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Virtual Rival: Optimizing Motivation and Performance in Racing Games

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Affidavit

I declare that I have authored this thesis independently, that I have not used other than the declared sources/resources, and that I have explicitly indicated all material which has been quoted either literally or by content from the sources used. The text document uploaded to TUGRAZonline is identical to the present master's thesis.

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Abstract

Racing simulators attempt to transfer the emotional and physical roller coaster of piloting a vehicle over the racetrack and competing against the best drivers of the world into the living room. Although driving simulators have become very popular in areas besides racing (e.g. teaching, entertainment, automotive development), only a few studies have investigated the behaviour and emotions of drivers. This work has two main contributions: the *Virtual Rival Framework* and the *Virtual Rival Ghost*.

The *Virtual Rival Framework* is an attempt to design a 3D racing simulation that allows to test new concepts that increase and measures driver *Engagement*, *Education* and *Performance*. The main objective of the *Virtual Rival Framework* is to provide a sandbox for researchers and game developers with a focus on psychological and performance evaluation of players. The *Virtual Rival Ghost* is a special virtual competitor for players on the track. To enhance the drivers *Engagement*, *Education* and *Performance* the *Virtual Rival* adjusts automatically to the current skill level of the driver.

The practical work includes the development of the *Virtual Rival Framework* and the *Virtual Rival Ghost*. The development is based on the Unity game engine. The resulting race simulation can be run in different browsers: *Edge*, *Chrome* and *Firefox*. Driving data is stored in the cloud and can be accessed and analysed online. The developed framework integrates all questionnaires needed for the evaluation of the *Virtual Rival Ghost*. A study on *Amazon Mechanical Turk* was conducted to evaluate the framework and to measure the effectiveness of *Virtual Rival Ghost*. The relationships between the *Sensation Seeking* personality measure and risky driving behaviour identified in previous research on real-world drivers were confirmed for virtual drivers. The result indicates: (1) players are not able to estimate their own skill level and (2) racing against a *Virtual Rival* is generally more satisfying in close races.

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Contents

List of Figures

1. Introduction

Racing is about mastering the race track, perfect car control, high-speed decision making and risk taking. Race drivers are constantly working to improve their physical and mental strength (Ebben, 2010). In many racing series, the track testing time is limited. This has led to an increased focus on simulators ("Mercedes-AMG Petronas Motorsport," 2011). Simulators offer a realistic experience to the drivers and data to the engineers. The technology is similar to commercial racing games but the level of detail is no way comparable. Motorsport teams and car manufacturers are constantly pushing their boundaries which leave a lot of room for innovations in the simulation and video game market.

While simulators can be used for driver education, optimize car setups in racing and car development, racing games are only used for entertainment. To combine the educational aspects of driving simulators with the entertainment created by racing games we have developed a universally applicable method to improve *Engagement*, *Education* and *Performance* in racing simulators. We created a prototype that demonstrates the functionality of the developed methods. Our prototype provides a realistic environment for the evaluation of driver performance.

1.1. Goals and Objectives

The barriers between driving simulation and real-world driving are blurring. The tools we use to perform better in racing games may be implemented in future cars. Car manufacturers already develop virtual assists, like racing lines with braking guidance and ghost cars (Rezaei & Klette, 2017). We focus on the improvement of entertainment and performance in educational driving games. Figure 1.1 illustrates the theoretical background of the work. We cross traditional approaches of improving *Engagement* in games with an algorithm to automatically adjust the difficulty of opponents to improve motivation.

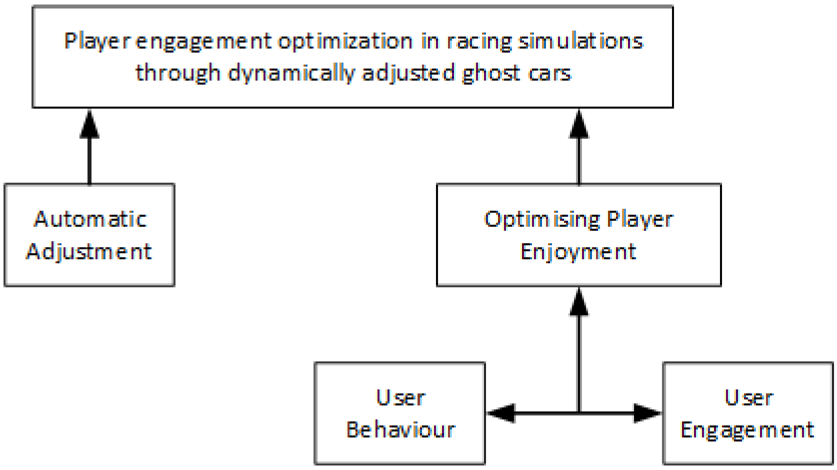


Figure 1.1.: Theoretical basis to optimise racing simulations.

For the creation of our *Virtual Rival*, prototype the game engine Unity has been used. Unity provides tools to design immersive experiences and game worlds, as well as developer tools to implement high-performance game logic (Unity, 2019a). The development of *Virtual Rivals* in Unity includes:

- Research factors that improve *Engagement*, *Education* and *Performance*.
- The implementation of a prototype racing game that supports and motivates drivers.
- The evaluation of the created prototype and psychological effects on the drivers.

The development of *Virtual Rival* should display a first prototype of how to improve racing games and simulators. The created tools can are specially designed to be resource-saving and simple to implement.

1.2. Methodology and Structure

This thesis is divided into three main parts. The first part outlines the theoretical background of the work (see Chapter 2). The second part focuses on the practical approach (see Chapters 3 and 4). The third part addresses the first evaluation of the racing simulation prototype (5). Figure 1.2 gives an overview of the isolated steps of this work.

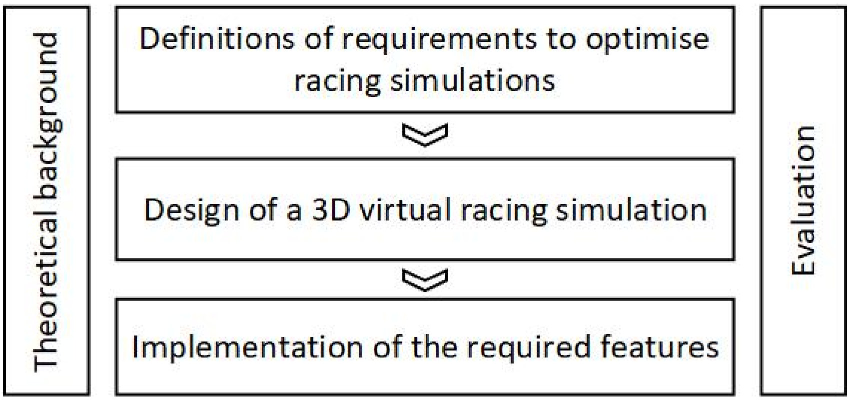


Figure 1.2.: Structure of this work: Theoretical background as a basis for the proceeding of the design and implementation of a optimised racing simulation.

Chapter 2 comprises a literature review on racing games, learning and the various aspects of psychology involved in *Engagement* and *Performance*. First, we discuss the traits of traditional racing games and simulators. After a brief introduction of common psychological models in games, we focus on what creates *Engagement*, *Performance* and a good learning environment in driving. After that, we discuss key game design principles and how they relate to player *Engagement*. Finally, we describe different technologies and algorithms related to *Engagement*, *Education* and *Performance* and how they can be integrated in racing games. Chapter 3 identifies the requirements and lists the different challenges of the *Virtual Rival* design, with a focus on *Engagement*, *Education* and *Performance*. On this basis, *Unity* is subsequently selected as the appropriate platform for building the project. To conclude the chapter, the conceptional architecture and developed tools are outlined. Special attention is paid to the competitive skill adjustment module. Chapter 4 introduces the developed Virtual Rival modules and how they fulfil the defined requirements.

We introduce the specific structure and functionality of each module and how they work together. This chapter should form a good understanding of how a competitive, motivating and exciting racing game can be developed. Chapter 5 describes the preliminary evaluation of the developed *Virtual Rival* driving simulator. We conducted a study to estimate the effect on *Engagement*, *Education* and *Performance*. We outline the procedure, methodology and the tasks for the participants. Furthermore, we present the psychological questionnaires for *Engagement* and *Performance*. In the end, we summarize and discuss the results of the user study. Chapter 7 explains different advancements. Furthermore, we outline different ideas for future development. Chapter 8 sums the results up. We also outline potential outcasts.

2. Background and Related Work

Simulator games attempt to represent the precise reality and offer ways to play inside the recreated reality (Kapell & Elliott, 2013). The challenge in race simulations is to transfer the emotional and physical roller coaster of piloting a vehicle over the racetrack and competing against the best drivers of the world into the living room. In that respect, racing games made a big leap forward in terms of realism, but there is a massive amount of work still needed to deliver the entire racing experience. We focus our research in the area of human factors to monitor driver behaviour and performance. In this project, we developed a model for driver education and entertainment with a focus on improving and measuring performance. Our main objectives are:

- **Engagement**: Create enjoyment and motivation for the players by providing balanced competition.
- **Education**: Improving gameplay using direct feedback.
- **Performance**: Measuring and improving performance.

We want to find an individualized competitive learning approach for racing simulations with limited computational resources. This chapter will give an overview of different aspects of race simulations, ranging from conventional racing simulations over game-based design principles to player psychology. This chapter addresses the challenges of developing a racing simulation with an emphasis on the main objectives: *Engagement*, *Education* and *Performance*. The first section is dedicated to existing racing games and driving simulators and their development over the past decade. The following sections will focus on introducing basic game design principles, concepts to generate entertainment for the players and the building blocks of challenging environments.

2.1. Racing Games and Simulators

> A race isn't won until it's over.
>
> Lauda (2011)

Humans have always been fascinated by speed and competition (Sheen, 2014). One sport which combines both aspects is racing. Race competition has come a long way from the first nomadic horse races around 4500 B.C. in Asia to the international, technology-driven motorsport events today (Crego, 2003). Since the beginnings of video games in the 1970s, racing games have been a popular game type (pinrepair.com, 2017). Car racing is challenging for engineers and drivers, which creates excitement for fans (Togelius & Lucas, 2005). Hugh amount of money and time is invested in engineering race cars, creating events and in developing and playing racing games. This section introduces racing simulators and their applications. First, we analyse existing games to learn how to improve them.

2.1.1. Racing Game Genres

There are various forms of motor racing e.g. stock car, road racing, touring car racing and drag racing. Each genre is unique and needs a different driver skill set (Hassan, 2014). The same can be said about racing games. The three main categories are: *Arcade Racing*, *Simcade Racing* and *Simulators*. In this section, we want to introduce each category, give examples, and examine the main differences.

- **Arcade Racing**
  The arcade genre originates from coin-operated entertainment machines in the 1940s (Grolleman, 2016). Shortly after the first video arcade games appeared Atari innovated the race game format with "Space Race" in 1973 (Wolf, 2008). The arcade game genre does not refer games that originated as arcade machines, but fast-paced action games with very simple gameplay similar to coin-operated arcade games (MobyGames.com, 2019). In arcade racing games, it is all about fun by just accelerating and steering. Towell (2014) defines the main properties of arcade racers:

  - **Limited time:** The race is against the clock as well as other cars
  - **Larger-than-life graphics:** Excessive, unrealistic scenes stimulating the imagination.
  - **Incredible track design:** Race tracks are not based on real locations.
  - **Crashes:** Massive crashes, car damage and destruction.
  - **High score:** Lap time score is supplemented with bonus points for drafting, jumping and causing crashes.

- **Simcade Racing**
  Grolleman (2016) defines simcade racing games: "*Simcade racing games try to hit the sweet spot between fun and realism, between the easy to play arcade games, and the highly technical simulators.*" These games are designed for the masses. The games feature a high degree of realism, with tire management, weight distribution and suspension models, but still endorse gameplay features at the cost of realism (Grolleman, 2016). The founder of Gran Turismo, Kazunori Yamauchi explains his philosophy behind Gran Turismo Sports: "*Current car models are pretty close to the optimum level of modelling you could want in a game. we don't think any higher precision is necessary anymore we are almost there. However, the hardest part isn't creating realistic cars and handling - the Gran Turismo team has 20 years' experience in that. Today's biggest challenge is about creating an entertaining broadcast*" (Sodah, 2018).
- **Simulators**
  The game needs to have a high level of realism to be considered a simulator (MobyGames.com, 2019). Simulators are tools for real racing drivers to learn the tracks and cars for real life racing (MobyGames.com, 2019). Hirsch and Bellavance (2017) showed that driving simulators are an excellent tool to learn driving. For an average person, it's extremely hard to control the car and drive a clean lap. Hyper-real racing simulations are indistinguishable from behind the wheel. Technologies such as three-dimensional laser-scanning, dynamic track conditions and weather effects create an astonishing racing experience (iRacing.com, 2019). The car models look very realistic and are typically laser-scanned. To generate realistic driving dynamics they work with manufacturers, race car constructors or even disassemble vehicles on their own (iRacing.com, 2019).
  Professional simulators are built around motion systems with force feed-

back systems. These systems manipulate the way we perceive our body and our surroundings (Simcraft, 2019). The three main classes in human physiology to generate immersion in simulations are:

- **Proprioceptors**: *Proprioception* is the sensation of body position and movement (Tuthill & Azim, 2018). It's often referred to as 'sixth sense'. The brain generates a feeling where you are in space as external forces act on your body. The simulator can generate a feeling of movement by moving the platform when accelerating, braking or turning.
- **Vestibular System**: The *Vestibular System* is the balancing system of the body (Jones, Jones, Mills, & Gaines, 2009). To stimulate a sense of motion the simulator has to move through all three planes in space e.g. longitudinal, lateral and vertical.
- **Visual Input**: The *Visual Input* is the most basic way to generate immersion. It's important to synchronise all sources of information in motion simulation to avoid motion sickness (Simcraft, 2019).

This section discussed different race game genres and their attributes. All racing games are designed to create *Engagement* but challenge the players in different ways. Table 2.1 shows how racing games can be categorised in terms of realism (Grolleman, 2016). Arcade racing focuses only on fun and has no implication for driver education. Simcade racing provides all mechanism to create an environment for driver education but is mainly used for entertainment. Players have to be incentivised to turn of assisting systems to achieve an educational effect. Simulators have the highest grade of realism. They can be used as a substitution for real-world driving and have numerous applications. In the next section, we focus on racing simulators and how they are used for *Education*.

Table 2.1.: Race game categories based on Grolleman (2016)

	Arcade Racing	**Simcade Racing**	**Simulators**
Focus	Fun	Fun / Realism	Realism
Engine	Simple Physics	Realistic Physics	Realistic Physics
Learning Curve	Flat	Moderate	Steep
Audience	Casual Gamers	Race Game Enthusiast	Professional Race Drivers

2.1.2. Application Scenarios of Simulators

The previous section introduced the main racing genre. Each genre is unique and enables different playstyles. Arcade racing and simcade racing are designed for *Engagement*. This section discusses where simulators are used besides racing and *Engagement* for *Educational* purposes. Driving simulators are a combination of software and hardware to simulate the process of driving. Driving simulators exist for different types of vehicles e.g. cars, motorcycles, trains, trucks and plains. They reduce the cost and allow simulating dangerous and complex scenarios. Training in advanced simulators has been found to have similar training effectiveness than using the real system (Uhr, Felix, Williams, & Krueger, 2019). The increasing complexity of driving systems made simulators popular for a wide range of applications. Driving simulations are used in teaching, entertainment, product engineering, product improvements and research. Important applications are (Carnetsoft, 2019):

- **Driver training**: Simulators are used in driving schools to teach basic driving and driving safety concepts (Vlakveld, 2005). In racing, simulators give drivers extra miles behind the wheel and engineers extra time to find the best car setups (Gitlin, 2018).
- **Research**: Scientific research simulators are used in studies to test the effects of the impairment on driver performance. Researchers can experience how it feels to drive under the influence of alcohol or drugs (Furniere, 2019).
- **Eco drive simulations**: Eco-driving simulation systems are used to train efficient driving to reduce green-house gases (Gardelis, Lalos, & Moustakas, 2018). Direct feedback while driving is a powerful approach to change driving behaviour.
- **Risk management**: Simulators are used in crisis management exercise in the police, ambulance and firefighter training (Carnetsoft, 2019). Training in a simulator helps to practice driving in traffic and the recognition of hazards. Special scenarios offer excellent opportunities to train rare unexpected real-world situations.
- **Entertainment**: Realistic race simulations are a popular video game genre (ESA, 2018). Fans enjoy racing, realism and the diversity of cars and tracks.

- **Car development**: Driving simulators are used in the development process of a vehicle. Engineers can model vehicle dynamics, ride comfort, design and simulate smart assistance systems (Cruden, 2018).

Table 2.2 shows a comparison of professional simulator. We identified three common applications for simulators: racing simulation, driver training and virtual testing. Racing simulators prepare drivers and engineers in a realistic environment. Engineers optimized and tested car setup while drivers increase speed and consistency. The focus is on realistic race cars and optimization. These systems provide the highest immersion for drivers by stimulating motions on a high level. Simulators for driver training simulate a variety of driving situations for research institutions, driving schools and government institutions. The goal is to prepare for real dangerous driving scenarios. The focus is on a natural training environment by matching the décor of the target vehicle. Virtual testing is used by manufacturers to save money by testing early. The simulators implement large worlds and realistic vehicle dynamics to test ADAS systems and autonomous driving.

Table 2.2.: Professional Driving Simulators

Simulator	**Application**	**Method**
SimCraft	Racing simulation	Physics
CXC	Racing simulation	Seat Mover
VRX	Racing simulation	D-BOX
AVL RACING Driving Simulator	Racing simulation	AVL Vehicle Simulation Model
Cruden	Driver training, autonomous driving, vehicle dynamics	Hexapod
rFpro	ADAS, autonomous driving, vehicle dynamic	rFpro workstation
Adiona Safety	In-vehicle driver training: police, driving schools, government agencies	Drive Square Simulation System

This section discussed racing game genres and how they are used. *Arcade Racing* and *Simcade Racing* focus on creating *Engagement* for players. *Simulators* pay particular attention to realism for *Driver Education*. We want to find a way to combine the educational aspects of *Driver Simulators* with the entertainment effects of *Arcade Racers*. The next section explores the psychology of gamers. Understanding what drives gamers helps to improve *Engagement*, *Education* and *Performance* in racing simulations.

2.2. Gamer Psychology

> A wonderful fact to reflect upon, that every human creature is constituted to be that profound secret and mystery to every other.
>
> Dickens (1859)

Asendorpf (2009) defined personality psychology as "*Personality psychology attempts to describe, predict and explain those recurrent behaviours that set an individual apart from some or all other agemates*". The stable tendencies that characterise the personality of an individual are called personality traits (Funder, 1991). On a biological basis, we can define our self as a network of memories in our brains (Fuster, 1997). Joseph (2003) emphasises that memory, experience and our gene history contributes to who we are. Genes and experience can be seen as different ways of doing the same thing. Understanding core personality traits are critical to understanding mental disorders and making effective diagnostic and treatment decisions (Whittle, Allen, Lubman, & Yücel, 2006).

In this chapter, we provide an overview of personality, with a particular focus on the relations between personality and driving. Psychology theory helps to identify how to improve *Engagement*, *Education* and *Performance* in driving games. Persons are different and prefer different play styles in games (Hamari & Tuunanen, 2014). Section 2.2.1 introduces personalities in gaming with a focus on the correlation of personality and *Engagement*. The section 2.2.2 introduces the psychological factors in real-world driving and risk-taking. Risk-taking is a key aspect of *Driving Performance*. Section 2.2.3 emphasises on the physiological aspects of *Motivation* in *Education* with focus on gaming and driving.

2.2.1. Personality Theory in Games

Video games are more widespread than ever. The classic gaming demographic group playing console or computer still exists but smartphones drive the growth

(ISFE, 2017). Popular games go from casual games like Candy Crush[1] to graphically stunning action games like Anthem[2]. Not everyone likes playing video games equally and different people like different genres of games. Research has shown that this relates to one exemplification of an individual: personality Nagle, Wolf, and Riener, 2016. The concept of personality in general aims to explain human behaviour (Ferro, 2018). Researchers found relationships between game genre and personalities (Chory and Goodboy, 2011, Jackson et al., 2012). Tekofsky et al. (2013) found also a significant correlation between personality and playstyle. There is also a link between personality and emotions. Fang and Zhao (2010) showed that choosing the correct video game for a player personality has a significant and positive effect on *Engagement*. It can also lead to better *Performance* (Bauer, Brusso, & Orvis, 2012). This section focuses on the correlations between gamer personality and *Engagement*.

Nagle et al. (2016) suggests that games should be individualized for a player based on their personality, to make games more enjoyable and incentivise players to play for a longer time. Video game publishers are always looking for new ways to sell games. Individualised games could open games for broader audiences. There have been attempts to individualize the game experience. Only a few were successful. van Lankveld, Spronck, van den Herik, and Arntz (2011) attempted to individualize a top-down role-playing game using personal questions, but the test group was only small. Silent Hill: Shattered Memories[3] is the only successful commercial video game we found using psychological profiling. Every action changes your personality score and influences the storyline. The exact mechanism has not been made public. The game had great reviews and the innovative personality profiling system played a big part in its success. Mark Simmons, the director of Silent Hill: Shattered Memories mentioned in this context: "*Certainly a lot of anecdotal evidence from the forums is that families are playing this game together, they're seeing what personality the game is giving each person and how the game's changing differently for each of the family that's played it*" (Kelly, 2010). Game individualisation has a lot of potential for game designers with small resources, especially in domains like casual games and serious games. However, it requires more research into what makes games enjoyable (Nagle et al., 2016). The next sections introduce two personality

[1] facebook.com/candycrushsaga/, 2019.
[2] ea.com/games/anthem, 2019.
[3] konami.com/games/eu/en/products/shsm/, 2010.

measures. Personality measures help to identify what enhances *Engagement* and *Performance* in our project.

Big Five Personality

The game experience is influenced by the gameplay, competitive environment, emotions as discussed in the previous section. The use of gaming offers an engaging alternative to doing ordinary tasks in the fields of health, lifestyle, and education. To fit the applications to the users, game designers and scholars use tools such as personality tests. It is an accepted method of understanding individuals and gaming experiences (Ferro, 2018). The most popular method to categorise personality is the *Big Five.* It was introduced by Goldberg (1993) and further refined during the time. The Big Five theory presents a model in which personality is organized into five factors: extraversion, agreeableness, conscientiousness, neuroticism and openness. Extraversion manifests in an outgoing and energetic behaviour. The trait of agreeableness is a personality characteristic that is perceived as kind and cooperative. The conscientious characteristic implies the desire to do a task well, being careful and efficient. Another personality trade is neuroticism where people tend to be emotionally unstable. They are more likely to feel anger and frustration. The last trade is openness. Open people are more likely to be creative and tolerant. Their curiosity and learning ability positively influences the general knowledge and intelligence.

There are multiple instruments to estimate the *Big Five* personality traits. Most take about five minutes or more. Rammstedt and John (2007) developed a shorter version for tasks with limited assessment time. The shorter version has proven to be very effective in research settings.

- **Big Five and Gaming**
  The *Big Five* personality traits are observable across ages, genders, and cultures. There is a significant correlation between personality and video games. By observing the personality traits of gamers, Braun, Stopfer, Müller, Beutel, and Egloff (2016) found a connection to their favourite game genres. For example, participants who preferred action games had high extraversion and low neuroticism. Their findings expand to health

care since challenging personality trades are an indicator of gaming addictions. Regular gamers had low neuroticism. The study shows the importance of differentiate between gamers and understanding their personalities. In terms of competition, studies have shown a relationship between athletes and personality. Wilson and Dishman (2015) found a significant relationship between physical activity and the traits extraversion, neuroticism, conscientiousness, and openness. These findings are in line with Nia and Besharat (2010). Sport as a collection of systematic behaviours generally requires high scores of extraversion and conscientiousness and relatively low scores of neuroticism. In particular positive emotions like happiness, liveliness, optimism, high level of energy prepares the individual for involvement in sports activities. The creativity indicated by a positive openness score can also help. On the other hand, negative emotions like fear, worry, hastiness, anger, and guilt compromise athletes.

- **Big Five and Driving**
  The driving performance for professional drivers can also be correlated with *Big Five* personality traits. A study on truck drivers showed that conscientiousness correlates with lower mean speed (Linkov, Zaoral, Řezáč, & Pai, 2019). Extraversion relates to driving more on the right sight, giving more overtaking opportunities. Riendeau, Stinchcombe, Weaver, and Bédard (2018) provides further support for the link between personality factors and driving performance. The result indicates that extraversion and neuroticism were significantly associated with driving simulator performance. Persons with high scores of extraversion engaged in a significantly more unsafe driving manoeuvre in a safe environment (e.g. simulated drives). Neuroticism shows in decrease cognitive and performance capacities. This leads to more driving errors. Persons with high neuroticism are vulnerable to stress, lacking in confidence, moody, and easily frustrated. The results also show the importance of conscientiousness towards safe driving. Cautious individuals have significantly fewer crashes. A study of 100.000 accidents showed that extraversion had a positive relation to the amount of traffic fatalities (Lajunen, 2001). Countries with high extraversion scores have more traffic accidents. Apart from that neuroticism correlated negatively with accidents but to a smaller degree. Based on the study result shown above, we expect to find positive associations between driver skill and extraversion and conscientiousness, and a negative

association with neuroticism.

Sensation Seeking

The *Big Five* (See section 2.2.1) is a good indicator of emotions and can be connected to driving behaviour and traffic accidents. Another personality characteristic studied in connection with driving is *Sensation Seeking*. *Sensation Seeking* can be described as a behavioural and social dimension of personality expressed in the generalized tendency to seek novel sensations and experiences and the willingness to take risks for the sake of such experiences (Zuckerman, 2014). Zuckerman also created an instrument for measuring *Sensation Seeking*. The instrument has been well tested and refined for different applications. It has been translated into many languages and works for all ethnicities and age groups. It consists of a self-report questionnaire where the questions are split into four groups. The four factors are *Thrill and Adventure Seeking*, *Disinhibition*, *Experience Seeking*, *Boredom Susceptibility*. For each group, Zuckerman selected 10 questions. Hoyle, Stephenson, Palmgreen, Lorch, and Donohew (2002) introduced a short version the *Brief Sensation Seeking Scale* (*BSSS*) with 2 questions. The evaluation of the questions generates a number for each group. Added together they form the *Sensation Seeking Score*.

- **Sensation Seeking and Gaming**
  Research into online gaming has steadily increased over the last decade. Especially the negative impact of online games has received a lot of attention (Wan & Chiou, 2006). Overuse of computer and internet can lead to addiction with consequences such as failing school, family, and relationship problems (Ng & Wiemer-Hastings, 2005). Mehroof and Griffiths (2010) showed a relationship between *Sensation Seeking* and gaming addiction. Aggressive gameplay is particularly dangerous for players with the *Sensation Seeking* trait. It is very pleasing for those players and can lead to excessive play (Mehroof & Griffiths, 2010). Joireman, Fick, and Anderson (2002) showed that gaming can serve as an exciting opportunity for experiencing relatively novel experiences and demonstrating dominance, which correlates with the *Sensation Seeking* personality trait. There research also indicated that winning close games is correlated with high *Sensation Seeking* scores. This is consistent with Mazur and Booth

(1998), which found a high testosterone level when winning.

- **Sensation Seeking and Driving**
  The *BSSS* significantly predicts intention to and actual engagement in a number of health risk behaviours. It is especially popular in substance abuse research. X. Chen et al. (2013) found correlations alcohol consumption, cigarette smoking, and sexual risk behaviours. The sensation seeking trait can also be found in risky driving activities. When analysing the driving performance of professional truck drivers, Linkov et al. (2019) found a correlation between *BSSS* higher mean speed and more risky driving manoeuvres. A study on Chinese motorcyclists showed that sensation seekers are more likely to present risky motor vehicle behaviours besides speeding e.g. operating after drinking, using a mobile phone while operating, and receiving a traffic ticket (Fan et al., 2014). This instrument is already used to create future prevention strategies for road accidents. Therefore are more likely to be involved in traffic accidents. The biology basis of *Sensation Seeking* is another area of research. Lukas (1987) found that the brain responds to augmented reality sensory stimulation determines how people respond behaviourally to intense sensations. Analysing *Sensation Seeking* together with blood samples showed that sex hormones are also related. The result shows that high testosterone levels correlate with a high *Sensation Seeking* score (Daitzman, Zuckerman, Sammelwitz, & Ganjam, 1978).

Personality has a huge impact on risk-taking. Both *Sensation Seeking* and *Big Five* personality show a strong correlation towards risk-taking. Risk-taking is an important factor in racing and *Performance*. The next section analyses risk-related symptoms in driving for *Driver Education*.

2.2.2. Driving and Risk-Taking

Racing games are different from other games driving is a big part of the day-today life. Driving is a safety critical task. According to the U.S. Census Bureau (McKenzie, 2015), 86% of all workers commuted to work by private vehicle. Given the amount of time spend with driving, it‘s important to consider all the risks. Section 2.2.1 analysed gamer personalities and revealed a clear correlation between the Sensation Seeking personality trait and risk-taking. Driving is a safety critical task and taking risks can lead to accidents. This section discusses risk-taking as part of driving. Taking the right amount of risks reduces driving errors and increases *Performance*.

Real World Driver Safety

Traffic injuries have become a major health problem. To protect all road users we need to design safer vehicles, roads and infrastructure (WHO, 2009). Great efforts have already been made to improve vehicles and safety equipment. Crash analysis data shows a reduction of traffic accidents in recent years (Statistics-Austria, 2016). Driving assistance systems focus on the major causes of crashes. Unintentional lane departure is responsible for about 40% of crashes in Europe. Navarro, Mars, and Young (2011) showed that Lateral Control Assistance reduces the number of loss of control accidents by 25%. Advanced driver assistance systems reduce the risks and improve the driving experience. They are a vital part of modern cars, motorcycles and trucks. German-Insurers-Accident-Research (2016) found that the theoretical safety potential ranges from 2% for simple blind spot detection systems up to 45% for Emergency Break Assistance Systems. The advanced driver assistance system is a fast-growing sector. The market is expected to reach USD 67.43 billion by 2025 (Research, 2018). In order to realise an intelligent transportation system researchers focus on inter-vehicle communication and smart roads (Nadeem, Dashtinezhad, Liao, & Iftode, 2004). Trending research questions are safe driving, dynamic route scheduling, emergency message dissemination and traffic condition monitoring.

Risk Groups and Driver Education

Despite all efforts in assistance systems, statistics indicate two high-risk groups in young, inexperienced drivers and elderly drivers above 65 years. Young drivers have only a little experience in complicated situations. Clarke, Ward, and Truman (2005) found that young drivers have a tendency to take higher risks. Driving is a fun and exciting way of testing limits. It is important that young drivers are confronted with high-risk situations in a safe way. Tada et al. (2014) investigated elderly driver behaviour. They demonstrated a lack of scanning behaviour to identify possible threads. Safe driving skill can be identified by the drivers head motion and pedal operation. It‘s important to provide personal training programs based on the shortcomings of a driver. Fischer, Kubitzki, Guter, and Frey (2007) showed that playing violence encouraging racing games increases risk-taking behaviour in critical road traffic situations. Playing and watching reckless driver causes risk-related symptoms including blood pressure, risk-related cognitions and emotions (Fischer et al., 2007). The study found that nonviolent race games (e.g. F1[4], Gran Turismo Sport[5], Project Cars[6]) arouse greater self-perception and a more positive driver attitude.

In this section, we displayed that simulators are an effective tool for driver education. It's important to identify risk groups and provide personalised learning approaches. Driving simulators have been found to improve car control, self-perception and driving attitude. The next section discusses ways to improve the educational effects by increasing the *Motivation* in driving simulators.

2.2.3. Learning and Motivation

The key to successful learning is motivation. Prensky (2003) emphasised in this context: “*A motivated learner can't be stopped.*” Unfortunately, more often than not the content that needs to be learned is not motivating. Teachers and trainers struggle to motivate students. For today's generation of digital natives, traditional teaching techniques are no longer suitable. Computers, Smartphones and the Internet are an integral part of their life. Prensky (2001) proposes that the brains of digital natives are physically different: “*It is now clear that as a result of this ubiquitous environment and the sheer volume of their interaction with it, today's students think and process information fundamentally differently from their predecessors.*” Educational games integrate learning in games to increase motivation and make learning an enjoyable experience.

The better a player performs, the more one enjoys the game. A special form of motivation is social collaboration or competition. Social motives operate within a context where there is interdependence between own and other's outcomes

[4]formula1game.com, 2019.
[5]gran-turismo.com, 2019.
[6]projectcarsgame.com, 2019.

and strategies (McClintock, 1972). People can be distinguished with regard to their social value orientation e.g. preference about how to allocate resources (Vorderer, Hartmann, & Klimmt, 2003). The next section examines how video game developers use competitive and cooperative environments to increase the *Engagement* felt by computer game players.

Cooperative Motivation

It's well known that groups of people can solve problems and make decisions that none of their members could do alone (Fraidin, 2004, Laughlin and Ellis, 1986). Group work can also improve the motivation and *Performance* of individual members (Hertel, Kerr, and Messe, 2000, Tindale and Larson, 1992). Working in groups requires coordination. The task of coordination can decrease productivity. Lampridis (2000) found that the loss depends on the characteristics of the group members and the size of the group. A mixed-sex group introduces more motivation than same-sex groups or individuals (Kerr & Sullaway, 1983). There are multiple studies which reported group motivation gains under different conditions:

1. **Cover Up:** Co-workers cover up for poor performances of individuals in important tasks (Williams & Karau, 1991)
2. **Audience:** Performing in front of an audience can facilitate the performance (Zajonc, 1965)
3. **Difficult Goals:** Setting difficult goals makes groups work harder than individuals (Matsui, Kakuyama, & Onglatco, 1987)
4. **Physical Tasks:** People performing physical persistence task perform better when working together (Hertel et al., 2000)

For most tasks, group work does not increase performance (Hertel et al., 2000). Another downside of cooperation is that it can restrict creativity (Diehl & Stroebe, 1987). The three major problems in groups with low productivity are:

1. **Production Blocking:** Individuals inhibit the ideas of others (Diehl & Stroebe, 1991)
2. **Evaluation Apprehension:** Fear of negative evaluations prevents more original ideas (Collaros & Anderson, 1969)

3. **Free Riding:** Lesser effectiveness and identifiability of individual contributions decreases the performance of some individuals (Stroebe & Frey, 1982)

Jackson et al. (2012) found that playing videogames is associated with greater creativity. The type of videogame (e.g., violent, interpersonal) was unrelated to the effects on creativity. The next section investigates the relationship between video games and cooperative motivation in detail.

Cooperative Motivation in Video Games
In terms of motivation, playing video games together beats playing alone. Inkpen, Booth, Klawe, and Upitis (1995) found that children playing together in a cooperative setting were more successful. In addition, the level of motivation to continue playing was higher. The desire to continue working well with other people is one of the reasons cooperative games are successful (Ewoldsen et al., 2012). Even in the era before online gaming, people would meet with their friends, or visit LAN-Events to play face to face. Jansz and Martens (2003) analysed that people at LAN-Events are motivated by social contact. Today, cooperation based games are very successful. The most popular cooperation based games on the gaming platform steam (Steam250, 2019) are:

1. Portal 2 [*Puzzle*]
2. Terraria [*Sandbox*]
3. Factorio [*Base Building*]
4. Left 4 Dead 2 [*Zombies*]
5. The Binding of Isaac: Rebirth [*RPG*]

Commercial cooperative games are limited to specific genres. Most games in that list are building or survival games. They have an only trivial story. These games generate engagement and challenge using a balance between construction, survival and cooperation. Researchers have noticed a highly motivating effect of cooperation in educational games and exergames. Jong, Lai, Hsia, Lin, and Lu (2013) analysed a cooperative online learning game for students. They found an amplified desire to win the game, which motivates students to learn from online course materials before they play. Cooperative exergames produced higher intrinsic motivation and related to higher energy expenditure (Staiano, Abraham, & Calvert, 2012). Cooperative play is a promising method for engaging overweight youth and improving teaching.

Competitive Motivation

A widespread social phenomenon is a rivalry. It is closely connected to the competition. A rivalry is a broader culture pattern going beyond our hunting instinct, aggression and the need to excel in sports (Sipes, 1973). In traditional sports, excellence is the quality of being outstanding in relation to others. Many people believe that doing well means doing better than other people (Stanne, Johnson, & Johnson, 1999). It's the essence, which drives elite persons in sport, science and economy. Proponents argue that competition brings out the best in a person. According to one of the all-time greatest coaches Vince Lombardi, "Winning is not everything, but wanting to win is". The downside is that people with no chance of winning can experience a lack of motivation. A rivalry is the combination of a relationship and history between competitors. Kilduff (2014) showed that rivalry motivates and boosts the performance independent of the stakes. He also defined three important factors which can cause rivalry. First, similar competitors increase social comparison. People are naturally driven towards self-evaluation and the comparison with other persons (Festinger, 1954). Second, the level of competitiveness can increase when facing the same opponent multiple times. Finally, evenly matched games, when narrowly decided, result in greater emotional responses. Kilduff (2014) evaluated that rivalry can improve motivation and performance. The results indicate that the odds of victory are more important than previous results. In some situations, motivation can transform into a desire to win. In this state, the person maximizes relative pay-outs at all costs. Bazerman, Loewenstein, Blount White, and Blount (1992) evaluated that people display more apprehension for personal profit than overall profit. The desire to win has a high impact on the decision-making process. It diminishes concerns and increases the aggregation with the focus on beating the opponent (Malhotra, 2010).

Competitive Motivation in Video Games

Interacting with other players can make the game more exciting. Researchers have mixed opinions if competition also increases motivation.

Kohn (1986) makes a case that competition almost never increases performance. In contrast, Chang, Yang, and Yu (2003), argues that a competitive environment not only motivates winners and losers but also that players prefer playing against competitive opponents. There is also danger in having competitors. Competition can cause a lack of confidence, interest and efficiency when not handled correctly. Pedro Munoz-Merino, Molina, Munoz-Organero, and Kloos (2014) found that the negative effects can be mitigated when the challenge is modified for the individual person. The study indicated a strong motivation effect when players with equal skill level are matched. The woman had a slightly worse perception of their own motivation than men. Similar effects are shown in competitive learning systems (Regueras et al., 2009). A study of Ravaja et al. (2006) found that the nature of the opponent also influences emotional responses and the perception of the challenge. The presence of a stranger increases attention. Additionally, playing against a friend results in higher arousal. The positive impact of playing with other people in video games can be measured with Electromyography (EMG). (Ravaja2004) found that playing against a friend increased positive and decreased negative emotional responses.

Observation 1: Competitive Motivation for Race Simulations

The desire to win is a powerful motivation boost. The effect is hard to measure. Good indicators are the presence of rivalry and time pressure. Both are presents in real-life racing competitions and racing games.

Collaboration and competition can also be combined. Bruno Silva proposed a mixture of collaboration and competition as a rich learning environment. The learning system works in a tournament system. The students are divided into groups and work in a tournament system with elimination rounds. Therefore, groups do not play the same amount of rounds or make the same amount of tasks. The combined approach supports teaching and learning activities. This section emphasised that both competition and collaboration can have a positive impact on motivation. Research suggests that collaboration and competition can be used in racing simulations to boost *Motivation*. To find the best method we need *Motivation* metrics. The next section introduces tools to measure *Motivation*.

Measuring Motivation

To improve and measure the performance of a player we have also have to understand emotions and cognition. Overlaps between cognition, motivation, and emotion make it difficult to separate and distinguish their respective territories (Lazarus, 1991). Emotions have an important role in the determination of behaviour (Ravaja et al., 2006). Most theories agree on three major aspects of emotion: subjective experience, expressive behaviour and the physiological component (Scherer, 1993). The subjective experience is the "feeling" part of the emotion. Expressive behaviour covers the body signals which are related to the experienced emotion. The physiological component is the response of the body to an emotion e.g. releasing hormones.

Effective methods to measure emotional arousal are heart rate monitors and electrodermal activity sensors. Scherer (2005) introduced the Geneva Emotion Wheel (GEW) to measure emotions. It's a simple method realised with paper and pencil or a computer program. The *GEW* is an instrument that evaluates emotion qualities and intensity of the feeling. Smith and Ellsworth (1985) measured the properties of emotions. We state only the relevant emotions for gamers:

- *Pride:* A extremely pleasant state. Persons are filled with pride when receiving personal achievements, awards or winning in general.
- *Happiness:* In disparity personal achievements are not associated with happiness. Most persons relate happiness with spending time with friends or relatives.
- *Interest:* Pleasant state supported by desire and little control over the situation.
- *Challenge:* Is similar to interest but with total control over the situation. The most challenging experience is when the desired goal takes a lot of effort but is still reachable.
- *Surprise:* Appears in unexpected situations gotten with little effort.
- *Boredom:* The experience of boredom comes with low effort and low attention. It appears when the mind is not challenged.
- *Anger:* Comes in unfair situations.
- *Frustration:* When success is expected, failure is often accompanied by frustration.

GEW can be integrated into racing games to analyse players emotions. The most impactful variables are challenge and certainty in both positive and negative experiences. Racing simulations have to control the challenge and the certainty of the situation to optimize *Engagement* and *Performance*. The next section introduces game design guidelines to meet the specific requirements for *Engagement*, *Education* and *Performance* discussed in this chapter.

2.3. Game Design

> Gamers are everywhere coming in all ages and genders, and developers have grown up, too.
>
> Spector (2013)

Video games are everywhere. Theesa.com[7] reports that about 60% of Americans play video games daily. The same report states that the U.S. game industry made $43.4 billion in revenue in 2018, matching the U.S. film industry for the first time. Creating an enjoyable and profitable video game is a challenging task and requires a multitude of skills. Video game development teams include software developers, artists, musicians, writers and many other (Drew & Dennis, 2011). Video game developers have to adopt a set of good practises for creating the best experiences for the players, handle complex development tasks and achieve profitability. This chapter introduces universal design principles to ensure *Engagement*. They assist with the integration of competitive motivation (see Section 2.2.3) and the implementation of the features discussed in Section 2.2.3. The next section discusses the general development process. Section 2.3.2 discusses principles to improve *Engagement* in games. Section 2.3.3 introduces principles to assimilate and optimize games to fit the player.

Many of the software practices come from traditional software engineering. Researchers have developed additional guidelines to deal with the complex game development specific requirements (Aleem, Capretz, & Ahmed, 2016). Figure 2.1 illustrates the stages of the game study development process. The main stages are: *Idea*, *Preperation*, *Development* and *Study*.

1. **Idea**
   The game development process always starts with an idea. The ideas can originate from a single person or a whole team (Dörner, Göbel, Effelsberg, & Wiemeyer, 2016). Common idea generation methods are brainstorming and idea sketchbooks. The central vision of the game should never be lost. Rogers (2014) emphasized in this context: "*Gamers can feel when developers are passionate about their games. They can smell it like a dog*

[7] ESA, 2018.

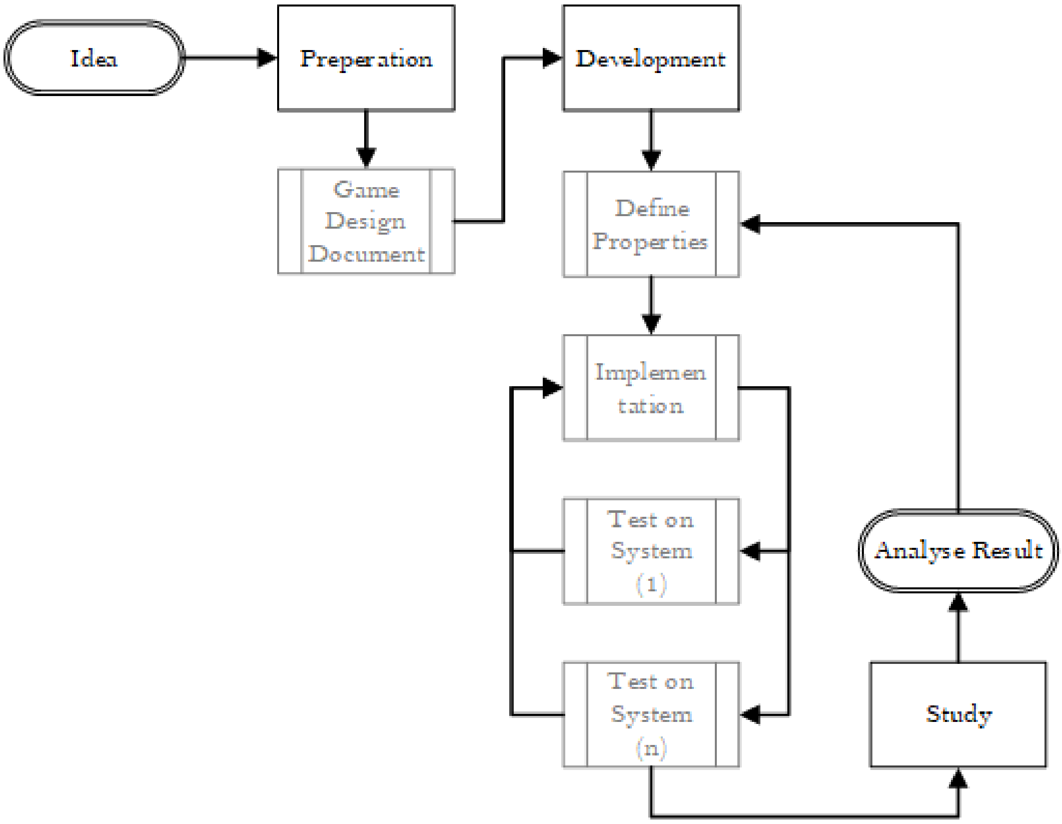


Figure 2.1.: Game study development process based on Dörner, Göbel, Effelsberg, and Wiemeyer, 2016.

smells fear. Don't be afraid to hold onto your unique vision: just be aware that it may not turn out exactly how you envisioned."

2. **Preparation**
   The preparation phase focuses on planning the project, having a clear concept, set up the team and financing. The result is a design document with all design decisions and organisational conditions. Every subsequent step extends the design document.
3. **Development**
   The development phases consist of iterative implementation and testing cycles. The focus is on agile software development to deal with the cross-functional teams and rapidly respond to bugs. As illustrated in the Figure 2.2, the testing process is an iterative process itself between testers and developers. Testers report bugs back to the developers, who fix them and release a new build, which the testers check again and so on (Chopra, 2009). Every build has to be checked for all supported systems to detect errors early.

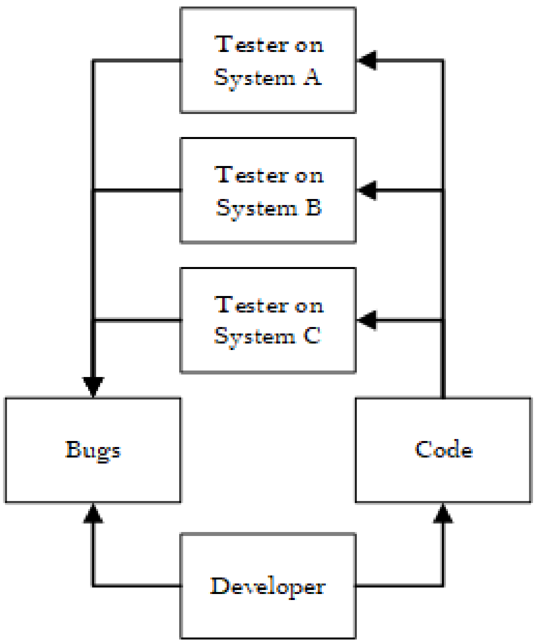


Figure 2.2.: Iterative testing process for multiple systems based on Chopra, 2009.

4. **Study**

In the last phase of the development process contains running a study and analysing the result. While in traditional game development the final deployment stage also includes maintenance, the study should not be changed (Moore & Novak, 2009).

2.3.1. Game Design Principles

A core task in game design is creating a positive player experience. Making a game is a very complex process. Only a few games are excellent and profitable (Bethke, 2003). The developers have to model extensive functionality while maintaining usability and optimizing player experience. Game genres provide very different experiences, but there are some common fundamental design features. Looking at different game design principles can inspire and help to identify problems. Despain (2012) collected 100 widespread principles of game design. The principles can be classified into four universal categories:

- **Game Innovation:** Idea creation, Brainstorming, Analyse existing games
- **Game Creation:** Software design, Artistic guidelines
- **Game Balancing:** Level design, Skill adjustment, Assistance systems
- **Troubleshooting:** Bug fixing, Find vulnerabilities

Out of the large number of principles we want to find the key principles, which can take a game from good to great. In Table 2.3, we compare independent articles which rank game design principles and assign the principles to the universal categories. We classify most mentioned principles as central and universally applicable.

- **Central Game Innovation Principles**
  The most mentioned innovation principle is to understand the domain. This includes everything from documentation to gameplay and balancing. It can also help to investigate similar games and analyse what works for them.

- **Central Game Creation Principles**
  The most mentioned creational principle is rewarding the player. Reward systems are important player motivators. Koster and Wright (2004) found that people like learning but lean towards laziness. Cheung, Zimmermann,

Table 2.3.: Comparison of four game design pattern rankings (gamedesigning.org, 2018, Santos, 2018, Stillman, 2019, Academy, 2019)

Universal Principles	**gamedesigning.org**	**nyfa.edu**	**thedesigngym.com**	**binpress.com**
Game Innovation	Understanding the Domain		Thinking up first	
Game Creation	Reward the player	More rewards than punishments	Balancing rewards	Feeling of accomplishments
	Build around a core mechanic	Start with a core mechanic	Clear objective and success criteria's	Introduce new objectives isolated
Game Balancing	Easy to learn, fun to master	Easy to learn, hard to master		Teach without teaching
Troubleshooting				

Notes: The principles provided in the table are based on the highest ranked principles of each site. Each principle is assigned to one of the four universal principles defined by Despain (2012).

and Nagappan (2014) found that momentary enjoyment is less valuable than intriguing and engagement. Balanced rewards incentivise players to keep playing.
Another vital principle is to build around core game mechanics. Game mechanics create gameplay and are the key to a great game (Adams & Dormans, 2012). Core mechanics are the most influential aspects of a game; they influence almost all moving objects (e.g. strength of gravity in a platform game). The Table 2.4 shows core game metrics and non-core metrics for different game genres. For race simulations, the focus is on realistic and detailed physics.

- **Central Game Balance Principles**
  The central game balance principle is "Teach Without Teaching". Even in complex games, the users should be able to learn the game as they play it. Learning curves come in different shapes but must match the skills of the target audience in order to avoid frustration (Nacke, 2011).
  A central factor for basically all software applications which is not mentioned in the Table 2.3 is the ease of use (Pagulayan, Keeker, Wixon, Romero, & Fuller, 2003). This includes controls and interfaces for video games. Challenge is a critical factor in the enjoyment of a game. It must be adapted to every individual player for the best results.

Table 2.4.: Core Game Mechanics based on Adams and Dormans (2012)

	Physics	Economy	Progression	Tactical Manoeuvring	Social Interaction
Action	**Detailed physics for movement, shooting etc.**	Power-ups, Health	Storyline		
Strategy	Detailed physics for movement and fighting.	**Unit building,** resource harvesting	Scenarios New challenges	**Positioning of units**	Competition between players
Role Playing	Detailed physics for movement and fighting.	**Character equipment**	**Storyline**	Party tactics	Play-acting
Sports	**Detailed simulation**	Team management	Seasons, Tournaments	Team tactics	
Vehicle simulation	**Detailed simulation**	Vehicle upgrades	Seasons, Tournaments		
Management simulation		**Management of resources**	Scenarios, New challenges	Management of resources	Coordinated actions, Competition
Adventure		Inventory management	**Storyline**		
Puzzle	**Physics to create challenges**		Short levels with increasing difficulty		
Social games		**Resource harvesting**	Quest, Challenges		**Resource exchange, Cooperation**

Notes: Core mechanics are emphasized in boldface.

- **Central Game Troubleshooting Principles**
  An important troubleshooting metric is pacing. It is the rate in which players go through new challenges. Playtest can show if there is a problem with pacing (Despain, 2012). Designers at Microsoft have their own version of ”Powers of Ten” (Eames & Eames, 1977). One of the most famous short films ever made. The game must keep the user’s attention at 10 seconds, 10 minutes, 10 hours and 100 hours. It is important to give players a great experience at these critical junctions. The first hour is of special importance (P. Davis, Steury, & Pagulayan, 2005). It is the entry point into the main experience of the game and vital time in the learning process.

This section introduced universal game design principles. The gameplay should be built around core mechanics depending on the genre to ensure *Engagement*. The core mechanics for racing simulations are realistic and detailed physics. Furthermore, a well-adjusted challenge is a critical factor to improve *Engagement*. The next section discusses the physiological background of *Engagement* in games and universal concepts to maximize the benefits of video games.

2.3.2. Engagement in Games

The last section introduced how games should be built around core mechanics to ensure *Engagement* for players. This section further examines the physiological background of *Engagement* in games and the implications on *Education* and *Performance*. Understanding human nature and understanding emotions have been a central research topic for a long time (Marcus, 2003). Plato examined how emotion influences human decision making: “Human behaviour flows from three main sources: desire, emotion, and knowledge” (“Plato Quotes,” 2019). Studying emotions in games is a popular research topic. Most of the research concentrates on the negative effects of gaming (Granic, Lobel, & Engels, 2014). Brunborg, Mentzoni, and Frøyland (2014) showed that video game addiction is associated with depression, decreased academic achievement, and conduct problems. Game developers are looking at the psychological side of enjoyment and happiness, to extract features that generate entertainment for the player. Granic et al. (2014) discusses a multitude of benefits in different areas. Figure 2.3

illustrates the different areas. The following section introduces each benefit in detail.

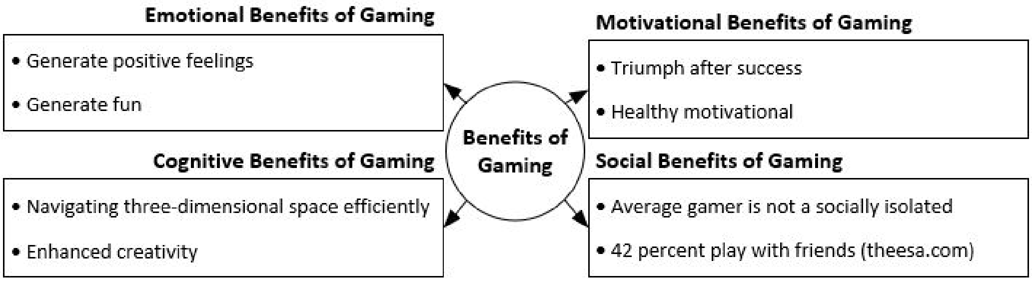


Figure 2.3.: Benefits of Gaming

- **Cognitive Benefits**
  Action games provide mostly cognitive benefits. Green and Bavelier (2012) showed that gaming enhances learning and attentional control. The spatial skills learned in games are also useful in science, technology, engineering, and mathematics (Uttal et al., 2013). Bavelier, Achtman, Mani, and Föcker (2012) used brain imaging to compare attentional network recruitment and distractor processing. They found that gamers have developed more efficient resource management and the ability to filter out irrelevant information more effectively. One of the biggest cognitive benefits is the enhancement of creativity. Independent of the video game type, gender or race-ethnicity, gaming facilitates creative thinking (Jackson et al., 2012).

- **Social Benefits**
  Gaming has become a social experience. Over 97% of teens ages 12-17 play video games and only a quarter plays alone (Lenhart et al., 2008). Farmville[8] one of the most popular social games on Facebook[9] had 40 million active users every month in 2012 (Sarkar, 2013). Social gaming opens a new dimension for the developers, like the addition of special events features. In 2019 over 10.7 million people attended the virtual

[8]zynga.com, 2019.
[9]facebook.com, 2019.

concert of the US-DJ Marshmello[10] in Fortnite[11] (Webster, 2019). Ferguson and Garza (2011) found that playing action games is associated with small increased civic engagement in the real world. In particular the ability to organize groups and lead like-minded people in social causes. Games with civic learning opportunities (e.g. helping others) raise the interest in politics and charities (Lenhart et al., 2008).

- **Emotional Benefits**
  People use diverse forms of media like video games to escape from routines or for emotional release (Ruggiero, 2000). Enjoyment goes beyond the feeling of pleasure. It is characterised by achieving something unexpected and special. In games, we want to create enjoyment, the deep involvement that removes the frustrations of everyday life and makes hours pass like minutes. Several studies have shown that playing video games generate positive feelings (Ryan, Rigby, and Przybylski, 2006, Russoniello, O'Brien, and M Parks, 2009). Csikszentmihalyi (1991) defines the major building blocks for enjoyment. Some important components are:
  - Clear goals
  - Reasonable chance of completion
  - Immediate feedback
  - Control over the actions
- **Motivational Benefits**
  Granic et al. (2014) describes the motivational power of game designers: "*Game designers are wizards of engagement. They have mastered the art of pulling people of all ages into virtual environments, having them work toward meaningful goals, persevere in the face of multiple failures, and celebrate the rare moments of triumph after successfully completing challenging tasks.*" Csikszentmihalyi (1991) describes the most important features of motivating activities. The feeling of pleasure is essentially a feeling of contentment when a personal or social expectation has been met. Sweetser and Wyeth (2005) found that in order to get the optimal conditions for motivation you have to balance the level of challenge. Malone (1980) analysed the theoretical principles of a challenging environment. For an environment to be challenging it needs uncertain goal

[10] marshmellomusic.com, 2019.
[11] epicgames.com, 2019.

attainment. There are at least four ways to create uncertain goals in video games: variable difficulty level, multiple level goals, hidden information and randomness. G. Yannakakis and Hallam (2005) follows the principles to make predator/prey games more interesting. The criteria for the best predator/prey opponents are:

- Balanced (neither too hard nor too easy)
- Diverse behaviour (strategy is not predictable)
- Aggressive behaviour (rather than static)

This section discussed the benefits of gaming and how to generate them. To generate *Engagement* the game has to integrate clear goals, balanced competition and fast feedback. The player should always feel in total control over the situation. To create *Motivation* the competitive elements should unpredictable and aggressive. Additional to the positive effect of balanced competition on *Engagement*, discussed in Section 2.3.1, it also raises *Motivation*. The next section discusses how to individualise the universal principles to specific player preferences.

Observation 2: Optimize Benefits for Race Simulations

In race simulations, the environment is mostly set. Nowadays, race tracks are laser scanned to create venues from around the world. The scanning technology records every pothole and comes extremely close to reality. It has become common practice to collaborate with car manufacturers to translate car designs and driving characteristics into the game. When all put together including weather, day-and-night transitions and natural vegetation game developer are able to create "living" tracks. The environment already reflects very well the authenticity and beauty of motorsport, but to further improve the Engagement *we can refine the gameplay. Applying the recommendation from Csikszentmihalyi (1991) to racing games results in an emphasis on clear objectives, rapid feedback on sector times and having a well-adjusted chance of winning a race.*

2.3.3. Incorporate Player Preferences

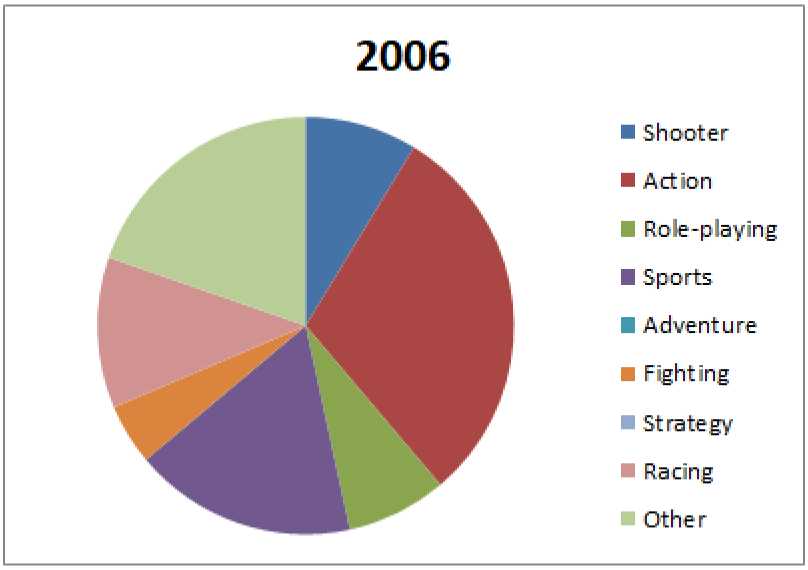
One of the central game design principles discussed in Section 2.3.1 is to understand the domain first. In this section, we examine the player base of racing simulations and how to adapt and innovate new functionality suited for the racing simulation community. In today's competitive market, developing new products that satisfy consumers' needs and preferences is a very important issue (Dagher & Petiot, 2007). Research in marketing on product positioning and product design suggests that a firm should optimize its goals with respect to product attributes and then translate these attributes into marketing (Kaul & Rao, 1995). Player preferences in video games are most commonly expressed in terms of genre (Klevjer & Hovden, 2017). Every year the Entertainment Software Association (ESA, 2018) conducted a customer survey in American households and listed the bestselling genres. Figure 2.6 illustrates how the best selling genres evolved over the years. Video game developers have a tradition of innovation and variation of games (Arsenault, 2009). New technologies and technical improvements are fuel for video game innovation.

Observation 3: Innovation in Race Simulations

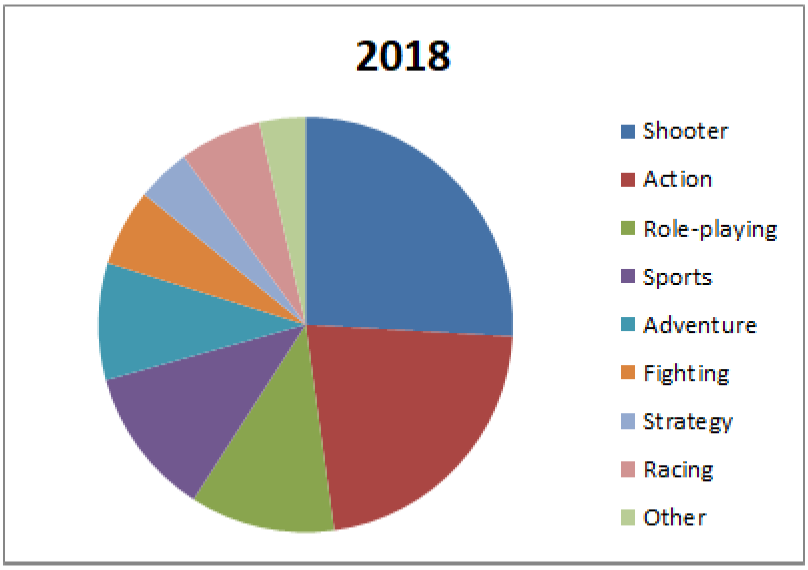
Figure 2.6 illustrates that player preferences are constantly changing (See Figure 2.5). It's vital for games to innovate artistically, aesthetically, functional and technologically. Racing simulations are aesthetically and technologically already on a very high level where innovation is difficult and expensive (Sodah, 2018). Functional innovations are a simpler way to improve Driver Education, Player Engagement and Performance.

- **Understanding the Player-Base**
  Among the bests selling game-genres are sport and racing (see Figure 2.4). To provide the best player experience within a genre, it's important to understand the preferences of the players. To reach a brought audience it's beneficial to allow a vast number of different playstyles. One of the best practical implementations of this principle is the action role-playing game "*Deus Ex*"[12]. It offered unprecedented freedom of action at that time and was an important milestone for video games. Other games like the "*The*

[12] Ion-Storm-Austin, 2000.



(a) Popular game genres in 2006



(b) Popular game genres in 2018

Figure 2.4.: Popular game genres based on data extracted from ESA, 2018

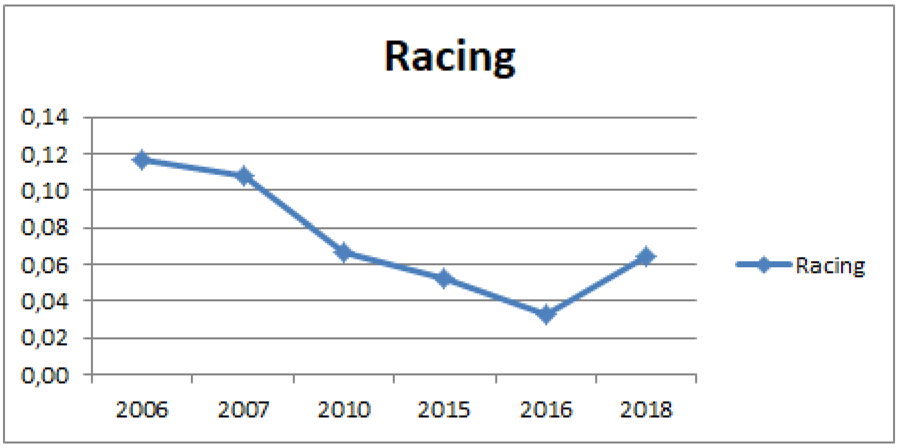


Figure 2.5.: History of the racing genres based on data extracted from ESA, 2018

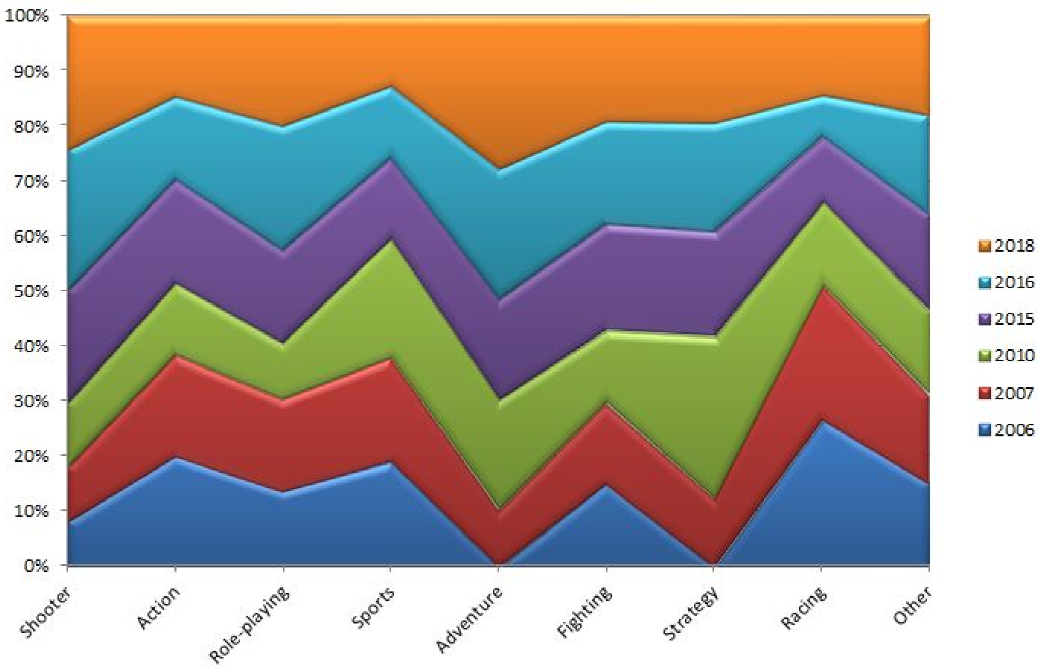


Figure 2.6.: History of gaming genres based on data extracted from ESA, 2018

Elder Scrolls"[13] series persuade the players with big open worlds and stimulate the creativity with diversified narratives. Canossa and Drachen (2009) found the game mechanics and the main character already defines the audience and expected behaviours. To understand the player base in "*Forca Motorsports 5*", Harpstead et al. (2015) analysed log data to create engagement profiles. This method visualises the player behaviour on a high abstraction level. It also is used to analyse the effectiveness of reward systems.

Table 2.5.: Task-Centred System Design vs Goal-Directed Design

Requirements	Task-Centred System Design	Goal-Directed Design
Systems	Only for non-critical systems	Complex systems
Budget	Cost-effective	Needs a big budget
Method	Simple	Complex
Result	Vaque	Precise

- **Development Guidelines**
  The next step is to translate the user needs to the game. Researches in Human-Computer Interaction have created guidelines to develop applications for specific user groups. In the book "*The Inmates are Running the Asylum*", Cooper (1999) introduces the Goal-Directed Design. In Goal-Directed Design, developers define personas based on the target group. The personas have to be defined as very specific and detailed. The whole development process is based around these fictional users. This strategy is very simple and incredibly powerful. The alternative is Task-Centred System Design. In Task-Centred System Design the developers think of tasks which are presented and tested with real users (Lewis & Rieman, 1993). Both methodologies present effective strategies to ensure user requirements are fulfilled. Table 2.5 summarises the advantages of each approach.

This chapter discussed the integration of the psychological concepts using design principles to improve *Engagement*, *Education* and *Performance*. Design principles assist developers to find ideas, implement features and optimize player

[13] Bethesda-Game-Studios and Zenimax-Online-Studios, 1994-2016.

experience. Game balancing plays a central major role in player engagement. Individualising the challenge level for players can be used to optimise player *Engagement*. Challenge is also one of the most important features to create *Performance*. It is important to find an individualised approach based on the players' skill level. The next chapter introduces algorithms that adjust and individualise the difficulty level for players to improve *Engagement* and *Performance* in racing games.

2.4. Racing Game Algorithms

> Perhaps the most important principle for the good algorithm designer is to refuse to be content.
>
> Aho (1974)

In computer science, an algorithm is a set of instructions designed to perform a specific task (Christensson, 2013). It's important to design efficient algorithms to perform the task fast and needing only minimal resources. As Aho and Hopcroft (1974) emphasizes: *"The designer should continue to examine a problem from a number of viewpoints until he is convinced that he has the most suitable algorithm for his needs."* In the previous Chapter 2.2 and Chapter 2.3.1 we discussed the influence of challenge on *Engagement* and *Performance*. In this work we explored algorithms related to driving and gaming to adjust difficulty:

Section 2.4.1 focuses on race game algorithms which solve two related problems:

- How to model intelligent agents (e.g. virtual opponent) in games to increase *Engagement*?
- How to dynamically adjust the difficulty of the game to increase *Engagement*?

Section 2.4.2 explores algorithms to estimate the skill level of a player. These algorithms allow players to be matched with other players of similar skill leading to interesting, balanced matches (Herbrich, Minka, & Graepel, 2006).

Section 2.4.3 introduces advanced analytics for games and driving. This includes methods for data transformation and analysis to uncover trends and patterns within the data. Advanced analytics can be used to improve games and real-life driving behaviour.

2.4.1. Artificial Intelligence in Games

Not only the level design but also the enemies should challenge the player in games. Section 2.3.2 determines the key factors to model opponents in games for optimal *Engagement*. Balanced, diverse and aggressive behaviour are key factors when it comes to promoting *Engagement*. This section focuses on modelling diverse behaviour by creating human-like opponents.

AI in games refers often time to intelligent agents which act autonomously towards a goal. Artificial Intelligence research found multiple ways to model intelligent agents. They are used to cover complex problems in computer science e.g. autonomous cars, speech recognition. The agents in videos games often times need to satisfy specific requirements (Nareyek, 2000):

- **Real Time:** Processing needs to be fast.
- **Dynamics:** Computer games have a dynamic environment.
- **Resources:** System resources are sometimes restricted.

Many computer game developers circumvent the problem of applying sophisticated *AI* techniques by allowing agents to cheat (Nareyek, 2000). The authenticity of cheating agents is very hard to ensure and creates often times static behaviour which makes it not suited for *Education* where players should learn from their opponents (van Lent, 2007). The design of artificial intelligence in computer games is an important component of the players *Engagement*. As computational hardware improves and games are becoming more life-like the need for more realistic game *AI* increases. In the next segment, we discuss universal AI models for games and specific approaches for race games.

- **Evolutionary Learning in Games**
  An often used method of creating human-like opponents in games is evolutionary learning. Evolutionary learning approaches can be applied to all kinds of games. A lot of research on learning in games has been done on board and card games. Fogel (1993) created a simple AI able to play tic-tac-toe. Richards, Moriarty, and Miikkulainen (1998) showed that Neuronal Networks can be used to model an opponent for GO. It‘s one of the most complex board games and very difficult to master, even for computers. With the increased computational power in recent years, the generated opponents are capable of beating even expert humans in a

multitude of games. Today's best Computer GO program AlphaGo[14] uses a Monte Carlo algorithm based on learned knowledge. It was the first algorithm to consistently beating the world No.1 ranked player at the time. Modern computer game AI research focuses mainly on real-time strategy (RTS) and first-person shooter (FPS) games due to their popularity. Khoo and Zubek (2002) developed a simple and computationally inexpensive AI mechanism to produce engaging character behaviour. The system uses behaviour based action selection techniques taken from robotics. It showed mixed results, some of the testers could not defer the AI from humans, others could not be deceived. Cole, Louis, and Miles (2004) used a generic algorithm to balance parameters for bots. Ponsen and Spronck (2004) is using RTS games to propose adaptive game AI with dynamical scripting. Their approach significantly improves the performance of adaptive game AI. Thurau, Bauckhage, and Sagerer (2004) learned strategies by observing human players. The investigated movement patterns resulted in a wide range of situation-dependent human-like strategic movements. Their research presents a first step towards the development of more human-like computer game bots.

- **Artificial Intelligence in Racing Games**
  In conventional games, non-player moving objects are controlled by predetermined algorithms. The problem in racing games is that automatically controlled cars tend to bunch together. Different performing race car algorithms can improve the problem considerably but produces monotonous race results. For this reason, Nintendo introduced the rubber banding algorithm mainly for arcade games ("Nintendo, Racing game program and video game device," 2004). The artificial intelligence is designed to prevent computer-controlled opponents to get too far ahead or fall back. When done well, rubber banding can provide a consistent level of challenge. But in many cases, it becomes evident that the player can't escape regardless of skill and effort. This completely ruins the experience for the player. This approach is similar to cheating agents not suitable for Education. More complex algorithms are used for autonomous vehicles. Autonomous vehicles are developed to construct driverless transport systems, essentially revolutionising the way we live. The vision is to make driving safer

[14]DeepMind-Technologies, 2017.

> and more efficient. A lot of car manufacturers and start-ups are working to make the vision reality. Self-driving software is simulated on powerful computers for testing and validation purposes. Photorealistic simulation runs on GPUs simulate cameras and sensors. It allows to processes the data as if it were actually driving on the road ("NVIDIA — DRIVE," 2019). This method would also be suited to generate a variety of diverse autonomous vehicle scenarios for racing games but it requires powerful hardware.

This section introduced some AI mechanics, generating diverse behaviour for agents. Despite all these complex algorithms, there is little research done on how these behaviours contribute to the player experience (G. N. Yannakakis and Hallam, 2007). There is no evidence that by generating human-like opponents we can create more satisfaction. It exists research in general board games. For chess Iida, Takeshita, and Yoshimura (2003) defined a metric of entertainment. The metric is based on average game length and the number of possible moves per turn. The discussed algorithms focus on diverse and aggressive behaviour. To improve Engagement we need to also focus on balanced AI based on the player skill level. The next section examines the players skill level. Balancing AI based on players skill is key to improve *Engagement* and *Performance* (see Section 2.3.1).

Skill Level Progression

Most skill level estimation research focuses on traditional sports. To measure sports skills (e.g. soccer skill) a sequence of tests like dashing, jumping and endurance shuttle runs are performed (Malina et al., 2007). There are applications where the style of movement is important. A method for complex movements uses a combination of computer vision and machine learning (Ilg, Mezger, & Giese, 2003). Computer vision allows the detection of trajectories. Utilizing machine learning on these trajectories generates models for sequences of movements with different styles. This method can be used in sport for example to analyse complex karate movements or in medical gait analysis to quantify the movement disorders. This section discusses automatic difficult adjustment in games to increase *Engagement*.

Driver Rating	% of Players
A	18.5
B	13.6
C	12.2
D	16.0
E	9.6
F	11.9
G	8.5
H	9.7

Table 2.6.: Driving rating statistic based on the 6.7 million players in the competitive sport mode with 5 games or more (“Kudosprime, Gran Turismo Sport,” 2018)

- **Player Skill Level in Racing Games**
  To understand the skill distribution in racing games we can look towards the most popular racing games. *Gran Turismo*[15] is the most played race game on the *PlayStation*[16] and has been a special institution throughout the years for both race fans and car enthusiasts. A look into their data helps us to identify important game mechanics and user groups for racing games. The player driver skill in their competitive online mode is categorised in 8 levels as shown in Table 2.6. The rating includes not only race driving skill but also sportsmanship, respecting track limitations and other drivers. Only a relatively small group falls into the bottom categories G and H. The top 0.2% is an elite group consisting of professional drivers and the best amateur drivers of each region. This illustrates that race simulations are a highly competitive environment. There is only a small amount of players without race experience. To improve *Engagement* developers have to emphasize the competitiveness of the race game audience in the game conception. The next segment introduces concrete skill adjustment systems in race games.

- **Assistance Systems in Racing Games**
  Players have different skill levels as shown in Table 2.6. To balance skill

[15]gran-turismo.com, 2019.
[16]playstation.com, 2019.

level and progression, game developers often provide an option for the players to specify the level of difficulty. Most racing games provide several customizable assists like trajectory lines, braking assist, traction control or automatic gear. Debeauvais et al. (2014) found that players don't always know what level of difficulty will work. The players are often not confident enough to disable an assist or turn them on again after a bad experience. Racing games should have models to predict when a player is ready to disable an assist and encourage him to do so. Furthermore, some games provide several levels of AI difficulty but don't progressively recommend increase the degree of difficulty. Hullett, Nagappan, Schuh, and Hopson (2012) analysed games modes, vehicles and race tracks in Project Gotham Racing 4. They found that players use only a small amount of race tracks and vehicles. This means reducing the number of options can improve the game experience for the players and decrease development cost. Also, developers have to encourage players to switch vehicles.

For level design, it's important to match skill to difficulty. Recently, the *Procedural Content Generation* attracted the attention of researchers. For platform games Mourato, dos Santos, and Birra (2011) introduced a framework for automatic level creation with personalised content. Furthermore, Jennings-Teats, Smith, and Wardrip-Fruin (2010) utilized machine learning to automatically construct platform levels with continually-appropriate difficulty and understand the player skill. To make race tracks more interesting, Togelius, Nardi, and Lucas (2007) developed an evolutionary algorithm to procedurally generate race tracks. The generation strategy is based on player driving styles to maximum entertainment value. Their previous paper dealt with player modelling approaches and provided a definition of fun race tracks (Togelius, Nardi, & Lucas, 2006). The main factors to make race tracks fun are speed, versatile composition and the right amount of challenge for the player. There is no research on automatically generating levels for *Education*.

This section introduced methods to improve *Engagement* by automatically adjust the level of difficulty by adopting the opponent and the game. The research demonstrated that players can't estimate their own skill level. Two approaches to automatically adjust the race game difficulty are to consider.

Firstly, the level can be generated automatically based on skill level. This approach is unsuitable for educational racing simulations where the race track is dictated. Secondly, *AI* with different difficulty levels can be used. The level of difficulty has to be adjusted automatically to the player. The following section introduces ranking algorithms. Ranking systems assign and update skill levels for players.

2.4.2. Ranking Systems

The last section discussed the importance of balanced agents in video games for *Engagement*. This section introduces ranking systems as an idea to balance agents. A ranking is a relationship between a set of items. Tucker (2006) describes a ranking mathematically: *"A ranking is simply an arrangement, or permutation, of the n candidates."* Mathematics and statistics offer different strategies for assigning rankings. For example, it isn't always possible to assign each candidate a unique rank, then two or more candidates should have the same rank. Cichosz (2014) lists the most common ranking strategies:

- **Competition ranking:** Instances with equal attribute values receive the same rank and then a gap is left to adjust for the number of those instances e.g. (1 2 2 4)
- **Dense ranking:** Instances with equal attribute values receive the same rank and then no gap is left e.g. (1 2 2 3)
- **Ordinal ranking:** Instances with equal attribute values receive different consecutive ranks in an arbitrary order e.g. (1 2 3 4)
- **Fractional ranking:** Instances with equal attribute values receive the same rank, equal to the mean of ranks they would receive under ordinal ranking e.g. (1 2.5 2.5 4)

When humans are asked to express preferences among a set of options, they prefer to report a partial order—where comparisons are made between certain pairs of options but not between others (Keller & Trotter, 2016). They are known as partially ordered sets. This section focuses on rating systems in sport. Section 2.4.2 introduces sport rating systems in general. Section 2.4.2 focuses on the *Elo* system, originally used in chess.

Rating Systems

Rating systems are vital in different application domains. The most common application is to calculate the competitive strength of sports teams. Skill ratings in competitive sports serve three main functions (Herbrich et al., 2006):

- They allow players to be matched with other players of similar skill leading to interesting, balanced matches.
- The ratings can be made available to the players and to the interested public and thus stimulate interest and competition.
- Ratings can be used as criteria of qualification for tournaments.

Until several years ago, the rankings were decided purely based on the collective opinion of experts (Boginski, Butenko, & Pardalos, 2004). Nowadays, computer-based ranking systems utilizing various mathematical techniques and remove possible biased opinions of experts. Colley (2002) introduced a matrix based to rank colleague football teams. Colley (2002) identified: *"The scheme adjusts effectively for the strength of schedule, in a way that is free of bias toward conference, tradition, or region."* The provided ratings can also be used to make power rankings and predict the outcome of future matches. Timmaraju, Palnitkar, and Khanna (2013) used pseudo-likelihood statistics to predict the outcome of English Premier League matches. They took the number of goals for each team in a match to train a machine learning algorithm. The model predicted the matches with up to 66% accuracy. It outperformed experts and the betting market. *TrueSkill* is a skill-based ranking system patented by *Microsoft*(Herbrich et al., 2006). It is used for matchmaking on *Xbox Live*(xbox.com, 2019). Section 2.4.2 introduces a similar but licenses free system e.g. *Elo*.

Elo Rating System

The *Elo* system is a rating system original proposed to rate chess players. Nowadays, variations of the algorithm are used in sports, economy, and science. The *Elo* system gives every player a rating which represents the strength. The outcome of a match can be predicted by comparing the player ratings. The initial rating is estimated. It goes up when you win, and goes down when you lose. Strong players have high *Elo* numbers. Hvattum and Arntzen (2010) showed that the *Elo*-System is a reasonable method to predict match results in football. It's a useful tool to encode information about past results. Lehmann and Wohlrabe (2017) measured the quality of scientific paper based on the *Elo* rating system. The impact of a paper is encoded in his *Elo* number. The *Elo* ranking is very easy to compute and a promising alternative to existing paper ranking approaches. Competition on the website kaggle.com, 2015 was arranged to find an approach that predicts the outcomes of chess games more accurately than the *Elo* rating system. Most teams used machine learning to improve the rating system (Pennington, 2010). The drawback of this method is that it needs large datasets to give optimal predictions.

This section discussed rating systems to estimate and update player skill levels. There are multiple algorithms in use in sports and games. The *Elo* rating system is an easy, free and promising ranking approach for racing simulations. The system estimates the skill of player and matches players with similar skill level, giving the players a balanced chance of winning. The goal is to improve *Engagement*, *Education* and *Performance*. The following section introduces driving performance measures to analyse the effect of skill adjustment in games on *Performance*.

Observation 4: Elo System for Race Simulations

The Elo rating system can be adopted for racing games. We can calculate an initial strength using previous lap-times. Winning increases the score and losing decreases the score. The opponent should have a similar score. The optimal match has players with identical Elo score, but this situation is extremely rare.

2.4.3. Measuring Driving Performance

Driving performance measurements are used for a wide range of applications, including driver drowsiness and/or drug influence detection, driver training, road infrastructure evaluation and the assessment of effects of in-vehicle systems (Johansson et al., 2008). The driving task can be described on different levels of abstraction. Michon (1985) proposed a widely adopted scheme where the driving task is divided into three levels of skills and control:

- **Strategic level:** Defines the general planning stage of a trip.
- **Tactical level**: Execution of driving manoeuvres e.g. lane changes
- **Operational level:** Vehicle control at every moment.

This chapter reviews metrics that quantify *Performance* on the tactical and operational levels.

In section 2.4.3, a range of metrics is presented related to driving performance. Driving performance deals with the driver's ability to control the car.

Section 2.4.3 introduces spatiotemporal pattern recognition to analyse movement patterns and create driving models. Spatiotemporal pattern recognition can be used to identify risky driving behaviours (Guo, Liu, Zhang, & Wang, 2018).

Driving Performance Assessment Methods and Metrics

This section of driving performance metrics is structured based on the concrete physical and behavioural quantities that are measured (Johansson et al., 2008): The metrics are grouped into the three main categories:

- Longitudinal control metrics
  - Speed
  - Vehicle following
- Lateral control metrics
  - Steering wheel movement
  - Lane keeping
- Event detection metrics

Speed metrics
There is strong evidence that speed is a major factor affecting road accident frequency and severity of (Mountain, Hirst, & Maher, 2005). A large number of speed metrics could be computed. The most commonly used in automotive engineering are (Johansson et al., 2008):

- **Mean speed:** The average of the longitudinal speed relative to the road surface.

- **Standard deviation/variance of speed**
- **Maximum speed:** The single maximum speed value.

Vehicle following metrics
Drivers tend to drive faster or slower than the surrounding traffic depending on their driving style (Saad, n.d.). Vehicle following entails the interaction of nearby vehicles in the same lane (Bevrani & Chung, 2011). Distance-based metrics are based on the car in front. The distance headway is defined as the average distance to the lead vehicle e.g. from bumper to bumper (Johansson et al., 2008). Common distance-based metrics are (Johansson et al., 2008):

- **Mean distance headway:** The average distance headway.
- **The standard deviation of distance headway**
- **Minimum distance headway:** The minimum value of the distance headway signal.

Time headway is defined as the distance to the lead vehicle divided by the travel speed of the own vehicle(Johansson et al., 2008). Common time-based metrics are (Johansson et al., 2008):

- **Mean time headway**
- **The standard deviation of time headway**
- **Minimum time headway**

Steering wheel metrics
Steering wheel metrics are very common in driver performance assessment. It is used to observe changes in the steering wheel activity relate. A low activity can indicate that the driver performs a secondary task (visual or cognitive) or the driving demand is low (e.g. straight and wide road, low traffic) (Macdonald & Hoffmann, 1980). The most common metrics are (Johansson et al., 2008):

- **Standard deviation/variance of steering wheel angle**
- **Steering wheel reversal rate:** Number of times that the steering wheel is reversed by a magnitude larger than a specific angle, or gap.
- **Steering wheel action rate:** Number of steering wheel movements per second faster than a threshold velocity.

Lane keeping metrics
Lane keeping metrics are almost always included in In-Vehicle-Information-Systems evaluation studies, especially when the lane position standard deviation/variance and the proportion of the lane exist (Johansson et al., 2008). Many studies showed a correlation between lane keeping and visual tasks and e.g. tasks on a navigation system or a cell phone. Farber et al. (2000) demonstrated a strong relationship between visual tasks and lane keeping performance. Oestlund et al. (2008) observed that lane keeping tended to be a sensitive measure for the visual tasks especially, for elderly drivers. Similar to the vehicle following metrics there are distance-based and time-based metrics. The most common distance-based lane keeping metrics are (Johansson et al., 2008):

- **Mean lane position:** The mean lane position is defined as the mean distance between a reference point on the vehicle and an arbitrary position in the lane.
- **Standard deviation/variance of lane position**
- **Lane exceedances:** The most common measure is LANEX. Defined as the proportion of time any part of the vehicle is outside the lane boundary.

To time-based metrics are based on the time-to-line-crossing concept, representing the time necessary for the vehicle to reach either edge of the driving lane (Godthelp, Milgram, & Blaauw, 1984). Based on the time-to-line-crossing computation, different statistic metrics can be computed (Godthelp et al., 1984):

- **Median TLC**
- **15% level TLC:** 15% of the time-to-line-crossing values are below this value

Event detection metrics
Event detection is strongly related to crash probability, and thus one of the performance metric classes with the strongest safety relevance (Johansson et al., 2008). It can be measured to stimuli that relevant to the primary task. Typical driving-related detection tasks are the detection of braking lead vehicles or suddenly appearing pedestrians (Johansson et al., 2008). Event detection can be used to evaluate cognitive tasks. Alm and Nilsson (1995) found that a mobile telephone task has a negative effect on the drivers' choice reaction time and that the effect is more pronounced for elderly drivers. McKnight and McKnight

(1993) observed increased non-responses by about one-third under all of the telephone distractions for drivers over age 50. The main event detection metrics are (Johansson et al., 2008):

- **Response time:** The metric is defined as the time from presentation of a specified stimulus (with specified start time) to the time that the driver responds correctly, either verbally or with appropriate hand or foot motion.
- **Response distance:** The distance of the driver from the stimulus when the driver responds correctly, either verbally or with appropriate hand or foot motion.
- **Errors of omission:** The number of times that the driver fails to respond to a specified stimulus presentation.
- **Errors of commission:** The number of times that the driver responds incorrectly to a specified stimulus presentation.

This section introduces various driver performance measures. All measures estimate the driver's ability to control the car. The following section introduces pattern recognition algorithms to analyse more complex movements and accidents.

Spatiotemporal Driving Pattern Recognition

Spatiotemporal patterns appear almost everywhere in nature. Spatiotemporal data has spatial relations (e.g. distance, direction, position) and temporal relations (e.g. time, duration). With the rise of positioning technologies in sensor networks, smart devices, RFID tags and GPS tracking systems a vast amount of spatiotemporal information is generated. In this section, we provide an overview of spatiotemporal pattern recognition systems. These systems act as real-time monitoring platforms. Analysing the extremely high amount of data can solve many research questions. Researchers already found a wide range of applications. Social media interactions reveal complicated social network structures. Traffic patterns help to identify risky driving behaviours (Guo et al., 2018). Tracking people can be used to detect suspicious human movements and could help to prevent crimes and terrorism. Recent advantages in video analysis and computer vision algorithms made it possible to track movements, even in extremely crowded scenes (Kratz & Nishino, 2010). Tracking technologies are widespread in all major sports where they're tracking the players and the ball (C.-H. Chen et al., 2015). This helps coaches and improves training techniques. This section focuses on spatiotemporal driving pattern recognition to measure *Performance*.

Spatiotemporal pattern recognition starts with the data mining process. Most frequently the data is collected from tracking devices (such as GPS sensors). The data has to contain spatial and temporal information. The next step is data pre-processing since the raw sampled data can be faulty. Pre-processing has to take care of incomplete, noisy, and unevenly sampled data. The mining process can also include background information. Public transport follows a preplanned schedule. Vehicles have to follow the roads. Taking background information into account leads to more complex algorithms (Li, 2014). One of the most valuable applications is to find frequent periodic patterns. For example, people follow regular daily routines. These regular patterns can facilitate traffic control applications. The data for these patterns can be extremely complex. More complicated than what mathematical formulas are able to describe. Assuming periodic routines helps to simplify models (Jeung, Liu, Shen, & Zhou, 2008). Sometimes it is useful to find patterns between multiple objects. Pairwise patterns describe the relationship between two objects. Pairwise movement patterns analyse the similarity between two trajectories. To measure similarities we need a similarity measure. A simple measure is a p-norm distance. The p-norm distance between trajectories of R and S is defined in equation 2.1:

$$L_p(R,S) = \left(\sum_{i=0}^{n-1} (r_i - s_i)^p \right)^{1/p} \tag{2.1}$$

The pairwise relationship can be classified as attraction, avoidance or neutral. In an attraction relationship, the presence of an object causes them to move closer. This can be observed in nature among herding animals. The avoidance relationship can be detected in a human movement when criminals try to avoid the police (Li, 2014). In a neutral relationship, the movement patterns do not defer. As this section discusses, there are many spatiotemporal mining methods. Spatiotemporal patterns are also found in racing games. The analysis of pairwise patterns gives insights into the patterns of driving errors. The data mining step, aggregates time, position and velocity data. The Euclidean-distance in Equation 2.2 is used to measure similar trajectories (p-norm with p=2).

$$L_p(R,S) \quad = \quad \left(\sum_{i=0}^{n-1}(r_i - s_i)^2\right)^{1/2} \tag{2.2}$$

This section discusses the spatiotemporal driving pattern to analyse driving errors and how they develop. Driving patterns describe extremely complex relationships and give essential insights for driver performance. The following section reviews the important sections of this chapter.

2.5. Summary

Learning racing is a challenging task. Racing simulations offer a safe environment to learn racing principles. Simulators for driver training can simulate a variety of driving situations. Traditional racing games and racing simulations focus on either *Engagement* or *Education*. Drivers and gamers could benefit from a combined approach. Researchers found that textitEngagement and *Performance* benefit the learning outcome. In particular, learning models based on the competition can be applied to racing games.

To maximize *Engagement* and *Performance* games have to be balanced. Rating systems estimate the skill of the players. The correct estimation of the race driver skill level allows matching the racer with the optimal opponent. To make a race “fair”, each player should have a winning chance of around 50%. The Elo rating system can be adopted for racing games. The best match is constructed the Elo ratings of the participating players are very close. The optimal match has players with identical Elo score, but this situation is extremely hard to achieve. Having fair matches is a huge priority to ensure the race is competitive, but there are other factors to consider. Long loading times are frustrating. The algorithm has to be fast. A further restriction is that skill is normal-distributed on the player base. This can make it difficult to find equal skilled opponents for very low or very high rated players.

Game design principles help to create a positive player experience, find vulnerabilities and optimize runtime performance. Task-Centred System Design revolves around tasks which are presented and tested with real users (Lewis & Rieman, 1993). They offer an effective strategy to ensure player satisfaction.

To validate our method we have to measure *Engagement*, *Education* and *Performance*. The Geneva Emotion Wheel is a tool to evaluate emotions qualities and the intensity of the feeling. The most impactful variables are challenge and certainty in both positive and negative experiences. When designing a game we have to control the challenge and the certainty of the situation to control the emotion of the player. An effective technique to evaluate driver performance is the analysis of driving metrics. Speed, vehicle following, steering wheel movement and lane keeping are important metrics for driving. Driving pattern analysis helps to identify risky driving behaviours. In the next chapter, simulation requirements are identified to design and adapt the corresponding concepts in a virtual 3D racing environment.

3. Design and Requirements

The goal of the project is to develop a virtual 3D racing environment where the difficulty of the opponent racer is dynamically adjusted. We implemented a time trial mode. The goal is to drive a lap as fast as possible. Players are challenged by a “transparent” opponent e.g. ghost car. In traditional race games, the ghost car is a reproduction of your previous runs. We additional introduce the *Virtual Rival*. *Virtual Rival* is a ghost car adjusted on the players estimated skill level. The skill level is estimated from the players’ previous runs. The trajectory of the *Virtual Rival* run is taken from a database of runs from all players. The goal of *Virtual Rivals* is to teach and guide while entertain and challenge the players. Players can improve driving skills in every lap and the *Virtual Rivals* improve with them. There are different stockholders involved in this project:

- **Developers:** Developers want to create a challenging environment and improve racing simulations.
- **Players:** Players want *Engagement* and need *Motivation*.
- **Analysts:** Track the players’ *Engagement*, *Education* and *Performance*.

Therefore, different requirements have to be met. The solution should be easy to implement and meet the requirements for all parties. In this chapter we want to set the practical foundation on how to improve *Engagement*, *Education* and *Performance* in racing simulations based on the groundwork discussed in Chapter 2.

Players need an environment that is easy to use and supports competitive racing. To improve *Performance*, the design of the world also focuses on the advantages of a competitive and balanced environment in comparison to conventional race game approaches. The strength of *Virtual Rival* in comparison to traditional systems is potentially increased *Engagement*, *Education* and *Performance*. Hence the design of the *Virtual World* concentrates on emphasizing these factors:

- **Simplicity**
  The key game creation principle for race simulation design to improve *Engagement* discussed in Section 2.3.1 are built around a core mechanic, clear objectives and clear success criteria's. The focus is on realism and detailed simulation that enhance players driving understanding. The elements should be simple and the goals should be clear.
- **Competition**
  In-world competition, such as traditional ghost cars and *Virtual Rival* raise the players understanding, *Engagement* and *Performance*. Different algorithms such as rating systems enhance the balancing of the competition.
- **Assessability**
  Analysts should be able to follow and assess the players' activities and question answers to measure the actual *Engagement*, *Education* and *Performance*.

This section introduced the primary stakeholders for this project: developers, players and analysts. The main goal is to create a race environment that increases and measures player *Engagement*, *Education* and *Performance*. This project centers around three key factors in racing games: *Simplicity*, *Competition* and *Assessability*. The next section discusses the demands of the stakeholders and the main functional requirements and non-functional requirements.

3.1. Architectural Analysis

This section outlines some basic requirements of developers and players which have to be satisfied. Since multiple players should be able to play at the same time, a suitable platform has to be identified. Developers should be able to integrate tools to measure the learning effect in different situations. The generated player data should be stored in a structured, reliable and everywhere accessible way. Finally, there are some requirements for data analysis. The requirement analysis ensures the quality by checking (Paetsch, Eberlein, & Maurer, 2003):

- **Necessity:** Ensures requirement is needed.
- **Consistency:** Dissolves contradictory requirements.

- **Completeness:** Ensures all requirements are modelled.
- **Feasibility:** Practicable in the context of budget and time.

The requirements engineering community classifies requirements as either functional or non-functional (Chung & do Prado Leite, 2009). In the next section, we discuss the functional and non-functional requirements of the *Virtual Rivals Framework* to ensure quality and usability.

3.1.1. Functional Requirements

Functional requirements describe what the system should do (Robertson & Robertson, 2012). In this section, we discuss the functional requirements of the *Virtual Rivals Framework*. The functional requirements are listed in descending order of priority. High priority features should be implemented first.

1. Players are able to access the game through the *itch.io* website.
2. The players can abort when feeling uncomfortable.
3. The data evaluation tool processes *Engagement*, *Education* and *Performance* information.
4. The game supports multiple players at the same time.
5. Driving data is recorded in the background at all time.
6. Questionnaires are clear and contain simple questions.
7. Developers are able to add new functionality:
    - Additional questionnaires
    - New driving behaviour
    - Additional opponents
    - Record additional driving metrics
8. The framework provides functions to identify software bugs.
9. Data evaluation is able to statistically analyse personality measures.
10. Data evaluation is able to identify driving patterns.
11. The race car contains an automatic gearbox.
12. Study participant recruitment is performed using *Amazon Mechanical Turk*.
13. Display size is adjustable.
14. The sound volume is adjustable.
15. The race car produces realistic engine sounds.

16. When driving through nature environment animal and wind sounds are played.
17. The race tracks is built out of basic building blocks: straights, turns, plants, rocks, water, finish lines and trees.
18. Every player and game data is identifiable by a unique id.

3.1.2. Non-functional requirements

The previous section introduced the functional requirements of the *Virtual Rivals Framework*. This section introduces non-functional requirements. Non-functional requirements describe how the system works (Robertson & Robertson, 2012). They are not related to the functionality of the software e.g. performance, usability. The non-functional requirements are listed in descending order of priority. Requirements with high priority should be warranted at all time.

1. The player data is protected.
2. The frame rate is above 60 frames per second at all times.
3. The data is accessible at all time.
4. The controls provided for the players are simple and self-explanatory.
5. Data integrity is ensured at all times.
6. Data evaluation is flexible for big data sets.
7. Data evaluation is expandable for new metrics and graphs.
8. The graphics and objects used evoke associations with a real race track.
9. Loading times are fast.
10. All data is stored in the cloud.
11. System response time is unnoticeable for the player.
12. The data evaluation is reasonably fast, even for large data sets.
13. Data upload is fault resistant.
14. The game supports multiple platforms: *Windows*, *Edge*, *Chrome* and *Firefox*.

This section introduces the main functional requirements and instruments to improve *Engagement*, *Education* and *Performance* in racing simulations and measure the effectiveness. The main tasks are to create a virtual racing environment with integrated questionnaires and a statistical evaluation tool. The virtual racing environment is the race game where players are challenged by traditional ghosts and *Virtual Rivals*. The structure and realism of the race environment influences the players' *Engagement*, *Education* and *Performance*. It is essential that the created race game is designed in a way that invites players. The objects should evoke associations with a real race track. The questionnaires are the main tool to gather information about the players. It is important to have clear and simple questions. Statistical evaluation is used to uncover trends and patterns within the data. The main goal is to analyse and compare players' *Engagement*, *Education* and *Performance*. The next section gives a short overview of the structure of the project and how the elements discussed in this section are integrated.

3.2. Architectural Synthesis

For the virtual rival framework, several modules will be developed and implemented to create a competition based race simulation which ensures *Engagement*. The goal should be to improve while having fun. This section focuses on models that can be integrated into virtual driving environments.

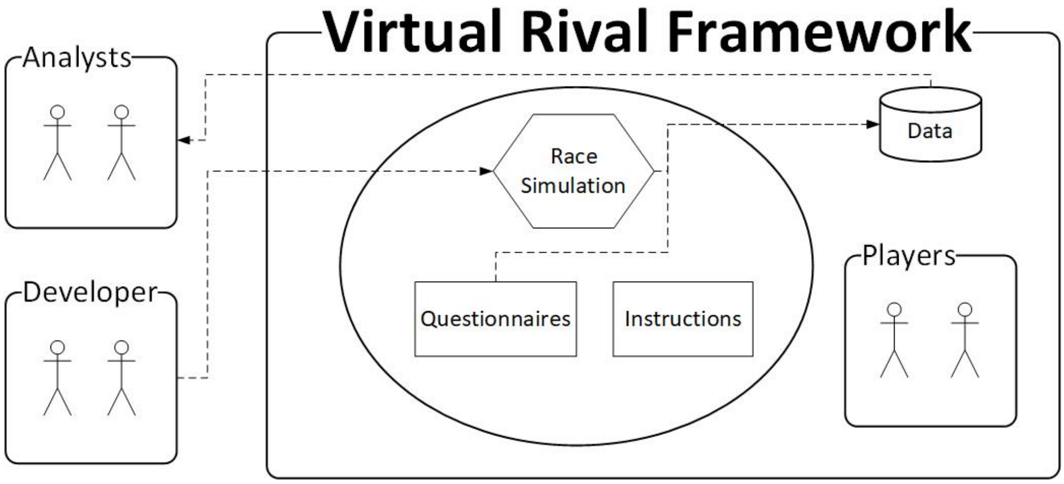


Figure 3.1.: Abstract overview of the general structure

Figure 3.1 shows a simplified version of a potential scenario using a distributed approach to impart driving skills. Analysts can add new race tracks and modify the artificial intelligence of non-player characters. Accompanying concept questions before and after the races are used to assess the learning progress and find driving patterns. Players can access the Virtual Rival World whenever they want. There is no limit of players the world can handle at the same time. The players start by reading introductions and finishing a first tutorial drive. A first data analysis assesses their initial driving skill. After that, they try to improve their times in additional rounds. Questionnaires are used to track their motivation. The next section illustrates the game engine selection process.

3.2.1. Selecting a Game Engine

Game engines are tools that simplify the game development process. Choosing the game engine impacts also player
textitEngagement, depending on what features are provided. There are various game engines with different philosophies on game development and aiming at a wide range of different needs (Christopoulou & Xinogalos, 2017):

1. Engines that don't require programming
2. Web-technology based engines
3. Open-Source engines which are customizable
4. Professional game engines

The game engine massive influences the game development process and potentially has technical limitations. Petridis et al. (2012) introduced a framework for comparing engines based on six criteria's:

1. *Audiovisual Fidelity:* Rendering, Animation, Sound
2. *Functional Fidelity Scripting:* Supported AI Techniques, Physics
3. *Composability:* Import/ Export Content, Developer Toolkits
4. *Accessibility:* Learning Curve, Documentation, Support, Licensing, Cost
5. *Networking:* Client Server/ Peer–to- peer
6. *Heterogeneity:* Platform Support

This section compares the four of the most popular game engines (gamedesigning.org, 2019) with additional focus on our requirements 3.1:

1. Unreal

   a) Key property: Powerful
   b) Games: Gears of War, Mass Effect

2. Unity
   a) Key property: One size fits all
   b) Games: Overcooked, Superhot

3. Game Maker
   a) Key property: No programming needed
   b) Games: Super Crate Box, Undertale

4. Godot
   a) Key property: Completely free
   b) Games: Fluffy Horde

Audiovisual fidelity
Table 3.1 shows an overview of the audio visual features. *Game Maker* supports only sound. The *Unity* engine, *Unreal* engine and *Godot* engine support all graphics technologies. These features are important to provide a realistic environment for the player.

Table 3.1.: Audiovisual fidelity

Metrics	**Game Maker**	**Unreal**	**Unity**	**Godot**
Texturing	✗	✓	✓	✓
Lightning	✗	✓	✓	✓
Shadows	✗	✓	✓	✓
Special Effects	✗	✓	✓	✓
Animation	✓	✓	✓	✓
Sound	✓	✓	✓	✓

Notes: Audiovisual fidelity based on
Petridis et al. (2012), Christopoulou and Xinogalos (2017) and extended.

Functional fidelity
Table 3.2 summarises the result regarding functional fidelity. All the nominated game engines provide support for various AI techniques and scripting. The *Unity* engine and *Unreal* engine have build in support for all specified functionalities in Table 3.2. *Game Maker* and *Godot* is has no assistance systems in modeling

vehicle dynamics. This makes creating realistic driving behaviour more difficult and expensive.

Table 3.2.: Functional fidelity

Metrics	Game Maker	Unreal	Unity	Godot
Script	✓	✓	✓	✓
Collision Detection	✓	✓	✓	✓
Path Finding	✓	✓	✓	✗
Decision Making	✓	✓	✓	✓
Basic Physics	✗	✓	✓	✓
Rigid Body	✓	✓	✓	✓
Vehicle Dynamics	✗	✓	✓	✗

Notes: Functional fidelity based on
Petridis et al. (2012), Christopoulou and Xinogalos (2017) and extended.

Composability
It is important that the engine provides features to import from common data sources (see Table 3.3). *Game Maker* is the only engine which does not support importing/exporting from the best-known CAD platforms (Blender, 3D Studio Max, MAYA). *Unity* and *Game Maker* require a separate installation of developer toolkits while *Unreal* and *Godot* include the required toolkits automatically.

Table 3.3.: Composability

Metrics	Game Maker	Unreal	Unity	Godot
Import/Export content	✗	✓	✓	✓
Developer Toolkits	✗	✓	✓	✓

Notes: Composability based on
Petridis et al. (2012), Christopoulou and Xinogalos (2017) and extended.

Accessibility
Table 3.4 shows *Unity* seems to be the most used game engine, providing a high amount of free tutorials, examples and assets, while its community is very large (Christopoulou & Xinogalos, 2017). *Unreal* Engine is the only engine which

provides free technical support. *Game Maker* is designed to allow users to easily develop computer games without having to learn a complex programming language (wikibooks.org, 2019). *Gadot* is also suited for novice programmers. It provides completely free support, examples and assets but the small community limits the range of offered products in the asset store.

Table 3.4.: Accessibility

Metrics	Game Maker	Unreal	Unity	Godot
Learning Curve	✓	✓	✓	✓
Documentation	✓	✓	✓	✓
Technical Support	✗	✓	✗	✓
Community Support	✓	✓	✓	✓
Free	✓	✓	✓	✓
Open Source	✗	✓	✗	✓

Notes: Accessibility based on
Petridis et al. (2012), Christopoulou and Xinogalos (2017) and extended.

Networking and Heterogeneity
The last step in the selection process is to weight the heterogeneity of the engines and their network support (see Table 3.5). All the nominated game engines have a similar network model and support multiplayer games. *Unity* and *Godot* have an important advantage in game development since they support all platforms (especially consoles and mobile).

Conclusion
Based on our analysis of four leading game engines we can draw some important conclusions regarding the effectiveness of each game engine for our race simulation.

Game Maker is not suited for 3D games. Therefore, it can't be used for realistic race simulations. However, it is ideal for people without programming experience.

Godot is mainly used and optimized for 2D games. It wins over users with the unrestricted and free license system. Due to the relatively young age and the smaller community, it is less evolved than *Unity* and *Unreal*.

Table 3.5.: Networking and Heterogeneity

Metrics	**Game Maker**	**Unreal**	**Unity**	**Godot**
Client-Server	✓	✓	✓	✓
Peer-to-Peer	✗	✗	✗	✓
Multiplayer	✓	✓	✓	✓
Operating Systems	✓	✓	✓	✓
Mobile Devices	✗	✗	✓	✓
Consoles	✗	✓	✓	✓

Notes: Networking and Heterogeneity based on Petridis et al. (2012), Christopoulou and Xinogalos (2017) and extended.

Unity and *Unreal* are the most powerful game engines, which support almost all of the features needed for race simulations.

Unreal supports all features and is completely open source.

Unity is the best all-around engine. The main reason for choosing *Unity* over *Unreal* for our race simulation is the big asset store, which allows us to focus on developing. While the *Unreal* Marketplace has grown tremendously, the *Unity* Asset store is still the industry frontrunner (Orland, 2018).

This section compares the three most popular game engines. *Unity* fits the architectural requirements defined in Section 3.1. The next section defines the conceptual architecture based on the requirements and the limitations of *Unity*.

3.2.2. Conceptual Architecture

For the *Virtual Rival Framework*, several software modules will be developed and implemented to create a scenario which ensures that competitive driving can take place. The goal should be an acquisition of player driving data in a stimulating environment. The design of the *Virtual Rival Framework* itself will be the subject of chapter 4, whereas the current section is going to describe the functionality of the developed modules based on the requirements imposed by the concepts of motivation, emotion and performance in competition and the players. Figure 3.2 illustrates the modular structure of the *Virtual Rival Framework*.

(A) **Data Management Module**
The Data Module extends the Virtual Rival Framework and stores player information.

(B) **Data Analytics Module**
The Data Analytics Module accesses player information through the Data Management Module. The data is used to measure trends and analyse player performance.

(C) **Visual Analytics Module**
The Visual Analytics Module accesses player information through the Data Management Module. It exemplifies data using graphs, maps and diagrams.

(D) **Driving Module**
The Driving Module is the main component of the framework. The Driving Module incorporates the main car mechanics: car controls, gear shift, exhaust sound, data capture.

- *Car controls:* Vehicle drivetrain capable of providing torque to two or four wheels. Accelerating, Steering and Braking based on player input.
- *Gear shift:* Automatic gear shift similar to real life automobile gear shift systems.
- *Engine:* Characterises the engine speed and exhaust sound.
- *Data capture:* Records important driving metrics e.g. acceleration, speed and position.

(E) **Skill Adjustment Module**
The Skill Adjustment Module has two functions. Primarily, adjusting the skill level of players based on race results. Secondly, estimate the initial skill level of new players.

(F) **Player Engagement Assessment Module**
The Player Engagement Assessment Module measures the emotions and motivation of the players at all times.

Schematic process
Figure 3.3 gives an overview of how a typical racing experience in the virtual rival environment with the help of the implemented tools could look like.

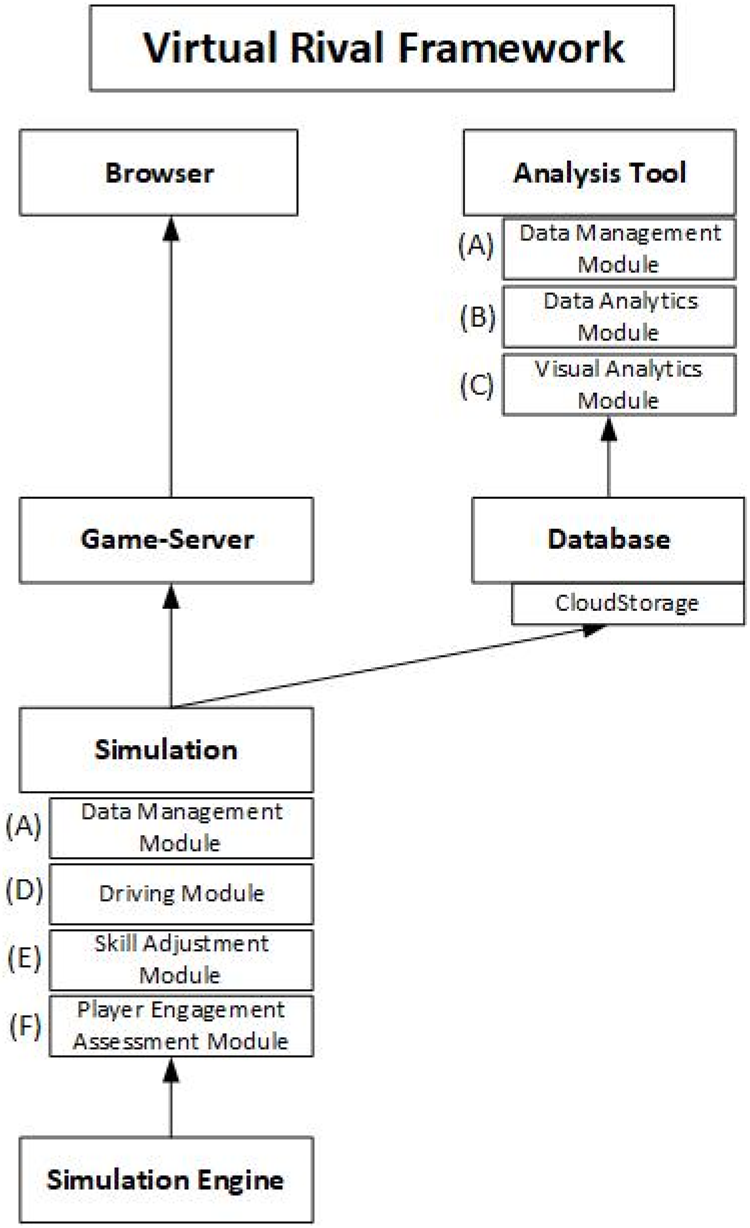


Figure 3.2.: Modular design of the Virtual Rival Framework

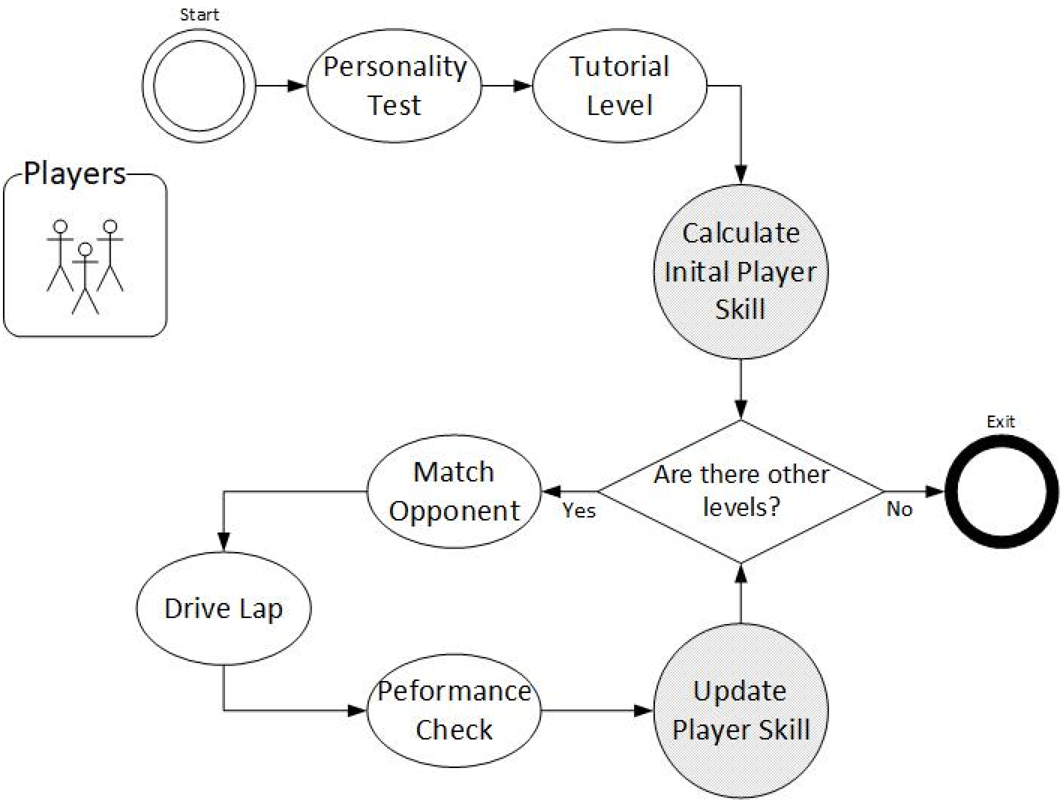


Figure 3.3.: Schematic process of a driving round-trip in the Virtual Rival World

First, players will have to complete initial questionnaires and personality tests where a first impression of the player is generated. Subsequent, players have time to learn the controls when completing the tutorial levels.

After they have completed the tutorial levels, they have to compete on race tracks against ghost opponents. In the end, the evaluation of the performance of the current player lap follows, to update the estimated skill level and adjust the opponent.

3.3. Summary

Before developing the first prototype, different requirements have been defined. First of all, general design aspects like availability, performance, scalability, and extensibility have to be considered. In addition, the players' motivations, emotions and performances should be tracked. For this purpose, a closer look at the important psychological aspects was taken. The different focuses of players and analysts regarding a scientific racing environment were also taken into account.

Unity was chosen as the game engine and development platform. It meets all the requirements, especially in terms of the network model, support and accessibility. *Unity* already includes many tools with the free standard installation. Some components for the *Virtual Rival Framework* have to be implemented from scratch:

- Driving Module
- Skill Adjustment Module
- Player Engagement Assessment Module
- Data Management Module
- Data Analytics Module
- Visual Analytics Module

These modules will include various functionalities which allow the analysts to define the race properties and track performance. The players produce vital data while exploring the race tracks. A typical virtual rival round-trip was identified to consist of six steps:

1. Perform initial questionnaires
2. Exploring the race controls in the tutorial levels
3. Estimate initial skill level
4. Drive lap against ghost competition
5. Update skill level based on driving performances
6. Go back to (4) until the end of the challenge

The next chapter will deal more specifically with the tools developed, namely the *Skill Adjustment Module*, the *Player Engagement Assessment Module* and the *Data Analytics Module*. The final result of the *Virtual Rival Framework* will be the topic of Chapter 5.

4. Implementation

This chapter focuses on the development of the *Virtual Rival Framework*. At first, the general architecture and the main components are outlined. After that, we discuss the structure of the developed modules and their functionality in detail. The modules have to fulfil the requirements discussed in chapter 3.1.

4.1. General Architecture

This section gives an overview of the main components of this project. Figure 4.1 illustrates the components and how they work together.

Game Server
We use *itch.io* to host our project. The website allows hosting games for free[1]. Players can connect to the server and access the game client in their web browsers. The server manages the game data and synchronizes the actions of the players. We created a customised landing page for the players. It is a simple way to distribute the project.

Amazon Mechanical Turk
Amazon Mechanical Turk is a *Amazon Web Service* enabling individuals to coordinate human tasks. Crowdsourcing has a dramatic impact on the speed and scale at which scientific research can be conducted (Chandler & Shapiro, 2016). Berinsky, Huber, and Lenz (2012) showed that respondents recruited with *Amazon Mechanical Turk* are often more representative of the U.S. population than in-person convenience samples. The integration of *Amazon Mechanical Turk* allows us to perform easy and low-cost field experiments.

[1] itch.io, 2019.

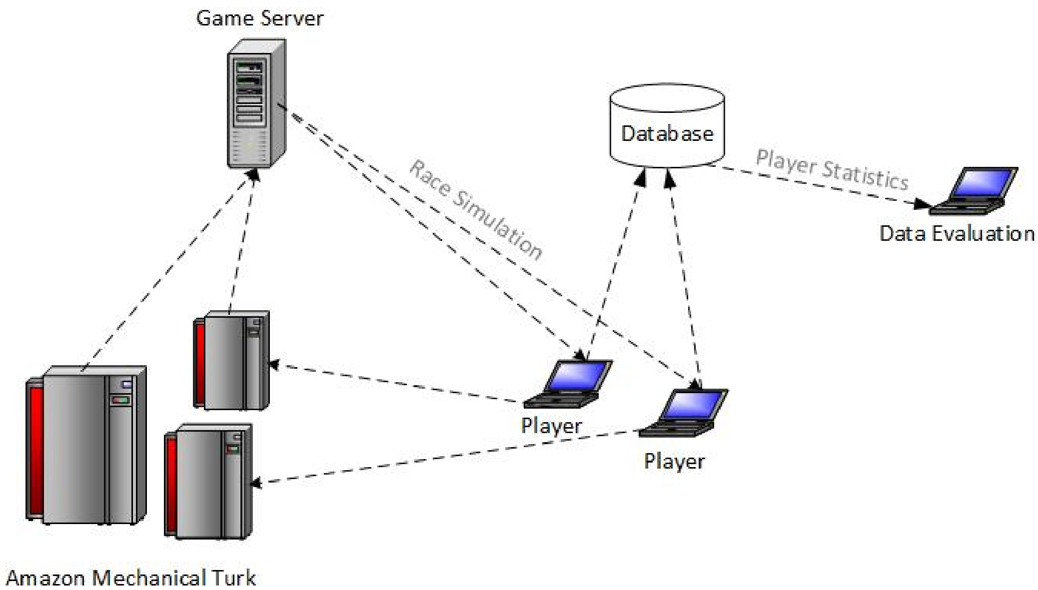


Figure 4.1.: Abstract overview of the general structure

Player Client
The client is accessed from the *Game Server*. It is available as Web Application and Desktop Application. The client was released with simultaneous support for *Windows*, *macOS*, and *Linux*. The *Web Application* supports all major browsers e.g. *Firefox*, *Chrome* and *Internet Explorer*. Other systems are not tested. The player client includes the race simulation and the questionnaires.

Data Evaluation
The Data Evaluation Tool is decoupled from the *Player Client* and *Game Server*. It's a standalone *Python* application. The player statistics are accessed from the database. The *Data Evaluation Tool* consists of a visualisation module and a statistic module. The visualisation module plots trajectories, lap-times-charts and personality graphs. The statistic module identifies trends using statistical data analysis methods e.g. mean values, standard deviations and hypothesis testing.

4.2. Race Simulation Design

Unity empowers game designers to make games. This section will explain the core concepts we used to create the Virtual Rival World. The environment is designed using obstacles and decorations. The game is rendered in the browser. Different browsers demand different standards. In order to have a stress-free transition between different platforms, we focused on a simple, plain design and the most trivial functions. This also helps to enhance performance. Unity is structured in Scenes. A Scene is a unique level containing the environments or menus of a game. Figure 4.2 illustrates the gerneric structure of the *Virtual Rival Framework* in *Unity*. In general, we designed three different scenes types for our project:

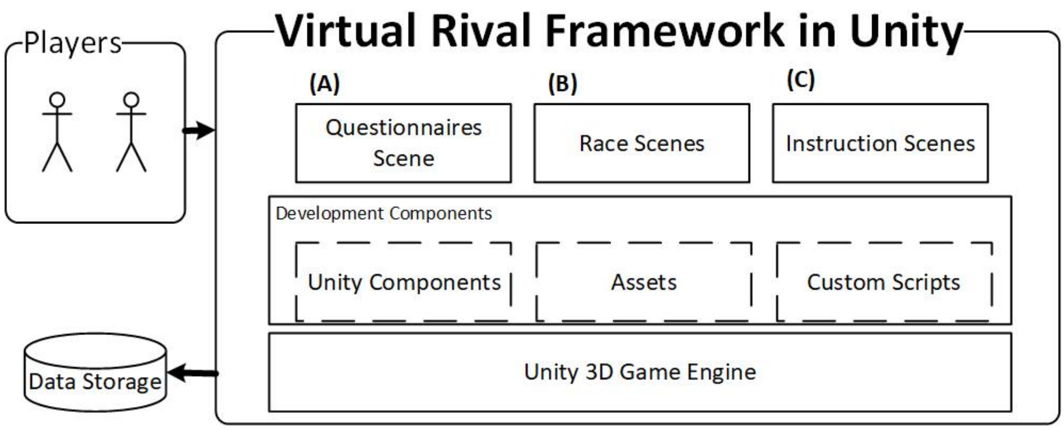


Figure 4.2.: Virtual Rival Unity Scenes

4.2.1. Questionnaire Scene

The developed questionnaire unit is a useful instrument to run questioners. One can think of many different questionnaires to integrate into this project. The *Questionnaire Scene* fits every type of self-reporting psychological questionnaires. In our case, the questionnaires are *Sensation Seeking* (see Section 2.2.1) and *Big Five* (see Section 2.2.1). Figure 4.3 shows the *Big Five Questionnaire Scene*.

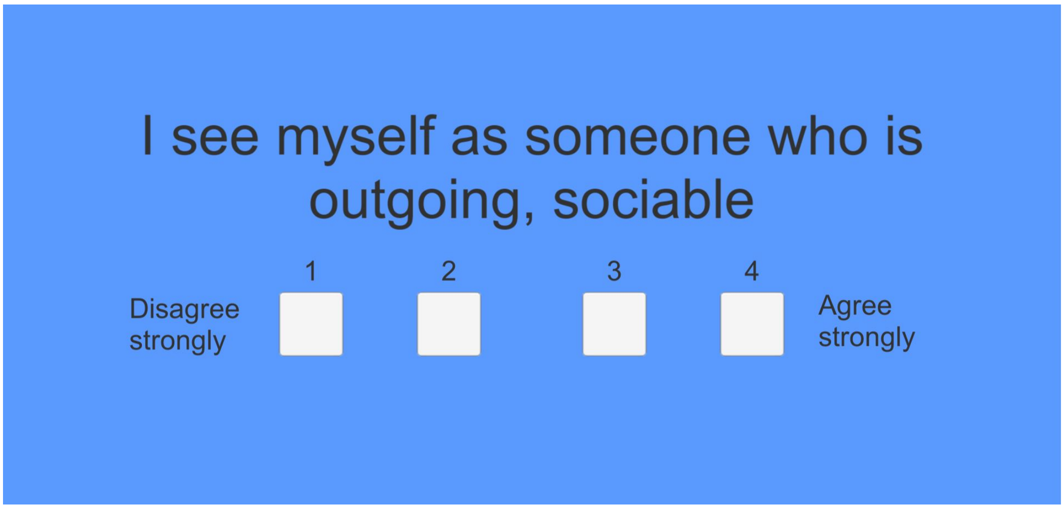


Figure 4.3.: Design of the Questionnaire Scene in Unity

The *Questionnaire Scene* is constructed out of three major components. The *Question Module* and the *Range Module* are view components that show the question and answer possibilities. The *Choice Module* and the *Confirm Module* are interactive components that let the user choose an answer. The main components of the scene are illustrated in Figure 4.4. The modules are specified in detail below:

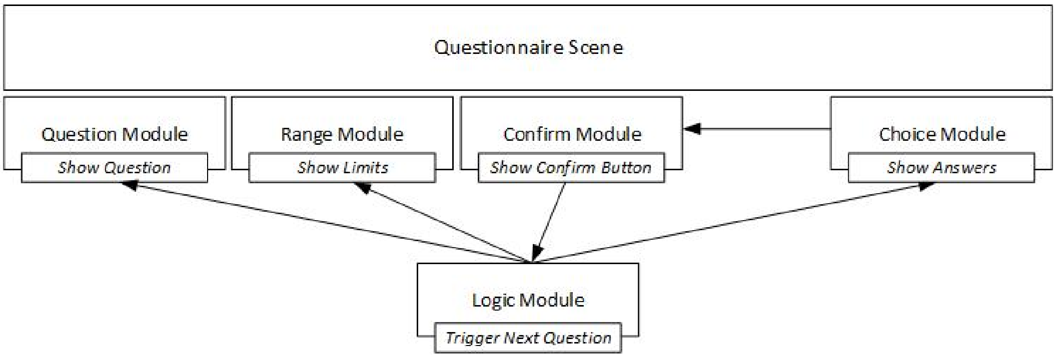


Figure 4.4.: Design of the Questionnaire Scene in Unity

- **Logic Module:** The *Logic Module* includes the logic which selects the questions. The questions are randomized. The module tracks answered questions and then uploads them onto the server. The logic of the scene is specified in more detail in Section (Unity, 2019b).

- **Choice Module:** The *Choice Module* consists of multiple radio buttons. Only one answer can be selected. Making a choice triggers the *Confirm Module*.
- **Range Module:** The *Range Module* specifies the answer possibilities of the question. The basic question answers range from ”1” to ”5” or “Disagree Strongly” to “Agree Strongly”.
- **Question Module:** The *Question Module* shows the current question. The current question is retrieved from the logic module.
- **Confirm Module:** The *Confirm Button* is only visible when an answer is selected. Pushing the button triggers the *Logic Module* to select the next question.

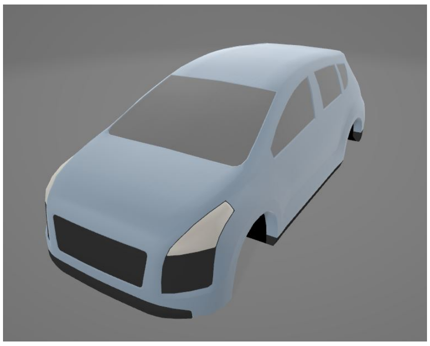
4.2.2. Race Scene

The Race Scene is the central element of the project. We want to create a physical realistically driving simulation. To ensure convincing physical behaviour, the car must accelerate correctly and be affected by collisions and gravity. Unity's built-in physics engine provides components that handle the physics calculations. Using the built-in Unity components we create objects that behave in a realistic way. The concrete movement is controlled by scripts. A typical object in unity holds both build-in physics components and scripts. Section 4.3 discusses the scripts controlling the objects. The main graphics primitives in Unity are 3D Meshes. Unity offers various components to import and render meshes, trails or 3D lines. Meshes make up the largest part of our 3D world. The main Unity components we use for every object are (Unity, 2019b):

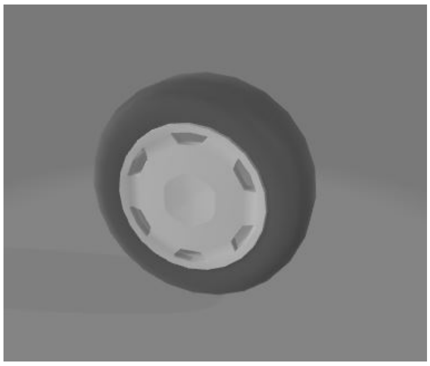
- **Texture:** Wrap around the object to decorate the surface.
- **Material:** Defines how the object is displayed. The properties if a *Material* are determined by the *Shader* in use. A *Shader* is a special program that combines texture and lightning information to generate pixels.
- **Transform:** Defines position, rotation and size of the object.
- **Colliders:** Are used to detect environment collisions. Can be generated out of the mesh data.

Every object in the *Race Scene* integrates the main Unity components. All race tracks are building out of similar building blocks. They only differ in the race track layout. The main building blocks of the race scene are:

- **Race Car:** Figure 4.5 illustrates the model used for the race car. The model is divided into the car and tyres. To optimise performance we reduced the number of vertices. The main components that specify the physical behaviour of the car are the *Rigidbody* and *WheelCollider* component. The *Rigidbody* handle's motion using the *Unity* physics engine (Rigidbody, 2019). The body will regulate forces e.g. gravity, acceleration and react to collisions. Every tyre integrates a *WheelCollider* component. The *WheelCollider* is a special built-in collider for grounded vehicles (Collider, 2019). It integrates wheel physics and friction. By adding spring and damping forces we created a realistic suspension model for the car. Section 4.3 introduces the *WheelDrive* script which controls the driving physic properties: motor torque, brake torque and the steering angle.



(a) Car Model used in the race scene



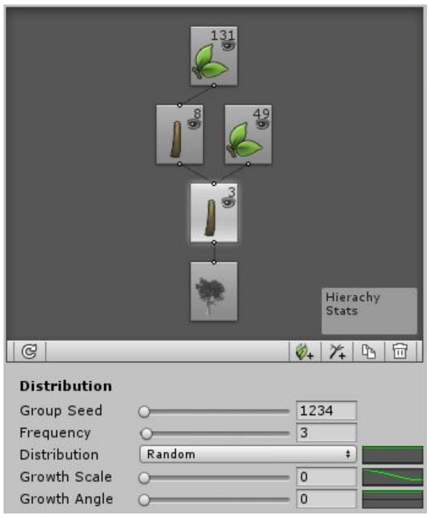
(b) Tyre Model used in the race scene

Figure 4.5.: Models used in the *Unity* project

- **Roadway:** The roadway and the *Race Car* are the main gameplay elements. The race track is assembled out of basic road elements e.g. straights, curves and s-curves in different sizes. Guide rails are placed on the edges to prevent players to leave the track. Crashing into the rails triggers a collision in the *WheelDrive* script (see Listening 2).
- **Environment:** The *Environment* presents visually appealing surroundings. *Unity's Terrain* system allows us to create vast landscapes (Terrain,

2019). We modified the height map and applied rocky surface textures to create a valley. The scene is completed by adding rich vegetation: grass, trees, bushes and flowers. Figure 4.6b shows the *Unity* environment tool to automatically generate vegetation. To create a wind effect we added a *Unity* wind zone. Trees within a wind zone bend in a realistic fashion and create a natural movement pattern among the trees. Figure 4.8 illustrates the final scene design in *Unity*. To enhance the rural feeling we added nature noises in the background.

(a) Example tree model in *Unity*



(b) Tree editor for randomised tree generation

Figure 4.6.: *Unity* vegetation tool

- **Cameras:** *Unity* uses cameras to render the scene. It is one of the most essential components in *Unity*. We use three cameras for our Race Scene. The main camera is attached to the vehicle and gives us a third person view over the scenery. The rear camera is similar to the main camera but points backwards. Figure 4.7 shows how the rear camera is rendered on top of the main camera to create a rear-view mirror effect. The map camera is an orthographic camera with a top-down view of the scene. Normally, things far away are rendered smaller. An orthographic camera has no diminishing perspective. The frustum is straight and front and back have the same size. We use the orthographic camera to generate an isometric projection of the scene which visualises the three-dimensional world in two dimensions as a map.

Figure 4.7.: Camera system of the Race Scene in Unity

4.2.3. Instruction Scene

The Instruction Scenes are the main tool to inform and advice players. Instructions can come in various shapes, depending on the task. We implemented three types of Instruction Scenes, with different functionalities: Basic Instruction Scene, Loading Information Scene and Individualised Information Scene. The scenes are constructed out of the four main unity elements from above. The Instruction Scene types are described in more detail below:

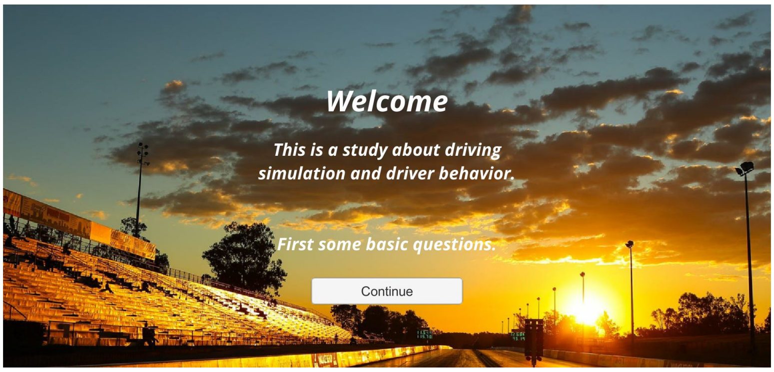
- **Basic Instruction Scene:** The *Basic Instruction Scene* is constructed out of an *Image Component* for the background and one or multiple Text Fields. This scene type is used at the beginning to give the user instructions on how to do the questionnaires and the controls of the car on the race track. Figure 4.9a exemplifies the Basic Instruction Scene used at the beginning of the racing segment.
- **Loading Information Scene:** The *Loading Information Scene* is visually similar to the *Basic Instruction Scene*. In the background, data is

Figure 4.8.: Bird's-eye view of the Race Scene in Unity

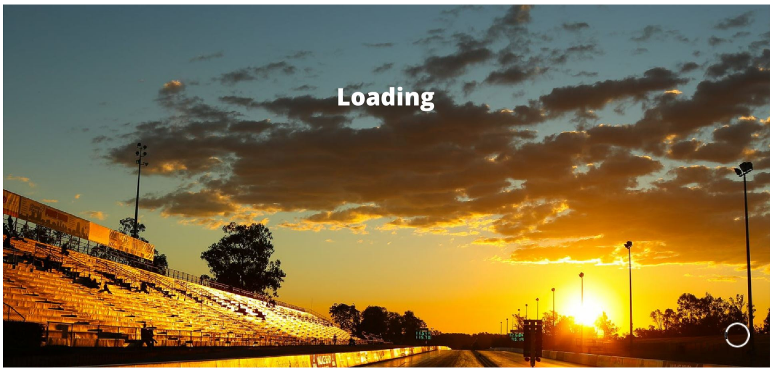
transmitted asynchronously to and from the server. The data is player information, questionnaire records and player trajectories. Figure 4.9b illustrates the Loading Information Scene between questionnaires.

- **Individualised Information Scene:** The Individualised Information Scene retrieves individual player information from the server and displays it. Figure 4.9c illustrates the Individualised Information Scene to retrieve the unique player id.

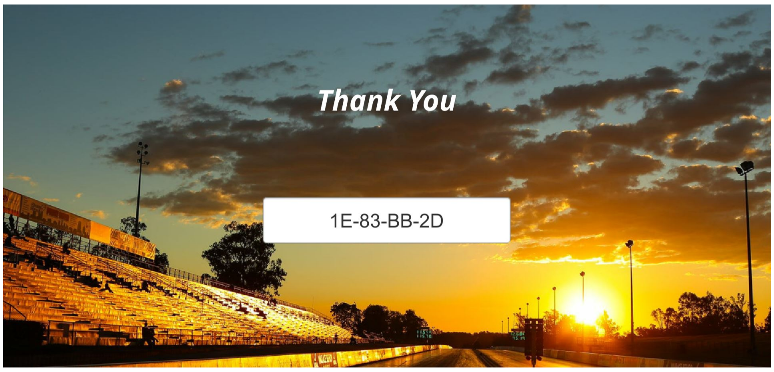
This section discussed the core *Unity* concepts we used to create the *Virtual Rival World*. We designed three different scene types for racing, questioning and general information. Each scene is created out of build-in *Unity* components. The functionality is added with customised scripts. The next section focuses on the main scripts for gameplay.



(a) Basic Instruction Scene



(b) Loading Information Scene



(c) Individualised Information Scene

Figure 4.9.: Three types of Information Scenes

4.3. Race Simulation Architecture

The previous section discussed *Unity's* built-in components. This section will explain the core concepts we used to create the gameplay mechanics. We implemented scripts to create our own gameplay features. *Unity* scripts are small programs which trigger events, modify component properties and handle user input. We use C# to write scripts. The script is connected to the *Unity* engine by deriving from the build-in *Unity* class *MonoBehaviour*. There are two main functions defined inside the class. The code inside the update function is called each frame. We use the update function to create movement, trigger actions and handle user input. The start function is called when the scene is instantiated. We use the start function to initialise components and variables.

In the following section, class diagrams and descriptions of the most important classes can be found. For the sake of readability, some classes have been omitted from the class diagrams. The class diagram in Figure 4.10 shows the most important classes.

WheelDrive
The *WheelDrive* script defines the driving behaviour of the car. It is directly attached to the race car as well as a *WheelCollider* and *Rigidbody* component. The *Unity WheelCollider* component implements basic graphical wheel representations and roll mechanics. The *Rigidbody* connects the vehicle to the physics engine (see Section 4.2.2). Listing 2 shows the essential parts of the script. The script defines the car handling characteristics. In the initialisation phase, we set up the wheels. During the continuous updates handle the user input. Pressing the acceleration button applies a positive force in the forward direction. Depending on the *DriveType* we apply the force on two or all of its wheels simultaneously. The force is calculated with Formula 4.1. Changes in gearing are important when looking at torque because the gears act as torque multipliers. The engine rpm is calculated to evaluate the engine sound. Engine rpm is correlated to the pitch.

$$\underbrace{\vec{M}}_{\text{Torque M(Nm)}} = \underbrace{P}_{\text{Power P (bhp)}} * \underbrace{\alpha}_{\text{Gear ratio}} * \underbrace{\vec{v}}_{\text{Direction}} \tag{4.1}$$

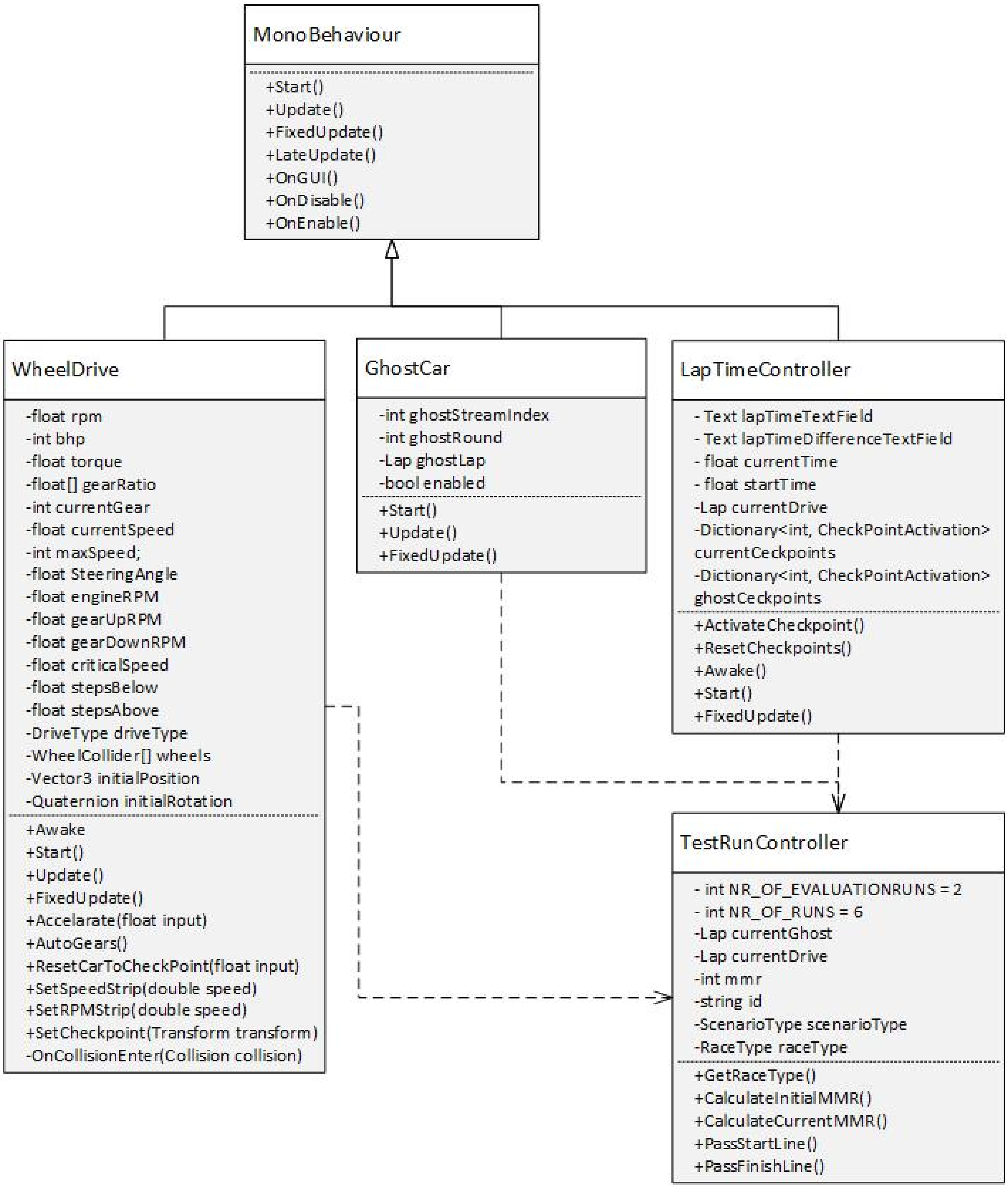


Figure 4.10.: Main classes in the Race Scene

User steering modifies the steering angle of the two forward wheels. When pressing the reset button the car will be placed on the last checkpoint. The *WheelDrive* script also tracks the collisions while driving.

GhostCar The *GhostCar* script uses data from previous runs to create an opponent. The *TestRunController* selects suitable opponents. It is attached to the ghost car model. Algorithm 1 illustrates the process. At the start, we place the ghost car at the start line. In every frame, we update the position by interpolating to the next location of the recorded ghost opponent.

Algorithm 1: Run ghost car

```
Data: Position, rotation data from previous runs
Result: Ghost car update for every frame
Initialization
                                                    // init wheels
while Simulation running do
    Read current position
    Read current rotation
                                  // Position / Rotation at timestep
    if Position changed then
        Interpolate position
        Interpolate rotation
        Update wheel position
```

LapTimeController
The *LapTimeController* traces the lap time and the activation of checkpoints. The timer is stopped at the finish line. During the run, the timer is visualised on the upper edge of the screen. At the checkpoint, we compare the timer with the opponent's timer. The difference in time is displayed to inform the player and give feedback.

TestRunController
The *TestRunController* tracks the internal state during the run. The script tracks the players' progress and skill level. The current skill level is updated after every lap. Since the real strength of a player is unknown to us, we have to estimate it by a rating. The *Elo* system is a rating system of competitive games

Algorithm 2: Anatomy of the WheelDrive script controlling the car

```
Data: Steerangle, rpm, bhp, torque, gearratio, enginerpm, speed
Result: Car update for every frame
Read input
                                                        // Get user input
Configure vehicle substeps
              // Set lower accuracy at high speeds (performance optimization)
Auto gears
                   // Change gears when necessary (automatic transmission)
if Reset key pressed then
    Reset car to checkpoint
if Accelerate key pressed then
    Apply force
speed = rigidbody.velocity * 3.6f
enginerpm = rpm * gearRatio[currentGear]
torque = bhp * gearRatio[currentGear]
                                                   // Update engine params
Set sound rpm
                                                    // Update engine sound
Update wheels
```

(Lehmann & Wohlrabe, 2017). We modified the original system to fit the race game genre. Section 2.4.2 describes the *Elo* algorithm in detail. The match between the player and the ghost can be approximated with the Formula 4.2:

$$EP = \frac{1}{1 + 10^{\frac{(RP-RG)}{\Lambda}}} \tag{4.2}$$

The expected score for the player to win the race based on the unknown strengths for the player (RP) and ghost (RG). An expected score of 1 predicts a win and a loss by 0. Lambda (Λ) describes the spread of the ratings. We chose Lambda with 400 which results in the win probability distribution in table 4.1.

Table 4.1.: Win probability distribution

Rating difference (RP-RG)	Estimated win probability for player
0	0.50
50	0.42
100	0.35
200	0.24
400	0.09
800	0.01

After a race, we have to update the strength. To update the player strength (RP) we use formula 4.3. The race result is modelled in SP (WIN = 1, LOSS = 0). The expected result and the estimated strength are known quantities. The factor k bounds how fast algorithm involves. We set k to 128. A large k allows us to quickly find the correct skill level, but we lose precision.

$$RP_{new} = RP_{prev} + k * (SP - EP) \tag{4.3}$$

4.4. Data Models

The run data is persistently stored in a cloud database. We use *Google Forms* to save the questionnaire data. The data is directly transferred from *Unity* to the server using the *UnityWebRequest*. The data can be visualised on the web. For the analytics tool in Section 4.5, we use the *Anaconda oauth2client* library to access the data. The database model is shown in Figure 4.11. During the driving course, we save position and rotation information every 25ms. Additionally, we save driving faults like accidents and reset points. The questionnaire data is saved in separate tables. The *ID* uniquely identifies a player. *ID* and *Round* form the foreign key for the questionnaires after each round.

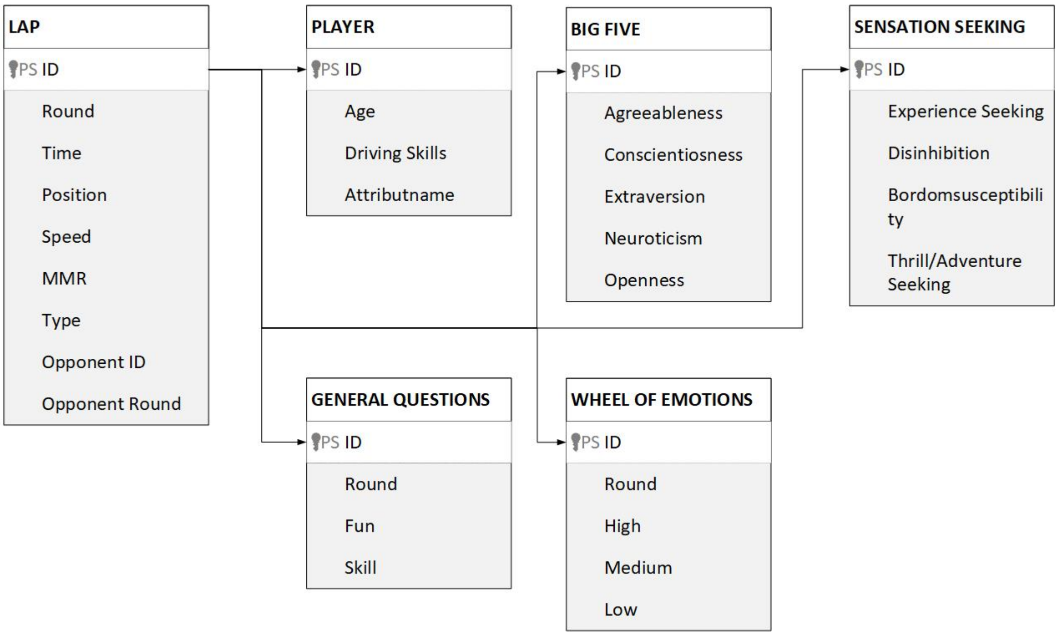


Figure 4.11.: Logical Data Model for Player Data

4.5. Analysis Tool

The analysis tool visualises and interprets the stored data (see section 4.4). It's a standalone *Python* application, independent from the other components. We use the data science platform *Anaconda* and the open source package management system *Conda* to manage libraries and dependencies (Anaconda, 2019). The main libraries are:

- **NumPy:** *NumPy* is one of the most fundamental *Python* libraries (NumPy, 2019). It provides data structures for big, more dimensional matrices and efficiently implements numerical calculations.
- **Pandas**: *Pandas* provides high-performance data structures for data analysis (Pandas, 2019).
- **Scipy:** The *scipy.stats* module contains a large number of probability distributions and a wide range of statistical functions (Stats, 2019).
- **Matlibplot:** *Matplotlib* is a basic *Python* 2D plotting library (Matplotlib, 2019). We generate plots, histograms, errorcharts, and scatterplots using *Matplotlib*.
- **Seaborn:** *Seaborn* is a data visualization library for making statistical graphics (Seaborn, 2019). It provides convenient views for complex datasets.

Anaconda allows us to analyse data with scalability and performance with *NumPy* and *Pandas*. The results are visualised using *Matlibplot* and *Seaborn*. Visualisation is a central part of understanding data. We use *Seaborn* onto data snippets to produce informative plots. Figure 4.12 shows the composition of the analysis tool. The tool is constructed out of three components:

- **Reader Module:** The *Reader Module* accesses the data from the server and parses them into suitable data container. Every data type has a special reader implementation e.g LapReader, QuestionsReader. The *Graph Module* and the *Statistic Module* manipulate the data.
- **Graph Module:** The *Graph Module* visualises the data using *Matplotlib* and *Seaborn*. We plot histograms and scatterplots to analyse driving data.
- **Statistic Module:** To find trends inside the data we use the statistics module of *SciPy*. The *Statistic Module* measures the linear relationship between two datasets. We calculate correlation coefficients and use p-value testing for non-correlation.

4.6. Summary

In this chapter, a brief overview of the structure was given and the modules that were developed for this work were presented. In addition, we introduce the used libraries and tools. We modelled a 3D race environment with an integrated

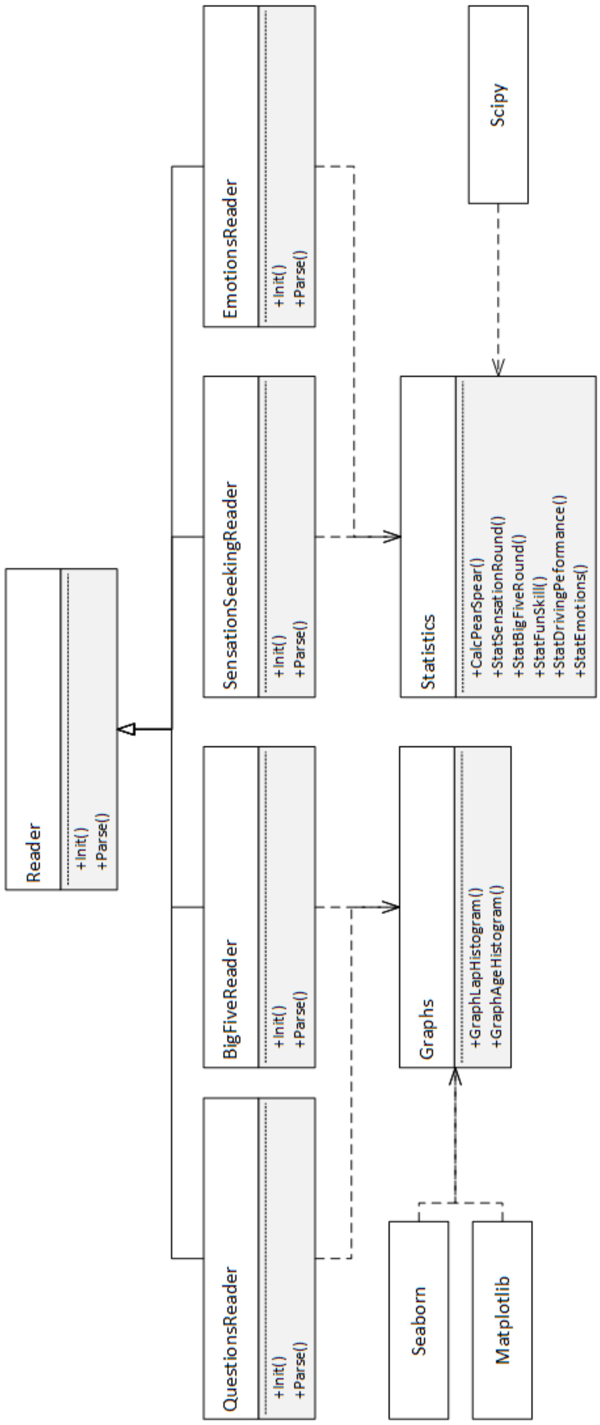


Figure 4.12.: Main classes of the Analysis Tool

questionnaire using *Unity*. The implemented analysis tool allows us to find trends and correlations inside the data. In Section 3.2.1 we selected the *Unity* game engine as main platform. This section focused on the implementation details using the *Unity* game engine.

First, we discussed the graphical design of the *Virtual Rival Framework* in *Unity*. The functionality is split across multiple *Unity* scenes. A scene represents an independent level in *Unity*. We differentiate three types:

- **Instruction Scene:** Show information to players e.g. controls, instructions, loading progress.
- **Questionnaire Scene:** Integrates different questionnaires to measure *Engagement*, *Education* and *Performance*.
- **Race Scene:** Each scene includes different race tracks, race cars and terrains.

Secondly, we go into the implementation of gameplay for each scene. Gameplay in *Unity* is mainly constructed with predefined components and individual scripts. The race behaviour and physics calculation are specified to fit web application with restricted resources. To simulate a realistic race we implemented a ghost car using the Elo algorithm to match the players' skill.

Third, we introduce the data management part of the *Virtual Rival Framework*. Data collected during the race and from questionnaires are directly uploaded to the cloud. Google services are used to store and access the data. The focus is on privacy, consistency and reliability.

The created 3D environment should give an example of what types of psychological research in race scenarios are possible with the implemented tools. It is the first prototype and many more applications are thinkable. In the next step we have evaluated the *Virtual Rival* scenario with a user study in which we have collected data with the help of a set of standardized questionnaires. The next chapter will discuss this evaluation and its results.

5. Evaluation

The last chapter discussed the key implementation details and concepts. We also conducted a study to evaluate the implemented learning tools and how they work together. Participants were divided into two groups and asked to carry out a test run in the *Virtual Rival World*. Given the broad scope of functionalities and measurements, it was not possible to test everything in one test session. For that reason, only the players' standpoint was taken into account.

The remainder of this section will discuss the methodology and results of this study. The outcome of this study will help to understand racing games, improve*Engagement*, *Education* and *Performance* of drivers.

5.1. Research Questions

The Virtual Rivals development focus was on player usability. The data is recorded during the runs and feed into the Analysis Tool. We initially defined two research questions (See Section 1):

- How does personality influence driving performance in racing simulations?
- What is the effect of virtual rivals on *Engagement*, *Education* and *Performance*?

We want to understand players in racing games and improve*Engagement*, *Education* and *Performance* of drivers. For this evaluation, we defined six more detailed questions:

(I) What is the difference between self-assessment and real driving skill?
(II) How is the relationship between personality and speed?

(III) How is the relationship between personality and accidents?
(IV) How does competing against a *Ghost Car* and *Virtual Rival* influence players' *Engagement*?
(V) How does competing against a *Ghost Car* and *Virtual Rival* affect *Education*?
(VI) How does competing against a *Ghost Car* and *Virtual Rival* affect players' *Performance*?

We want to find out if automatic skill-adjustment is necessary to improve *Engagement*, *Education* and *Performance*. Personality plays a role in how we drive. We investigate personalised racing simulations to improve *Education* and *Performance*. Our main focus is how the implementation of *Virtual Rivals* affects *Engagement*, *Education* and *Performance*. The next section introduces the study process in more detail.

5.2. Methodology

Chapter 2 introduced the theoretical background of this work. Central points are the psychology foundation of *Engagement*, *Education* and *Performance*. It also covered the most important aspects of game design and race games. In this chapter, we build on the theoretical foundation to investigate driving behaviour. We developed a racing game with an integrated survey. The game allows analysing driving behaviour, improving the learning process and identifying risk factors. We built our own game to have total control over the recorded data tailored to our requirements. A total of 38 people participated in this study (14 female / 24 male). The study consists of three major parts:

- Personality test
- Driver skills evaluation
- Motivation assessment

The first step is to measure the personality traits of participants. Section 5.2.1 explains the two instruments we used: *Big Five* and *Sensation Seeking*. The *Big Five* is a reliable way to measure the five domains of personality: *Extraversion*, *Neuroticism*, *Conscientiousness*, *Agreeableness*, and *Openness*. *Sensation Seeking* indicates a willingness to take risks. We expect to find relationships between personality trades and unsafe driving practices based on previous research.

The second step is to measure driving skill. In Section 5.2.2 we introduce the racing part of our video game. It's a first-person simulation style racing game. Participants have to drive several rounds. We aimed for a medium grade of driving skill, focusing on realistic physics. Drivers have to master proper cornering technique and precision racing manoeuvres in order to manufacture a fast and clean lap. We record the position, velocity while driving to compare drivers, detect driving errors and find correlations.

The third step of the study focuses on measuring the emotion between runs is explained in Section 5.2.3. The emotions can only be assessed with self-report measures. The instrument we use is the *Geneva Emotion Wheel*. It's a very successful visual tool. We integrated the tool after each lap. *Engagement* influences our driving and learning behaviour.

5.2.1. Personality Types

This framework includes two personality surveys. In this section, we want to discuss how we measure personality. We also elaborate on how the tools are integrated into the survey. In this section, we discuss the *Big Five* and *Sensation Seeking* personality traits. The *Big Five* personality traits have been found to influence learning behaviour and performance. The second personality measurement tool was the *Sensation Seeking Scale*. The *Sensation Seeking* trait indicates a willingness to take risks. In total we extract six personality-variables: *Extraversion*, *Neuroticism*, *Conscientiousness*, *Agreeableness*, *Openness* and *Sensation Seeking*.

Big Five

Chapter 2.2.1 introduces the theoretical background of the *Big Five* personality traits. For our study, we implemented the short evaluation questionnaire illustrated in Table 5.1 based on Rammstedt and John (2007). The *Big Five* theory presents a model in which personality is organized into five factors:

- **Extraversion:** Manifests in outgoing and energetic behaviour.
- **Agreeableness:** Perceived as kind and cooperative.
- **Conscientious:** Implies a desire to do a task well, being careful and efficient.
- **Neuroticism:** Tend to be emotionally unstable e.g. more likely to feel anger and frustration
- **Openness:** More likely to be creative and tolerant.

The *Big Five* evaluation questionnaire should help to find a relationship between personalities, driving and gaming. In the next section, we discuss our second personality metric specialised on risk-taking.

I see myself as someone who…	Disagree strongly	Disagree a little	Agree a little	Agree strongly
… is reserved	(1)	(2)	(3)	(4)
… is generally trusting	(1)	(2)	(3)	(4)
… tends to be lazy	(1)	(2)	(3)	(4)
… is relaxed, handles stress well	(1)	(2)	(3)	(4)
… has few artistic interests	(1)	(2)	(3)	(4)
… is outgoing, sociable	(1)	(2)	(3)	(4)
… tends to find fault with others	(1)	(2)	(3)	(4)
… does a thorough job	(1)	(2)	(3)	(4)
… gets nervous easily	(1)	(2)	(3)	(4)
… has an active imagination	(1)	(2)	(3)	(4)

Table 5.1.: Big Five Questionnaire based on Rammstedt and John (2007)

Sensation Seeking

Chapter 2.2.1 discusses *Sensation Seeking* personality traits as an indicator for risk-taking. For our study, we implemented the *Brief Sensation Seeking Scale* illustrated in Table 5.2 based on Hoyle et al. (2002). The *Brief Sensation Seeking Scale* significantly predicts intention to and actual engagement in a number of health risk behaviours. We are particularly interested to find a relationship between *Sensation Seeking*, driving and gaming. In the next section, we introduce the integrated driving measurements.

I...	Disagree strongly	Disagree a little	Agree a little	Agree strongly
... would like to explore strange places.	(1)	(2)	(3)	(4)
... would like to take off on a trip with no pre-planned routes or timetables.	(1)	(2)	(3)	(4)
... get restless when I spend too much time at home.	(1)	(2)	(3)	(4)
... prefer friends who are excitingly unpredictable.	(1)	(2)	(3)	(4)
... like to do frightening things.	(1)	(2)	(3)	(4)
... would like to try bungee jumping.	(1)	(2)	(3)	(4)
... like wild parties.	(1)	(2)	(3)	(4)
... would love to have new and exciting experiences, even if they are illegal.	(1)	(2)	(3)	(4)

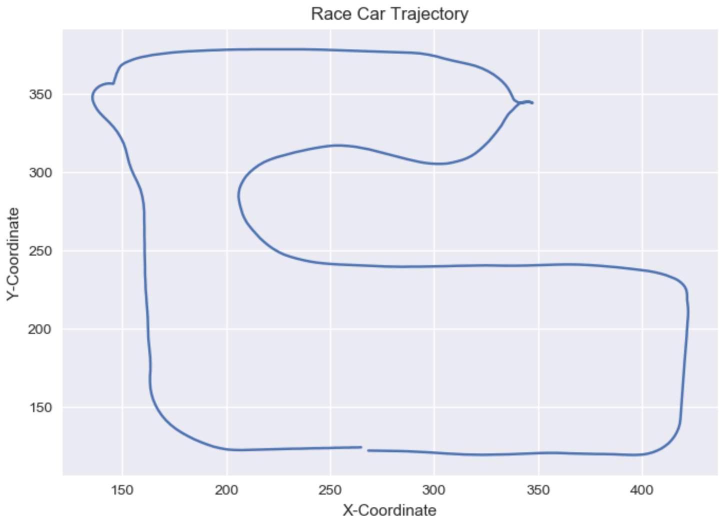
Table 5.2.: Sensation Seeking Questionnaire based on Hoyle, Stephenson, Palmgreen, Lorch, and Donohew (2002)

5.2.2. Driving Data

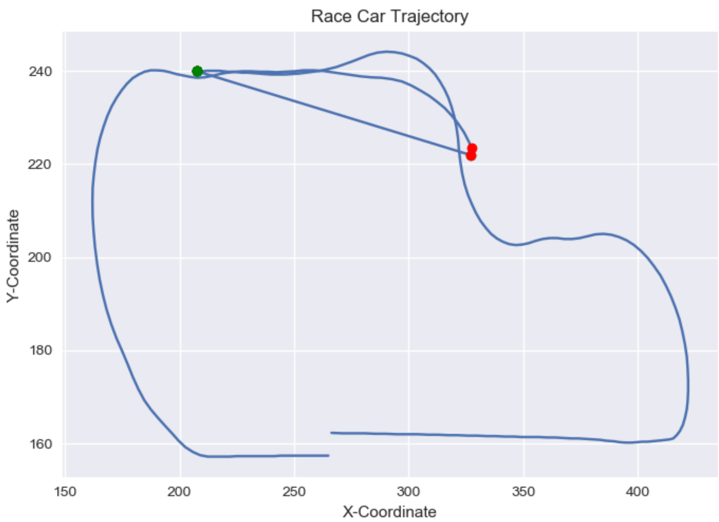
Chapter 2.4.3 introduced driving metrics to measure performance. For our study, we measured various driving metrics e.g. speed, trajectories, driving errors and resets. Figure 5.1a illustrates the recorded driving trajectories. Data points are captured every 200ms. Accidents, where the player touched the barrier are marked in red. Reset points are indicated in green. Additionally, we record speed for every time-step, lap times and sector times. The driving data is vital to measure and analyse performance. The next section introduces a method to capture Emotions.

5.2.3. Emotions Capture Methods

Chapter 2.2.3 discussed the *Wheel of Emotions* as tool to measure *Engagement* and *Performance*. Figure 5.2 illustrates the integration of the *Wheel of Emotions* in our *Virtual Rival Framework* based on (Scherer, 2005). The most important emotions we need to track in race games are:



(a) Basic Lap



(b) Lap with contact points

Figure 5.1.: Visualisation of race lap data.

- **Pride:** When winning in general.
- **Interest:** Desire and little control over the situation.
- **Challenge:** The desired goal takes a lot of effort but is still reachable.
- **Surprise:** Unexpected situations with little effort.
- **Boredom:** When the mind is not challenged results in low effort and attention.
- **Anger:** Arises in unfair situations.
- **Frustration:** When success is expected, failure is often accompanied by frustration.

Racing simulations have to control the challenge and the certainty of the situation to optimize *Engagement*, *Education* and *Performance*. The next section introduces the background of the participants in this study.

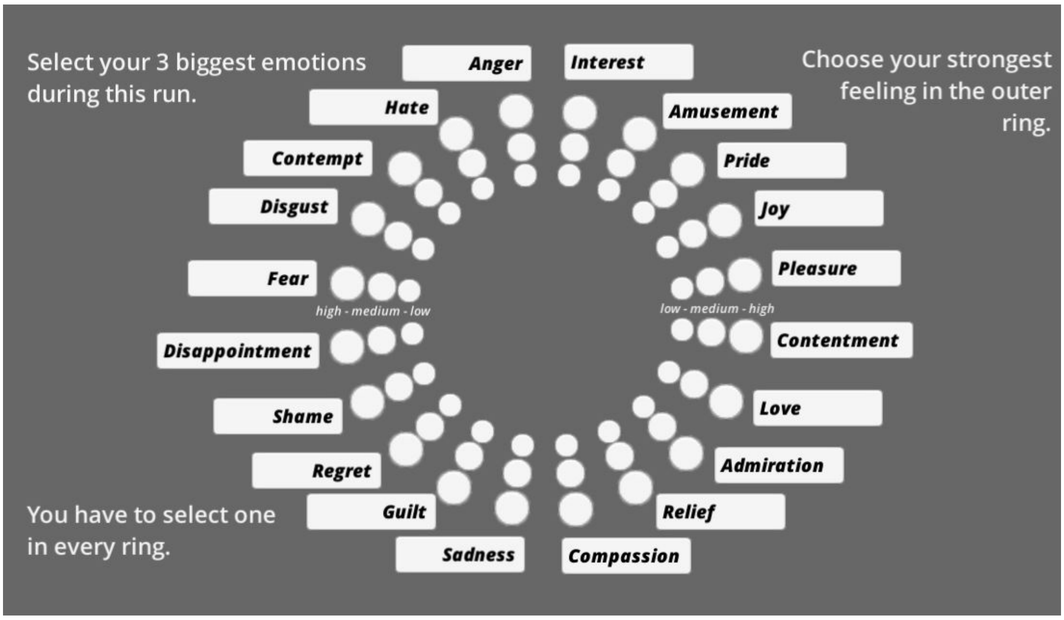


Figure 5.2.: Wheel of Emotions

5.3. Participants

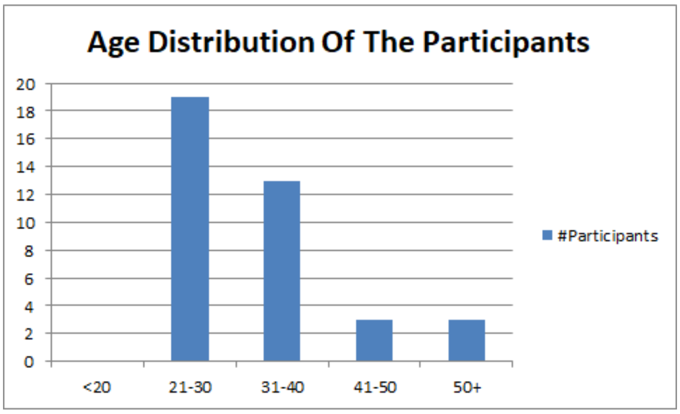
A total of 38 people participated in this study (14 female / 24 male). Participants came from different backgrounds and between the ages of 20 and 50 years (M=27.3; SD=9). Figure 5.3a illustrates the age distribution. In order to participate, they only needed a computer or laptop. The participants were recruited using *Amazon Mechanical Turk*. All of the participants have real-world driving and gaming experience. In the questionnaires, we model *Excellent* as (1) and *Bad* as (5). Figure 5.3b illustrates the results of the real-world driving skill self-evaluation. Most participants rated their driving skill as average (M=2.8; SD=0.9). The gaming skill self-evaluation had similar results as shown in Figure 5.3c. The majority of participants rated their gaming skill as below-average (M=3.6; SD=0.7).

5.4. Procedure

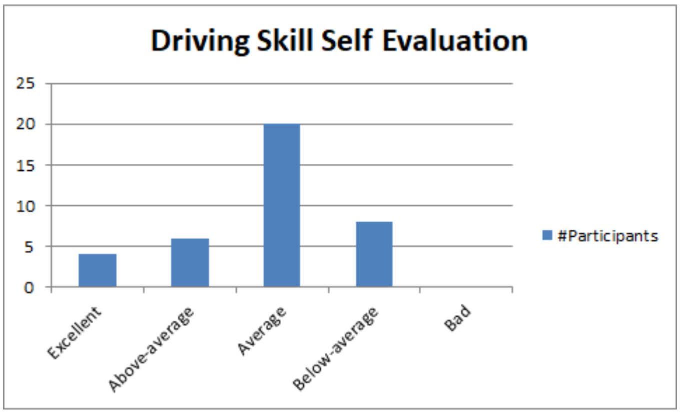
Two test sessions were carried out over the course of two weeks. In each session, we invited a group of users to try our game. First, the participants were greeted and informed about the structure of the study. In a short tutorial level, we showed how to control the car. Each task was given to the students only after they have completed the previous one. The participants received their tasks from *Amazon Mechanical Turk*. Every participant receives a unique ID. Entering the ID confirms the completion of the tasks. The procedure is described in Figure 5.4.

Tasks

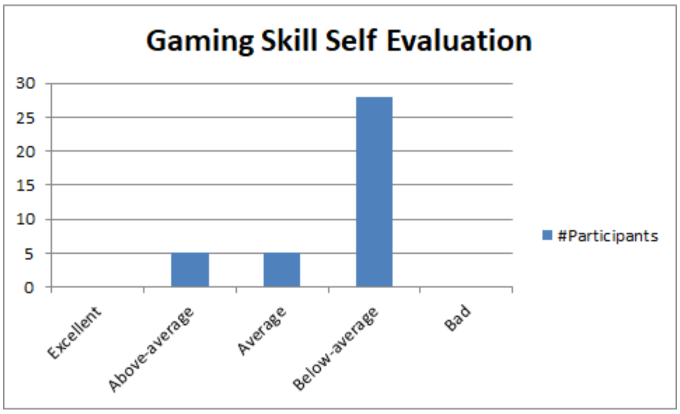
1. The first task is to drive around and explore the race track. This is used to learn to control the car. The participants were not given any specific tasks or opponents.
2. The second task is to enter basic information used to characterise the participant e.g. age, driving skill, experience with video games.
3. In the third tasks participants have to complete two personality tests. We implemented the *Big Five* and *Sensation Seeking* personality test, consisting out of multiple questions. The *Big Five* personality labels the



(a) Age distribution



(b) Driving skill self-evaluation



(c) Gaming skill self-evaluation

Figure 5.3.: Participants information

human personality broadly in five dimensions. The *Sensation Seeking* personality test is specialised on risk-taking.

4. The fourth tasks are two evaluation rounds. Participants have to drive as fast as possible. During the evaluation rounds, we estimate the initial skill.
5. The main task consists of three parts. Participants are randomly assigned in two groups. The first group is the reference group racing against a classic race ghost, a shadow of the last round. The second group races against a virtual rival with automatically adjusted difficulty. After each lap, the participants have to self-evaluate their performance. The last part is a short evaluation of the current emotions and motivation of the participant. This procedure will be performed multiple times.
6. The last task is to confirm the successful completion by entering the participant ID.

5.5. Results

We used Pearson's r to investigate the relationship between variables. Pearson's correlation coefficient assumes the normality of variables. We assessed the normality of the data with the p-value to test for non-correlation. In cases where one of the variables would not meet the assumption of normality, we used Spearman's correlation coefficient q to find correlations. We used Scipy.stats version 1.3.0 to compute the correlations. Because of the large variations commonly present in human behaviour and a large number of factors influencing this behaviour (personality, intelligence and learned associations), psychologists consider the following correlations to be indicative for effect sizes in a relationship between personality and the participants' game behaviour (Cohen, 2013):

- Weak Correlation: r=0.1 (1% of variance explained)
- Medium Correlation: r=0.3 (9% of variance explained)
- Strong Correlation: r=0.5 (25% of variance explained)

In this section, we discuss the data gathered during the study. Our analysis tool helps to process the data (See Section 4.5). The focus is on answering the six core research questions of this work:

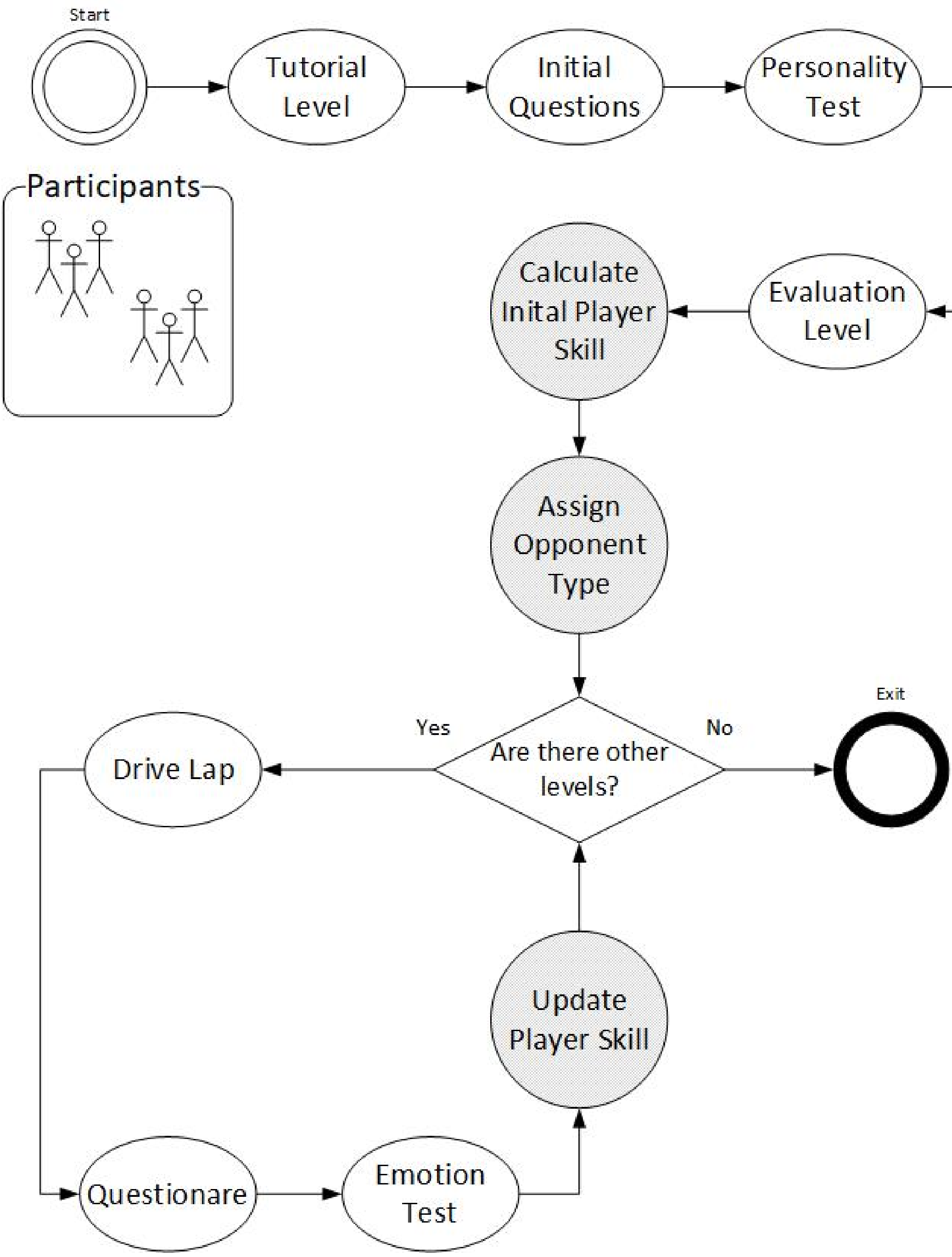


Figure 5.4.: Sequence of study tasks

(I) What is the difference between self-assessment and measured in-game driving skill?

Each of the 38 test users stated that they have some knowledge in both real-world driving and gaming. We define performance as the best lap time achieved, in a limited time frame, without touching the barriers. Figure 5.5 shows the relationship between the self-assessment of real-world driving and the one-lap performance in our *Virtual Rival Framework*. We found no skill difference between *Good* (M=81.5; SD=11.8) and *Average* (M=81.6; SD=13) drivers. A similar skill relationship was found between *Above Average* (M=85.2; SD=24.5) and *Below Average* (M=84.1; SD=27.5) drivers.

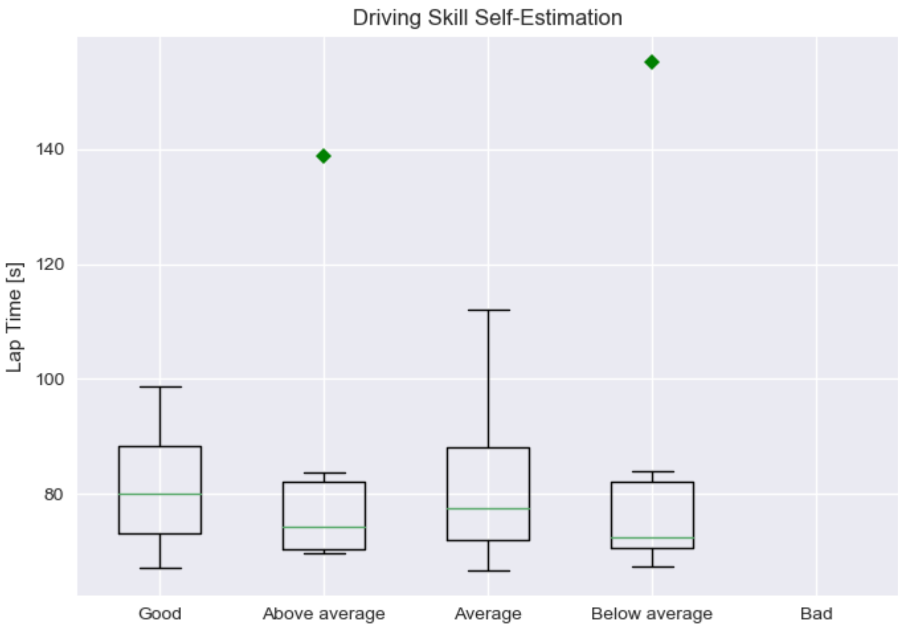


Figure 5.5.: Real Performance vs Driving Skill Estimation

Figure 5.6 shows the relationship between the self-assessment of gaming skill and the one lap performance in our *Virtual Rival Framework*. None of the participants rated their skill level with the extreme values *Excellent* and *Bad*. *Above Average* (M=117.2; SD=25.3) participants had generally worse performances than participants that rated themselves with *Average* (M=76.4; SD=7.1) and *Below Average* (M=77.6; SD=10.9). We found no general relationship between self-estimation and driving skill in the *Virtual Rival World*.

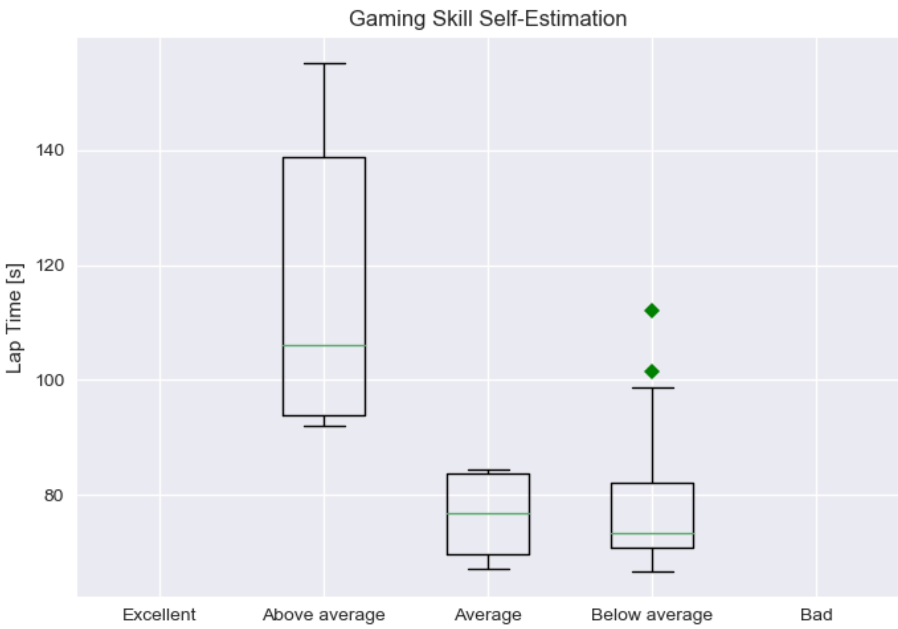


Figure 5.6.: Real Performance vs Gaming Skill Estimation

(II) How is the relationship between personality and speed?
In Section 5.2.1 we discussed our personality measures: *Big Five* and *Sensation Seeking*. Table 5.3 shows the detailed result of the personality evaluation in relationship with speed in the *Virtual Rival Framework*. Correlations between speed and the *Big Five* personalities: *Agreeableness*, *Conscientiousness*, *Extraversion*, *Neuroticism* and *Openess* were not significant. *Sensation seeking* was found to be related to higher speed in every scenario. We found a medium correlation with mean speed ($q = 0.35, p \leq 0.05$) and high speed ($q = 0.32, p \leq 0.05$).

(III) How is the relationship between personality and accidents?

Table 5.3.: Pearson correlations between personality variables and both the mean speed, the maximum speed and number of driving errors(n=38)

	Mean speed	High speed	Driving errors
Agreeableness	-0.15	-0.03	-0.03
Conscientiousness	0.02	-0.07	-0.12
Extraversion	-0.19	-0.15	-0.03
Neuroticism	-0.02	-0.14	0.19
Openess	-0.11	-0.21	-0.04
Sensation Seeking	0.35*	0.32*	-0.3*

Notes : Pearson p-value:

** $p \leq 0.01$
* $p \leq 0.05$.
+ $p \leq 0.1$.

Table 5.3 shows the detailed results of the personality evaluation in relationship with driving errors in the *Virtual Rival Framework*. We mainly focused on the number of collisions and resets during the run. Correlations between speed and the *Big Five* personalities: *Agreeableness*, *Conscientiousness*, *Extraversion*, *Neuroticism* and *Openess*, were not significant. *Sensation seeking* was found to be related with a higher number of driving errors ($q = 0.30, p \leq 0.05$).

(IV) How does competing against a *Ghost Car* and *Virtual Rival* influence players' *Engagement*?

To investigate *Engagement*, we mainly focused on positive *Entertainment*. We looked into the differences between *Traditional Ghost Cars* and *Virtual Rivals*. Table 5.4 compares the statistical evaluation for *Traditional Ghost Cars* with *Virtual Rivals*. We found a medium correlation between winning a race and *Entertainment* for the players with *Traditional Ghost Cars* ($q = 0.42, p \leq 0.01$) and *Virtual Rivals* ($q = 0.41, p \leq 0.01$). The negative impact of causing an accident was slightly higher when driving against a *Virtual Rival* ($q = 0.26, p \leq 0.1$). We found the biggest difference between driving against a *Traditional Ghost Cars* and *Virtual Rival* when the race was close. Winning a close race was more satisfying against a *Virtual Rival*, where we detected a clear correlation ($q = -0.31, p \leq 0.05$). The data indicated that winning a close race against a *Traditional Ghost Cars* also raises the *Entertainment* level, but with no significant statistical relevance.

Table 5.4.: Pearson correlations comparing a *Traditional Ghost Car* to *Virtual Rival*

	Traditional Ghost		Virtual Rival	
	Entertainment	Motivation	Entertainment	Motivation
Errors	-0.20+	0.17	-0.26+	0.05
Winning	0.42**	0.20*	0.41**	0.05
Time Difference	-0.19	0.17	-0.31*	0.03

Notes : Pearson p-value:

** $p \leq 0.01$
* $p \leq 0.05$.
+ $p \leq 0.1$.

(V) How does competing against a *Ghost Car* and *Virtual Rival* affect *Education*?

When looking at the educational benefits of racing games, we mainly focus on motivation to keep playing and improve. Table 5.4 compares the result of the statistical evaluation for *Traditional Ghost Cars* with *Virtual Rivals*. We found only a weak correlation between motivation and winning against a *Traditional Ghost Cars*. No correlations to *Virtual Rivals* have been detected. We compared the trajectories and contact positions during the rounds in Figure 5.7 and Figure 5.8. Participants driving against *Traditional Ghost Cars* showed a higher error potential in straight sections.

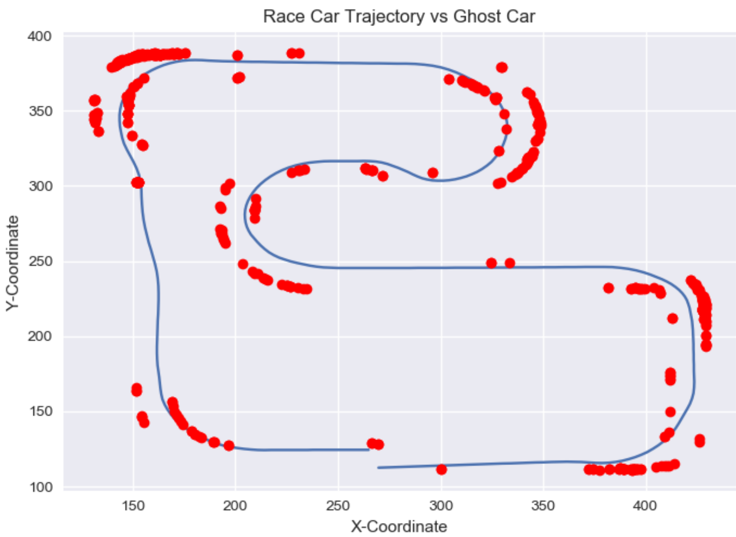


Figure 5.7.: Racing Peformance vs Tratitional Ghost Car

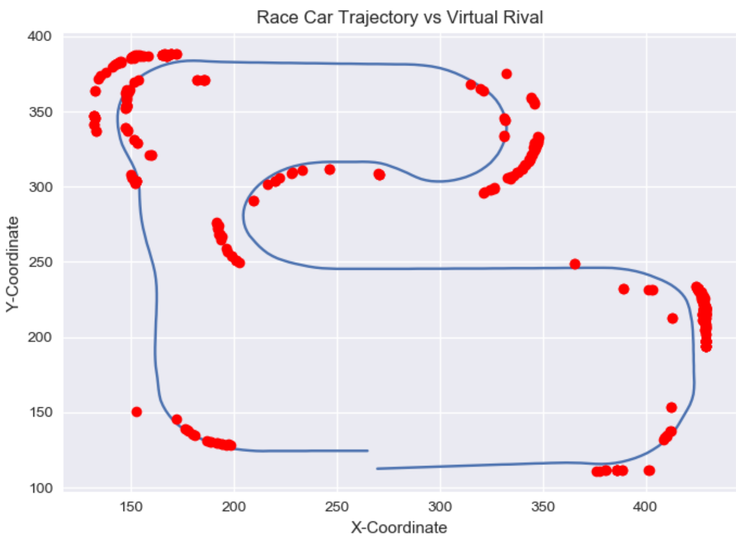


Figure 5.8.: Racing Peformance vs Virtual Rival

(VI) **How does competing against a *Ghost Car* and *Virtual Rival* affect players' *Performance*?**
For our study, we measured various driving metrics e.g. speed, trajectories and driving errors. Our main metric for performance is the best lap in a limited time frame. We also track driving errors. Table 5.5 compares the performance against *Traditional Ghosts* with *Virtual Rivals*. We found no performance statistical correlation. Figure 5.9 illustrates the best laps of all participants. Comparing the best lap times we found that participants playing against *Virtual Rivals* (M=80.4; SD=10.5) outperformed *Traditional Ghosts* (M=88; SD=33).

Table 5.5.: Performance of players, comparing first round and best round

	Traditional Ghost		Virtual Rival	
	Mean	Standard Deviation	Mean	Standard Deviation
Improvement per Round [s]	2.5	3.3	1.8	2.4
Driving Errors per Round [#]	2.3	1.6	2.4	1.2

Notes: Performance evaluation showed no significant statistical significance.

5.6. Discussion

Overall the evaluation showed promising results. The study and automatic analysis worked well for all participants. Our findings can help to improve racing game design and the automatic progression of skill-level in virtual driving. The evaluation has outcomes in three major areas:

Firstly, the evaluation indicates that players are not able to estimate their skill level. Both, the self-estimated gaming skill and driving skill, was not related to the in-game driving performance. Most players tended to evaluate themselves as average skilled drivers. The result is consistent with previous research of Debeauvais et al. (2014), that players have trouble selecting the optimal assist

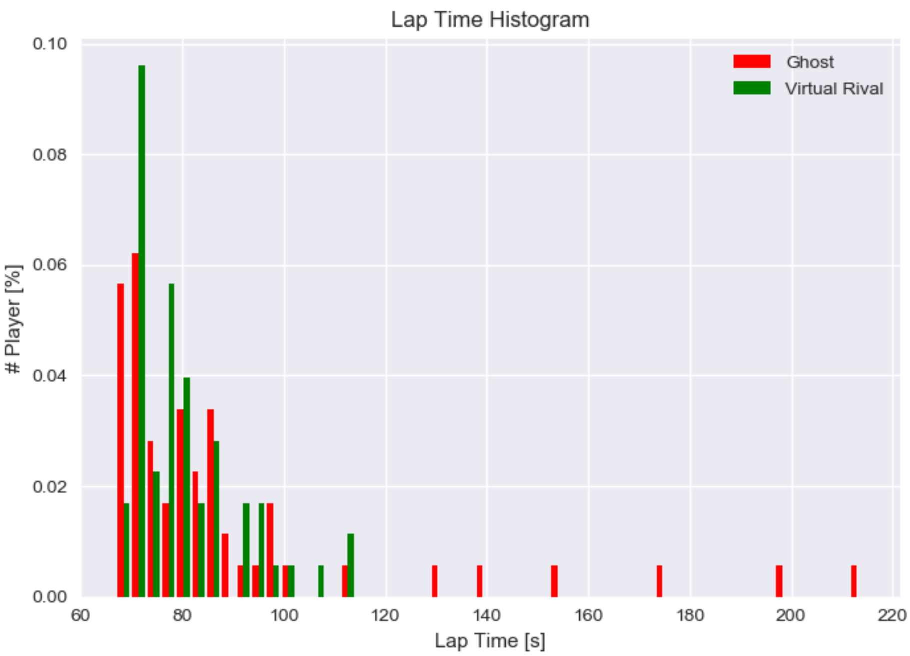


Figure 5.9.: Histogram of Lap Times for one Track

systems for their skill level in racing games. To balance the game between players of different skills automatic skill adjustment is necessary.

Secondly, we found a connection between personality and risk related symptoms in virtual driving (e.g. speeding, driving errors). The *Sensation Seeking Score* showed a high correlation with risky behaviour in virtual driving. Personalising gameplay has been discussed, as an option, to improve *Enjoyment* (See Section 2.2.1). The *Sensation Seeking Score* could be used as foundation for such a personalised racing system. In contrast to previous research (See Section 2.2.1) we found no relationship between virtual driving and the *Big Five* personality measure.

Thirdly, we investigated the impact of our automatically skill adjusted *Virtual Rival* on *Engagement*, *Education* and *Performance*. We compared racing against a *Virtual Rival* with racing against a *Traditional Ghost*. The key finding was that racing against a *Virtual Rival* is generally more satisfying in close races. In most other areas of *Engagement* the results where similar. When looking at *Education* we only found a weak correlation between *Traditional Ghost*. For further studies, it would be crucial to use an extended version of the framework, including more questionnaires and driving metrics to measure the learning progress in a more detailed way. The *Performance* evaluation showed promising results. Comparing the best lap times we found that participants playing against *Virtual Rivals* (M=80.4; SD=10.5) outperformed *Traditional Ghosts* (M=88; SD=33).

Altogether, it can be said that the key questions for our limited scope were answered. Due to the small number of participants (n=38) we have some deficits in terms of statistical significance. We also need better metrics to measure learning in racing. Overall the system allows to measurement *Engagement*, *Education* and *Performance*.

6. Lessons Learned

In this chapter, we take a look at different experiences made during the literature study, development and evaluation. The following Chapter, future research, is inspired by the experiences made during this work.

6.1. Theory

The theoretical part of this work investigates methods and tools to improve *Engagement*, *Education* and *Performance* in race games. Existing racing games focus on maximizing either *Engagement* or the *Educational* effect. A combined approach has not been attempted. In literature, there are various design guidelines for game developers to improve *Engagement*. Two key principles are applicable for racing games: build around one core game mechanic and well-adjusted challenge for the players. Most of the existing research focuses on creating new innovative strategies to improve the game development process. There is a desperate need to measure and compare different approaches. Only little insight is given on how commercial games solve these problems. Most advanced algorithms are kept secret or are patented.

6.2. Development

The *Virtual Rival Framework* should be used as *Educational* environment, so it is really important to provide a realistic racing simulation as a foundation. Considering the graphical requirements, multiple players and large data sizes, it becomes clear the framework has to be based on a powerful platform. The game engine Unity has stood the test for all defined requirements. The built-in components have made it easy to model a racing game. The integrated asset store was a valuable source for 3D models and predefined scripts. Unity's scene system has been proven to be a powerful tool for structuring and integrating user-studies without compromising the game flow. However, it turned out to be difficult to develop and test the application for multiple platforms, especially different browser types.

6.3. Evaluation

The evaluation was based on standardized questionnaires from psychology. The integration and evaluation of the questionnaires worked exceptionally well. The use of python for statistical evaluations turned out to be very beneficial in terms of usability, scalability and customizability. For instance, the questionnaires could be read, statistically processed and visualised with a few simple lines of code. Visualising the data was especially helpful to get a feeling for the data structure and the possible implications on the next processing steps and the final result. The standard psychological questionnaires delivered clear and definite results. An interesting outcome was that winning a close race against *Virtual Rivals* was more satisfying as traditional ghost cars. The results indicate that automatically difficult adjustment and personalisation are the keys towards more *Engagement* in racing games.

7. Future Work

In this work, we showed that automatic difficulty adjustment and personalisation are the keys towards more *Engagement* in racing games. The next steps will contain a more detailed investigation of *Education* and Performance. To improve the statistical value, the number of test users needs to be extended. Due to the promising outcome of this project, many future expansions are conceivable. The main ideas and suggestions discussed in this section are centred around the initial idea to improve *Engagement*, *Education* and *Performance* in racing games. This section will outline the most promising suggestions.

7.1. Framework Improvements

At the moment, only a prototype is developed. It will require major reworks to fit the requirements of a sophisticated tool for researchers and game developers. The current implementation of the racing simulation only supports one player and one ghost car on one track. To investigate multiplayer behaviour an extensive upgrade is needed. The users were satisfied with the provided level of realism. Matching the graphical quality and realism of state-of-the-art racing simulations will probably never be possible but upgrading to a more performant platform will help reduce the gap. Currently, all assets are taken directly from the Unity asset store. Cooperation with artists and graphic designers could improve the whole scenery. Having assets from one source would make the scene more harmonic.

7.2. Further User Studies

A big restriction in our study is the relatively low number of participants ($n = 38$). Additional studies should include more participants. A key outcome of our evaluation was that the current methods to measure the learning process and driving skill are not sufficient. A simple solution is to integrate more detailed performance metrics and extend the investigation on driving patterns. In a next step we suggest developing special race tracks with track layouts that test specific driver skills. Integrating these tests should give a more complete and exact performance estimation.

7.3. Outside Data

A central idea is to integrate Virtual Rival in a commercial racing game. Gathering information off millions of players increases the statistical significance and allows a more detailed and exact evaluation. A completely different idea is to use existing data provided by commercial simulations. Analysing the data on similar patterns can further reinforce the results of this work.

8. Conclusion

Racing is about mastering the race track, perfect car control, high-speed decision making and risk taking. Racing simulators attempt to transfer the emotional and physical roller coaster of piloting a vehicle over the racetrack and competing against the best drivers of the world into the living room. Hardware and software improvements allowed a big leap forward in terms of realism. The increasing complexity of real-world driving systems and the high grade of realism made driving simulators also popular for a wide range of applications besides racing. Driving simulations are used in teaching, entertainment, automotive development, automotive testing and research. The increased attention towards driving simulators opened a big market and the necessity of creating new tools and concepts to improve driver *Engagement*, *Education* and *Performance*.

This work introduces the design, implementation and evaluation of a *Virtual Rival Framework* to improve and measure *Engagement*, *Education* and *Performance*. The framework includes a customisable racing simulation where racing related studies can be performed. The simulation helps to understand players' emotions and thought processes during the race. Therefore, the key aspects of racing, competition and realism, were integrated into the *Virtual Rival Framework*. An additional aspect of this work was the implementation of the *Virtual Rival* ghost car. The *Virtual Rival* competes against the players on the track. To enhance the drivers' *Engagement*, *Education* and *Performance* the *Virtual Rival* adjusts automatically to the current skill level of the driver.

The foundation for the implementation is the Unity game engine. Unity provides the physics simulation platform on which the racing simulation is built. The *Virtual Rival Framework* includes also mechanisms to measure *Engagement*, *Education* and *Performance*. All driving data is stored in the cloud and can be accessed and analysed online. The developed framework integrates all questionnaires needed for the evaluation of *Virtual Rival*. The questionnaire data is also stored. A first user study was conducted with 38 participants. The evaluation had three major outcomes:

- Players are not able to estimate their own skill level.
- There is a strong correlation between the Sensation Seeking personality measure and risk-related symptoms in virtual driving.
- Racing against a *Virtual Rival* is generally more satisfying in close races.

Overall, the system allows to measure *Engagement*, *Education* and *Performance*. The results indicate that *Virtual Rival* can be used to improve racing simulations. For the next step, we suggest, developing special race tracks, with track layouts, that test specific driver skills additional to conducting a second study with more participants.

Appendix

A. CD Content

The attached CD contains the following resources:

A.1. Package 'Development'

- Unity setup v2018.2.17f1 (64-bit)
- The latest Virtual Rival Version used for the experiment:
  - PC, Mac, Linux Standalone
  - WebGL Build

A.2. Package 'Theory'

- PDF version of this document
- A summary of the evaluation results

B. Host Game On Itch.io

The entire game can be easily be hosted on an online gaming platform. This chapter explains the standard setup to host a game on itch.io.

Important settings in the “Edit game” page:

1. Set project type to “HTML”
2. Upload WebGL build folder as .zip.
3. Select “This file will be played in the browser”
4. Set embed options to “Embed in page”

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