Master Thesis

Influence of Crash Experience on Driver's Situation Awareness

Toward safe driving

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Abstract

Driving a vehicle requires practices and exercises, particularly for hazardous situations. In general, driving is an activity that requires the humans mental and physical abilities to achieve safe driving. In hazard situations, drivers must have the cognitive abilities to detect and anticipate hazards. In additions, they must have knowledge that empowers them to react in a proper way. In such situations, a wrong action may lead to significant damages and dramatic consequences. At the same time, physical real training of driving hazard situations is limited, due to crash consequences. In this thesis, we argue using the crash experience to enhance drivers' hazard perception. From a cognitive perspective, raising drivers' awareness of the crash and its physical damage consequences would influence their driving behaviours. We utilized BeamNG.drive that provides a dynamic soft-body physics vehicle simulation. We developed a practical study, when participants are required to drive certain scenarios - typically to reality - to learn a specific traffic situation (e.g. yield to priority road). We implemented various learning scenarios for hazard situations. In this study, two learning modules are proposed: instructional video experience and dynamic physical crash experience. After learning, participants drive an evaluation scenario, where their driving performance is assessed by quantitative and qualitative measures. The study usability and usefulness, as well as, participants' enjoyment and tensions are evaluated by qualitative questionnaires. Statistical analysis shows significant influences of crash experience in raising participant's awareness of crash regardless of their age or their previous driving experience. The findings illustrate the feasibility of the developed study and consequently proofs the proposed hypotheses.

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CHAPTER 1

INTRODUCTION

Driving a car is not an easy task; a small mistake might result in loss of human life or tragic situations. According to annual global road crash statistics of 2015, around 1.3 million people lost their lives in accidents, in addition to about 20-50 million injured in traffic crashes (ASIRT.org, 2016). Due to the fatal consequences of crashes, strict examination processes must be passed to obtain a driving licence. In most countries, driving licence exams consist of theoretical and practical parts to ensure drivers' mental and physical abilities. However, these exams give novice drivers only superficial concepts and ideal situations of driving; they provide abstract levels of learning without paying more attention to drivers' hazard perceptions. Besides, they neither provide a sufficient training of hazardous situations nor ensure drivers' awareness of crash consequences. According to Center of Disease Control and Prevention (CDC)[1], novice drivers are more likely to die or be injured due to car crash particularly in the first months after obtaining the licences. They are at greater risk of road crashes than experienced drivers due to their lack of scanning hazard situations. Previous studies found that the major causes of accidents are breaking traffic laws, speeding, passing improperly, and being distracted while driving (Fisher, Pollatsek, and Pradhan, 2006).

With increasing the numbers of crashes, drivers' awareness of hazardous situations has become of national concern. Several studies investigated and evaluated the driver's situation awareness of hazardous situations. Due to high risks, fatal damages, and consequences of crashes, subjecting drivers to real crashes is not a practical methodology for evaluation. Therefore, recorded road scenes have been used as an alternative to assess drivers' awareness of hazardous situations. In this method, a recorded video is presented to drivers, while they have to identify the potential hazards and their expected reactions (Currib, 1969; Chapman and Underwood, 1998; Deery, 1999). Among other factors, research founded that drivers' hazard perception is the most important component of driving that controls both theoretical and practical issues. There was a consensus among the researcher on the significant role of training drivers to improve their hazard anticipation. From a cognitive perspective, hazard perception is a cognitive ability that could be improved by training and practices (McKenna and Crick, 1994; Horswill and McKenna, 2004).

[1] https://www.cdc.gov/

During the last decade, advanced information technologies inspired researchers to design virtual training programs that mimic driving hazard situations. They leveraged the IT to develop computer-based training programs and interactive instructional video-based programs. Among others, Zero Errors Driving (ZED) (Fisher, 1992), Risk Awareness and Perception Training (RAPT) (Fisher, Pollatsek, and Pradhan, 2006; Fisher et al., 2007), Road Aware (RA) (Samuel et al., 2013), Act and Anticipate Hazard Perception Training (AAHPT) (Borowsky et al., 2010; Borowsky et al., 2012), and Engaged Driver Training System (EDTS) (Zafian et al., 2016) are examples of these training programs.

In the meanwhile, the concept of *Serious Games* has been developed when computer games are used for other purposes rather than entertainment (Zyda, 2005). Serious games have been utilized particularly for training and learning of various application domains (Guillén-Nieto and Aleson-Carbonell, 2012; Breuer and Bente, 2010). The development of game controllers, computer graphics, and visualization technologies stimulate researchers to use the serious game to design driving training programs. Several games have been developed to assess and enhance drivers' hazard anticipation (Backlund et al., 2010; Rodrigues et al., 2015).

To the best of our knowledge, no study investigated drivers' awareness of crash consequences or employed physical crash consequences as a tool to enhance drivers' hazard anticipation. From a cognitive perspective, a crash experience can have extensive influence on drivers' behaviours; First, it raises drivers' awareness of hazardous situations by simulating the physical damage consequences of crashes. Second, it improves drivers' hazard perception and encourages them toward cautious driving behaviours. In particular, this thesis examines crash experience influences on drivers' behaviours. It uses BeamNG.drive, as a realistic physics driving simulation, to introduce the experience of crash consequences. We conducted an empirical study to compare two different learning methodologies: instructional recorded video and simulated crash experience. The research adopts utilizing serious game when learning and entertainment are targeted. In this study, the participants drive simulated scenarios and subjected to real situations, and hence, they are actively involved in making decisions and receive feedback based on their decisions.

This chapter encloses the problem description and the proposed solution, in addition to research methodologies and hypotheses. Organization of the remaining parts of this document is presented at the end of this chapter as well.

1.1. Motivation

One essential part of being a good driver is to understand and strictly follow road signs. Across countries, there are various types of road signs: information, warning, prohibition, and special signs. Ignoring a traffic sign is one of the most common causes of car accidents. According to the World Health Organization (WHO)[2] most accidents happened because drivers either misunderstand or neglect road signs. Many research exploited serious games to enhance drivers' awareness of traffic signs and improve their hazard anticipation. Several games have been developed for learning traffic signs. Some of them use Multiple Choice Questions (MCQ) technique,

[2] http://www.who.int/

while others developed a driving simulation when players are instructed based on their behaviour. Other games also use an error feedback technique (Rodrigues et al., 2015), whereas combining multiple methods is a possible scenario. In most studies, participants had either passive (watching a recorded video) or active (take action and receive feedback) experience, but without real immersive experience of the crash.

Most of the studies developed learning tools for traffic signs to raise drivers' awareness of such critical situations. During traditional driving learning classes, hazard situations and expected crash consequences are explained with illustrations of abstract details. Novice drivers might visit such hazard locations once in the learning phase if they have an experienced trainer. Thus, they may not have enough perception of hazard situations and expected crashes. Sometimes, they simplify strict instructions due to their limited hazard perception. For example, they might decelerate instead of completely stopping, they might ignore scanning at road intersections, or likely they may wrongly prioritize traffic rights. Hence, the lack of crash consequences experience can be considered one of the main reasons for accidents. In addition, raising drivers' awareness of crash consequences can significantly affect their driving behaviours.

1.2. Proposed Solution

Due to the risks of crash consequences, train drivers in a real physical environment is impractical. Thus, this research aims to investigate drivers' crash experiences and its influence on driving behaviours by utilizing real physical vehicle simulation. This thesis utilizes a soft-body physics vehicle simulator, which is called BeamnNG.drive. This research adopts the approach of developing a serious game for learning purpose as well as for data collection.

This thesis presents an empirical study when participants drive various scenarios that simulate real hazard situations. Participants are heavily immersed in taking actions and are asked to follow traffic signs/rules as in the reality. Based on their actions, they received feedback for learning purpose. They drive various scenarios and experience two learning methods: classical instructional video (Video Experience) and experiencing physical crashes (Crash Experience). The study aims to examine the following hypotheses:

Hypothesis I (H_1)

The proposed learning approaches have significant influences on participants' driving behaviours and their hazard anticipation.

Hypothesis II (H_2)

Learning by crash experience affects the hazard anticipation significantly higher than learning by instructional video experience.

In general, the study aims to analyse influences of the proposed learning methods on driving performance, while it examines particularly cognitive effects of crash experience on the enhancement of drivers' hazard perception and their driving behaviours. We expect that participants will have an enhanced driving behaviours by following any of the proposed learning method (HYPOTHESIS I). In addition, the influences of crash experiencing are expected to have higher impacts on raising drivers' awareness of hazardous situations (HYPOTHESIS II).

1.3. Research Methodology

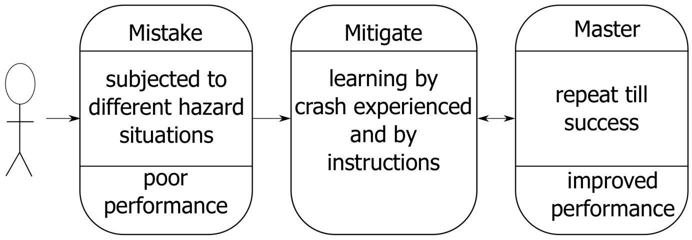


Figure 1.1.: The adopted research methodology

In this research, we adopted the 3M learning model (Ivancic IV and Hesketh, 2000) as indicated in Figure 1.1. According to the figure, participants will be exposed to driving scenarios of hazardous situations, in which they are expected to do incorrect actions (**M**istake). Wrong actions will result in a kind of crash and a physical damage to the vehicle. Then, classical instructional video and physical crash experience are utilized to introduce proper driving behaviours in such situations (**M**itigate). Participants are allowed to repeat a given scenario until they successfully pass it (**M**aster). Finally, participants are assessed on similar driving scenarios and they are expected to show enhanced driving performance. To examine the proposed hypotheses, we follow this methodology:

- First: an empirical study is conducted to understand participants' driving behaviours, particularly in hazard situations.
- Second: participants are divided into two groups with various previous driving experience. Within groups and pairwise groups comparisons are conducted to examine the effectiveness of the proposed learning methods.
- Third: a qualitative questionnaire is designed to measure the feasibility and effectiveness of the proposed study.
- Forth: the results are statistically analysed to assess the significance of each learning method.

1.4. Thesis Structure

The remaining of this thesis is organized as follows: Chapter 2 presents the literature review and related work regarding utilizing computer simulator to assess and enhance drivers' hazard perception. Chapter 3 shows the proposed study and more details regarding BeamNG.drive features. The implementation and technical aspects are described in Chapter 4. The results and findings of the user study are presented in Chapter 5. Finally, Chapter 6 concludes the findings and points to future works.

CHAPTER 2
STATE OF THE ART

Limited hazard anticipation skills of vehicle drivers are the major cause of crashes and fatal damages. During last decade, the issue has been investigated by several researchers from different perspectives. Studies have been conducted to find out cognitive reasons behind the limited skills of novice drivers in comparison to experienced drivers. Several training programs have been developed to ensure a sufficient level of hazard anticipation and situation awareness of drivers before sitting behind the real wheel on roads. With advances in IT, multiple computer-based driving training programs and simulators have been developed to enhance drivers' hazard anticipation by raising their situation awareness. In some research, they looked for the potential use of computers to assess drivers' capabilities, while in others they studied utilizing computer-based programs to enhance their driving behaviours. On the other hand, some research focused particularly on assessment and enhancement of drivers' situation awareness particularly in terms of latent hazard, while others exploited serious games to enhance drivers' hazard situation awareness. Therefore, this chapter gives insights on various related research.

2.1. Conventional driving learning procedures

In most countries, drivers are permitted to get the driving licence after passing theoretical and practical exams. In general, these exams exist in most countries, however, they might have different formats and structures. The main aims behind the theoretical exam are to test drivers' recognition and understanding of traffic signs and regulations. Traffic signs have different formats, e.g., traffic lights, traffic signs, and road markers, but they all convey information to road users and require mental attention and physical reactions. The practical exam checks the drivers' physical abilities to drive and control a vehicle. During the practical part, an examiner asks drivers to perform specific tasks to assess their driving behaviour. In most countries, these tasks are common to examinees in advance.

As consequences, there exist numerous drivers with limited driving capabilities and the number of deaths and fatal injured people involved in car crashes has increased. during the last decade (*Motor Vehicle Safety/Teen Drivers* 2015).

No serious actions have been taken until the Graduated Driving Licensing (GDL) program has been introduced in the 1990s in some US states and Canadian provinces. The program aims to reduce teen driving deaths by granting the full driving licence over three stages: supervised learning, intermediate licence, and full-privileged licence (Foss and Evenson, 1999; MAYHEW et al., 2001; Shope et al., 2001). The GDL programs have reduced teenagers fatality rate in car crashes (Shope, 2007), however, there is no clear evidence whether the exposure of teens for crashes have delayed or moved to later stages (MAYHEW et al., 2001). The reason behind that is it's hard to control the exposure of novice drivers to risk during the supervised stage. Moreover, due to high fatal and physical damages, it is not possible to practice such situations. In addition, it is not guaranteed that all elements of risky situations are correctly identified by novice drivers, even under supervision by experienced drivers. (Foss and Evenson, 1999).

Thus, different studies started to investigate the novice drivers' behaviours. Most of the studies founded that novice drivers – mostly of 16-years – are more prone to be involved in car crashes than adults and experienced drivers (Williams, 2003; *Motor Vehicle Safety/Teen Drivers* 2015). This might be due to the following reasons: 1) novice drivers likely have limited driving experience to anticipate hazard situations, 2) driving experience is increasing with time and their abilities to anticipate hazards as well, and 3) traditional learning procedures are insufficient to enhance drivers' hazard situations awareness (Williams, 2003; Horswill and McKenna, 2004; Pollatsek et al., 2006; Horrey and Wickens, 2007).

The drawback of traditional learning and training programs is that drivers are not subjected to the real hazard situation due to safety aspects. In additions, passing these theoretical and practical parts are not sufficient to judge on drivers' behaviour and their reactions at hazard situations. These points stimulate researchers to think about new procedures to reduce crashes and to enhance situation awareness of young drivers.

2.2. Computer-based Driving Training Programs

With advanced computer technologies in place, researchers started to investigate driving behaviour of novice drivers. Chapman, Underwood, and Roberts, 2002; Horswill and McKenna, 2004; McKenna, Horswill, and Alexander, 2006 found out that improper road scanning, incomplete visual search, speeding and distracted attention was responsible for crashes and they are mostly about 70% related to driver inexperience. Therefore, several computer-based training programs have been developed to assess and enhance drivers' hazard anticipation. We discuss the related literature on computer aided driving simulations in alignment with categories of McDonald et al., 2015 in the following sections. According to the review, the training programs could be categorized into three types: interactive computer-based, instructional video-based, and simulation-based programs McDonald et al., 2015.

Figure 2.1.: RAPT multimedia simulator (Fisher, Pollatsek, and Pradhan, 2006)

2.2.1. Interactive computer-based programs

According to literature, Zero Errors Driving (ZED), Risk Awareness and Perception Training (RAPT), Road Aware (RA), Act and Anticipate Hazard Perception Training (AAHPT), and Engaged Driver Training System (EDTS) are the most common programs that have been developed to enhance drivers' hazard anticipation.

Most of these studies targeted novice drivers 16–21 years old. They followed the 3M learning approach: Mistakes, Mitigate, and Master. Participants are exposed to scenarios in which they might make improper actions (*mistakes*). Then, they receive feedback or instructions (*mitigate*). Finally, they are given the opportunity to gain the skill (*master*) (Ivancic IV and Hesketh, 2000).

Zero Errors Driving (ZED) is one of the earliest programs that address the issue of hazard recognition and risk-taking during driving (Blank and McCord, 1998). The program has been developed and sponsored by the AAA Foundation for Traffic Safety[1], and thus, it is also known as the AAA program. The program presented multiple real-world driving scenarios of various levels of difficulty. In these scenarios, drivers are provided with a real view of the road in addition to rear, and side mirror views. Passengers are added in some scenarios to add more distractions. The program is evaluated with 80 participants on the driving simulator after 1 week of training. The results show that trained young drivers made maneuvers in risky scenarios, that were different, than untrained young drivers. The evaluations have shown that PC-based training could help novice drivers perform better on a driving simulator (Fisher, 1992).

Based on the evaluation of the AAA program in (Fisher, 1992), an enhanced program for risk awareness and hazard perceptions has been developed. The Risk Awareness and Perception Training (RAPT) is one of the common programs that has been developed at the University of Massachusetts, USA to study the potential utilization of information technology to improve hazard anticipation of novice drivers. The program employs different kinds of virtual and physical simulations (Fisher et al., 2002; Fisher, Pollatsek, and Pradhan, 2006; Fisher et al., 2007). The program had been designed to call for advanced training of novice drivers on a PC-based training simulator. The program utilizes certain mechanisms to enable

[1] http://aaafoundation.org/

participants to retrieve what they learn in a real situation (e.g., self-exploration of the hazard). RAPT consists of three phases: pre-test, training, and post-test. It has three versions of the evaluation: PC-based (RAPT-1) (Pradhan et al., 2003), simulator-based (RAPT-2) (Pradhan, Fisher, and Pollatsek, 2005), and on-road evaluation (RAPT-3) (Fisher et al., 2007). As indicated in Figure 2.1, they utilized a real car, as a controller, to increase participants cautions and to make them feel the reality of the driving situation. They tested the influence of new and far transformation of the learning process. The results from the driving simulator indicate more correct glances at predetermined locations of potential risk in (near and far transfer) by trained than untrained drivers. There was clear evidence that RAPT training improved hazard anticipation skills, but it did not have an impact on measures of attention (Pradhan et al., 2003; Pradhan, Fisher, and Pollatsek, 2005; Fisher et al., 2007).

The Road Aware (RA) program is a flash-based training program that runs on the web (Samuel et al., 2013). The program is developed by State Farm Mutual Automobile Insurance Company (State Farm) based on RAPT-3. In RA, they extended participants' abilities to look at scene sides in addition to rear and side mirror views. The program has been designed to check the abilities of trained participants to anticipate situations that were not included in the training. In RA evaluation, participants' performance was compared with experienced and inexperienced untrained drivers. The results indicate achievement of far transfer when a trained driver performed well in the situation that was included and others that were not included in the training. RA trained novice drivers show relatively similar driving performance as experienced drivers (Samuel et al., 2013).

The Act and Anticipate Hazard Perception Training (AAHPT) program aims to enhance novice drivers' ability to anticipate potential hazards by exposing them to a vast array of actual traffic hazards (Borowsky et al., 2010; Borowsky et al., 2012). The program has three versions: active, instructional, and hybrid. In active mode, participants watch a real-life driving scene and interactively press a button when they detect a hazard given no feedback. In the instructional mode, a written material and video-based tutorials are provided, while participants are not required to respond to hazard. A combination of active and instructional methods composes the hybrid mode of AAHPT. The evaluation studies of AAHPT include young trained, young untrained, and experienced untrained groups. The evaluation is carried out one week after training on different driving scenarios. They use eye-tracking to assess scanning patterns of hazards. The evaluation shows the following: 1) hybrid and instructional trained groups reported significantly more potential hazards involving pedestrians in residential areas than experienced or untrained young drivers; 2) the hybrid and instructional groups were more sensitive to the presence of pedestrians than the other groups (Meir, Borowsky, and Oron-Gilad, 2014).

The Engaged Driver Training System (EDTS) is another program that follows RAPT and RA programs. It is a computer tablet-based program targeted at teaching novice drivers. The contribution of EDTS is that it aims to improve latent hazard anticipation and decrease distractions (Zafian et al., 2016). (Krishnan et al., 2015), evaluate the effectiveness of EDTS training and the results showed that EDTS-trainees detected more latent hazards and were less distracted than drivers without EDTS training. The authors in (Zafian et al., 2016) extends the work of

(Krishnan et al., 2015) by conducting an on-road evaluation of the EDTS, they examined the impact of training parents along with their teens. The results showed that EDTS-trained teens visually detected 71% of latent hazard on the on-road drive scenarios as compared to only 44% for Placebo-trained teens.

2.2.2. Video-based instructional programs

In these studies, a verbal commentary is used as a way to enhance drivers' hazard anticipation. Commentary driving is a technique by which a person verbally describes what he/she watches, thinks, or plans to do in a particular driving situation. The difference between the studies is whether the commentary is provided by experienced or by participants. The other difference is whether participants include experts or were just grouped as trained and untrained participants. Most of the following studies focus on young drivers of age means 18-19 years old. The assessment of participants is done mostly immediately after the training depending on mouse-clicks as a way to measure participant response.

In (Isler, Starkey, and Williamson, 2009), the authors conducted a commentary video training study. First, participants are asked to identify potential hazard (by mouse clicks) and describe their reaction (verbal commentary) on a video driving scene. They keep doing the second task in the meanwhile of tracking a moving object. Afterwards, participants watch commentary training. The results show that before commentary training young drivers detected and identified hazards, however, they had slower reaction times compared with experienced drivers. Immediately after commentary training, there were no differences among young trained and experienced drivers in detecting and identifying hazards. In addition, after training, young trained drivers detected and identified more hazards than untrained young drivers (Isler, Starkey, and Williamson, 2009).

In studies of (McKenna, Horswill, and Alexander, 2006), they use pre-recorded expert commentary as a training module. Participants are provided with an instructional video of pre-recorded audio training. Afterwards, participants were examined other video scenarios without commentary and the studies measure their hazard anticipation behaviour. During the evaluation, participants are requested to verbally comments. The findings indicate that trained drivers were faster in perceiving hazards than untrained drivers. In additions, trained drivers were able to identify more hazard situations than untrained drivers (McKenna, Horswill, and Alexander, 2006).

Advanced video commentary is introduced in (Wetton, Hill, and Horswill, 2013) through "what happens next" scenarios. In these studies, a video paused in a hazardous situation and participants were asked what they expect to happen next. The studies measure response time enhancement over various methods of training: (1) what happens next training; (2) expert commentary training; (3) hybrid commentary training (i.e., expert plus self-generated commentaries); or (4) the full training package (i.e., what happens next plus hybrid commentary training). Participants' hazard anticipation is assessed immediately after training and again after one week. Findings show that the full training group had the largest improvement with regards to response times both immediately and 1 week after training. Otherwise, in general, trained drivers performed better than untrained drivers, while there are differences between the employed strategies (Wetton, Hill, and Horswill, 2013).

A mixture between theoretical and practical driving parts is presented in (Petzoldt et al., 2013a) and (Petzoldt et al., 2013b). They present an animated driving video and in a hazard situation the scene is paused and the participant is asked by Multiple Choice Questions (MCQs) in an interactive way to mark a hazard area (by mouse clicks). The study is carried out over two sessions with a questionnaire each: The first session asked participants about their understanding and prediction of a traffic scene and the second session examined the participant's assessment of the need to take action. During both sessions, inaccurate responses were corrected and feedback was provided (Petzoldt et al., 2013b). The evaluation is conducted on three groups: computer-based training, paper-based trained, and untrained participants. Findings show that the computer-based training group glanced on the hazards sooner and completed appropriate glance sequences faster than the paper-based or untrained groups (Petzoldt et al., 2013b).

2.2.3. Simulation-based instructional programs

Simulation-based training programs were also developed to enhance drivers' hazard anticipation. Authors in (Allen et al., 2011) conducted a training program over 8 weeks. They presented a weekly session supported by slides and videos to participants. After the last training session, they carried out an evaluation based on trained and untrained groups. The results showed better performance of the trained group than untrained ones.

The Simulator-based Risk Awareness and Perception Training (SimRAPT) is a version of RAPT that has been developed based on simulation (Vlakveld et al., 2011). This program particularly focused on latent hazards and involved errors (i.e. the situation which is difficult for drivers to avoid). Participants drove three scenarios with different levels of difficulty on a simple driving simulator. Hazards are either materialized aggressively or non-aggressively or not materialized at all. Participants had evaluated immediately after training on an advanced simulator with an eye tracker. Eye gazes showed an enhanced driving behaviour of trained groups relative to untrained groups.

2.2.4. Discussion

From this sample of related work, we could conclude the procedures of computer-based driving training programs as follows: participants are subjected to hazard situations virtually and their driving behaviours are monitored and recorded, then they are provided with training using adequate techniques, and finally, they are evaluated. In the training phase, they utilized different methods: interactive computer programs, commentary videos, or driving simulators. In the evaluation phase, they conduct a comparison to assess the influence of learning for participants. They compare the driving behaviours between trained and untrained groups or they compare between trained novice drivers and experienced one. The evaluation is carried out either immediately after training (near transfer of knowledge) or after the training with one or two weeks (far transfer of knowledge). In all of the studies, findings indicate potential utilization of such programs to enhance drivers' behaviours.

2.3. Gamification-based driving training

Advanced game technologies and development of modern input controllers, like Wii, Kinect, driving wheel, etc., move the game beyond fun and entertainment purposes. This kind of games has been known as “serious games” when the adjective “serious” refers to purposes like education, training, health care, city planning, situation awareness and marketing (Abt, 1987; Ferreira, 2002; Michael and Chen, 2005) (Section 2.3.1). Serious games are games that use computer games and simulation approaches or the technologies for, primarily, non-entertainment purposes. Nowadays, people play games everywhere and the number of gamers increased dramatically (Riley, 2018). These facts foster the potential use of games as a training tool for driving. Simple games have been developed to teach traffic rules, while complex 3D games have been developed to enhance drivers’ performance and raise their situation awareness about dangerous situations (Section 2.3.2).

2.3.1. Serious games

According to (Zyda, 2005), serious games are “a mental contest, played with a computer in accordance with specific rules, that uses entertainment to further government or corporate training, education, health, public policy, and strategic communication objectives.” (Zyda, 2005). Serious games come up as a result of interdisciplinary research include scientists of psychology, philosophy, computer science, and educational backgrounds. The evolution of gamification and serious games contributes to use serious games intensively in learning programs (Breuer and Bente, 2010; Guillén-Nieto and Aleson-Carbonell, 2012). The magic behind serious games is that they provide an experience mixed with fun and enjoyment which ensures motivation and learning.

A considerable body of research emphasized the role of serious games in learning (Breuer and Bente, 2010; Girard, Ecalle, and Magnan, 2010). The success of serious games for learning and training comes from the following points:

- Stimulate the mind: playing games trains and drives capabilities such as decision making, logical thinking, and cognitive functions.
- Increase self-esteem: as it allows interaction with others and breaks social and cultural barriers. Thus, it enhances the self-esteem of players while they are trying to find alternative ways to solve a problem.
- Applicable to the real world: it allows the practice of real situations, which might be critical, in a virtual world before facing them in the real world. That makes the serious game one of the best practical learning methods of hazard and critical situations.
- Immediate feedback: it permits monitoring trainees behaviours with capabilities to provide them with immediate feedback.
- Allow development and task mastery: it encourages trying until mastering a particular task. In case of a challenging task, players strive harder to solve the challenge and master the task.

- Interactive nature: games allow for interactive communication. Usually they are not in a form of one-to-many like a teacher to students, or TV and Radio to audiences. However, it builds on the interaction among players and game elements, which engage players to learn in a fun way.
- Collaborative nature: players who were involved in playing collaborative games perform well within teams and have higher creativity and innovation capabilities.
- Unique model: it is not like traditional learning models. It targets learning with interaction, collaboration, and fun.

However, developing such kind of games inherits a big challenge; the game should include fantasy and learning elements. In particular, educational games integrate challenges with educational contents, in addition to learning and entertainment objectives. By completing challenges, the learner acquires the required skills to solve the challenges by following the educational contents which are presented in a virtual and entertaining way. Due to serious games, designing challenges, (Mitgutsch and Alvarado, 2012) proposed an assessment framework to evaluate the formal conceptual design of serious games.

2.3.2. Game-based driving training programs

With the focus on serious games, the projects concerning games and traffic learning, research pay more attention to develop studies to evaluate games use in traffic and road safety learning. Backlund, Engström, and Johannesson, 2006 conducted a study to investigate the influence of games on traffic school students' driving behaviour. At three driving schools, the study investigates students' experience in racing, action, or sports games. These kinds of games are mostly perceived as destructive games. The study employs an advanced simulator that has a real car as a controller. Students are divided into two groups to drive two versions of the same driving scenario: game and non-game versions. The participants fill in a questionnaire afterwards regarding game's entertainment value, task-orientation, and usefulness. They are also evaluated by instructors of the schools for assessment purposes. They found out that experienced gamers have better driving behaviour than less experienced or non-gamers. However, no further analysis was conducted to judge experienced gamers attitude towards road-users or traffic safety. The study encouraged further work in the development and use of computer games for traffic safety and education purposes (Backlund, Engström, and Johannesson, 2006).

The study is extended afterward in (Backlund et al., 2010) to achieve the following: 1) study effects of games and driving education; 2) check the feasibility of developing game-based driving simulator; and 3) study learning enhancement by utilizing games as a learning tool. They enhanced the simulator to observe participants' driving behaviour like observing preview mirrors, scanning traffic signs, and following safety guidelines and speed limits. During the whole experiment, parameters, such as speed, position, use of break, and use of turn signals are recorded to measure drivers' skills and attitude.

In (Backlund et al., 2010), the authors summarized the potential use of the game in training drivers. They concluded a positive influence of game-based driving simulation on learning traffic safety. In (Rodrigues et al., 2015), authors used non-traditional input devices as controllers and developed a 3D interactive educational game for traffic rules. In particular, they utilized mobile devices such as tablet and smartphone as a simulation of driving wheels, in addition to traditional controllers such as the keyboard, joystick, and steering wheel. In this study, participants have to drive safely taking in considerations pedestrians, traffic signs& lights, and other vehicles in 3D environment game. Participants were grouped into two groups: -1 year experience/no experience and +1 year experience. The study consisted of a questionnaire before and after playing. In case of traffic violations, participants are informed immediately and have to give a new attempt. The evaluation is done immediately and one week later to check the learning progress. Participants were evaluated qualitatively and quantitatively. The results showed the potential role of the game to enhance participants' understanding and increase their awareness of traffic rules and regulations. Both groups had improved perceptions after playing the game (Rodrigues et al., 2015).

Another example of traffic rules serious game is found in (Ismail, Abdennadher, and Abouelsaadat, 2016). The authors developed a simple game that combined a simulated driving environment with MCQs within the context of the game. They developed *Rules On Wheels* as a game to teach traffic signs through a game-based interface. They tested different learning hypothesis; They even have different interfaces and multiple ways of participants' assessment. The MCQs part runs twice, before and after playing. The findings showed that participants were highly engaged to learn through fun and games. All participants who played the game version got significantly higher scores on the post-test (Ismail, Abdennadher, and Abouelsaadat, 2016)

2.3.3. Discussion

Although serious games have been developed to support education and data collection purposes for various applications, there still exist multiple challenges to develop a real driving simulator adopting serious games. Several issues related to physical damage, realistic, and enjoyment have to be considered. Most of the studies successfully proofed the significant role of serious games in enhancing driving performance, however, no study looked for the physical crash experience influences. Based on the literature, previous research developed abstract games for training or learning purposes. They usually compared between trained and untrained groups, which always indicated the potential role of the proposed games in training. They were mostly focusing on developing games as a module for learning traffic signs and latent hazards. In this thesis, we use advantages of serious games for learning and enhancing driving performance. We will focus on physical crash and damage experience towards improved driving behaviours.

CHAPTER 3 STUDY

In this research, we carried out an empirical study to check the effectiveness of the proposed approach. The study aims to raise drivers' awareness of hazard situations, particularly the situations that result form misunderstanding or neglecting traffic rules. Moreover, the study utilized the concept of serious games to achieve learning purpose; It aims to study crash experience influences on enhancing driving behaviours. To do so, we utilized two different methods to introduce learning to participants; Crash Experience (CE), when participants are exposed to experience the crash and its physical consequences as a cognitive learning method, and Video Experienced (VE), when participants would learn by watching an instructional recorded video that introduces most proper driving behaviour. We selected two traffic rules, particularly at road intersections. In additions, we used BeamNG.drive, a game which has a well-developed realistic physical model. During designing the study, we considered use of various qualitative (e.g., questionnaires) and quantitative (e.g., parameters) measures to interpret the results.

3.1. BeamNG Driving Simulator

In this study, BeamNg.drive[1] will be utilized as a driving simulator. BeamNg.drive is a configurable simulator with particular focus on driving physics, which makes it suitable for presenting realistic physical damages and for evaluating drivers' behaviour. It is a realistic, immersive driving simulator that offers different possibilities to explore driving. It implements soft-body physics to both control vehicle dynamics as well as to control the collisions between objects and vehicles. BeamNG.drive software uses physical laws to calculate how and which part of the vehicle responds to external influences. When vehicle crashes or collides with another object the software independently calculates which components are particularly badly deformed. The main focus of BeamNG.drive is on how things move rather than how things look on the screen, which makes it a game that realistically simulates driving movements and crashes. The physics engine simulates every component of a vehicle in real time, resulting in realistic and dynamic behaviours. Figure 3.1 shows how the real damage can be represented in BeamNG.drive simulation (on the left hand side) in comparison to reality (on the right hand side).

[1] `https://www.beamng.com/`

Figure 3.1.: The physics of damage in BeamNg.drive Vs. reality

3.1.1. Simulator Physics

In BeamNG.drive a vehicle is represented as a network of interconnected nodes as shown in Figure 3.2. The physics engine simulates a network of interconnected nodes that chain to get an invisible skeleton of a vehicle with realistic weights and masses. In this skeleton, a node is a point in 3D space that has realistic weight and mass. Each node is represented in a list of four values ID, PosX, PosY, and PosZ. The connection between nodes is called beams. A beam is represented as a list of two nodes' IDs to define the connection.

In a normal situation, each vehicle is created as indicated in Figure 3.2. There are two types of physics simulation: rigid body and soft body. Soft body simulator, which is used in BeamNG.drive, simulate objects as the sum of their parts where the objects have flexible skin. If the object hits with other objects its behaviour and shape will be changed. In case of collision, vehicles are flexed and deformed due to collision stress of the vehicle skeleton. This results in a very realistic simulation of crash consequences as indicated in Figure 3.3. The figure shows physics influences on crash on vehicle skeleton.

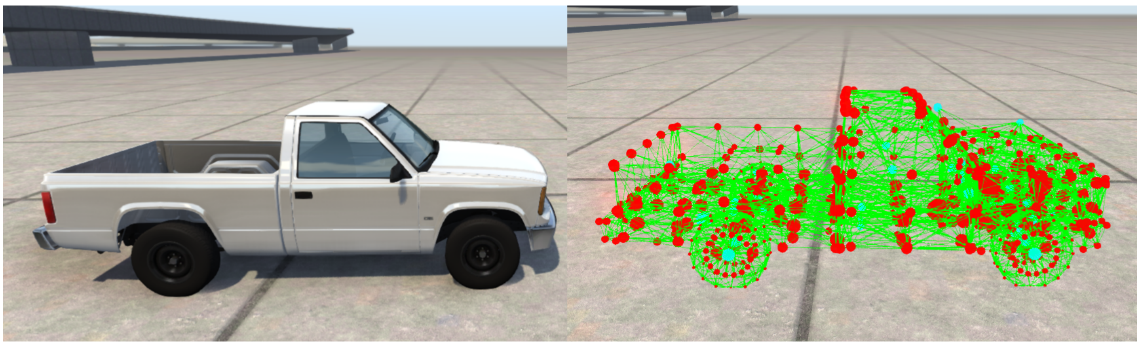


Figure 3.2.: Vehicle skeleton as interconnected graph of nodes and beams

Figure 3.3.: Deformed beams results from collision between two vehicles

3.1.2. Simulator Controllers

BeamNg.drive supports different kinds of controllers. In addition to traditional controllers such as a keyboard, joystick, steering wheel, BeamNG.drive has a mobile app as a controller. However, in this study, we will use the driving seat as an input controller to give participants a real experience of driving. Figure 3.4 shows the FANATEC CSL seat that will be used as an input controller during the study.

The seat is used in combination with ClubSport pedals and Porsche 918 RSR steering wheel. The pedals have magnetic hall sensors, adjustable brake stiffness, and vibration feedback on the throttle and brake, while the wheel has force feedback. During the study, a wide screen of 40 inches is mounted to the seat. Use the seat as an input controller and a widescreen gives participants nearly a real driving environment.

Figure 3.4.: CSL driving seat with manual speed transmission

3.2. Study Design and Workflow

There exist several scenarios of high risks, which might cause accidents and crashes. To develop such a study, we selected particular scenarios of high risk as a demonstration. The sequential flow of the study is required to be designed carefully to avoid biased results. The following subsections present the selected traffic rules and describe designing the study workflow.

3.2.1. Scenarios Selection

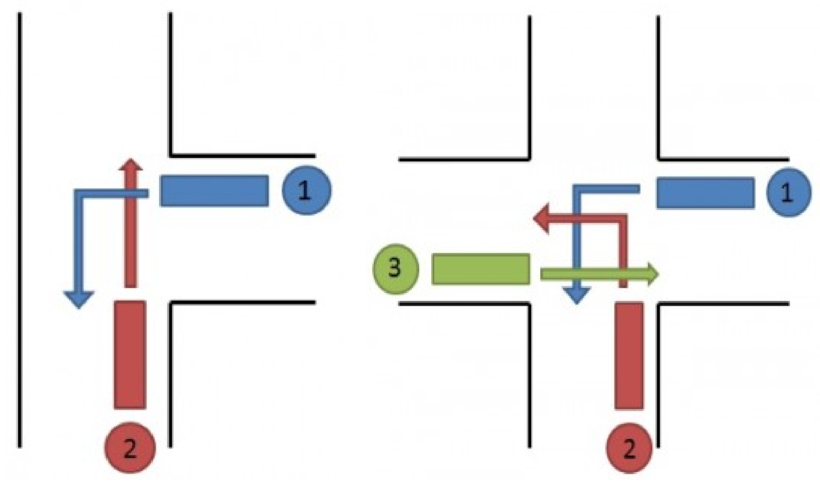
Figure 3.5.: The traffic sign of Yield to Priority Road (YtoPR)

In general, driving as a task requires a high level of mental concentration to avoid collisions. However, particular situations need a higher concentration than others. In this study, we focus on the intersection situations, which are the most common places of crashes (Samuel et al., 2013; Zafian et al., 2016). In intersections, traffic flow is regulated by a traffic officer, traffic light/sign, or following “right before left” rule in case of absence of previous regulators. We implemented different scenarios according to traffic sign of Yield to Priority Road (YtoPR) and Right before Left (RbL) rules.

Figure 3.5 illustrates the Yield to Priority Road (YtoPR) sign, which means that the driver on this direction (thin black lines) should take care of the other coming traffic that has higher priority (wide black line). In this situation, the correct driving behaviour should be as follow:

- *Stop* on the line-of-sight to be able to see the incoming traffic.
- *Look* carefully for the incoming traffic.
- *Drive* slowly once there is no incoming traffic.

Figure 3.6 shows the Right before Left (RbL) driving rule, where the priority of traffic is given for the right vehicle over the left one. Figure 3.6a shows the case in residential areas, especially in low-traffic areas. As a general rule, in the case of non-existent traffic lights or signs that could indicate a right of way, the right-to-left rule applies here. In this case, the road user traveling straight ahead (driver No.2) must pay attention to the vehicles coming from the right (driver No.1) and grant him/her the right of way. Figure 3.6b shows a more complex situation in the case of four intersections, where the high attention of drivers is required. The first vehicle on the right (driver No.1) has first priority, which then leaves, determines



(a) Simple Situation (b) Complex Situation

Figure 3.6.: Right before Left (RbL) scenarios

the further right of way among driver No.2 & driver No.3. The driver coming from the right (driver No.2) is the first person who is allowed to drive. In this situations, the correct driving behaviour should be as follows:

- *Slow* down to walking speed and *look* carefully for the traffic on the right.
- *Stop* completely, in case of incoming traffic from the right.
- *Drive* slowly once there is no incoming traffic from the right.

3.2.2. Study Procedure

Figure 3.7 shows the proposed study workflow. The workflow is divided into the following 4 phases:

- **Phase 1**: In the beginning, participants get an introduction to the game and the study. They receive two documents titled "Information about the Participation in a Research Experiment" and "Consent to Participate in a Research Study" (See Appendices A & B). After the agreement, we offer participants free driving scenarios to get used to the game and the seat controller. Once they are ready to start the experiment, they fill in some anonymous information like age, gender, driving experience years, gamer or non-gamer ... etc.

- **Phase 2.a**: Participants are assigned randomly to two groups: Group I (GI) and Group II (GII). GI begins with learning from Crash Experience (CE_L), while GII starts with learning from Video Experience (VE_L). Both groups start by learning about the YtoPR scenario till mastering it. Participants are allowed to repeat the scenarios several times until they pass the challenges correctly. As a check for learning, they play an evaluation scenario for the YtoPR rule (YtoPR_E).
- **Phase 2.b**: Following the evaluation scenario, participants have to fill in two questionnaires (see details Section 3.3.2) and take a break for 10 minutes.

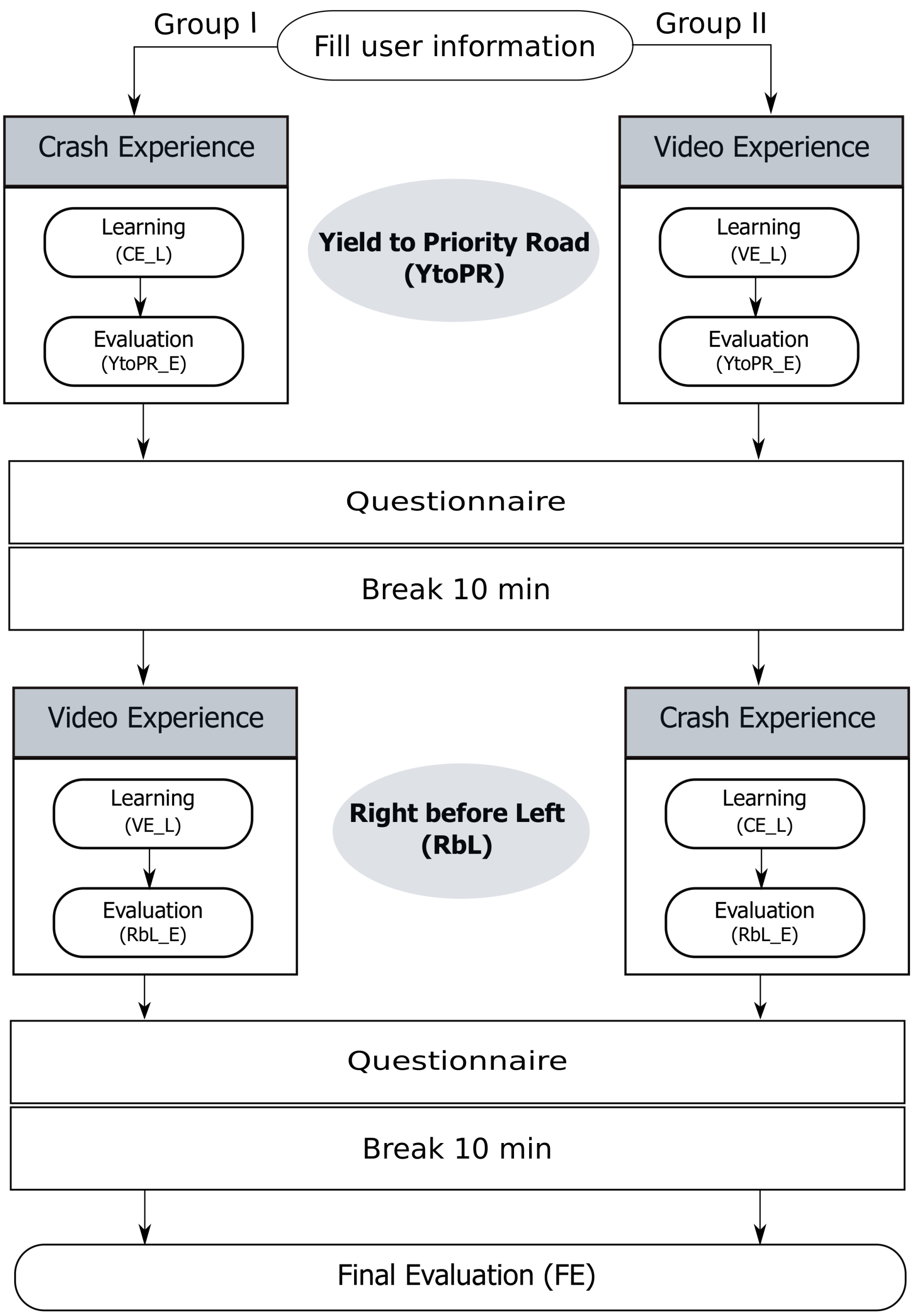


Figure 3.7.: Workflow of the proposed study

- **Phase 3.a**: After the break, the learning methods are switched between groups; Participants in GI start to learn by VE_L, while the participants of GII learn by CE_L. In the second learning phase, they train on the Right before Left (RbL) scenario until they master it. Then, they play evaluation scenarios for the rule (RbL_E).
- **Phase 3.b**: Following phase 3.a, participants are requested to fill the same two questionnaires again corresponding to this learning method. Then, we gave them another break for 10 min to prepare the final evaluation (FE).

- **Phase 4**: Participants of both groups play a final scenario which includes both YtoPR and RbL scenarios. They are allowed to repeat the scenario until they successfully complete it. This phase acts as a final evaluation of participants' performance. It indicates whether participants' driving behaviour is influenced by learning or not.

3.3. Analysis and Assessment

The study aims to investigate crash experience influences on participants' hazard perception and analysing participants' driving behaviours before and after learning. To achieve that, we designed quantitative and qualitative measures. We monitor driving behaviours by collecting quantitative parameters, such as, speeding, slowing down, scanning road intersections, response time etc. Moreover, we utilized quantitative questionnaires to judge the effectiveness of the game as a tool for learning.

3.3.1. Performance Measurements

During the study, one of the main aims is to assess participants' driving performance before and after the learning process. The traditional way of doing that is to prepare a list of items and check them manually by an observer. However, to get accurate results and to avoid manual mistakes, we implemented a module to observe driving performance based on a combination of factors. During playing any scenario, to assess driving behaviours data for the following parameters was gathered:

- Speed: the driving speed is monitored in all scenarios to check whether participants follow speed limits or not.
- Acceleration/Deceleration: based on the speed, the acceleration pattern is calculated. Slowing down and complete stopping is required to be monitored in both YtoPR and RbL scenarios.
- Response time: once YtoPR sign appears or once a participant arrives at intersection a certain slowing down response is required. The time a participant takes to respond is recorded as well, as a factor of participant's driving behaviour.
- Scanning: whether a participant looks to the right and left directions to scan an intersection scene.
- Following road marks: some road marks are encoded in scenarios. For example, the solid/dashed lines when participants are not allowed/allowed to change the driving lane.
- Vehicle damage: it is a percentage value which indicates car damage that results from crashes. It is calculated based on deformed beams in the network node of the vehicle.
- Final Status: a boolean flag indicates whether participants finished a given scenario successfully or failed. A participant fails, if one rule (minor or major) is broken.

3.3.2. Questionnaire Design

As indicated in Figure 3.7, we ask participants to fill in two questionnaires two times; one after each learning phase. The aim of the questionnaire is to assess the participant's viewpoint in each learning method. There is no unique questionnaire which could answer all questions regarding workload, performance, enjoyment, perceived value, and usefulness. Thus, we utilize a combination of two questioners: Intrinsic Motivation Inventory (IMI) and NASA-Task Load indeX (NASA-TLX).

IMI The Intrinsic Motivation Inventory (IMI) is a multidimensional measurement. It assesses participants subjective experience related to a particular task. It has been used in several experiments related to intrinsic motivation and self-regulation. IMI consists of seven subscale scores: participants interest/enjoyment, perceived competence, effort/importance, pressure/tension, perceived choice, value/usefulness, and relatedness.

In this study, we are interested in assessing three subscales: enjoyment, tensions, and usefulness. Therefore, we customize an IMI questionnaire that includes items of these subscales. The items are listed in random order and each item has an assessment score of seven degrees (from 1: *not at all* to 7: *very true*). For some item, we have to find its reserve score. To do that, subtract the item response from 8, and use the resulting number as the item score. Each subscale is calculated independently as follows .

$$Subscale(A) = \sum_{i=1}^{n} score_i/n \tag{3.1}$$

Where, the subscale A $\in \{enjoyment, tensions, usefulness\}$, that has n items in the questioner associated with $score_i$.

NASA-TLX The NASA-Task Load indeX is a subjective assessment tool that measures perceived workload as an indicator of participants' performance and task effectiveness. It has been developed by the Human Performance Group at NASA's Ames Research Center over 3-years [XX]. The index divides workload into six subscales: mental demand, physical demand, temporal demand, performance, effort, and frustration. Each subscale has a score of 100 points. The description of each subscale is provided clearly to participants as seen in Appendix C. Then, the TLX is calculated as follows:

$$TLX = \sum_{i=1}^{6} score(i)/6 \tag{3.2}$$

Appendix C includes the customized IMI questioner, in addition to, an adapted version of NASA-TLX questioners.

CHAPTER 4

IMPLEMENTATION

This chapter describes the technical aspects of the study. It demonstrates the different phases of the study and how they are implemented. The selected features of BeamNG.drive, which influence the study, are illustrated. The implementation of the selected traffic rules and the difference between Video Experience (VE) and Crash Experience (CE) learning modules are presented in this chapter as well.

4.1. BeamNG.drive Technical Features

(a) The Free-Room Mode

(b) Scenarios Mode

Figure 4.1.: Various modes of BeamNG.drive

BeamNG.drive is a vehicle simulation video game available for download on the Steam Early Access[1]. It is a Microsoft Windows game that has been developed based on the Torque Game Engine (TGE). The most important features of BeamNG.drive are vehicles and maps. The game is fully configurable when players can choose between various maps and real simulated car. Maps and vehicles diversity makes the game rich and fascinating. BeamNG.drive includes five modes: Scenarios, Campaign, Free-Room, Time-Trials, and Bus modes. In this study, we utilized only `Scenarios` and `Free-Room` modes as indicated in Figure 4.1. Figure 4.1a shows the `Free Roam` mode, where the player can drive and crash several different vehicles on a few pre-provided default environments. Use this scenario will allow participants to get used to the game controller. Figure 4.1b represents the `Scenario` mode, when drivers have to follow a set of predefined checkpoints. In this mode, traffic signs and rules are encoded, while predefined checkpoints will guide participants through a determined driving path.

[1]`https://store.steampowered.com/app/284160/BeamNGdrive/`

4.2. Study Implementation

According to Figure 3.7, the study consists of 4 phases. In this section, the implementation of these phases would be described.

4.2.1. Participants' Data Collection module

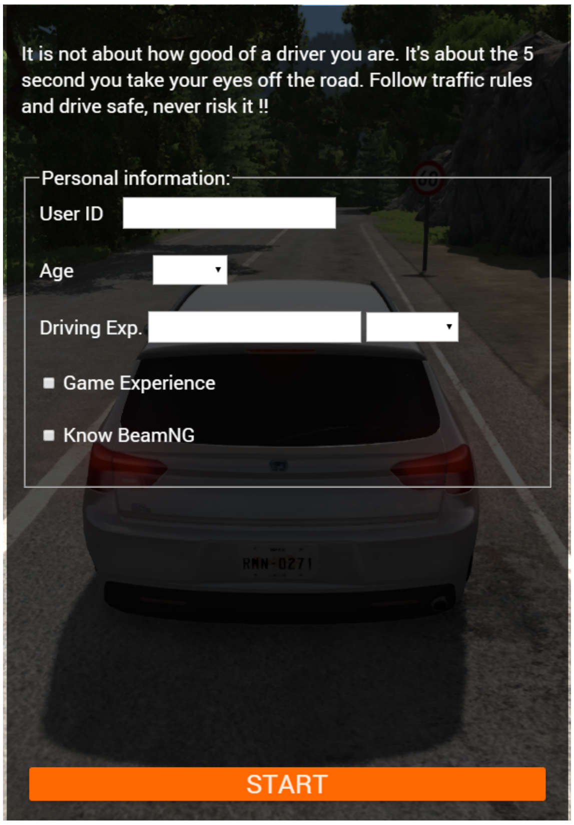


Figure 4.2.: A HTML form to collect participant information

At the beginning of the study, participants read, study instructions and sign a participation approval. Then, they are asked to fill personal information regarding their age (in range), previous driving experience (in terms of time periods), gaming experience, and their familiarity with BeamNG.drive. To collect this information, a form is implemented in HTML, CSS, and JavaScript as indicated in Figure 4.2. This form aims to create a separate directory for each participant to organize participants' data. These data is collected to investigate the relationship between participants' experience and their driving behaviour before and after the learning.

4.2.2. Scenario Design and Implementation

A scenario is defined as a self-contained experience, where a specific task or set of tasks is required to be completed given a set of constraints. For example, the task might be to stop a vehicle in a specific parking spot within a fixed time limit. A participant wins, only and only if he/she accomplished the entire task(s) without break any constraints.

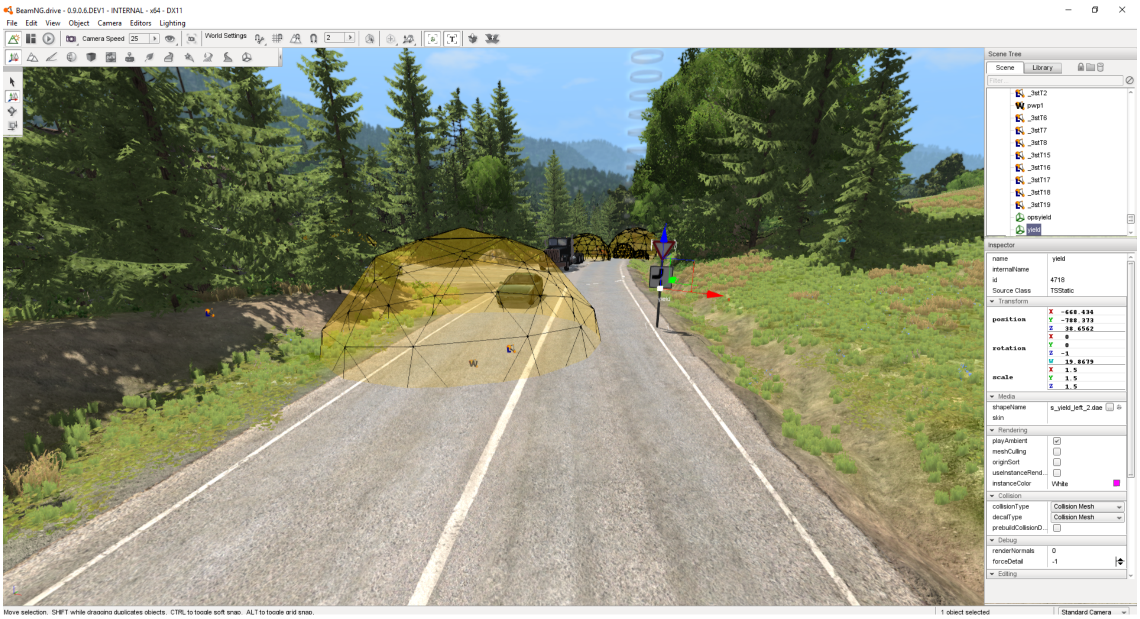


Figure 4.3.: BeamNG Editor while encoding YtoPR rule in a scenario

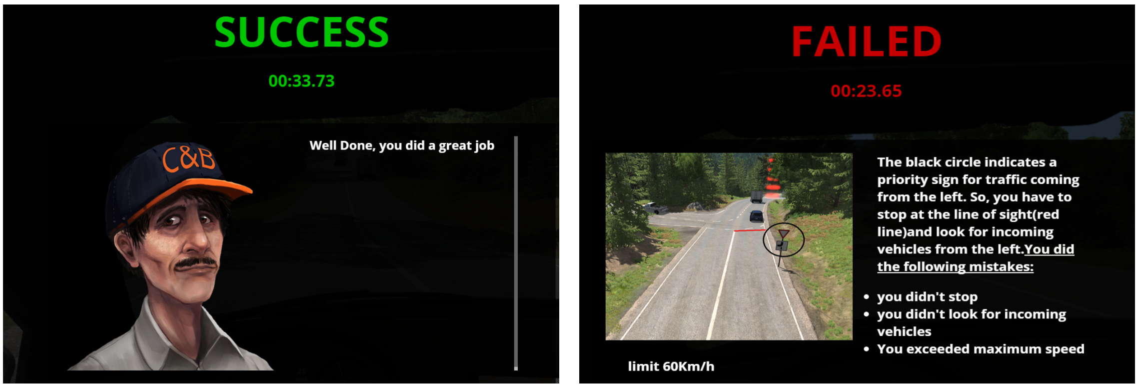
In this study, we designed some scenarios for YtoPR and RBL traffic rules. In the scenarios' design, we kept in consideration to offer participants an experience, when they are actively involved in making decisions. The participants are immersed in the gaming experience and are receiving feedback over their own decisions. Each scenario consists of a set of files: Prefab, JSON, Lua, HTML and JavaScript files.

Prefabs are collections of different pre-designed game objects that are loaded into the scene. All these objects are edited by the BeamNG editor then packed into prefab file, which includes waypoints, vehicles' position, traffic signs, road signs, and player starting position. The properties of an object can be adjusted to the desired specification, thus, we are able to customize the route and place different objects in the scene as shown in Figure 4.3. The figure shows editing an object of the YtoPR sign on the right side of the road.

Each scenario is associated with a JSON file, which contains a single object. The scenario object encloses a list of fields with their respective values, which define the behaviour of the scenario. In general, this JSON file includes information about the scenario, such as scenario title, description, failed and passed messages, all vehicles in the scenario, and scenario goals. The variable of scenario goals is defined by an object that consists of variables and values, such as, maximum damage, maximum speed, maximum distance, position,...etc. In each scenario, participants need to achieve the given goals to pass the scenario successfully. The JSON file includes also an array of prefab file names to be loaded when the scenario starts.

BeamNG.drive scenario system provides a wide variety of pre-built systems that allow the creation of standard scenarios. However, the need might arise to provide a custom behaviour by processing events that occur during the scenario. This can be achieved by using an accompanying custom Lua file. This Lua file can be used to control how a scenario runs and what logic executes for the various events can occur during the scenario. When the scenario is loaded, if a Lua file with the same name as the scenario is present, it will get loaded as well. The Lua file has a particular structure. It has to return an object, which will handle the processing for the scenario. During a scenario, the scenario system uses extension hooks to communicate with the external world.

At the end of a scenario, participants will get a feedback based on their driving behaviour. In a failure situation, a feedback is presented in two ways depending on the learning module. In VE_L, an instructional video would be displayed to illustrate failure reasons and how to tackle them. In CE_L, UI messages would be displayed to clarify the reason behind the failure. Both ways should have clear, readable, and amply illustrated messages. They are implemented in HTML and JavaScript as indicated in Figure 4.4.



(a) UI message in case of success (b) UI message with failure reason(s)

Figure 4.4.: UI messages implemented by HTML and JavaScript

AI module In order to simulate a real situation, another driven cars required to be added to each scenario. In some situations, a fixed movement path of another vehicle is required, while there is also a need for complex movement paths in other situations. BeamNG.drive has an Artificial Intelligence (AI) system that can be used to control the automated vehicle. This module has four modes, which control vehicle movements:

- Random mode: the agent will drive on random routes to any given point.
- Flee mode: the agent will try to escape the player
- Chase mode: the agent will try to catch the player
- Manual mode: allows the AI to drive according to pre-determined conditions

In this study, we used BeamNG.drive AI module in its manual mode. It allows the car to drive toward pre-selected fixed waypoints. For each agent vehicle a set of parameters is required to be adjusted; Target waypoints: a predefined set of ordering points that should be navigated by the agent. They can be freely placed at any desired position to define the route; Route speed: it is one of the following modes: "limit", "set", and "off" modes, which determines the speed of the agent; In this study, we used the default speed mode ("off"), when the agent calculates its speeds automatically depending on other conditions; And "driveInLane" flag: it is a boolean flag that restricts the agent to drive exclusively on one side of the road. The agents are placed through the editor and their driving path is defined by hidden waypoints as indicated in Figure 4.5. The figure shows the editing process of AI vehicles in the YtoPR scenario.

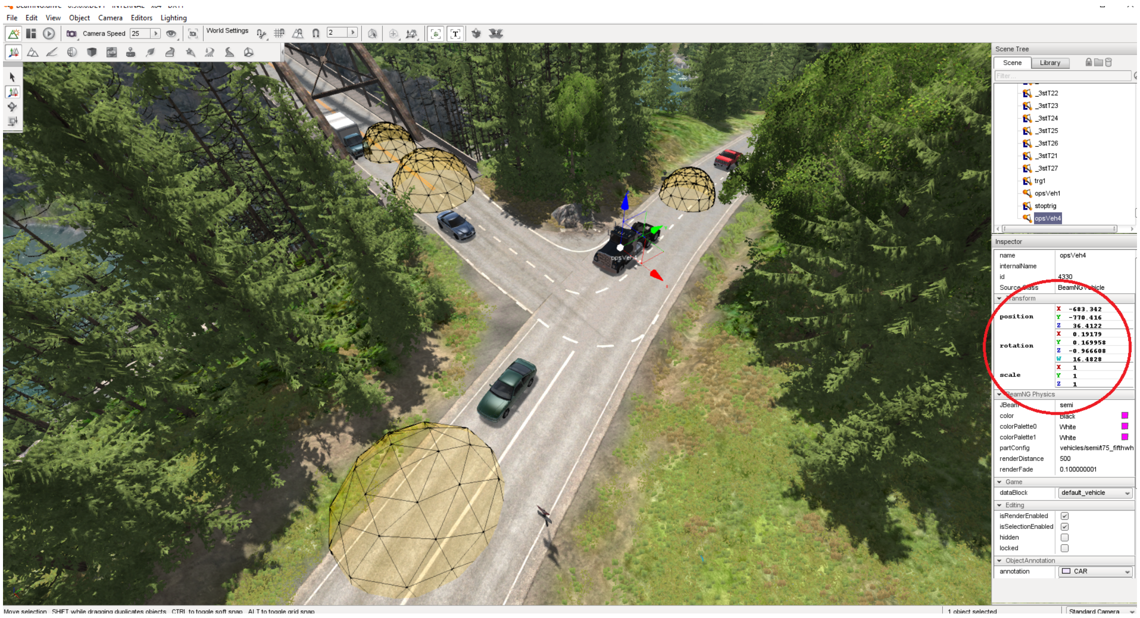


Figure 4.5.: Adding agents' vehicles and setting the parameters in YtoPR scenario

These agents are programmed by Lua to be triggered at a certain point. The role of these agents is to create additional difficulties to participants, for example, in simulating a complex situation of RbL rules as described in Figure 3.6b or to add the realistic experience of the driving environment.

Utilization of Head-tracker As we target intersection scenarios, thus, participants' gazes are very important to be tracked. The successful and safe crossing of an intersection depends on a good scanning on the scene in a correct time. To identify whether participants are looking to the right or left direction, we utilized a head tracker. An alternative to that is to use an eye tracker, which was not affordable. We used the TrackIR[2] as a head tracking input, which is used for gaming and simulation. It consists of two parts, as indicated in Figure 4.6; Infrared camera (the left object), which would be mounted to the top of the screen. It sends tracking orientation and position of the head of BeamNG.drive interface; And TrackClip (the right object), which could be used with a standard baseball cap. For each participant, we made positioning adjustment and calibration processes by using the TrackIR software.

Figure 4.6.: The TrackIR head tracker: infrared camera and TrackClip

[2] https://www.naturalpoint.com/trackir/

4.2.3. Learning Modules Implementation

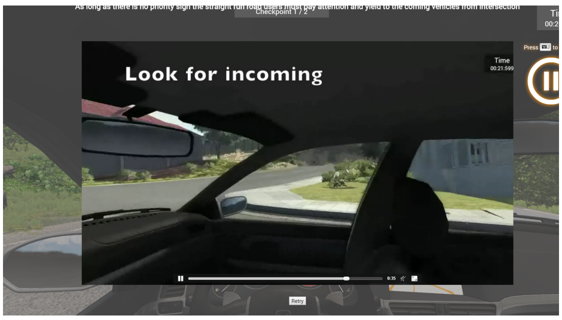
As mentioned before, we used two methods in the learning phase: classical instructional video or Video Experienced (VE_L) and Crash Experienced (CE_L). The participants will be divided into two groups; Group I (GI) begins with CE_L, while Group II (GII) begins with VE_L first. We implemented both YtoPR and RbL rules with both learning modules. Both learning modules start immediately when a participant breaks the target rule of a scenario. The game stops immediately if a participant makes a fatal mistake that leads to a car crash.

Video Experienced Learning (VE_L) module

In VE_L, when a participant makes a mistake the game is paused immediately, and instructional video is popped-up to describe the right behaviour for this situation as illustrated in Figure 4.7. The Figure shows a situation from RbL scenario when a participant did not pay attention to incoming traffic from the right direction. Immediately, a video is popped-up with chronological order instructions (steps) as indicated in the Figures 4.7a–d. In this situation, a good driving behaviour should be: slowing down, looking for incoming right traffic, and continue driving smoothly in case of no more traffic coming from the right direction. The video with slow-motion animation tries to transfer the good driving behaviour to the participant. Afterwards the participant would have another chance to practice what he/she has learned from the video until mastering the rule successfully.

(a) Pointing to the broken rule

(b) Step 1: slow down



(c) Step 2: pay attention for incoming traffic

(d) Step 3: continue driving when no traffic

Figure 4.7.: Instructional video in RbL scenario when a participant did not stop to give priority for incoming traffic from the right direction

Crash Experienced Learning (CE_L) module

In CE_L, when a participant breaks the scenario rule, dynamic AI vehicles will crash the participant's vehicle. The resulting physical damages and crash consequences will be visualized to the participants using the features of BeamNG.drive as indicated in Figures 4.8a and 4.8b. The figures are from the YtoPR scenario when a participant cross to a priority road without the attention for the incoming traffic. Different viewing perspectives and slow-motion cameras are implemented to transfer the realistic experience of the crash and its damage consequences to the participant. In addition, participant's mistake(s) and the proper driving behaviour in such a situation will be introduced to the participant in UI message as shown in Figure 4.8c. Listing mistakes and the proper actions in such situation guides the participant to enhanced driving attitude. The participant will have another chance to repeat the scenario until mastering the rule and pass encoded challenges successfully.

(a) Physical damage (camera view 1)

(b) Crash consequences (camera view 2)

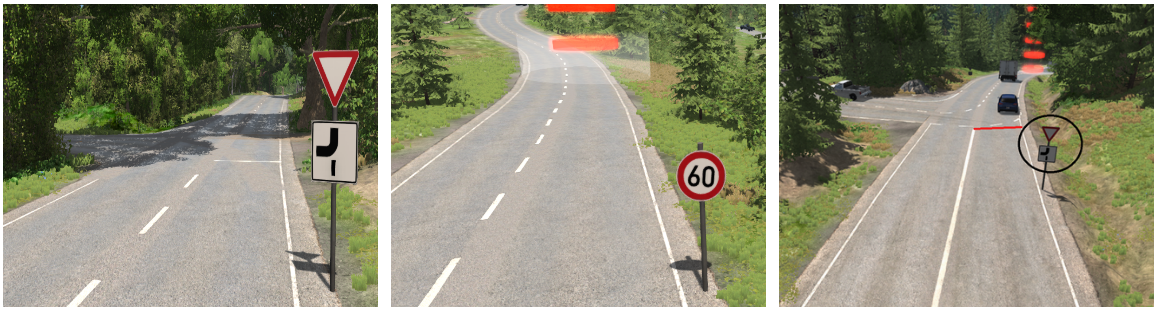
(c) Instructional UI message of failure reason(s) and proper driving behaviour

Figure 4.8.: CE learning in YtoPR scenario when a participant crossed into a priority road ignoring the traffic sign meaning

4.2.4. Evaluation Modules Implementation

In our scenarios, participant's success does not depend exclusively on passing scenario rule, but it depends on the overall driving behaviour. For example, if a participant reaches successfully to the final destination, while in the meanwhile he was driving above the speed limit, we consider this as a failed trial and participant has to repeat it. In our study, multiple factors are used to determine participant's driving behaviours, such as, following traffic rules, careful scanning of roads, and fast/correct response, as discussed in Section 3.3.1.

According to Figure 3.7, both groups of participants, after trying learning scenarios with VE and CE modules, play a Final Evaluation (FE) scenario. In this scenario, we encoded major rules (i.e., YtoPR and RbL) and minor rules (i.e., speed limits, road marks) as indicated in Figures 4.9b–c. The optimal duration of both learning scenarios is ≈ 50-60 seconds, while the FE scenario takes ≈ 90-120 seconds. The FE scenario aims to measure and evaluate the enhanced driving behaviour of participants after learning.



(a) YtoBR (b) Speed limits (c) Solid line

Figure 4.9.: Implementation of minor and major traffic rules within scenarios

4.3. Summary

In summary, this chapter gives a brief description of how the study was implemented and which features of BeamNG.drive are utilized. Both VE and CE learning modules are discussed and the differences are clarified. We utilized two learning module: classical instructional video and crash experience. We argue that presenting real physical damages and crash consequences will have cognitive influences on participants. The major objective of the study is to examine the influences of crash experience learning on the enhancement of driving behaviour. In this study, we developed quantitative and qualitative measures to analyse our findings (See Chapter 5).

Chapter 5

Evaluation and Validation

After designing and developing the study, we called for voluntary participation. We targeted university students of various levels of driving experiences. The proposed research hypotheses and their feasibilities are discussed in this Chapter. To assess the findings, we utilized quantitative and qualitative measures that are illustrated in this Chapter as well. This Chapter includes participants' characteristics, observations of their driving behaviours before, during, and after learning, enhancement of their behaviours, and their feedback on the proposed studies. Findings and interpretations are presented qualitatively and quantitatively.

5.1. Participants' Demographics

ID	Gender	Age	Driving Exp.
P1	M	25-29	14 months
P3	F	30-34	1.5 years
P5	M	25-29	5 years
P7	F	20-24	—
P8	M	25-29	1 year
P10	M	20-24	—
P12	M	20-24	2 years
P14	M	25-29	13 months
P16	M	25-29	1 year
P18	F	25-29	1 year

Table 5.1.: Group I: 10 participants

ID	Gender	Age	Driving Exp.
P2	M	25-29	3 years
P4	F	20-24	1 month
P6	M	25-29	—
P9	M	20-24	8 months
P11	M	25-29	10 months
P13	M	25-29	6 months
P15	M	30-34	10 months
P17	M	25-29	—
P19	M	25-29	—

Table 5.2.: Group II: 9 participants

First, we utilized various channels to announce the study. For example, we published it on various social media channels in addition to public announcements. Two weeks had been dedicated to run the study. Table 5.1 and 5.2 represent participants' characteristics. A total of 19 participants (4 female) with a mean age of 26.2 years voluntarily participated in the study. They are divided into two groups; GI (Table 5.1) has a mean driving experience of 16.5 months, while GII (Table 5.2)has a mean of 7.5 months driving experience. Figure 5.1 shows two participants while doing the study. They wear a baseball cap with TrackClip and heading to a screen with the infrared camera. The environment set-up has been adapted to provide them with realistic driving experiences.

Figure 5.1.: Participants driving in the simulator

5.2. Results Evaluation

In this research, we aim to investigate two research hypotheses; First, we would like to check the feasibility of using the game for raising drivers' awareness and improving their behaviour in hazard situations. We offered two learning methods: instructional video experience and crash experience. Secondly, we intended to analyse crash experience influences on learning. These hypotheses can be summarised as follows:

HYPOTHESIS I (H_1)

The proposed learning approaches have significant influences on participants' driving behaviours and their hazard anticipation.

HYPOTHESIS II (H_2)

Learning by crash experience highly affects enhancing drivers' hazard perception than learning by instructional video experience.

In this study, participants were allowed to repeat a given scenario until they master it. The number of trials needed to successfully finish a scenario is used as indicators of enhanced performance. Participants' driving behaviours are assessed by multiple factors as argued in Section 3.3.1. The evaluation process is based on within groups as well as pairwise groups comparisons.

5.2.1. Group I: Crash Experience then Video Experience

A total of 10 participants were assigned to GI. They started by Crash Experience Learning (CE_L) on the YtoPR scenario followed by Video Experience Learning (VE_L) on the RbL scenario. In the end, they played the Final Evaluation (FE) scenario that includes both rules for assessment purpose. They filled in questionnaires immediately after each learning method.

Results In the CE_L, participants finished the YtoPR scenario in an average of 2.8 (SD =1.1352) trials, while in VE_L they passed the RbL scenario in an average of 2.3 (SD = 0.4830). In the FE scenario, they took an average of 1 trial to pass the YtoPR rule, whereas the RbL rule was passed within an average of 1.5 trials (SD =0.527). The lower number of trials in FE scenario indicates the enhanced performance.

Driving Performance As mentioned in Section 3.3.1, in any scenario participants' driving behaviours were monitored and several quantitative indicators were collected. Figure 5.2 shows the performance of P12 who has an age between 20-24 years and 2 years of driving experience. The left side graph represents the YtoPR scenario when the participant was learning by CE_L. The right one shows the RbL scenario when he was following VE_L. In both graphs, each line represents driving speed (Y-axis) against time series (X-axis). A single line shows an individual trial; The consequent trials of the same failure reason are represented by one line when the number of trials is indicated in the legend. The order of trials in the legend from top to bottom indicates their sequences. In addition, the time interval between red dots indicates the participant's response time; It represents the time interval between the sign appearance on the scene or when the rule should be applied until participants respond to it.

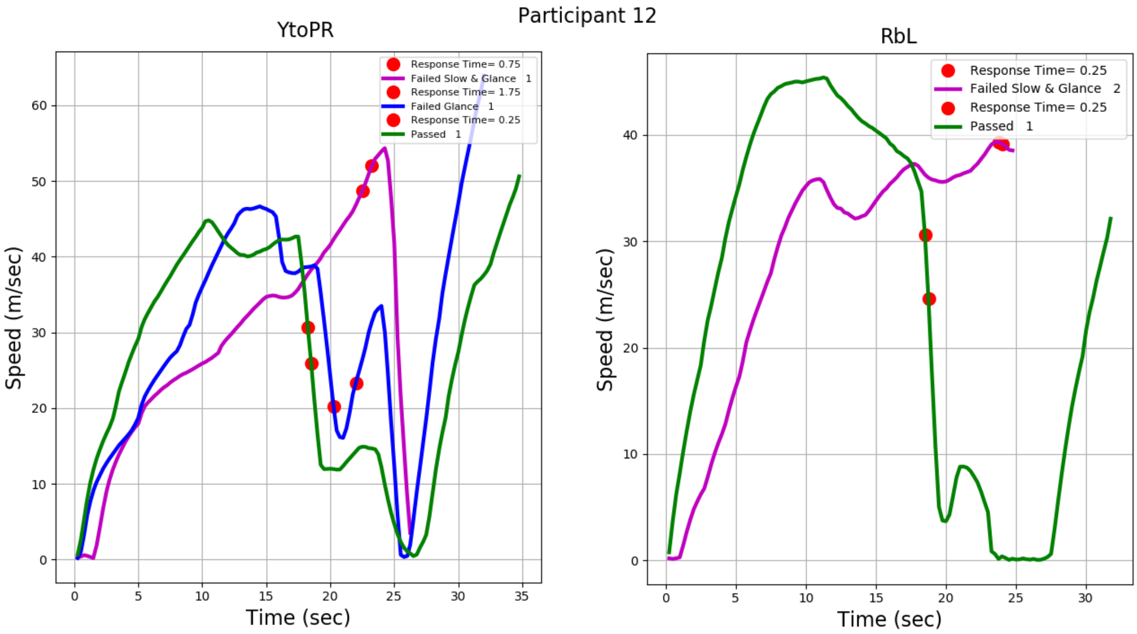


Figure 5.2.: Driving performance of P12 during the learning phase

According to Figure 5.2, the participant had three tries to learn the YtoPR scenario; In the 1st trial (purple line), he failed because he neither stopped nor looked for the incoming vehicles from the intersection. He had a response time of 0.75 second. In the 2nd trial (blue line), he did not scan the intersection and had a long response time of 1.75 seconds. In the 3rd trial (green line), he did both slowdown and scan the intersection in relatively low response time of 0.25 seconds. On the right side, the participant had three trials to learn the RbL rule as well. In the first two trials (purple line), he neither did slowdown nor looked around at the intersection. In the 3rd trial, he passed successfully with a response time of 0.25 seconds.

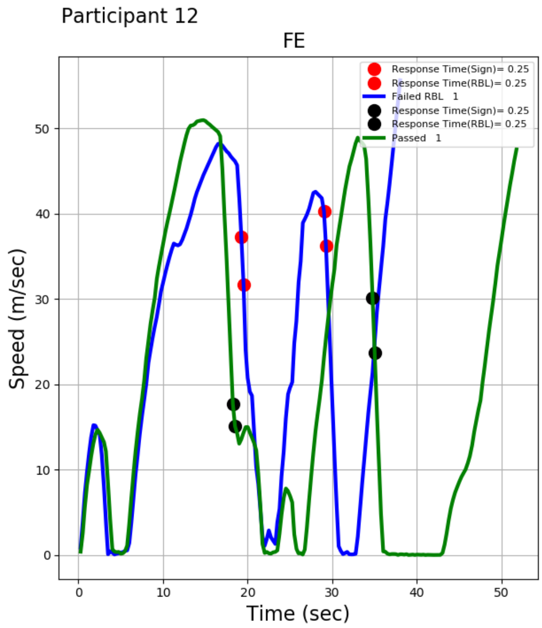
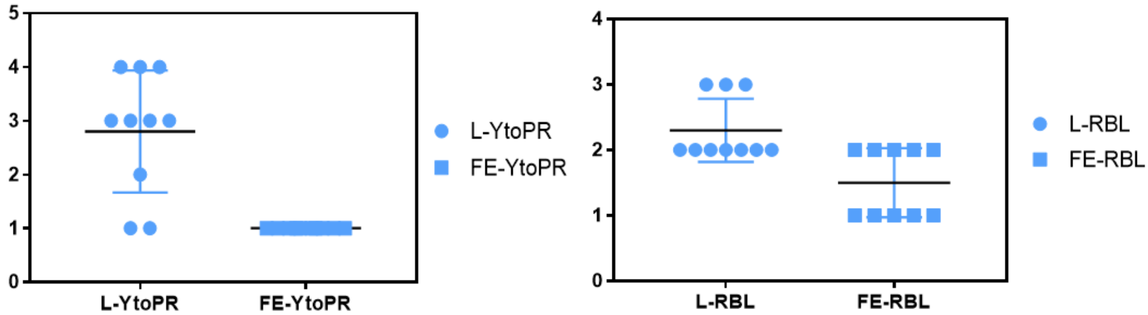


Figure 5.3.: Driving performance of P12 during the evaluation process

Figure 5.3 demonstrates the driving performance of P12 in the FE scenario which contains both rules. He successfully passed the scenario in two trials with an improved response time of 0.25 seconds. In the 1st trial (blue line), although he passed the YtoPR rule (learned by CE), he did not make correct actions in the RbL rule (learned by VE). The participant stopped correctly, but he did not scan the road well. In the 2nd trial (green line), he successfully passed both rules and did correct actions at each rule.

Result Analysis We conducted a paired t-test to examine our hypotheses. Figure 5.4 illustrates the number of participants' trials (Y-axis) during the learning and evaluation scenarios (X-axis) for each rule. Figure 5.4a shows the significant difference in the number of trials between the learning and evaluation scenarios of the YtoPR scenario (p <0.0007); All participants passed the rule in the FE scenario from the 1st trial. Likewise, Figure 5.4b shows the differences of the RbL scenario (p <0.01), when half of the participants required two trials and the others required one trial to pass the rule in the FE scenario.



(a) Learning by CE in the YtoPR scenario (b) Learning by VE in the RbL scenario

Figure 5.4.: Number of trials in the learning and evaluation scenarios of GI

The results confirmed our hypotheses of H_1 and H_2; On the one hand, both of the learning methods (CE and VE) results in a lower number of trials which indicates the enhanced driving performance of participants. On the other hand, the CE has a higher influence in the FE scenario than the VE, when the YtoPR rule had on average fewer trials than the RbL rule ($p < 0.01$).

5.2.2. Group II: Video Experience then Crash Experience

GII had 9 participants, who started by VE_L on the YtoPR scenario followed by CE_L on the RbL scenario. In GII, participants had relatively low average driving experience (7.5 months) than participants of GI (16.5 months).

Results In the learning phase, participants took an average of 2.6 trials (SD =0.707) to pass the YtoPR and RbL scenarios following the VE_L and CE_L consequently. In the FE scenario, participants passed the YtoPR rule in an average of 1.5 trials (SD =0.53), whereas they performed an average of 1.1 trials (SD =0.33) to finish the RbL rule. The decreased numbers of trials during the FE scenario indicate the significant influence of the proposed learning methods on participants' driving performance and their enhanced awareness.

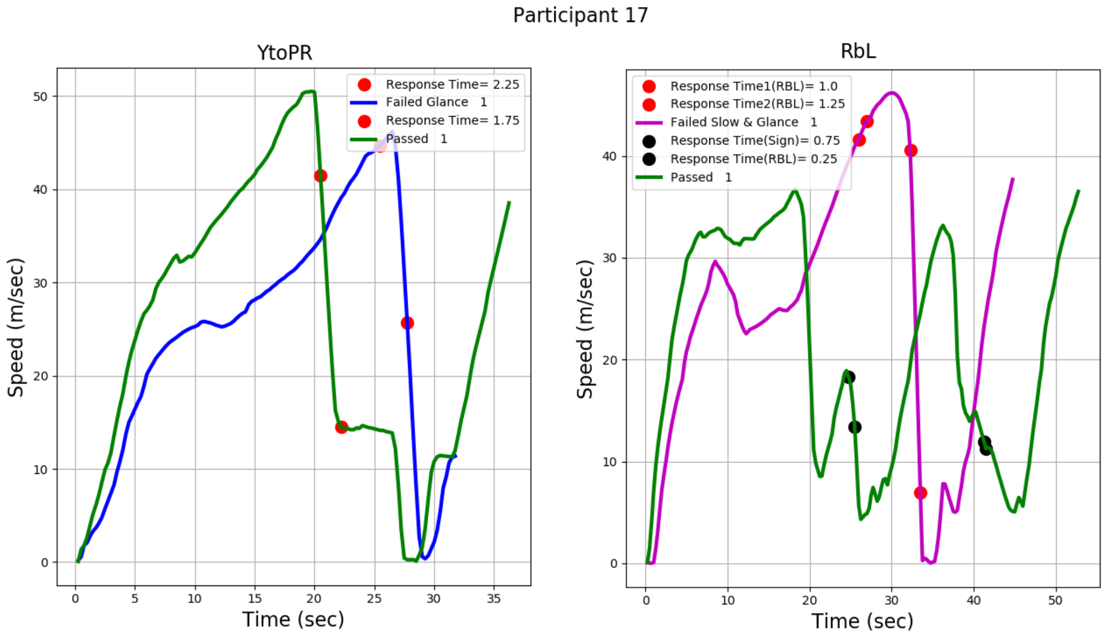


Figure 5.5.: Driving performance of P17 during the learning phases

Driving Performance Figure 5.5 demonstrates the driving performance of P17 during the learning phase. He passed both scenarios in two trials. On the left side, the graph shows that he failed in the 1st trial (blue line) of the YtoPR rule because he did not scan the road intersections and he had a relatively slow response time of 2.25 seconds. In the 2nd trial (green line), his response time was improved to 1.75 seconds and he performed the correct slowing and scanning actions.

In Figure 5.5, the graph on the right side shows the participant performance in the RbL scenarios. In this scenario, particularly there are two locations, where the RbL rule should be applied. In the 1st trial (purple line), the participants had a response time of 1.0 and 1.25 seconds at these locations, which are improved in the 2nd trial (green line) to 0.75 and 0.25 seconds respectively. He failed in the 1st trial because he neither slowed down nor scanned the intersections correctly, however, he performed well in the 2nd trial and passed the scenario successfully.

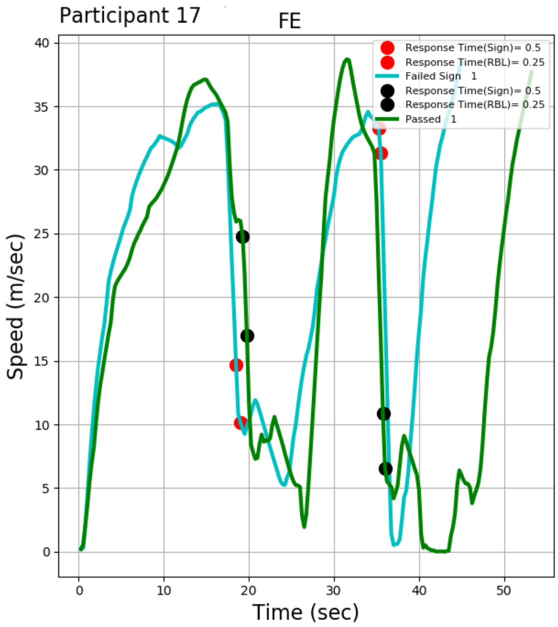
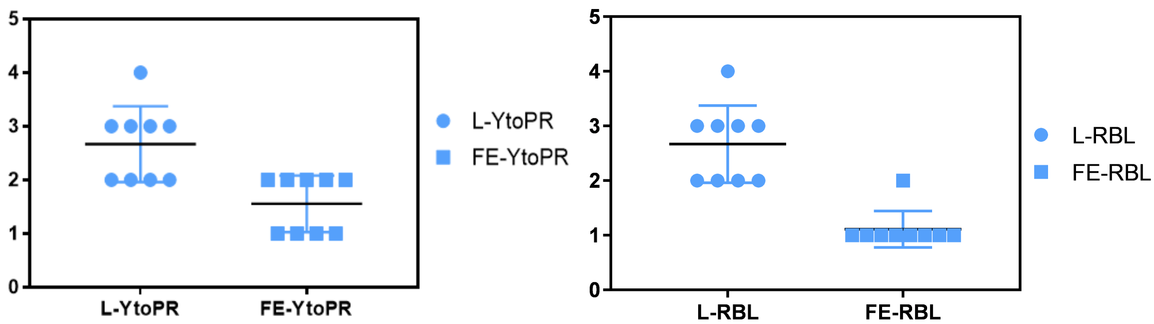


Figure 5.6.: Driving performance of P17 during the evaluation process

Figure 5.6 demonstrates the driving performance of P17 in the FE scenario. It shows that the participant passed the scenario successfully in two trials. In both trials, he had an improved response time of 0.5 and 0.25 in the YtoPR and the RbL rules respectively. In the 1st trial (turquoise line), he failed in the YtoPR rule (learned by VE), while he passed the RbL rule (learned by CE). In the 2nd trial (green line), he passed both rules correctly and performed the correct actions.

Result Analysis The same as for GI, we conducted a paired t-test to examine our hypotheses. The results indicate that there is no significant difference between the learning and evaluation phases ($p > 0.08$) in the YtoPR scenario (Figure 5.7a), while there is a high significant difference ($p < 0.0002$) in the RbL scenario (Figure 5.7b). These findings partially prove H_1.Regarding H_2, Figure 5.7b shows a significant improvement of participants' behaviours to pass the RbL challenge, in which the CE_L was followed; Nearly all the participants passed the rule in one trial, while they required more trials to pass the YtoPR challenge, in which the VE_L was followed ($p < 0.03$).

The statistical analysis of participants' behaviours of both groups shows the significant influences of the proposed learning methods on participants' driving behaviours. It also illustrates the effectiveness of crash experiencing in learning. The findings imply that using the game to learn and practice hazard situations will result in raising drivers' awareness and will improve their driving behaviours in such situations.



(a) Learning by VE in the YtoPR scenario (b) Learning by CE in the RbL scenario

Figure 5.7.: Number of trials in the learning and evaluation scenarios of GII

5.3. Questionnaires Analysis

In addition to the statistical analysis, participants filled in two customized questionnaires; after each learning method. These questionnaires aim to measure qualitative aspects, such as cognitive loads, tension, and enjoyment of participants, in addition to, usability and usefulness of the study. We employed raw NASA-TLX to measure cognitive loads of participants as an indicator of usability, while we used the IMI to find out more indicators regarding participants' tensions and enjoyments, and study usefulness as well.

5.3.1. NASA-TLX

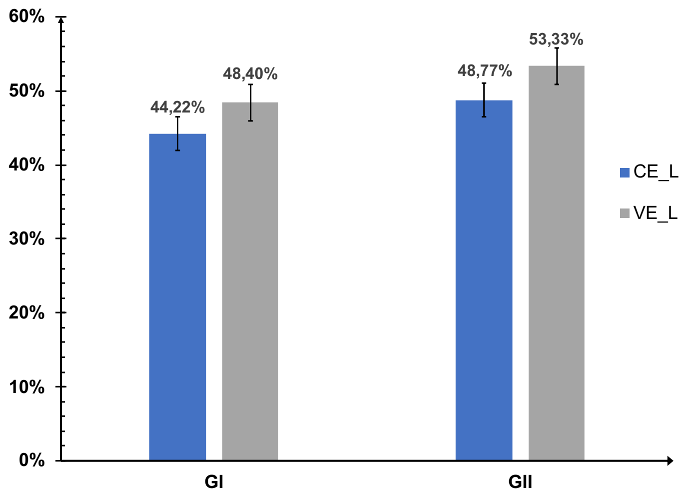


Figure 5.8.: NASA-TLX of GI and GII corresponding to CE and VE learning

Figure 5.8 shows the TLX measures (Y-axis) against the proposed learning methods for both groups (X-axis). For both groups, the TLXs corresponding to the CE_L and VE_L are <55%; These numbers indicate the high usability of the proposed learning methods. For CE_L, the TLX has an average of 46.5%, while for VE_L it has an average of 51%. Although there is no significant differences, the numbers reflect low cognitive loads of CE_L relative to VE_L. That can be considered as another proof of H_2, which argues the potential role of experiencing the crash in enhancing driving behaviours and increasing drivers' awareness of hazardous situations.

5.3.2. IMI

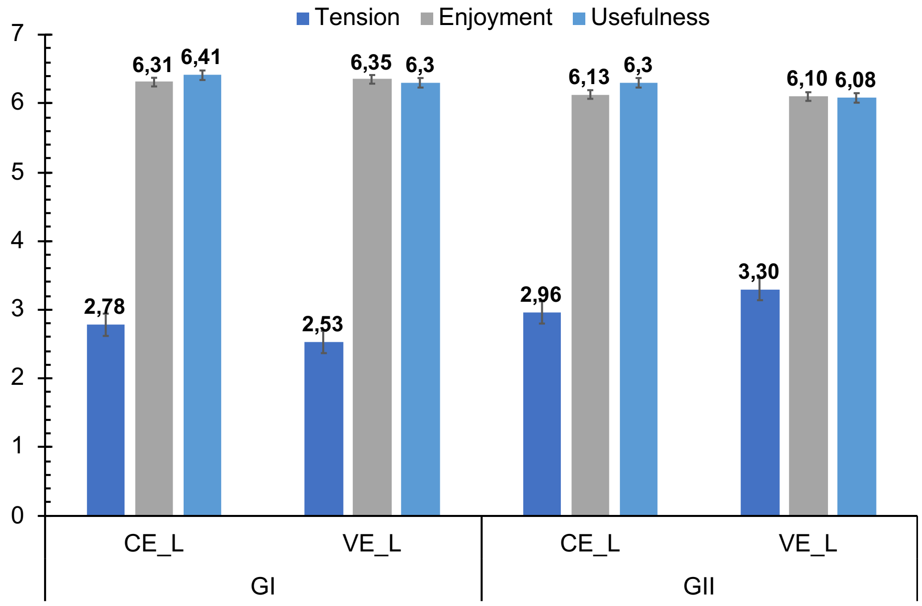


Figure 5.9.: Results of the IMI questionnaire of GI and GII

The IMI standard questioner has 7 scale to assess participants' subjective experience. Each scale consists of items each assigned to a value from 0 (low) to 7 (high). In this study, we focused on a 3 scale: tension, enjoyment, and usefulness scale. Figure 5.9 illustrates average values of each subscale (Y-axis) regarding the proposed learning methods of CE and VE for GI and GII participants (X-axis). According to the figures, there are no significant differences between the subscale of both groups and the learning methods. However, both groups indicate high acceptable levels of enjoyment and usefulness (>6), while they also reported a low level of tension (<3.5).

5.4. Discussion

In the previous sections, we assessed each group individually, however, comparing and analysing the findings among both groups is important as well. Regarding the YtoPR rule, GI followed CE_L to master it, while GII followed the VE_L. During the FE scenario, GI passed the rule in an average of 1 trial, while GII had an average of 1.5 trials to pass the same rule. Using one-tailed test gives a signal to the significant influence of crash experience on learning the same rule ($p < 0.0038$). On the other hand, in the RbL rule when GI participants followed the VE_L and GII participants followed the CE_L. In the FE scenario, the rule is mastered by GI participants with an average of 1.5 trials, while it required less from GII participants, who had an average of 1.1 trials to pass the rule ($p > 0.05$).

Although quantitative and qualitative analysis supports the proposed hypotheses, The study has few limitations as well. First, we have a small number of participants with unbalanced demographics. We intended to study more young novice drivers with a fresh driving licence, however, most of our participants mostly above

20's years old and have considered previous driving experiences. Second, the study examined exclusively hazard situations at road intersections, while there exist numerous driving scenarios that require a high level of hazard perception. Regarding technical issues, we intended to use an eye tracker to record participants gazes, however, a professional eye tracker was not affordable. The study were conducted in a non-isolated environment. Definitely, designing a well isolated environment with support of larger screen and a proper sound system might results in more interesting findings.

In summary, this chapter presented supports and assessments of our research hypotheses. All findings indicate the potential influence of the proposed learning methods for enhancing driving behaviours and on raising their awareness of hazardous situations. The results indicate that both methods are significantly improving the driving behaviours of participants. However, the crash experience method has more potential influences on driving behaviours of participants, regardless of their previous driving experience.

CHAPTER 6

CONCLUSION AND FUTURE WORK

This thesis addressed a new influential factor on drivers' behaviours in hazard situations. In contrast to the reviewed studies in the literature this thesis looked for drivers' awareness of crash consequences and its influences toward safe driving behaviours. Several drivers may have many years of accident-free driving experience, however, they have limited knowledge of crash consequences. Some of them simplify traffic rules trusting their long-term experience. In unexpected situations, this might lead to crashes and dramatic consequences. This research argued exploiting crash experience on enhancing drivers' awareness of hazard situations.

In traditional driving learning schools, hazard situations and the proper driving behaviours in such situations are illustrated visually or theoretically. In particular, crash consequences are not introduced to trainees in a way that significantly influences their behaviours. They learn the ideal driving situations and the safest behaviours to cope with each situation. Thus, this thesis investigated the issue through an empirical study. We used a real physics vehicle simulation to present crash experience to our participants. BeamNG.drive (a soft-body physics vehicle simulator) was utilized to transfer crash experience and physical damage consequences to the participants' perceptions.

In developing the study, serious game concepts had been adopted for learning purpose as well as for data collection. Participants drove scenarios that simulate real hazard situations, whereas they received learning instructions when they failed in a scenario. In this study, we designed two kinds of scenarios regarding traffic rules at the intersections. Two learning methods had been proposed to introduce the proper driving behaviours: classical instructional video (Video Experience) and simulation of crash experience (Crash Experience). Participants' driving behaviours were assessed by quantitative parameters. In additions, the feasibility of the study had been evaluated by qualitative questionnaires.

We had 19 voluntary participants contributed to the study. The findings emphasised potential role of the proposed learning methods in enhancing drivers' behaviours. Although the participants had previous driving experience, most of them failed to pass the designed scenarios successfully in one trial during the learning phase. This might back to their assumptions of being in a game experience. Once they failed, a proper driving behaviour was introduced using one of the learning modules. The results indicated the significant influences of the proposed learning modules, when participants passed scenarios successfully within 2-3 trials. In rare cases (5 times), participants required maximum 4 trails to master a scenario. During the assessment phase, participants showed enhanced driving behaviours when they all passed similar designed scenarios within fewer trials.

Regarding the effectiveness of one learning method over the other, the findings pointed to the higher effectiveness of learning by CE with respect to learning by VE. The traffic rules that had been learned by CE was mostly passed in one trial during the evaluation phase (Figures 5.4a and 5.7b). During the evaluation phase, it was noticed that when participants has a failure, they failed in the scenarios in which they learned by VE module. The statistical analysis demonstrated a significant influence of CE in raising drivers' awareness of hazards, and hence, in enhancing their driving behaviours.

Finally, participants' feedbacks in the questionnaires indicated the feasibility of the study. The TLX showed no significant difference between the workloads of both learning methods. Participants reported acceptable levels of workloads with averages 46.5% and 51% for CE and VE methods respectively. The relative high workloads of VE implied the effectiveness of CE as well when learning was performed combined with fewer work loads. Again the IMI subscale indicated no difference between both methods. Participants' feedback demonstrated how they had high levels of enjoyments and usefulness ($\simeq$ 6 out of 7) with less tension ($\simeq$ 3 out of 7). The interpretation of both questionnaires reflected the feasibility of the study.

As a future work, utilizing technologies of virtual reality (VR) may be a potential alternative to present crash consequences experience to drivers. Designing more scenarios of hazard situations, considering latent hazards, targeting non-experienced drivers, and assessment long-term transfer of knowledge are all aspects that require further research. Further studies can investigate utilizing the proposed simulator in driving schools and examine crash experience influences in the physical field.

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APPENDIX A

PARTICIPATION DESCRIPTION

Information about the Participation in a Research Experiment

Please read the following information carefully.

Study:	**experience driving on a realistic physics based driving simulation**
Conductors:	Nourelhoda Mohamed
Organization:	BeamNG GmbH CEO: Thomas Fischer
Contact:	nour@beamng.com | +49 (0)421 40894390

Description: You are invited to participate in a research study that serves to record driving data for an anonymized analysis. The study aims to investigate the feasibility of using our driving simulator as a training program to assess and enhance driver's situation awareness. This research supports the development of a game-based driving simulator for driving and traffic education.

In this study, you will be asked to play driving scenarios several times to achieve a certain goal. Afterwards, you have to fill in two questionnaires for further analysis. The experiment require that you sit on a driving simulator seat and wear a head tracker. The exact procedure will be explained to you in the beginning of the session. It is required that you have a fresh driving license or you are in the process of taking it.

Your participation in this research is voluntary. You may choose to participate or to withdraw your participation at any time without any penalty. You have the right to refuse to answer particular questions. Your individual data will be kept private. Please do not hesitate to let the conductor know if you have any questions, or would like to take a break at any time.

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APPENDIX B

CONSENT OF PARTICIPATION

Consent to Participate in a Research Study

With my signature below, I certify that I have read the attached document *"Information about the Participation in a Research Experiment"* and I am well informed about the motivation and procedure of this research experiment of "Experience driving on a realistic physics based driving simulation".

I am aware that my participation in this study is voluntary and that I may withdraw from participation at any time without explicit reason and with no further consequences.

I agree that the data resulting from my participation in this experiment will be subject to anonymous scientific analysis and publication.

Please tick the boxes if you agree:

[ ] <u>I agree to participate</u> in this research experiment under the conditions described above and in the attached document.

[ ] <u>I agree to being recorded</u> on photos / film for the purpose of anonymized analysis.

[ ] <u>I agree to the publication</u> of portions of the photo / film materials.

First and last name: ____

Place and Date: ____________ Signature: _______________

For internal use only (do not fill):
P____ | **G** ____ | Comment: ____________

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Appendix C

Questionnaires

Name:

Questionnaire

For each of the following statements, please indicate how true it is for you, using the following scale:

	1 Not at all true	2	3	4 Somewhat true	5	6	7 Very true
1. I enjoyed doing this activity very much.							
2. I was very relaxed in doing these.							
3. I believe this activity could be of some value to me.							
4. I did not feel nervous at all while doing this.							
5. I think this is important to do because it can simulate realistic driving situations.							
6. I would describe this activity as very interesting.							
7. I was anxious while working on this task.							
8. I think doing this activity could help me to realize hazard situation.							
9. This activity did not hold my attention at all.							
10. I felt pressured while doing these.							
11. I thought this was a boring activity.							
12. I believe doing this activity could be beneficial to me.							
13. This activity was fun to do.							
14. I think that doing this activity is useful for improving drivers' situation awareness.							
15. I thought this activity was quite enjoyable.							
16. I think this is an important activity.							
17. I felt very tense while doing this activity.							

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Name:

Please, mark scale at the point that best indicates your experience of the task:

Mental Demand How much mental and perceptual activity was required (e.g. thinking, deciding, calculating, remembering, looking, searching, etc.)? Was the task easy or demanding, simple or complex, exacting or forgiving?	Low 1	2	3	4	5	6	7	8	9	High 10
Physical Demand How much physical activity was required (e.g. pushing, pulling, turning, controlling, activating, etc.)? Was the task easy or demanding, slow or brisk, slack or strenuous, restful or laborious?	Low 1	2	3	4	5	6	7	8	9	High 10
Temporal Demand How much time pressure did you feel due to the rate of pace at which the tasks or task elements occurred? Was the pace slow and leisurely or rapid and frantic?	Low 1	2	3	4	5	6	7	8	9	High 10
Performance How successful do you think you were in accomplishing the goals of the task set by the experimenter (or yourself)? How satisfied were you with your performance in accomplishing these goals? **Note:** *Good* on the *left* & *Poor* on the *right*	Good 1	2	3	4	5	6	7	8	9	Poor 10
Effort How hard did you have to work (mentally and physically) to accomplish your level of performance?	Low 1	2	3	4	5	6	7	8	9	High 10
Frustration How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?	Low 1	2	3	4	5	6	7	8	9	High 10

Thank you

Best regards,

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