Section 1.6 details the research methodology that was employed.

1.5 RESEARCH QUESTIONS

The range of real-life traits that could be investigated far outstrips the research that can be covered in a dissertation. Therefore we have focussed our attention on three promising subsets of real-life traits: personality, age, and motivation. The resulting research questions and their embedding in the field of player modeling is as follows.

Research Question 1. *What is the relationship between the personality traits of a player and his play style in video games?*

Chapter 3 describes our research into the relationship between personality and play style. It continues the psychometric tradition set in motion by Lankveld et al. [82, 83, 84] that focusses on determining how personality traits relate to play style. At the time the research was conducted, it was one of the first of its kind in tackling personality research in gaming. In essence, this research question explores the potential of using video games as a form of personality assessment. In the same way that people show their personalities in their real world behaviour, it might be the case that people similarly show their personality in behaviour inside video game worlds. The potential of video games as a tool for personality assessment hinges on the nature and strength of the relationship between the personality traits of an individual and his play style in video games.

Research Question 2. *What is the relationship between the age of a player and his play style in video games?*

Chapter 4 describes our research into the relationship between age and play style. It tackles an important pillar of the demographic data that is often readily available about players but rarely utilized in video game research. It is well-documented that age is accompanied by a host of changes in our physiology and psychology [5, 7, 28, 49, 59]. Both these shifts hold potential for strong expressions in video game behaviour. Depending on the strength of the relationship between age and play style, we might even come to fairly accurate age estimates based on game behavior.

Research Question 3. *What is the relationship between the motivational traits of a player and his play style in video games?*

This research question digs into the movement around creating player typologies based on self-reported gaming motivations and how these may relate to play style. It is split across two chapters. First, chapter 5 describes the behavioural expressions that might result from varying gaming motivations, and how these motivations may be deduced from game behaviour. We suggest a new model for determining gaming motivations from game behaviour. Secondly, chapter 6 describes the background, construction, and validation of a cognitive model of gaming motivation. Such a model would describe the cognitive constructs that underly the drive to engage in video game play. Together, chapters 5 and 6 cover both the behavioural and cognitive side of gaming motivation by presenting models for each.

1.6 METHODOLOGY

Our research methodology can be classified as a *hybrid* approach to player modeling. It combines the model-based and model-free approaches posited in the player modeling taxonomy by Yanakakis et al. [92]. In their work, the terms *model-based* and *model-free* do not refer to any specific model in the literature. Instead, the word 'model' refers to the use of any function for structuring and interpreting the player's behavior. For the remainder of this chapter, we will use the word 'model' in the same manner as Yanakakis et al. [92]. Our problem statement and research questions all pertain to the *player profile* input in their model of the Components of Player Modeling. As such, it constitutes an extension of the *player profiling* subfield of player modeling to which Lankveld et al. contributed [82, 83, 84].

The model-based side of our research is expressed through a strong reliance on top-down theories of personality (Research Question 1) and motivation (Research Question 3). Both personality and motivation are psychological constructs with strong theoretical traditions with a rich breadth of validated cognitive models. We shall make use of the statistical analysis practices of the psychological research tradition to validate our hypotheses. Each chapter will include details on the statistical tests employed in the relevant studies described in that chapter.

The model-free side of our research is expressed in a general "big data" approach to sample construction as well as an exploratory bent to our data analysis approach. The data sets used in our research are described in Chapter 2. They are characterized by their sample size running in the thousands of participants, as well as the richness of the data on each participant that could be accessed online. This big data approach to data collection suits the format of video game research as video games are played by large groups of people and supply vast amounts of data per individual. Academic research pertaining to video games benefits from creating analoguously large and rich samples to more closely aproximate the position a game developer finds himself in as well as leverage all the potential power of video game behavior as a data source. Additionally, the exploratory bent to the research methodology opens up the potential to gain deeper understanding of the shape of each data set, instead of limiting our understanding solely to hypothesis testing.

We consider the hybrid approach described above exceptionally suited to the field of player modeling research. Video games bring humans into a digital space. Consequently, the study of the interaction between human and machine would be most aptly determined by combining the methodologies from the study of humans (Social Science) and the study of computers (Exact Sciences). Our hybrid research methodology combines the top-down and bottom-up approaches of these research traditions.

1.7 STRUCTURE

This dissertation is structured as follows. Chapter 2 will outline the data collection methodology used in our research, as well as describe the two resulting data sets that were collected in this manner: PsyOps and GAMR. Chapter 3 describes our foray into personality research in video games using the PsyOps data set. Chapter 4 delves into the connection between age and play style in games, utilizing the PsyOps data set. Chapter 5 proposes a behavioural model of gaming motivation. Chapter 6 describes the construction and validation of a cognitive model of gaming motivation using the GAMR data set. Where relevant, each chapter will refer to the original published work of the author that the chapter is based on. Each chapter will include the literature review conducted for the original published work, covering the literature that was available at that time. Lastly, chapter 7 presents a general discussion and conclusion of our research, and ties our findings back to the research questions posited in the current chapter.

2 DATA SETS

Across our research we employed statistical analysis techniques on data sets from large volunteer samples of online players (see Section 1.6). Each data set contains a selection of real-life traits and game behaviour descriptions per player. While the statistical analysis techniques we employed are different per research question, the data set acquisition and characteristics are common across research questions. Thus the statistical techniques will be described per chapter, while the data sets are explained once in this chapter to avoid repetition.

The research in the next chapters is based on two data sets: PsyOps and GAMR. PsyOps is a data set that includes the Big Five profiles of more than 13,000 Battlefield 3 players, tied to their game accounts in Battlefield 3 on the relevant platform (PC, Xbox 360, or Playstation 3), and a few basic demographics about the player. GAMR (Game And Mind Research) is a data set that includes the Big Five personality profiles, and gaming motivation scores of over 3,000 PC gamers, tied to their basic demographic data and user names in one or more of the following games: World of Warcraft, League of Legends, Battlefield 4, and Battlefield: Hardline. The PsyOps data set additionally includes play style data in the form of the Battlefield 3 game statistics of the participants involved.

2.1 PSYOPS DATA SET

The PsyOps data set was initially constructed to explore the relationship between play style and personality, using Battlefield 3 as a case study (see Chapter 3). Battlefield 3 is a realistic, military-themed, team-based, first-person shooter (FPS) game where players cooperate within teams, to compete against other teams for objectives. The following is a flavor description of an in-game scene to give the reader a sense of the gameplay in Battlefield 3. (Readers who are familiar with the multiplayer shooter genre of video games can skip across the italicized text to the continuation of the data set description.)

You see the countdown running for the start of the match. It gives you a few seconds to select the class of soldier you want to play, and tweak your loadout. Every class offers a different set of items you can choose for your loadout so you can fulfil different roles in the team. You go for the Assault class because you enjoy the self-sufficiency of its high fire power and its ability to heal and revive team mates.

Then you "spawn" into the match with your soldier, meaning you appear on the Battlefield and are given control of your character. Depending on the game mode you have chosen, you might now want to focus on taking out enemy players or tactically approaching game objectives such as areas that need to be conquered or target locations that need to be destroyed. This is a Conquest game mode, so your focus is on conquering flags (i.e. areas of the map) for your team.

You rush out of your spawn (default starting location) with your team mates. Some of your team mates grab the tanks or helicopters in the spawn and move out. You try to grab a ride with a team mate in a jeep, and manage to take the passenger position in the car. It allows you to peer out the side of the vehicle and shoot your regular weapon to provide the jeep with protection.

Your driver races off to the objective, and you jump out together at arrival. You both take cover as an enemy tank just rolled on to the scene and you can see the barrel of the tank gun try to line up with you. You manage to duck behind a building just in time. The tank shell clips away the corner of the wall, but your health bar shows you are unharmed.

You keep running, making sure the building blocks line of sight between you and the tank. You can't see what's going on, but you can hear the sound of an RPG being fired.

It's your buddy, the jeep driver. He has the engineer class equipped, which sports an anti-tank missile launcher. As you peek around the opposite edge of the building, you can see him peeking and taking shots at the tank from behind the garage *across from you. The tank has been crippled and is on fire, but manages to take a last pot shot at the engineer.*

He's down.

Your screen shows a heartbeat icon over his body. You know you can revive him, and together you might take over and repair the tank for your own uses. You will have to sprint across the open area with the tank to reach him in time for a revive though ... Might there be other enemies lurking around, waiting to pop out and mow you down?

You make a snap decision, and sprint across to the garage, whip out your defibrillators, and revive your team mate. He gets up again, and together you go on to take over the tank and roam the map together.

The abovementioned scene is a typical experience for a Battlefield 3 player. Figure 2 gives an additional visual impression of the game. The intricacies of the gameplay run deeper than can be explained in this dissertation. We refer the reader to the IGN *Battlefield 3 Wiki Guide*[1] for more information.

Next to the play style data, the PsyOps data set contains both personality data and demographic data such as age (Section 2.1.2.1) and country (Section 2.1.2.2) of residence. Age turned out to have interesting relationships with play style, and became the center piece of answering our second research question (Chapter 4).

2.1.1 *Data Collection*

All data was automatically collected and stored via the PsyOps website. Data collection took place over a period of six weeks in the summer of 2012, 8 months after release of the game. During this time, participants could visit the website to submit their data. The data form contained six fields: age, player name, gaming platform, 100-item International Personality Item Pool (IPIP) questionnaire, country of residence, and credits. The participant was asked to give permission for anonymous use of his game statistics, which were then automatically retrieved from a public database.[2] Player name was used as the key

1 http://www.ign.com/wikis/battlefield-3/Multiplayer
2 http://bf3stats.com/

Figure 2: A screenshot from a player playing Battlefield 3. He is currently reloading his weapon after having killed two enemy players. In front of him is a friendly tank (driven by a team mate) and another team mate on the right of the screen. They are all currently "capturing a flag" by being within the control zone of the flag. The left lower corner shows the minimap, game progress, and player squad. The right lower corner indicates player health and ammo. The right upper corner is a rolling list of all kills made by either team. The middle lower portion of the screen shows a rolling list of notifications relevant to the current player. Tiny green, blue, and red icon overlays across the screen highlight strategically important assets such as flags in the distance, enemy players or friendly players.

for game statistics retrieval. It is a unique identifier of a player account in Battlefield 3. Therefore, it was used to increase the likelihood that participants were unique individuals. The credits field was a tick box where participants indicated if they wished to have their player name listed on the credits page of the final research report. For each player, 826 game statistics were extracted. Different subsets of game statistics were used for different studies. The details of each subset will be outlined per study. After submitting all their data, participants were forwarded to a page showing their Big Five scores (see Figure 3) and an overview of what the different personality dimensions entail.

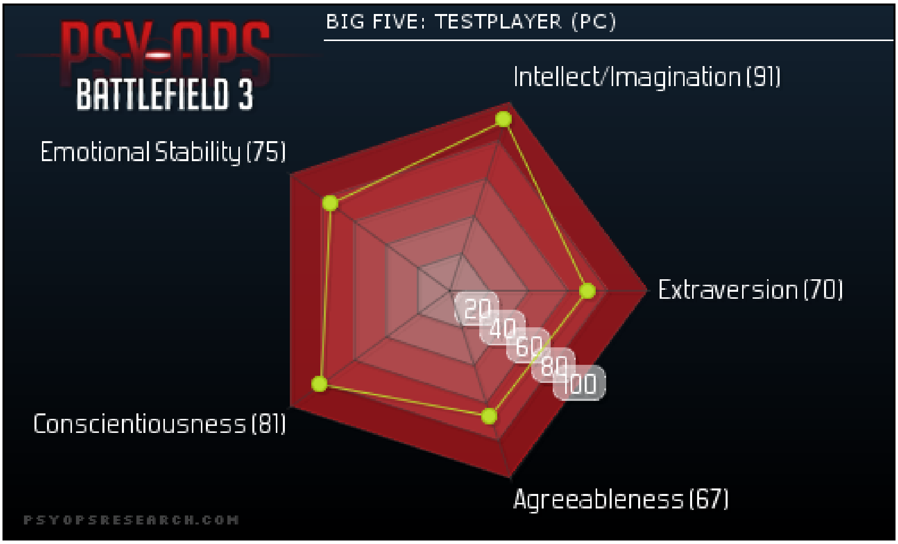

Figure 3: Example Personality Profile Shown to Users in the PsyOps Research.

2.1.2 *Data Description*

Data was collected from 13,367 Battlefield 3 players. One player was removed for being an extreme outlier in terms of play style by more than 80 standard deviations. An internet search of the relevant player showed that the person in question was documenting a public challenge to play the entire game in an atypical manner. In order to protect the anonymity of the person in question, no further details are provided on the play style of this individual. Additionally, 38 players who indicated an age below 12 or above 65 were also removed. Extreme age values are plausibly considered unlikely to be truthful entries. The total sample thus contained 13,328 participants.

2.1.2.1 *Age*

The distribution of age in the sample can be seen in Figure 4. The distribution looks like a skewed normal distribution with an average of 24.87 ($\sigma = 8.26$), and spread over all mature ages. From the age of 17 to 18 there is a noticeable dip followed by a peak. Battlefield 3 is a

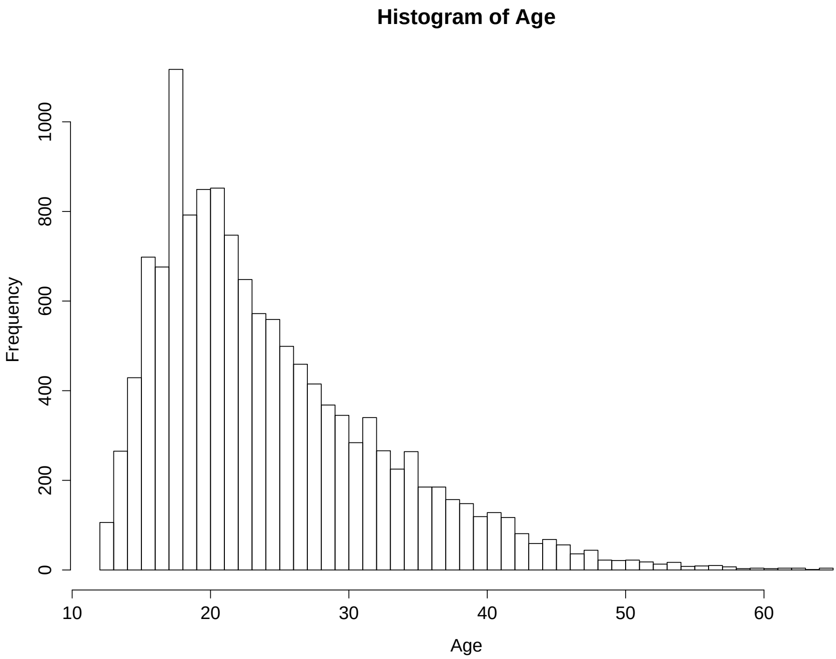

Figure 4: Age Distribution in the PsyOps Data Set.

game rated 18+ in most countries. It is possible that some participants that were 17 years old reported their age as 18 due to the age threshold for the game.

2.1.2.2 *Country*

Country data was extracted from the third-party game database. It resulted in 9367 uncorrupted entries (correct player accounts without missing data). It showed that participants hailed from 90 different countries. Table 1 shows the distribution for the 13 countries that were logged by at least 100 participants each (7893 in total). An additional 33 countries were logged by 10-99 participants per country, and 22 countries were logged by 2-9 participants per country. The remaining 22 countries were logged by 1 participant per country. The top 4 countries account for 6040 participants and consist solely of Western countries with English as the native language. The remaining 9

Table 1: Country Distribution in the PsyOps Data Set. Countries with less than 100 participants are not listed.

Country	**N**
United States	4039
United Kingdom	1099
Canada	499
Australia	403
Germany	371
Sweden	366
The Netherlands	266
Finland	229
South Africa	141
France	139
Russia	135
Brazil	106
Republic of Ireland	100

countries are all Western countries, with the exceptions of Russia and Brazil.

2.1.2.3 *Credits*

When asked if they would like to be mentioned (by player name) in the credits of the research, 9788 participants answered 'yes', and 3540 participants answered 'no'. The credits option was added in an effort to increase the reliability of the responses. It was intended as an accountability feature. We hypothesised that participants would be more likely to provide reliable responses with such a feature in place. Players had to actively opt in to the credits feature by checking a check box on the response form.

2.1.2.4 *Personality*

Figure 5 shows the distribution of the scores the participants obtained on the International Personality Item Pool (IPIP). The IPIP version is a validated instance of the Big Five Personality Inventory [36]. Scores on each of the dimensions can range from 20 to 100. They reflect the Openness, Conscientiousness, Extraversion, Agreeableness, and Emotional Stability dimensions of the participants according to the Big Five model of personality [18]. Openness describes the tendency toward novelty, abstract thinking, and creativity. Conscientiousness denotes the tendency to be organized, timely, and meticulous. Extraversion refers to the tendency to be socially outgoing with a general preference for higher stimulation. Agreeableness measures the tendency to be concerned with the wellbeing of others and to put effort into being socially pleasant. Lastly, Emotional Stability is the inverse of the Neuroticism dimension described by Costa and McCrae in their Five Factor Model [18]. Neuroticism traditionally taps into the tendency to experience negative emotions. Conversely, Emotional Stability does *not* refer to tendency to experience positive emotions, but describes how *unlikely* someone is to experience negative emotions.

The IPIP does not provide or endorse benchmark scores on the personality dimensions.[3] As such, we cannot provide any. In the PsyOps data set, the personality scores across the sample are high and cover a wide range of values. The high scores are defined as scores above the midpoint of possible values (60). They indicate a sample bias. On the other hand, the wide range of values indicate high heterogeneity. Sample bias has a negative effect on external validity, while heterogeneity has a positive effect on external validity.

2.1.2.5 *Platform*

Battlefield 3 can be played on different devices. The devices are referred to as platforms. At the time the research was conducted, the game was available on PC, as well the Playstation 3 game console, and the Xbox 360 game console. In our sample, platform distribution is fairly even at 5551 PC players, 3716 Xbox 360 players, and 4061 Playstation 3 players. The Xbox 360 and Playstation 3 versions of Bat-

3 http://ipip.ori.org/newNorms.htm

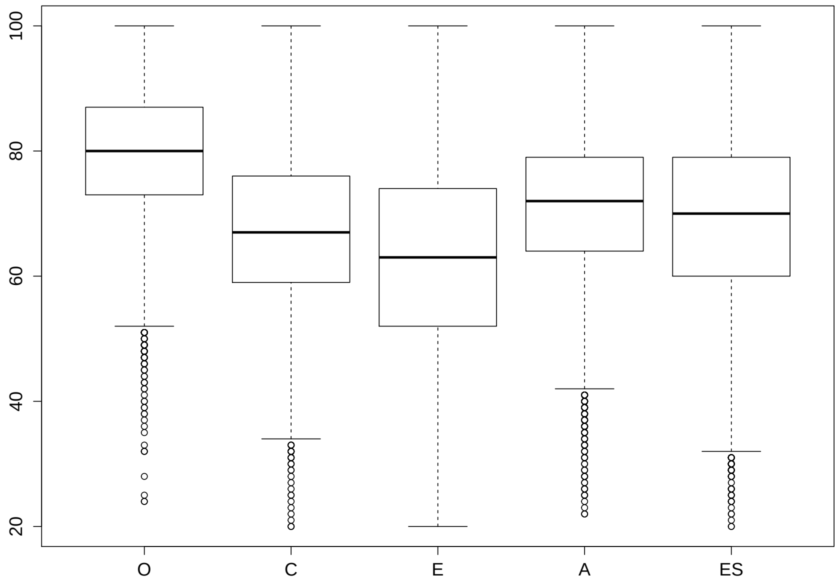

Figure 5: Big 5 Personality Distribution in the PsyOps Data Set. The Y axis denotes the score on each of the personality dimensions: (O)penness, (C)onscientiousness, (E)xtraversion, (A)greeableness, and (E)motional (S)tability.

tlefield 3 are identical in mechanics, content, and controls. The PC version of Battlefield 3 is equal to the Xbox 360 and Playstation 3 version of the game in terms of mechanics, but it contains additional content and employs different controls. The additional content consists of bigger versions of the same maps and higher player counts in matches (64 instead of 32). The PC version of the game uses the classic keyboard and mouse controls that allow for faster inputs and higher accuracy than the controller input on Xbox 360 and Playstation 3.

2.1.2.6 *Play Style*

Core game performance statistics were reviewed to gain an idea of what the dominant play style in the sample was. Overall it was found that mean scores on core performance metrics (e.g. win-loss ratio, kill-death ratio, score per minute) were well above the norm of the populace, while high standard deviations indicate that there was a wide range in performance within our sample. High performance metrics indicate that our sample may have been biased toward expert players.

2.2 GAMR DATA SET

The GAMR data set was constructed in collaboration with the MIT Media Lab to explore the relationship between play style across multiplayer game genres on the one hand, and player demographics and cognitive traits on the other hand. Players could only participate in the study if they signed in with a valid game account of one of the games included in the study. However, the extraction of the game statistics per player per game has not been performed by the time of writing of this dissertation. Therefore, the GAMR data set does include data on which games are played by each participant, but not how they behave inside the game (game statistics). For that reason, the gameplay of each of the games will not be explained in as much detail as that of Battlefield 3 in the PsyOps data set.

2.2.1 *Data Collection*

Data was collected online from anonymous volunteers. Data consisted of gender, age, country of residence, English skill level, 50-item IPIP, the short forms of the empathizing and systematizing quotient surveys [86], a survey of gaming motivation [41, 69, 95], and a valid game account in at least one of four games: World of Warcraft (WoW), League of Legends (LoL), Battlefield 4, and/or Battlefield: Hardline. Battlefield 4 and Battlefield: Hardline are functionally identical games. For that reason, the players of these two games are grouped and jointly referred to as 'Battlefield' (BF) players for the remainder of this dissertation.

Each game represents one of the most popular online multiplayer games and supports an active player base of at least 10 million players each. World of Warcraft (see Figure 6) represents the fantasy themed, third-person, cooperative/competitive, story and exploration driven

Figure 6: A screenshot from a player playing World of Warcraft. The game takes place in a persistent world that the player explores. The player is currently in a town where he can explore, trade, craft, and interact with computer and player characters. The in-game chat is visible in the lower left. Details on skills, abilities, and items are visible around the screen.

genre of Massively Multiplayer Online Role Playing Games (MMO-RPG). League of Legends (see Figure 7) represents the fantasy themed, third-person, team-based competitive, match-structured genre of Multi-player Online Battle Arena games (MOBA). Battlefield (see Figure 2, Battlefield 4 and Hardline look and play largely the same as Battlefield 3) represents the realistic military shooter, first-person, team-based competitive, match-structured genre of First-Person Shooter games (FPS). No further gameplay details are provided as the GAMR data set does not yet contain game behaviour per game.

2.2.2 *Data Description*

The original sample included entries from minors (age $<$ 18). The GAMR data set was not permitted by the ethics board of the Mas-

Figure 7: A screenshot from a player playing League of Legends. The characters with striped red bars above them are enemy players, while those with striped green bars are team mates of the player. The players are currently fighting, trying to kill players on the opposing team, while moving up to each other's bases. The team that the destroys the other team's base first, wins the match.

sachusetts Institute of Technology [4] (research collaborator) to contain data from minors. Therefore, data from minors was permanently removed from our records before any form of analysis or reporting was conducted. After the exclusion of minors, 2817 players remained in the sample. Of these, 28 players were excluded as outliers for showing no univariate variance in their responses on the surveys (only indicating 1 single response on the Likert scale for every item), and 26 players were excluded for indicating the gender value 'other' instead of 'male' or 'female'. The gender category 'other' was excluded as it was too small to meaningfully contribute to the analysis of gender, and it was likely to attract a disproportionate number of respondents who offered unreliable responses. Similar reasoning was applied to the 4 participants who indicated an English level of "None". The participants in question would either have not been able to understand the questionnaire items due to their lack of English skill, or were not

4 https://couhes.mit.edu/

providing reliable responses. The remaining sample contained 2759 entries.

2.2.2.1 *Age*

Age shows a zero-inflated distribution around the minimum age value of 18 (see Figure 8). This might be due to some minors misunderstanding the Informed Consent document. They might have incorrectly concluded that they could not view their results on the surveys if they entered an age below 18. Additionally, we removed all the entries of people below the age of 18. It might be the case that age was normally distributed around the 20 years of age point, but that the removal of the data from minors and some minors misunderstanding the Informed Consent has led to the zero-inflated distribution shown in Figure 8. For the current distribution, the average age of the participants was 26.03 ($\sigma = 7.68$).

2.2.2.2 *Country*

Participants reported 93 different countries of residence. Table 2 shows the distribution for the 6 countries that were reported by at least 100 participants each (1824 in total). An additional 28 countries were reported by 10-99 participants per country, and 35 countries were reported by 2-9 participants per country. The remaining 24 countries were reported by 1 participant per country. The sample is biased toward American players with more than one third of the sample indicating "United States" as their country of residence.

2.2.2.3 *English Skill Level*

There were 5 levels of English skill to choose from: None (n = 4), Basic (n = 47), Intermediate (n = 312), Advanced (n = 943), and Native (n = 1457). Players who indicated an English level of None were excluded from the sample for all analyses as they either did not supply reliable answers (i.e. misrepresenting their English level), or were not able to understand the survey items due to their lack of English language skills.

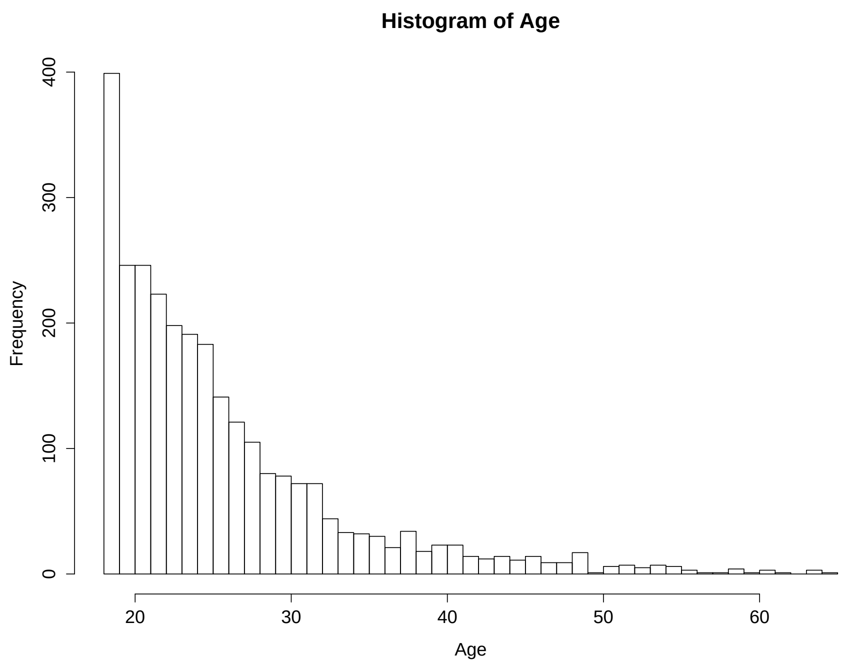

Figure 8: Age Distribution in the GAMR Data Set.

2.2.2.4 *Gender*

The sample consisted of 2402 males and 361 females. Though the sample is heavily biased toward males, the ratio of males to females is common for self-selection samples in gaming research [93]. People who indicated the gender option 'other' (n = 26) were filtered out of the sample. They were too few to contribute to the analysis, while the additional gender option is a likely target for participants who provide unreliable responses.

2.2.2.5 *Personality*

Figure 9 shows the distribution of the scores the participants obtained on the 50-item version of the IPIP (see Section 2.1.2.4 for more details on the IPIP). Scores on each of the dimensions can range from 10 to 50. The personality scores across the sample are high (> 30), with the

Table 2: Country Distribution in the GAMR Data Set.

Country	N
United States	1002
United Kingdom	203
Germany	173
The Netherlands	165
Canada	156
Brazil	125

exception of Extraversion. They also generally cover a wide range of values, except for Openness. The high scores indicate a sample bias, while the wide range of values indicate high heterogeneity. Sample bias has a negative effect on external validity, while heterogeneity has a positive effect on external validity.

2.2.2.6 *Gaming Motivation*

The survey of gaming motivation was compiled by using a short form of 13 motivational factors validated by Yee et al. [95], Hilgard et al. [41], and Sherry et al. [69]. The short forms are reliable as they correlate with the original long forms with effect sizes over .9. The construction, content, and validation of the motivational survey is further elaborated on in Chapter 6.

The 13 motivational factors are Competition, Challenge, Fantasy, Arousal, Story, Escapism, Loss Aversion, Customisation, Grinding-Completion, Autonomy-Exploration, Socialising, Relationships, and Teamwork. Each motivation is scored on a range from 3 to 15. None of the motivations show normal distributions, except for the Competition motivation. Additionally, the Competition, Escapism, Loss Aversion, Customisation, Grinding-Completion, and Relationships motivations show a high variance with values spread across the entire score range. The remaining motivations are skewed toward high score values. Appendix A shows the details of the distributions of the motivational scores of the participants.

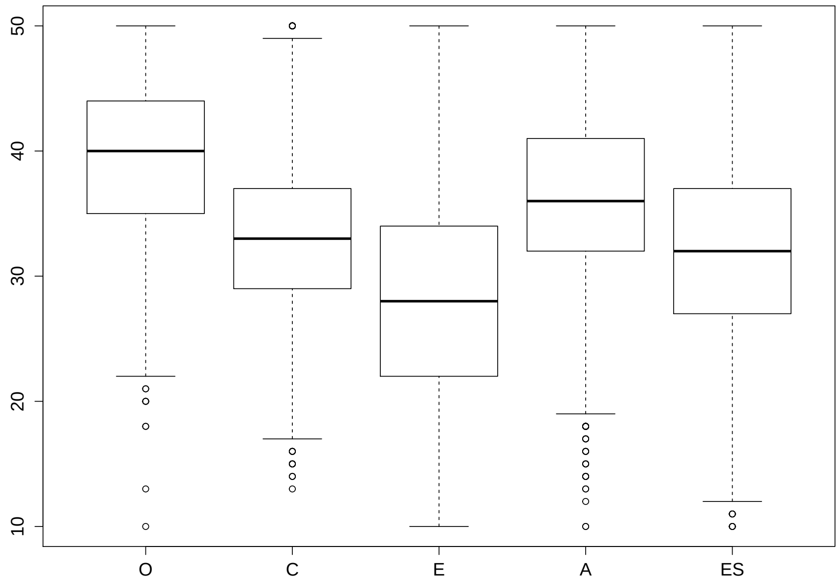

Figure 9: Big 5 Personality Distribution in the GAMR Data Set. The Y axis denotes the score on each of the personality dimensions: (O)penness, (C)onscientiousness, (E)xtraversion, (A)greeableness, and (E)motional (S)tability.

2.2.2.7 *Game Accounts*

The 2763 participants provided a total of 3353 game accounts with the following distribution across the three games: There were 1263 entries on World of Warcraft, 1058 entries on League of Legends, and 1031 on Battlefield.

Table 3 shows the distribution of players for each combination of games played. A 0 (zero) indicates that a game is not played and a 1 (one) indicates that a game is played. Players did not tend to play both World of Warcraft and Battlefield, while League of Legends is frequently combined with the other two games. The distribution makes conceptual sense as World of Warcraft and Battlefield are very different games. On the other hand, League of Legends shares the fantasy

Table 3: Game Account Distribution in the GAMR Data Set. 0 indicates a game is not played. 1 indicates a game is played. N denotes the number of players in the given segment.

WoW	LoL	BF	N
0	0	0	0
		1	808
	1	0	585
		1	107
1	0	0	831
		1	66
	1	0	315
		1	51

and third-person themes with World of Warcraft, and the competitive, match-based play with Battlefield.

2.3 DISCUSSION

Before we dive into the research presented in the next chapters, a brief discussion of the data quantity and sample size is presented, followed by a review of the sample biases present in the PsyOps and GAMR data sets. The discussion points presented below are relevant for all the studies presented in this dissertation.

2.3.1 *Data Quantity & Sample Size*

Though the PsyOps and GAMR data sets are sizeable, even more data could have been gathered from the participants at the risk of reducing the sample size. There is a fine line to tread between generating enthusiasm in the potential sample and the investment in the research that may be expected in return. We expect that if we had asked for more data, our samples would have been much smaller. The point is clearly illustrated by looking at the visitor statistics from the PsyOps website. The following describes the statistics and reasoning behind the participant acquisition of the PsyOps data set. The same themes apply for the GAMR data set.

The front page of the PsyOps website gained about 30,000 unique visits. It contained the promotional material to enthuse prospective participants. The questionnaire page received 20,000 unique hits. Subsequently, little over 13,000 participants completely filled out the data form and submitted their results. Of the 17,000 potential participants lost from front page to submission, it is likely some could have not been enticed into the research no matter what tweaks would have been made to the website or the data gathering process. However, it is also likely that a substantial part was discouraged by the 100-item IPIP questionnaire. It follows that even more people would have dropped out if additional questions would have been added to the data form. The current expected time investment of 5-20 minutes was considered an optimal balance between depth of information and participant retention.

Just as the PsyOps data set benefited from minimising the number of questions presented to the participants, the GAMR data set might have taken a hit to its participant retention by presenting too many questions. The GAMR website contained 150 questions for the participants to fill out. It constituted a 150% increase in time investment for the participants compared to the PsyOps website. The GAMR data set now contains 3,000 participants. In contrast, the PsyOps data set contains 13,000 participants. While other factors are surely at play as well, it is likely that the larger volume of questions on the GAMR data set substantially lowered the sample size we were able to acquire. Overall, there were different trade-offs made between data quantity and sample size for each of the data sets. The PsyOps data set contains 4 times the sample size that the GAMR data set does, while the GAMR data set contains 1.5 times the trait data per participant that the PsyOps data set does.

2.3.2 *Sample Bias*

The PsyOps and GAMR data sets offer a high level of heterogeneity by representing a broad range of ages, nationalities, personality, and gaming motivations. However, they also suffer from three (potential) biases in terms of gaming skill, game preference, and gender.

2.3.2.1 *Skill Bias*

The PsyOps data set is may be biased toward expert players, while the same bias is suspected in the GAMR data set. The bias may have occurred due to the method of participant recruitment. The most feasible approach to reaching out to and enthusing a large group of gamers for our research, was to address those that are already deeply invested in a game. Players with lower investment in a game are by definition less likely to involve themselves with game-related actions outside of direct play, and are therefore hard to find and reach. Arguably, they would also have been less likely to invest their time in the research even if they did know of it.

It is an open question whether the expertise level of the players mediates the relationship between personality, age, and motivation on the one hand and gaming behavior on the other hand. We hypothesize that expert players are more likely to have meaningful play styles, while novices are more likely to exhibit play styles focused on exploration and experimentation. In other words, the play style of experts may converge toward optimality while the play style of novices may contain more variability. The variability in play style among novices might plausibly be shaped by external factors such as personality, age and gaming motivation. Conversely, expert players would be less likely than novice players to show clear relationships between their play styles and their personality, age, and motivations. Therefore, a potential expert player bias in the PsyOps and GAMR data sets would result in weaker relationships among these constructs. The result is that any relationships that are found to be significant are likely more robust in the general populace where novice players form the majority. All in all, an expert player bias may exist in our sample. We hypothesise that such a bias is likely to decrease the chances of finding significant results, while increasing the significance of any results that are found.

2.3.2.2 *Game Genre Bias*

Though the research questions in this dissertation pertain to all video games in general, the actual research can only be applied to a limited range of video game genres. Saying you like video games is like saying you like food. There are so many varieties of each that general statements should be made with the utmost caution and discernment. In our work we have focussed on popular online multiplayer games with player bases running into the millions. However, we do not cover large swathes of game genres such as all single-player games, creativity/exploration-based games such as Minecraft, or games on mobile platforms. Nevertheless, we expect that the effects of personality, age, and motivation will generalise across game genres.

2.3.2.3 *Gender Bias*

The GAMR data set (and presumably the PsyOps data set) contains a strong gender bias towards men, with a male-female ratio around 5:1. This ratio is common in the field of video game research [93], eventhough the source of the gender bias is unknown. There are no public statistics available on the gender distribution for the games included in this dissertation. However, the gaming population in general is known to have largely equalized in terms of gender distribution over the years. The Entertainment Software Association reports that in 2015, 44% of the gaming population consisted of women.

It is likely that the gender distribution is not equal across game genres and that the online game genres of MMORPG, FPS, and MOBA contain a large bias toward male audiences. It is possible that the gender distribution that we acquired in our samples is representative of the audience for each of the relevant game genres. It might also be the case that females are less vocal in sharing their gaming interest and engaging in the video game culture online where most game research samples are drawn from. Therefore, they become underrepresented in online volunteer samples of video game players.

2.4 CONCLUSION

The PsyOps and GAMR data sets each contain thousands of records on the demographic, cognitive, and game behavioural traits of international players of various age groups. Both data sets contain age, country, and personality data. The PsyOps data set contains four times more entries than the GAMR data set, and also lists game statistics for Battlefield 3 for each participant. The GAMR data set includes additional gender and gaming motivation data, as well as containing participants from each of the three major online gaming genres (MMORPG, MOBA, and FPS). Both data sets contain biases in player skill, game genre preference, and gender.

The studies described in the coming chapters will use either the PsyOps or GAMR data sets. In each study, an appropriate subsample is taken from one of the data sets to answer the relevant research question of that chapter. To avoid repetition, the data set descriptives mentioned above will not be repeated, unless a subsample deviates significantly from the relevant total sample described in this chapter.

3 PERSONALITY

This chapter tackles Research Question 1 on personality, and is based on the following original work.

Research Question 1. *What is the relationship between the personality traits of a player and his play style in video games?*

Definition 1. *Personality - a construct made up of a number of personality traits, which are "convenient summaries of consistent behaviors across different situations" (Humprey and Revelle [46]).*

Original Work. *Shoshannah Tekofsky, Pieter Spronck, Aske Plaat, Jaap Van den Herik, and Jan Broersen. Psyops: Personality assessment through gaming behavior. In Proceedings of the International Conference on the Foundations of Digital Games. SASDG, 2013.*

The first validated personality assessment tools date back to 1920 with Woodworth's Personal Data Sheet [91]. Since then, many different personality assessment tools have emerged, each with their own method and selection of personality types and traits. Traditionally, personality assessment methods fall into the categories of behavioral, observational, and self-report measures [32]. With the application of player modelling, we hope to uncover the potential of adding another approach to this arsenal: personality assessment through video games. Video games combine the strengths of behavioral and observational measures, while side-stepping the reliability issues inherent in self-report. Additionally, video games can offer a higher ecological validity than the traditional personality assessment methods. The potential of video games as personality assessment tools hinges on the answer to Research Question 1.

Previous research [83, 84] has yielded interesting results with small sample sizes. In order to validate these results with greater statistical power, we have chosen to focus on gathering a large data sample. The resulting data set is the PsyOps data set described in Chapter 2. In this chapter we present a general review of current research into personality assessment through video games (Section 3.2), followed by the details of our own study relating the Big Five personality traits and its individual items to play style in Battlefield 3 (Section 3.2). Lastly, we discuss our findings and present our conclusions (Section 3.3 and 3.4).

3.1 BACKGROUND

Research into personality assessment in video games is evaluated on three key requirements: (1) Play style should be meaningfully quantified; (2) Personality data should be meaningfully benchmarked; (3) Sufficient participants should be recruited to supply the data of requirements (1) and (2).

Requirement 1 ensures that underlying play style constructs (i.e. speed of play) are reflected in the data. Requirement 2 ensures that personality is accurately measured. Requirement 3 ensures that the results have a strong external validity and statistical power. Our study was set up to meet all three requirements. To our knowledge this had not been done before at the time our study was conducted (2011). The following three research endeavors approached our aims most closely.

A small-scale exploration of personality and play style by Van Lankveld et al. [83, 84] fulfilled requirements (1) and (2). The first requirement was met by creating a custom module for the role-playing game Neverwinter Nights that involved an extensive and meaningful quantification of play style. The second requirement was met by measuring the Big Five personality inventory [18]. The third requirement was not met due to a small sample size of 24 participants. Significant correlations were found between play style and Extraversion, with an effect size of $.40 < r < .50$. Their follow-up study used a similar measure of play style but included all five of the Big Five personality dimensions. The sample size was increased to 44 individuals. The research yielded significant correlations between the play style variables and the Big Five dimensions with effect sizes of $.10 < r < .50$. Meeting requirements (1) and (2), their findings showed a clear relationship between play style and personality. However, falling short on requirement (3), the findings lack statistical power due to the relatively small sample sizes.

A play style analysis on 260,000 gamers by Drachen et al. [27] fulfilled requirements (1) and (3). The first requirement was met by extracting game statistics from proprietary and public databases. The second requirement was not met as no personality data was gathered. The third requirement was met by simply extracting the data of many individuals from the game statistics databases. In this manner 260,000 gamers were included in the sample for two games: the online role-playing game Tera, and the online shooter Battlefield Bad Company 2. Such a large sample could be achieved because participants were not individually approached for permission or additional data. With the use of clustering algorithms behavioral profiles were constructed that gave a meaningful description of different play styles. Meeting requirements (1) and (3), their findings show distinct play style profiles with high statistical power. However, falling short on requirement (2), these findings are not related to personality.

A large meta-analysis of personality and job performance research by Barrick et al. [8] fulfilled requirements (2) and (3). The first requirement was not met because the research was conducted in the domain of job performance, but the relevant analogue data for that domain was analyzed. The second requirement was met by reviewing data on the Big Five personality dimensions. The third requirement was met by only including large participant databases in the meta-analysis. They found significant correlations between Big Five scores and job performance for five different occupations. Effect sizes were trivial with most correlations having $r < .1$. Conscientiousness was most predictive with $.20 < r < .25$. In essence, this endeavor meets all the three requirements when adjusted for the domain of job performance, resulting in a high statistical power of the correlations between job performance and personality.

Our study combines the first two approaches described above to offer a correlational analysis of the link between play style and personality with sufficient statistical power to achieve meaningful results. Fulfilling all three requirements, the study endeavors to bring large-scale personality assessment to the gaming domain in a similar way as has been done in the field of job performance.

3.2 STUDY

The study consisted of constructing and analysing the PsyOps data set described in Section 2.1. In order to answer our research question, the experimental design had to fulfill the three requirements mentioned in the previous section. They can be reiterated as (1) meaningfully quantified play style data, (2) benchmark personality data, and (3) large sample size. The following is a brief explanation on how the requirements were met.

Requirement (1) was met by selecting a game that offered a publicly accessible game statistics database: the online first-person shooter Battlefield 3. The data was meaningfully descriptive as it detailed play style in terms of interesting choices ranging from player specializations to player performance on various metrics (see Section 3.2.1 for more details). Additionally, the game is familiar to the author.

Requirement (2) was met by measuring the Big Five personality dimensions. The NEO-PI-R used in the research by Lankveld et al. [83, 84] demanded a high time investment of the participants. This would have negatively impacted requirement (3) as it would have limited the sample to people willing to invest 45-60 minutes in a personality test. Therefore, we decided to use the 100-item IPIP version of the Big Five which required 5-20 minutes of the participant's time. The test consisted of 100 statements that a participant was asked to grade on a 5-point Likert scale, indicating how much he felt the statement described his personality. Scores on the statements were collated into the same five personality dimensions as the NEO-PI-R, with one exception. While the NEO-PI-R measures Openness, Conscientiousness, Extraversion, Agreeableness, and *Neuroticism* (OCEA*N*), the IPIP measures the inverse of the last dimension and labels it *Emotional Stability* (OCEA-*ES*). The IPIP version is a validated instance of the Big Five Personality Inventory [36]. It was also used by Nick Yee et al. [96] in a concurrently progressing research project on personality and play style (see Section 3.3). This is most likely due to the IPIP Big Five being the only freely available, validated version of the Big Five at the time the research was conducted.

Requirement (3) was met by *marketing* the research toward the participant pool in such a manner as to create an almost viral enthusiasm to contribute. Our research project was dubbed 'PsyOps', and data collection performed through a dedicated website. Here, participants could find promotional material such as game-related art work, as well as a promotional trailer explaining the basics of the research initiative. We reached out to community websites to request them to feature PsyOps on their web pages and encourage their members to participate in the research project.

3.2.1 *Methods*

The PsyOps data set (see Section 2.1) was filtered, processed, and partitioned before data analysis was performed. Filters were applied to the credits, IPIP, age, and game statistics values in the sample. Data processing consisted of determining the play style of a player from his game statistics. Partitioning was performed based on gaming platform and country of residence. The subsequent data analysis consisted of a correlational analysis using the Pearson's correlation coefficient. The four data filters were as follows.

First, the *credits filter* was based on the question if a participant wanted their player name to be mentioned in the credits of the research. The question was added to the data form as an integrity check. It was theorized that people who were more serious about filling in their data, would also be more likely to want their name associated with the results.

Secondly, the *response set filter* was applied to remove participants who overused one response on the IPIP. This filter removed individuals with a biased response style ('response set') [20]. It effectively embodied a method to ensure a minimum multivariate distance.

Thirdly, the *age filter* was applied to age, excluding individuals indicating an age below 12 or above 65. Age values could be selected from 1 to 99, and some people might enter the extreme or near-extreme values. To ensure the inclusion of the maximum number of participants, the limits were set to the onset of puberty (12) and end of working age (65).

Fourthly, the *player rank filter* excluded players with a player rank lower than 10. Ranks range from 0 to 145, with the last 100 ranks being honor ranks. The first 45 ranks gain the player access to additional items in the game that matter strategically. After 10 ranks, the player has unlocked a few items in his preferred class and gained a basic familiarity with the game.

Next, data was processed to determine a player's play style from his game statistics. In order to understand the reasoning related to this process, a basic grasp of the game mechanics of Battlefield 3 would be necessary. The reader is referred to Chapter 2 for more details on the game play of Battlefield 3. Domain knowledge was employed to select game statistics that reflect purposeful actions (i.e. no chance involved) and to remove duplicates. An example of duplicate variables are the "medal" and "ribbon" categories of variables. A medal is awarded when a set number of ribbons have been earned. As such, medals function as a summary value for ribbons. They do not add further information. Such duplicate variables were excluded from the analysis.

In this manner the 826 game statistics in the PsyOps data set were processed and combined to reflect gaming behavior more accurately. The result was that 170 play style variables were defined over nine categories: Ribbon (7), Global (40), Equipment (8), Rank (1), Class (4), Score (19), Game Mode (10), Vehicle Category (7), and Weapon (74) (see Appendix B for the full variable list). Different combinations of variables describe play style characteristics. We present three examples: tendencies toward team work (i.e., Ace Squad Ribbons, Wins per Loss), focus on kill efficiency (i.e., Kills per Death, Nemesis Kills), and preference for long versus short games (i.e., Play Time per Round, Conquest Rounds per Round).

Subsequently, the sample was partitioned into subsamples based on the demographic variables 'gaming platform' and 'country of residence'. Gaming platform had three possible values: PC, Xbox 360, and Playstation 3. The relevance of gaming platform is threefold: (1) Platform preference might contain an inherent sample bias. (2) The interface is different between PC and the two consoles, and slightly different between the two consoles. (3) PC supports larger maps and higher server capacities than the two consoles. The relevance of country of residence was used to create a distinction between native and non-native English speakers, because the IPIP questionnaire was only administered in English. Participants were considered native English speakers if their country of residence was predominantly (>75%) English-speaking. As such, four countries in the PsyOps data set qualified as English-speaking: the United States, the United Kingdom, Canada, and Ireland.

Initially we had intended to create subsamples based on age as well. Through post-hoc analysis we found this was not meaningful, but correlations with play style and personality were interesting (see Chapter 4 for more details). Thus, four partitions of the sample were made, resulting in 12 different (sub)samples: total sample (1), partition on gaming platform (3), partition on native English speakers (2), partition on gaming platform and native English speakers (6).

Overall, 170 game variables, 100 personality statements and 5 personality dimensions were correlated for the 12 (sub)-samples. Correlations were determined by means of the Pearson's Correlation Coefficients (r). Correlations were considered significant at $\alpha < .05$ with application of a Bonferroni correction for multiple comparison. A Bonferroni correction involves adjusting the p value at which a correlation is found to be significant by dividing the chosen α level by the number of correlational tests being performed. In the case of our examination of the personality dimensions, the Bonferoni correction resulted in p values being found significant when they were lower than $0.05/(170 * 5) = 5.88 * 10^{-5}$. In the case of our examination of the individual personality items, the Bonferroni correction resulted in p values being found significant when they were lower than $0.05/(170 * 100) = 2.941176 * 10^{-6}$.

3.2.2 *Results*

The final data set contained data from 13,376 participants. During the data collection phase, the third-party game statistics database was restructured to accommodate an upcoming expansion of the game. The restructuring process shifted the format of the collected data so only the first 9366 submissions were usable. The result of applying the four filters mentioned in the previous section were as follows.

The credits filter excluded 2584 participants; the response set filter excluded 501 participants; the age filter excluded 31 participants; the player rank filter excluded 85 players. In total, 2995 entries were excluded, leaving 6373 participants in the sample (206 participants were excluded by more than one filter). An additional 930 participants had to be dropped for exhibiting 'infinite' (INF) values on play style variables. Infinite values occur when $x/0$ with $x \neq 0$. For instance, if WinsPerLoss returns INF, then a player has never lost a match. This is most commonly seen when a player has only played a limited number of matches. Such a player cannot meaningfully be compared to other players. All in all, the resulting sample contained 5426 participants. The credits filter excluded the highest number of participants but was not found to impact the results either way. The resulting sample did not significantly differ from the total sample described in Section 2.1 in terms of personality, age, or play style descriptives.

The total sample was partitioned on native English speakers and gaming platform (individually and combined), resulting in 11 subsamples. The distribution of the partitioning variables was as follows. The native English speaker distribution is such that about 67% of participants were classified as native English speakers, while 33% were classified as non-native English speakers. The platform distribution is about 39% on PC, 28% on Xbox 360, and 33% on Playstation 3.

Correlations between play style and personality were calculated for the total sample and each of the subsamples. For the total sample the result was 58 significant correlations between the 170 play style variables and the Big Five dimensions. The 11 subsamples offered lower correlational frequencies than the total sample. None of the significant correlations exceeded an effect size of .2 and the correlations did not cluster into meaningful patterns (e.g. performance-related play style variables consistently correlating with a certain personality dimension). In order to give the reader some overview of the results obtained, Table 4 shows the *number* of significant correlations per subsample and per personality dimension. It shows that Conscientiousness shows the most significant correlations with play style, and that these correlations persist across most subsamples. However, as the significant correlations lack effect sizes exceeding .2 or a coherent pattern in their connections between play style and personality, we do not suggest any conclusions be drawn from Table 4. Lastly, there were no significant correlations between the 170 play style variables and the 100 IPIP scores.

3.3 DISCUSSION

In this section three topics will be discussed. First, the hypothesized connection between personality and play style will be reviewed in light of the findings in this chapter (Section 3.3.1). Next, the culture and platform components of the subsamples are discussed (Section 3.3.2). Lastly, directions for future work are suggested (Section 3.3.3).

3.3.1 *Personality and Play Style*

Our analysis determined that there was no relationship between the play style of players in Battlefield 3 and their personality. There were few significant correlations with only trivial to small effect sizes ($r < .2$). Our findings and conclusions contradict those of three prominent research initiatives in the field.

First, Lankveld et al. [83, 84] reported significant correlations with higher effect sizes between personality and play style in Neverwinter Nights. Secondly, work by Canossa et al. [13] supports the conclusion by Lankveld et al. with equally high effect sizes for correlations between play style and personality in a custom-made modification of the RPG Fallout: New Vegas. Thirdly, Yee et al. [96] found correlations with a magnitude of $r < .2$ among MMORPG players (World of Warcraft). Though the effect sizes were of a similar magnitude as was found in our research, they contrastingly did conclude a connection exists between play style and personality in their sample. We discuss three possible explanations for the discrepancies in conclusions between our work, and that by Van Lankveld et al., Canossa et al., and Yee et al.

First of all, the work by Lankveld et al. and Canossa et al. was performed with more detailed data on personality and play style. Their personality data included facet-level measurements that can

Table 4: Number of Significant Pearson's Correlations between the Big 5 Personality Dimensions and the Play Style Variables. This table functions as an overview of the results. Correlations are considered significant when p is lower than Bonferroni correction on $alpha = .05$. All significant correlations showed an $r < .2$. Abbreviations: O = Openness, C = Conscientiousness, E = Extraversion, A = Agreeableness, ES = Emotional Stability, N = Sample Size.

	O	**C**	**E**	**A**	**ES**	**N**
Total Sample	10	19	10	16	3	5426
Language Subsamples						
English	4	8	5	14	1	3626
Non English		2	2	1		1800
Platform Subsamples						
PC		7	1	1	2	2133
Xbox 360		4	2			1520
Playstation 3	4	1	1	5		1773
English Platform Subsamples						
PC			1	2		1102
Xbox 360		2	1	1		1284
Playstation 3	2	2				1240
Non English Platform Subsamples						
PC		1				1031
Xbox 360						236
Playstation 3						533

more readily be related to (game) behavior, while their play style data included measurements of actions the player was performing from moment to moment (such as option choices in conversations). In our sample, both personality data and game behavioral data consisted entirely of higher level aggregates. It might be the case that the link between personality and play style is more strongly expressed in the details of our dispositions and responses, than in the overall patterns. In constrast to Van Lankveld et al. and Canossa et al., Yee et al. used personality and play style aggregations in their work on World of Warcraft. Their aggregations included an equal to lower amount of detail than our work on Battlefield 3. Subsequently, their work showed effect sizes of a similar magnitude as our work on Battlefield 3. Thus, data aggregation with respect to personality and play style may potentially obfuscate their relationship to each other. However, aggregation does not explain the discrepancy in results between our work and that by Yee et al.

Secondly, our work included a large sample size in an uncontrolled, naturalistic environment. In contrast, the studies by Van Lankveld et al. ($n = 24, n = 44$) and Canossa et al. ($n = 41$) were performed with small samples of locally recruited students in a lab environment. The methodological rigor of such an approach is more likely to uncover evidence for stronger links between personality and play style than administering a survey online in an uncontrolled environment. On the other hand, an online survey is more difficult to tap into the natural behavior of the participants than an experiment conducted in a lab environment. In our work and in the work by Yee et al., we extracted the existing, naturally occurring game behavior of each of the participants. Additionally, our sample was more heterogenous in terms of age and country of residence than that of Van Lankveld et al. and Canossa et al. For instance, in our study there was a variety of countries of residence among the participants. A followup study by Mateusz et al. and De Vries and Spronck showed that culture impacts game behavior (see Section 3.3.2), and therefore constitutes a confound in the exploration of the link between play style and personality. The research by Yee et al. further supports the point that research design and sample size may explain why effect sizes may differ between various studies on personallity and game behavior. They used a similar methodology to ours, which resulted in effect sizes of a similar magnitude. Their sample size was $n = 1040$. Therefore, we would argue that sample size, heterogeneity of the sample, and more naturalistic (uncontrolled) research design is likely to have resulted in the smaller effect sizes found in our study than that in the studies performed by Van Lankveld et al. and Canossa et al.

Thirdly, it may be that personality is expressed (more strongly) in Role-Playing Games (RPG) than in FPS games. The potential cause for this could be that FPS game such as Battlefield 3 lack the right action space for the player to express his personality. However, the research by Yee et al. on the MMORPG World of Warcraft resulted in effect sizes of a similar magnitude as those found in our study. They concluded the connection between play style and personality is robust. These conclusions go back to a more fundamental discussion on what effect sizes should be considered relevant. Both our study and that of Yee et al. showed correlations between personality and play style with an effect size of $.05 < r < .20$. Therefore, the current research is not sufficient to conclude that FPS games with sufficient depth, such as Battlefield 3, do not offer sufficient space for personality to be expressed in video game behavior. Our study does show that such a connection only allows for trivial to small effect sizes in our sample.

Overall, we conclude that our results, in conjunction with those of Yee et al., show that aggregates of personality and game behavior are slightly to not at all correlated when looking at naturalistic behaviors across a heterogenous samples online. However, more detailed aspects of game behavior and personality are correlated for small, homogenous samples tested in a controlled lab environment. The work by Yee et al. shows that measuring personality through a complex online FPS is as effective as using an MMORPG. It also exposes a clear dichotomy between Yee et al. and the current authors on what magnitude of effect sizes constitute a relevant finding.

3.3.2 *Culture and Platform*

In our study we compared subsamples based on native English speaking (proxy for culture) and gaming platform. As there were no significant results above the expectancy value, it remains unclear if the subsample construction was a meaningful step. Follow-up work by Mateusz et al. [12] and De Vries and Spronck [22] on Battlefield players offer insights on the connection between culture, nationality, and gaming platform on the one hand, and play style on the other hand.

Mateusz et al. [12] dug farther into the PsyOps data set to determine the link between culture and play style. They split off subsamples for each of the countries with 100 or more participants in the sample. Subsequent MANOVA tests showed that national culture accounts for 5.6% of variance in competitive, and 4.2% in cooperative play style. Pairwise comparisons showed that in particular German and Swedish players (i.e. non-English speakers) demonstrated cooperative behavior significantly more often than players from the United Kingdom and United States (i.e. English speakers). Overall, culture turned out to show a connection to play style where personality did not.

De Vries and Spronck [22] went a step farther and collected a new data set of 100,000 Battlefield 4 players. It describes the play style, country of residence, and gaming platform of the participants. No measures of psychometric or other demographic data were included. They found that a deep neural net could predict gaming platform, nationality, and culture with an error rate of 16.43%, 55.75%, and 39.31%, respectively. It far surpassed the base line model, while also improving on the performance of logistic regression, and random forest. They did not report on the nature of the link between play style and gaming platform. However, the especially high accuracy on predicting gaming platform from play style, highlights the relevance of taking gaming platform into account when analysing play style.

3.3.3 *Future Work*

In light of our findings we do not expect personality to be exhibited in FPS games or in general summaries of play style across game genres. We do consider that it is an open question if a link between play style and personality might be found if more detailed data is used from games outside the FPS genre. For instance, data from other games offers the potential to explore interactions that are not available in shooters (e.g. dialogue) and their relationship to player personality.

At the same time, more detailed data collection on the side of both the game and the player might uncover more fine-grained patterns. On the game side, it is conceivable that certain *action sequences* in the game relate to personality traits (e.g. being the first to jump in a vehicle and drive off or waiting for other players to get in before heading into battle). On the player side, it is likely that certain traits mediate the expression of personality traits in games. For instance, ability for abstract thinking might influence how a player expresses explorative behaviour in the game world, while explorative behaviour may show a link to the Openness personality dimension. Also, personality traits that are more closely related to emotions and their physiological expression might hold promise. For instance, Shaker et al. [68] found strong correlations between emotions and controllable game variables, while Drachen et al. [25] found the same between heart rate and player experience.

3.4 CONCLUSION

Our aim was to answer the question: *What is the relationship between the personality traits of a player and his play style in video games?* Our research specifically focused on the online tactical shooter Battlefield 3. In contrast to previous research by Lankveld et al. [83, 84] and Canossa et al. [13], we only found a few significant correlations with trivial to small effect sizes ($r < .2$). Our findings are in line with the work by Yee et al. [96] on MMORPGs.

4 AGE

This chapter tackles Research Question 2, and is based on the following original work.

Research Question 2. *What is the relationship between the age of a player and his play style in video games?*

Original Work. *Tekofsky, S., Spronck, P., Plaat, A., Van Den Herik, J., & Broersen, J. (2013, August). Play style: Showing Your Age. In Computational Intelligence in Games (CIG), 2013 IEEE Conference on (pp. 1-8). IEEE.*

Original Work. *Tekofsky, S., Spronck, P., Goudbeek, M., Plaat, A., & van den Herik, J. (2015). Past Our Prime: A Study of Age and Play Style Development in Battlefield 3. Transactions on Computational Intelligence and AI in Games, IEEE Transactions on, 7(3), 292-303.*

In the past, video games were stigmatized as child's play [89]. Nowadays, the medium has matured into a pastime for everyone, regardless of age [48]. The Entertainment Software Association reflects this fact, reporting that in 2013 58% of Americans played video games. Their average age stood at 30, while 68% of gamers were 18 years or older.[1] Despite the recent shift in the age of the gamer demographic [89], the relationship between age and how people play games has remained largely unexplored. Age is known to influence many facets of human behavior, such as the purchase patterns of consumers [40]. In this chapter we endeavor to find out if age exerts a similar influence on an individual's play style (Research Question 2).

Aging is accompanied by a host of physiological and psychological changes, such as a decline of cognitive performance, and a decrease

1 April, 2013: http://www.theesa.com. 2013 is used as reference year as it is the year in which the findings in this paper were first published.

in achievement-based gaming motivations (See Section 4.1). Despite the strong and wide-ranging effects of aging on the human body and mind, age is not commonly incorporated into player models (to our knowledge). We conjecture that the physiological and psychological developments from aging are expressed in play style. Consequently, we believe that play style is a strong predictor of age. If our conjecture is correct then player models would become more accurate if they control for age.

In Section 4.1 we expound further on the theoretical grounding of the potential relationship between age and play style. Sections 4.2 and 4.3 describe the methods and results of our two-part study to test the existence and strength of the relationship between age and play style using the PsyOps data set. Lastly, Sections 4.4 and 4.5 serve to discuss and summarise the methods and results used in our study.

4.1 BACKGROUND

As the link between age and play style has remained relatively unexplored so far, we turn to two research areas that form a "bridge" between age and play style for a deeper understanding of the nature of a potential relationship between the two. These bridging constructs are cognitive performance and motivation. Though the two areas are intertwined, both merit separate consideration as previous research shows how each uniquely relates to both age and play style. The authors know of no other research areas that share this dual relationship.

4.1.1 *Cognitive Performance*

Age is accompanied by a deterioration in cognitive performance. We provide three examples of cognitive decline and how they relate to gaming [5]. First, age is negatively correlated with performance on various components of spatial tasks [7], such as spatial pattern completion [59], and spatial memory [49]. Spatial skills are relevant for efficient navigation of a game world. Secondly, age is negatively correlated with learning and memory skills in general [28]. Both learning and memory skills are crucial in mastering game mechanics and completing tasks in video games. Thirdly, age is negatively correlated with performance on attentional tasks [3]. Many games are based on speed of action and dealing with high input and output rates. Attentional resources mediate the speed and quantity of the tasks that a player can perform at a given time.

Play Style has only been linked to cognitive performance in one manner: how improvements in game performance (the player's effectiveness at fulfilling the goals of the game) lead to improvements in cognitive performance. Green and Bavelier [37] reported multiple cognitive performance improvements due to video game training, such as improvements in spatial cognition and attention. Chandramallika et al. [10] specifically explored the cognitive effect of video game training on older adults. They found that improvements in game performance were accompanied by improvements in various cognitive processes, including memory.

4.1.2 *Motivation*

We follow Humpreys and Revelle in defining "motivation" as "a hypothetical construct that has traditionally been used to describe and explain differences in intensity and direction of behavior. It is the state that results from a combination of individual needs and desires with the stimulus properties of the situation." (Humphreys and Revelle [46]). Gaming motivations can be approached top-down as a subdomain for the application of general motivational theory (e.g. applying Self-Determination Theory to gaming [67]), or bottom-up by modeling motivational traits from game behavior and self-report of gamers (e.g. applying principal component analysis to self-reported motivations of gamers [94, 93]). Chapters 5 and 6 go into more detail on the major movements within gaming motivational research. With respect to the link that gaming motivation may form between age and play style, we can say the following.

Age correlates with motivations for gaming. Yee [94, 93] conducted research into the motivations of a large sample (3000+) of massively multiplayer online role-playing game (MMORPG) players. He found that motivations for gaming cluster into three categories: Achievement, Social, and Immersion. The scores for all three motivations decrease significantly with age. Achievement motivation decreases moderately with age, while Social and Immersion motivations decrease slightly with age. We confirmed that gaming motivation decreases with age using the GAMR data set (See Chapter 6 for further details).

Play Style has not been linked to motivation in any of the literature we have found. Yee's findings do contain indirect measures that combine motivations and play style [93]. He measured gaming motivations by asking participants how they enjoyed different game play elements. By definition motivation shapes one's actions. Therefore, Yee's work contains an implicit link between play style and the Achievement, Social, and Immersion motivations in gaming. Chapter 5 proposes a new model to analyse the link between motivation and play style. Chapter 6 describes a study with the GAMR data set that shows that around 10% of game genre preference can be explained by gaming motivations.

4.1.3 *Overview*

Overall, the potential link between age and play style is plausibly mediated by the changes in cognitive performance and motivation that accompany aging. To explore the link directly, we employed data from the PsyOps data set to conduct a study in two-parts: an initial cross-sectional study of play style data (Section 4.2), and a follow-up longitudinal study of play style data (Section 4.3). Part 1 of the study served as an initial exploration to determine how much of the variance in play style *averages* over time can be explained by age. Part 2 of the study delved deeper by looking at the relationship between age and play style *progression* over time.

4.2 PART 1: CROSS-SECTIONAL STUDY

To determine how much of the variance in play style can be explained by age, two requirements had to be met: (1) Play style should be meaningfully quantified in order to reflect underlying play style constructs (e.g., speed of action); (2) A sufficient number of participants should be recruited to attain high statistical power and external validity. Both requirements are met by the PsyOps data set (see Chapter 2 for more details). For the first exploration of the data set, we did a cross-sectional study. A cross-sectional study is an observational study that focusses on analysing the data collected from a sample at a specific point in time. Section 4.2.1 further describes the methods employed, and Section 4.2.2 describes the results that were obtained.

4.2.1 *Methods*

Data analysis progressed in four steps: defining integrity filters, determining play style based on game statistics, calculating correlations between age and play style, and determining the percentage of variance in age explained by play style. Below we will detail the reasoning and processes underlying each step. The Results Section (4.2.2) will report on the overall outcomes from the data analysis.

First, the integrity filters for the sample were defined. The only relevant variable that was vulnerable to misreporting was age. Play style and platform could not be misreported as this data was drawn directly from the third-party statistics database. Therefore, age was the only relevant variable to filter on. The same age filter was used as in Chapter 3. It excludes individuals indicating an age below 12 or above 65.

Secondly, play style was determined from the 826 game statistics available for each player. The 173 gameplay variables from Chapter 3 were reevaluated. The 75 weapon variables were dropped as we had no reason tot suspect weapon preference would be related to age. The remaining 98 variables were refactored into 60 play style variables over 4 categories. Almost all variables are ratios of 2 or more statistics to ensure that play style is measured independent of confounds. For instance, the absolute number of kills a person obtains is not informative until it is made relative to time played (speed of kills) or number of deaths (skill of the player). The 4 categories of play style variables were defined on the type of ratio used in the category. In the following overview, the number of variables per category is displayed in brackets.

- *Time* variables (26): actions per second played
- *Score* variables (13): proportion of a certain score per total score

- *Ratio* variables (16): unrelated variables that have been made relative to different criteria (e.g., Wins per Loss, Hits per Kill)
- *Absolute* variables (5): absolute values instead of ratios (e.g., ELO rating)

The 60 play style variables only reflect behaviors that every player can show at any time in the game. It does not follow that every behavior a player *can* exhibit *is* exhibited by each player. If a player never engages in a certain behavior, then he will show a missing value for the relevant play style variable. We have chosen to enter 0 for missing values on play style variables. Lower values on play style variables generally indicate less skill with the relevant behavior. We consider it plausible that (barring a few exceptions) a player who never exhibits a certain behavior, has little to no skill with that behavior. Therefore, it follows that 0 is a representative value for play style variables with missing values.

Thirdly, the Pearson's Correlations were calculated between age and the play style variables. Correlations were considered significant at $\alpha < .05$ with Bonferroni correction. The Bonferroni correction resulted in correlations be found significant at a p value lower than $.05/60 = .008$. Both individual correlations as well as related groups of correlations will be placed into the relevant context to aid the reader's understanding of the meaning of our findings.

Fourthly, Multiple Linear Regression (MLR) was used to determine the percentage of variance in age that can be explained by play style. This was done for both the total sample, as well as for subsamples based on gaming platform. There are three possible values for gaming platform: PC, Xbox 360, and Playstation 3. Players on different gaming platforms cannot interact with each other. Gaming platform can influence the relationship between age and play style in three ways: (1) Platform preference might contain an inherent sample bias. (2) The interface is different between PC and the two consoles, and slightly different between the two consoles. (3) PC supports larger maps and higher server capacities than the two consoles.

The beta coefficients of the MLR models will not be presented nor interpreted due to the high inherent covariance among play style variables. The play style variables describe game actions that are designed to be interconnected. For instance, choosing to play one class forgoes playing the remaining classes. Classes, weapons, and vehicles offer unique combinations of action options to the player. The weapons available per class and vehicle determine the limits on how far, how fast, and how accurate a player can shoot. Some vehicles allow faster movement, while others limit movement speed in return for additional protection. Therefore, it is not meaningful to look at the beta coefficients of the models. The Pearson's correlations fill this gap by describing the individual links between age and each of the play style variables. The MLR results presented add to these results by showing how much of the variance in age can be explained by taking *all* the available play style variables together.

Overall, the link between age and play style was explored on the basis of a large sample of data from individuals aged 12-65, reviewing 60 play style variables, and characterizing the sample on personality, country of residence, and the credits question (see Section 2.1). For a comprehensive insight into the statistical methods described above, we refer the reader to [31].

4.2.2 *Results*

The final data set contained data from 13,376 participants. As mentioned previously in Chapter 3, the third-party game statistics database was restructured during the data collection phase to accommodate an upcoming expansion of the game. The restructuring process shifted the format of the collected data so only the first 9366 submissions were usable for the current analysis. The 9366 participants are a random sample of the total sample of 13,376 participants. The subsample shows broadly the same sample characteristics as the main sample described in Chapter 2. Conversely, the sample characteristics of the current subsample are not further discussed. Instead we will directly describe the progression and results of our analysis.

Initial data processing consisted of applying the age filter and calculating the play style variables. The age filter excluded 31 participants who had indicated an age below 12 or above 65. The 60 play style variables that were calculated can be viewed in Tables 5 and 6. It also shows the correlations discussed in Section 4.2.2.1. 1263 participants exhibited one or more missing values on the play style variables which were substituted with a 0 value.

4.2.2.1 *Correlations*

The correlations between age and play style can be found in Tables 5 and 6. The first column displays the names of the play style variables (See the IGN *Battlefield 3 Wiki Guide*[2] for more information on the game play elements described.) The second column displays the p values of the correlations with age. The p value describes the probability that a correlation occurs in the data by chance. The third column displays the r values (effect sizes) of the correlations with age. The r value describes the strength of a correlation using the interval $[-1, 1]$.

Of the 60 play style variables, 54 correlate significantly with age at a level of confidence of $\alpha < .05$ (after correcting for multiple comparisons: $p < .0008$). The largest effect sizes can be found for Unlock Score per Total Time ($-.417$), Kills per Total Time ($-.368$), Savior and Avenger Kills per Total Time ($-.330$), and Assault Score per Assault Time ($-.319$). These four correlations are highlighted as they surpass an effect size of .3.

We present the following five observations made from the correlations between age and play style variables, to give the reader an idea of the shape of the relationship between age and play style. In the Discussion (Section 4.4) we offer a further tentative interpretation of how age and play style are related.

1. OLDER PLAYERS KILL AND DIE LESS. Age is negatively correlated with the frequency of both kills and deaths per time unit. Age is negatively correlated with accuracy, and positively correlated with Deaths per Kill.

2. OLDER PLAYERS SCORE LESS. Age is negatively correlated with all measures of score per time unit, with the exception of Objective Score.

3. OLDER PLAYERS FOCUS ON WINNING. Age is negatively correlated to Wins per Loss, but with a trivially small effect size (-0.076) that is two to five times lower than would be expected given the

2 http://www.ign.com/wikis/battlefield-3/Multiplayer

correlations between age and the other two performance metrics (kills and score). Matches are won by gaining kills or performing actions that earn score. Score earned by performing actions directly related to winning, is counted as Objective Score. Objective Score is the only score variable that is not significantly correlated to age in a negative manner. Therefore it can be deduced that older players focus more on winning, but are not as skillful at the relevant actions necessary to win (observations 1 and 2).

4. OLDER PLAYERS INVEST MORE TIME IN THE GAME. Age is positively correlated with total play time. Further analysis shows play time correlates *positively* with all measures of performance (kills, score, wins) with effect sizes around .2. The relationship runs counter to observations 1 and 2. A slower play style (observations 1 and 2) does not lengthen play time as Battlefield is a match-based game where a low performance in the game can only *shorten* the length of individual matches.

5. AGE INFLUENCES CLASS AND VEHICLE PREFERENCES. Age correlates positively with use of the Support and Engineer classes, and negatively with the Assault and Recon classes. Age correlates positively with use of the tank (MBT), while it correlates negatively with use of aircraft (jets and helicopters). Despite class and vehicle preferences, younger players score better with all classes and vehicles (observation 2).

4.2.2.2 *Multiple Linear Regression*

In the total sample, 45.7% of the variance in age can be explained by 46 of the 60 play style variables. This was determined by applying backward selection. It removed 14 play style variables under an entry condition of .005, and a removal condition of .01. The conditions were a factor 10 stricter than is usual. Therefore, the remaining 46 variables in the model are significant with a maximum of $p = .01$. ANOVA shows the model itself to be significant at $p < .01$.

Using the same procedure on subsamples based on platform, we find the following. For PC players, 43.1% of the variance in age can be

Table 5: Pearson's Correlation between Age and Play Style.

Play Style Variable	p	r
Time Variables		
VehicleTimePerTotalTime	.004	-.030
VehicleDestroyedPerTotalTime	<.000	-.146
VehicleDestroyAssistPerTotalTime	<.000	-.111
KillsPerTotalTime	<.000	-.368
KillAssistPerTotalTime	<.000	-.263
NemesisKillsPerTotalTime	<.000	-.217
SaviorAvengerPerTotalTime	<.000	-.330
DogTagsPerTotalTime	<.000	-.165
DeathsPerTotalTime	<.000	-.164
ShotsPerTotalTime	<.000	-.174
GrenadeShotsPerTotalTime	.196	-.013
SuppressionPerTotalTime	<.000	-.197
ResuppliesPerSupportTime	.991	.000
RevivesPerAssaultTime	<.000	-.236
RepairsPerEngineerTime	<.000	-.126
RadioBeaconSpawnsPerReconTime	.054	-.020
SupportTimePerTotalTime	<.000	.164
AssaultTimePerTotalTime	<.000	-.085
ReconTimePerTotalTime	<.000	-.174
EngineerTimePerTotalTime	<.000	.186
VehicleMBTTimePerTotalTime	<.000	.221
VehicleAHTimePerTotalTime	<.000	-.098
VehicleAATimePerTotalTime	<.000	.072
VehicleJetTimePerTotalTime	<.000	-.238
VehicleSHTimePerTotalTime	<.000	-.172
VehicleIFVTimePerTotalTime	<.000	.089

Table 6: Pearson's Correlation between Age and Play Style (Continued from Table 5).

Play Style Variable	p	r
Ratio Variables		
DogTagsPerKill	<.000	-.061
DeathsPerKill	<.000	.279
WinsPerLoss	<.000	-.076
MVP123PerRound	<.000	-.203
AceSquadPerRound	<.000	-.075
SaviorAvengerPerKill	<.000	-.063
HitsPerKill	<.000	.087
HitsPerShot	<.000	-.244
HeadShotsPerShot	<.000	-.186
GrenadeHitPerShot	<.000	-.140
GrenadeKillsPerShot	<.000	-.137
MComDefenseKillsPerMComDestroyed	<.000	.049
FlagDefendKillsPerFlagCapture	<.000	-.104

Table 7: Pearson's Correlation between Age and Play Style (Continued from Table 6).

Play Style Variable	p	r
Score Variables		
UnlockScorePerTotalTime	<.000	-.417
ObjectiveScorePerTotalTime	.020	-.024
ScorePerTotalTime	<.000	-.268
TeamScorePerTotalTime	<.000	-.134
SquadScorePerTotalTime	<.000	-.131
SupportScorePerSupportTime	<.000	-.265
AssaultScorePerAssaultTime	<.000	-.319
EngineerScorePerEngineerTime	<.000	-.299
ReconScorePerReconTime	<.000	-.274
VehicleScorePerVehicleTime	<.000	-.050
VehicleMBTScorePerVehicleMBTTime	<.000	-.173
VehicleAAScorePerVehicleAATime	<.000	-.144
VehicleSHScorePerVehicleSHTime	<.000	-.198
VehicleIFVScorePerVehicleIFVTime	<.000	-.125
VehicleAHScorePerVehicleAHTime	<.000	-.177
VehicleJETScorePerVehicleJETTime	<.000	-.273
Absolute Variables		
TimeHours	<.000	.204
Rank	.002	.032
Elo	<.000	-.227
LongestHS	<.000	-.107
LongesthandHS	<.000	-.126

explained using 31 play style variables. For Xbox 360 players, 53.9% of the variance in age can be explained using 30 variables. For Playstation 3 players, 51.7% of the variance can be explained using 28 play style variables. All models are significant at $p < .01$. It is interesting to note that dividing the sample along gaming platform generates models with only two thirds of the number of variables used for the model of the full sample.

4.3 PART 2: LONGITUDINAL STUDY

The results from Part 1 of the study (Section 4.2) showed a robust relationship between age and play style *averages* over time (cross-sectional results). Next, we set out to determine if the relationship between age and play style *progression* over time (longitudinal results) might be even stronger than the play style averages over time. To determine the play style progression over time, Part 2 of the study involved a longitudinal study.

In a longitudinal study, data is collected from a sample at various points in time. The player names from the previous study were used as keys for the extraction of the longitudinal data in the current study. The original data only contained a snap shot ('history entry') of player behavior at one point in time, 8 months after release of Battlefield 3. For the current study we extracted all history entries per participant from the release of the game up until the time of data extraction, 2 years later. Each entry is a snap shot of a player's play style at the moment that entry was made. However, a string of entries for a particular player shows the development of play style over time. Participant data was only extracted if at least 2 history entries were available. The history entries were successfully extracted for 10,942 of the 13,367 participants. The history entries of the remaining 2,425 participants were not extracted. Their history entries could either not be found (i.e., they had changed their player name), were not sufficient for the purposes of our research (i.e., fewer than 2 history entries), or were corrupted.

4.3.1 *Methods*

The resulting data set was further analyzed using Regression Coefficient Analysis (RCA) [53, 78]. RCA broadly consists of performing regression analysis on a set of variables, and subsequently performing an additional analysis on the beta coefficients of the regression. We performed regression (line of best fit) of each play style variable (outcome variable) per individual against his play time (predictor variable). Secondly, we analyzed the beta coefficients (slope and intercept) by calculating the Pearson's correlation of age and the average beta coefficients per age group. We decided to use RCA instead of more sophisticated analysis methods. It is a straight-forward and insightful analysis that provides sufficient depth to answer our research question, cf. [34, 35, 64, 73, 80, 81, 97].

The data analysis procedure will be described in three parts. First, the manner of play style quantification is explained (Section 4.3.1.1). Secondly, the process of feature extraction is discussed (Section 4.3.1.2). Thirdly, the statistical techniques used in the data analysis are reviewed (Section 4.3.1.3).

4.3.1.1 *Play Style Quantification*

Moving forward with our experiences and insights from Part 1 of our study, we developed a more rigorous definition of play style quantification for Part 2 of our study. We returned to the basic definition of play style: any (set of) patterns in game actions performed by a player. Battlefield 3 offers the player a wide set of game actions. We make a distinction between *free* and *locked* game actions. Game actions are *free* when they are *not* dependent of unlockable game assets. Game actions are *locked* when they are dependent of unlockable game assets. We only include free game actions in our play style analysis in order to compare participants fairly.

For each player all 826 available game variables were collected. In order to adhere to our definition of play style, we extracted a set of 59 play style variables that described *patterns* in *free* game actions performed by the player. In order to reflect *patterns*, all play style variables were ratios of two of the following types of variables: *Action*, *Score*, and *Time*.

- *Action* variables (38) count how often a certain game action has been performed by a player. The vast majority of game actions are *locked*, such as the usage of unlockable guns or support abilities. The set of *free* game actions in Battlefield 3 is 38.
- *Score* variables (16) count how much a player has earned of a certain type of score. Each type of score is earned by a set of actions related to the type. For instance, Engineer Score is earned by using Engineer-specific equipment and guns, while Objective Score is earned by performing game actions directly related to the objective of the game mode. Battlefield 3 distinguishes between 16 types of score.
- *Time* variables (11) count how much time a player has spent on a certain activity. Battlefield 3 tracks 11 types of time variables, such as time spent in a particular vehicle or time spent playing a particular class.

The 65 Action, Score, and Time variables each track the sum total of actions, score or time a player has accumulated for that particular variable. To extract information about play style, the 65 variables were converted into 59 ratio variables by dividing Action, Score and Time variables with each other where relevant. There are six unique permutations (called *categories*) for the division of Action, Score, and Time variables: Action over Action, Action over Score, Action over Time, Score over Time, Score over Score, and Time over Time. Action over Score variables were not included. They describe the points that are scored by performing certain actions. Points per action is a fixed value in the game and thus not descriptive of play style. The remaining five categories are descriptive of play style in the following manner.

- *Action over Action* variables describe a player's preference and skill at performing certain actions, such as how often he chooses to defend an objective instead of attack it, or how often he wins a round per time he loses one.
- *Action over Time* variables describe the frequency with which a player performs different actions, such as shots fired per time unit.

- *Score over Time* variables describe the rate at which a player earns a certain type of points, such as objective or team score points.
- *Score over Score* variables describe the proportional distribution of the different types of score a player earns, such how much of the player's total score is objective score.
- *Time over Time* variables describe what actions the player prefers to spend time on, such as proportion of time the player spent playing the engineer class.

All play style variables only reflect behaviors that every player can show at any time in the game. It does not follow that every behavior a player *can* exhibit *is* actually exhibited by each player. If a player never engages in a certain behavior, then he will show a missing value for the relevant play style variable at that time. However, a player may not show a certain type of behavior early in his game career, but can exhibit it later on. Therefore, if a player shows a missing value on a certain variable at a certain time, that time point is discarded for that variable.

4.3.1.2 *Feature Extraction*

Two features were extracted per play style variable: the slope (s) and the intercept (i). The slope signifies the improvement of the participant over time on the relevant play style variable. The intercept signifies the starting point of the participant on the relevant play style variable. The slope and intercept are determined as follows. Each participant has a number of history entries. History entries are snap shots of a player's play style variables at a certain point in time. Such snap shots are made automatically when players view their profile on a particular website where they can view their game statistics.[6] The result is a set of irregular time series data: each player has a different number of history entries with a different distribution over time. The number and distribution of history entries only relates to how often and when the participant visits the statistics website. They do not correspond to play time or play frequency.

Per play style variable, per participant, the line of best fit is determined (regression). The line of best fit is defined by its slope and intercept (beta coefficients). It is relevant to note that the intercept is a hypothetical, extrapolated value that corresponds to neither the first history entry, nor to the actual value of the play style variable at time zero. The first history entry is not informative as starting point as each participant has their first history entry at a different time. The actual value of the play style variable at time zero is also not informative because this value is zero for everyone (no actions have been performed). This leaves the intercept of the line of best fit as the most useful estimate of the value of a play style variable at time zero. It denotes the hypothetical, extrapolated value at time zero that would have resulted if the participant had started the game performing in line with subsequent history entries. Together, the slope and intercept of the play style variables of an individual constitute a within-subject analysis.

The line of best fit for an age group is determined by taking the mean of the slope and the mean of the intercept of all the participants that fall within that age group. By using the mean values all participants contribute equally to the line of best fit for a particular age group, and each age group contributes equally in the subsequent analysis of play style development. Thus, each age group contains 59 pairs consisting of one slope and one intercept (one pair per play style variable). Age groups are defined by year (i.e., 20, 21, and 22 year olds all have their own age group). Each age group must consist of sufficient participants to be a representative sample of that age group. We have settled on a generous minimum of 100 participants per age group.

When referring to the specific age of a participant there is a 2 year time window related to our age measurement. The play style data was gathered over a period of 2 years. The age measurement took place 8 months into this period. So if a participant is reported to be of age x, then he was either of age $x-1$ to age $x+1$, or age x to age $x+2$ during the 2 year research period. The two cases cannot be discerned from each other as we have not tracked specific birth dates in our data set. The time window does not impact the data analysis, because age data is accurately measured in a relative sense. Additionally, we will largely discuss our findings in terms of age brackets consisting of three or more age groups (see Section 4.3.2).

4.3.1.3 *Statistical Methods*

Each individual contributed to the mean intercept and mean slope for each variable for their age group. There are only as many data points per variable as there are age groups. Therefore, considering the human age range, the sample size is small. RCA was performed by calculating the Pearson's r for age on the one hand, and the slope and intercept of each variable per age group on the other hand.

Care should be taken when interpreting the correlations between age and the slope of a variable. The slope of a variable signifies the *speed at which the variable changes*. In our study, a correlation between age and the slope of a variable signifies the *acceleration* of the change in a variable over the span of years that people age. A negative correlation indicates a negative acceleration and a positive correlation indicates a positive acceleration. We consider two examples.

First, Figure 10 illustrates a positive correlation between age and the slope of a play style variable. Slope values are positive for both young and old players. Four data points are highlighted to illustrate the progression of the slope values for the different age groups. Note how a positive correlation between age and the slope of a variable means that players increase their values on a play style variable more rapidly as they age. It does not mean that older players score higher on the relevant variable than younger players. To determine who scores the highest on a relevant variable, both the slope and intercept of a variable need to be combined. The slope of a variable only describes the *increase* (or *decrease*) of that variable over time. As such, slope is a measure of play style development over time. The correlation between the slope of a variable and age indicates the acceleration of the play style development over time in relation to age.

Secondly, we consider the following example. A variable has a negative acceleration over the years. What can be concluded from that? It means that younger players display a higher slope than older players (i.e., younger players increase more on this variable than older players). The information is about the relationship between the slopes of younger and older players. It does not tell us what direction the slopes run in. All slopes might be either negative or positive, or the slopes might run from positive to negative with age. It cannot be that the slopes run from negative to positive, as this would indicate a positive

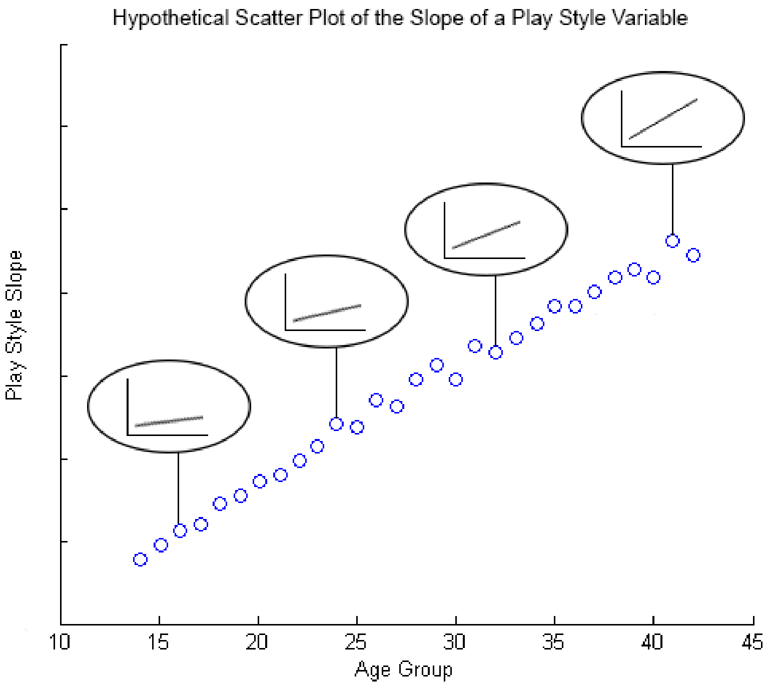

Figure 10: A hypothetical example of a positive correlation between age and the slope of a play style variable. The slope values for all age groups are positive. Therefore, the positive correlation means that players increase their values on the relevant play style variable more quickly as they age.

correlation. To alleviate the ambiguity of the development of the slope direction over the years, the direction of the slope (positive/negative) will be indicated for both young and old players for every significant correlation presented in our results.

4.3.2 *Results*

The correlations between age and play style can be found in Tables 8 and 9. The first column displays the names of the play style variables (see the IGN *Battlefield 3 Wiki Guide*[3] for more information on

3 http://www.ign.com/wikis/battlefield-3/Multiplayer

the game play elements described). The second column displays the Pearson's r of the correlation between age and the slope (s) of the relevant variable ($r(s)$). Each significant slope correlation is followed by two arrows. The first arrow indicates if the slope is positive (↑) or negative (↓) for younger players. The second arrow indicates if the slope is positive (↑) or negative (↓) for older players. Most slope correlations describe an increase or decrease in a uniformally positive (↑↑) or negative (↓↓) slope. Some correlations describe a change from positive to negative (↑↓) slope or vice versa (↓↑). The arrows indicate which is the case. For one variable (VehicleAHScorePerVehicleAHTime), indicated with ??, it is unclear from the distribution of the data if the relationship between the play style variable and age is positive or negative, as all the values are scattered around the zero-point. The third column displays the Pearson's r of the correlation between age and the intercept (i) of the relevant variable ($r(i)$). The r value describes the strength of a correlation using the interval $[-1, 1]$. The r value is only displayed if the correlation has $p < .01$. A * indicates the correlation is significant at $\alpha = .05$ after Bonferroni correction. In one case (KillAssistsPerTotalTime) there was not sufficient data available to calculate Pearson's r. The $r(s)$ and $r(i)$ for KillsAssistsPerTotalTime is indicated with a '—'

A significant correlation is assumed to model a linear relationship (definition of Pearson's r). However, some of the distributions of slope and intercept values were non-linear. A typical pattern observed is the peaking of values within certain age brackets. In order to describe the results more concisely, we define the following age brackets: *middle teens* (age 14-16), *late teens* (age 17-19), *early twenties* (20-22), *middle-to-late twenties* (23-29), and *thirty plus* (30-42). Variables with significant correlations that peak at a certain age, did so in either the late teens or early twenties. In those cases, the shape of the scatter plot is an asymmetrical (inverted) u-shape, with the long edge covering the higher age groups (older than late teens or early twenties), and the short edge covering the lower age groups (younger than late teens or early twenties). When this is the case, a variable is denoted with a $\triangle$ symbol (see Figures 11 and 12 for examples).

The skewedness of the distribution of age did not meaningfully impact the results. Although there exists a debate around the importance

Table 8: Age to Play Style Correlations: Effect sizes (r) are displayed for the slope (s) and intercept (i) of play style variables that correlate significantly with age at $p = .01$. A * indicates that the correlation is significant at $\alpha = .05$ with Bonferonni correction ($p < .0004237288$). Arrows indicate the direction of the slope of a variable for young and old players, respectively, with ↑ indicating a positive slope and ↓ indicating a negative slope. The △ indicates a correlation that peaks for participants who are either in their late teens or early twenties.

Play Style Variable	**Longitudinal**	
	$r(s)$	$r(i)$
Action over Action Variables, range [-Inf, Inf]		
DeathsPerKill	* -.84 ↓↓ △	* .89 △
WinsPerLoss		* -.75 △
MVP123PerRound	.53 ↑↑	* -.86 △
AceSquadPerRound	.59 ↑↑	-.54 △
HitsPerKill		* .67
HitsPerShot		* -.87 △
HeadShotsPerShot		* -.90 △
DogTagsPerKill		* -.97
SaviorAvengerPerKill	* .88 ↑↑	-.54 △
GrenadeHitsPerShot		* -.81 △
GrenadeKillsPerShot	* -.65 ↑↓	* -.76 △
MComDefenseKillsPerMComDestroyed		* .67
FlagDefenseKillsPerFlagCapture		* -.73 △

Table 9: Age to Play Style Correlations (Continued from Table 8).

Action over Time Variables, range [0, Inf]						
VehicleDestroyedPerTotalTime	*	-.66	↑↑	*	-.85	△
VehicleDestroyAssistsPerTotalTime				*	-.73	
KillsPerTotalTime		-.51	↑↑	*	-.97	△
KillAssistsPerTotalTime		—			—	
NemesisKillsPerTotalTime	*	-.96	↑↑	*	-.97	△
SaviorAvengerKillsPerTotalTime		-.53	↑↑	*	-.98	
DogTagsPerTotalTime				*	-.97	
DeathsPerTotalTime	*	.72	↑↑	*	-.79	
ShotsPerTotalTime	*	.62	↑↑	*	-.94	△
GrenadeShotsPerTotalTime	*	.85	↑↑			
SuppressionPerTotalTime		.53	↑↑	*	-.96	
ResuppliesPerSupportTime		.49	↑↑			
RevivesPerAssaultTime	*	.81	↑↑	*	-.97	
RepairsPerEngineerTime				*	-.88	
RadioBeaconSpawnsPerReconTime	*	.67	↑↑			

Table 10: Age to Play Style Correlations (Continued from Table 9).

Play Style Variable	Longitudinal	
	r(s)	r(i)
Score over Time Variables, range [0, Inf]		
ScorePerTotalTime	* -.72 ↑↑	* -.94 △
UnlockScorePerTotalTime	* .71 ↓↓ △	* -.98
ObjectiveScorePerTotalTime		
TeamScorePerTotalTime	* .74 ↑↑	* -.93 △
SquadScorePerTotalTime		* -.89 △
SupportScorePerSupportTime		* -.96 △
AssaultScorePerAssaultTime		* -.98 △
EngineerScorePerEngineerTime	-.48 ↑↑	* -.97 △
ReconScorePerReconTime		* -.95 △
VehicleScorePerVehicleTime		-.47 △
VehicleMBTScorePerVehicleMBTTime		* -.84 △
VehicleAAScorePerVehicleAATime		* -.93 △
VehicleSHScorePerVehicleSHTime		* -.91 △
VehicleIFVScorePerVehicleIFVTime		* -.81 △
VehicleAHScorePerVehicleAHTime	-.56 ??	* -.90 △
VehicleJetScorePerVehicleJetTime		-.53

Table 11: Age to Play Style Correlations (Continued from Table 10).

Score over Score Variables, range [0,1]							
UnlockScorePerScore		.58	↓↓		*	-.87	
ObjectiveScorePerScore	*	-.91	↓↓	△	*	.94	△
TeamScorePerScore	*	.94	↓↑			-.60	
SquadScorePerScore					*	.87	
Time over Time Variables, range [0,1]							
SupportTimePerTotalTime					*	.93	
AssaultTimePerTotalTime	*	-.65	↑↑			-.60	
ReconTimePerTotalTime					*	-.83	△
EngineerTimePerTotalTime	*	-.91	↑↑		*	.98	
VehicleTimePerTotalTime		-.60	↑↑		*	-.70	
VehicleMBTTimePerTotalTime					*	.80	
VehicleAHTimePerTotalTime							
VehicleAATimePerTotalTime		.54	↑↑		*	.67	
VehicleJetTimePerTotalTime	*	-.80	↑↑		*	-.81	
VehicleSHTimePerTotalTime							
VehicleIFVTimePerTotalTime		.60	↑↑				

of the normality assumption for the Pearson's correlational analysis [30], we decided to err on the side of caution and repeated our analysis with the Spearman's test. While Pearson's r is generally considered a parametric test of linearity, Spearman's ρ is a non-parametric test of monotonicity, which does not require an assumption of normality. The results from the Spearman's test were near-identical to the results from the Pearson's test in both probability and effect size values. This highlights the validity of the values we report for Pearson's r.

Tables 8 and 9 show that 81 of the 118 potential correlations have $p < .01$, while 61 correlations are significant at $\alpha = .05$ after applying a Bonferonni correction for multiple comparison. Though that number is high, it should be considered that play style variables are not independent of each other. In many video games, one choice (e.g., class or weapon) impacts another (e.g., frequency of engaging the enemy or accuracy). Therefore, one correlation can have many knock-on effects. We did not control for variable dependence in the data analysis, but we do take it into account in the interpretation of the results.

Looking at the significant correlations in Tables 8 and 9 more closely, patterns can be discerned at three levels of generalization: across a single variable, across a variable category, and across all variables. Tables 8 and 9 offer the necessary data for uncovering patterns on all three levels of generalization. The reader can discern patterns across single variables from Tables 8 and 9 in a straight-forward manner. We discuss one example variable to illustrate how the data across single variables should be interpreted. Subsequently, we will discuss patterns across variable categories (Action over Action, Action over Time, Score over Time, Score over Score, Time over Time), and across all variables.

4.3.2.1 *Patterns across Single Variables*

Patterns across single variables are a combination of the correlations of the slope and intercept of the relevant variable. We will guide the reader through the interpretation of one single variable. Using Tables 8 and 9 the reader can interpret the patterns in the remaining single variables in a similar manner.

We consider the question how kill-death ratio is influenced by age. Kill-death ratio is a central performance measure in First Person Shooters. In our analysis we have measured the inverse of kill-death ratio (DeathsPerKill), as the variable 'Kills' is also a quantifier for Hits (HitsPerKill), Dogtags (DogtagsPerKill), and Savior and Avenger kills (SaviorAvengerPerKill). Figures 11 and 12 show the average slope and intercept of the variable DeathsPerKill per age group. Both plots show a u-shaped distribution with a peak around the early twenties age bracket. The overall trend is that players start out with a higher DeathsPerKill as they age (intercept), and decrease their DeathsPerKill more rapidly as they age (slope). The trend is reversed for players in their middle and late teens. As kill-death ratio is the inverse of DeathsPerKill, we may conclude that players in their early twenties start out with the highest kill-death ratio and the lowest decrease of kill-death ratio over time. Players who are progressively older or younger than the early twenties age bracket have progressively lower initial kill-death ratios and progressively higher gains in kill-death ratio over time. Kill-death ratios will converge over time. In other words, with practice players compensate for the influence of age on their kill-death ratio. Considering the units on the y-axis in both figures, we see that initial (intercept) DeathsPerKill are a factor 10 higher than the increases over time (slope). Therefore, there is considerable practice time involved before the influence of age on kill-death ratio is entirely compensated for.

4.3.2.2 *Patterns across Variable Categories*

While individual correlations sketch patterns in particular actions of the players as they age, the patterns across variable categories paint a picture of overarching themes in play style that emerge with aging. The following is an overview of the patterns in significant correlations across variable categories.

ACTION OVER ACTION variables describe ratios of actions. The first seven variables in Table 8 are measures of performance, with DeathsPerKill and HitsPerKill being inverse measures of performance. Younger players start out with a higher performance in the game in terms of Action over Action variables, with a predominant trend toward peaked correlations. Over time, older players decrease their DeathsPerKill more quickly (inverse mea-

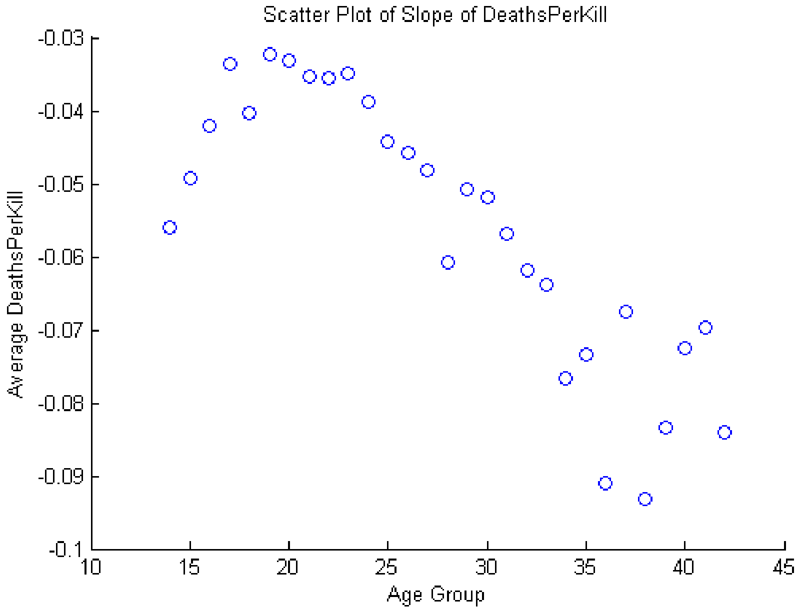

Figure 11: The slope of DeathsPerKill shows a negative, u-shaped relationship with age, peaking around the early twenties age bracket. The DeathsPerKill values are negative for both young and old players, indicating that players of all ages decrease their DeathPerKill over time. As players age past their early twenties, they decrease their DeathsPerKill more rapidly. DeathsPerKill is a negative measure of performance.

sure of performance). The remaining six variables describe strategic and preference decisions. We have discerned no overarching patterns in the correlations of these variables with age.

ACTION OVER TIME variables describe the frequency of actions over time. The first seven variables measure game actions that require the player to kill, or assist in the killing of, an enemy. Therefore, these variables are performance-related. The remaining variables are not. Older players start out playing more slowly than younger players across all Action over Time variables. Over time, all players improve their speed. However, younger players improve faster at performance-related variables, while older

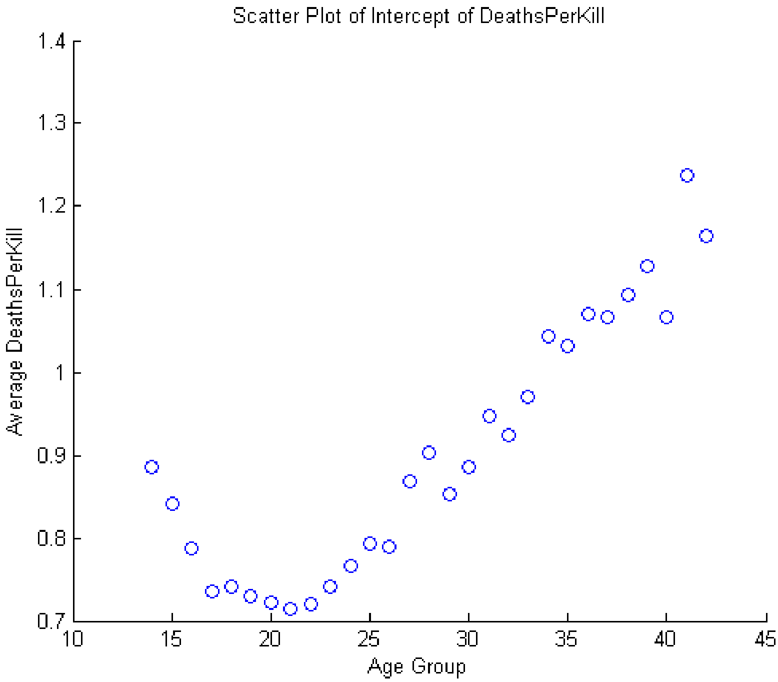

Figure 12: The intercept of DeathsPerKill shows a positive, u-shaped relationship with age, peaking around the early twenties age bracket. As players age past their early twenties, their initial (base line) score on DeathsPerKill becomes higher. DeathsPerKill is a negative measure of performance.

players increase faster at variables that are not performance-related.

SCORE OVER TIME variables describe the frequency of scoring points over time. ScorePerTotalTime is an aggregate of all types of score. UnlockScorePerTotalTime is the only score-related variable that is limited: Battlefield 3 offers a limited number of unlockable items that offer Unlock Score. Once a player has earned all unlockable items, he cannot earn any more Unlock Score. Older players start out with lower scores over time than younger players, with a predominant trend toward peaked correlations. Correlations between the slope of the Score over Time variables and age are relatively sparse, which precludes the possibility of making overarching conclusions about the progression over time of Score over Time variables. As ScorePerTotalTime is an aggregate variable of all score variables, it does show that all players improve how quickly they score over time, with younger players improving more rapidly than older players.

SCORE OVER SCORE variables describe the proportion of the scores that are earned. Initially, older players strongly focus on playing the objective and supporting their squad, while younger players focus on earning unlockable items and supporting their team (a *squad* is a smaller, more interdependent subset of a *team* in Battlefield 3). Over time, all players lose interest in playing the objective, with older players losing interest more rapidly than younger players.

TIME OVER TIME variables describe the proportion of time spent on different classes and vehicles. Older players initially prefer 'slower' classes (Support and Engineer) and vehicles (MBT and AA), while younger players prefer the faster or riskier recon and jet play. Over time, all players chose to spend more time as an Assault, Engineer or flying a jet, with younger players showing the faster preference increase.

4.3.2.3 *Patterns across All Variables*

Reviewing the results more generally, we see that 61 of the 118 play style features correlate significantly with age (Tables 8 and 9). The effect sizes of the significant correlations are moderate ($r = .6$) to large ($r = .9$). Three major patterns are visible in the significant correlations: (1) Over a third of the significant correlations (mostly intercepts) is not *linear*, but *u-shaped*; (2) *speed* decreases with age; (3) *performance* decreases with age.

Linearity: 28 of the 61 play style features with a significant correlation with age peak around the age of 20. The vast majority of the peaked correlations are found among correlations between the intercept of different play style features and age. In other words, about half of the play style features exhibit a peaked correlation between the intercept and age. When a correlation is peaked (△ in Tables 8 and 9) it exhibits a counter-correlational trend among early teens, peaking among either late teens or early twenties, followed by the dominant correlational trend from either early twenties or middle-to-late twenties onward (See Figures 11 and 12 for examples). The (linear) correlations are still significant and strong despite the u-shaped relationship, because relatively few age groups run counter to the dominant trend. The general theme of the correlations is that the younger a participant is, the better he performs at the game, and the faster he plays. When a relationship between age and a play style variable is linear, the highest or lowest value (depending on the direction of the correlation) is reached by the youngest age groups. However, the variables for which a u-shaped relationship exist, show that middle teens to late teens or early twenties deviate from the linear relationship that mostly exists between age and play style in (older) age brackets. Wherever a u-shaped relationship exists between age and a play style variable, most often the middle teens behave in a similar manner as the middle-to-late twenties. In these cases, the extreme value is reached by either the late teens or early twenties, depending on the variable in question. In other words, for many of the play style variables measured, there is a development as we age that changes direction once someone reaches their late teens or early twenties, i.e., one "peaks" around 20 years of age.

Speed of play decreases with age. Younger players start out playing faster ($r(i)$) than older players. Over time ($r(s)$), all players improve their speed of play, with older players improving more than younger players. The decrease of speed of play with age can be seen in the negative correlations of all the intercepts of the Action over Time variables. The slope feature of the Action over Time variables correlate either positively or negatively with age. The slope features that correlate negatively with age are related to variables that measure performance against another player. The slope of variables that are independent of the performance of other players, correlate positively with age. Therefore, we may conclude that all players improve their speed of play over time (slope). Older players increase their speed more quickly in regards to actions that do not depend on performance, while younger players increase their speed more quickly at actions that do depend on performance.

Performance decreases with age. Younger players start out performing better in the game in terms of kills, deaths, score, and winning ($r(i)$). Over time ($r(s)$), all players improve in terms of kills, deaths, and score. The decrease of performance with age can be seen in the correlations of the first seven Action over Action variables as well as all Score over Time variables. Initially (intercept) older players die more than they kill (DeathsPerKill), win less than they lose (WinsPerLoss), score less (MVP123PerRound, and all Score over Time variables), and have a lower shot accuracy (HitsPerShot, HeadShotsPerShot). Over time (slope), all players improve their performance. There is no consistent trend in improvement favoring either younger or older players.

4.3.2.4 *Summary*

Overall, the slope and intercept of 59 play style variables have been correlated with age for a heterogeneous sample of expert Battlefield 3 player between the ages of 14 and 42. Of the 118 possible correlation, 61 were found to be significant at $\alpha = .05$ after Bonferonni correction. 28 of the 61 significant correlations (mostly intercepts) showed a non-linear, u-shaped relationship with age, peaking around the late teens and early twenties age brackets. As players age, they start out playing slower and worse. Over time, older players slowly make up for their speed disadvantage compared to younger players, but do not consistently make up for lower performance. Therefore, aging sets players at a disadvantage in a First Person Shooter such as *Battlefield 3*.

4.4 DISCUSSION

Our findings show that a strong link exists between age and play style. This section will discuss the pros and cons of our analysis methods (Section 4.4.1), the implications of our findings (Section 4.4.2), and directions for future work (Section 4.4.3).

4.4.1 *Analysis*

The data analysis in Part 1 of the study (Section 4.2) consisted of straightforward correlational analyses and MLR, while showing unambiguous results concerning the link between age and play style. Part 2 of the study (Section 4.3) included the more complex RCA methodology, while additionally uncovering a nonlinear u-shaped relationship between age and play style for more than a third of the play style variables. The choice for RCA as well as the meaning of the u-shaped curves in our data merit further explanation.

4.4.1.1 *Regression Coefficient Analysis*

Regression Coefficient Analysis (RCA) was chosen over more sophisticated data analysis methods such as mixed effect modeling [11] which might have given us deeper insights into the data. We selected RCA due to its simplicity and transparency. The computations and reasoning behind RCA are intuitive and easy to follow. This ensures that our results can be interpreted in a straight-forward manner. Conversely, each of the results can easily be traced back to the raw data that gave rise to it. The downside of RCA is that it does not implicitly take confounds into account such as mixed effect modeling do.

We could have added an extra step to RCA to test explicitly for confounds such as play time and gaming platform. We have chosen not to go this route because we did not expect play time and gaming platform to be strong confounds. Play time actually increases with age in our sample [77], while we would expect players to become faster and better at the game with more play time (practice). Our findings run counter to this expectation. It might be the case that younger players accrue more play time over different FPS games. The skills attained from different FPS games might generalize across the genre. However, we were unable to test this hypothesis with the PsyOps data set. Gaming platform is unlikely to impact the relative differences in age due to the fact that every individual on a certain platform faces the same challenges. Therefore, the benefits of mixed effect modeling are small (more insight into confounds and interactions of variables) while the down sides are large (less insight into how the results relate to the data). Yet, for future work, we do consider mixed effect modeling a promising avenue for potentially uncovering more intricate patterns in the data.

4.4.1.2 *U-Shaped Curves*

28 of the 61 significant correlations displayed u-shaped curves. The age-related developments in cognitive performance and motivation (see Section 4.1) led us to expect that the relationship between age and play style would be mostly linear. Based on an additional literature review, we suggest that the discrepancy is due to two factors: a) the age range under consideration, and b) the interaction between underlying factors.

Most age-related research focuses on the effect of aging on adult development, while the human development before adulthood is split off in the field of developmental psychology. In our sample we included participants that had not yet entered adulthood, as well as those that had. We suggest that the relationship between age and play style may be different for individuals before and after the onset of adulthood. The resultant u-shaped curves are common in age-related research [71]. For example, u-shaped curves are observed in research related to executive thinking (peaking around 22 years of age) [98], and job performance (peaking around 49 years of age) [74].

Additionally, we find it plausible that different age-related factors with opposite developmental trajectories interact to create the u-shaped curves in our findings. For instance, experience and expertise develop with time, and are expected to increase with age. In contrast to this additional result we note that the cognitive benefits of youthfulness decrease with age (see Section 4.1). The combined effect of such opposite trends would most likely lead to a u-shaped performance curve. Applied to our findings, we would like to suggest that the prevalence of u-shaped curves in initial performance and speed (intercepts) are due to such an interaction effect. We would like to suggest that future research into the relationship between age and play style will benefit from both linear and quadratic (u-shaped) modeling.

4.4.2 *Implications*

The implications of our study hinge on the relevance and causality of our results. The relevance of our study is determined by the strength of our results, while the causality is inferred from the background literature.

We would like to argue that the relevance of our findings is high due to the strength of the relationship between age and play style. In Part 1 of the study (Section 4.2), MLR showed that about half the variance in age can be explained by play style. In other words, the correlation between the model generated by the MLR and age has an effect size of around .7. Cohen classifies such an effect size as 'large' [16]. Part 2 of the study (Section 4.3) shows similarly strong results concerning the relationship of age and play style over time with effect sizes between .5 and .9. As such, the effect of age on play style has a strong relevance to player modelling.

The causality of our results cannot be strictly determined, but it can be inferred from the theoretical grounding of our work. We would like to venture a few suggestions on how age and play style might relate based on our findings and the theoretical insights on the two bridging constructs presented in the Background Section (4.1). First, cognitive performance in the form of spatial cognition, memory, learning, and attention declines with age. The result is that older players play less effectively and more slowly than younger players. Older players score less and earn fewer kills. Additionally, they adapt their play style to their speed of play by picking vehicles that focus on slower game play. Secondly, motivation for Achievement declines with age. The result is that older players perform worse in the game in terms of kills and score. Chapters 5 and 6 further explore the relationship between motivation and play style. Taken together, both bridging constructs help explain the decrease in performance and speed of play for the older players.

4.4.3 *Future Work*

We believe that our findings offer valuable implications for both game developers and game researchers. Our findings provide empirical support for the intuition that aging goes hand in hand with a reduction in speed and performance in an FPS game. Additionally, the trend peaks around the age of 20, and sports high effect sizes. The main aim of future work should be to test the effect of aging on play style *across different game genres*. In the mean time, we suggest two possible directions for player modelling based on our findings so far.

First, more accurate player models can be constructed that control for age. The following example illustrates this. It might be the case that younger and older players respond differently to difficulty increases in a game, even though both groups of players are at the same initial skill level. It might be so that an older player would respond favorably to a difficulty increase despite his low skill level, because he values other aspects of the game more than performance. He might savor a challenge or feel more motivated when the game "ups the ante". In contrast, it is conceivable that a younger player with a low performance would find an increase of difficulty discouraging and give up on the game all together.

Secondly, player models that determine age from play style can pave the way to creating tweaks to game mechanics that were not possible before. For instance, an RPG might create a back story for a player based on his behavior in an introduction level. Imagine a game that accurately deduces the age of the player from the player's behavior. Such a game could increase the player's immersion by creating a more relatable back story for the player that taps into the interests and experiences of different age cohorts.

4.5 CONCLUSION

We conducted a two-part study to answer our Research Question 2: *What is the relationship between the age of a player and his play style in video games?* Using subsamples of the PsyOps data set we determined the age and play style features of Battlefield 3 players. In a two-part study we found that age and play style are strongly related.

In Part 1 of our study, we found that 45.7% of the variance in age can be explained by 46 play style variables. Additionally, when the sample is divided along gaming platform we see the following: (PC) 43.1% by 31 variables, (Xbox 360) 53.9% by 30 variables, and (Playstation 3) 51.7% by 28 variables. Older players were found to kill, die, and score less, while being more strongly focussed on winning the game. Additionally, older players invested more time in the game than younger players, and showed a distinct preference for "slower" classes and vehicles than younger players.

In Part 2 of our study, we found that age relates significantly ($\alpha = .05$) and strongly ($.6 < r < .9$) to both initial play style and play style development over time. Three major trends were observed in the correlations: (1) Half the play style features that correlate significantly with age, display a purely linear relationship. The other half of the play style features display a u-shaped relationship with age, where peak performance is reached by players in their late teens or early twenties. Peaked correlations were especially prevalent when relating age to initial play style (intercept). (2) Speed of play decreases with age. Over time, all players increase their speed of play, with older players improving mostly on play style features that are unrelated to performance. (3) Performance decreases with age. Over time, all players increase their performance, with no consistent benefit going toward either younger or older players. Overall, the speed and performance of the player peaks around the age of 20, and declines with age. Practice only compensates partly for the disadvantages of age by mitigating the difference in speed of play between the younger and older players.

Our findings have a high external validity due to the large and heterogeneous nature of the sample we acquired through an elaborate promotional campaign (PsyOps). The strength of the relationship between age and play style is classified as 'large' according to Cohen [16]. As such, our findings indicate that player models can benefit greatly from incorporating age as a predictive or controlling variable. Future work will focus on determining the exact contributions of different components of play style in explaining the variance in age. We expect that changes in cognitive performance and motivation form the link between age and play style.

5 BEHAVIORAL MODEL OF GAMING MOTIVATION

This chapter tackles the behavioural modeling side of Research Question 3 on motivation through a literature review and model proposal, and is based on the following original work.

Research Question 3. *What is the relationship between the motivational traits of a player and his play style in video games?*

Definition 2. *Motivation - "a hypothetical construct that has traditionally been used to describe and explain differences in intensity and direction of behavior. It is the state that results from a combination of individual needs and desires with the stimulus properties of the situation." (Humphreys and Revelle [46])*

Original Work. *Shoshannah Tekofsky, Pieter Spronck, Eric Postma. A Theoretical Review and Behavioral Model of Video Game Motivation. (In Progress)*

The last two decades has seen a growing interest in explaining the powerful appeal of video games. At the same time research into how these motivations might translate into actual game behavior is still in its infancy. On the one hand we lack a fully comprehensive, validated model of how motivations might be expressed in gaming behavior (behavioral model of motivation). On the other hand we equally lack a fully comprehensive, validated model of the internal structure and nature of our gaming motivations (cognitive model of motivation). The key differences between the models is that *a behavioral model uses actions while a cognitive model uses self-report to measure and represent a construct such as motivation.*

Both a behavioral and a cognitive model will be necessary to fully answer Research Question 3: *What is the relationship between the motivational traits of a player and his play style in video games?* The current chapter consists of a theory-driven proposal for a *behavioral* model of gaming motivation that can be used to deduce the player's gaming motivation from their game behavior. The model is intended to inform and structure data analysis toward the likely behavioral expressions of the various gaming motivations. While it is strongly grounded in the literature, the model is currently untested. Chapter 6 contains a data-driven proposal for a *cognitive* model of gaming motivation that can be used to gain greater insight into what drives player behavior in game. The model is instantiated and validated in a survey of gaming motivation that was administered to a large sample of gamers.

Throughout both chapters, *gaming motivation* will refer to the psychological driving force leading a player to play a game (see Section 5.1). *Game behavior* will refer to the actions a player performs in a game. Increasing our understanding of the link between gaming motivation and game behavior would serve two purposes.

First, it could support the implementation of the motivating power of video games for educational and awareness initiatives. In the field of "serious gaming", researchers and game developers are working together to try and create video games that combine the societal value of awareness or educational programs with the motivating power of video games. So far, the results have been tentatively hopefully, but generally inconclusive, or heavily debated [17, 75]. We propose that increasing our understanding of the motivating forces in commercial video games, will allow us to more effectively create serious games with the same motivational pull as their commercial counterparts. The result would be more effective and engaging educational and awareness games.

Secondly, an increased understanding of how motivation and game behavior relate, can support our ability to detect desirable or undesirable motivations from a player's game play and intervene accordingly. As such, we might be able to determine if a player is developing a problematic behavioral pattern in a game that could be symptomatic of addiction or other disorders. Conversely, we might also be able to detect if a person is still sufficiently engaged in a game to continue playing. By increasing our understanding of how motivation to play is expressed in video game behavior, we may be able to minimize detrimental motivations while maximizing beneficial motivations for maximum engagement.

As gaming motivation is a new field of research which lacks a definitive behavioral model, this chapter will provide a theoretical base for empirical research aimed at uncovering how gaming motivations are expressed in game behavior. To that end, we will review the most prominent psychological theories on video game motivation, and integrate their insights into a proposal for a behavioral model of video game motivation: the Directed Action Model (DAM).

5.1 MOTIVATION

The study of human motivation is an extensive subfield of psychology, where different researchers propose competing theories on what drives human behavior. We will employ the theory-neutral and general definition of motivation proposed by Humphreys and Revelle [46]. They state that motivation is "a hypothetical construct that has traditionally been used to describe and explain differences in intensity and direction of behavior. It is the state that results from a combination of individual needs and desires with the stimulus properties of the situation." In this chapter we will only discuss general theories of motivation in as far as they have been empirically validated on video game behavior.

Within the field of video game research, different researchers measure motivation in different ways. As we discuss the different motivational frameworks that have been applied to video game play, we will also emphasize in what manner motivation was measured in the relevant research. The reader is encouraged to take note of the measure of motivation used in each research when evaluating the merit of the relevant research initiative. There are three broad categories of motivation measurements in video game research: self-reported enjoyment of video game play, self-reported length and frequency of (intended) play time, and directly measured length and frequency of play time. The first measure could be a considered a subjective, qualitative measure of motivation, while the last can be considered an objective, quantitative measure of motivation. The second measure is a combination of both because it samples a player's feelings or intentions to exhibit a behavior. All three measures hold merit for different research purposes, but may give differing results when reporting on "motivation" in general. The subjective, qualitative measures give deeper insight into the inner mechanics of motivation. The objective, quantitative measures give a direct hook for computational implementations for measuring motivation in game behavior.

5.2 EXISTING MODELS

Many researchers have endeavored to explain the motivational force of video games with varying levels of success. We will focus on the psychological theories that describe empirically supported, over-arching motivational models that have been directly applied to video game play. Four motivational models fit this criterion: flow theory [21], theory of complexity of the entertainment experience [85], uses and gratifications theory [70], and self-determination theory [66]. Each theory will be discussed in terms of conditions for the motivations to occur, and the actual proposed motivations. Additionally, each theory will be cross-referenced with the theories discussed before it, and evaluated based on empirical evidence from other researchers. Table 12 offers a summary of the conditions, motivations, and motivational measures of each theory.

5.2.1 *Flow Theory*

In recent years, the motivational theory that has gained most traction in the video game arena is probably flow theory. In 1990, Mihaly Csikszentmilhalyi [21] proposed 'flow' as an active state of ultimate, intrinsic motivation. Flow theory enjoys strong support in the scientific literature, while lacking a method to directly sample its occurrence or strength. By its nature, flow is disrupted when individuals are asked to report on it. Additionally, post-hoc reporting on flow is unreliable due to a proposed loss of self-consciousness and self-awareness in the flow state. Nevertheless, flow remains a prominent theory of motivation both in and outside the arena of video game research.

5.2.1.1 *Flow Conditions*

Csikszentmilhalyi [21] describes three necessary conditions that must be fulfilled for flow to occur. It is possible that flow does not occur even when the conditions are met. However, to be able to enter a flow state at all an individual must be involved in an activity with clear goals, immediate feedback, and a balance between perceived skill and perceived challenge. Video games by their very nature offer the three necessary conditions for flow. Consequently, many game designers have studied flow in video games in the hope of optimizing the video game experience [14, 19, 76].

5.2.1.2 *Flow Motivation*

When flow occurs an individual is presumed to experience the following six factors simultaneously during an activity: intense concentration on the present moment, merging of action and awareness, a loss of reflective self-consciousness, a sense of personal control or agency over the situation or activity, a distortion of temporal experience, and an experience of the activity as intrinsically rewarding [57]. In the literature, the occurence of flow during video game play has been explored with both neuro-biological measures and self-report measures.

Both Weber et al. [88] and Klasen et al. [50] endeavoured to use video games to uncover the neural correlates of the flow state. They reported that subjects do show distinctive neural activation profiles when they are expected to be in a flow state during video game play. However, they also point out that the flow state is only conjectured in their experiments. Any possible validation of the flow state in a given moment would have broken the flow state per definition, and thus have made measuring its neural correlates impossible. Still, the fact that subjects showed unique neural profiles while conjectured to be in the flow state, is a promising step forward in the field.

Lee and LaRose [52], and Hsu and Lu [44] both used self-report measures of flow after video game play to determine the relationship between flow experience and video game motivation. Lee and LaRose found a high correlation between flow and enjoyment ($r = 0.91$), as well as moderate indirect correlations between flow and intention to play. Hsu and Lu did not test for enjoyment, but found only weak correlations between flow experience and intention to play (r = .12). The inconsistency in results between Lee and LaRose, and Hsu and Lu can be seen as underlining the issue of weak construct validity when testing for flow through self-report measures.

5.2.2 *The Complexity of the Entertainment Experience*

Vorderer et al. [85] propose an all-encompassing theory of media enjoyment. The theory of the complexity of the entertainment experience (CEE) posits that 'enjoyment' is the result of satisfying clusters of user and media prerequisites, and the presence of initial motivations to engage in video game use. Enjoyment is felt through its manifestations, and results in three effects. The effects feedback onto the initial user and media prerequisites in combination with the existing motivations. We limit our review to the user and media prerequisites, and the motivations for play, as they pertain to the topic of behavioral modeling of video game motivation.

5.2.2.1 *CEE Conditions*

According to Vorderer et al. [85], the user must satisfy five user prerequisites to be able to enjoy any media type, including video games: suspension (of disbelief), empathy, parasocial interaction / relationship, presence, and interest. Suspension of disbelief is a necessary condition to allow oneself to be absorbed in a fictional world. Empathy is the ability to care about the characters in the fictional world. Parasocial interaction / relationship is the ability to relate to the characters in the fictional world. Presence is the experience of being in the fictional world. Interest is the desire to know about the fictional world or the characters in it. Video games per definition offer a fictional world. However, not all video games contain fictional characters (e.g. Tetris or Minecraft). Therefore, we argue that empathy and parasocial interaction/relationship cannot be user prerequisites for engagement in video games.

Additionally, Vorderer et al. [85] suggest that the media itself has to satisfy two media prerequisites for a user to be able and willing to engage with it: technology / design / aesthetics (TDA), and content. TDA refers to the usability and aesthetic appeal of the media, while content refers to the match between the media's content and the user's preference. In terms of video games, TDA can broadly be considered to line up with the appeal of the hardware, while content lines up with the appeal of the software.

5.2.2.2 *CEE Motivations*

The CEE highlights three motives that drive media use (including video game play): escapism, mood management, and achievement / competition. Vorderer et al. [85] propose that more motivations are likely to exist but that these three are the most researched and discussed.

Escapism was originally defined as an 'aspect of hedonic behavior [which] deals with activity in order to escape a reality that the individual finds difficult or is unable to deal with adequately' [42]. More recently, researchers have come to consider the motivation toward escapism as a desire that is present in all individuals regardless of levels of hardship. However, escapism motivation does peak during periods of boredom or deprivation [85]. Olson [58] found strong support for the escapism motivation to play video games among a sample of 1,254 middle school children. Respondents were asked to rate a number of statements about their reasons to play video games. Respondents strongly agreed with the statements "... something to do when bored" (>40%), "...there's nothing else to do" (>20%), "...helps me forget my problems" (>15%) and "...helps me feel less lonely" (>5%). Research by Demetrovics et al. [23] warns against confounding 'escapism' with 'coping' motivations. A factor analysis of a 56-item motivation questionnaire showed escapism and coping items to load on to two distinct factors. Reflecting these findings back to the data from Olson, we can see that escapism motivation ranks highly ("... something to do when bored" (>40%), "...there's nothing else to do" (>20%)), while the coping motivations that might be confused for escapist behavior are lower ranked ("...helps me forget my problems" (>15%) and "...helps me feel less lonely" (>5%)). In contrast, Demetrovics et al. [23] found escapism to have the lowest reported mean score ($\mu = 1.91$) as a motivation for video game play compared to Skill Development ($\mu = 2.25$), Fantasy ($\mu = 2.33$), Competition ($\mu = 2.42$), Coping ($\mu = 2.49$), Social ($\mu = 3.03$), and Recreation ($\mu = 4.12$). Thus, it can be concluded that escapism contributes to video game play as a motivational factor, but it is unclear how great that contribution is.

The second motivational factor that Vorderer et al. [85] propose is 'mood management'. Consuming media for the purpose of mood management was first proposed by Zillman [99]. The premise is that media consumption takes place to create, enhance, or perpetuate a positive mood. Vorderer et al. [85] point out that mood management motivation has considerable overlap with the escapism motivation. Arguably, escapism can be viewed as a form of mood management that involves creating a positive mood by 'escaping' from the awareness of daily life. However, if we take this reasoning a step farther, we can conclude that every possible motivation to play video games (or engage in any other activity) can be cast as an instance of mood management. Vorderer et al. [85] even point out that actions which do not lead to *immediate* positive effects on mood invariably lead to *delayed* positive effects on mood through detours such as 'downward comparisons' (i.e. immersing oneself in the role of an individual who is worse off then the self). Therefore, it is unclear how mood management can contribute to our understanding of the motivations to play video games.

The last motivation Vorderer et al. [85] propose is achievement / competition (hence referred to as 'achievement'). It is a motivation that sets video games apart from other forms of media. Vorderer et al. [85] do not cover why achievement would be innately motivating. However, research by Olson [58], Demetrovics et al. [23], and Yee [93] all found achievement to be a strong motivator for video game play. The achievement motivation can also be linked back to the flow state. Flow is conditional on a balance between skill and challenge. Such a balance is by definition also conditional for achievement. If someone's skills are not sufficient for the challenge, then the person will fail. If someone's skills surpass the challenge, then overcoming the challenge is not considered an achievement. In other words, being in a flow state means working toward an achievement. Overall, achievement as a motivating factor in video game play is strongly supported in both the theoretical and empirical literature.

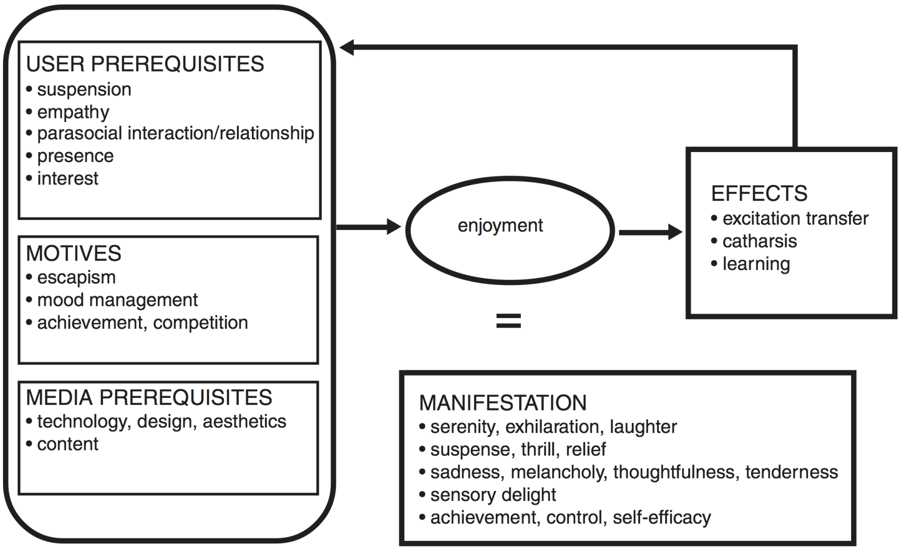

Figure 13: Vorderer's Model of the Complexity of the Entertainment Experience [85].

5.2.3 *Uses and Gratifications Theory*

Uses and gratifications (UG) theory [70] is a psychological paradigm based on systems theory. In systems theory, the physical and psychological features of an individual are considered a homeostatic system in the context and under influence of other such systems. When applied to media usage, UG theory states that "basic needs, individual differences, and contextual societal factors combine to result in a variety of perceived problems and motivations to which gratifications are sought from the media and elsewhere leading to differential patterns of media effects on both the individual and the societal levels." [70].

Sherry et al. [70] have applied UG theory to video games. A notable difference between the UG approach to video game motivation and that of other theories is that no conditions for video game usage are outlined. Instead, the first step to the application of UG to any media type is to identify the motivations for the usage of a certain medium. The motivations for media use are expected to be different per medium, and so cannot be generalized from other fields.

5.2.3.1 *UG Motivations*

In order to determine what motivations drive video game usage, Sherry et al. [70] constructed a list of potential motivations through focus group research. A factor analysis resulted in the identification of six general motivations that respondents reported for video game use: arousal, challenge, competition, diversion, fantasy, and social interaction.

The arousal motivation refers to the motivating power of experiencing the emotions that result from the action elements of video games. It is not proposed or conceptualized as a motivation in the other motivational models. However, there is considerable support in the literature for arousal as a physical reward response to video games [4, 6, 51].

The challenge and competition motivations both concern reaching some standard of performance. However, the challenge motivation refers to reaching a performance standard set by the game (e.g., solving puzzles or beating levels), while the competition motivation refers to reaching a standard of performance that is higher than that of the player's peers (i.e., beating opponents). The challenge and competition motivations are compounded into one motivation in CEE [85]. In UG, the competition motivation is seen as separate from the challenge motivation. In the Olson [58] sample it was found that competition is a highly motivating factor. Over 50% of males agreed with the statement that they "...like to compete with others and win", while a little under 30% of females reported the same. In the sample by Demetrovics et al. [23] competition was found to load on a distinct factor from 'skill development'. Skill development measures the same underlying construct as challenge (UG). Therefore, it can be concluded that eventhough challenge/achievement and competition are conceptually strongly interrelated, there is considerable support for them to be distinct motivational forces within the field of video game play.

The diversion and fantasy motivations describe different elements of the escapism motivation put forth in CEE [85]. The diversion motivation describes the drive to play video games as a way to avoid responsibilities. The fantasy motivation describes the drive to experiment with identities and activities that are not available in daily life. The diversion motivation lines up with the coping motivation in the research by Demetrovics et al. [23], while the fantasy motivation lines up with the escapism motivation in their research. It is notable that escapism is differently defined in different theories. In CEE [85] escapism is conceptualized as one coherent motivation for video game usage. However, both Sherry et al. [70] and Demetrovics et al. [23] found escapism to split into two seperate factors: one related to avoiding an awareness of negative emotions stemming from real life, and one related to experiencing positive emotions from immersing one's self in a fantasy world.

The social interaction motivation refers to the reward inherent in participating in social activities. Not all video games are social endeavors, yet the ones that are, are generally cited to be motivating in part due to their social elements. Olson [58], Demetrovics et al. [23], and Yee [93] all found social interaction to a strong motivating force for playing video games.

Sherry et al. [70] tested how much of the variance in actual play time could be explained by the six motivations. They sampled 1,265 students between the ages of 10 and 23 on the six motivations. Next, they performed a regression analysis with the motivations as independent factor and reported play time as the dependent factor. It was found that 28% of the variance in reported play time could be explained by the six motivations. Diversion, social interaction, and arousal, respectively, were the strongest predictors of reported play time. It is notable that the challenge or competition motivations did not explain much of the variance in reported play time, while these motivations are prominent in every motivational model discussed so far.

5.2.4 *Self-Determination Theory*

Over the last two decades self-determination theory (SDT) has gained considerable support as a motivational model for video game play [62, 67]. Self-determination theory (SDT) is a macrotheory of human motivation that states that every individual is intrinsically motivated to fulfill three basic human needs in order to maximize well-being: competence, autonomy, and relatedness [65]. The application of SDT to video game motivation has led to the development of a validated self-report measure of the competence, autonomy, and relatedness need satisfaction in video games, titled the *Player Experience of Need Satisfaction* [62, 67].

5.2.4.1 *SDT Conditions*

Ryan et al. [67] propose that two mediating variables must reach a sufficient threshold to allow for need satisfaction through video game play: intuitive controls, and presence. Both factors have been found to significantly correlate to game enjoyment and continued play. Intuitive controls were found to be a threshold variable for game enjoyment and continued play, while presence correlated strongly to game enjoyment ($r = .62$). The presence variable conceptually lines up with the suspension prerequisite in CEE [85]. It is also supported by the immersion motivation found by Yee [93], as well as the escapism motivation suggested in CEE [85] and UG theory [70].

5.2.4.2 *SDT Motivations*

The need for competence is satisfied by opportunities for skill acquisition and experiencing skill mastery. Video games naturally offer ample opportunity for the satisfaction of the need for competence. In support for the motivating role of competence in video game play, Ryan et al. [67] found that competence need satisfaction is significantly correlated with self-report measures of game enjoyment and post-play well-being, as well as intended future play time. Conceptually, competence need satisfaction overlaps with the achievement motivation in CEE [85] and the challenge and competition motivations in UG theory [70]. However, competence need satisfaction was found to only mildly correlate ($r = .20$) with achievement motivation as measured by Yee [93]. This raises concerns about the validity of the measures used in different experiments to measure achievement / competition / competence motivations. In line with findings by Sherry et al. [70] and Demetrovics et al. [23], it might be possible that the motivational factor is actually a construct of multiple motivational subfactors and that different researchers measure different subfactors. Ryan et al. [67] went on to explicitly conjecture the relationship between the SDT application to video games and flow theory. They suggest that the satisfaction of the competence and autonomy needs are not equal to the experience of flow but necessary conditions for the occurrence of flow. This is in line with Csikszentmilhalyi's [21] proposition that flow can only occur when an activity offers clear goals, immediate feedback, and a balance between perceived skill and perceived challenge.

The need for autonomy is satisfied when an individual experiences a sense of volition or willingness to pursue a certain activity. As such, it is one of the bedrocks of intrinsic motivation [65, 67]. As a leisure pursuit, video games generally satisfy the need for autonomy as a general activity. However, different types of video games offer different levels of autonomy within their actual game play. Ryan et al. [67] found that autonomy scores according to the PENS were positively correlated to game enjoyment, but correlations with intended play time and post-play well-being were absent, mixed, or weak. In a survey among MMO players it was found that satisfaction of the autonomy need correlated fairly strongly with satisfaction of the competence need ($r = .45$). The need for autonomy barely overlaps with achievement, social, and immersion motivations as sampled by Yee [67, 93]. The motivations listed by children in Olson's sample do not include any that can be construed as autonomy need satisfaction [58]. Additionally, in the sample by Demetrovics et al. [23] all the statements that could be construed toward autonomy were dropped from their analysis as they did not coherently load on to any one motivational factor. Autonomy need satisfaction was also not put forward in the focus group research done by Sherry et al. [70] when constructing their UG model for video game play. The question thus remains if autonomy is a distinct and informative construct to use when modeling video game motivation.

The need for relatedness is satisfied when an individual feels connected to others. Multiplayer games offer the player a direct avenue for connecting with other people. Ryan et al. [67] found that relatedness need satisfaction correlates fairly highly with autonomy ($r = .45$) and competence ($r = .45$) need satisfaction in MMO players. The same study also shows that Yee's sampling of social motivation correlates strongly with relatedness need satisfaction ($r = .66$). In Olson's sample of children, a number of motivations were volunteered that overlap with the relatedness need satisfaction. However, these motivations were relatively weakly endorsed. In the sample by Demetrovics et al. [23], of the seven motivations they found, social motivation was the second most highly rated motivation ($\mu = 3.00$) behind Recreation ($\mu = 4.10$). These results all concern multiplayer games. It is unclear if and how the relatedness need might be satisfied in single-player games.

5.2.5 *Overview of Motivational Models*

Four prominent motivational models of video game play were presented (See Table 12). First, flow theory offers a simple, straightforward, unidimensional model of gaming motivation. It enjoys strong consensus and intuitive support in the literature, but offers a weak empirical grounding. Secondly, CEE gives a broad perspective of possible prerequisites and motivations for video game usage. It embeds video game usage in a general model of motivation that can be applied to any entertainment media. Thirdly, UG theory has explored what specific motivations people report for video game usage. Additionally, it links these motivations to actual play time. Fourthly, SDT draws on general theory of motivation to explain why people play video games. Subsequently, it enjoys extensive empirical support for its model.

Overall there is no consensus on a single model of video game motivation. At the same time, the four most prominent models do share a number of characteristics, such as posing prerequisites for video game usage, and recurring themes of achievement/competence/challenge motivations and social/relatedness motivations.

5.3 DIRECTED ACTION MODEL

In this section we would like to propose a new behavioral model of gaming motivation: the Directed Action Model (Section 5.3.1). The previous models were psychological models based on *self-report* measures of motivation to play video games. The model we propose is a *behavioral* model of video game motivation. *A behavioral model uses actions instead of self-report to measure and represent a construct such as motivation.* Video games are exceptionally suited to the implementation of behavioral models, as all actions in a game can be precisely and extensively logged and analyzed.

Currently there is no behavioral model of gaming motivation that can be applied across games. Modeling and reporting of gaming motivations across games is purely done in terms of self-report. Relying on self-report has two major drawbacks. First, we have to invest significant resources in sampling players of different games or game genres on their gaming motivations through a self-report questionnaire. Secondly, self-report questionnaires can only be as accurate as the researcher's ability to ask the right questions and the participant's ability (and willingness) to provide the (most) correct answers. Both the cost and the inaccuracy of self-report measures of motivation can be circumvented if motivations could be directly deduced from the factual data on game behavior that is automatically logged for most video games.

We would suggest that the current lack of behavioral models of gaming motivation is due to the fact that behaviors can normally not

Table 12: Overview of Psychological Models of Gaming Motivation. Names of conditions, motivations and measures have been abbreviated. The reader is referred to the sections about each theory for the full names. Motivations and measures that are (conceptually) similar between the models are displayed in-line. Conditions varied too much between models to meaningfully connect them across models. SR indicates self-report.

	Motivational Models			
	Flow	**CEE**	**UG**	**SDT**
		Suspension		
		Empathy		
	Clear Goals	Parasocial		Controls
Conditions	Feedback	Interest	(N/A)	
	Skill balance	Presence		Presence
		TDA		
		Content		
	Flow State	Achievement	Challenge	Competence
		Mood	Diversion	
		Escapism	Fantasy	
Motivations			Social	Relatedness
			Competition	
			Arousal	
				Autonomy
	Enjoyment	Enjoyment		Enjoyment
Measures	SR Play Time		SR Play Time	SR Play Time
				Play Time

be reliably mapped to motivations. In daily life, there is no meaningful way to connect behavior to motivation because any behavior can result from a complex range of possible motivational factors. Consider the example of a simple daily behavior: eating a sandwich. We might be tempted to conclude that someone would exhibit this behavior because they are hungry. However, there are numerous other motivations that might be in play, such as habit ("I always eat a sandwich at 1 PM"), politeness ("I was offered a sandwich and did not want to create social tension by turning it down"), boredom ("I am bored, so I might as well already have lunch"), anxiety ("eating makes me feel better"), etc.

Applying the same reasoning to game behavior, would have us quickly conclude that behavioral models of gaming motivation cannot be accurate across games. However, we would like to propose that video games offer a crucial caveat: *games are simplified, crafted interactions which we purely engage in to directly satisfy our immediate motivations*. This sets it apart from our general, daily behavior. Though specific game behaviors may fulfill multiple motivations at once or may be ambigious, some game behavior is only worthwhile to fulfill very specific, unambigious motivations. For instance, reading the lore (background stories) from in-game books can serve no other purpose than satisfying a certain curiosity about the world and a desire to engage with the fantasy. In the same manner, collecting difficult to attain trophies that have no additional functionality in the game can only be satisfying to those people with a drive toward completion.

Of course, a generalizeable, behavioral model that functions across games can only tap into game actions and their motivations in broad strokes. The potential variety of game actions and contexts is too great to meaningfully analyse in detail. However, the *direction* of the actions of the player can give unique insights into his gaming motivations in general, while circumventing the cost and inaccuracy of self-report.

5.3.1 *New Proposal: Directed Action Model*

Our novel proposal is the *Directed Action Model* (DAM) of video game motivation. DAM categorizes each action a player performs in a game as *goal-directed*, *player-directed*, and/or *fantasy-directed*. Every action in a game moves a player in none, one, two, or all three directions. When an action does not move the player in any of the three directions, the action is considered *undirected*. Viewing actions solely by merit of their direction allows for unambiguous labeling of game actions within in the context of a game. The action direction may be meaningfully interpreted as one of three basic gaming motivations derived from the psychological theories previously reviewed. *Goal-directed* actions are hypothesized to stem from achievement motivation, *player-directed* actions from social motivation, and *fantasy-directed* actions from immersion (i.e., escapism, diversion, fantasy) motivation. *Undirected* actions cannot be meaningfully interpreted toward any gaming motivation. They result from failure, experimentation, or whimsy.

The three action directions line up with the three motivational clusters determined by Yee [93] in his research on MMORPG players. His model was created through a data-driven, bottom-up approach. We consider that DAM supports and extends his findings by grounding the three motivational categories in psychological theory and proposing an extension to link the model to game behavior. The following is an explanation of the theoretical grounding of each action direction and how it can be used to determine gaming motivations from game behavior.

5.3.2 *Goal-Directed Actions from Achievement Motivation*

Achievement motivation enjoys strong support from each of the four motivational models discussed previously. Achievement motivation is a compound of the flow state [21], CEE's achievement motivation [85], UG's challenge motivation [70], and SDT's competence need satisfaction [67]. We expect that achievement motivation can be measured by looking at effective goal-directed actions. Findings by Drachen et al. [26, 27] support this expectation. They found *goal-directed* action patterns in models of player behavior in MMORPGs (Terra), FPS (Battlefield: Bad Company 2), and Action games (Tomb Raider: Underworld).

In the psychological literature, achievement motivation can both refer to *reaching* a high performance criterion as well as *working toward* a high performance criterion. Therefore, we suggest that *goal-directed*

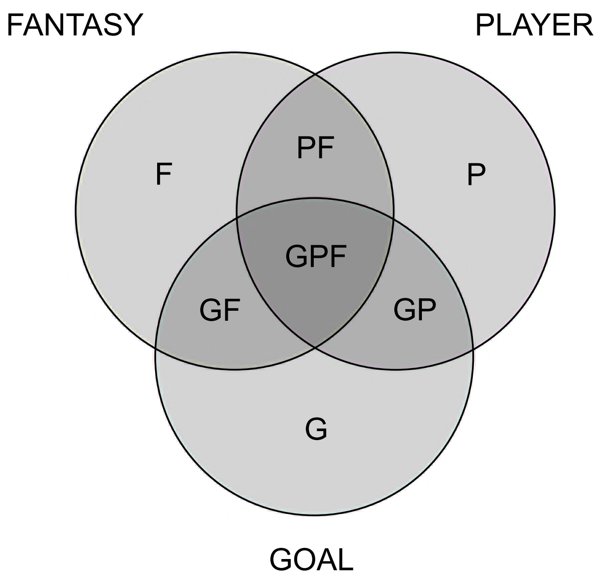

Figure 14: Directed Action Model of Video Game Motivation. Actions can be any combination of (P)layer-directed, (G)oal-directed, and / or (F)antasy-directed, generating seven permutations of action direction. Undirected actions form a last category of action direction that lies outside the confines of the Venn diagram above.

actions should similarly encompass two behavioral components: *performance* in the game, and *improvement of performance* in the game. In this manner, the behavioral measurement of achievement motivation is not wholly dependent on skill level. Players who strive to improve themselves toward a high performance criterion will rank highly on *goal-directed* behavior, even if their current performance is low. The best suited games for measuring achievement motivation from player behavior would be those video games that offer clear performance criteria, such as shooters, action games, sports games, and strategy games.

5.3.3 *Player-Directed Actions from Social Motivation*

Social motivation is strongly supported by the two motivational models that were exclusively adapted to video game play: UG theory [70] (social interaction) and SDT [67] (relatedness). Additionally, many self-report studies on motivation found that participants volunteered social aspects of gaming as motivations for play [23, 58, 70, 93]. The general popularity trend of MMO games further underlines the appeal of the social component of playing with or against other players directly.

Social motivation would be fairly straightforward to measure in game behavior by looking at games where social interaction is possible but not necessary. A behavioral measure of social motivation is likely to be the number of voluntary social interactions a player engages in and how much time the player spends on these interactions. Social motivation can be measured in any game with a multiplayer component.

5.3.4 *Fantasy-Directed Actions from Immersion Motivation*

The immersion motivation is the most elusive of the three motivations. It covers the escapism motive in CEE [85], the diversion/fantasy motivation in UG theory [70], and the autonomy need in SDT [67]. It also captures self-report motivations put forth by many gamers which refer to exploration of the game world, trying out actions and identities that are not accessible in the real world, and distracting oneself from the real-world [23, 58, 70, 93]. We expect parasocial interactions to also be covered by the immersion motivation as they concern fictitious relationships with fantasy characters. However, it might be possible that parasocial relationships are a mix of immersion and social motivation.

The immersion motivation can be satisfied by any game that offers an engaging story, world, or other level of fantasy for the player to become immersed in. Behaviorally, the immersion motivation can only be directly measured by actions that are pure engagement with the fantasy of the game, without any *goal-* or *player-directed* components. Single-player Role-Playing Games are most suited to this purpose.

5.3.5 *DAM in Detail*

The following is a complete and systematic overview of DAM. The model consists of eight action categories. Seven categories are a combination of *action-*, *player-*, and *fantasy-directed* actions (See Figure 14). The eighth category consists of *undirected* actions. The following is an overview of all eight categories with descriptions of relevant game action examples.

- **G**: Pure *goal-directed* actions such as farming, grinding, and meta-achievements (e.g., PSN trophies or XBox LIVE achievements).
- **P**: Pure *player-directed* actions such as chatting, and use of emotes.
- **F**: Pure *fantasy-directed* actions such as reading lore, and (aimlessly) wandering the game world.
- **GP**: *Goal-* and *player-directed* actions such as player-versus-player competition, and player cooperation for meta-achievements.
- **GF**: *Goal-* and *fantasy-directed* actions such as story progression, and purposeful exploration of the game world.
- **PF**: *Player-* and *fantasy-directed* actions such as aimless, role-play-based cooperation and competition.
- **GPF**: *Goal-*, *player-*, and *fantasy-directed* actions such as cooperative story progression.

- **U**: *Undirected* actions could not be labeled as any of the above, and are likely to be due to failure, experimentation, or whimsy.

Undirected actions can be displayed in every game, and will be displayed by every player eventually. *Undirected* actions are both a necessary and a useful category in DAM. *Undirected* actions are a necessary category because not all actions will always have a clear direction. *Undirected* actions are a useful category because they can be used as a measure of the *reliability* of the scores that are attained on the other seven categories. Just as part of the *undirected* actions are unintentionally undirected (failure), part of the directed actions (remaining seven categories) can be unintentionally (labelled as) directed. For instance, a player might shoot a gun on whimsy and hit another player by accident. Such an action will be labeled as *player-directed* instead of *undirected*. A certain level of error in labeling actions is acceptable, as the majority of actions will give a clear view of what directions a player acts in over time. However, a player who performs a high number of *undirected* actions, is likely to also have many mislabeled cases of directed actions. Therefore, *undirected* actions serve as a reliability measure for the action directed categories.

Mixed categories can show dependencies with their constituent categories. For instance, GP actions in a certain game may be more motivating to players who score high on G and P actions as well. Players will differ in their preference for each of the seven categories of directed action. The patterns in directed action preferences that a player displays across games can be considered the player's DAM profile. Conversely, each game differs in how strongly each of the seven categories of directed actions are represented and how well they are executed. The patterns in the quantity and quality of the actions of each category that can be executed in a game can be considered the game's DAM profile.

The action set of a certain player playing a certain game, will be a combination of the DAM profile of the player and the DAM profile of the game. The DAM profile of the player describes the player's tendency to execute actions in each of the eight categories across all games. The DAM profile of the game describes the quantity and quality of the available actions in each category across all players. To determine a particular player's DAM profile, his/her actions would have to be sampled across a representative sample of games and compared to a representative sample of players. To determine a game's DAM profile, the action set of the game needs to be sampled across a representative sample of players.

To determine the DAM profile of a player playing a certain game, five steps would have to be taken. First, each action in the game is turned into a time-related variable. One shot actions can be turned into time frequency actions by dividing the action total by the total time that action was available to the player. Persistent actions can be turned into time proportion actions by dividing the total time spent performing the action by the total time spent with that action available. Secondly, each action variable is labeled for one of the eight action categories described above. Thirdly, the action set over time of a representative sample of players is collected. Fourthly, the values of the action variables are standardized over all players in the sample. Fifthly, the average standardized score of the action variables in each action direction category is calculated per player. Players will distinguish themselves both on actions they perform exceptionally often, exceptionally rarely, and combinations of relative action scores on different action direction categories. The result is the DAM profile for each individual player for the particular game in question. The profile explicitly describes the player's action preferences in the game, and implicitly describes the player's motivational preferences in the game.

5.4 CONCLUSION

This chapter endeavoured to answer the behavioural side of Research Question 3: *What is the relationship between the motivational traits of a player and his play style in video games?* Based on literature review, we propose that the answer to the research question is given by the Directed Action Model (DAM). DAM was developed based on insights from the existing literature. A review of flow theory, uses and gratifications theory, theory of the complexity of the entertainment experience, and self-determination theory led us to propose DAM as a novel behavioral model of gaming motivation that is in line with

Yee's theory-neutral, data-driven model of gaming motivation among MMORPG players.

DAM offers a three-fold answer to the research question: *goal-directed* actions in a game reveal how much a player is driven by *Achievement* motivations, *player-directed* actions in a game reveal how much a player is driven by *Social* motivations, and *fantasy-directed* actions in a game reveal how much a player is driven by *Immersion* motivations. Many game actions can be classified as a combination of 2 or 3 of the motivational directions. By looking at the proportion of time and resources a player spends on each action direction, we can determine a player's motivational profile. Actions that are not directed toward goals, players or fantasy, are labelled as *undirected* actions. These actions function as a measure of consistency and reliability of the relationship between a player's action directions and his motivations. Overall, a general profile of a player's game motivations can be deduced from the *direction* of his actions in a video game.

6 COGNITIVE MODEL OF GAMING MOTIVATION

This chapter tackles the cognitive side of Research Question 3 on motivation, and is based on the following original work.

Research Question 3. *What is the relationship between the motivational traits of a player and his play style in video games?*

Definition 2. *Motivation - "a hypothetical construct that has traditionally been used to describe and explain differences in intensity and direction of behavior. It is the state that results from a combination of individual needs and desires with the stimulus properties of the situation." (Humphreys and Revelle [46])*

Original Work. *Shoshannah Tekofsky, Paul Miller, Pieter Spronck, Kevin Slavin. The Effect of Gender, Native English Speaking, and Age on Game Genre Preference and Gaming Motivations. In Proceedings of the 8th International Conference on Intelligent Technologies for Interactive Entertainment (INTETAIN). EAI, 2016.*

Original Work. *Shoshannah Tekofsky, Paul Miller, Chrissy Cook, Theo Klimstra, Eric Postma, Kevin Slavin, Pieter Spronck. Cross-Genre Validation of 13 Factor GAMR Motivation Model. (In Progress)*

With a *behavioral* model of gaming motivation in place (Chapter 5), we now turn to the task of researching a *cognitive* model of gaming motivation. We reiterate that *a behavioral model uses actions while a cognitive model uses self-report to measure and represent a construct such as motivation.* While a behavioral model works with objective and accurate data (behavior) that is easy to log in video games, a cognitive model has the major benefit of offering *insight* into how players subjectively experience their motivations.

At the time of writing, there is no publicly accessible, fully validated, comprehensive model of gaming motivation. The field has been growing, with numerous attempts providing incremental insights into the structure and nature of our motivations to play video games. Chapter 5 offered an overview of empirically-grounded, behavioural models of motivation. In the current chapter we describe our endeavour to construct and validate a *cognitive* model of video game motivation based on the existing literature. Thus the current chapter addresses the *cognitive* side of Research Question 3.

In this chapter we briefly review the major gaming motivation models that offer publicly available surveys and peer-reviewed supporting literature [41, 69, 93] (Section 6.1). Next, we present our method for constructing a cognitive model (GAMR) from the aforementioned validated models (Section 6.2). Subsequently, the GAMR model is validated on the GAMR dataset (Section 6.3). Lastly, the results are discussed (Section 6.4) and general conclusions are drawn (Section 6.5).

6.1 SURVEY SELECTION

The GAMR model is a combination of three existing, validated motivational models by Sherry et al. [69] (UG theory, Section 5.2.3), Hilgard et al. [41], and Yee [93]. Their work was selected for offering fully validated gaming motivational surveys that are theory-grounded, peer-reviewed, and publicly accessible. Their original surveys are listed in Appendix C.

First, Sherry [69] employed Uses and Gratifications Theory (Section 5.2.3) to construct 20 items that loaded on to 6 motivational factors for gaming (see Table 13). The items were generated through a series of interviews with focus groups of 18-22 year old American undergraduate students. The responses resulted in 27 items over 6 factors. The 27 items were subjected to clarity tests and thus reduced to 20 items over 6 factors. It is unclear from the literature which analytical techniques were used for this reduction [69].

Secondly, Hilgard et al. [41] formulated the Gaming Attitudes, Motives, and Experiences Scales (GAMES) consisting of 59 items over 9 factors (see Table 13). The 59 items were extracted from an original 120 items through a sequence of Exploratory and Confirmatory Factor Analysis. The 120 items were created by using 20 of the items outlined by Sherry [69] and supplementing these with 100 items generated directly by the researchers themselves. The generated items show a strong bias to pathological play, with such factors resulting as Violence Catharsis, and Violent Reward. The violence-related motives cannot be applied to all game genres, as many games do not feature visceral violence such is referred to by items like "It feels good to shoot or slice parts off of enemies. (e.g., shooting a head off, or cutting an arm off.)".

Thirdly, Yee [93] constructed a motivational survey specific to the MMORPG genre. It consisted of 40 items across 10 factors. The items were generated based on the Bartle types and previous work with MMORPG players done by Yee, with no further explanation on the process. The survey was validated on a sample of 3000 MMORPG players, consisting of 2769 males and 431 females. Sample distributions of age and nationality are not known. The factors are listed in Table 13. Factors showed strong Cronbach's alphas ranging from .65 to .87. Principal Component Analysis showed the 10 factors to group together into three overarching factors: Achievement, Social, and Immersion.

Of the motivational models described in Chapter 5, only UG theory is part of the theoretical grounding of the GAMR model. Sherry et al. [69] offer a peer-reviewed, theory-grounded, publicly accessible survey for using the UG model to tap into the cognitive experience of motivation of the player. The Flow, CEE, and SDT models in Chapter 5 do not offer publicly accessible surveys to measure the relevant underlying cognitive constructs of the respective models. Of the three, SDT is the most strongly supported [66]. The Player Experience of Need Satisfaction (PENS) survey is a validated survey that employs SDT with great success. However, the PENS is not available for public use, and the data per item is not published in peer-reviewed journals. Overall, Sherry et al. [69], Hilgard et al. [41], and Yee [93] offer the most robust cognitive models of motivation that are publicly accessible.

6.2 MODEL CONSTRUCTION

The GAMR model was constructed by combining the factors of the gaming motivation models proposed and validated by Sherry et al. [69], Hilgard et al. [41], and Yee [93]. The construction of the GAMR model progressed in 5 steps.

First, all 25 factors by Sherry (6 factors), Hilgard (9 factors), and Yee (10 factors) were sorted on semantic similarity (See Table 13). Semantically similar factors are displayed on one line. Factors that share no similarity with factors of other models are listed on an empty line and can be considered unique to the relevant model. Note that the Social Interaction factors of Sherry and Hilgard line up with *three* factors listed by Yee (Socialising, Relationships, Teamwork).

Secondly, unique, cross-genre factors were included in the GAMR model. The Violence Catharsis, Violent Reward, and Mechanics factors are not included as they are specific to game genres that feature violence and complex mechanics (e.g. MMORPGs). As the GAMR model was intended to function across game genres, genre-specific factors were excluded. All remaining unique factors (Arousal, Grinding-Completion, Story, Loss Aversion) were included in the GAMR model.

Thirdly, duplicate factors were resolved through a precedence ordering of the model. Sherry's model was given first precedence as the items of the relevant survey are game genre neutral and acquired from focus groups. The Hilgard model was given secondary precedence as the items are game genre neutral. The Yee model was given least precedence as every factor contained items worded specifically to MMORPG play. Items from Yee's model that were elected for inclusion in the GAMR model would need rewording that could potentially lower the validity of the items. Through this precedence scheme, duplicate factors were resolved to use the factors from Sherry when available (Competition, Challenge, Fantasy), use the factors from Hilgard when Sherry's factors were not available (Escapism, Customization, Autonomy-Exploration), and use the factors from Yee when they were unique (none). As an exception, the Escapism factor of the GAMES survey was selected over the Diversion factor of the Sherry's model because the Diversion factor only consisted of 2 items.

Fourthly, precedence ordering of duplicate factors was ignored when the duplicate factors involved one survey measuring the relevant factor through multiple subfactors. This was the case for the Social Interaction factor in Sherry and Hilgard's models. The equivalent construct in the Yee's model was measured through three factors: Socialising, Relationships, and Teamwork. To maximise the utility and strength of the GAMR model, Yee's factors were included to measure socially-related gaming motivations. The factor items were paraphrased to pertain to all game genres instead of only MMORPGs. After performing this fourth step, 13 factors were elected to form the GAMR model.

Fifthly, the GAMR model was instantiated in survey-format by taking the short forms of each of the factors of the original models. Short forms were elected over the original long forms so as to equalize the item count for each factor and keep the total survey at a feasible length despite measuring 13 factors. Short forms were constructed by selecting the three items with the highest factor loading per factor based on the original research papers from Sherry et al. [69], Hilgard et al. [41], and Yee [93]. The Pearson's correlations between the 3-item short form and the original long form were above .9 for the items by Hilgard and Yee, as calculated on their original data sets. For Sherry the correlation could not be calculated, but the original long forms only contained a maximum of 4 items. The resulting GAMR survey contains 39 items, grouped into 13 factors of 3 items each (see Tables 15, 16, 17).

6.3 MODEL VALIDATION

The GAMR model was validated on a sample of 2400 players (after filtering) of the three most prominent multiplayer online game genres. Validation progressed in four steps. First, the model structure was tested using Confirmatory Factor Analysis (Section 6.3.1). Secondly, the effectiveness of the model was determined by testing for significant differences in the motivational scores between groups with different game preferences (Section 6.3.2). Thirdly, the relationship of the model to personality traits was tested (Section 6.3.3). Lastly, the robustness of the model across demographic groups was determined

Table 13: Review of Factors per Motivational Model. The motivational models by Sherry, Hilgard, and Yee were taken as the basis of the GAMR model. Factors on one horizontal line are semantically near-identical. Factors in *italics* were integrated into the GAMR model. Factors below the double line were excluded from the model.

Sherry	**Hilgard**	**Yee**
Competition		Competition
Challenge		Advancement
Fantasy		Role-Playing
Arousal		
	Grinding-Completion	
Diversion	*Escapism*	Escapism
	Story	
	Customization	Customization
	Autonomy-Exploration	Discovery
	Loss Aversion	
Social Interaction	Social Interaction	*Socializing* *Relationships* *Teamwork*
	Violence Catharsis Violent Reward	Mechanics

by performing Ordinary Least Squares Regression with demographic traits as input and the motivational scores as output (Section 6.3.4).

All validation was performed on the GAMR dataset (see Chapter 2 for more details), which was filtered on four criteria. First, data from minors (age < 18) was excluded from the sample, resulting in the inclusion of 2817 players. Secondly, 28 players were excluded as outliers for showing no univariate variance in their responses. Thirdly, 19 participants were excluded as outliers for indicating the gender value "other" while all remaining participants indicated either "male" or "female" for gender. Lastly, 363 participants were excluded for indicating an English skill level other than "Advanced" or "Native". Both advanced and native speakers of English are expected to fully understand all survey items. Therefore, native English speaking became a proxy for culture (Anglosphere cultures versus non-Anglosphere cultures).

The characteristics of the remaining sample are as follows. It contained 2400 participants, including 2073 males and 327 females, of which 943 were advanced English speakers and 1457 were native English speakers. The average age was 26.17 ($\sigma = 7.72$). Most participants played World of Warcraft (n = 1181), with fewer participants playing League of Legends (n = 919) and Battlefield (n = 824). In total, 436 participants indicated playing two of the aforementioned games, and 44 participants indicated playing all three games.

6.3.1 *GAMR Model Fit*

Confimatory Factor Analysis (CFA) showed that the 13 factor model surpasses all the relevant threshold values for good model fit outlined by [43]. Table 14 shows these values compared to a 5 and a 1 factor model. The 5 factor model was considered semantically the most likely counter model to the 13 factor model. It groups the motivational factors on Achievement, Social, and Immersion motivations in the same manner as Yee's model and DAM (see Figure 15). After grouping, two factors are left out (Arousal and Autonomy-Exploration), leading to a 5 factor model. The 1 factor model was employed as the standard baseline model.

Figure 15: The 13 Factors of the GAMR Model Grouped on Semantic Similarity. The three major motivational categories line up with DAM and Yee's model. The Arousal and Autonomy-Exploration factors stand on their own. A Confirmatory Factor Analysis (Table 14) showed that a 13 factor model showed a better fit than a 5 or 1 factor model.

Overall, Table 14 shows there are consistently higher χ^2/df and RMSEA values and increasingly lower CFI values for models with fewer factors. Thus, the 13 factor model substantially outperformed a 5 and a 1 factor model. The 13 factor model could not be tested against a model with more than 13 factors as there is no other meaningful dimensional reduction of the 39 items that would result in more than 13 factors. In other words, none of the 13 factors can meaningfully be split into a higher number of factors without resorting to single-item factors. As such, 13 factors is a good and optimal fit for the 39 survey items presented in the GAMR survey.

Tables 15, 16, and 17 show the standardized latent variable estimates for each item in the 13 factor model, sorted by the Cronbach's alpha of each factor. Cronbach's alphas for the factors range from .91

Table 14: GAMR Model Fit Per Number of Factors using CFA. A 13 factor model shows the best fit when compared to a 5 and a 1 factor model.

	13 Factors	**5 Factors**	**1 Factor**
χ^2/df	6.58	24.22	35.47
CFI	.90	.52	.28
RMSEA	.05	.10	.12
p value RMSEA	.98	<.01	<.01

on Customization to .46 on Teamwork. The Cronbach's alpha indicates how much the items of each factor relate to each other. The maximum value of 1.0 is reached when all items in a factor are identical, while the value of 0.0 is reached when all items are completely unrelated to each. A Cronbach's alpha in the .6-.8 range is ideal, as it indicates that items are strongly related but complimentary. All factors fall into this range except Customization (.91), Challenge (.49), and Teamwork (.46). When we look at the factor loadings of the items in these three factors then we see the following. The Customization factor loadings are all around .9 mark, indicating that the items are likely experienced as near-identical by respondents. On the other hand, the Challenge and Teamwork items have very low factor loadings, indicating that respondents interpreted the items of each factor as relatively unrelated.

6.3.2 *GAMR & Game Preference*

Gaming motivations were found to be significantly different across game genres. Motivation scores were compared by testing 3 subsamples against each other. Each subsample consisted only of players of one game: Battlefield (n = 232), League of Legends (n = 225), and World of Warcraft (n = 563). Table 18 shows the results of a Mann-Whitney U test comparing the 13 motivational scores across the three groups. If a difference was significant at $\alpha = .05$, then the highest scoring game is listed. Overall the patterns in the differences are in line with expectations of the motivational profiles of the players of

Table 15: GAMR Survey Part 1. Each factor is instantiated by 3 items. Factors are sorted from highest to lowest Cronbach's α value. L: Factor loading of the item onto the relevant factor within the 13 factor CFA.

Factor	**Item**	**L**
Customization $\alpha = .91$	I really like to customize my character's outfit.	.89
	I like to personalize and customize my character.	.91
	I will put considerable time into designing my character's appearance (e.g., clothes, face).	.82
Escapism $\alpha = .88$	Video games allow me to escape from the problems associated with everyday life.	.83
	I play video games because it allows me to escape real life.	.92
	I play video games to keep my mind off my problems.	.77
Relationships $\alpha = .80$	I talk to my online friends about my personal issues.	.77
	My online friends offer me support when I have a real life problem.	.79
	I find myself having meaningful conversations with other players.	.72
Gr.-Compl. $\alpha = .79$	I like taking the time to pick up every single collectible item in the game.	.81
	I will play a game until I get 100% on it, completing everything in the game.	.73
	I rarely complete collections of in-game items.	-.68

Table 16: GAMR Survey (Continued from Table 15).

Factor	Item	L
Story $\alpha = .78$	Video game stories are not important to me.	.77
	Stories in video games just get in the way.	.71
	I am excited to find out what happens next in the story.	-.72
Socializing $\alpha = .75$	I enjoy getting to know other players.	.80
	I enjoy chatting with other players.	.82
	I enjoy helping other players.	.54
Loss Aversion $\alpha = .75$	Losing is frustrating and detracts from my experience.	.75
	Winning is fun; losing is not.	.72
	Losing a game always makes me mad - what a waste of time!	.65
Fantasy $\alpha = .72$	Video games allow me to pretend I am someone/somewhere else.	.76
	I like to do something I could not normally do in real life through a video game.	.62
	I enjoy the excitement of assuming an alterego in a game.	.67

Table 17: GAMR Survey (Continued from Table 16).

Factor	Item	L
Competition $\alpha = .63$	It is important to me to be the fastest and most skilled person playing the game.	.72
	I like to play to prove to my friends that I am the best.	.76
	I get upset when I lose to my friends.	.40
Arousal $\alpha = .62$	I play video games because they excite me.	.62
	Video games keep me on the edge of my seat.	.58
	I find that playing video games raises my level of adrenaline.	.57
Aut.-Expl. $\alpha = .59$	I prefer games that allow me to play however I want.	.61
	I like games that do not put a lot of constraints on the player.	.46
	I like games that offer you a lot of options and choices.	.62
Challenge $\alpha = .50$	I find it very rewarding to get to the next level.	.52
	I feel proud when I master an aspect of a game.	.57
	I enjoy finding new and creative ways to work through video games.	.44
Teamwork $\alpha = .43$	I would rather play as part of a team than solo.	.63
	It is important to me that my character does not need support from other players to do well.	-.27
	It is important to me that my character can support other players well.	.49

the different genre games. Specifically, we observe the following three patterns

First, Battlefield players significantly outscore World of Warcraft players on Competition, Arousal, Loss Aversion, and Teamwork motivations. These four motivations precisely embody the unique gameplay elements of a high-paced, competitive, team-based shooter such as Battlefield. Secondly, World of Warcraft outscores Battlefield and League of Legends on the gaming motivations that embody completionist (Grinding-Completion), social (Socialising, Relationships), and pretend play (Fantasy, Story, Escapism, Customization) that lie at the heart of the MMORPG genre. Lastly, League of Legends outscores Battlefield on Challenge, Story, Customization, and Relationships, and outscores World of Warcraft on Teamwork. This possibly reflects League of Legends position as a blend between the competitive play style prominent in games such as Battlefield, and the social and pretend play of games such as World of Warcraft.

Overall, 12 of the 13 gaming motivations differed significantly across the three genres, underlining the discerning power of the GAMR model. The factors of the model also meaningfully lined up with the core gameplay elements of each game genres, further strengthening the case for the GAMR model's descriptive qualities.

6.3.3 *GAMR & Personality*

Personality traits correlate significantly with gaming motivation. Table 19 shows the correlations between each of the personality traits measured and the 13 motivational factors. All personality traits correlate significantly with a range of gaming motivations at $\alpha = .05$ with the application of a Bonferroni correction. The patterns are as follows.

Openness is positively related to Challenge (.25), Arousal (.15), Story (.14) and Autonomy-Exploration(.13) motivations. It shows a draw toward motivations related to curiosity and pushing one's abilities. It is complemented by a negative correlation with Loss Aversion (-.12). The interest and willingness of people with a high Openness score to experiment with and explore new experiences is naturally in line with a low Loss Aversion.

Table 18: Mann-Whitney U Test on Differences in Gaming Motivations between Battlefield (BF), League of Legends (LOL), and World of Warcraft (WOW) Players. Only significant differences ($\alpha = .05$) are listed. For each significant difference, the game with the higher value on that gaming motivation is listed.

Motivational Factor	**BF-WOW**	**BF-LOL**	**LOL-WOW**
Competition	BF		
Challenge		LOL	
Fantasy	WOW		WOW
Arousal	BF		
Story	WOW	LOL	
Escapism	WOW		WOW
Loss Aversion	BF		
Customization	WOW	LOL	
Grinding-Completion	WOW		WOW
Autonomy-Exploration			
Socializing	WOW		
Relationships	WOW	LOL	
Teamwork	BF		LOL

Conscientiousness is negatively related to Escapism (-.15), possibly reflecting a diligence to stay on top of issues in real life instead of trying to mentally avoid them. At the same time, there is a positive correlation with Challenge (.12) and Grinding-Completion (.17) which is in line with an organized and meticulous manner of conduct.

Extraversion shows positive correlations with the social dimensions Socializing (.29), Relationships (.16), and Teamwork (.17). It is complemented by an additional positive correlation with Challenge motivation, and a negative correlation with Escapism (-.19) motivation. Overall, Extraversion seems related to a preference for engaging with more social, realistic, and achievement-oriented gaming experiences.

Agreeableness shows higher correlations with the social dimensions Socializing (.39), Relationships (.25), and Teamwork (.27) than Extraversion. In contrast to Extraversion, Agreeableness shows a pattern of aversion to "negative" social interactions, with negative correlations with Competition (-.16) and Loss Aversion (-.23) motivation. Agreeableness seems related to the “pleasantness” of social contact while seeming aversive to “negative" social interactions (competition, loss). There is also a relationship with the more 'aesthetic'-related motivations of gaming such appreciation for Story (.14) and Customization (.10).

Emotional Stability is notable for showing exclusively negatively correlations to gaming motivation, with a strong peak negative correlation to Escapism (-.37). Presumably, a high Emotional Stability removes the desire for emotional coping strategies such as escapism as there is not a high level of emotional distress to manage. This is additionally emphasized in reduced immersion motivations such as Customization (-.11) and Fantasy (-.17). Additionally, Loss-Aversion (-.25) and Competition (-.12) are also negatively related to Emotional Stability. Overall, those scoring higher on Emotional Stability might be less drawn to video games in general due to a lower drive toward the Immersion- and Achievement-related motivations.

6.3.4 *GAMR & Demographics*

Ordinary Least Squares (OLS) regression was used to model the relationship between the demographic variables and the motivational fac-

Table 19: Effect Sizes of Pearson's Correlations between GAMR Motivational Factors and Big Five Personality Traits. Effect sizes (r) of Pearson's correlation are listed if the correlation is significant at $\alpha < .05$ after Bonferroni correction and $r > .1$. An * is displayed when the correlation is significant, but $r \leqslant .1$. Abbreviations: O = Openness, C = Conscientiousness, E = Extraversion, A = Agreeableness, ES = Emotional Stability.

Motivational Factor	**O**	**C**	**E**	**A**	**ES**
Competition			*	-.16	-.12
Challenge	.25	.12	.11	.11	
Fantasy			*		-.17
Arousal	.15		*		
Story	.14			.14	
Escapism		-.15	-.19		-.37
Loss Aversion	-.12	*		-.23	-.25
Customization	*			.10	-.11
Grinding-Completion		.17			
Autonomy-Exploration	.13				
Socializing	*		.29	.39	*
Relationships	*		.16	.25	
Teamwork			.17	.27	*

tors. Some might argue that (ordinal) logistic regression would have been a more appropriate technique for this regression as it is specifically optimized for dealing with ordinal outputs. However, Pohlman et al. [60] found that in practice OLS and logistic regression often resolve to similar models. At the same time, OLS has the benefit of providing coefficients that are intuitive to interpret, which in turn increases understanding of the underlying relationships that are being modelled. The coefficients in OLS represent linear proportional differences in the outcome variable, while the coefficients in (ordinal) logistic regression represent differences in log-odds.

OLS regression showed that gender, native English speaking, and age (demographic variables) produce significant models for all motivational factors, but the variance explained is low (See Table 20). R^2 values average around .01 with a maximum of .07 on Customization. Looking at the patterns of the coefficients per demographic variable, we see the following.

Gender is positively related to about half the motivations, with one notable negative coefficient on Competition. Positive coefficients indicate a trend toward female preference while negative coeffiecients indicate a trend toward male preference. The positive coefficients on Fantasy, Story, Escapism, Customization, Grinding-Completion, and Relationships line up with the stereotypical pattern of females having a greater interest in social and pretend play. The negative coefficient on Competition motivation is in line with the stereotypical pattern of males being more interested in competition.

Native (English) speaking only shows significant coefficients on Fantasy and Escapism. Both coefficients are positive, which shows a trend toward native English speaking instead of non-native English speaking at an advanced level. It might be the case that both Native and Advanced English speakers play games in English (larger selection), but that advanced English speakers are hampered in their full engagement with the fantasy of the game world.

Age negatively relates to about half the motivations. The coefficient values are low, reflecting the large value range for age (18-65). Thus, a 20 year age difference ($\beta(Age) = -.02$) would impact the Competition motivation equally as much as being male instead of female ($\beta(Gender) = -.40$). The decrease of gaming motivations with age is in line with cohort difference between younger and older players. Younger players are likely to have grown up playing video games, while older players might not. Additionally, gaming motivations might decrease with age as other concerns take over (work, family life, etc.).

6.4 DISCUSSION

The GAMR model has been shown to be robust and meaningful in an initial analysis in relation to game preference, personality, and demographic traits. We consider how the model could be improved (Section 6.4.1), and how the model ties back to the Directed Action Model from the previous chapter (Section 6.4.2).

6.4.1 *Improving Current Factors*

The validation and testing of the GAMR model have uncovered a few potential weaknesses that could be alleviated with further testing and development. Overall, the internal coherence of some factors could be improved by rewording items or adding additional items. We highlight four ways that the current factors could be improved.

First, the short-form of the factors stemming from the work by Sherry et al. were not validated against their original long-form. The relevant factors are Competition, Challenge, Fantasy, and Arousal. Each contained 4 items in the original long form and 3 items in the short form used in the GAMR survey. To ensure these factors are as robust as those derived from the work by Hilgard et al. and Yee et al., the short and long form would have to be highly correlated within a representative sample of gamers. Despite their lower validity, the factors derived from Sherry's work showed significant correlations with personality, demographics and game preference that are in line with remaining validated factors derived from the work by Hilgard et al. and Yee et al.

Second, the Customisation factor has a high Cronbach's alpha, indicating that the three items in this factor are interpreted as fairly equivalent in meaning. The factor might be enriched by keeping the item with the highest factor loading ("I like to personalize and customise my character.", loading .91), and swapping out the remaining two

Table 20: OLS Regression of the Predictors Gender, Native English Speaking, and Age on the Outcome Variables of Gaming Motivation. Gaming motivations are continuous variables. Gender is (M)ale or (F)emale. Native (English) speaking is (A)dvanced or (N)ative. Age is a value from 18-65. * indicates that $R^2 < .01$. All models are significant at $\alpha = .05$. Coefficients are listed when $R \geqslant .01$ for the relevant model and $p < .05$ for the relevant coefficient.

	Gender 1=M, 2=F		English 1=A, 2=N		Age 18-65		Model Fit
	β	t	β	t	β	t	R^2
Competition	-.40	-6.90			-.02	-9.09	.06
Challenge							*
Fantasy	.22	3.79	.23	5.48	-.02	-5.87	.03
Arousal					-.01	-5.15	.01
Story	.22	3.70			-.02	-8.12	.03
Escapism	.27	4.50	.24	5.65	-.01	-3.51	.02
Loss Aversion							*
Customization	.65	11.20			-.02	-8.06	.07
Gr.-Compl.	.40	6.76					.02
Aut.-Expl.							*
Socializing							*
Relationships	.39	6.57			-.01	-5.21	.03
Teamwork							*

items with farther differentiated items that still pertain to Customisation. For instance, a negatively scored statement about customisation in general might elicit a slightly different response than the current items (e.g. "I enjoy a game less if there is no option to customise the look of my character").

Third, the Challenge and Teamwork factors suffer from the opposite problem in having a very low Cronbach's alpha. Here we would suggest removing the two lowest scoring items per factor, and adding new items through focus testing until a higher Cronbach's alpha is attained in validation testing.

Lastly, the Autonomy-Exploration factor has an acceptable Cronbach's alpha, but barely relates to game preference, personality, or demographic traits. The literature on gaming motivation does prominently feature support for the motivating power of Autonomy-Exploration (also sometimes referred to as "Discovery') [93, 61, 41]. Therefore, we hypothesise that the Autonomy-Exploration factor in the GAMR model is weakly instantiated by the items loading onto this factor. The factor could be improved by either using items from previously validated surveys with a conceptually similar factor included, or developing relevant items from scratch through focus group testing and additional validation. In terms of research results relating to game preference, personality, and demographic traits, we expect that a reconstructed Autonomy-Exploration factor would relate significantly and more strongly to preference for World of Warcraft play, a higher Openness score, as well as a lower age bracket.

6.4.2 *GAMR & DAM*

The DAM and GAMR model were not explicitly designed to build on each other. Nevertheless, they resolved to a similar motivational structure. DAM was constructed from a top-down, theory-driven approach based on the existing literature on gaming motivation. GAMR was constructed in a bottom-up, data-driven manner by combining the available gaming motivational surveys and testing it on samples of players across game genres. Despite these opposite approaches, the models came to pivot around the same three conceptual motivation categories originally proposed by Yee [93]: Achievement, Social, and

Immersion. We propose that DAM and GAMR expand on Yee's original work in the following manner.

DAM contributes to the Achievement-Social-Immersion model by proposing a method to connect gaming motivations to game behavior directly. By employing the concept of *action direction*, game variables can be meaningfully aggregated into the same three-part structure. GAMR contributes to the Achievement-Social-Immersion model by testing the factor structure across game genres. Though CFA showed that the 13 factors do not collapse into the 3 factors proposed by Yee and DAM (with an additional 2 outlier factors) in our cross-genre sample, the 13 factors do semantically reflect the same motivational themes of Achievement, Social, and Immersion motivations. We propose to explore the factor structure further based on the hypothesis that the GAMR model is not limited to the 13 factors currently included. We posit that additional factors may exist. As factors can only be found when they are specifically tested for it might be necessary to step outside the current motivational paradigms to find "missing" factors. For instance, how would the appeal of rhythm/music games be explained by any of the motivational models reviewed in the last two chapters? Questions like these may be explored in future work.

6.5 CONCLUSION

The GAMR model has provided insights on the *cognitive* side of Research Question 3: *What is the relationship between the motivational traits of a player and his play style in video games?* The model has shown promise in accurately measuring gaming motivation in terms of 13 factors, derived from existing, validated models for players of MOBAs, MMORPGs and FPS games. In our sample, all factors significantly correlate with one or more personality traits in an intuitive manner. Additionally, 12 of the 13 gaming motivations could be used to uniquely distinguish the gaming preferences of MMORPG, FPS, and MOBA players among each other. Lastly, our study showed that gender, native English speaking, and age have a significant effect on 8 of the 13 gaming motivations in our sample. The proposed model seems robust and with a promising predictive value for both real life and in-game behavior.

In general, the GAMR model has shown that MOBA, MMORPG and FPS players in our sample choose to play games with game design features that line up directly with their gaming motivations. We see that the FPS players focus on the excitement of competition and teamwork, the MMORPG players enjoy the immersion of a fantasy world to explore while socializing with other players, and the MOBA players combine a little of both in a mix of competitive and socially motivated play. In this manner, the GAMR model supports the premise that players exhibit game behavior that can be directly mapped to their gaming motivations.

Future work on improving, expanding and grounding the model in behavioural game data will further strengthen its value and generalizability as a definitive tool for understanding and measuring video game motivation across the board. The ultimate utility test for a model of gaming motivation would be to determine if the results of the model line up with how gamers actually play games. Thus the next step is to connect the GAMR model with a behavioural model such as DAM (Chapter 5).

7 CONCLUSION

Cutting across personality, age, and motivations, we have explored the connection between the traits we exhibit in our day-to-day lives and the behaviors we express in video games. The research constituted a three-pronged approach to our problem statement:

Problem Statement. *To what extent are a player's real-life traits related to their play style in video games?*

First, we saw that exploring Research Question 1 uncovered no connection between the Big Five personality traits and play style in a tactical shooter such as Battlefield 3. Counter to findings by Lankveld et al. [83, 84] and Canossa et al. [13] , there were only few significant correlations between personality and play style with none exceeding an effect size of .2. Our findings are in line with work done by Yee et al. [96] with MMORPGs. The lack of results is most likely due to the high level of aggregation of the data we collected, as well as the fact that we conducted our study online instead of in a lab environment. Follow up work by Mateusz et al. [12] and De Vries and Spronck [22] did show that native English speaking and gaming platform themselves significantly correlate to play style in Battlefield. Though our current work did not uncover a relationship between personality and play style, we do consider the possibility that such a link may exist when more detailed data is collected in a controlled lab environment.

Secondly, diving into Research Question 2 exposed a robust connection between age and play style in Battlefield 3. Players show their age in their play style in both a cross-sectional and a longitudinal study. The cross-sectional study grabbed a "snapshot" of play style at a certain time. It showed that 45% of the variance in age can be explained by play style. Specifically, a correlational analysis showed effect sizes up to .4 between age and reductions in performance and speed of play. The longitudinal study elaborated further on these insights. It showed that older players already start out with a lower performance and slower play style than younger players. All players improve their speed and performance over time, but older players show additional gains in speed of play over time. These findings are in line with both the physiological and psychological effects of aging.

Thirdly, tackling Research Question 3 led to the development of both a behavioral and a cognitive model of gaming motivation. The behavioral model was developed to fill a vacuum where no validated models yet existed on the link between play style (game behavior) and gaming motivations. The Directed Action Model (DAM) posits that actions in any game can be labelled based on their direction toward any combination of Goal, Player, and/or Fantasy of the game. Each direction lines up with one of the major gaming motivation categories recognized across the literature, and originally proposed by Yee [93]: Achievement, Social, and Immersion (respectively). The model is as yet not validated but constitutes a novel approach that may be used to understand and process game behavior in terms of motivational traits. On the other hand, the cognitive model that we have suggested is a validated amalgam of existing models. The GAMR model is a 13-factor model of motivation that is instantiated in a validated questionnaire. The 13 factors held up in a confirmatory factor analysis across a diverse sample of MOBA, MMORPG, and FPS players. Additionaly, they line up with demographic and personality traits, as well as game preference within that sample.

Tying back to our problem statement, we see that some real-life traits are expressed in play style, while others are not. In our work, we see a pattern of connections between real-life traits and game behaviors being moderated by what behavioral expressions any particular game allows. Traits with physiological effects, such as aging, seem to be strongly reflected in game behavior, provided the game in question taps into the relevant physiological systems. In contrast, more preferential (instead of ability-related) variations in behavior can only be exhibited in games that allow for meaningful choices and do not punish preferential choices more so than in real life. This may explain why personality traits are not as clearly reflected in game behavior while motivational traits are. Personality traits are often coded to certain real-life behaviors, while motivations tap into the underlying driving forces that generate behavior giving a certain situation (e.g. a video game environment). We have proposed the DAM and GAMR models as frameworks to further explore the expansive field of gaming motivations and how they relate to our behaviors in and outside of gaming.

The findings presented in this dissertation can serve to inform both game design, as well as research on player modeling. In terms of game design, it is interesting for developers to consider how game elements may appeal to different parts of their audience that vary in age or motivations. In terms of research, there is a lot of ground left to cover to complete our understanding of what motivates us to play video games. The DAM and GAMR models of motivation can serve to inform and contribute to such understanding. Their combined top-down and bottom-up approaches both converged to the Achievement-Social-Immersion model of motivation that Yee [93] first proposed for MMORPGs. Their behavioral and survey instantiations can serve as a starting point for developing an all-inclusive, definitive model of gaming motivation.

Overall, the insights presented in this dissertation shed a new light on the games that have become part of our daily lives. Video games have been a growing industry for the last 40 years, and there is no reason to suspect their influence will taper off in the future. As hardware technologies become more advanced, the purposes that video games can be applied for, and the people the medium can appeal to, will only broaden further. Player modeling might one day be as commonplace as the user modelling that helps us find what we need on our search engines and online stores. The work in this dissertation has served as one step among many toward that future.

A

DISTRIBUTION OF GAMR SCORES IN GAMR DATA SET

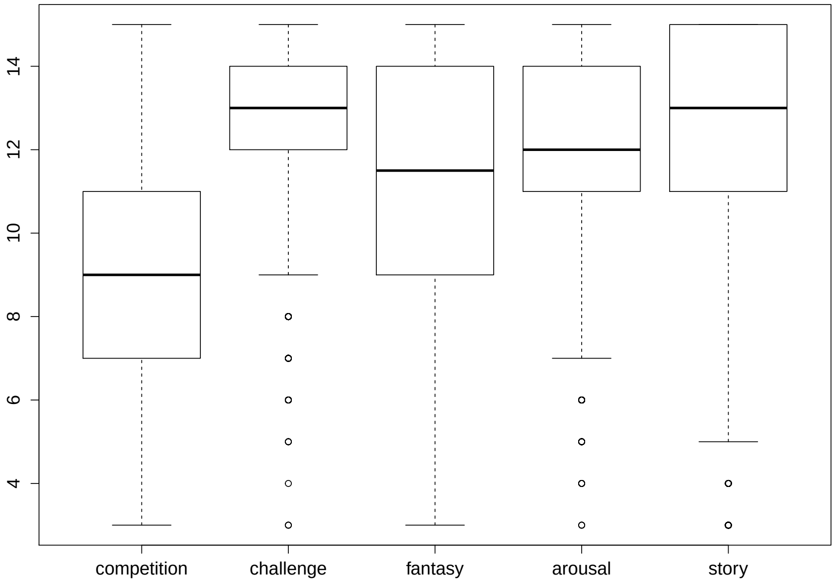

Figure 16: Distribution of Gaming Motivations in the GAMR Data Set.

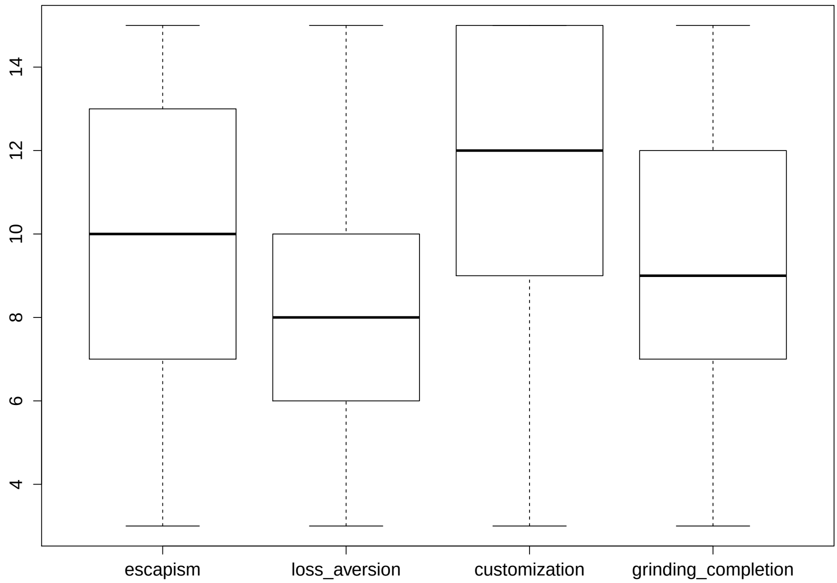

Figure 17: Distribution of Gaming Motivations in the GAMR Data Set (Continued from Figure 16).

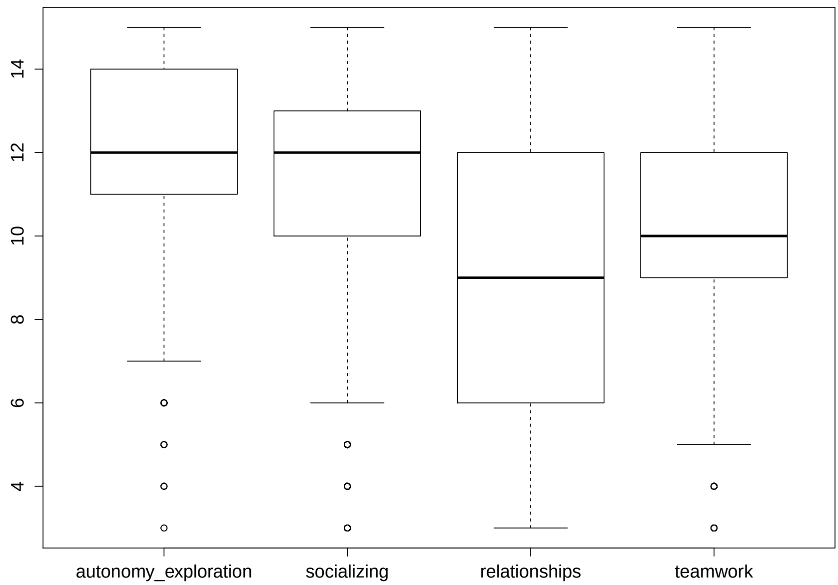

Figure 18: Distribution of Gaming Motivations in the GAMR Data Set (Continued from Figure 17).

B

PSYOPS DATA: PLAY STYLE VARIABLES IN PERSONALITY RESEARCH

Table 21: Playstyle Variables used in Personality Research, Part 1.

Play Style Variables Per Category	
Ribbon Variables	
AceSquadPerRound	MVP3PerRound
MVP2PerRound	MVPPerRound
CombatEfficiencyPerRound	SquadWipePerRound
SquadSpawnPerRound	
Equipment Variables	
MAVSpotsPerReconTime	TUGSSpotsPerReconTime
C4HitsPerSupportTime	BeaconSpawnsPerReconTime
MortarTimePerSupportTime	GrenadeShotsPerSecond
ClaymoreShotsPerSupportTime	MineShotsPerEngineerTime
Kit Variables	
SupportTimePerTotalTime	ReconTimePerTotalTime
EngineerTimePerTotalTime	AssaultTimePerTotalTime
Score Variables	
UnlockScorePerSecond	ObjectiveScorePerSecond
SupportScorePerSupportTime	VehicleMBTScorePerVehicleTime
ScorePerSecond	VehicleAAScorePerVehicleTime
AwardScorePerSecond	EngineerScorePerEngineerTime
ReconScorePerReconTime	TeamScorePerSecond
VehicleSHScorePerVehicleTime	GeneralScorePerSecond
VehicleIFVScorePerVehicleTime	VehicleJetScorePerVehicleTime
SquadScorePerSecond	VehicleAHScorePerVehicleTime
AssaultScorePerAssaultTime	BonusScorePerSecond
VehicleALLScorePerVehicleTime	
Game Mode Variables	
ConquestPerRound	ConquestWinsPerLoss
SquadDeathmatchPerRound	SquadDeathmatchWinsPerLoss
RushPerRound	RushWinsPerLoss
SquadRushPerRound	SquadRushWinsPerLoss
TeamDeathMatchPerRound	TeamDeathMatchWinsPerLoss

Table 22: Playstyle Variables used in Personality Research (Continued from Table 21).

Play Style Variables Per Category	
Vehicle Variables	
MBTTimePerSecond	AHTimePerSecond
JATimePerSecond	AATimePerSecond
JFTimePerSecond	SHTimePerSecond
IFVTimePerSecond	
Global Variables	
VehicleTimePerSecond	LongestHandheldHS
SaviorKillsPerSecond	SaviorKillsPerKill
PlayTime	PlayTimePerRound
VehiclesDestroyedPerSecond	DogTagsPerSecond
DogTagsPerKill	DeathsPerSecond
NemesisKillsPerSecond	NemesisKillsPerKill
ShotsPerSecond	ShotsPerKill
KillsPerSecond	KillsPerDeath
MComDefencesPerRushTypeRound	FlagCapturesPerConquestRound
KillstreakBonusPerSecond	VehicleDestroyAssistsPerSecond
ELO	ResuppliesPerSupportTime
HealsPerAssaultTime	KillAssistsPerSecond
KillAssistsPerKill	SuppressionAssistsPerSecond
MComDestroyedPerRushTypeRound	VehiclesKillsPerSecond
HitsPerSecond	HitsPerShot
HeadShotsPerSecond	HeadShotsPerHit
RevivesPerAssaultTime	NemesisStreaksPerSecond
AvengerKillsPerSecond	AvengerKillsPerKill
FlagDefencesPerConquestRound	RepairsPerEngineerTime
LongestHeadShot	WinsPerLoss
Rank Variables	
Rank	

Table 23: Playstyle Variables used in Personality Research (Continued from Table 22).

Play Style Variables Per Category	
Weapon Variables	
srM39TimePerSecond	smVALTimePerSecond
sgM1014TimePerSecond	pM9FTimePerSecond
caG36TimePerSecond	arAEKTimePerSecond
caSG553TimePerSecond	mgQBB95TimePerSecond
sgSaigaTimePerSecond	sg870TimePerSecond
pM1911TimePerSecond	arL85A2TimePerSecond
wLATRPGTimePerSecond	arG3TimePerSecond
pM9STimePerSecond	mgM240TimePerSecond
caSCARTimePerSecond	caAKSTimePerSecond
mgM249TimePerSecond	caM4TimePerSecond
pG17STimePerSecond	mgT88TimePerSecond
srSV98TimePerSecond	arAN94TimePerSecond
pMP443STimePerSecond	pTaurSTimePerSecond
wLATJAVTimePerSecond	smPDRTimePerSecond
smPP19TimePerSecond	mgMG36TimePerSecond
wLAAFIMTimePerSecond	srQBU88TimePerSecond
sgJackHTimePerSecond	pMP443LTimePerSecond
sgDAOTimePerSecond	arF2TimePerSecond

Table 24: Playstyle Variables used in Personality Research (Continued from Table 23).

Play Style Variables Per Category	
Weapon Variables Continued	
sgUSASTimePerSecond	wahUGLTimePerSecond
wasKTimePerSecond	mgPechTimePerSecond
srM98TimePerSecond	mgM27TimePerSecond
pMP443TimePerSecond	wahUSGTimePerSecond
srSVDTimePerSecond	caQBZ95BTimePerSecond
srL96TimePerSecond	mgM60TimePerSecond
srMK11TimePerSecond	smUMPTimePerSecond
caHK53TimePerSecond	pM412TimePerSecond
mgRPKTimePerSecond	arFAMASTimePerSecond
pM93RTimePerSecond	pM9TimePerSecond
wLAAIGLTimePerSecond	pG17TimePerSecond
arM416TimePerSecond	pM1911LTimePerSecond
pg18TimePerSecond	arM16TimePerSecond
wLATSMAWTimePerSecond	arAK74TimePerSecond
pM1911TTimePerSecond	pM1911STimePerSecond
smP90TimePerSecond	pg18STimePerSecond
arKHTimePerSecond	srSKSTimePerSecond
srM40TimePerSecond	pTaurTimePerSecond
caA91TimePerSecond	smMP7TimePerSecond

C

SOURCE SURVEYS FOR GAMR MODEL

Table 25: The Analysis of Video Game Uses and Gratifications Instrument formulated by Sherry et al. [69]. L denotes the factor loading of the relevant factor within Sherry's model. Items in **bold** were included in the GAMR model.

Sherry, Analysis of Video Game Uses and Gratifications Instrument, Part 1	**L**
Competition	
It is important to me to be the fastest and most skilled person playing the game.	.81
I like to play to prove to my friends that I am the best.	.79
I get upset when I lose to my friends.	.78
When I lose to someone, I immediately want to play again in an attempt to beat him/her	.72
Challenge	
I find it very rewarding to get to the next level.	.84
I feel proud when I master an aspect of a game.	.70
I enjoy finding new and creative ways to work through video games.	.64
I play until I complete a level or win a game.	.64
Social Interaction	
My friends and I use video games as a reason to get together.	.83
Often, a group of friends and I will spend time playing video games.	.83

Table 26: The Analysis of Video Game Uses and Gratifications Instrument formulated by Sherry et al. [69]. L denotes the factor loading of the relevant factor within Sherry's model. Items in **bold** were included in the GAMR model.

Sherry, Analysis of Video Game Uses and Gratifications Instrument, Part 2	**L**
Diversion	
I play video games when I have other things to do.	.90
I play video games instead of other things I should be doing.	.90
Fantasy	
Video games allow me to pretend I am someone/somewhere else.	.88
I like to do something that I could not normally do in real life through a video game.	.82
I enjoy the excitement of assuming an alter ego in a game.	.78
I play video games because they let me do things I can't do in real life.	.75
Arousal	
I play video games because they excite me.	.83
Video games keep me on the edge of my seat.	.79
I find that playing video games raises my level of adrenaline.	.74
I play video games because they stimulate my emotions.	.69

Table 27: The GAMES Survey formulated by Hilgard et. al [41]. L denotes the factor loading of the relevant factor within Hilgard's model. Items in **bold** were included in the GAMR model.

Hilgard, GAMES Survey, Part 1	**L**
Story	
Video game stories aren't important to me.	-.95
Stories in video games just get in the way.	-.92
I'm excited to find out what happens next in the story.	.84
I mostly play video games for their stories.	.82
Some of my favorite stories are in video games.	.74
I feel emotionally attached to the characters in my favorite games.	.72
I love to learn about the backstories of the characters in video games.	.71
I'm interested in learning the lore or history of video game worlds.	.68
I really do my best to put myself into the main character's shoes.	.67
The feeling of immersion is important to me. (Immersion is feeling like you are really there.)	.60
In video games, it's hard for me to identify with my character.	-.51
It's hard for me to play a game if I can't relate to my character.	.46
Violence Catharsis	
I express my anger in violent video games so I don't act angry in real life.	.94
Playing violent video games helps me be less violent in real life.	.88
Being violent in a game helps me 'get it out of my system.'	.74
Violent games allow me to release negative energy.	.71
I play violent games to act out my anger without really hurting anyone.	.68
I play violent games when I'm angry or upset to avoid arguing with people I know.	.68
Video game violence makes me feel better when I'm frustrated.	.60

Table 28: The GAMES Survey formulated by Hilgard et. al [41]. L denotes the factor loading of the relevant factor within Hilgard's model. Items in **bold** were included in the GAMR model.

Hilgard, GAMES Survey, Part 2	**L**
Violent Reward	
It feels good to shoot or slice parts off of enemies. (e.g., shooting a head off, or cutting an arm off.)	.88
Shooting someone in the head in a game is deeply satisfying.	.80
Video game violence is exciting and rewarding.	.78
I like violence in my video games - the more violent the better.	.71
Sometimes I'll hack up or shoot enemy corpses, just for fun.	.69
Killing things in the game makes me feel powerful.	.54
Social Interaction	
I enjoy playing video games with a group of my buddies.	.87
Often, a group of friends and I will spend time playing video games.	.83
I like playing with a group, online or in the same room.	.80
My friends and I use video games as a reason to get together.	.69
I make more friends by playing video games.	.57
When I play video games, I don't feel connected to the other players.	-.54
Escapism	
Video games allow me to escape from the problems associated with everyday life.	.88
I play video games because it allows me to escape real life.	.83
I play video games to keep my mind off my problems.	.80
I play video games because they let me do things I can't do in real life.	.58
I like to do something that I could not normally do in real life through a video game.	.57
Games calm me down when I'm feeling nervous.	.38

Table 29: The GAMES Survey formulated by Hilgard et. al [41]. L denotes the factor loading of the relevant factor within Hilgard's model. Items in **bold** were included in the GAMR model.

Hilgard, GAMES Survey, Part 3	**L**
Loss-Aversion	
Losing is frustrating and detracts from my experience.	.76
Winning is fun; losing isn't.	.72
Losing a game always makes me mad - what a waste of time!	.66
I get upset when I lose to other players.	.58
It makes me mad if there are consequences when I mess up in a game, like losing points or getting a bad ending.	.57
Even when I lose, I still have fun.	-.56
If I could, I would only play games against weaker players, so I could	.50
Customization	
I really like to customize my character's outfit.	.89
I like to personalize and customize my character.	.88
I'll put considerable time into designing my character's appearance (e.g., clothes, face).	.87
I like making things in video game, like houses or outfits.	.64

Table 30: The GAMES Survey formulated by Hilgard et. al [41]. L denotes the factor loading of the relevant factor within Hilgard's model. Items in **bold** were included in the GAMR model.

Hilgard, GAMES Survey, Part 4	**L**
Grinding/Completion	
I like taking the time to pick up every single collectible item in the game.	.81
I'll play a game until I get a 100% on it, completing everything in the game.	.80
I rarely complete collections of in-game items.	-.78
I will often level up my characters until they reach the level cap (i.e. they can't level up any further).	.60
I'm excited to unlock achievements or earn trophies in games.	.40
I don't mind grinding for an hour or two to get an item I want. (Grinding is doing the same thing over and over).	.32
Autonomy/Exploration	
I prefer games that allow me to play however I want.	.69
I like games that do not put a lot of constraints on the player.	.68
I like having a choice of several different places or levels to try.	.64
I like games that offer you a lot of options and choices.	.64
I like games that offer different ways to get to the next level or area.	.56

Table 31: An Emperical Model of Gaming Motivation formulated by Yee et. al [93]. L denotes the factor loading of the relevant factor within Yee's model. Items in **bold** were included in the GAMR model.

Yee, Emperical Model of Gaming Motivation, Part 1	**L**
Advancement	
How important is it for you to become powerful?	.81
How important is it for you to acquire rare items that most players will never have?	.77
How important is it for you to accumulate resources, items or money?	.69
How important is it for you to level up your character as fast as possible?	.68
How much do you enjoy being part of a serious, raid/loot-oriented guild?	.60
How important is it to you to be well-known in the game?	.53
Mechanics	
How interested are you in the precise numbers and percentages underlying the game mechanics?	.78
How important is it for you to know as much about the game mechanics and rules as possible.	.69
How often do you use a character builder or a template to plan out your character's advancement at an early level?	.67
How important is it to you that your character is as optimized as possible for their profession / role?	.65
Competition	
How much do you enjoy doing things that annoy other players?	.82
How often do you purposefully try to provoke or irritate other players?	.81
How much do you enjoy dominating/killing other players?	.72
How much do you enjoy competing with other players?	.64

Table 32: An Emperical Model of Gaming Motivation formulated by Yee et. al [93]. L denotes the factor loading of the relevant factor within Yee's model. Items in **bold** were included in the GAMR model.

Yee, Emperical Model of Gaming Motivation, Part 2	**L**
Socializing	
How much do you enjoy getting to know other players?	.82
How much do you enjoy chatting with other players?	.77
How much do you enjoy helping other players?	.65
How much do you enjoy being part of a friendly, casual guild?	.63
Relationship	
How often do you talk to your online friends about your personal issues?	.88
How often have your online friends offered you support when you had a real life problem?	.86
How often do you find yourself having meaningful conversations with other players?	.71
Teamwork	
Would you rather be grouped or soloing?	.79
How important is it to you that your character can solo well?	.77
How important is it for you to have a self-sufficient character?	.63
How much do you enjoy working with others in a group?	.60

Table 33: An Emperical Model of Gaming Motivation formulated by Yee et. al [93]. L denotes the factor loading of the relevant factor within Yee's model. Items in **bold** were included in the GAMR model.

Yee, Emperical Model of Gaming Motivation, Part 3	**L**
Discovery	
How much do you enjoy exploring the world just for the sake of exploring it?	.82
Exploring every map or zone in the world.	.80
How much do you enjoy finding quests, NPCs or locations that most people do not know about?	.77
How much do you enjoy collecting distinctive objects or clothing that have no functional value in the game?	.55
Role-Playing	
How often do you role-play your character?	.85
How often do you make up stories and histories for your characters?	.83
How much do you enjoy trying out new roles and personalities with your characters.	.66
How much do you enjoy being immersed in a fantasy world.	.62
Customization	
How important is it to you that your character's armor / outfit matches in color and style?	.81
How important is it to you that your character looks different from other characters?	.80
How much time do you spend customizing your character during character creation?	.73
Escapism	
How important is it to you that the game allows you to escape from the real world?	.83
How often do you play so you can avoid thinking about some of your real-life problems or worries?	.81
How often do you play to relax from the day's work?	.62

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