Get ready for automated driving with Mixed Reality

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Get Ready for Automated Driving with Mixed Reality

Préparation à la conduite automatisée en Réalité Mixte

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Abstract

Driving automation is an ongoing process that is radically changing how people travel and spend time in their cars during journeys. Conditionally automated vehicles free human drivers from the monitoring and supervision of the system and driving environment, allowing them to perform secondary activities during automated driving, but requiring them to resume the driving task if necessary. For the drivers, understanding the system's capabilities and limits, recognizing the system's notifications, and interacting with the vehicle in the appropriate way is crucial to ensuring their own safety and that of other road users. Because of the variety of unfamiliar driving situations that the driver may encounter, traditional handover and training programs may not be sufficient to ensure an effective understanding of the interaction between the human driver and the vehicle during transitions of control. Thus, there is the need to let drivers experience these situations before their first ride.

In this context, Mixed Reality provides potentially valuable learning and skill assessment tools which would allow drivers to familiarize themselves with the automated vehicle and interact with the novel equipment involved in a risk-free environment. If until a few years ago these platforms were destined to a niche audience, the democratization and the large-scale spread of immersive devices since then has made their adoption more accessible in terms of cost, ease of implementation, and setup. The objective of this thesis is to investigate the role of Mixed Reality in the acquisition of competences needed for a driver's interaction with a conditionally automated vehicle. In particular, we explored the role of immersion along the Mixed Reality continuum by investigating different combinations of visualization and manipulation spaces and the correspondence between the virtual and the real world. For industrial constraints, we restricted the possible candidates to light systems that are portable, cost-effective and accessible; we thus analyzed the impact of the sensorimotor incoherences that these systems may cause on the execution of tasks in the virtual environment. Starting from these analyses, we designed a training program aimed at the acquisition of skills, rules and knowledge necessary to operate a conditionally automated vehicle. In addition, we proposed simulated road scenarios with increasing complexity to suggest what it feels like to be a driver at this level of automation in different driving situations. Experimental user studies were conducted in order to determine the impact of immersion on learning and the pertinence of the designed training program and, on a larger scale, to validate the effectiveness of the entire training platform with self-reported and objective measures. Furthermore, the transfer of skills from the training environment to the real situation was assessed with test drives using both high-end driving simulators and actual vehicles on public roads.

Résumé

L'automatisation de la conduite est un processus en cours qui est en train de changer radicalement la façon dont les gens voyagent et passent du temps dans leur voiture pendant leurs déplacements. Les véhicules conditionnellement automatisés libèrent les conducteurs humains de la surveillance et de la supervision du système et de l'environnement de conduite, leur permettant d'effectuer des activités secondaires pendant la conduite, mais requièrent qu'ils puissent reprendre la tâche de conduite si nécessaire. Pour les conducteurs, il est essentiel de comprendre les capacités et les limites du système, d'en reconnaître les notifications et d'interagir de manière adéquate avec le véhicule pour assurer leur propre sécurité et celle des autres usagers de la route. À cause de la diversité des situations de conduite que le conducteur peut rencontrer, les programmes traditionnels de formation peuvent ne pas être suffisants pour assurer une compréhension efficace de l'interaction entre le conducteur humain et le véhicule pendant les transitions de contrôle. Il est donc nécessaire de permettre aux conducteurs de vivre ces situations avant leur première utilisation du véhicule. Dans ce contexte, la Réalité Mixte constitue un outil d'apprentissage et d'évaluation des compétences potentiellement efficace qui permettrait aux conducteurs de se familiariser avec le véhicule automatisé et d'interagir avec le nouvel équipement dans un environnement sans risque. Si jusqu'à il y a quelques années, les plates-formes de Réalité Mixte étaient destinées à un public de niche, la démocratisation et la diffusion à grande échelle des dispositifs immersifs ont rendu leur adoption plus accessible en termes de coût, de facilité de mise en œuvre et de configuration.

L'objectif de cette thèse est d'étudier le rôle de la réalité mixte dans l'acquisition de compétences pour l'interaction d'un conducteur avec un véhicule conditionnellement automatisé. En particulier, nous avons exploré le rôle de l'immersion dans le continuum de la réalité mixte en étudiant différentes combinaisons d'espaces de visualisation et de manipulation et la correspondance entre le monde virtuel et le monde réel. Du fait des contraintes industrielles, nous avons limité les candidats possibles à des systèmes légers portables, peu chers et facilement accessibles; et avons analysé l'impact des incohérences sensorimotrices que ces systèmes peuvent provoquer sur la réalisation des activités dans l'environnement virtuel. À partir de ces analyses, nous avons conçu un programme de formation visant l'acquisition des compétences, des règles et des connaissances nécessaires à l'utilisation d'un véhicule conditionnellement automatisé. Nous avons proposé des scénarios routiers simulés de plus en plus complexes pour permettre aux apprenants d'interagir avec ce type de véhicules dans différentes situations de conduite. Des études expérimentales ont été menées afin de déterminer l'impact de l'immersion sur l'apprentissage, la pertinence du programme de formation conçu et, à plus grande échelle, de valider l'efficacité de l'ensemble des plateformes de formation par des mesures subjectives et objectives. Le transfert de competences de l'environnement de formation à la situation réelle a été évalué par des essais sur simulateurs de conduite haut de gamme et sur des véhicules réels sur la voie publique.

Contents

Abbreviations

ADAS	Advanced Driver-Assistance Systems
ADS	Automated Driving System
AR	Augmented Reality
AV	Autonomous Vehicle
DOAS	Driving and On-board Activities Simulator
FB	Fixed-base
FOV	Field-Of-View
FOR	Field-Of-Regard
HF	Human Factors
HMD	Head-Mounted Display
HMI	Human-Machine Interface
HUD	Head-Up Display
LVR	Light Virtual Reality
MR	Mixed Reality
NDRT	Non-Driving Related Task
OOTL	Out-Of-The-Loop
RtI	Request to Intervene
SA	Situation Awareness
SRK	Skills, Rules, Knowledge
SS	Simulator Sickness
SSQ	Simulator Sickness Questionnaire
TOR	Take-Over Request
TOT	Take-Over Time
VLE	Virtual Learning Environment
VR	Virtual Reality
UM	User Manual

Chapter 1

Introduction

1.1 Context of the thesis

This thesis has been conducted at the Center for Robotics (CAOR) of Mines ParisTech and at the Scientific and Future Technologies Department (DSTF) at Groupe PSA. The research was jointly supervised by Dr. Alexis Paljic (Mines ParisTech) and Luciano Ojeda (Groupe PSA), and supported by the French Foundation of Technological Research (*Association Nationale de la Recherche et de la Technologie ANRT*) under grant CIFRE 2015/1392.

1.2 Motivations

Are you reading this manuscript in your car as you drive on the highway?

If not, try to imagine the situation.
If yes, and you are allowed to do it without fearing a ticket and you feel it is a fairly common situation, it means that, probably, automated cars are out there and you are riding one of those. Otherwise, you should stop reading right now and focus on the driving task!

At the time of writing, performing a non-driving related task while driving breaks numerous laws and is potentially very dangerous, but in the not too distant future it would be allowed and safe. This is because vehicles provided with a certain level of automation (SAE Levels 2,3,4,5) will be able to handover part or the totality of the driving task without requiring you to monitor the system or your driving environment (SAE Levels 3,4,5). You can, therefore, engage in secondary activities such as reading, writing emails, watching videos and so on. However, at *conditional* automation level (SAE Level 3), when the automated system encounters unexpected situations and reaches its functional boundaries, it will assume that drivers who are sufficiently warned will adequately respond to a request to intervene.

It means that when your car notifies you with the alert

TAKE OVER!

you must know what to do.

Although human drivers are freed from the driving task, they must be aware of their role at all time and know how to react to car's demands to transition of control. Interacting with the automated system in the proper way from the first ride is crucial for car and road safety in general in order to keep yourself, passengers and other vehicles out of harm's way.

The increased automation and system complexity can turn experienced drivers into novices when it comes to interacting with the vehicle. For this reason, before operating an automated vehicle for the first time, it is necessary to properly familiarize drivers with the automated system in order to learn the best practice to interact with the novel vehicle's equipment in a safe way.

The information given during the handover phase performed at car dealerships or written in the owner's manual may not be sufficient to ensure a correct understanding of the system or an adequate use during driving due to the lack of prior practice. Test drives performed with an instructor and appropriate vehicles would allow for on-road experience but with critical constraints in terms of security, time, cost, and generalization of the driving scenario.

For this reason, it is necessary to allow future drivers to master the vehicle, understand the capabilities and limitations of the system and allow them to experience, in a safe environment, a variety of safety-critical and unforeseen driving situations. In this context, Mixed Reality technologies and simulation can represent valuable tools for this purpose. In addition, *light* Mixed Reality systems (in terms of portability, accessibility, cost) would allow for the easy deployment of such training programs in driving schools, car dealerships or even customers' house.

With this research we aim to fulfill a lack in the literature. From one side, extensive research on interaction with autonomous systems, human factors for automated vehicles and transition of control had already been conducted; from the other side, the topic of training in Mixed Reality and the evaluation of transfer of training in various domains had as well been extensively addressed. However, the intersection between these two research communities had been only slightly investigated.

1.3 Objectives of the Thesis

The objective of this research is to explore if *light* Mixed Reality systems can foster the acquisition of skills in the context of conditionally automated cars. By using the adjective *light*, we want to mark the difference between MR systems that are cost-effective, portable and easy to set up and systems that are cumbersome, expensive and require dedicated space to operate. The idea is that a light mixed reality training system could be easily deployed to train a large amount of people in an risk-free environment in an effective way.

The main objectives of the thesis are the following:

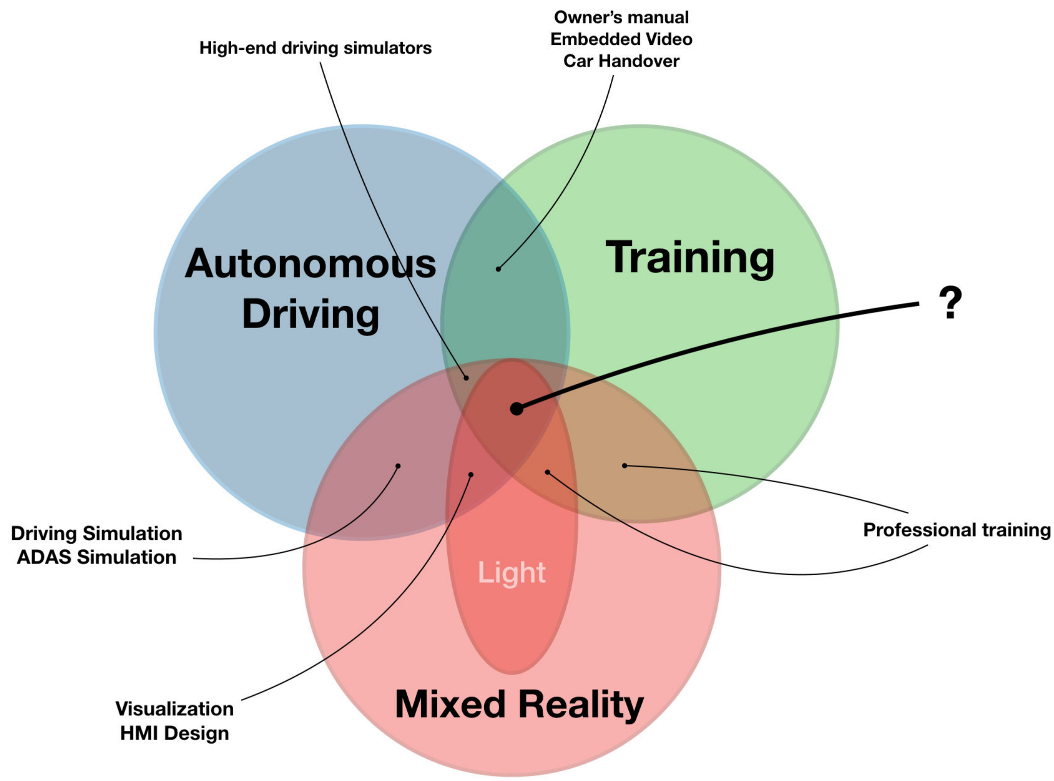


Figure 1.1: The context of the thesis

1. *Define the characteristics of the training system(s) and analyze their entailed limitations*
   Starting from the analysis of the training needs, we will explore the Mixed Reality continuum, from physical reality to digital reality, in order to identify the aspects of the MR systems that meet the training requirements. In particular, we will describe these systems in terms of visualization and manipulation characteristics, that are the aspects that will help us in categorizing them according to the level of immersion they provide.

   Moving towards virtuality means sacrificing some of the characteristics of reality. We will address the following questions: What are the characteristics of Mixed Reality systems that support drivers in familiarizing themselves with a conditionally automated system? What are the limitations introduced by MR systems in terms of sensori-motor incoherences and how it would be possible to reduce their consequences?

2. *Design a training protocol on the basis of the choices made in terms of content and systems*
   After having identified the characteristics of the desired class of training systems, we focus on the content of the training and on its presentation form.

   What are the necessary information that a user should be provided with before driving? How this information should be presented to the user? To answer to this questions, the content of the training will be designed with the aim of providing the user with a set of knowledge (e.g. information about the automated system, the identification of the HMI), rules (e.g. the role of the human driver during automation and the actions to perform when its interaction is required) and skills (e.g. using this information to accomplish driving situations) that support the interaction with the autonomous vehicle.

Importance will be also given to the possibility of providing the users with simulated driving scenarios (e.g. highways, traffic jams) in which they can experience driving automation in both non-critical and safety-critical transitions of control, the interaction with future HMI as well as the possibility to perform non-driving related activities on board.

The whole training will be designed in order to be easily implemented in MR systems with different level of immersion in terms of visualization (e.g. screens, HMDs), and manipulation (e.g. steering wheel, controllers) space.

3. *Evaluate training effectiveness and assess the transfer of skill to the driving scenario.*
   At the experimental level, we aim at realizing user studies to assess the effectiveness of the training systems, the pertinence of the information provided during the training and the transfer of skills from the training environment to real driving scenarios.

   What are the appropriate metrics to consider in order to evaluate the efficacy of the training? What does it mean to be able to operate a conditionally automated vehicle and to what extent drivers trained with a Mixed Reality training program are able to operate an actual vehicle?

   These user studies, oriented towards the achievement of ecologically valid results, will thus make use, besides the proposed Mixed Reality systems, of professional high-end simulators and industrial prototypes of actual vehicles for test drives.

1.4 Structure of the document

The remainder of the manuscript is organized in two parts.

Part I rolls out the research question and presents the industrial and theoretical background. It is made up of two chapters:

- In *Chapter 2* the industrial context is introduced by presenting the concept of Autonomous Driving and the characteristics of the levels of automation with a particular focus on Level 3 Conditional Automated Driving System. The crucial problem of the transition of control is described from the human factors perspective and the aspects that can have an influence on the take-over performance are illustrated. Finally, considering the relevant work in the field, the motivations for a familiarizing training phase prior to the use of the automated system are presented and as well as the constraints that prevent from doing so in real scenarios.

- In *Chapter 3* the Mixed Reality (MR) continuum is presented. Across this spectrum from physical to digital reality, we describe systems according to the level of immersion they provide in terms of visualization and manipulation characteristics and their inherent limitations. In addition, we present how MR has been used in literature for training purpose. The question of skill transfer from the training environment to real world task is also addressed by presenting a summary of the literature.

Part II presents the training design and the evaluation of the training systems. It is made up of three chapters:

- In *Chapter 4* the design and development process which led to the implementation of the experimental platform is described. The experimental platform included a HMD-based VR system and a training program. First, the training requirements are described in terms of skills, rules and knowledge: they were used as guidelines to design the training content, which included a learning and a training environment implemented in the MR system. Subsequently we present a pilot study conducted to validate the manipulation interface for the interaction with the training environment of such MR system.

- In *Chapter 5* the first user study conducted to evaluate the role of immersion in VR-based training is presented. We compared a light VR-based training with a fixed-base simulator and a traditional user manual. Sixty participants trained with these systems were evaluated with a test drive in a high-end driving simulator.

- In *Chapter 6* the second user study is presented. In this experiment sixty participants were trained with an Augmented Reality training program, an improved version of the VR HMD training and an on-board video tutorial. They were evaluated in a Wizard-of-Oz test drive in real driving scenario on public road.

Finally, in *Chapter 7* the findings from the experimental studies are discussed and summarized, the current limitations of the thesis are described and hints for future research perspectives are proposed.

Part I

Context and theoretical background

Chapter 2

Driving Automation

Cowboy: If everybody's got one of these auto-whats-its, does anybody walk or run any more?
Doc: Of course we run, but for recreation. Fun.
Cowboy: Run for fun? What the hell kinda fun is that?!

Back to the Future Part III

Contents

2.1 Introduction

Significantly reducing the number of accident and casualties on the road; increasing traffic efficiency; allowing people with disabilities to move around; improving environmental quality and sustainability. These are just few of the promises around the introduction of the autonomous vehicle in everyday life. Since the invention of the car, the automotive industry has never seen such a period of rapid and radical innovation. Automated Vehicles are expected to change not only the way in which people get around, but also the shape of cities, the road design, our relationship with technology, the concept of vehicle ownership and how we spend time in the car. These expectations are corroborated by the fact that we are already experiencing partial autonomy with the use of vehicles equipped with Advanced Driver-Assistance Systems (ADAS) capable to adapt their speed according to the traffic condition and to perform emergency brake if needed.

2.1.1 Perceiving the road environment

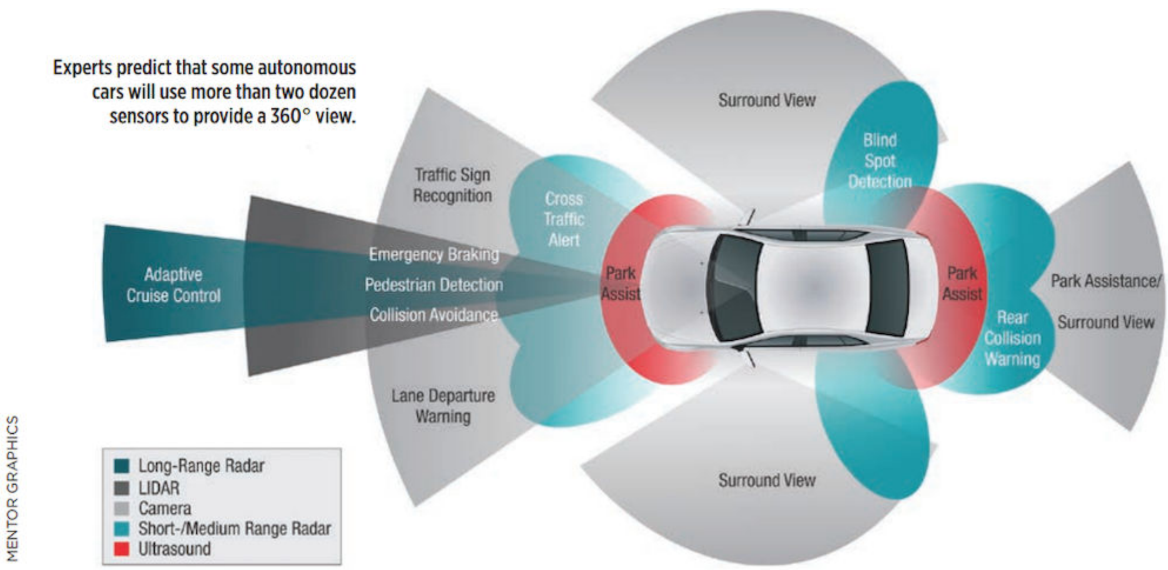


Figure 2.1: Sensors on automated vehicles. Image from SAE [2019]

To substitute a driver, Autonomous Vehicles (AVs) have to perform the driving task at least as good as a human being. In detail, following the Sense-Plan-Act robotic paradigm, the autonomous driving system has to perceive the driving environment around itself, take the (most) correct decision among several possible ones, and finally send the command to the control system. To do so, AVs are equipped with a large number of sensors, actuators and powerful computation systems.

First of all, the vehicle needs to know, with great precision, where it is in the world: novel GPS coupled with other information and high-definition maps would be able to provide better accuracy than today. Then, in order to perceive the surrounding environment, data coming from cameras, radars and laser scanners is fused together to have a more complete and dependable information of fixed (roads, signs, buildings and so on) and moving (other vehicles, pedestrians) objects.

The data relative to the ”ego vehicle”, may be then actively integrated by the other road participants in a continuous exchange of information. This approach is at the basis of the concept of connected and cooperative autonomous vehicles, which gives rise to several challenges for what concerns fast and reliable network communication, privacy of information and cybersecurity.

All this information is then used to predict several driving scenarios according to the behaviors of all the road actors, pick the most accurate decision, and compute trajectories and vehicle’s motion with high precision. Finally the commands are sent to the actuators to control steering and speed. All this process happens at high frequency.

However, besides fully automated cars (also known as self-driving cars), the human driver will be still present in the car and have crucial roles.

2.1.2 Levels of Driving Automation

SAE level	Name	Narrative Definition	Execution of Steering and Acceleration/ Deceleration	*Monitoring* of Driving Environment	Fallback Performance of *Dynamic Driving Task*	System Capability *(Driving Modes)*
***Human driver* monitors the driving environment**						
0	No Automation	the full-time performance by the *human driver* of all aspects of the *dynamic driving task*, even when enhanced by warning or intervention systems	Human driver	Human driver	Human driver	n/a
1	Driver Assistance	the *driving mode*-specific execution by a driver assistance system of either steering or acceleration/deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	Human driver and system	Human driver	Human driver	Some driving modes
2	Partial Automation	the *driving mode*-specific execution by one or more driver assistance systems of both steering and acceleration/ deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	**System**	Human driver	Human driver	Some driving modes
***Automated driving system* (“system”) monitors the driving environment**						
3	Conditional Automation	the *driving mode*-specific performance by an *automated driving system* of all aspects of the dynamic driving task with the expectation that the *human driver* will respond appropriately to a *request to intervene*	System	**System**	Human driver	Some driving modes
4	High Automation	the *driving mode*-specific performance by an automated driving system of all aspects of the *dynamic driving task*, even if a *human driver* does not respond appropriately to a *request to intervene*	System	System	**System**	Some driving modes
5	Full Automation	the full-time performance by an *automated driving system* of all aspects of the *dynamic driving task* under all roadway and environmental conditions that can be managed by a *human driver*	System	System	System	**All driving modes**

Figure 2.2: Taxonomy of Level of Automation proposed by SAE [2018]

Autonomous Vehicles are generally classified according to the level of automation they provide, the capabilities of the system and the role of the human driver. In this manuscript we adopt the taxonomy proposed by SAE (*Society of Automotive Engineers*) International, in which 6 levels of automation are identified, from 0 (where the human driver performs the entire driving task) to 5 (where the driving task is performed by the automated driving system). In the document *Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles* International [2016] these levels are described in great detail. An important distinction is made between the first three levels (0-2) of automation, in which it is the human driver who monitors the driving environment, and the last three levels (3-5) in which it is the automated driving system that takes care of the monitoring. The aim of the document is also to clarify for each level what role (if any) drivers have in performing the dynamic driving task while a driving automation system is engaged.

Level 0 - No Automation
At level 0, all aspects of the driving task are executed by the human driver at all time who is solely responsible for monitoring the roadway and for safe operation of all vehicle controls. This level includes also contemporary driver assistance systems that have no direct repercussion on steering nor speed, but issue visual and auditory alerts (such as Forward Collision Warning, Lane Departure Warnings).

Level 1 - Driver Assistance
Level 1 includes contemporary vehicles equipped with ADAS aimed at avoiding collision with a brake support (Emergency Brake Assist, Lane Keep Assist System). The human driver is still in charge of the entire driving task and s/he is not allowed to leave the steering wheel; for this reason we usually refer to this level as *"hands-on"*.

Level 2 - Partial Automation
At level 2 the execution of steering and acceleration / deceleration is performed by the automated system; however, the monitoring of the driving environment is still required to the human driver. For this reason, this level is also known as *"eyes-on"* (which might include both *"hands-on"* and *"hands-off"*) and the driver takes the role of *supervisor*. There already exist examples of commercially available vehicles equipped with the Level 2 automated driving system, such as Tesla Autopilot [Tesla, 2019].

Level 3 - Conditional Automation
The main difference with the previous level is that at Level 3 the automated driving systems performs also the monitoring of the driving environment without requiring driver's constant attention. This implies that automated vehicles equipped with this level, also known as *"eyes-off"*, would enable the human driver to perform secondary activities with the requirement that s/he will resume the driving task if necessary.

Level 4 - High Automation
At level 4 the AV is able to execute the driving task even if the human driver does not respond appropriately to a request to intervene. In other words, when the automated driving system encounters situations in which it can no longer perform the driving task at hand, and the human driver is not available to resume the driving task, the vehicle will eventually assume a minimal risk conditional (*"mind-off"*).

Level 5 - Full Automation
At level 5, the human driver is no longer required at all. In principle, the car can reach a starting point without the presence of the passenger on board. The passengers are only required to set the destination. This level will bring a complete renovation of the driving space inside the car. Although there already exist some prototypes or concepts of Level 5, the first commercial AV are still far from hitting the public road, even at low speed and on dedicated lanes.

Although in a given moment a vehicle belongs to a specific level of automation, in the same vehicle may coexist more levels of automation according to the situation. For example, if the car is driving on the highway at Level 3 (so without human monitoring) it could require to switch to Level 2 because the infrastructure does not yet allow for it. This coexistence of different levels of automation introduces a challenge for the driver which could play the role of driver, supervisor or just passenger according to the situation.

2.2 Level 3 - Conditionally Automated Vehicles

The target of this thesis are Level-3 AVs. This category of automated vehicles brings with it interesting and very challenging issues in particular for what concerns the interaction between the human driver and the automated system.

The general use case of L3 AVs would be the following: the driver takes the car and manually drives towards a destination; if the itinerary includes an area enabled for automated driving, the driver may decide to activate the Automated Driving System (ADS); the ADS will thus perform the entire driving task, without requiring the human driver to monitor the environment, but with the expectation that s/he would regain control of the vehicle if the ADS is no longer capable, for various reason, of performing the driving task at hand.

Operating this kind of vehicles, thus, requires the understanding of system capabilities and limits, trust in automation, and some operational skills when it comes to switch back to manual driving. At this level, the improvement of road safety will be dependent on the ability of human drivers to intervene in those situations that the automated driving system cannot handle Endsley [2018]: in fact, if from one hand the automotive industry claims that AVs will reduce accidents caused by human drivers, the interaction between human drivers and AVs, and other road users and AVs may introduce new forms of accidents.

Car manufacturers do not have a common vision about L3 AVs. Some car companies have already commercialized vehicles with this level of automation (e.g. Audi's Traffic Jam Pilot [Audi, 2019], a system which allows autonomous driving on a divided highway up to 60km/h).

Other companies are planning to commercialize this level of automation: Groupe PSA, for example, is currently testing two L3 driver assistance systems: *Traffic Jam Chauffeur* [PSA, 2019b] which works only in traffic jams on dual carriageways at speeds of under 50-70 km/h; and *Highway Chauffeur* [PSA, 2019a] which works on dual carriageways at full speed (130 km/h) and performs lane changes if necessary.

On the other hand, other car companies are just considering to not commercialize this level of automation and to move to a higher one. Ford, for example, is skipping L3 to work on L4-AVs after having found that even the engineers supervising the AV lost situation awareness.

Same decision to skip L3 was taken by Waymo (former Google Self-Driving Car Project) in 2015, after user tests with their employees:

> *We saw human nature at work: people trust technology very quickly once they see it works. As a result, it is difficult for them to dip in and out of the task of driving when they are encouraged to switch off and relax.* [Waymo, 2015]

In other word, they claim that instantaneously switching from autonomous driving to manual is not only potentially dangerous due to short take-over time and the challenge of context, but also it is not fair for the driver itself. Waymo is thus working only on L5 fully AVs.

Level 3 of automation is thus the most challenging from the human driver's point of view; it denotes an important move in the situation awareness requirement, with the monitoring of the driving environment that switches from the driver to the vehicle, with the human driver who is still responsible for fallback performance. While the technical development of the AV is rapidly improving, the human factor research is not moving at the same pace: the role of humans in AVs is not yet clearly established and, worse, automation is being developed without sufficient consideration of the human abilities to take over control Herzberger et al. [2018].

2.2.1 Human Factors in Autonomous Driving

"The more advanced a control system is, the more crucial may be the contribution of the human operator" [Bainbridge, 1983]. When it comes to autonomous cars, Bainbridge's *ironic* statement could sound inaccurate; however, before reaching fully automated or driverless cars, the automation level will actually increase in parallel with the necessity of a human driver ready to take over. According to Cunningham and Regan [2015] the main human factor issues associated with partially automated driving are drivers' inattention and distraction, reduced situational awareness, manual skill degradation and motion sickness.

Kyriakidis et al. [2017] presented the perspective of researchers in the field of Human Factors (HF) and AVs. They identify the main challenge for the mass deployment of AVs as being the intervention of the human driver after a period of automated driving. The authors thus selected six axis of research in this direction: (1) design HMI capable of informing the occupants of the vehicle about system capabilities and operational status, (2) determine the automation functionalities that the human driver would use, (3) define the interaction between the human driver and the automation system during transition of control, (4) establish procedures to assess and ensure safety during the transition from automated to manual driving, (5) investigate the interaction between AVs and other road users, (6) “explore the modification of the current driver training program” in order to instruct drivers about the use of automation “in a safe and acceptable manner”. From this analysis it is clear that driver training programs should be updated in order to guarantee that humans are capable of using AVs [Reed in Kyriakidis et al. [2017]], of understanding system capabilities, limitation and expected actions in order to resume control when required. For Andersson (in Kyriakidis et al. [2017]) is important to understand the way in which people will be interacting with the automated functionalities, in order to ensure a smooth process for the human drivers to regain control of the vehicle [Kyriakidis et al., 2017].

Stanton (in Kyriakidis et al. [2017]) stated that “AVs are meaningful only if drivers are freed from the driving task, are not anticipated to supervise the system, and are not liable for it” [Kyriakidis et al., 2017]; however, extensive research revealed, in fact, that humans are not particularly good at tasks that require vigilance and sustained attention over long periods of time (Warm et al. [2008], as cited in Kyriakidis et al. [2017]).

Boelhouwer et al. [2019] identify in the misuse and disuse of automated driving systems one of the main human factor issues. In the case of misuse there is an over-reliance on the system which may lead to hazardous situations when a driver relies on the automated systems for situation it cannot actually cope with; disuses occur when a driver does not use the automated driving system in driving situations where the vehicle could cope and thus it nullifies potential benefits of driving automation. In order to avoid these situations “the driver’s mental model needs to be corresponding to the actual system capabilities”.

Another challenge is represented by the degradation of driving skill due to lack of practice arising from sustained automatic control [Walker and Stanton, 2017]. “If drivers are not performing a function”, Stanton and Marsden [1996] asked, “how can they be expected to take it over adequately when the automated systems fail to cope?”

2.2.2 Situation Awareness: the Out-Of-The-Loop problem

Research showed that automation induces a reduction of situation awareness of the operators, by creating the so called out-of-the-loop (OOTL) problem.

Being cognitively OOTL, thus, is usually referred to a loss of situation awareness, which is defined as “the perception of elements in the environment within a volume of time and space, the comprehension of their meaning and significance of the situation, and the projection of their status in the near future” [Endsley, 1988] SA contributes to create the individual’s mental model of the world around them, which plays a crucial role in effective decision making and control of dynamic systems [Endsley and Kiris, 1995].

Endsley’s definition was subsequently extended to the driving context by Matthews et al. [2001] who proposed a model identifying five components of situation awareness, which are considered highly relevant for semi and fully AVs by McCall et al. [2018]: (1) Spatial awareness refers to the location of all relevant features relative to the environment; (2) Identity awareness refers to the knowledge of salient items; (3) Temporal Awareness refers to changes of the current situation over time; (4) Goal Awareness refers to how high-level (e.g. navigation) or low-level (e.g. controlling the vehicle) can be achieved; (5) System Awareness refers to the awareness of the current status of the system.

Humans are thus expected to experience a decrease in situation awareness as they progressively shift from the role of driver to the one of passenger [McCall et al., 2018]. However, the driving task will always require a certain level of SA and, according to the level of automation, the SA will be shared in a different amount between the system and the driver.

Since L3 Automated driving will allow the human driver to not focus on the driving task at all time, this reduction of workload may contribute also in a reduced situation awareness when it comes to regaining control of the vehicle.

A loss of SA underlies a great deal of the out-of-the-loop problem, formalized for the first time by Endsley and Kiris [1995] and then extended to automated driving by Merat et al. [2018]: the authors suggest that "being in the loop can be understood in terms of (1) the driver's control of the vehicle, and (2) monitoring the current driving situation". They propose a continuum of levels of engagement that can make drivers *in-*, *on-*, and *out* of the loop. Drivers are in-the-loop when they are both physically controlling the vehicle and monitoring the driving situation; on-the-loop when they are still monitoring the situation but not in physical control of the vehicle; out-of-the-loop when they are not in physical control of the vehicle nor monitoring the driving situation, or when they are in physical control of the vehicle, but not monitoring the driving situation. With driving situation authors refer both to the surrounding driving environment and to the actions performed by the ADS.

A constant in-the-loop drivers is thus required only at L0-1 of driving automation since they are in continuous charge of the driving task. While at L2 the driver may be on-the-loop, at L3-4 they can be out-of-the-loop. Thus, at L2-3-4 a re-engagement of the driver may be required in order to brought them back into the loop. At L5 these definitions may not be appropriate since there is no loop in which the driver would be involved, or even no driver at all.

In L3-AVs the OOTL problem is referred to both physical and cognitive aspects of the driving task [Merat et al., 2018]: physical OOTL occurs because the driver no longer controls the steering wheel and the pedals; cognitive OOTL occurs because the driver is no longer monitoring the system and the driving situation.

2.2.3 Transition of Control

The most critical part of L3 automated driving is when the control of the vehicle changes between the ADS and the human driver [McCall et al., 2018].

This transition of control can occur in two directions: from the driver to the vehicle and from the vehicle to the driver. In the first case, the human driver delegates control of the car to the automated driving system; literature refers to this action with the term handover. In the second case, the vehicle asks the driver to regain control of the vehicle, or the human driver just takes back; terms such as takeover, handover, giveback and take back usually refer to this action. For the sake of clarity in this manuscript we refer with the term *handover* to the transfer of control from the driver to the vehicle and with the term *takeover* for the transition of control from the vehicle to the driver.

	Handover		Takeover	
	Automated Driving System	**Human Driver**	**Automated Driving System**	**Human Driver**
Before the transition	Inform the Human Driver (HD) that the Autonomous Driving (AD) is available	Keep performing the driving task	Detect HD's situation awareness and alert the HD that its intervention is required	Stop the NDRT and reestablish the driving context
During the transition	Inform the HD that the AD has been activated	Interact with the HMI to validate the handover	Display the RtI and keep performing the driving task	Regain the control of the car
After the transition	Start performing the driving task and keep the HD informed with the current state of AD	Release the control of the car to the ADS	Assist the HD if possible, otherwise leave them alone	Resume the driving task

Figure 2.3: Handover and Takeover taxonomy. Adapted from Borojeni et al. [2017]

2.2.3.1 Handover

At level 3, the transfer of control from the human driver to the AV is not possible in all situations. This control delegation, in fact, is available only when some conditions such as the type of road, the traffic, the weather satisfy some requirements. However, this transition would not be very problematic on the ADS side since it is assumed that it would be possible only when the ADS allows it. The main concern of this transition is to develop effective HMI that notifies the drivers about the correct occurrence of the control transition and keep them informed about the current state of the vehicle.

2.2.3.2 Takeover

The other direction of transition of control, from the AV to the human driver, is holding the automotive sector in a sort of "deadlock situation" [Borojeni et al., 2017]: the dilemma is whether it is more convenient to ask a potentially distracted or unprepared driver to takeover (L3 of automation), or to require constant supervision to a driver who is not performing the driving task (L2 of automation). In either case humans performance are poor [Endsley and Kiris, 1995] and some of the advantages of automated driving are sacrificed. This dilemma is obvious to such an extent that human factors experts claim that L2 vehicles would be introduced on the market only if their reliability is actually L3 ready [Martens in Kyriakidis et al. [2017]]; and that car manufactures "will not introduce L3 unless the automation can bring the vehicle to a minimal risk condition if no driver response is detected" [Kyriakidis et al., 2017], which actually represents a L4.

Extensive research has been focused on deriving models to identify potential safety critical transitions between the driver and the vehicle. One of this models, proposed by Herzberger et al. [2018] is reported in Figure 2.4.

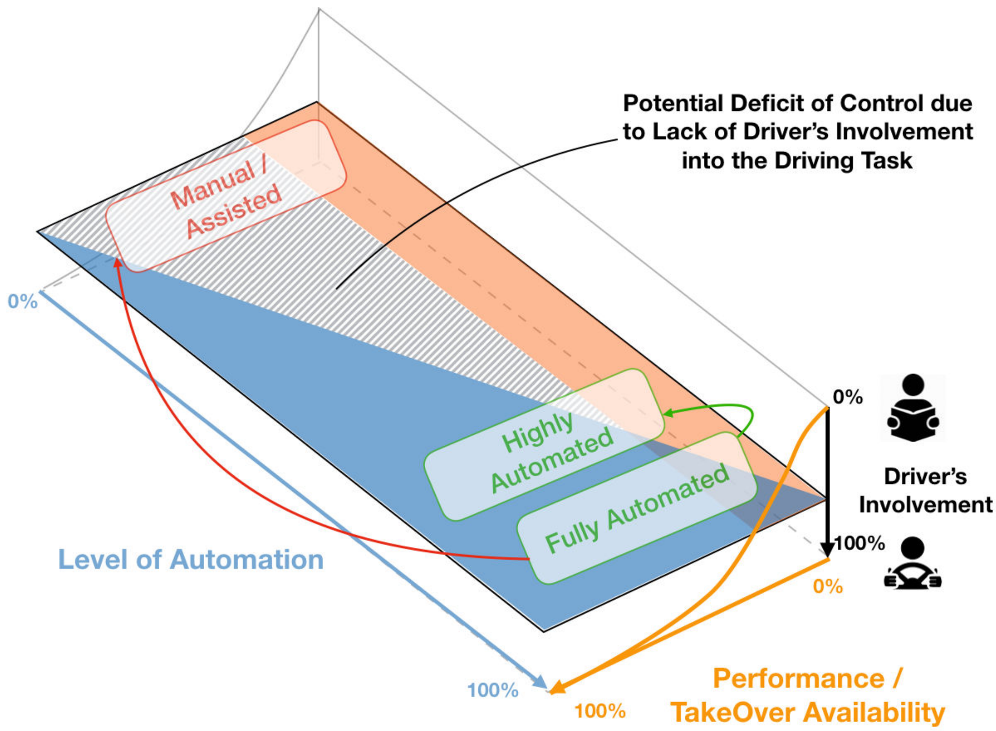


Figure 2.4: The Herzberger et al. [2018] model with training effect on take-over performance

In the Herzberger et al. [2018] model, three driving modes are identified (Fully Automated, Highly Automated and Manual/Assisted) and the transitions between them are analyzed. The blue shaded area represents the system-sided task fulfillment; the orange shaded area the driver-sided takeover ability, which depends on the driver's involvement in the driving task. In fully automated driving the blue shaded area and the orange shaded area overlap and thus no deficit of control is expected. From this fully automated mode we can have transitions to lower level of automation. If the new mode provides a driving task fulfillment that still "overlaps" the driver take-over ability the transition is "uncomplicated and safe" (green transition): this is the case of transition of control, for example, from fully automated driving to highly automated driving as depicted in Figure 2.4. Otherwise, if the new automated mode does not provide a sufficient driving task fulfillment (i.e. blue and orange area do not overlap) it means that the driver and the system are not able to execute the driving task at 100% and thus the transition is considered safety critical (red transition). The white space between the blue and the orange space represents the resulting deficit of control: "the smaller the orange area, the bigger the expected deficit of control in case of a safety critical transition". The authors thus propose that a slow or a stepwise transition would be necessary for the driver to adapt and restore the required level of involvement.

For a taxonomy of takeover situations in autonomous driving we refer to the work of McCall et al. [2018]. The authors propose a taxonomy that links five forms of take-over situations to Matthews's model of SA [Matthews et al., 2001] according to the planning of the take-over (scheduled and non-scheduled), the actor who initiates the takeover (system initiated and driver initiated) and the time buffer (emergency takeover) given to the human driver.

1. *Scheduled (or planned) take-overs* happen when the ADS has the knowledge, in advance, that an area would not be enabled for autonomous driving (e.g. when the vehicle is approaching the end of the highway, presence of planned workroad); this is made possible thanks to the information in the back hand, provided by high-definition cartography, other vehicles and so on. In this case the driver is given sufficient time to become fully aware of the situation, to reestablish the driving context and to take over adequately

2. *Non-scheduled or Unplanned take-overs* occur due to a sudden change in road conditions or when unexpected situations are detected by the ADS: accident, missing road marking or adverse weather condition which may interfere with the proper functioning of the sensors are examples of causes that may trigger this kind of handover. In this case the human drivers do not expect the transition of control, but they are still notified in a reasonable, but considerably lower, amount of time respect to scheduled take-over.

3. *Non-scheduled driver initiated take-overs* happen when the human driver decides to take control when it is not required or in situations in which there is no specific need to do so. The human driver can at all time decide to take-over (just because s/he wants to drive, or for changes in plans) and, at present, there is no situation for in which the ADS would prevent a human driver taking control of his vehicle.

4. *Non-scheduled driver initiated emergency take-overs* occur when the human driver detect an imminent risk on the road and decide to immediately takeover. In terms of SA, the human driver judges him/herself to have a better understanding of the environment than the vehicle. It remains unclear how to discriminate an emergency handover from a non-emergency one and how to distinguish them from unintentional handovers (e.g. the human driver accidentally deactivates the ADS).

5. *Non-scheduled system initiated emergency take-overs* are mainly originated by internal system failures that make the system not properly functioning. If possible, the driver is notified, but s/he would be asked to take over only if the system judges that there is a reasonable timeframe for an adequate handover manoeuvre; otherwise, the system will bring the vehicle to a minimal risk condition.

In the case of scheduled and non-scheduled system initiated take-overs the vehicle notifies the human drivers that they are expected to regain control with the so called Request to Intervene (RtI). RtI can occur at Level 2, 3 and 4 of automation. These RtI are usually notified to the human driver with visual (icons, lights) auditory (sounds, voice messages) and possibly tactile (vibrating seat, seatbelt pretensioner) notifications. How to support the human driver during the take-over phase is a crucial, still open, question for both scientific researchers and automobile manufacturers [Zhang et al., 2018].

2.2.4 Evaluation of Take-Over

Evaluating the ability of a driver to adequately respond to a TOR is a complex question and assessing the quality of the take-over performance remains an open problem. In literature several measures, both objective and subjective, have been proposed to assess take over performance in highly automated vehicles. However, there is no consensus on which metrics are more important or relevant to fully characterize the quality and the security of a take-over.

Among objective measures, reaction times are often used as metric to evaluate, during the transition of control, the quality of take over [Happee et al., 2017; Vogelpohl et al., 2018].

Driving metrics such as time-to-collision, maximum acceleration, lateral accelerations and maximum deviation from lane center are usually used to evaluate take over performance after driver's reaction [Happee et al., 2017]. According to the reaction required to the driver after the take-over, other metrics can be taken into account, such as the control of rear-view mirrors before performing an evasive manoeuvre or a lane change.

Concerning subjective measures, drivers are usually asked to reply to questionnaires: the Driver Skill Inventory (DSI) [Spolander, 1983] and Driver Behaviour Questionnaire (DBQ) [Reason et al., 1990] have been largely used to evaluate the self-assessment of driving skills [Roy and Liersch, 2013] in the last decades. In recent studies, questionnaires have been used to investigate the importance of initial *skilling* and to predict the *deskilling* in automated vehicles [Trösterer et al., 2016]. In the same field, surveys have also been used to evaluate usefulness and satisfaction of take-over requests Bazilinskyy et al. [2017].

All these objective and subjective measures have been analyzed and combined by Radlmayr et al. [2018]. Starting from the analysis of these metrics, the authors proposed an integrative framework called "Take Over Performance Score" (TOPS) that includes the most relevant metrics from the RtI to the system limit and aggregates them to three parameters:

- Vehicle Guidance Parameters include the time to collision, maximal lateral and longitudinal acceleration;
- Mental Processing Parameters include lane check, gaze reaction time, eyes on road reaction time and take-over time;
- Subjective Rating Parameters include perceived criticality and complexity of the situation and subjective time budget.

Take-Over Time

The time that the human driver takes to resume control after a system-initiated RtI is called Take-Over Time (TOT). Although several response time measures can be distinguished (i.e. gaze reaction time, eyes-on-road time, head-movement time, hands-on-wheel time, intervention time), take-over time is usually defined as "the time

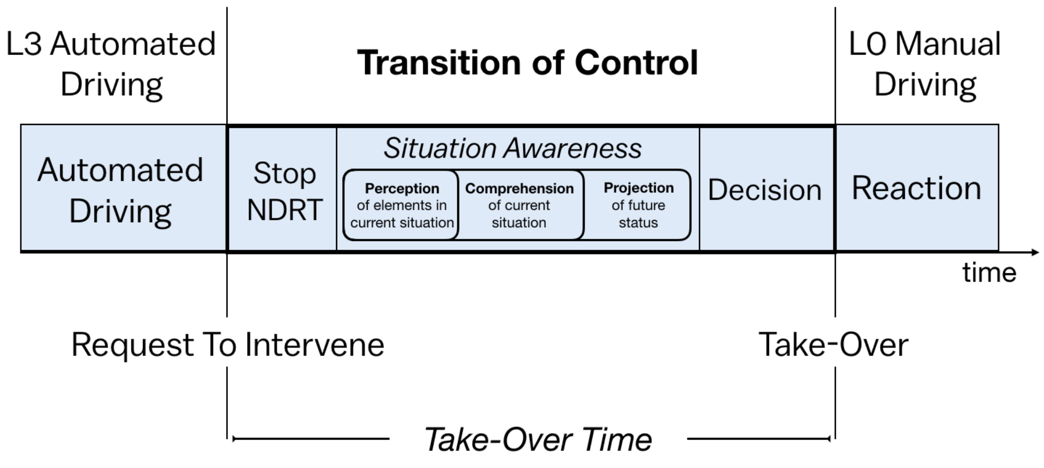


Figure 2.5: Taxonomy of Take-Over Time. Adapted from Son et al. [2017]

interval between the occurrence of the stimulus that marks the start of the take-over until the implementation of driver intervention either by steering or braking" [Zhang et al., 2018]. The authors conducted a meta-analysis of 93 studies concerning take-over time from automated driving. They found that the TOT across studies ranged from 0.69 s to 19.79 s, with an average mean of 2.76 s (SD = 1.55, N = 373).

They found that, when given adequate time, drivers do not take over as quickly as they can; instead, they assess the driving situation (e.g. by checking side and read mirrors) and decide on an optimal action (e.g. changing lane) prior to actually intervening.

For this reason, TOT should be considered cautiously because as Radlmayr et al. [2018] state "a very fast reaction time is good in situation with limited time budget, but it may be interpreted to be hasty in uncritical and planned take-over situations".

2.2.5 Factors influencing the take-over

Thanks to these metrics for take-over evaluation, it has been possible to identify the factors which influence the take over from both performance-related and subjective point of view.

When an RtI occurs, the human driver in that moment is *"out-of-the-loop"*. Recent studies are focused in monitoring drivers' behavior during autonomous driving or just before an RtI to infer the amount of time they would need to correctly respond to it. From the moment the RtI occurs, the human driver has a limited amount of time to perform a number of actions that influence the quality of the take-over procedure: perception of the visual/auditory/vibrotactile stimuli, cognitive processing of the information, response selection, resuming motor readiness, and the actual reaction [Zhang et al., 2018].

It has been proven that the modality of the RtI has a significant effect on take-over times [Petermeijer et al., 2017]: drivers alerted with visual-only TORs react generally slower than those alerted with auditory or vibrotactile notifications [Zhang et al., 2018].

Besides these *interface design* questions, out of the scope of this thesis, we propose to categorize the factors that influence the take over according to the situation on the road that caused the take-over, and the state of the human driver before the RtI.

2.2.5.1 Nature of the TOR

Gold et al. [2017] proposed a taxonomy for testing scenarios used in human factors research of L3 automated vehicles. The authors structured and categorized these testing scenarios according to four factors:

- Urgency: *associated with the time budget, it indicates how fast a take-over reaction of the driver is required.* To ensure security and to succeed in the take-over process, it is important to understand how much time before a system boundary a driver who is out of the loop should be warned. Literature showed that with shorter TOR-time, human drivers usually react faster, but the quality of take-over is generally worse: "the gazes in mirrors and shoulder checks decrease, the accelerations increase, and the brake is used excessively." Gold et al. [2013].

- Predictability: *the time of the detection of a take-over.* The end of the autonomous zone, critical weather conditions are usually highly-predictable situations. Presence of obstacle, accidents and system failures are considered to have low predictability.

- Criticality: *the impact of failing in the take-over scenario.* It can be either low (e.g. missing to exit the highway) or severe (e.g. colliding with other road users or obstacle) and it determines the behavior of the driver and the strategy of take-over.

- Drivers' Response: *the required action in reaction to the RtI.* It can be either simple (stabilizing the vehicle in its lane) or complex (evasive maneuver). It influences both the timing and the quality of the take-over reaction. Zhang et al. [2018] found that complex drivers' responses are more likely to be performed in high-urgency take-over situations which are usually associated with shorter take-over times.

This taxonomy is particularly helpful when designing a take-over study. To correctly evaluate take over performance it is thus important to simulate a variety of driving scenarios. Most of the studies about take over in highly automated vehicles implement safety-critical take-over scenarios caused by an obstacle (usually a broken down vehicle) on the current lane [Happee et al., 2017; Körber et al., 2016; Navarro et al., 2016; Zeeb et al., 2016] and non-critical scenarios caused by the absence of lane markings [Payre et al., 2017a; Zeeb et al., 2016] or presence of roadwork [Zeeb et al., 2015].

Other factors influencing the take over are related to the general driving environment and include a distinct negative influence of traffic density on takeover time and quality [Gold et al., 2016; Radlmayr et al., 2014]. This can be explained by the fact that human drivers, in case of surrounding traffic, need more time for visual scanning and reenstablish situation awareness prior to take over [Zhang et al., 2018].

2.2.5.2 Driver's factors

Once the drivers are alerted with a Request to Intervene, they have to "go back into the loop", become aware of the driving situation, and take the correct decision for taking over. Besides personal driving styles, which may influence driver's response after the take-over, a part of this process, regardless of the nature of the TOR, can be affected by factors related to the state of the driver when the RtI is issued.

Non-Driving Related Tasks (NDRTs)
While the automated driving system is activated, as the human driver is not required to monitor the driving environment, they can engage in NDRTs. These activities may include the use of both personal devices and in-car entertainment (or in-vehicle infotainment) systems to read, watch movies, work, make phone calls and so on [Naujoks et al., 2017]. However, sleeping would not be allowed. The execution of a NDRT has an influence on the time and the quality reaction: the use of a handheld device (e.g. smartphone, tablet) strongly increases the mean TOT [Zhang et al., 2018] because it requires an additional physical maneuver to put it aside before taking over; performing a NDRT without handheld devices slightly increases the mean TOT compared to not performing such task. However, researchers have not yet found a common agreement about the influence of the type of task (cognitive, visual) on the takeover performance.

To study the influence of NDRTs during automated driving, researchers generally use standardized and naturalistic tasks. Standardized tasks (such as the cognitive n-back task (a cognitive distraction task) [Happee et al., 2017], the SuRT task (a mainly visual distraction task) [Gold et al., 2013; Happee et al., 2017], the Twenty Questions Task (TQT) [Gold et al., 2013; Körber et al., 2016] provide experimental control, but they do not usually correspond to what the driver will do in the vehicle. The different standardized tasks show similar effects on driver behavior during the take-over [Radlmayr et al., 2014]. Naturalistic tasks (such as playing games on tablet, reading, watching a movie), instead, provide ecological validity, but they could introduce experimental bias. Zeeb et al. [2016] studied how visual-cognitive load impacts take-over performance by examining the engagement in three different naturalistic secondary tasks (writing an email, reading a news text, and watching a video clip). The authors found that the drivers' engagement in secondary tasks only slightly affected the time required to regain the control of the vehicle, but drivers who were not involved in the task performed better in the lane-keeping task. For this reason they conclude that for a comprehensive understanding of driver take-over, both response times and take-over quality must be considered.

Clark and Feng [2017] found significant age differences in the type of activities that younger and older drivers engaged in (i.e., while younger drivers mostly used an electronic device, older drivers tended to converse): however, they observed that being engaged in a greater amount of activity did not seem to have significant impacts on driver performance during takeover.

Gaze behavior
Performing a NDRT, as described, may require the drivers to shift their gaze from the road environment. Zeeb et al. [2015] studied driver's gaze behavior during automated driving. Driver's gaze was analyzed one minute before the TOR was prompted and until an evasive manoeuvre was executed. Drivers were classified in high, medium and low risk according to the number and the length of glances at the central display and the eyes-off-road time. The authors confirmed their hypothesis that drivers with maladaptive monitoring behavior (few glances at the central display, and high eyes-off-road time) reacted slower and more often incorrectly in sudden emergency takeover situations; consequently the authors propose that gaze behavior during automated driving can be used as a predictor for the readiness to take over a vehicle. In this context, Herzberger et al. [2018] proposed ARI (which stands for Awareness for Relevant Information), an estimator able to determine the driver's level of involvement in the driving task. The estimator is based on the driver's visual fixation, namely whether the driver looks at the road or not.

Driver's age
Körber et al. [2016] showed that drivers are able to solve critical traffic events no matter the age; the authors showed that, although they use a different modus operandi in the evasive maneuver, older drivers ($\geq$ 60 years) react as fast as younger drivers ($\leq$ 28 years). Also, both groups are influenced by traffic density and engagement in a NDRT and they adapt to the experience of take-over situation in the same way. Clark and Feng [2017] investigated the effect of age, level of activity-engagement and takeover notification interval on vehicle control performance during the takeover: the authors did not find an effect of age on take-over time; however, they suggest that older drivers who were more engaged in non-driving-related activities benefited from longer take-over notification time.

2.3 The need for training

Besides professional or industrial context, human interaction with automated systems is usually limited to very simple operations for which training is not needed: taking the elevator or using the coffee machine are examples of everyday interactions which do not require any particular training. Other more complex systems could require the learning of some instructions. However, in no case the humans are required to takeover the task from an automated system.

Conditionally automated cars are, to the best of our knowledge, the first and only systems in which non-professional users are required to takeover the task from automation they are not required to supervise. Simpler forms of take-over already happen at lower levels of automation (Level 1 and Level 2) with the use of cruise control. As Abraham et al. [2017] report in their study, research conducted on the use of the Adaptive Cruise Control (thus a lower level of automation) [Dickie and Boyle, 2009; Piccinini et al., 2015] indicated that potential risks associated with its use may be due to users' unawareness of how the system works and of its limitations.

Human factors experts and researchers agree that efforts should be directed towards ensuring that drivers of automated cars are aware of which parts of the driving task can be conducted by the system [Herzberger et al., 2018] and adequately prepared to take over [Kyriakidis et al., 2017; Zhang et al., 2018] in order to avoid loss of potential benefits of automated driving [Boelhouwer et al., 2019].

Therefore, a learning and training program is essential to allow safe interaction and to foster the correct acquisition of the operational skills.

Without training, a driver may have idealistic expectations about the operation of the autonomous system. Research about *imperfect* automation showed that an operator who experiences a series of "successes" of automation, coupled with prior expectations about reliability, is likely to experience a marked loss of trust, and resulting loss in reliance, when an initial failure in a previously perfect system occurs [Wickens and Xu, 2002]. The authors state that these "first failure effects" can be remarkably strong according to the belief that the automated system is perfectly reliable. However, when operators are instructed about system limitations, and in particular when consequences of imperfect automation are experienced in practical trials prior to the real-time use, "first failure effects" may be overcome.

According to SAE, Requests to Intervene during automated driving are considered intentional notifications or warnings of imminent system limitations rather than automation failures. However, experimental research indicates TORs are instead perceived as automation failures by drivers and thus they may temporarily lower automation trust [Hergeth et al., 2015]: this last effect was in particular observed after the first and second TOR. Nevertheless, the authors showed that the participants automation trust scale was higher after the experimental session than before.

The need for training, in addition to being necessary to ensure security on the road, would be also an obligation for car manufacturers. In fact, according to the *Product Liability Directive of the Council of the European Union* [Directive, 1985], a product is considered defective when "it does not provide the safety which a person is entitled to expect", including "the use to which it could reasonably be expected that the product would be put". In other words, putting an automated driving system on the market without providing adequate information and formation to the end users would not be allowed. For these reasons, there is the need for car manufacturers to familiarize future drivers with the car interfaces and the interaction modalities. In addition, the introduction of supplementary training or licensing for partially automated vehicles is currently under examination by governments and road security organizations [Boelhouwer et al., 2019].

In most of the aforementioned studies it is not always clear how participants were familiarized with the automated system and TORs. Besides some studies that assumed that participants were already familiar with the automated driving system from earlier experiments [Merat et al., 2014], the familiarization phase has been implemented in many different forms. Zeeb et al. [2016] used a traditional approach that provided the participants with an oral description of the system, the functional boundaries and the alert notifications. In the vehicle, participants were also instructed to activate and deactivate the automated driving system. In other studies participants could freely practice in the high-end driving simulator before the actual test drive [Gold et al., 2013; Hergeth et al., 2015; Lorenz et al., 2014]. The variety in prior familiarization with the automated driving system makes these studies and the effectiveness of the familiarization phase difficult to compare.

Also, these solutions are not adequate to be implemented in the real case either because they do not ensure the correct acquisition of knowledge, and thus the drivers would not be sufficiently skilled to safely respond to a take-over request, or because they are not feasible in terms of costs, space and maintenance (e.g. they would require every car dealership to be equipped with a high-end simulator).

2.3.1 Current state of driver's training in automated vehicles

Only a few studies in literature addressed specifically the question of drivers' prior familiarization with the partial automated system and the request to intervene.

Hergeth et al. [2017] conducted an experimental driver simulator study to investigate the effects of prior familiarization (no-familiarization, description, experience, description and experience) with TORs on takeover performance and automation trust. The results indicate that prior familiarization does affect take-over time, take-over performance and automation trust. In particular, participants familiarized with description and experience had better performance (in terms of takeover time and time to collision) in the first take-over situation with respect to the no-familiarization group. The description-and-experience group had also similar performance at the first and second TOR, while other groups had performed significantly worse at the first TOR compared with the second one. Concerning automation trust, the authors show that it was initially higher for the no-familiarization group and that it increased after the driving experience regardless of prior familiarization. Finally, they found that familiarity with TORs is also relevant for a less critical evaluation of takeover situations. However, the authors claim that "prior description of TORs could elicit similar behavior in critical situation as more exhaustive training session" and they propose as useful solutions for familiarization a tutorial or an introduction to such systems during vehicle delivery.

Payre et al. [2017a] addressed the problem of familiarization by comparing the impact of two types of training on manual control recovery: a simple training based only on practice in a driving simulator and an elaborated training which included a text, a tutorial video and a more elaborated practice in the simulator. The results show that training improved human-automation performance. In particular, elaborated training group allowed participant to react faster to take-over requests and decreased pedal interaction; in addition, participants in the elaborated training group trusted the system more than those in the simple training condition.

Boelhouwer et al. [2019] conducted an experimental study in a video-based driving simulator aimed at investigating whether current methods of providing information on car systems to drivers are adapted for bringing driver's mental model (i.e. "the mechanisms whereby humans are able to generate descriptions of system purpose and form, explanations of system functioning and observed system states, and predictions (or expectations) of future system states" [Rouse et al., 1992]) in accordance with the actual capabilities of a partially automated car. In particular, the authors studied if prior *written* information based on the owner's manual helps the drivers in understanding the driving situations in which they need to take back control. Results show that drivers who read the manual were neither better or worse at correctly identifying takeover situations than those who did not read. This seems to suggest that "structural system information in this form might not be a successful strategy to support drivers in understanding and interacting with partially automated cars during actual driving". One of the main limitations of the owner's manual that arise from this study is the unfeasibility "to incorporate procedural rules for all possible situations in highly complex automated car systems". Authors thus state that combining theoretical training with practice may be the most accurate and efficient learning method, besides the risks associated with the real driving.

2.4 Concluding remarks

The intense multidisciplinary scientific interest in recent years suggests that the interaction between the human driver and the automated car is a valuable research topic worth investigating from the design stage of automation to the final implementation of the new systems.

We will focus in particular on the training of drivers and their familiarization with their new role, the novel equipment, the interaction modalities and the unforeseen driving situation they may face. Indeed, the drivers should be aware of the capabilities and limitations of the system and of the actions to perform when their intervention is required.

Summarizing the human factors findings and perspective of automated driving, we hypothesize that an enhanced training session performed prior to the first use of the automated vehicle may produce the following benefits:

- make drivers aware of the automated system capabilities and limitation;
- make drivers aware of their role during automation and understanding the actions they can and cannot perform during automated driving;
- support drivers during the firsts transitions of control, in particular when they have to take over the driving task after a period of automation in critical situations;
- equalize expectation about automation trust and alleviate the "first failure effects"

With respect to the model proposed by Herzberger et al. [2018], we expect that the training would *improve* the slope of the take-over ability curve (at least for the first transitions of control) in order to increase the driver-side task fulfillment (orange shaded area) as shown in Figure 2.6.

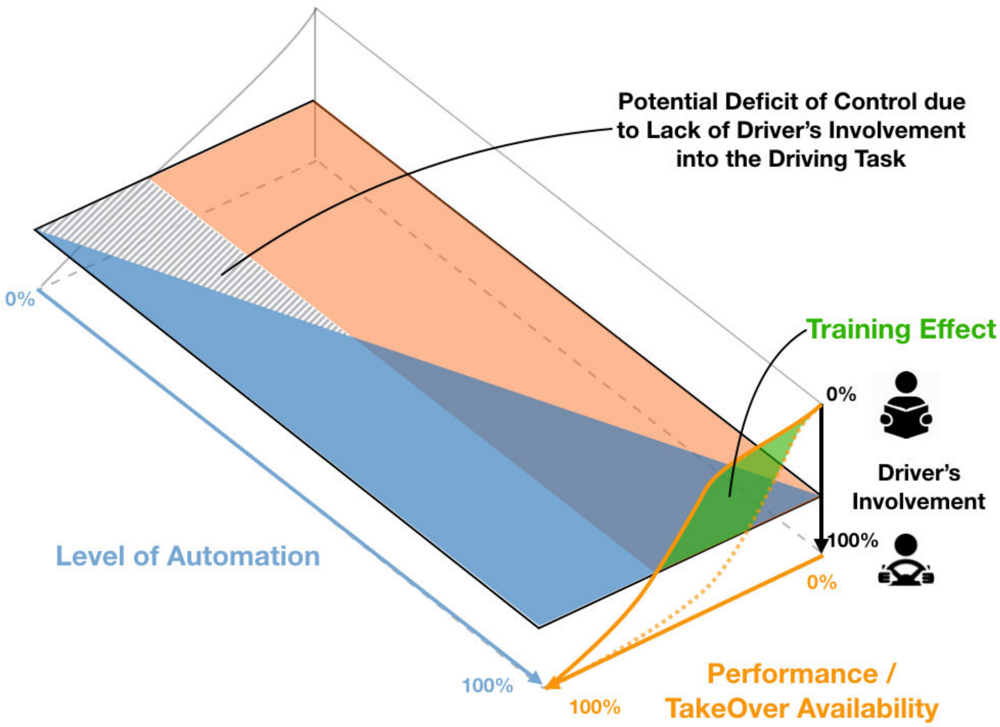


Figure 2.6: Model of safety critical transition between driver and vehicle in automated driving [Herzberger et al., 2018] with a possible training effect

Traditional car handover performed by car dealers may not be sufficient to accustom drivers to the vehicle, and we saw how traditional informative mediums (i.e. owner's manuals) may not ensure the acquisition of skills because of the lack of practice. We thus hypothesize that even a simple practice of the driving scenario would help driver in the interaction with the vehicle. However, since conditionally automated cars operate on highways rather than urban driving scenario, familiarize with safety critical situations in the real traffic is clearly an unsafe strategy [Boelhouwer et al., 2019].

For this reason we think that immersive digital technologies, such as Mixed Reality, may represent valuable solutions for this purpose, allowing drivers to discover and test car functionalities in a controlled environment without putting them and other road users at risk.

Chapter 3

Design of Mixed Reality Training for Automated Cars drivers

La realidad no siempre es
probable ni plausible.
(Reality is not always probable or likely)

Jorge Luis Borges

Contents

3.1 Introduction

In the last section of the previous chapter we explained why prior training is crucial to enable safe interaction between the driver and the automated car. Without training, in fact, the drivers might interact with the system in the wrong way and thus put themselves and other road user at danger. The few research work focused on this topic highlighted the inadequacy of traditional training (e.g. owner's manual) and highlighted the necessity of a more elaborated training.

Operating a traditional car is already a complex activity, that includes tasks categorized in three levels [McCall et al., 2018]: *operational level tasks* which includes low-level interactions (e.g. pressing a pedal, steering); *tactical level tasks* which represent more complex manoeuvres (e.g. obstacle avoidance); *strategic level tasks* which consist in longer term objectives (e.g. navigation planning). Although these tasks may sound very complex, those skills are acquired by humans with practice in driving schools and improved with everyday experience.

When it comes to automated cars, the driver, besides these skills, needs to acquire a set of additional knowledge related to the automated system (capabilities and limits), their role (the activities they are allowed, not allowed and required to perform) and some (motor) skills related to the driving task, the interaction with the vehicle equipment (HMI) and the take-over. We will analyze the training requirements in more detail in Chapter 4. If a subset of this novel information can be acquired out of the car, the process of familiarization with the automated system (which moreover would mainly work on highways) and its equipment and with the take-over requires actual driving. However, familiarizing while driving in real traffic has lots of drawbacks. First, it would be unsafe and dangerous for the driver itself and the other road users. Second, it would be hard to generalize or diversify the driving scenario, since it would depend on real traffic situations. Last, it is demanding in terms of time, cost and availability of staff and trainer.

For these reasons, it is necessary to explore alternatives to *immerse* the driver in risk-free driving environments. One of the possibilities is given by environments based on Mixed Reality.

With its possibility of real time and pseudo-natural interaction, Mixed Reality can represent a potential solution to provide an *immersive* environment where drivers can be trained and familiarized with the car in complete safety. The use of this technology alters user's perception and transforms the way in which the activities are carried out.

Designing a learning environment in mixed reality requires making choices in terms of visualization of the information, manipulation techniques to modify the environment and pedagogical content.

In this chapter, to meet our goal, we define what a MR system should provide in terms of immersion by analyzing its visualization and manipulation characteristics and we examine the good practice to avoid possible conflicts that a user may experience due to the altered perception of the environment. Subsequently, we present how MR has been used for training purposes and how users can be evaluated in terms of their ability to transfer skills to the real environment.

3.2 The Mixed Reality spectrum

Over the past decades, the interaction between humans and computers, humans and environment and computers and environment were well distinguished and independently defined. In recent times, technological progresses in perception, processing and computer vision have unlocked possibilities to understand user's surrounding and to enhance human-computer interaction with inputs coming from the environment itself (e.g. user location and tracking, object recognition, spatial mapping, and so on).

Mixed Reality is the results of enhancing user's perception of the real world by combining together human inputs, computer generated content and the surrounding environment.

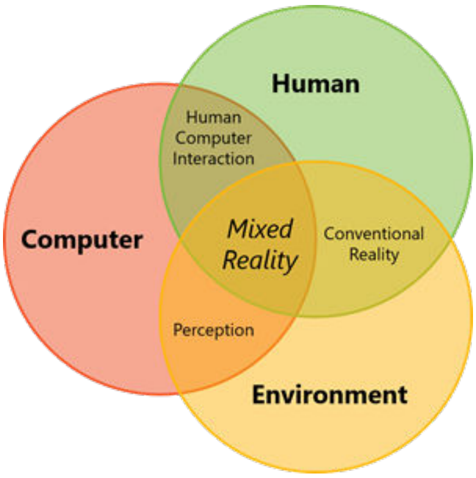


Figure 3.1: Venn diagram of Mixed Reality. Image from microsoft.com

The term "Mixed Reality" was introduced by Milgram and Kishino [1994]: "the most straightforward way to view a Mixed Reality environment is one in which real world and virtual world objects are presented together within a single display, that is, anywhere between the extrema of the virtuality continuum". Mixed Reality, therefore, can be considered an umbrella term which refers to a variety of hardware and software combinations used to create Virtual Reality (VR) and Augmented Reality (AR) applications.

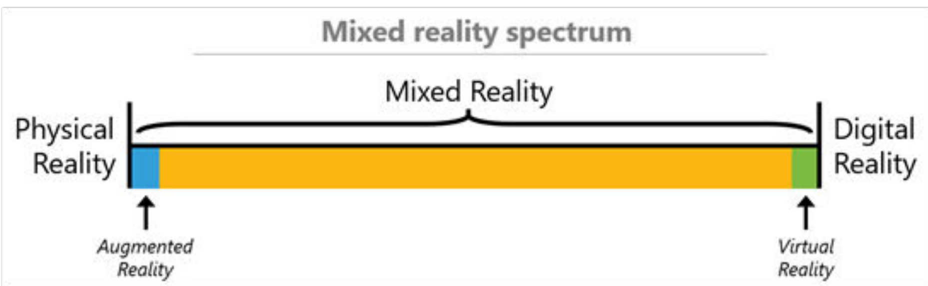


Figure 3.2: The Mixed Reality spectrum. Image from microsoft.com

At the left extreme of the Mixed Reality spectrum (Figure 3.2), there is the real environment consisting solely of real objects and with no computer-generated elements;

at the opposite extreme, we have fully Virtual Environments consisting solely of virtual objects, in which no elements from the real environment are present.

Mixed Reality, thus, is everything in between: it can either augment the real world with virtual features or augment the virtual world with real features [Wagner et al., 2009]; in other words, it blends the physical and the virtual worlds by anchoring digital content to real-world objects. Users can interact with virtual objects as they would do with real ones and these virtual objects do respond to user inputs and changes of the real environment as well. This is made possible thanks to the use of advanced sensors and processing algorithms that allow for real-time scanning of the environment, digital reconstruction and accurate object tracking. Increasing the amount of reality or virtuality means moving toward purely real or virtual experiences respectively. Where *systems* fall on the spectrum tends to be defined by how much interaction and awareness there is between the digital and physical environments. In our analysis we will consider Virtual Reality and Augmented Reality technologies at the extremes of the Mixed Reality continuum.

Virtual Reality is a technology which takes the users out from the real world and entirely immerse them in a digital computer-generated environment. According to Arnaldi et al. [2018] the objective of VR is "to allow the user to virtually execute a task while believing that they are executing it in the real world". Similarly, [LaValle, 2016] defines VR as follow: "Inducing targeted behavior (i.e. the VR experience) in an organism (i.e the individual who is living the experience) by using artificial sensory stimulation (i.e. the way in which one or more senses of the organism become hijacked), while the organism has little or no awareness of the interference (i.e. to what extent the organisms believe that the virtual world is the actual one)".

Augmented Reality is a technology that allows to overlay digital content to the real world objects. AR keeps the real world central to the experience and enhances it with information related to the environment.

Moving form AR to VR on the MR continuum implies that some of the real *elements* of the world are replaced by their virtual counterparts. This has important implications on:

- the extent to which the user is able to see the real environment;
- the possibility for the user to perform motor actions within the real environment;

and in turn on

- the coherence between the training environment and the environment in which the acquired skills will be applied.

The objective of our research is to explore the Mixed Reality continuum to identify adequate combination(s) of *immersion* in order to maximize the transfer of the skills acquired in the training environment to the real situation.

3.2.1 Immersion in Mixed Reality

Around the term *immersion*, researchers have given different definitions and interpretations over the years, in particular in the context of Virtual Reality. Slater gives the following definition of *immersion*: "the more that a system delivers displays (in all sensory modalities) and tracking that preserves fidelity in relation to their equivalent real-world sensory modalities, the more that it is immersive" [Slater, 2003]. Immersion, thus, refers to what the system delivers from an objective point of view and to the technological characteristics that can be objectively assessed. Also for Ragan et al. [2010] immersion is a function of the simulator's technology rather than the user's experience in the virtual environment.

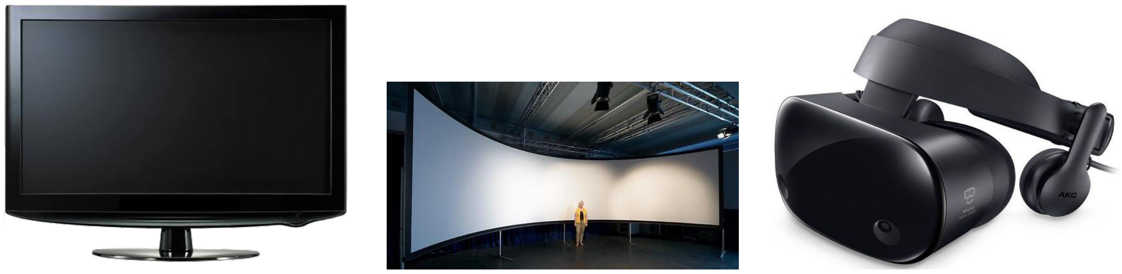
For Mestre et al. [2006], immersion is achieved by removing as many real world sensations and substituting them with the correspondent virtual ones. Bailenson et al. [2008] identify in unobtrusive tracking and minimization of real-world sensory information two of the components of immersion. This concept has been subsequently broaden by Bowman and McMahan [2007] who suggest that "immersion is not all or nothing, [...] but rather a multidimensional continuum", and thus "we should not consider immersion as a single construct, but rather as the combination of many components". In fact, when virtual counterparts substitute the real thing, several of the user's sensory channels (visual, auditory, tactical, etc) are stimulated in different ways.

Also, immersion is considered responsible (not in an exclusive way) for the extent to which a user can experience the feeling of "being in" or "existing in" the VE in which they are immersed. We refer to the user's subjective and context-dependent response to a virtual experience with the term "presence", which is defined as the psychological, perceptual and cognitive consequence of immersion [Mestre et al., 2006]. However, an analysis of presence is out of the scope of this thesis.

A consideration that emerges when extending the concept of immersion from Virtual Reality to the entire Mixed Reality spectrum is that while in *pure* VR it is possible and adequate to classify systems in term of ordinal immersion (VR system A is *more immersive* than VR system B because it delivers displays and tracking that preserve fidelity in relation to the real-world [Slater, 2003]), in MR the systems should be classified according to a nominal scale of immersion. In fact, a mixed reality system, it is strongly coupled with the real environment in which it is used and it relies on it to display (in all sensory channels) effective mixed reality experiences.
We thus define immersion in Mixed Reality as the objective technological characteristics that produce artificial stimuli in all the sensory channels. Immersion has an effect on how tasks are performed in the virtual environment. One of the reasons for this is that information can be presented as non-congruent between sensory channels. In this work we focus on the question of coherence between the visualization and the manipulation space (two of the components which in our case are the most significant descriptors of immersion), and the possible sensorimotor incoherences that these components may generate.

3.2.1.1 Visualization space

In order to display the virtual content different graphic rendering devices can be used, such as traditional screens, projection-based displays and head-mounted displays (Figure 3.7). The decisions taken at visualization space-level influence the visual cues and consequently the way in which user are able to perceive and observe the environment.



a b c

Figure 3.3: Examples of visualization devices : (a) a monitor display, (b) a panoramic projection-based display, (c) a head-mounted display

According to Milgram and Kishino [1994] there are six classes of MR display environments:

1. monitor-based video displays (“window-on-the-world”)
2. same as 1, but using HMDs
3. HMDs equipped with see-through capability with which computer-generated graphics can be optically superimposed (i.e. optical see-through)
4. same as 3, but using video viewing of the external world (i.e. video see-through)
5. completely graphic display environments to which video “reality” is added
6. completely graphic environment in which real physical objects in the user’s environment play a role in the computer-generated scene.

The technical characteristics and the nature itself of the visualization device may have an impact on:

- depth perception - The capability of the system affects the possibility to create the illusion of monocular depth cues (e.g. motion parallax, texture gradient) and binocular depth cues (e.g. binocular parallax)
- the possibility to display the virtual environment at a 1:1 scale
- the possibility for the user to see their own body - The use of Head-Mounted Displays may block the view of the real world, preventing the user to see their own body and visual proprioception. This should be taken into account if user’s interaction is considered important.

3.2.1.2 Manipulation space

Manipulating a Virtual Environment requires the implementation of interfaces and techniques which allow the users to perform motor actions (gestures, navigation and so on) in order to move inside the VE, select virtual objects and interact with them. The manipulation can be implemented with techniques aimed at preserving the correspondence with the action performed in the real case (i.e. interaction schemes [Fuchs, 2018], behavioral fidelity [Slater, 2003], natural interfaces [Bowman et al., 2001]) or with techniques which make use of abstract representations or skills in other domains (i.e. metaphors).

In the context of driving simulation and in particular for what concerns the longitudinal and lateral control of the car, for example, a natural interaction can be represented by an interaction technique which includes a steering wheel and pedals (e.g. racing wheel), and a non-natural interaction can exploit other interface such as keyboard, joystick, 6 DOF controllers and so on.

a b c

Figure 3.4: Examples of manipulation interfaces for the driving task: (a) a gaming racing wheel and pedals; (b) a RC car remote; (c) a mid-air interaction without hardware [image from F80SAKA [2011]]

Co-localization, namely the superposition of the visualization and manipulation space, is a core feature that distinguishes immersive virtual environments from other types of computer applications. It enables the visual-proprioceptive coherence when performing activities in virtual environments. MR can (or cannot) provide co-localization and, in turn, allows (or not allows) for coherence between different senses. The incoherences between senses are not limited to co-localization; other types can occur and we introduce some of them in the next section.

3.2.2 Sensorimotor Incoherences

As in the real world the set of sensory stimuli is received by an individual to construct a coherent representation of their environment, in the virtual world the user seeks this same coherence and will interpret what they perceive with respect to what they experience [Fuchs, 2018]. However, this process disrupts the user's physiological and sensorimotor functioning creating what Fuchs calls *sensorimotor incoherences*. Fuchs states that the user can adapt to certain incoherences, consciously or unconsciously, and some of these adaptations are almost naturally made.

A first category of conflicts, observation (or visualization) incoherences, is caused by the technical characteristics of display systems. These incoherences are [Fuchs, 2018]:

- *temporal visuo-motor incoherences* resulting from latency between the movement of a user's head and the display of the virtual environment from the updated point of view (this happens only in head-tracked systems).
- *visuo-temporal incoherences* originated by the frequency of displayed images.
- *visuo-spatial incoherences* resulting from the difference between the actual human field of view and the field of view of the virtual camera (1:1) .
- *accommodation-vergence conflict* resulting from the disparity between the physical surface of the screen (accommodation) and the focal point of the simulated world users are staring at (vergence).

A second category, manipulation SM incoherences, is caused by the implementation of unnatural or unreal interaction paradigms. These can originate visuo-manual incoherences [Fuchs, 2018] when, for example, there is a gap between the location of the user's real hand and the hand represented in the virtual environment.

A third category of conflicts concerns SM incoherences related to navigation which can be caused by the perception of virtual vection without real displacement or by a displacement in the real world without the virtual counterpart (visuo-vestibular).

3.2.2.1 Simulator Sickness

All these sensorimotor incoherences may induce in the user the so-called Simulator Sickness (SS), a term for describing a set of ill feelings including vertigo, headache, sweating, disorientation and nausea. SS is similar to terrestrial motion sickness or kinetosis. While terrestrial Motion Sickness is mainly caused by a motion that is felt but not seen (carsickness, seasickness), Simulator Sickness occurs also in absence of actual motion, namely when the motion is only seen but not felt.

Kennedy et al. [1993] proposed a categorization of the symptoms associated with SS and a questionnaire for evaluating and measuring the severity of a simulator. The Simulator Sickness Questionnaire (SSQ) includes 16 symptoms associated with simulator sickness. Participants indicate the level of severity of the symptoms in a scale from 1 (none) to 4 (severe). The SSQ provides 3 subscales and a Total Severity score calculated upon the three sub-scores:

- Nausea subscale takes includes symptoms related to sweating, nausea, increased salivation, stomach awareness and burping;
- Oculomotor subscale is composed by symptoms such as headache, eyestrain, fatigue and difficulty in focusing;

- Disorientation subscale takes into account vertigo, dizziness and blurred vision.

There are several theories, analyzed by Stoner et al. [2011], that try to explain the occurrence of simulator sickness. The primary theory is the Cue Conflict Theory [Reason and Brand, 1975] which identifies the determinant of SS in the incongruity between the motion perceived by the visual system and the motion detected by the vestibular system. Although CCT is the most widely accepted, it does not provide an explanation for some question such as why the incidence of SS is prevalent during first exposures to the simulator and tends to decrease with the practice.

Another theory, the Poison Theory [Treisman, 1977], attempts to explain the occurrence of SS from an evolutionary point of view. The PT claims that our brain associates the symptoms of SS (such as blurred vision, lack of sensory coordination and improper motion cueing) to the symptoms of being poisoned or intoxicated. Consequently the body response is to empty the contents of the stomach by vomiting.

The ecological alternative to CCT is the Postural Instability Theory [Riccio and Stoffregen, 1991] which claims that SS is caused by the unfamiliarity with the novel environment. More in detail, when we try to stabilize in a new environment and we have not yet learned the the strategies to accomplish the task, simulator sickness occurs.

Although there is not a common agreement on which theory completely explains the origin of SS, reducing or limiting the occurrence of SS is fundamental for having a pleasant and effective immersive experience.

The problem with SS is that it does not only produce a bad experience in a simulator, but it may impede or spoil the learning process leading to the transfer of adoption techniques in the real world [Stevens et al., 2015].

Thus, it is thus crucial to correctly evaluate and validate all the aspects relative to visualization and interaction/manipulation paradigms in order to design an experience that is first of all not disturbing for the trainee.

3.2.3 Stimulation vs Information correspondence

We have considered the visualization and the manipulation characteristics of a Mixed Reality system as responsible factors for the altered perception of the environment and the way in which a user performs an activity in the virtual environment. Another direct consequence of the positioning on the Mixed Reality continuum is the correspondence between the training and the real-world environment. This *physical* coherence plays an important role since the objective of the training is not just limited to the acquisition of *abstract knowledge* (like in education) or soft skills, but also to the acquisition of *motor* skills which will be then applied to a real scenario.

Although some researchers state that to foster training effectiveness the similarity between the training and the real environment should be improved and that more realism corresponds to greater comprehension, other researchers support the use of "low-fidelity" representation. For example Dwyer [2007] states that "an increase in the amount of realistic detail [...] will not necessarily produce a corresponding increase in the amount of information assimilated".

Stappers et al. [2003] state that “correspondence to the natural world is not always necessary or even desirable”. In their work the authors identify two approaches that drive the development of Virtual Environments: stimulation and information correspondence.

- *Stimulation correspondence* approach aims at producing stimulation to mimic the natural environment in the most realistic way. The supporters of this approach claim that the sense of experienced reality depends on the degree of correspondence between the stimulation that the user receives from the virtual world and those in the real one. According to this approach, perfect presence can be only achieved when the extent of sensory input, the ability to modify the environment and the controls over the sensors perfectly match the reality. As reported by Liu et al. [2008], “high fidelity means high complexity, which will require more cognitive skills, thus increasing trainee’s workload, which will, in turn, impede learning” [Alessi, 1988].

- *Information correspondence* approach, instead, is based on the paradigm that rather than try to imitate real-world stimulation, the virtual environment should target “the ecological aim of producing task-specific information” [Stappers et al., 2003] starting from task requirements, information that guides these tasks and means of making that information accessible to the user.

However, the use of one approach among the other one depends on the application. If the objective is to reproduce a scene in the most realistic possible way (e.g. rendering 3D models to make decision based on the appearance of an object) the correct approach is stimulation correspondence. If the objective is to provide information that are not only or mainly related to the visual perception of the scene, then the information correspondence approach may lead to better results.

Consequently, according to the application, a variety of realism may be more appropriate than another. In case of Virtual Reality applications for training purposes, Burkhardt et al. [2003] state that the aesthetics and the degree of graphic realism are not the essential point.

In this context, Ferwerda [2003] described three varieties of realism that a computer graphics application may have.

Physical realism : the image provides the same visual stimulation as the scene. Thus, the image has to be “an accurate point-by-point representation of the spectral irradiance values at a particular viewpoint in the scene”. Generating this kind of images remains, still nowadays a purely theoretical exercise for three reasons : the computational expensiveness; the impossibility to display them on existing displays (resolution, contrast, luminance constraints); the futility to create images for human observers that do not take into account the limitation of human vision.

Photo-realism : the image produces the same visual response as the real scene, which means that the image must be indistinguishable from a photograph of the scene.

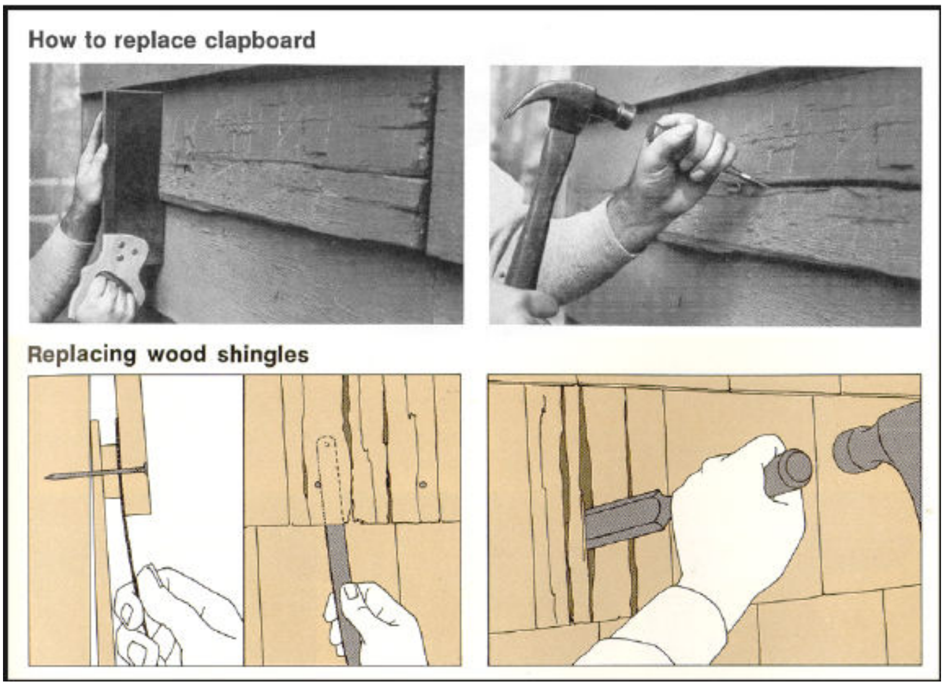


Figure 3.5: Functional realism vs photo-realism. From Ferwerda [2003]

This standard takes into account the eye's response to light energy and thus it reduce the requirements for describing colors from their fully spectral representation to their RBG equivalent. As for physical realism, also photo-realism requires a huge computational power which may limit its use in real-time graphics applications. Here, we find the same line of thought of Stappers et al. [2003] also in Ferwerda [2003] who state that it is unclear whether or not photo-realism "is necessary or even desirable".

Functional realism : the image provides the same visual information as the scene. With *information* Ferwerda [2003] refers to the meaningful properties of objects in a scene (position, size, shape, materials) that allow users to perform tasks. In other word, an image is functionally realist if it lets users perform the task they need to do as well as s/he could in the real world. This approach assumes that some information are irrelevant for or even counterproductive to the task. Let's consider the Figure 3.5, that show how to replace the siding on a house. Although the photographs are clear, the drawings offer several benefits over the photos: the elimination of irrelevant details such as shadow, the visualization of parts that are just not possible in a photo, the color visual segmentation. As Stevens et al. [2015] state, it is not always necessary to have the most faithful representation of the real environment if the task does not require it.

Thus, using functional realist environments rather than photo-realistic ones, may be more effective for skills and knowledge acquisition. Also, we think that photorealism may limit the generalization of the knowledge acquired in a specific environment. In fact, while photorealism aims at reproducing a specific real environment or object, functional realism allows for reproducing a class of objects which may, in turn, foster the transfer of training in similar but not identical environments.

3.2.4 The need for *light* training systems

Besides the need to train drivers in a risk-free environment, there are additional industrial constraints that we have to take into account when defining the physical settings of the system and its functional requirements. The main constraint is that the training platform should allow to train a large amount of people in numerous places: the training places include, but they are not limited to, car dealerships, showrooms and eventually customers' house. To satisfy this constraint we have to outline some criteria that help us in identifying a class of systems that we define *light systems*:

- Accessibility, which includes the portability of the system, its footprint and the ease of installation.
- Autonomy, which differentiate stand-alone systems from systems that require additional hardware to run.
- Cost, which affects the possibility of deployment of the system.
- Consumer availability, which, in future, would affect the possibility to train people at their place.

An example of non-light system is the CAVE (CAVE Automatic Virtual Environment). CAVE systems use room-sized cubes with projectors directed to the walls. The position of the user is recorded by a tracking system and it is used to update the point of view in the Virtual Environment. According to the user's point of view, two images, one for each eye, are generated. The user, thus, needs to wear stereoscopic shutter glasses, synchronized with the projectors, in order to perceive the 3D image. CAVEs are fixed systems which require a dedicated large space to be installed, physical props (projection walls) and dedicated high-end hardware including workstations and projectors. This characteristics make these systems difficultly accessible to general public and their deployment hard and expensive.

In recent years CAVEs have been progressively replaced -at least for some applications- by cheaper and less cumbersome systems: the Head-Mounted Displays (HMD).

Head-Mounted Displays

A Head-Mounted Display (HMD) is a device that provides the user with a pair of stereo images updated according to the position and/or the orientation of their head. Head-Mounted Displays embody all the characteristics of light systems that we defined beforehand.

The lack of high-performance devices at consumer-level price relegated Mixed Reality headsets to a niche audience (researchers and some industries) for a long time; nowadays MR headsets are more and more accessible thanks to the process of democratization in progress. Technological improvements, lower prices and the ease of integration in game engines are leading to a mass spread of many MR-enabled applications.

The introduction on the market of accessible Mixed Reality devices resulted in a radical paradigm shift and it accelerated the spread of this technology and applications

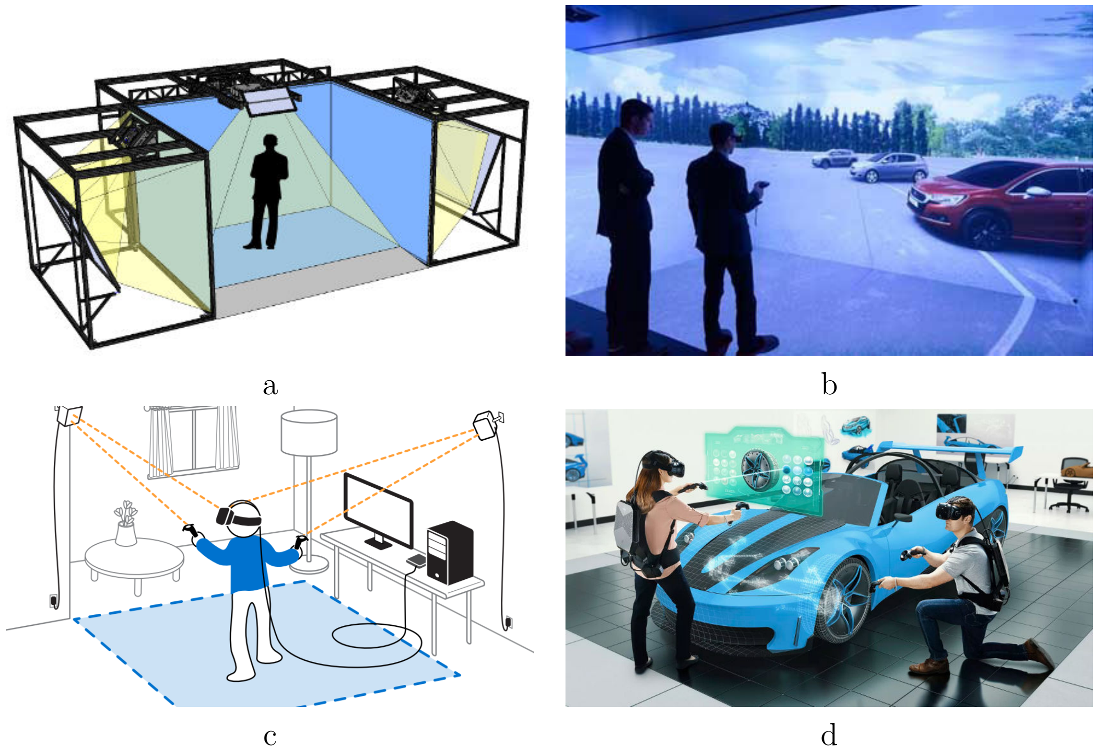


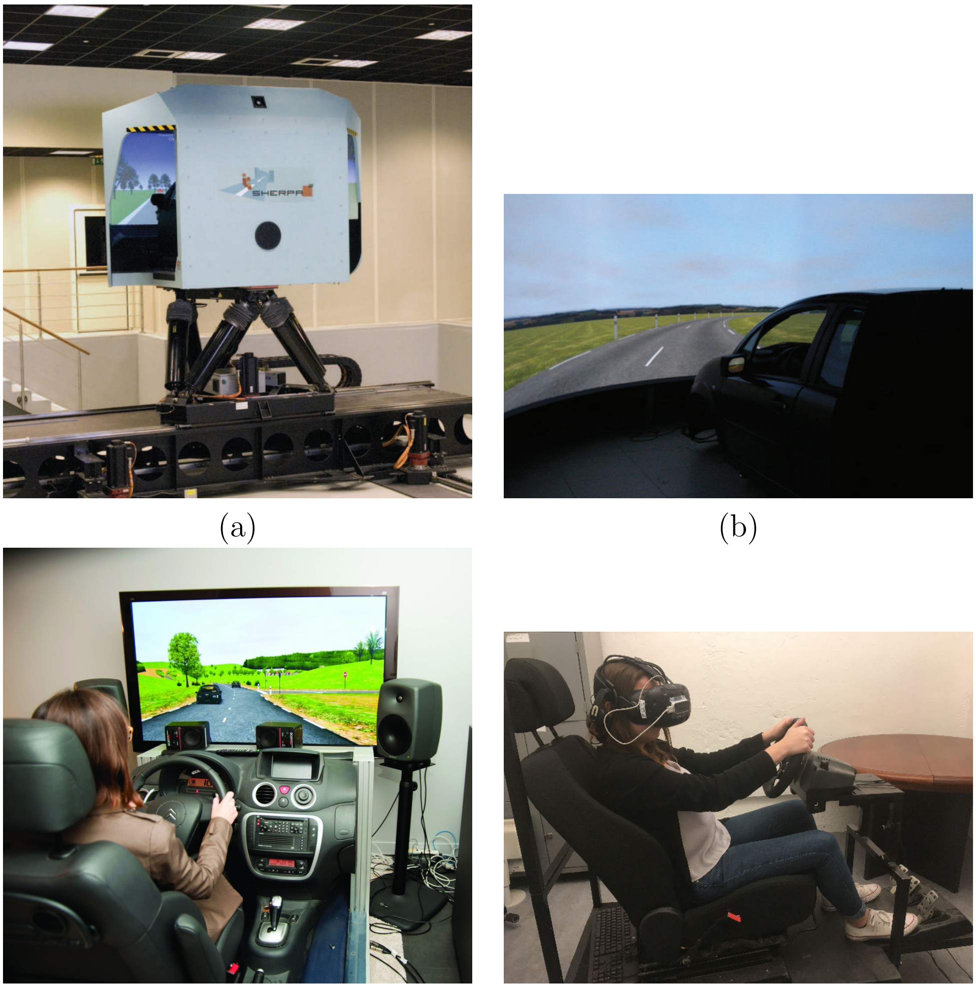
Figure 3.6: Comparison between a CAVE (a [image from visbox.com], b) and an HMD (c [image from vive.com],d [image from hp.com]) setups and visual rendering

among general public. Although it is possible to classify these headsets according to several technological specifications, we propose a taxonomy based on their ability to operate independently of other hardware or software. While in the past headsets required a VR-ready machine to operate, recent technological advancement is tackling the challenge of detaching the device from the physical machine. The *race to lightness* is observable in the technological improvements of the three generations of headsets that have been presented over the last few years.

- First generation of headsets (e.g. Oculus Rift, HTC Vive, PlayStation VR) requires a VR-Ready machine to operate and an external tracking (outside-in) system for positional tracking.
- Second generation is an hybrid generation. It includes: PC-based (optionally wireless) headsets with inside-out tracking (based on computer vision and localization algorithms), standalone headsets providing rotation tracking only (e.g. Oculus Go) and mobile-based headsets (e.g. Gear VR).
- Third generation includes *all-in-one* standalone systems with inside out tracking (e.g. Microsoft HoloLens, Oculus Quest, Magic Leap). They do not require a machine to operate or an external system to track user's position and orientation.

3.2.4.1 MR and Light Systems for Driving Simulation

As for Mixed Reality systems in general, also when it comes to driving simulation, according to the purpose and the constraints, there exists a number of different systems with a wide range of immersion, interaction fidelity, cost and footprint. Most complex driving simulators include full-sized vehicle body with a 360-degree visual systems. To increase fidelity, the vehicle body may be placed onto a moving platform to simulate longitudinal and lateral accelerations. Research has proven that moving-base simulators [Lee et al., 1998] are preferable to fixed-base ones [Fisher et al., 2002; Milleville-Pennel and Charron, 2015] for their closer approach to real-world driving [Klüver et al., 2016]; however some studies suggest that the motion does not need to match real-world forces in a 1:1 scale [Greenberg et al., 2003]. Simpler driving simulators are being increasingly adopted for in driving schools and private business. These simulators usually include a simple car cockpit (or even a racing wheel) and a visualization system.



(a) (b) (c) (d)

Figure 3.7: Examples of driving simulator systems: (a) a moving-base simulator [Chapron and Colinot, 2007], (b) a high-end fixed-base simulator with panoramic display, (c) a compact fixed-base simulator with single screen, (d) a HMD-based simulator

Due to their characteristics and for their behavioral validity, high-end driving simulators are mainly used at research facilities to study the use of novel HMI, test of novel functionalities and to investigate drivers behaviors in critical scenarios and hazardous situations which are ethically not possible to evaluate on real roads [Ihemedu-Steinke et al., 2017a]: distraction, alcohol and drug effects [Micallef et al., 2018]. Although most of the systems for this purpose uses static screens (2D and 3D) as the display system, in recent years, HMD-based driving simulators have been proposed [Ihemedu-Steinke et al., 2017a; Taheri et al., 2017] to analyze drivers' characteristics: these systems usually include gaming wheel and pedals as the driving interface. With respect to conventional 2D driving simulators, the HMD-based ones provide a set of visual and motion cues that enable a more realistic response to the driving situation.

Early research highlighted negative effect for HMD on driving performance [Kappe and Padmos, 2001]; it is important however to point out that the authors identified the causes of bad performance in technical limitations of HMDs of that time (large weight and considerable image delay). Still in 2011, Stoner et al. [2011] reported a trend in the literature that indicates that HMDs produce worse driving performance than fixed-base simulator. However, more recent studies with new generations of consumer HMDs (i.e. Oculus Rift, HTC Vive) showed that the technological improvement for this devices lead to a more similar physiological response and driving performance when compared to stereoscopic 3D or 2D screens [Weidner et al., 2017].

Stoner et al. [2011] suggested also that before the full potential of HMDs could be exploited, further research about the aforementioned Simulator Sickness is necessary.

3.3 Training and Learning in Mixed Reality

In this section we present an analysis of the state of the art about training and learning in Mixed Reality reflecting the scientific axes of this thesis: the role of immersion, the design of the training content and the evaluation of the training.

We remind that, at the time of writing, the two works [Hergeth et al., 2017; Payre et al., 2017b] described in Chapter 2.5.1 are the only ones that address the training of partially automated cars' drivers using Virtual Reality technologies. However, they make use of high-end driving simulators which, for the industrial constraints of this thesis, are not considered to be potential training systems candidates. Thus, a lack in the literature exists for what concerns the drivers' training in automated driving using HMD-based systems.

3.3.1 Immersive Training

Mixed Reality platforms have been historically adopted in training [Boud et al., 1999; Champney et al., 2016; Gavish et al., 2015] and education [Bacca et al., 2014; Freina and Ott, 2015] with important benefits in terms of performance [Boud et al., 1999], users' involvement and motivation [Freina and Ott, 2015] and transfer to real settings [Vince, 1993b].

According to Mikropoulos and Natsis [2011], when the content to be learned is complex, 3D and dynamic, immersive systems compared to a desktop system have a great advantage.

In their literature review about the comparison in performance between HMD and screen-based visual system for training purpose, Stevens et al. [2015] state that most experimental studies fail to demonstrate benefits of HMD-based training over more traditional training displays. In addition, the authors state that this lack of benefits may not justify the generally higher cost of HMDs. If in the past the cost of HMDs represented a barrier for innovation, nowadays this trend has reversed and some all-in-one HMDs, which include tracked visualization display, manipulation devices, are cheaper than other platforms. Thus, for the same performance or training effectiveness, HMDs would be preferred in terms of cost.

However, some studies proved that HMD-based VR turns out to be more effective when compared to other training systems for a wide range of applications, such as surgery [Hamilton et al., 2002] (HMD compared to video trainer), aircraft visual inspection [Vora et al., 2002] (HMD compared to PC-based training tool), power production [Avveduto et al., 2017] (HMD compared to traditional training), mining industry [Zhang, 2017] (HMD compared to screen-based and projector-base training).

Concerning Augmented Reality, promising results have been found for training of medical procedures [Azimi et al., 2018; Wilson et al., 2013]: using a HMD is more engaging, improves performance, the time-on-task, and increases the confidence level of users in providing emergency and critical care with respect to standard training. Besides the medical sector, Augmented Reality headsets are being also effectively applied to maintenance and training of complex military systems [Piedimonte and Ullo, 2018], assembly tasks [Evans et al., 2017].

Multiple studies compared the effects that VR and AR displays systems have on performance. Gavish et al. [2015] for example, compared the effectiveness of VR and AR for industrial maintenance and assembly task training with respect to two control groups (i.e. video training and training with a real object); besides a longer training time for VR and AR, AR performed better with respect to the training with the real object and no significant differences were found between VR and video training.

To study the effect of display fidelity Bowman et al. [2012] used a high-end VR headset (able to display both virtual imagery and "simulated real world") in order to simulate AR and VR systems. In this way the authors, while sacrificing ecological validity, have gained in experimental control for FOV, FOR, stereoscopy, resolution and so on. Using this methodology the authors performed three experiments in which they showed that increased display fidelity (in terms of FOV, software FOV and FOR) can improve performance in task. The authors combined also the display fidelity with different level of interaction fidelity: *low*-fidelity interaction with mouse and keyboard and *high*-fidelity interaction with tracked handheld controller. They found that high-fidelity interaction improved task performance (aiming and firing).

Drivers training

As Goode et al. [2013] report in their analysis of literature, in the context of drivers training, simulation is considered an effective tool for learning both technical (or procedural) skills [Allen et al., 2007; Falkmer and Gregersen, 2003; Morgan et al., 2011] and non-technical (or higher-order cognitive) skills [Burkhardt et al., 2016; Fisher et al., 2002] such as eco-driving rules [Gardelis et al., 2018].

Besides a few recent studies that make use of HMD-based systems [Abdelgawad et al., 2017; Gardelis et al., 2018], fixed-base and moving-base simulators are generally adopted for drivers training purpose. However, in the aforementioned studies the training refers only to traditional cars. There are only some recent technical propositions of HMD-based systems that might be potentially used for training [Goedicke et al., 2018; Ihemedu-Steinke et al., 2017b], but actually no studies include a training part.

Lessons learned from aviation: pilot's training

Event though in literature only a few studies address our specific question, to a certain extent, we can find some similarities between operating a partially automated car and operating an airliner equipped with the autopilot. Both systems, in automated mode, do not require the human operator to constantly monitors the system and both systems, when they are not able to perform the driving/flying task at hand, require the human operator to take over.

Thus, automated driving research can benefits, if not from the methodology, from at least the results in the field of aviation [Stanton and Marsden, 1996], and in particular in studies concerning flight simulation for pilot training [Vince, 1993a]. Important findings from this research include the occurrence of positive transfer and the fact that abstracted rendering simulators allow people to learn better than with the real thing [Stappers et al., 2003]. Pilots trained on a simulator are thus able to co-pilot a craft immediately after their simulation training [Vince, 1993a]. However, it is crucial that the training practices allow for the generalization of the skills acquired in the virtual environment and not only for an application of the rote-memorized skills specific to the training situation [Casner et al., 2013].

Although these encouraging findings, there are some crucial differences between pilots training and the training we are looking for. First, in aviation the training is targeted to professionals prepared especially for that purpose; the target of our research are general, non-professional users. Second, pilots usually undertake several weeks of long training sessions; we aim to a rapid training to be proposed as an additional tool, for example, during the handover of a new car. Third, the training equipment generally consists of professional high-end flight simulators; as we will see in the next chapters, the systems we will consider have constraints in terms of cost, portability and footprint.

3.3.2 Mixed Reality Environments for Learning

Mikropoulos and Natsis [2011] defines a Virtual Learning Environment as "a virtual environment that is based on a certain pedagogical model, incorporates one or more didactic objectives, provides users with experiences they would otherwise not be able to experience in the physical world and redounds specific learning outcomes".

Dalgarno and Lee [2010] highlighted the potential learning benefits of 3D Virtual Learning Environments (3D VLEs) by proposing a model (Figure 3.8) based on their two distinguishing characteristics:

- Representational fidelity: it includes aspects relative to visualization (such as realistic display of environment and smooth display of view changes), consistency of object behavior in responding to the user actions, user representation (e.g. avatar), audio spatiality and haptic force feedback.

- Learner interaction: it includes the ability to perform embodied actions (e.g. view control, navigation and object manipulation), verbal (e.g. text, voice) and non-verbal (e.g. gestures and facial expression) communication, control of environmental attributes (e.g. gravity, time, replay, but also real), and the possibility for learners to customize the learning environment.

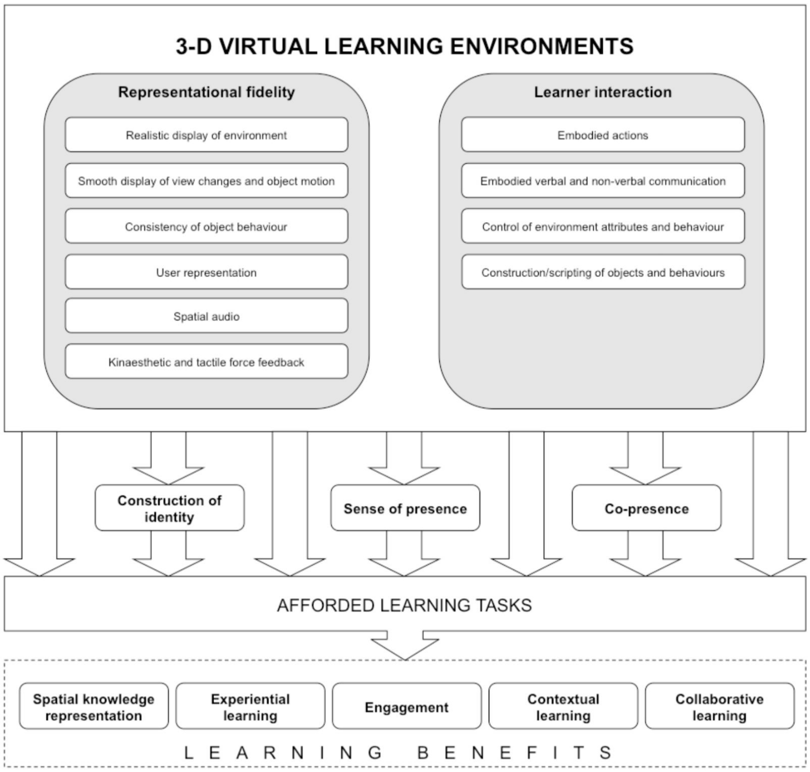


Figure 3.8: Model of learning in 3-D VLEs, incorporating unique characteristics and learning affordances [Dalgarno and Lee, 2010]

According to the authors, these characteristics contribute to the identification of the 5 learning affordances of 3D VLEs, which are:

1. Enhanced spatial knowledge representation - Thanks to locomotion techniques (e.g. natural or redirected walking, teleportation) the learner has the ability to move around the VLE and look at it from a point of view and thus to develop spatial knowledge of the real environment beyond the limits imposed by reality or 2D VLEs.

2. Experiential learning - The learner has the possibility to practice skills or perform tasks that would be impractical or impossible to undertake in the real world for many reasons (e.g. inaccessibility or inexistence of the equipment, cost, rare or dangerous scenario).

3. Motivation and engagement - The high degree of fidelity, the possible isolation from the real world, the natural interaction as well as the playful aspects, could make the learner psychological more present in the training environment.

4. Contextual learning - Since 3D technologies are able to provide high levels of visual or sensory fidelity consistent with the real world, "3D VLEs should be more readily recalled and applied within the corresponding real environment". This would, in turn, improve transfer of knowledge and skills to real situations.

5. Collaborative learning - Distributed and multi-user 3D environments that allow learners to share a space and perform task together (e.g. remote support by an expert) may improve learning outcomes.

Using Virtual Reality for training purposes has two main interests according to Burkhardt et al. [2003]: the first interest is to help solve training problems and to improve existing training situations; the second interest is to offer an original research tool for investigating learning and human behaviour and novel training technologies. In fact, according to the authors, Virtual Reality, by enabling the interaction between the learner and the training environment, provides an exclusive flexibility for presenting information to the learner in multiple formats and point of view; in particular, simulation allows for proposing *alternatives* to the environment as it is perceived in reality and enables the possibility of *enhancing* the representation of behaviors and actions offered to the trainee. Besides the aforementioned advantages of simulation and 3D VLE, Burkhardt et al. [2003] highlight the fact Virtual Reality unlocks the use of interaction and assistance modes that are just impossible in the physical world:

- modification of the relative size of trainees and virtual objects to enhance spatial representation;
- reification of abstract concepts in a more concrete form to present information normally outside the human perceptual field;
- limitation of the learner's ability to act by prohibiting certain operations and restricting degrees of freedom;
- superimposition of assistance information (i.e. sounds, text, visual effects) in the virtual environment
- involvement of a real or virtual trainer who can interact with the trainee through voice, text, or an avatar representing a character.

Concerning Augmented Reality, Petersen and Stricker [2015] observed that, although the concept of AR was introduced more that 20 years ago, most of the applications are still limited to simple visualization of virtual objects on spatially limited scenes: according to the authors, the reasons behind this limitation, besides ergonomic and hardware constraints, consist of the large effort required for creating the content of such virtual instructions and for building models allowing accurate tracking.

3.3.3 Training Evaluation and Transfer of Training

The main reason for using Mixed Reality for training purposes is the fact that doing it in reality is not convenient in terms of cost, safety, equipment availability, and so on. One of the expectation is that using these technologies would be, at least, as effective as traditional training. In other words, the expectation is that trainees are able to transfer the skills acquired during the training to the real situation. This ability, known as Transfer of Training, is extremely important and it is one of the most important metrics to evaluate when assessing the effectiveness of a training program.

Transfer of training can be defined as the extent of retention and application of knowledge, skills and attitude form the training environment to the environment in which they are normally used [Pennington et al., 1995] or to a variety of tasks or job skills in the real environment [Farr, 2012]. Transfer of Training can be taken as a way to measure the effectiveness of the VE, but “it is extremely difficult to track” [Bossard et al., 2008].

Transfer can be positive, negative or, nil [Stevens et al., 2015]. Positive transfer occurs when the trainee performs the task in the real world better after simulation exposure; negative transfer occurs when performance degrades in the real world, usually due to poor simulation design or mismatch between the training and the real task; nil transfer is neutral.

In some cases assessing transfer of training in a live system could be not possible or not adequate (due to costs, safety concerns, resource availability) and thus a typical strategy is to measure transfer or the degree of learning in the simulator itself [Stevens et al., 2015].

Grossman and Salas [2011] identify three main factors that are related with the transfer of training: (i) trainee characteristics (such as cognitive ability, self-efficacy, motivation, perceived utility of training), (ii) training design (such as behavioral modeling, error management, realistic training environments) and the work environment (such as transfer climate, support, opportunity to perform, follow-up).

One of the first attempts to evaluate the transfer of motor skill training from a Virtual Environment to the real world was conducted by Kozak et al. [1993]. The authors implemented a training program for pick-and-place task (which included a grasp gesture) and they compared the real-world task performance of three groups [trained] in different ways: VR training (using HMD and a Dataglove), Real training and No-training. Results showed that participants trained in VR were not able to transfer the learning to the real-world task and that no significant difference was found in the performance between the VR and the not trained group. In other words, what the subjects learned during VR training was specific only to the context of virtual reality. Although the result might appear disappointing for VR, the authors remained enthusiastic about the potential of this technology for human-computer interaction. They, in fact, identified many of the barriers to transfer in “the technological state-of-the-art, rather than VR per se”. Also, they assumed that “one way to improve transfer of training is to improve the similarity between the training context and task context”, but that “system limitations make this prospect unlikely for the near future.”

To identify the types of transfer, Bossard et al. [2008] takes into consideration the dichotomies indicating that transfer should be either vertical or horizontal and that horizontal transfer should be near or far. The first distinction is made between vertical and horizontal transfer. Vertical transfer of skills and knowledge refers to the “replication of the previously acquired knowledge and skills in all identical situations". Thus this type of transfer often involves procedural tasks in which a sequence of operational steps is repeated every time the task is performed. Although the transfer rate is usually high, "the learner is unlikely to adapt such skills and knowledge to a new environment and changing conditions" [Subedi 2004, quoted in Bossard et al. [2008]]. Horizontal transfer, from the other side, refers to the use of knowledge and skills acquired in the training environment to perform new tasks. An additional distinction is made between horizontal near transfer and horizontal far transfer: while in the former there is a correspondence between the training situation and the application, the latter requires an effort to be adapted to novel situation or unfamiliar environments.

According to this taxonomy, we assume that the training we are aiming at is the *horizontal near training*. The transfer is *horizontal* because the situations and the driving scenarios in which the trainee has to apply the knowledge and the skills are similar but not identical to the ones of the training environment. In other words the trainee has to adapt the skill acquired in the training environment to different kinds of road, traffic conditions, weather conditions and so on. Also, the training is *near* because there is a close correspondence to the actions performed by the driver in the training environment and the real situation.

3.4 Concluding remarks

The analysis presented in this chapter highlights that Mixed Reality would represent an effective tool for our research question both from the immersion and the training point of view. On the MR continuum we have defined a class of *light* systems, in terms of visualization and manipulation characteristics, that meet the training needs and we have analyzed their intrinsic limitations and the possible drawbacks.

The main limitation of the literature review illustrated in this chapter is represented by the fact that results are specific to the application they address and it is not possible to generalize them to other domains. In other words, most of the presented studies are targeted to professional training, while in this thesis we are interested in addressing non-professional general public.

In the next chapter we will see how, starting from this basis we designed and integrated the training program in a Virtual Reality experimental platform based on a Head-Mounted Display.

Part II

Training design, experimental platforms and user studies

Chapter 4

Experimentation platform

Knowing is not enough; we must apply; willing is not enough; we must do.

Johann Wolfgang von Goethe

Contents

4.1 Introduction

In this chapter we describe how we laid the groundwork for the user studies. Starting from the analysis of the context and the state of the art presented in Chapter 2 and 3, we will present the contributions which led to the design and development of a first experimental platform.

We start by defining the characteristics of a target conditionally automated vehicle and the training requirements to familiarize the drivers with it. Then we describe how the characteristics of the vehicle were implemented in an *Driving and Onboard Activities Simulator* and how the choice of the manipulation interface was justified with an empirical user study. Subsequently we present how this simulator was implemented as practice environment in the training program and how, the latter, was integrated in the training system.

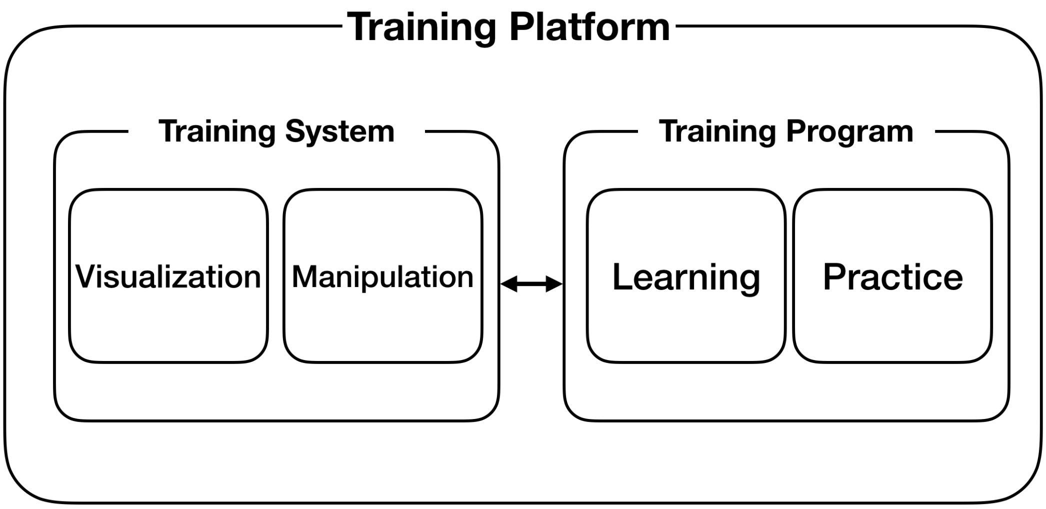


Figure 4.1: Experimental platform diagram

4.2 The characteristics of the target automated system

L3 conditional automation has specific technical constraints (described in Chapter 2). These characteristics can be implemented in many different ways in actual vehicles. For our case study, we defined a model of L3 vehicle with 5 possible states: Manual Driving, Autonomous Driving Available, Autonomous Driving Active, Take-Over Request and Emergency Brake. Each state requires different actions from the human driver.

Manual Driving corresponds to Level-0 of automation, which means that the vehicle does not provide any driving assistance to the human driver. When the vehicle enters in a zone enabled to Automated Driving, it switches to the *Autonomous Driving Available* state. From that moment the human driver can activate the Automated Driving System (ADS). Once the human driver enables the ADS the vehicle switches to *Autonomous Driving Active* state and the Level-3 of automation: steering and speeding are handled

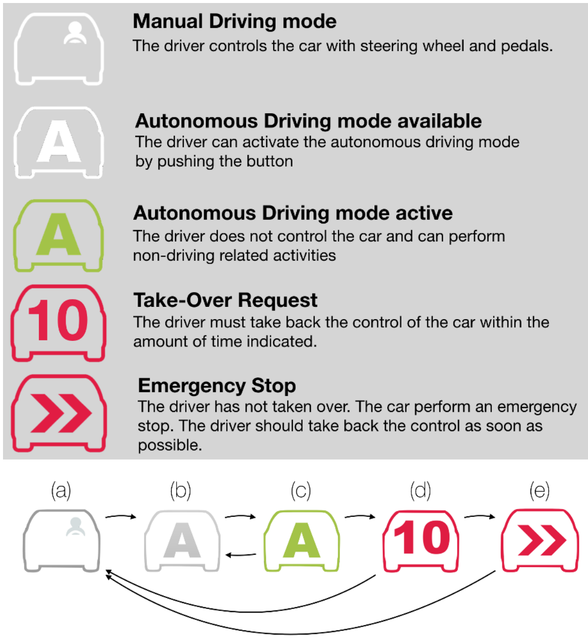


Figure 4.2: The description of each vehicle state and the associated icon

by the ADS which adapts the speed to the surrounding traffic. However, the vehicle does not perform lane changes. When the ADS is not able to perform the driving task at hand, it switches to the *Take-Over Request* state in which the vehicle still performs a Level-3 automated driving, but only for the time budget accorded to the human driver to take over. When the human driver takes over, the vehicle switches back to the Manual Driving state. Otherwise, if at the end of the time budget the human drives has not yet taken over, the vehicle switches to the *Emergency Brake* state, stopping on the current lane. During the *Autonomous Driving Active* state, the human driver can initiate a take-over at any time: the vehicle switches to the Autonomous Driving Available state. All the car's state changes are notified to the driver with visual-auditory alerts which consist of displaying an icon on the screens and playing a sound and a vocal message. The icons relative to each states are reported in Figure 4.2 and they were provided by VeDeCom Institute and already used in a study carried out by Bueno et al. [2016].

4.3 Proposed training design

Automated cars are complex systems and we cannot expect drivers to have a thorough understanding of how the vehicle or sensors work. Thus, the very starting point of the design of the training was to discriminate mandatory, useful and unnecessary information in order to define a program able to offer a reasonable coverage of the automated driving system.

It is important to say that the aim was to design a training program that would not substitute neither driving school training nor traditional car handover. We aim at providing an additional layer to current training programs, or to the car handover process, in order to allow already skilled drivers (namely drivers provided with regular driving license) to acquire new capabilities relative to the interaction with automated cars and novel driving situations.

4.3.1 Rasmussen's SRK model

The idea that the human behavior can be categorized according to the degree of conscious control exercised by an individual over their activities was introduced by Rasmussen [1983] with the development of the Skills, Rules, Knowledge (SRK) model. This classification describes the types of activity in which the human operator can engage and the ways in which they might react to the events and information depending on their degree of familiarity with the task and the environment. The SRK model was subsequently extended by Reason et al. [1990] who integrated, within the same framework, the different error mechanisms and the three levels of performance.

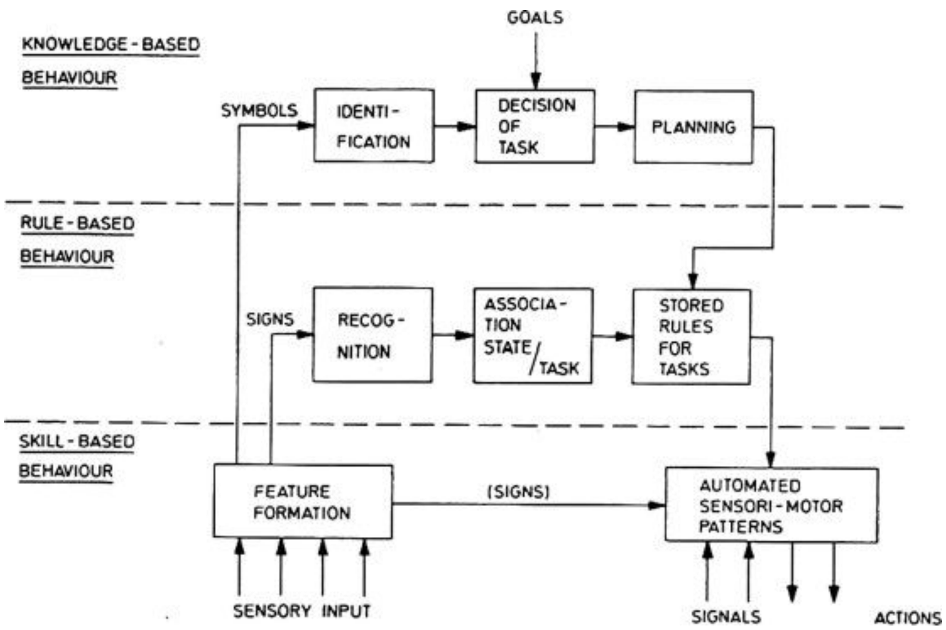


Figure 4.3: The Rasmussen's SRK model

The *Skill-based behavior* refers to the smooth execution of highly practiced actions in which there is virtually no conscious monitoring [Rasmussen, 1983]. The activities at this level are already experienced by the individual and are governed by integrated stored patterns of behavior. For this reason, the individual is usually unable to describe the procedure they make (e.g. think about when you tie your shoes; could you describe the procedure?). Almost the totality of the daily activities of a person are skill-based (sport, typing), including operating a vehicle. At this level, information is perceived as signals which have no intrinsic meaning or significance beyond indicating physical time-space data. Skill-based behavior can lead to two type of errors that mainly occur when attention is diverted, even momentarily. slips and lapses. Slips occur when a simple and frequently performed physical action goes wrong, while lapses occur when a required action is forgotten or in general not performed.

Rule-based behavior is controlled by stored procedures (i.e. rules) that may have been empirically derived from experience, or acquired with training. At this level, the performance of a task usually follows a IF (x) THEN (Y) model. Rasmussen [1983] points out that "the boundary between skill-based and rule-based performance depends on the level of training" of the individual. Individuals who perform activities at the rule-based level have explicit know-how and are familiar with the task, but do not possess the wide experience to perform it unconsciously. At the *rule-based level* the information is perceived in form of *signs* which cannot be directly processed, but they are used to activate stored patterns. Rule-based mistakes happen in case of decision-making failures due to intentional or non-intentional mis-application of a good rule or application of a bad rule.

When the situation is novel or unfamiliar and no pre-stored rules are available from experience, the control of performance becomes *knowledge-based* . This behavior refers to the execution of a task in an almost complete conscious manner: the goal is explicitly formulated and a useful plan is developed; it is then tested by trial and error or by means of understanding the functional properties of the environment and prediction of the effects of the plan considered. Information at the knowledge-based level is perceived as *symbols* which can be formally processed as they refer to concepts tied to functional properties. Knowledge-based mistakes result from shortcomings in operator's knowledge or errors committed due to misapplication of incomplete or incorrect knowledge to new situations.

4.3.2 Using the SRK model for transition of control

What arises from this classification is that training, defined by Rasmussen as "supplying people with a proper repertoire of possible behaviors for unexpected situations", can act at the three levels. At the knowledge-base level, training would provide the operator with the preliminary information about the activity; at the rule-base level, training would allow the operator to acquire the rules and to store pattern and procedures; at the skill-based level, training would give the possibility to practice those procedures to gain experience.

If we want to apply the SRK model to our case study, we can observe that letting a driver operate a conditionally automated car without any preliminary training may lead to knowledge-based mistakes ("I don't know what to do") and rule-based mistakes ("I thought what I did was right"). Let's take as example the *first time* a driver experiences a Request to Intervene (RtI) (summarized in Table 4.1):

- If the driver has no prior knowledge (so they act at knowledge-base level) the RtI represents a novel or unfamiliar situation. Thus, the driver has to process the information from the environment (e.g. alerts, driving conditions) in order identify the action to perform. It is clear that this approach can lead to possible failure such as a wrong reaction (because the driver does not know how to react) or even a lack of reaction (because the driver does not know what to do, or they take to much time to plan it); at this level we hypothesize that the problem of the out-of-the-loop driver (Section 2.3.2) and low situation awareness would be more severe.

- If the driver has received a preliminary training which includes rules about transition of control, the RtI may represent for them a familiar situation. In this case, the driver has stored procedures which they can apply to respond to the RtI (rule-base behavior). However, also at this level driver failures are possible, such as the confusion of the RtI with another alert or the opposite way.

- If the driver has practiced a lot of take-over scenarios, the RtI may represent for them an experienced situation (skill-base behavior). In this case, the driver responds automatically to the RtI. One of the failure at this level is represented by the assumption that the driver took over while they actually did not.

To make things worse, a human failure at this level of automation (L3 conditional automation) may be very dangerous and there may not be the possibility for the operator to try other solutions (in other words, the trials and error approach is not feasible). It is possible to observe that not only the RtI, but also the activation phase can lead to crucial errors. In fact, inexperienced drivers may try to activate the ADS in a situation in which actually they can't (knowledge-based error), or that they may keep controlling the car (using the steering wheel and pedals) even when the ADS is activated, which may result in a subsequent undesired deactivation of the ADS.

	Knowledge-based behavior	**Rules-based behavior**	**Skill-based behavior**
Familiarity	The RtI represents for the driver a novel or unfamiliar situation.	The RtI represents for the driver a familiar situation	The RtI represents for the driver an experienced situation
Response Action	The driver has to identify the goal, develop a plan and test it	The driver has the stored procedure to respond to the RtI. IF (RtI) THEN (Stop the NDRT and Take-over)	The driver responds automatically to the RtI.
Possible failure	The driver does not respond to the RtI because s/he doesn't know what to do or how to do. The driver responds to the RtI in the wrong way (e.g. wait until the time buffer expires, act on the wrong commands). The driver takes too much time to plan an action.	The driver confuses an RtI with another alert and so s/he does not take over (dangerous). The driver confuses another alert with an RtI and thus s/he takes over when it is not necessary (no harmful).	The driver assumes that s/he took over while he actually didn't.

Table 4.1: An example of SRK-based behaviors during Request to Intervene

Also, in case of human intervention required in very limited amount of time, there may not be the time to predict the effect of an action. We aim that the first time that drivers drive their L3 autonomous car, they are already familiar with the situations they may encounter on the road. It is obvious that, in this case, the HMI plays a crucial role in this context. However, designing intuitive, clear and effective HMI for autonomous cars is a necessary but not a sufficient condition to ensure an appropriate use of the system and a safe interaction.

4.3.3 SRK training requirements

The objective of the training program was not to teach the driver a sequence of actions to perform in a given situation; it aimed at providing the driver with a *generalizable modus operandi* to adopt when the interaction with the car was required in both critical and non-critical scenarios. For example, adverse weather conditions may require the human control of the car: however, there is no need to specify every single weather condition (such as pouring rain, heavy snow, thick fog etc).

Since the interaction with the AV involved motor skills and cognitive skills, it was important to design a training system that allowed to train users in both domains.

Starting from the Rasmussen's model, we formalize the requirements for the training according to the SRK classification:

- *Knowledge-base requirements*: To make users aware of system's capabilities and limits, help them localizing the control interfaces and identifying the HMI, the training should include *declarative knowledge* about a general description of the L3 automated driving, the presentation of the HMI and the visual and acoustic notifications relative to each state.
- *Rule-base requirements*: To let users understand their role during automated driving, the training must include *procedural knowledge* about the use of the HMI and the actions to perform when driver intervention is required.
- *Skill-base requirements*: To let users practice the acquired knowledge, the training should include the simulation of driving situations in which they could experience the autonomous driving in a safe environment. Also, the training should provide a way of ensuring the acquisition of skills. An hypothesis is that practice, associated with the acquisition of declarative and procedural knowledge, eases the development of skills.

These three classes of requirements of the training program were thus implemented in a step-by-step procedure in a Virtual Learning Environment. A preliminary work to the implementation of the training program was the design and development of a Driving and Onboard Activities Simulator (DOAS) for automated driving.

4.4 The Driving and Onboard Activity Simulator (DOAS)

In this section we describe the design and the development of a Driving and Onboard Activity Simulator for automated driving. We specify that the simulator was not developed with the aim of providing a *physical realism* of driving (like in a racing game) nor to faithfully simulate algorithms for autonomous driving (simulators like

CARLA [Dosovitskiy et al., 2017], AirSim [Shah et al., 2018]). The objective, instead, was to give the user the feeling of what it is like "to drive" a partially automated car, where *driving* is not only limited to the actual control of the vehicle, but also to the execution of secondary activities.

Also, its development was independent of the choices of immersion or training content; thus, an implicit requirement was to create a simulator easily deployable to a variety of MR platforms including visualization systems (e.g. traditional screens, HMDs) and manipulation interface (e.g. keyboard, controllers, steering wheel).

For this reason we chose to design and develop the driving simulator using Unity 3D, a game engine which offers the possibility to design virtual environment easily deployable to several platforms, including Mixed Reality systems.

4.4.1 Vehicles and roads

First of all, the characteristics of the target vehicle (Section 4.1) were implemented in the simulator. The basic scene included a 3D model of a car and a road network. The 3D model of the car represented a Citroën DS3. Usually the 3D models used for automotive purposes are extremely complex (meshes with a huge number of triangles), detailed (all the components of the car are included) and, require a number of draw calls which drastically reduce the frequency of displayed images. As presented in Section 3.2.2, a low frame rate is responsible for the occurrence of *temporal visuo-motor* and *visuo-temporal motor* incoherences, which contribute to create an unpleasant MR experience.

The first challenge was thus to simplify the 3D model to ensure an adequate frame rate for Mixed Reality (90 FPS): to do so, all the internal and unnecessary components were removed using Blender and only the parts of the car seen by the camera were drawn at each frame (frustum culling + occlusion culling).

a b

Figure 4.4: The Driving and Onboard Activities Simulator: (a) the 3D model of the car and (b) the interior view

Once we had an appropriate model of the car, we had to add the possibility of controlling longitudinal and lateral speed. As we presented at the beginning of this chapter, Level-3 conditional automation requires to provide both manual control and full automated control to the car. To add control capabilities to the driving simulator we used the package Realistic Car Controller [BoneCrakerGames, 2016]. This module provides two ways for controlling a car: manual control and AI control. Manual control allowed to control the speed and the steering of the vehicle by providing in input three values (acceleration [0-1], brake [0-1] and steering [-1, 1]) which were used in a control loop to generate a torque on the wheels. These values could be mapped to any input by a script. Thus, we implemented different interfaces including racing wheel, smartphone and keyboard.

The component "AI controller" was used to control and handle traffic in the scene. We also, modified and implemented this module in the ego car in order to simulate the automated driving. The AI controller required the definition of a path consisting in a set of waypoints and a target speed; thus, once activated, it controlled lateral and longitudinal speed in order to follow the list of waypoints.

Switching between manual and automated driving required the implementation of transition of control interfaces. In particular different autonomous driving activation/deactivation modalities (e.g. pushing a virtual button, pushing a real button, voice recognition) and visual and auditory alerts (e.g. HUD, icons, vocal messages, sounds) were designed and implemented in the driving simulator.

To create paths and roads in our scene we used a public available package (EasyRoads3D Pro [Andasoft, 2016]). We coupled this module with a tool we developed in order to automatically generate waypoints starting from the geometry of the road: a set of waypoints was generated for each lane. When a transition of control from manual to automated driving occurred, the AI module selected the closest next waypoint on the current lane and activated the AI controller.

4.4.2 On-road Driving Scenarios

Traffic Jam Highway Roadwork

Figure 4.5: The driving scenarios implemented in the DOAS

This framework allowed to easily implement many driving scenarios typical of the L3 automated driving. These scenarios included simple ones, such as large roads with no traffic, and more complex ones, such as traffic jams and highways. Simple scenarios were used to familiarize drivers with the control interfaces of the car, while complex ones were used to immerse drivers in more realistic situations.

Concerning take-over scenarios we implemented both critical and non-critical situations. Critical situations were represented by obstacle on roads or system failures: these situations required the user to take-over within a short time budget (usually 5 or 10 seconds). Non-critical scenarios included the end of automated driving enabled areas, the presence of roadwork and missing lane marking: these situations usually required the user to take over within a longer time frames (typically 30 or 50 seconds).

4.4.3 Non-Driving Related Tasks

One of the benefits for the drivers of automated vehicles is that they are freed from the driving task and they can perform other activities with personal or onboard devices. In order to simulate non-driving secondary tasks during autonomous driving in the proposed simulator, a 9.4 inch virtual tablet computer was placed on the right of the driver near the central console. The tablet was used to display webpages hosted in both local and remote servers. Since most of the applications we currently use on smartphones are web-based, displaying a webpage provided the possibility to implement a variety of different activities similar to those a driver would perform in their car: reading online newspaper, playing games, displaying videos and so on. The virtual tablet allowed the user to interact with it using their own hands. The collision between the virtual finger (displayed thanks to the Leap Motion controller) and the display of the virtual tablet generated a click in that point of the web page. Since the tablet was virtual, no haptic feedback was provided to the user.

4.5 Empirical validation of the VR manipulation interfaces

The first research question we addressed was to determine the most adequate interaction interface for the simulation of driving and on-board activities when a Virtual Reality HMD was used as visualization system. To do so, we conducted an exploratory user study to compare two different modes of interaction in terms of objective and subjective criteria. The interaction consists of both controlling the longitudinal and lateral speed of the car and performing a non-related driving activity with a virtual tablet.

The two interaction modalities chosen in the study were: (i) a realistic interaction interface based on steering wheel, pedals and direct user hand manipulation and (ii) the tracked controllers provided with the HTC Vive headset. The choice of this selection was motivated by the following reasons:

- Steering wheel and pedals are the most realistic interfaces for driving tasks. They allow users to perform the driving task as they normally would in real life.
- Controllers are a general purpose device, but they are specifically designed for interaction in HMD-based Virtual Environments.

4.5.1 Realistic interaction

For the first interface, the participants used their hands, a gaming steering wheel and pedals to interact with the environment. During the manual driving phase the steering

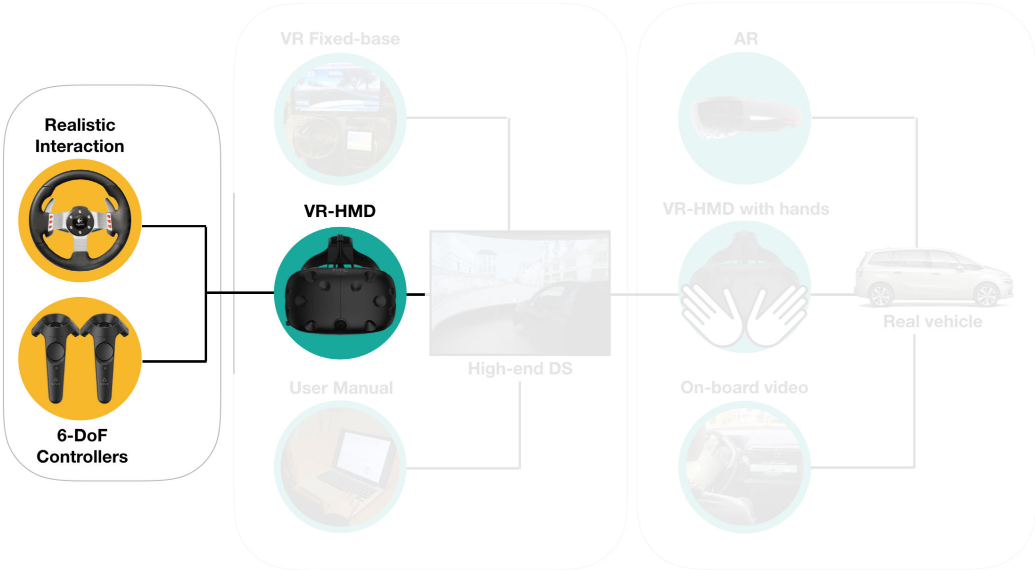


Figure 4.6: Plan of the thesis

wheel was used to control the lateral speed of the vehicle, and the throttle and brake pedals were used to adjust the longitudinal speed. To have a spatial correspondence between the real steering wheel and the virtual one, the steering wheel inside the virtual car was a 3D model of the real steering wheel with which the participants were interacting. Moreover, the position and the movements of the virtual model of steering wheel corresponded to the real one, allowing for co-located manipulation. In addition, the angle of the virtual steering wheel matched the angle of the real one. For the non-related driving task execution, we use a finger tracking device placed on the front face of the HMD to retrieve the relative position and orientation of the user's hands as well display a graphical representation. The contact between the index fingers of the user hands and a virtual tablet screen fires a click event in the contact point. No haptic feedback was provided.

4.5.2 6-DoF controller based interaction

The second interaction method made use of the two 6-DoF controllers, tracked in position and orientation in the Virtual Environment. The controllers were used both to interact with the virtual tablet and to drive the vehicle in manual mode. To start driving the vehicle, the subject must join the controllers together. The longitudinal speed is then controlled with two trigger buttons on the controllers: the right trigger is used to accelerate, while the left one is used to brake. The touchpad on the controller is used to interact with the virtual tablet. More precisely, the user touches the pad to move a pointer on the virtual screen, and clicks the pad to fire a click event at that point.

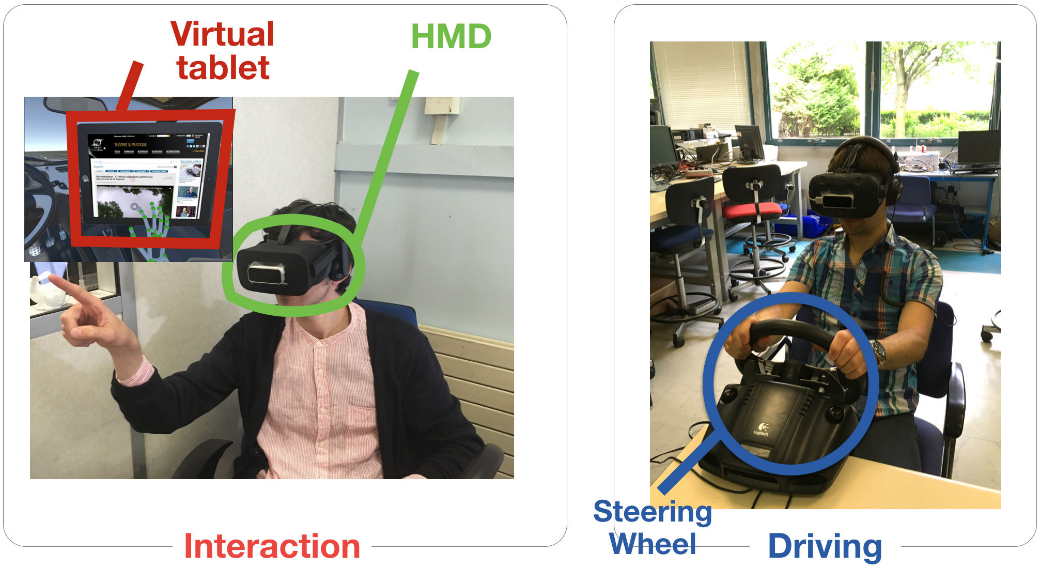


Figure 4.7: Realistic interaction interface

4.5.3 Non-Driving Related Task

During the autonomous driving phase, the subjects were asked to perform a non-driving related task involving interaction with the virtual tablet: they played some rounds of the memory skill game “Simon”(Figure 4.9). In each round of the game the device lights up one or more colored squares in a random order: the player must then reproduce the sequence by pressing each square in the right order. As the game progresses, the number of buttons that must be pressed increases. To implement the game, the tablet screen was split into 4 colored squares (red, green, yellow and blue), each of which represented one of the 4 buttons game. Simon was chosen as the non-driving activity because the game requires constant attention, high concentration, and fixed gaze in order to advance.

4.5.4 Experimental design

Ten subjects recruited from the university lab participated in the user study: they were asked to react to a take-over request to avoid an obstacle on the road. The participants were already familiar with the concept of automated vehicles and transition of control. Prior to the start of the experiment, the participants were orally briefed about the location of the autonomous driving button and the modalities of take-over requests.

Graphically, inside the virtual environment, the vehicle was placed on a two-lane dual-carriageway road. Three guardrails delimit the carriageways (two for the outer limits and one in the middle) and props, such as trees, buildings and power-poles populate the roadsides. Moderate traffic was simulated in the two directions.

The experiment contains 5 parts: (1) the pre-experience questionnaire to collect demographic data and information about driving skills and habits and previous experiences in Virtual Reality; (2, 4) two simulator sessions, one for each interaction mode, executed in random order; (3, 5) the post-experience questionnaire after each session to

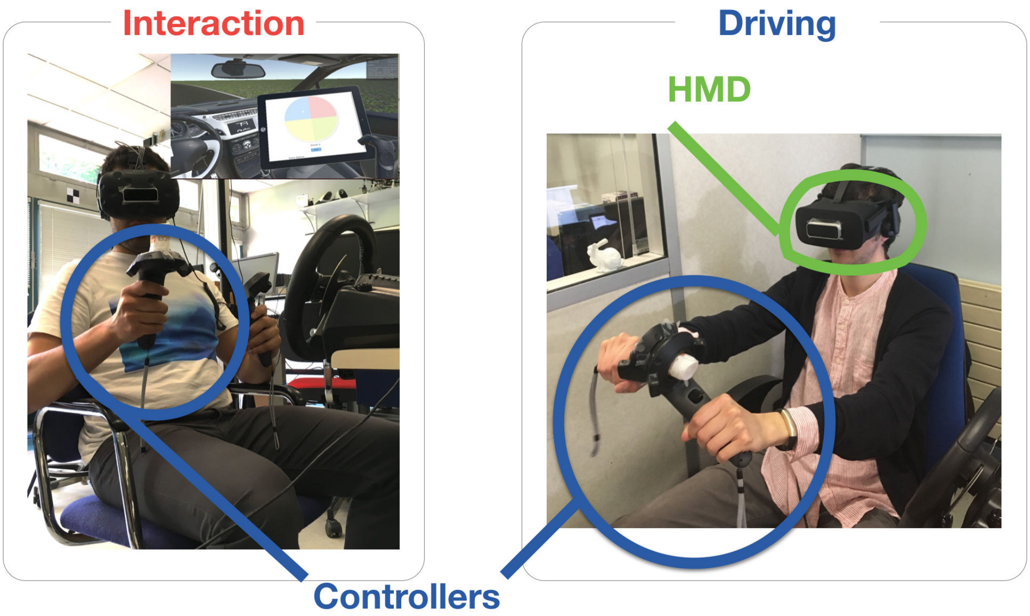


Figure 4.8: Realistic interaction interface

collect information about physical comfort, realism and acceptability. For this particular experiment, the maximum speed for the car was set to 80km/h for the autonomous mode and 130 km/h during the manual driving. After an acclimatization phase in which the participant became familiar with the simulator, the virtual environment and the given interaction interface, they were asked to perform the following sequence of steps three times:

1. Delegate control: the participant presses a button on the dashboard to delegate control of the vehicle to the autonomous system. The vehicle starts the autonomous driving with a maximum speed of 80 km/h.

2. Perform the Non-Driving Related Task: the participant interacts with the virtual tablet to perform the secondary activity, the Simon game.

3. Take-over: the participant continues the secondary activity until the TOR alerted them after 4, 5 or 6 completed rounds of the game. The participant reacted to the TOR, stopping the execution of the secondary activity and regaining the control of the vehicle.

4. Avoid obstacle: the participant had to perform a lane change and adjust longitudinal speed, in order to avoid the obstacle on the road. After doing this they returned on the right lane.

Request to Intervene

To communicate the Request to Intervene, RtI, the system alerted the user with a sound and a visual message. The sound consists of a looped "beep" emitted through the vehicle speakers, while the visual message "TAKE OVER" was displayed on an

Figure 4.9: Simon

Interaction	Reaction Time (s)	Subjects off road	Steering turns	Turns amplitude (°)
6-DoF	2.17	9	8.5	1.26
Realistic	2.67	5	5	2.23

Table 4.2: Summary of driving-related measure of the pilot study

HUD in front of the user with a ten second countdown; as soon as the driver performed the take-over, the TOR ended and the HUD displayed the message "MANUAL".

4.5.5 Results

To evaluate the impact of the interaction interface on the driving task, data such as position and orientation of the vehicle in the lane, its longitudinal speed and steering angle were collected in real time during the experiment. Based on this data we defined the following set of variables to describe the quality of control regain recovery:

- Reaction time: time between the notification of the TOR and the actual regain of control.

- Number of steering oscillations: how many times the steering angle changes sign.

The reaction time was lower when the user interacts with the driving simulator using the 6-DoF controllers. However, since the number of steering turns is lower in the realistic condition, it appears that the subjects were able to control the vehicle in a more stable way using steering wheel and pedals. The trajectories followed by the user are shown in Figure 4.11.

These images provide a qualitative representation of the concept of stability. In fact, we can observe from the trajectories that the use of the controllers to regain control produce a higher number of lane departures (pink zone) with respect to the use of steering wheel and pedals.

After the experience, the participants filled out a questionnaire designed to assess physical realism and comfort as well as ease of use and adaptation. With respect

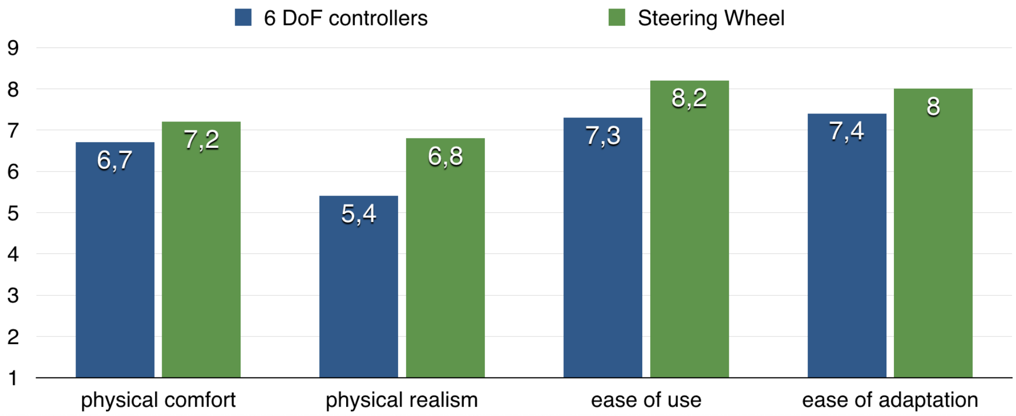


Figure 4.10: Self-reported measures

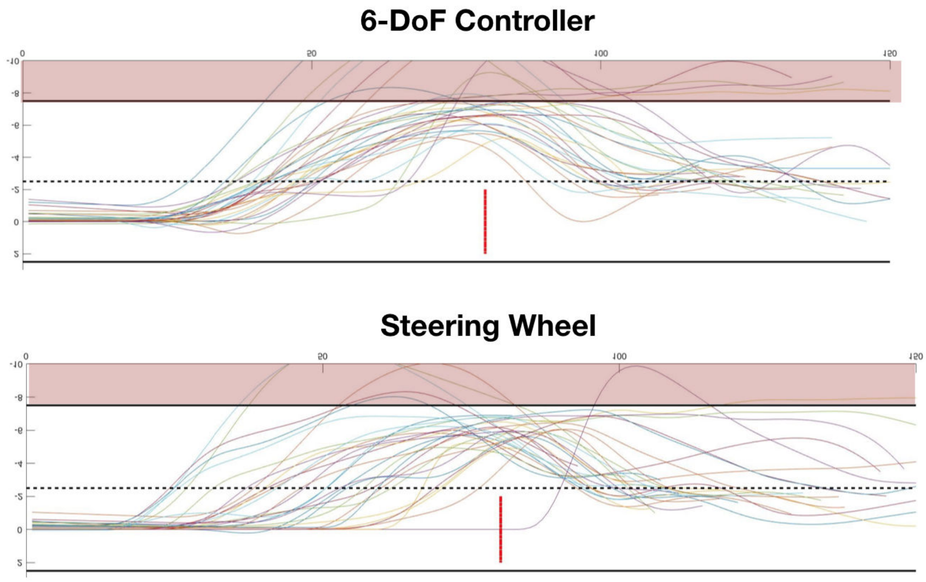


Figure 4.11: Obstacle (red line) avoidance trajectories. In light red the lane in the opposite direction

to these subjective measures, the participants expressed a preference for the realistic interface according to all the indicators. Figure 4.10 shows the results of the post-experience questionnaire. Considering the objective performance criterion, it is not possible to determine which of the two interaction modalities is the most adequate: this because even if 6-DoF controllers produced lower reaction times, the realistic interface provided better stability of control after the take-over. Also, considering the mean take-over time found by Zhang et al. [2018] ($\overline{rt} = 2.76s$), we can observe that the reaction time of the realistic interface group ($rt_{SW} = 2.67s$) is considerably closer to this value than the reaction time of the 6-DoF group ($rt_{6DoF} = 2.19s$).

Also, the indicators related to comfort and ease of use and adaptation provide us a clear preference for the realistic interface.

For these reasons, starting from the results of the pilot study we chose to implement our light VR system using the HMD and the realistic interaction interface consisting of a steering wheel and pedals.

4.6 The *Light* Virtual Reality Training System

In this section we present how starting from the development of the driving simulator and the results of the pilot study, we designed the light VR system aimed at providing the possibility to a user to discover the autonomous driving, the vehicle's functionalities and the HMI inside the vehicle without the need of the real vehicle or a test drive on real road.

Figure 4.12: The Light Virtual Reality System

4.6.1 The hardware

The hardware of the VR system included a head-mounted display as visualization device and and a steering wheel and pedals to manipulate the virtual environment.

Visualization device
The HMD chosen was an HTC Vive which provided stereoscopic vision at 90 FPS, 2160x1200 (1080x1200 per eye) resolution, a field of view of 110 degrees and low-latency positional tracking. Spatial sound was presented via headphones. The users were totally surrounded by the virtual environment, and once wearing the headset they lost the possibility to see any part of their own body. The HTC Vive was connected to a VR-Ready computer, a machine including a mid-range CPU (Intel i5) and a gaming GPU (NVIDIA GeForce GTX 1070).

Manipulation interfaces
The light VR system included the Logitech G25, a force-feedback steering wheel and pedals as driving interface. Co-localized manipulation was ensured by the use of the 3D model of the real steering wheel in the virtual car and by the overlapping of the virtual model of the steering wheel to the real one. A finger tracking device (Leap

Motion) was placed on the front face of the HMD to retrieve the relative position and orientation of the user's hands and display a graphical representation.

4.6.2 The Virtual Learning Environment

The DOAS was thus extended with a Virtual Learning Environment (VLE) whose content fulfilled the SRK requirements for training defined in Section 4.2.3. In detail, the training environment included an acclimatization environment where the *knowledge*-based information was presented, and a practice environment where *rules* and *skills* were acquired.

4.6.2.1 Acclimatization Environment

Figure 4.13: The Acclimatization Environment: The car is displayed with a transparent effect and the panel on the front wall shows the indicators for the accelerator and brake pedal and for the steering wheel.

At the beginning, the users were immersed in a reality-virtuality airlock (Figure 4.13), that we describe as an environment aimed at smoothing the transition from the real to the virtual world. As Stoner et al. [2011] propose, a gradual exposition to the environment could foster the user's adaptation to it. The purpose of this environment was twofold. First, novices of Virtual Reality and users who were using an HMD for the first time could become familiar with the new system by experiencing the effects of their actions (head rotation, head movement) on the system. Second, they could become aware of the car controls, identifying the position of the steering wheel, the pedals and the autonomous driving button. Subjects were thus asked to interact with the controls to see the results of their actions in the panel in front of them.

In this environment, an introductory video was also displayed to provide general *knowledge* about autonomous driving and the role of human driver.

Figure 4.14: The Virtual Learning Environment: (a) a post-production illustration of a participant in the VLE; (b) a view of the interior of the car with the training message (on the transparent panel placed over the steering wheel) and the virtual tablet used for the secondary activity, (c) the reduction of the field of view with the visual tunnel effect

4.6.2.2 Practice Environment

The practice environment aimed to allow drivers to acquire *rules* and *skills* by operating the car, with the help of a virtual assistant which provided step-by-step instructions.

The implementation of training was inspired by what happens in traditional car handover or what would happen in the real case: during a test drive, while a person drives, the trainer/car dealer provides information about the control or the functionalities of the car; the person then follows the instruction of the trainer to familiarize with the car.

The VLE thus provided content organized in some steps that were proposed to the users during a virtual driving session of 11 km, via both visual and auditory stimulus. The training messages were announced by the virtual assistant (whose voice was synthesized using a text-to-speech software) and displayed on a panel in front of the user; the panel appeared when the user intervention was required, and disappeared as soon as the trainee performed the required actions. No other actions were possible other than the required one. When an action was required, a visual tunnel by means of a vignette effect was added to reduce the field of view of the user and let the driver focus on the message (Figure 4.14c).

The training steps are reported in Table 4.3. These steps were presented in such a way that the user had to apply previously acquired knowledge in order to proceed: for example, the first message to activate the Automated Driving was: *"To activate the autonomous driving, push the button on the steering wheel"*. The successive times that the user was required to transfer the control to the car, the message was just: *"Activate Autonomous Driving"*. The same approach was also used for take-over requests. The first take-over request during the training was not caused by any apparent issued, and was used to explain to the driver the procedure to take-over: *"To take-over, hold the steering wheel and push a pedal"*. The successive take-over requests were notified to the user with visual and auditory alters, but without any additional information. If the user was not able to correctly take-over, the procedure was explained again.

Table 4.3: The tasks in the Virtual Learning Environment. Each action was notified to the driver with visual and auditory messages.

0 km	Manual driving
	The trainee operated the car in the manual mode to familiarize themselves with the simulator
1 km	Delegation of driving
	The trainee was required to activate the automated driving system by pushing the button on the steering wheel
2 km	Control take-over
	The trainee was required to switch back to manual mode by pushing the button on the steering wheel
2.75 km	Delegation of driving
4.25 km	Control take-over
	The trainee was required to switch back to manual mode by using the accelerator pedal and the steering wheel
5 km	Delegation of driving
5.75 km	Accelerator override
	The trainee was required to use the accelerator pedal in order to increase the speed of the vehicle without deactivate the automated driving system.
6.5 km	Steering override
	The trainee was asked to use the steering wheel to perform a lane change task without deactivate the automated driving system.
7.5 km	Take-over Request
	A 30-second TOR was issued. The trainee was assisted during the take-over phase
8.25 km	Delegation of driving
9.25 km	Take-over Request
	A 10-second TOR was issued and the trainee had to take-back without any assistance. An obstacle was placed 300 meter after. An emergency brake was performed if the trainee did not take-back in time.
10 km	Free driving
	The trainee was free to practice the delegation of driving and to take-back.
11 km	End of the training

4.6.3 Preventive measures for Simulator Sickness

Designing a mixed reality driving simulator without taking into account the occurrence of Simulator Sickness (SS), may significantly perturb the user and degrade the experience. Stoner et al. [2011] proposed good practice guidelines for SS in driving simulation. The authors separated the factors associated to SS in three categories: simulator, task and individual characteristics.

Simulator characteristics

The first separation the authors propose is represented by the type of simulator that can be chosen for driving simulation: fixed-base, motion-base or HMD-based. Adding equilibrioceptive motion cues appears to decrease SS or leave it unchanged; consequently motion-base simulators are usually preferred to fixed-base ones.

The VR system proposed in this section is HMD-based and for lightness constraints (examined in Section 3.2.4) does not include motion platforms.

One limiting factor of the use of HMD is the narrower Field of View (FoV) with respect to human vision. According to Stoner et al. [2011] wide FoV stimulates in a more severe way the peripheral visual system which produces more optic flow and vection, which, in turn, increase SS.

The HMD chosen for the VR system provides around 145 diagonal degrees when the eyes are about 10mm away from the lenses, which results in 100 horizontal degrees and about 110 vertical degrees. The importance of FoV varies according to the driving task performed in the simulator. While in the urban context and at a low speed, peripheral vision is important to detect other road users and to predict their behavior, in highway scenarios having a wide FoV is less important because most of the important elements are ahead. What instead is an important characteristic is the Field of Regard (i.e. the area that can be seen rotating the head) which in HMDs covers 4π steradian.

Therefore, the Field of View limitation in HMDs could actually represent a benefits to reduce the occurrence of SS. Moreover, in the VLE we implemented a further virtual reduction of the FoV (i.e. vignetting effect) when the user interaction was required.

Task characteristics

When designing the driving scene it is fundamental to take into account that objects that enhance the scenario from the realistic point of view (trees, buildings, static objects on the road side) actually contribute to the occurrence of SS. This is due to the fact that these objects enhance the perception of optic flow and vection giving more cues of motion to the driver [Stoner et al., 2011]. Of course, the bottom line is represented by a scene without any motion cues which does not produce SS; however this kind of environment is useless because it does not give to the user the feeling of displacement and thus driving. So it is important to find a trade-off between the presence of motion cues and the impact they have onto SS. One of the solution is to place the fixed objects far from the road side (or directly on the skybox) in order to reduce the relative motion. However, a study conducted by Ihemedu-Steinke et al. [2017b] with an HMD-based driving simulator showed that the addition of visual assets to the virtual reality driving simulator reduced the onset of simulation sickness and improved the driving session's duration. To reduce the occurrence of *visuo-vestibular incoherences* due to a motion that is seen but not perceived, another good practice when designing the driving scenario is to implement straight roads with no or few large curves rather than sharp curves. When HMD are used as display system, the authors suggest also to avoid to display the vehicle's pitch down as a driver brakes or pitch up as they accelerate: this because otherwise the horizon would move and increase the cue conflicts.

In the DAOS we implemented all these guidelines and we created driving scenarios with different complexity in terms of road type, traffic and surrounding environments.

Individual characteristics
A further guideline proposed by Stoner et al. [2011] concerns the individual difference that influences SS. Some people are just more susceptible to SS than others because of their age, health status, experience with simulators and so on. So the suggestion is to perform a screening prior to the driving session in order to identify individuals at risk. Also, it is important to consider to expose users more gradually over time to the driving simulator. This in order to foster the adaptation of the individuals to the novel environment. It has been proven that SS increases with time within a session and decreases over successive sessions [Kennedy et al., 2000]: this suggests that is better to have shorter and repeated driving sessions than fewer but longer. Also a familiarization phase, followed by the actual experimental or training driving session would satisfies both requirements of adaptation and session length. In this context, Domeyer et al. [2013] showed that participants who experienced a two-day delay between an initial acclimation to the driving simulator and the driving session experienced fewer SS symptoms than participants who did not receive a two-day delay.

To deal with individual characteristics we included as part of the training program the *acclimatization environment* and we kept the training duration as low as possible.

4.7 Concluding remarks

Now that we have presented the training system, the Driving and Onboard Activities Simulator and the implementations of the VLE, we can address the problem of assessing the level of training and the evolution of the trainees along the SRK levels.

To evaluate the effectiveness of the proposed training system, we compared it to other platforms (VR and non-VR systems). We thus conducted between-subjects user studies which included two parts: a training phase in which independent groups of participants were trained with different training systems, and an evaluation phase, in which the participants' ability to transfer the acquired skills from the training environment to the driving scenario was assessed with a test drive. During the test drive they were required to apply the skills, rules and knowledge previously acquired to operate a conditional automated vehicle in different driving situations.

Objective and self-reported measures from literature were used to evaluate trainee's ability to operate the vehicle and user's performance during transfer of control. This

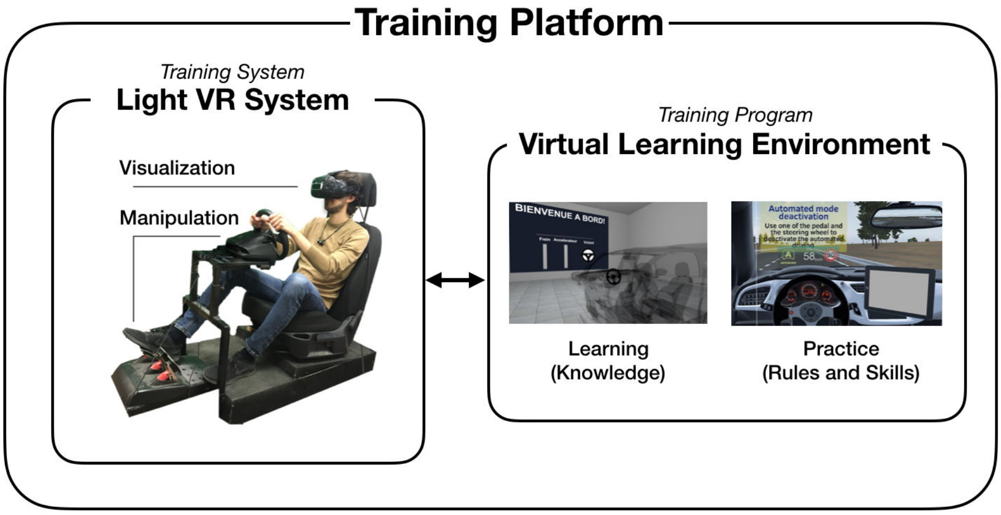


Figure 4.15: Experimental platform diagram including the Light VR system and the VLE

data, integrated with post-hoc interviews allowed us also to establish the effectiveness and the completeness of the training and eventual flaws in the training design.

In the next chapter we describe the first of these user studies, aimed at exploring the role of immersion in the process of skills acquisition for operating a conditionally automated vehicle.

Chapter 5

The role of immersion in VR-based training

> The unexamined life is not worth living
>
> Socrates

Contents

5.1 Introduction

In this first user study, we will compare the light VR system presented in the previous chapter with one of the solutions widely used in driving schools to enable future driver to practice the road scenarios: fixed-base simulators. This kind of systems differs from the Light VR system we propose in terms of visualization and manipulation aspects. The objective of this study is to evaluate if this difference plays a significant role for the acquisition of operating skills for conditionally automated vehicles.

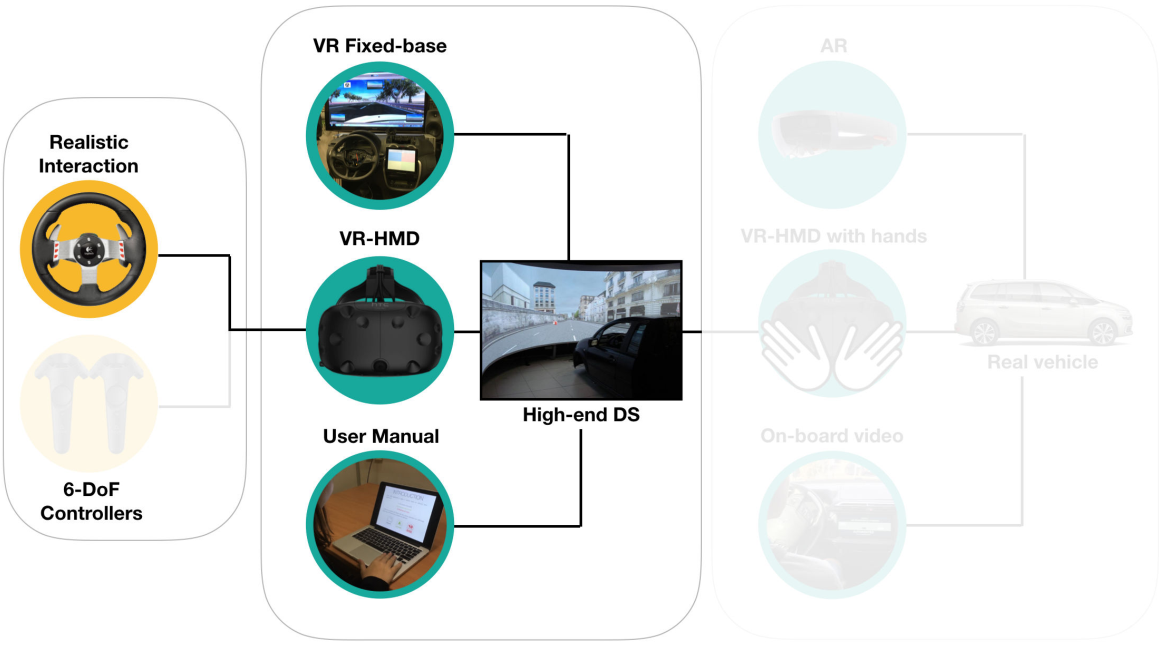


Figure 5.1: Plan of the study

5.2 Immersion characteristics of the systems

We focus our analysis of immersion to the visualization and manipulation characteristics that the systems deliver. The Fixed-base simulator and the Light VR system shared similar manipulation interfaces and had different visualization characteristics. We will analyze in details these systems.

5.2.1 Light Virtual Reality system

The Light VR (LVR) system was described in Chapter 4. It included the HTC Vive head-mounted display as visualization system and a driving seat with a Logitech G25 steering wheel and pedals as driving interface. This system was able to display in a 110 degree FOV a virtual environment in a scale of 1:1 with respect to the reality (car size, road size) and to track the position and the orientation of the user's head in order to update the point of view: this allowed the users to look around in the VE in 360 degrees (Field of Regard). However, the HMD visually isolated users from the real

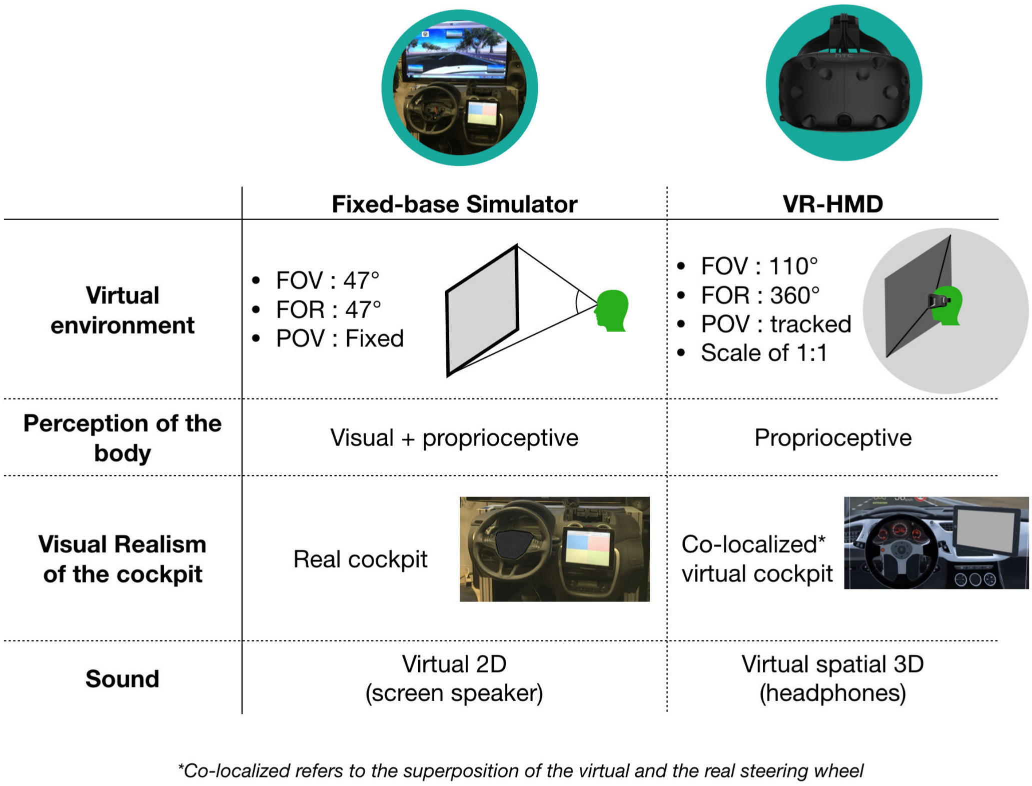


Figure 5.2: Characteristics of immersion of the fixed-base simulator and the Light VR system

world and thus prevented them to visually perceive their body. The perception of the body was thus mainly proprioceptive and not visual (i.e. visuo-manual incoherence).

Since, in this particular user study, the physical interaction with the cockpit was limited to the steering wheel and to a button on it to activate the autonomous driving, we did not include the finger tracking; however, the virtual steering wheel was co-localized with the real one.

5.2.2 Fixed-base driving simulator

The fixed-base simulator (FB) consisted of an actual car cockpit including a driving seat, a dashboard, a force-feedback steering wheel and a set of pedals (Figure 5.3b). All of these components were real components of a Citroen C3 car; this allowed participants to have a more natural interaction with the driving controls. A 9.7" tablet used by the driver to perform the secondary activity was placed in the center console.

To display the virtual environment a 65" plasma screen was positioned behind the cockpit at 1.5m from the driver. The limited size of the screen, however, did not allow the implementation a 1:1 scale between the virtual and the real world (i.e. lack of co-localization of the visualization space and visuo-spatial incoherence). Also, another implication of the reduced field of view was the lack of isolation for the participant who was surrounded by the experimental room during the training.

5.3 Experimental design

This study contained two parts: training and test drive. The aim of the training was to introduce the principles of the Level 3 Automated Driving System (ADS)-equipped vehicle, present the novel Human-Machine Interface (HMI), help the drivers to localize the HMI in the vehicle, and describe the actions to perform in order to appropriately respond to unplanned requests to intervene. A between-subject study with 60 participants was designed in order to compare a light Virtual Reality system to a user manual and a fixed-base driving simulator in terms of training effectiveness evaluated through a test drive. The test drive required the application of knowledge, rules, skills acquired during the training.

5.3.1 Training

The Virtual Learning Environment (described in Section 4.5.2) was implemented in the Fixed-base simulator as well: thus the FB and the LVR provided exactly the same training content. To compare the effectiveness of the two systems, we implemented the training program also in a more traditional medium, namely a User Manual displayed on a laptop, used as control group.

Thus, in total three different training systems were compared in this study (Figure 5.3):

- a User Manual (UM) displayed on a laptop;
- a Fixed-Base driving simulator (FB) with real cockpit and controls (pedals and steering wheel);
- a Light Virtual Reality (LVR) system consisting of a Head-mounted display (HMD) and a game racing wheel.

a b c

Figure 5.3: The three training systems: (a) the user manual displayed on the laptop computer, (b) the fixed-base driving simulator, (c) the light VR system

User manual training

The user manual (UM) consisted of a slide presentation displayed on a 13.3” screen of a laptop computer (Figure 5.3a). First, the introduction video was played. Then, the participants were asked to carefully read each of the 8 slides and to go to the next one when they felt ready. They did not have any time limit. The slides used text and images to present the actions to be performed during the manual driving, the automated driving and the take-over requests. For each situation the correspondent icons were also presented. An animated slide was included to show how to activate the automated driving.

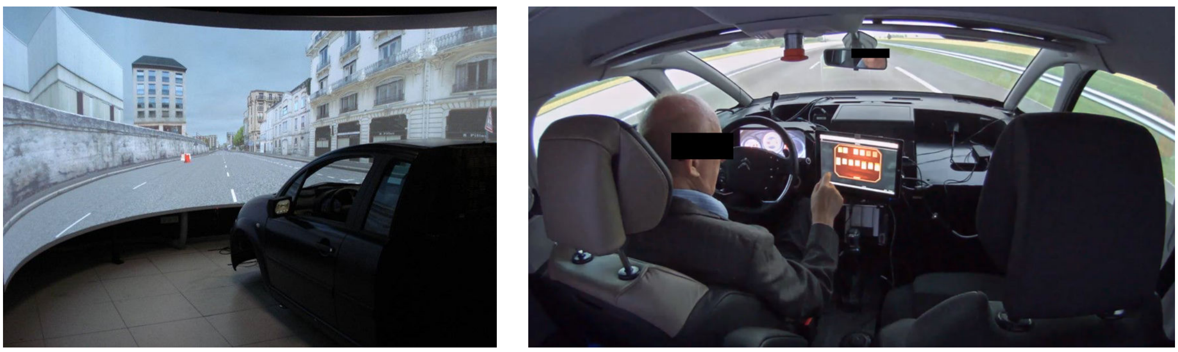
This system represented the non-immersive and non-interactive training environment. The participants could only browse the slides with no time limit; they were not involved in a driving situation and they could not practice the action required with the real equipment.

Since in the user manual the sensori-motor dimension of training was missing, with respect to the SRK requirements defined in Section 4.2.3, this method did not include the acquisition of skills through practice.

Non-Driving Related Task

Fixed-base and LVR training also included a secondary activity that required the use of a tablet (a real one in the case of the fixed-base simulator, a virtual one in the case of LVR system). The tablet was used to distract the human driver from the driving task during the automated driving. The distraction task was the same for all the participants and consisted of a video of a TEDx Talk in French [Peperkamp, 2016]. The participants were asked, but not forced, to look at the tablet; they were also told that, after the training, they would have answered some question about the video. The video was automatically played when the automated system was enabled and paused during the manual driving and the take-over requests.

5.3.2 The test drive



a b

Figure 5.4: The test drive simulator: (a) the real cabin with the 170 degree panoramic display and (b) a view of the cabin interior

After the training, the participant performed a test drive designed to evaluate their performance in a more realistic driving scenario. The system used for this purpose was a high-end driving simulator consisting of the front part of a real car surrounded by a panoramic display (Figure 5.4). The display was placed 2.5m from the driver and covered a field of view of 170 degrees. Three three-chip DLP projectors displayed the scene. The rear part of the car was substituted with a monitor that displayed the virtual environment from the rear window. The lateral mirrors consisted of two LCD displays as well. The cockpit was also equipped with a microphone to communicate with the experimenter and 4 cameras to record the scene inside the car. Data including position, speed and acceleration of the car, and current driving mode were recorded.

Inside the car, a 10.8 inch tablet was placed in the center console. It provided 9 different secondary activities: 3 games (a solitaire, 2048, Simon) and 6 videos (3 talks, 2 movies and 1 movie trailer). The tablet was only available during autonomous driving and it displayed the message "Take back control" during the requests to intervene.

Before starting the test, participants were instructed about the use of the equipment inside the car and were shown the button to activate/deactivate the automated driving system.

5.3.2.1 Driving scenario

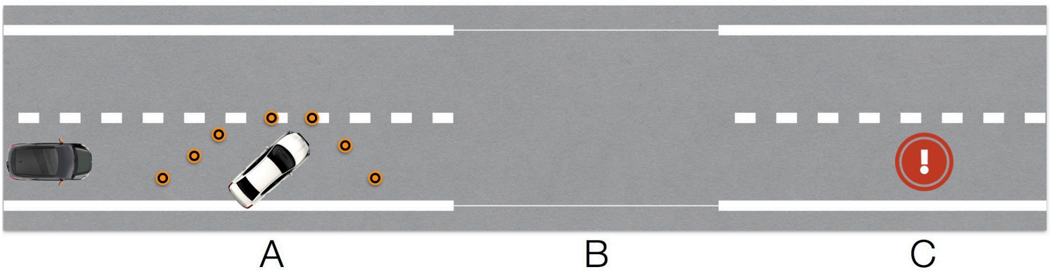


Figure 5.5: The test drive scenario with the three situations that provoked the TORs: (A) stationary car on the lane, (B) loss of ground marking, (C) sensor failure

The driving scenario of the test drive represented a dual carriageway with two lanes in each direction. Dense traffic was added to both directions. The aim of the test drive was to investigate the skills acquired by the participants during the training and their reaction when a take-over request was issued. We focused in particular on non-scheduled TORs and non-scheduled system initiated emergency TORs. For this purpose, 3 requests to intervene Figure 5.5 were issued during the test drive:

(A) a *10-second TOR* caused by a road narrowing provoked by a stationary car on the right lane; this situation (*Obstacle*) required the driver to brake and to change lane in order to avoid the obstacle.

(B) a *10-second TOR* caused by a loss of road marking (*Road Marking*); this situation required the driver to hold the vehicle inside the lane.

(C) a *5-second TOR* caused by a sensor failure (*Failure*); this situation did not require any specific actions from the driver, but just to take-over.

To control order effects, the arrival order of TOR A and TOR B was randomized. TOR C was always issued as the last one in order. The test drive lasted for about

TOR	Urgency	Predictability	Criticality	Drivers' Response
A	10 sec	Low	High	Complex
B	10 sec	Low	Medium	Simple
C	5 sec	Low	Low	Simple

Table 5.1: Take-Over Requests according to the taxonomy proposed by Gold et al. [2017]

20 minutes time during which the participants drove for 24 km. After a first phase of manual driving (4km) to familiarize drivers with the simulator, the three TORs were issued after an autonomous driving phase, at 11.5 km, 19km and 23km. During the autonomous driving, participants were asked to engage in one of the secondary activities proposed by the tablet.

5.3.3 Measures

Defining the quality of take-over is not an easy exercise, because assessing the ability to drive or to operate an automated vehicle requires the evaluation of various aspects related or not to the actual driving task. In literature there exists a set of well-known parameters which can be used to evaluate performance in driving scenarios like the once used in the test-drive. To evaluate the training systems and the learning environment, objective and self-reported measures were collected and treated anonymously.

5.3.3.1 Self-reported measures

In total 6 different questionnaires were proposed to the participants. A demographic questionnaire (containing also questions about driving habits, familiarity with Virtual Reality and previous experiences with driving simulators) (Q_A) was administered at the begininning of the study along with a survey about opinion concerning automated cars (Q_B). To evaluate the appreciation of the training, participants were asked to answer to 10 questions survey (Q_C) and to evaluate graphical and physical realism of the Virtual Environment (only for FB and LVR groups) (Q_D). After the training, the Simulator Sickness Questionnaire (Q_E) Kennedy et al. [1993] was administered to the LVR group. After the test-drive, all the groups answered to a final questionnaire (Q_F) and for a second time to Q_B.

5.3.3.2 Objective measures

To evaluate the take over quality and the state of the driver during the autonomous phase, objective measures were used as performance factors in the test drive with the high-end simulator. According to the take over situation, both raw data from the simulator (such as position and speed of the car, current driving mode, etc.) and video feeds were used to assess the following variables:

Table 5.2: Demographic features distributed across the different systems

System	**Gender** (F/M)	**Age** y (SD)	**Age Group**	**Car with Cruise Control?** Yes (no use) / No	**First time in a driving simulator** (Y/N)
UM	11/9	45 (12.9)	5/9/6	11(2) / 8	16/3
FB	10/10	46.9 (15.5)	7/6/7	16(4) / 4	16/4
LVR	9/11	43.5 (13.9)	6/8/6	11(1) / 9	14/6
Total	30/30	45.1 (14)	18/23/19	38(7) / 21	46/13

- Reaction time (measured in seconds), the elapsed time from TOR until the driver takes back control.
- Maximum deviation from the lane center (measured in meters), within an interval of 30s after the take-over request.
- Time To Collision (measured in seconds), "the time required for two vehicles to collide if they continue at their present speed and on the same path" Hayward [1972]. This measure was used to evaluate the evasive maneuver to avoid the stationary car.
- Stress and confidence in the vehicle, during the automated driving phases.

5.3.4 Procedures

Sixty subjects participated in the experiment. All of them had normal or corrected-to-normal vision, except for a participant in the LVR group affected by monocular impairment. The participants included 30 females (50%) and 30 males (50%) aged between 22 and 71 (M = 43, SD = 14). Three groups of age were identified: the first group contained participants aged between 22 and 34 years old (7 males, 11 females); the second group participants aged between 35 and 54 (14 males, 9 females); the third group participants older than 55 (9 males, 10 females). They were randomly assigned to one of the system in which they would be trained. The three groups contained 20 subjects each. All the subjects were volunteers recruited by a company specialized in hiring consumer tests participants and had a valid driving license. At the end of the experiment, each participant was rewarded with a 40 euros voucher. The duration of the full experiment was about 60 minutes for each participant. Participants were divided into three groups of 20. Each group underwent training with one of the systems described above. The study consisted of the following phases:

1. *Introduction (10 minutes)*
   The participants were welcomed and informed in detail about the purpose of the study. They signed the consent form.
2. *First questionnaire (5 minutes)*
   The participants completed questionnaires Q_A and Q_B.
3. *Training (15 minutes)*
   The training contained two parts: the introductory video (2 minutes) and the

actual training (slides for the user manual group, and the Virtual Learning Environment for the fixed-base and light VR system). The training for the user manual group generally lasted for less time with respect to the LVE one.

4. *Second questionnaire (5 minutes)*
   The participants filled out questionnaire Q_C. Participants of the VLE group filled out questionnaire Q_D. Participant of the LVR group filled out also the questionnaire Q_E.

5. *Test Drive (20 minutes)*
   The participants performed the test drive in the high-end simulator.

6. *Third questionnaire (5 minutes)*
   The participants completed questionnaires Q_F and Q_B.

5.4 Results

All the participants completed the experiment. Self-report and performance variables were tested for group differences using ANOVAs (and Tukey's HSD test for pairwise comparison) for continuous normally distributed data and Kruskal-Wallis (and Fisher's LSD for pairwise comparison) test for ordinal, categorical and non-normally distributed data. Paired t-test was used for PrePost questionnaires. The significance level of 5% was chosen for all the tests.

5.4.1 Self-report measures

Self-reported measures were collected through a set of questions at the beginning of the test, after the training and after the test drive. The measures of user appreciation and simulator sickness were tested for group differences using Kruskal-Wallis test. In case of significant differences among the three groups ($p < 0.05$), the Fisher's LSD test was used to identify which pairs of means were significantly different, and which were not. The measure of confidence on automated vehicles was tested using a paired t-test.

5.4.1.1 Appreciation of the training

To evaluate the appreciation of the training the participants filled out a 10-question survey containing questions about perceived usefulness, easiness, pleasantness, realism and so on. The Likert results are reported in Figure 5.6. The LVR scored better in all the questions, and in 4 of them the difference was significant. Moreover, to have a general score, all the questions were summed up. Up to a total of 50 points (the highest the better), results showed that the LVR scored significantly better (M = 43) than both the fixed-base simulator (M = 40, $p < 0.05$) and the user manual (M = 39.5, $p < 0.05$). The results of the survey about realism and comfort are reported in Figure 5.7.

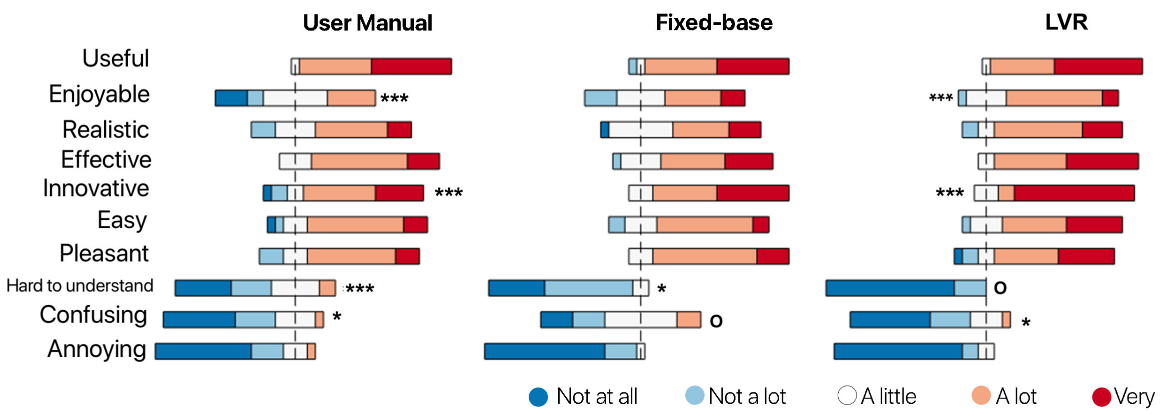


Figure 5.6: Likert responses to the questionnaire of training appreciation.

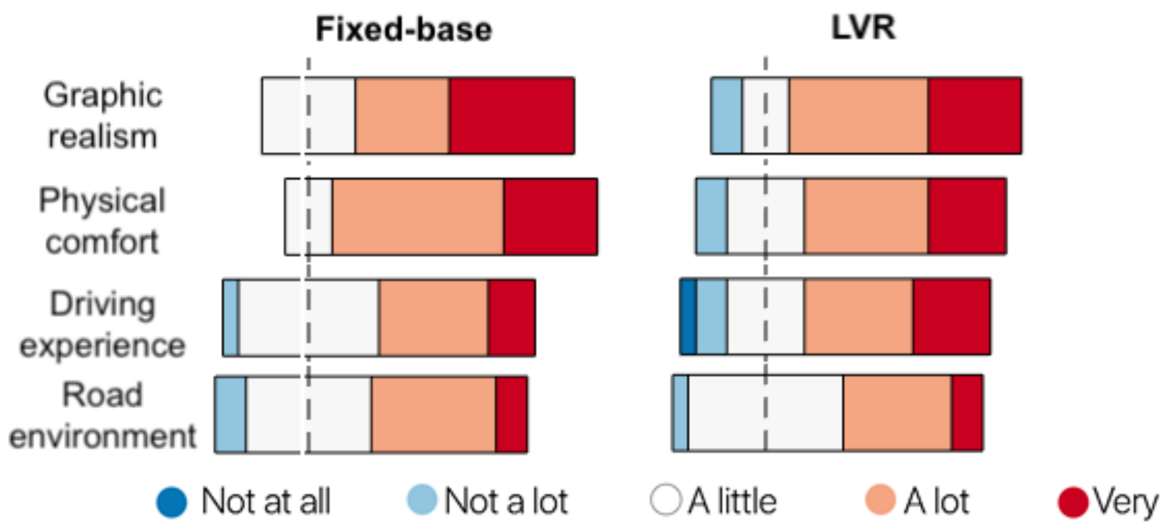


Figure 5.7: Likert responses to the realism survey for FB and LVR groups

5.4.1.2 Simulator Sickness Questionnaire (SSQ)

The SSQ was filled out only by the participants who performed the training with the LVR. The Total Score (TS) and the subscales relative to Nausea, Oculomotor and Discomfort symptoms were calculated according to the formulas described by Kennedy et. al Kennedy et al. [1993]. Results are reported in Table 5.3 and Figure 5.8. According to the categorization of SSQ proposed by Kennedy et. al. Kennedy et al. [2003], 50% of the subjects reported no symptoms (TS = 0) or minimal symptoms (TS < 10). The highest scores were reported by a participant affected by monocular vision impairment (TS = 71) and a participant affected by kinetosis also in traditional vehicles (TS = 97.24). However, they as well as all the other participants were able to complete the training (no dropouts occurred). There were no significant differences with respect to participants' age or gender. Analyzing the subscales, the Disorientation subscale (with symptoms related to vestibular disturbances such as dizziness and vertigo) registered the highest scores. This result was expected and is mainly due to the nature of the HMD, which causes conflicts between the vestibular and the visual signal.

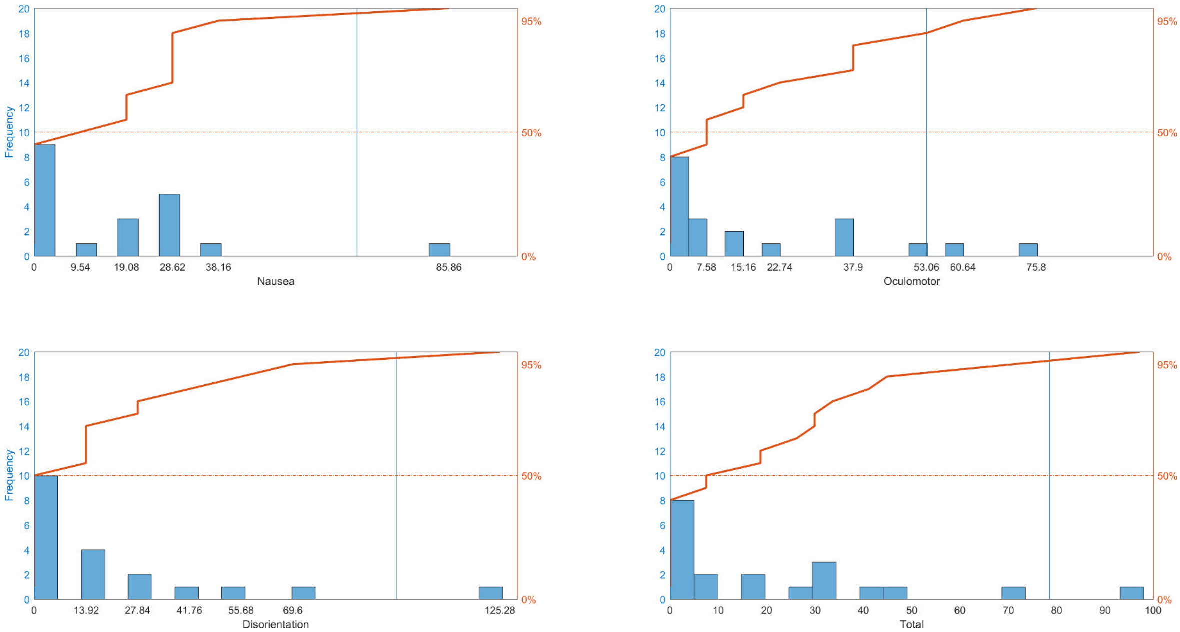


Figure 5.8: Results of SSQ scores (Nausea, Oculomotor, Disorientation subscales and Total) for the LVR group. In orange, the percentile graph. The vertical blue lines represent the value of SSQ if all the symptoms were reported as "slight" on that subscale.

Table 5.3: Results of the Simulator Sickness Questionnaire.

	Mean	**Median**	**SD**	**Min**	**Max**
[N]ausea	16.7	14.31	21.19	0	85.7
[O]culomotor	18.95	7.58	21.52	0	75.8
[D]isorientation	20.18	6.96	32.09	0	125.28
Total Score [TS]	21.32	13.09	26.7	0	97.24

5.4.1.3 Opinion on automated vehicles (Q_B)

At the beginning of the test, participants were asked to give a score from 1 to 5 to a set of 8 sentences to express their opinions on automated vehicles.

1. I think that a semi-autonomous car will be useful in my everyday life
2. I think that a semi-autonomous car will be useful for the society, from the point of view of the road safety
3. I think that a semi-autonomous car will be useful for the society, from the environmental point of view
4. I think that the semi-autonomous car can make my travels more enjoyable
5. The semi-autonomous car can reduce the risk of accidents
6. I think I would feel safe in a semi-autonomous car
7. I see myself doing other tasks than driving in a semi-autonomous car
8. In the current state of my knowledge, I have confidence in the decisions that the semi-autonomous car would take in my place

After the test drive, they reply to the same questionnaire for the second time. The questionnaire contained sentences about confidence in the actions performed by the automated system, perceived security, usefulness in the society and so on. The Wilcoxon Rank Sum Test was performed to compare the answers to the pre and the post questionnaires.

Results are reported in Figure 5.9 and they show a general increase of the post-questionnaire score. It is very interesting to point out that the sentence n. 5 is the only one for which the post-score was lower than the pre-score in all the system (*"I think that the semi-autonomous car can reduce the risk of accident."*). Nevertheless, the difference for this question was not statistically significant.
Important increases in the post-questionnaire score can be observer in particular for the sentences 7 (*"I see myself doing other tasks than driving in a semi-autonomous car"*) and 8 (*"I have confidence in the decisions that the semi-autonomous car would take at my place"*). The positive difference for n. 7 was significant ($p < 0.01$) only for the LVR group; for n. 8 it was significant ($p < 0.05$) for all the three groups.

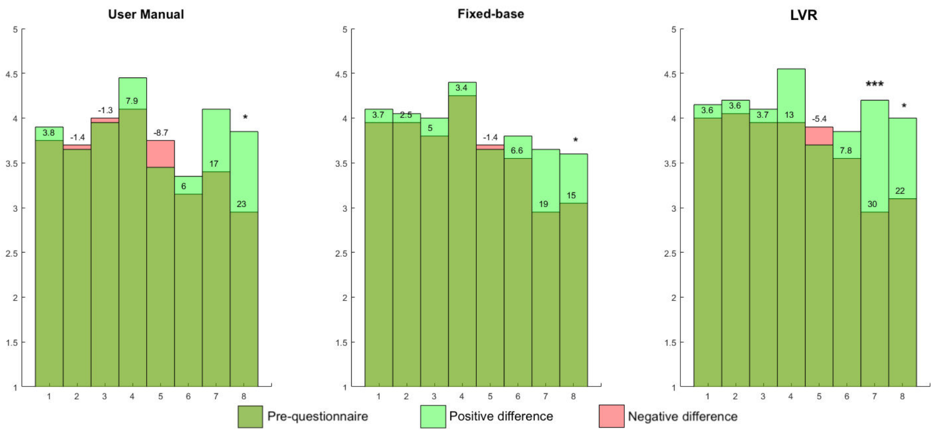


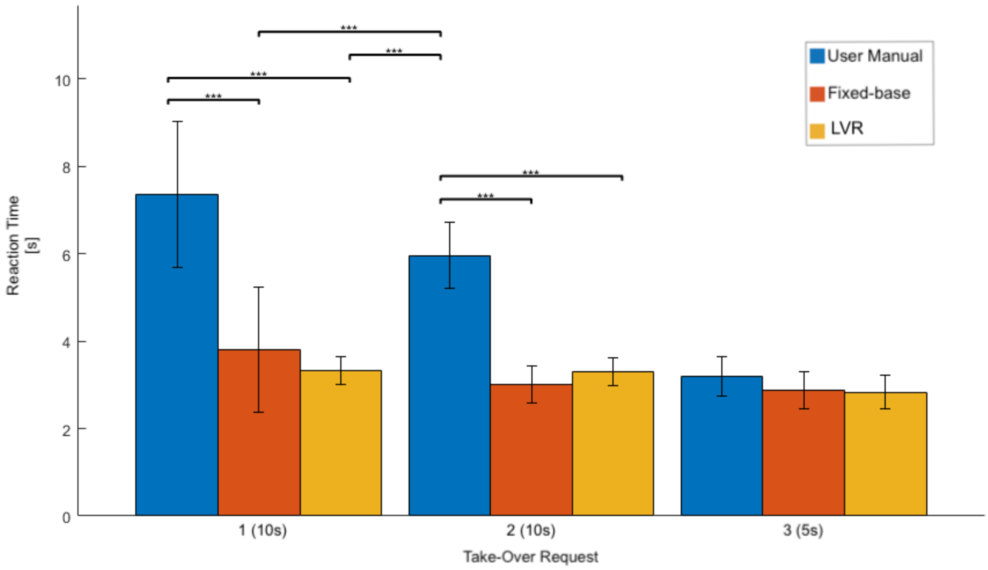
Figure 5.9: Mean of the answer to the pre-post questionnaires. A light-green bar indicates an increase in the post questionnaire for the given question. The values indicate the percentage of change in the questions.

5.4.2 Performance measures

The performance measures evaluated the quality of the take-over in terms of reaction time, maximum deviation from the lane center, and the trajectory during an evasive maneuver. These variables were tested for group difference using ANOVA (for normally distributed data) or Kruskal-Wallis (for non-normal distributed data); in case of significant differences ($p < 0.05$) each pair was tested with the Tukey's HSD test (after ANOVA) or Fisher's LSD test (after Kruskal-Wallis test).

5.4.2.1 Reaction time

Three TORs were issued during the test drive after an automated driving phase. In Figure 5.10 the mean of the reaction time per TOR for each system is reported. For the first and the second TOR, the participants trained with the LVR and the FB simulator reacted faster with respect to the ones trained with the user manual. Moreover, the reaction time of the second TOR of the User Manual group was significantly higher than the reaction time of the first TOR of the two other groups. No difference was observed for the third TOR between the three groups. The order of arrival of the three TORs did not impact the reaction time ($p = 0.51$).



(a) Mean and 95% Confidence Interval of reaction times for each Take-Over Request.

TOR	UM	FB	LVR	
1	7.36 (3.55)[a]	3.80 (1.61)[b]	3.34 (0.95)[b]	$p < .01$
2	5.97 (3.06)[a]	3.01 (0.92)[b]	3.275 (0.89)[b]	$p < .01$
3	3.20 (0.67)	2.87 (0.71)	2.84 (0.83)	$p = .17$
$\overline{1,2}$	6.66 (3.34)[a]	3.41 (1.37)[b]	3.32 (0.91)[b]	$p < .01$

(superscripts indicate significance groups)

(b) Mean and Standard Deviation

Figure 5.10: Take-over reaction times for each systems and for each TOR. The first two were 10-second TORs; the last one was a 5-second TOR.

5.4.2.2 Deviation from lane center

Considering the TOR caused by loss of road marking, the stability of the trajectory was evaluated. Performing lane change in situation in which is not required is usually considered a low-quality take over Braunagel et al. [2017]. In the driving scenario, given that the width of the lane was 3m and the width of the car was 2m, the maximum possible distance from the lane center beyond which the car does not cross the separation line is $d = 0.75m$. For each participant, the *maximum deviation from the lane center* in the 10 seconds after the TOR was calculated. The value was kept with the

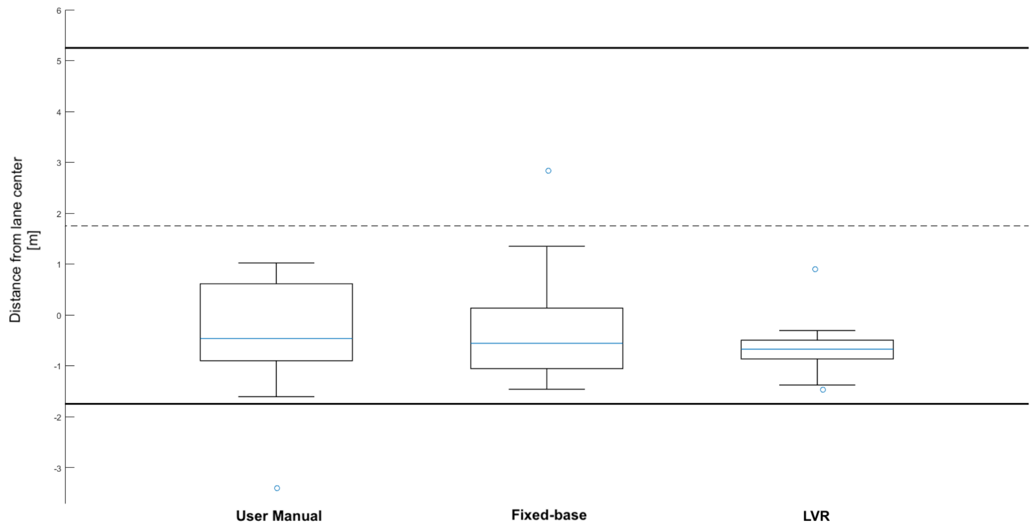


Figure 5.11: Box plot of deviation from lane center for each system. The two lanes are plotted. The value 0 in the y-axis represents the center of the right lane in the driving scenario.

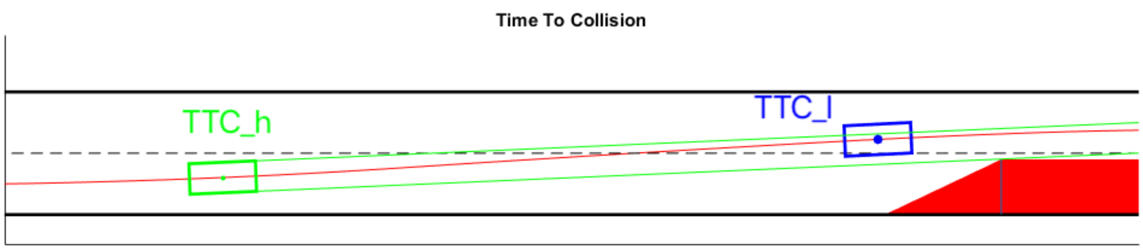


Figure 5.12: Time To Collision Happee et al. [2017]: the red block represents the stationary obstacle; the red line is the trajectory of the vehicle; in green, the position of the car when the TTC_h is calculated; in blue, the position of the car when the TTC_l is calculated.

sign (from $-1.75m$ to $+1.75m$). The difference between this value and the maximum deviation was evaluated. Results are reported in Figure 5.11. It can be observed that even though the medians are not significantly different, the LVR group has a lower standard deviation ($\sigma_{\text{LVR}} = 0.48$) than the UM ($\sigma_{\text{UM}} = 1.05$) and the FB ($\sigma_{\text{FB}} = 1.03$) group.

5.4.2.3 Time To Collision

One of the TOR was issued because of a stationary car on the right lane. The task of the trainee was to take over and avoid the car. The quality of the maneuver was evaluated with the Time To Collision (TTC) Figure 5.12 in the same way described by Happee et al. Happee et al. [2017]. The TTC was computed using the following formula $TTC = \frac{dx}{v}$, where dx was the distance of the car from the obstacle and v was the speed of the car at that moment. Two TTC were evaluated: TTC_h was computed when the heading of the car no longer intersected the obstacle; TTC_l was computed when the full vehicle front was in the new lane. The results are shown in table Table 5.4 and no significant differences were observed among the three groups.

Table 5.4: Means (and standard deviation) of Time To Collision (TTC) and Distance To Collision (DTC) used to evaluate the evasive maneuver

	UM	**FB**	**LVR**	
DTC_h [m]	54.21 (35.61)	58.45 (49.63)	67.5 (62.72)	$p = .70$
DTC_l [m]	18.64 (19.12)	33.35 (78.17)	23.8 (41.61)	$p = .67$
TTC_h [s]	4.01 (2.89)	3.87 (2.59)	3.43 (2.10)	$p = .77$
TTC_l [s]	1.27 (1.13)	1.09 (1.69)	1.25 (1.86)	$p = .93$

Table 5.5: Number of gaze switch between the secondary activity and the road environment for each autonomous driving phase; Eyes-on-Road is the ratio between the total amount of time spent looking at the road and the duration of the autonomous driving phase

	UM	**FB**	**LVR**
N. of gaze	17.9 | 16 | 5	26.6 | 22.9 | 5.6	18 | 18.9 | 6.5
Eyes-on-Road	0.25 | 0.32 | 0.16	0.21 | 0.33 | 0.15	0.22 | 0.25 | 0.16

5.4.3 Stress and confidence during autonomous driving

To evaluate drivers stress and confidence in the vehicle during automated driving, the video feed recorded during the test drive was analyzed and annotated with a video-labeling tool that was specifically developed for this purpose.

During the automated driving phase drivers were free to engage in non-driving related activities by using the tablet in the car. Before the beginning of the test-drive, participants were instructed in using the tablet to switch between active (games) or passive activities (videos, movies).

A score was attributed to each participant during the three autonomous phases (i.e. the time period preceding each TOR). The score ranged from 1 to 5 (the higher the better), where 1 corresponded to *"Complete monitoring of the driving environment"* and 5 corresponded to *"Complete focus on the non-driving activity"*. The score of 3 was assigned to drivers who occasionally monitored the driving environment.

To attribute this score several aspects were taken into consideration, such as the rate of gaze switch between the driving environment and the tablet and the length of the gazes, the insistence to talk to the experimenter, the position of the driver on the seat, the position of the hands. In Table 5.5 are reported the number of gaze switch and the ratio between the total amount of time spent looking at the road and the duration of each automated driving phase.

Results are reported in Figure 5.13 and they show that the group trained with the User Manual scored less in the first autonomous phase with respect to the others. Considering that those participants were experiencing autonomous driving for the first time, this behaviour is expected. It can be observed that the score for the UM group increases in the second autonomous phase, while for the FB and HMD groups the behaviour is almost the same. In the third and last phase the score for all the groups increases.

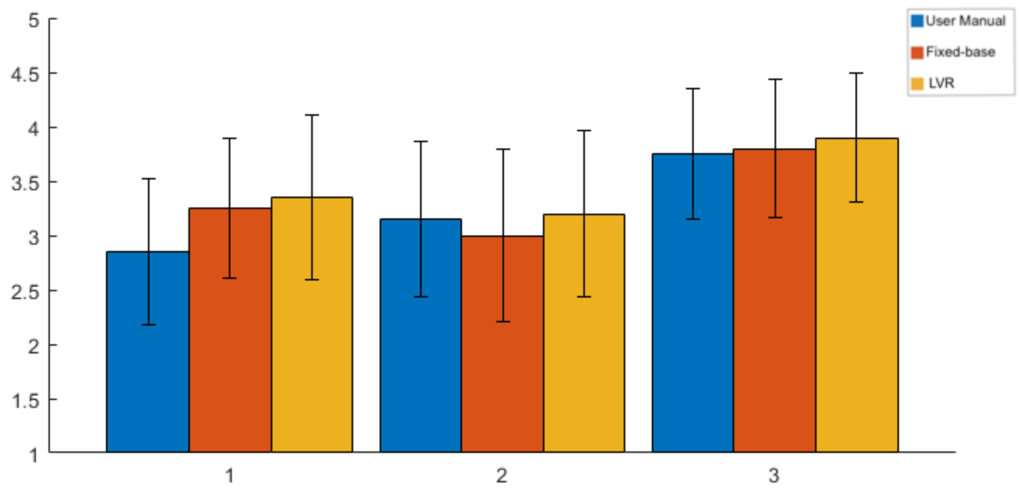


Figure 5.13: Means and 95% Confidence Interval of the stress and confidence score attributed to the participants during the 3 autonomous driving phases.

5.5 Discussion

A first outcome of the study is that whatever the training system, all the participants responded to the Take-Over Requests before the expiration of the time buffer. In summary, according to the objective metrics measured during the test drive, it is possible to identify two groups of participants that significantly differed for the reaction time. The group of participants trained with the Virtual Learning Environment (FB and LVR) were able to respond to the take-over request faster than the group of participants trained with the user manual. After the take-over, the training system did not significantly influence the driving performance in the lane keeping task and in the evasive maneuver. Furthermore, self-reported measures showed that users preferred the LVR training system. There are no variables (self-reported nor objective) for which the LVR system scored significantly worse than the other training systems.

5.5.1 Self-reported measures

Self-report measures showed statistically significant results. In particular, significant differences were observed in the answers to the training appreciation questionnaire in which participants evaluated, among other characteristics, its usefulness, ease of understanding and pleasantness. In this questionnaire the LVR system scored significantly better than the fixed-base simulator and user manual training. Analyzing each questions of the survey, we found that the participants considered the FB training more confusing than the LVR even though the training program was exactly the same. Another interesting outcome is that the LVR-based training was considered easier to understand than the other systems. Although it is possible that these results can be attributed to the perceived novelty and "fun" of VR, participants' previous experiences with driving simulators ($p = 0.41$) and their knowledge of the concept of Virtual Reality ($p = 0.25$) did not significantly impact the answers. A hypothesis to explain these results is that the technical characteristics exclusive to the LVR system, such as the large field of view, the head tracking, the 1:1 scale between the real and the virtual world, affected the learning experience. A second hypothesis is that since the participants of the LVR group were isolated from the real world, both visually and acoustically, they could better focus on the training.

There were no significant differences ($p = .66$) in the answers of the questionnaire D concerning the graphic realism and the physical realism of the simulator. This result suggests that even if with the LVR the participants interacted with a racing wheel instead of the real steering wheel this factors did not play a significant role. Some of the participants were surprised to not see their hands in the virtual environment, but the co-localized steering wheel and the fact that the autonomous driving button was placed on it limited the occurrence of incoherences. However, to enable the interaction with other parts of the cockpit besides the steering wheel (such as the central console, or a table) the visualization of the user's tracked hand is considered necessary.

Analyzing the single questions of the pre-post questionnaire about automated cars, it is important to point out that for all the questions but one, the post-questionnaire score was higher than the pre-questionnaire among all the three groups. The questionnaire aimed at evaluating the confidence on automated cars in terms of usefulness, perceived security, willingness to perform secondary tasks and so on. While at the end of the study participants trusted more the actions of the automated system than the beginning, they did not confirm their expectations that the conditionally automated car could reduce the risk of accidents. The hypothesis is that people tended to *idealize* the autonomous car as a perfect entity, but then their perception was influenced by the driving scenario. In fact, during the test drive the automated driving system prompted three non-planned take-over requests in a short time. This could let the participants think that this kind of TORs were more frequent than they actually are. Furthermore one of the TOR was caused by a critical situation (stationary car). This result suggests that the driving scenario should also present planned take-over requests with longer time buffers and no critical situation. The participants were also asked to self-evaluate on a 1-5 likert scale their readiness to drive an automated vehicle after the training and after the test drive. The answer after the test drive was higher among all the systems, but the difference (+10%) was significant only for the user manual group.

5.5.2 Simulator Sickness

The SS was evaluated only for the participants in the LVR group. The aim of the SSQ was not to compare the LVR and the FB groups since previous studies in literature already proved that HMDs usually produce more simulator sickness than fixed base simulators Aykent et al. [2014]; Weidner et al. [2017]. Instead, the experimental protocol included the SSQ Kennedy et al. [1993] with the objective of investigating if the use of an HMD would prevent participants from being trained in an effective way and analyzing the causes of sickness in case of dropouts. A first promising outcome is that no dropouts occurred; this result is very important in particular because 70% of participants in the LVR group used a Virtual Reality headset for the first time. Furthermore, the HMD produced no or minimal symptoms of simulator sickness in 50% of the cases. These results agree with Kennedy et. al Kennedy et al. [1993] who showed that in their survey "the 0-value (the zero point) contained at least 40%, and as much as 75%, of the observations". Although this study was not focused on the reduction of simulator sickness, we adopted some well-known strategies Stoner et al. [2011] on both the Virtual Environment (such as straight road, simple environment and low peripheral optical flow) and the physical system (positional coherence of the virtual and the real steering wheel) to limit the manifestation of oculo-vestibular conflicts. Thanks to these choices, the SSQ results (mean score $\overline{TS} = 21.32$ and the absence of dropouts), are comparable, or even lower, than the score found in recent studies about simulation sickness related to virtual reality driving simulation [Ihemedu-Steinke et al., 2017b; Weidner et al., 2017]. However, further studies focused on this issue are needed to validate this result and to improve the training experience.

5.5.3 Objective and performance measures

In the test drive, data in the high-end simulator were recorded to assess the take-over quality and the driver's behaviors during the automated driving. The take-over quality was evaluated according to the reaction time, the maximum lateral position on the lane, and the time to collision during the evasive maneuver to avoid the stationary car on the lane.

Concerning the reaction time in the two 10-second TORs, the participants in the FB and LVR group reacted faster than the UM group. No differences were observed between the FB and the LVR groups. For the 5-second TOR the difference was not significant among any of the groups. This result suggests that participants who actually performed a take-over during the training were able to respond better to the first request to intervene in a realistic situation. Furthermore, we hypothesize that the decrease of reaction time for the 5-second TOR is due to (i) a learning effect and (ii) the results of Gold et al. Gold et al. [2013] who showed that the reaction time depends on the time budget given for the take-over request. With respect to the TOR caused by the stationary car on the right lane, not all participants were able to perform a safe evasive maneuver to avoid the obstacle. However, no significant differences were observed between the three groups as far as the time to collision is concerned. According to the age group, no significant differences were observed regarding the reaction time nor the maximum lateral position; this result is in agreement with Korber et al. Körber et al. [2016] who found that older drivers handle critical traffic events and adapt to the experience of take-over situations as well as younger drivers. Finally, considering the TOR caused by loss of road marking, the stability of the trajectory in the 30 seconds after the TOR was evaluated and no significant differences between the groups were observed comparing the maximum lateral distance from the center of the lane.

5.5.4 About learning-by-driving

An observation that we made was that the participants trained with the VLE (FB and LVR groups) did not experience the training as an actual training program, but more like a session of automated driving simulator. Let us recall that the aim of the VLE was (i) to inform drivers about the characteristics of the automated driving system, (ii) help them in identifying and localize the HMI in the car and (iii) teach the appropriate response (activation and deactivation of the automated driving system) to a given stimulus. For the last two objectives, a virtual vocal assistant provided instructions to the participants; while instructions relative to the take-over were provided to the subjects during the secondary activity, those relative to the activation of the automated driving systems were given to them while they were performing the driving task; in other words, participants were asked to aim attention at the training instructions while they were already focusing on a high-demand cognitive activity. However, the driving scenario during the training was kept as simple as possible (no traffic, straight lane) in order to limit driver interventions. Although this hypothesis, all the trainees were able to assimilate the procedural skills. Thus, a separation of the learning environment (in which the knowledge and the skills are acquired) from the driving environment (in which the skills are applied) should be considered in future work.

5.6 Concluding remarks

The aim of this study was to investigate the role of the immersion, by means of three different systems, for the training of conditionally automated vehicle drivers: a light Virtual Reality system based on HMD was compared to a fixed-base simulator and a user manual to evaluate the usefulness of the system and to assess the effectiveness of the training; a test drive in a high-end driving simulator was performed by the participants after the training. To the best of our knowledge, this study represents the first attempt of use of HMD-based Virtual Reality for training purposes in automated vehicles.

Between the light VR system and the Fixed-base simulator we did not find any significant difference in terms of objective measures. Among the two groups, reaction times in the test drive were similar in all the three TORs and driving-related measures did not highlight any significant variations. This suggests that the characteristics of immersion we considered (i.e. FOV, FOR, perception of the body, 1:1 scale) did not play a significant role in the acquisition of skills during the training phase. However, a significant difference for what concerns the take-over time was observed between the groups trained with the Virtual Learning Environment (Light VR and Fixed-base) and the user manual group: the practice in the driving environment by means of the step-by-step tutorial impacted on the performance and provided faster reaction time in the test drive for the first and second take-over requests. Thus, in this case the ability to interact with the virtual environment played a crucial role because it enabled the possibility for the users to experience take-over scenarios during the training phase.

In addition, in terms of self-reported measures, among all the training systems, participants preferred the light VR system for the usefulness, ease of use and realism of the experience, although its limitations in terms of visual perception of the body and interaction with the virtual cockpit.

As a next step we aim at studying variations of the presented systems with different visualization and manipulation characteristics. To enable the interaction with other components of the cockpit besides the steering wheel, the tracking and visualization of user's hands in the HMD case may be an important added value: for this purpose, we propose to add finger-tracking devices. For what concerns the fixed-base simulator, instead, an important improvement would be represented by the possibility to overlap digital content to the real cockpit: for this purpose, we propose to take into account Augmented Reality systems. Finally, longer test-drives with actual vehicles are considered of primary importance to validate current results and to assess the transfer of skills from the training environment to real driving scenarios.

Chapter 6

On-Road Evaluation of VR and AR training

Curiosity keeps leading us down new paths

Walt Disney

Contents

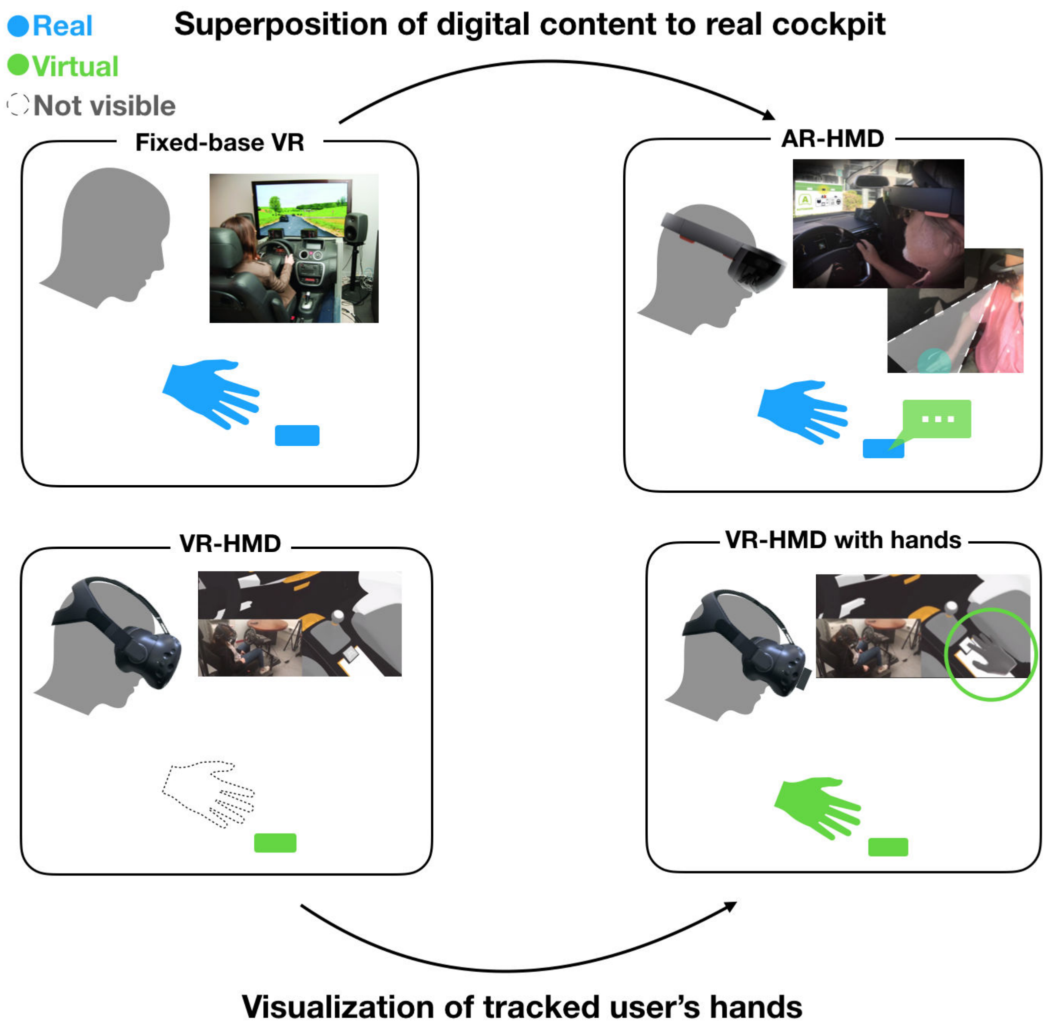
6.1 Introduction and motivations

The axes of improvement emerged from the previous study can be summarized according to immersion, training content and training evaluation.

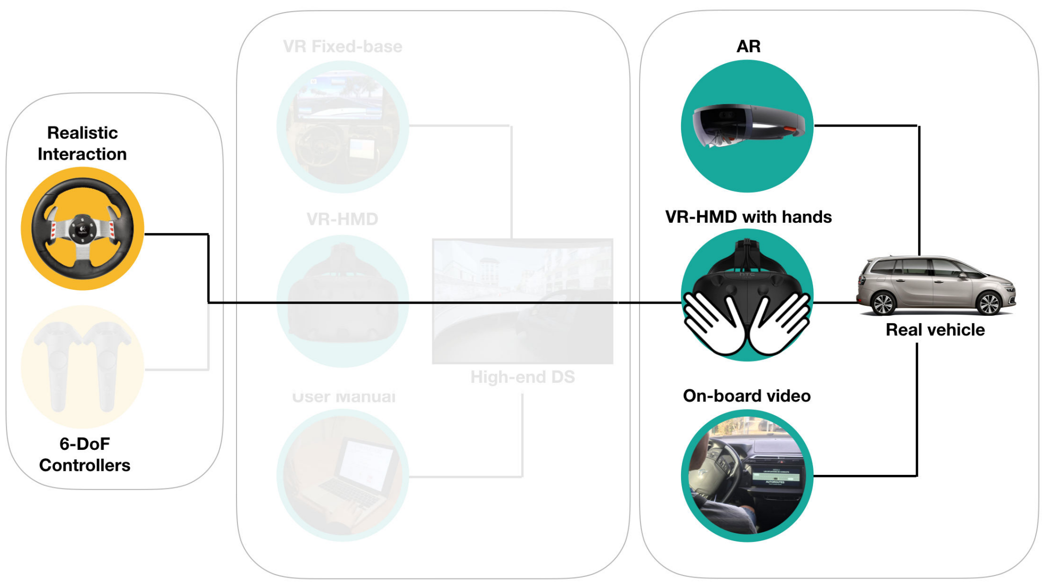
- For what concerns the characteristics of immersion of the systems:
  - adding the visualization of tracked user's hands in HMD systems may improve manipulation and interaction with the virtual cockpit and reduce the occurrence of visuo-manual incoherences.
  - overlapping visualization and manipulation space to superimpose digital content to the real cockpit may help drivers localizing the HMI.
- With respect to the design of the training content:
  - learning-by-driving, which refers to the acquisition of knowledge and skills during a simulated driving session, might not be ideal due to the mental workload already required for the driving task. A separation of the learning and the training environment is thus suggested.
- Regarding the evaluation of training:
  - the driving simulator used for the test drive provided high, but still limited fidelity in a virtual scenario which may raise issues about behavioral validity (drivers could not act as they would in real driving); therefore in order to assess the transfer of training to everyday driving situations, test drives in real driving scenarios should be considered.

Starting from these directions, in this chapter we present the second user study in which we compared the effectiveness of VR- and AR-based training and we evaluated the transfer of training to a real driving situation by conducting a test drive on public road.

Since (at the time of writing) in Europe Level-3 automated cars are not yet allowed on public roads without special licenses, the test drive was conducted applying the Wizard-of-Oz (WoZ) protocol: it resulted in making the participants believe that the vehicle was driven by an automated driving system when it was actually controlled by a human driver. To the best of our knowledge, this is the first WoZ study about autonomous driving on public road with inexperienced unaware participants.



(a)

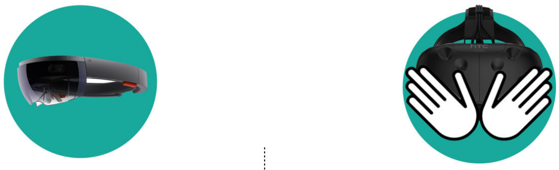


(b)

Figure 6.1: (a) The evolution of immersion from the first to the second user study; (b) The plan of the study

6.2 Characteristics of Immersion of the VR and AR systems

In this section we will present the evolution of the systems and the training program from the previous study and the characteristics of immersion of the two systems.



	AR-HMD	VR-HMD with hands
Virtual environment	FOV : 35, FOR : 360 POV : tracked	FOV : 110, FOR : 360 POV : tracked, Scale of 1:1
Perception of the body	Visual + proprioceptive	Visual (hands) + proprioceptive
Visual Realism of the cockpit	Real cabin + overlapped information 	Co-localized* virtual cockpit 
Sound	Real cabin + Spatial 3D (speakers)	Virtual spatial 3D (headphones)

**Co-localized refers to the superposition of the virtual and the real steering wheel*

Figure 6.2: Characteristics of Immersion of the fixed-base simulator the the VR-HMD system

6.2.1 The Light Augmented Reality Training System

The need to overlay digital content to the real cockpit has prompted us to explore the use of Augmented Reality.

The AR system was therefore designed to allow users to familiarize themselves with the automated driving functionalities inside a real vehicle (described in Section 6.2.1) and to provide augmented information about the onboard HMI (activation/deactivation interface, alerts).

Hardware

Different categories of AR systems can be used to augment physical reality, such as handheld devices (e.g. smartphone and tablet), projection-based systems and head-mounted displays. We chose to use an HMD as display system for the following reasons:

- a physical interaction with the car was required, thus holding a device was considered uncomfortable and counter-intuitive; also, a projection-based system would not have been easily implemented because of the car physical settings.

- in order to compare the effectiveness of training based on AR and VR, the systems involved should provide the stimulus on the user's channels as *similarly* as possible.

Among different Augmented Reality HMDs, we decided to use the Microsoft HoloLens for its availability on the market, the standalone capability and the ease of integration with the game engine Unity 3D.

In addition, thanks to advanced computer vision algorithms (SLAM), the headset is able to track user's position and orientation using only built-in sensors and without the need of external tracking systems. The system, first of all, recognize the environment by creating a 3D map based on information received from the cameras. Subsequently by fusioning the information from the inertial sensors with the camera feed, the system is able to find its the position and orientation in the space.

However, the HoloLens presents also some disadvantages. The most important drawback is its narrow field of view: 30x17 degree, which implies 34.5 degree diagonal FOV with a 16:9 aspect ratio. Another disadvantage is represented by the sensibility of the holograms to the sunlight which makes difficult using the headset outdoors.

6.2.1.1 The Augmented Learning Environment

As for the Virtual Reality system, the training program described at the beginning of this Chapter was also implemented in an Augmented Learning Environment (ALE) that the users self-administered.

The ALE and the VLE shared the same content: users were shown explanatory videos and they were guided in interacting with the HMI in the car. When an interaction was required, an arrow was displayed to guide user's gaze and to lead them interacting with the vehicle.

To create the augmented environment with respect to the user point of view, an accurate 3D model of the actual car cockpit was used as reference (Figure 6.3). The model was imported in the 3D engine (Unity 3D) and the visual content was placed in the scene according to it. However, it was not visible during the AR experience. This procedure significantly sped up the development process in particular because it avoided measurements and calibration which, in our case, would have required a very long time.

The Augmented Reality environment is shown in Figure 6.3: a panel in front of the user to display the videos, and a light blue sphere around the button used to activate the automated driving. Furthermore, to ensure that the position of the scene in the car was the same at each execution of the application, we placed the virtual content according to an initial reference frame represented by the pose of an image target. This capability was offered by the plugin Vuforia for Unity 3D and it required to look at the target in order to place the scene. A powerful advantage of Vuforia is the *Extended Tracking* [Vuforia, 2019], a feature that allows to visualize the object associated to the a target's pose, even when the target is no longer in the field of view of the HoloLens camera.

Figure 6.3: The design of the AR Learning Environment. The model of the cockpit and the virtual elements

Although it would have been feasible to implement the Driving and On-board Activities Simulator (presented in Section 4.3) also in the AR environment, due to the vehicle's technical constraints it was not possible to allow users to control the virtual car using the steering wheel and the pedals of the real one. These constraints included: (i) the fact that the car, in order to transmit CAN information, had to be turned on, and thus a pressure of the accelerator pedal caused an increment of the motor RPM; (ii) the difficulty to move the steering wheel of a stationary car. For these reasons, the driving scenarios (for activation and take-over) were implemented in the form of videos.

6.2.1.2 Communication protocol

To ensure the progress of the training as the user interacted with the vehicle, we implemented a communication protocol between the HoloLens and the car. The HoloLens was connected to the car's TCP server via a WiFi network; the server broadcasted CAN messages from the car to the clients and handled clients requests for updating the HMI: this allowed the HMI inside the car to be updated according to the training content and allowed the training to advance when the correct user action was detected. Figure 6.4 shows an example of the communication workflow between the vehicle and the HoloLens.

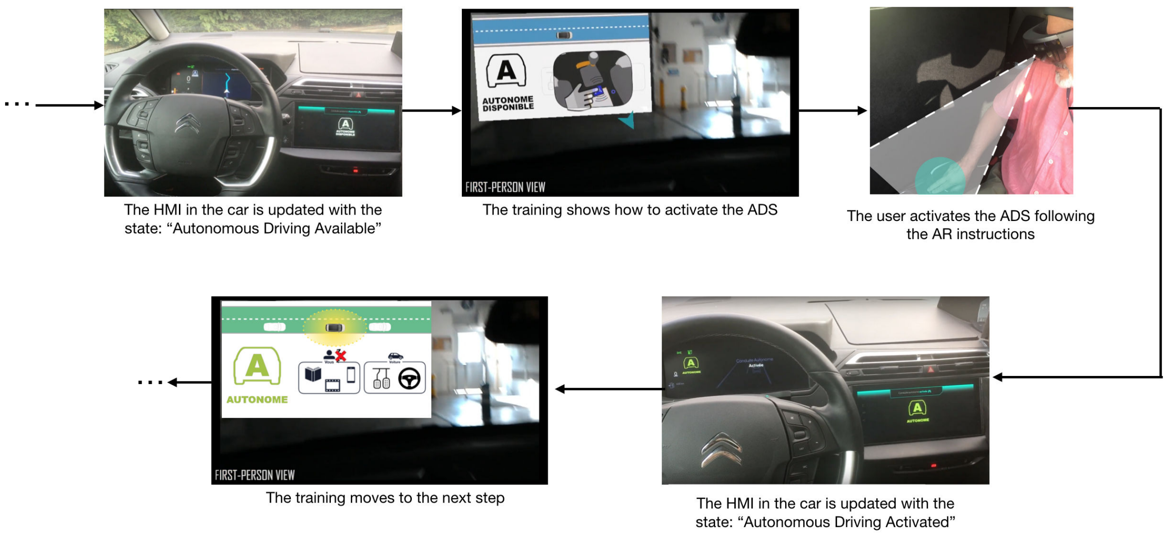
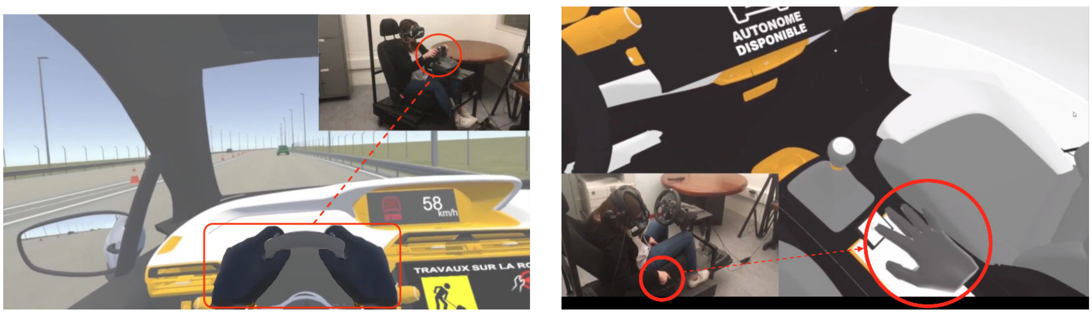


Figure 6.4: A step of the AR Learning Environment

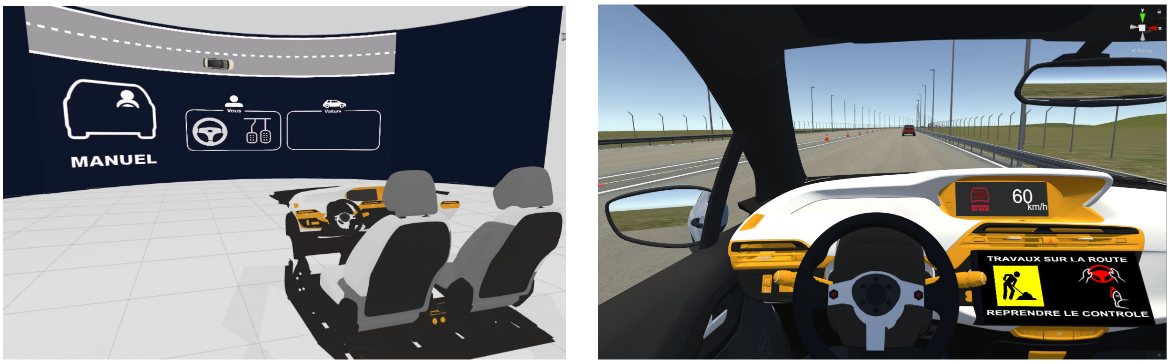
6.2.2 The Light Virtual Reality Training System

The VR system included the same hardware as the previous user study (a HTC Vive and a Logitech G27 racing wheel and pedals (Figure 6.8c)) to which a finger-tracking device (i.e. Leap Motion) was added to visualize a co-localized virtual model of the user's hands. This choice, besides the improvements emerged from the previous study, was justified by the fact that in this study the *Autonomous Driving button* was located on the center console and not on the steering wheel. Thus, the visualization of the tracked user's hand was a necessary condition to *virtually* push the button.



a b

Figure 6.5: The effect of adding the display of the user's hands in the virtual environment



(a) (b)

Figure 6.6: The VR training: (a) the learning environment; (b) the practice driving scenario.

6.2.2.1 The Virtual Learning Environment

From the previous study emerged the hypothesis that acquiring skills while performing a driving task (learning-by-driving) might be me an high-demand cognitive task. For this reason, this study included a second version of the VLE, implemented as a separated environment from the driving environment. The aim was to allow users to acquire knowledge and skills in a static car and then to practice them in a moving car that they drove in a road environment. The learning environment included a simple car cockpit (similar to the real one) and the two front seats; a virtual curved screen was placed in order to display videos that explained the states of the car and the interaction modalities associated to each state. After the presentation of each car state, a short driving simulation session, with increasing complexity, was performed by the participants in order to apply what they learned in the previous steps. In the first driving session, to familiarize users with the car controls, they were required to drive the car in manual mode in a very simple driving environment: a single lane with no traffic. In the subsequent session, the users were required to drive on a highway and activate the ADS when it was available. The last two driving sessions concerned take-over requests.

Another modification to the training environment concerned the simulated takeover scenario. In the first study both the RtI during the training and during the test drive were caused by an obstacle on the road that required the driver to perform an evasive maneuver. This might have given the feeling to drivers that they intervention was required only in emergency situations like the proposed ones and that consequently automated cars would not be able to reduce the risk of accident (self-reported measure). For this reason, the two RtI scenarios in this version were caused by the presence of roadwork on the lane, and by the end of the autonomy zone (exit from the highway).

6.3 Wizard of Oz for Autonomous Driving

According to Walker et al. [2018] real-life driving experiences can lead to a better understanding of vehicles' limitations and to improvements in trust calibration of automated vehicles.

All the studies about automated vehicles mentioned in Section 2.1, including our

a b

Figure 6.7: Two frame from the test drives: (a) the high-end driving simulator and (b) the real driving

previous study (Chapter 5), which contained a test drive, were conducted in high-end driving simulators usually consisting of a static real vehicle surrounded by panoramic displays. The few studies involving an on-road driving experience concerned a lower level (typically SAE Level-2) of automation [Eriksson et al., 2017; Walker et al., 2018].

This because, to date, conducting an experiment with automated vehicles requires strict authorizations; furthermore, for security and legal issues, only drivers with a special license are usually allowed to drive such cars in predetermined and controlled stretches of road. All these limitations are necessary and legitimate, but they confine user tests to experts in the field and keep final users distant from them. Driving simulators reduce this gap, but, although their effectiveness has been proven for traditional cars [Milleville-Pennel and Charron, 2015], very little is known about their validity when the level of automation increases.

The Wizard of Oz protocol represents a suitable research methodology for allowing subjects to interact with a system they believe autonomous but which is actually controlled by a human. Although in some HRI studies [Riek, 2012] the use of this protocol has been judged controversial for what concerns ethical issues and embarrassment related to participants' deception, when it comes to autonomous vehicle interaction, the potential benefits of the WoZ would make this protocol appropriate for conducting valid experiments with the general public in real driving scenarios. In fact, a robust illusion would make hard for the subjects to guess that someone is controlling the car; as a consequence, it would allow participants to behave more similar to the real case.

The use of the WoZ to simulate autonomous driving is not a novelty [Habibovic et al., 2016; Rothenbücher et al., 2016; Schmidt et al., 2008; Wang et al., 2017]. Most of the implementation of the WoZ in vehicles includes a dummy steering wheel with no function. In a recent study,Wang et al. [2017] presented Marionette, a system able to simulate Level 3 and 4 autonomous driving. The interest of this system is the ease of implementation in commercial vehicles in terms of cost and effectiveness. However, the driving task is still performed by the *pilot wizard* at all time by interpreting participants' input on the steering wheel and the pedals; this can introduce lags between the input and the action and break the deception. The main difference between these implementations and ours is that our participants used fully functional controls and they actually drove the vehicle when it was in manual mode. Moreover, they were completely unaware that the person next to them was controlling the car.

In this study we use the Wizard-of-Oz methodology to perform a test drive, with a prototype vehicle, on public road. We describe it in Section 6.4.2.

6.4 Experimental Design

In this between-subject study, 60 participants with valid driving licenses, were randomly assigned to one of three groups and trained with different methods: an on-board video tutorial, an Augmented Reality training program and a Virtual Reality simulator (Figure 6.8).

a b c

Figure 6.8: The three training systems: (a) the on-board video tutorial, (b) the light VR system, (c) the AR system

After the training, all the participants drove a prototype of an automated car on a public freeway. For security reasons, it was not possible to perform a test with an actual autonomous car on public roads. Consequently, the car was not actually autonomous, but it was controlled by a human pilot unbeknownst to the subjects. Since the test involved a modified version of a commercial car, a license plate for prototype vehicles was obtained, and an authorization for the study was issued by the local ethics committee. The study lasted about 2 hours for each participant.

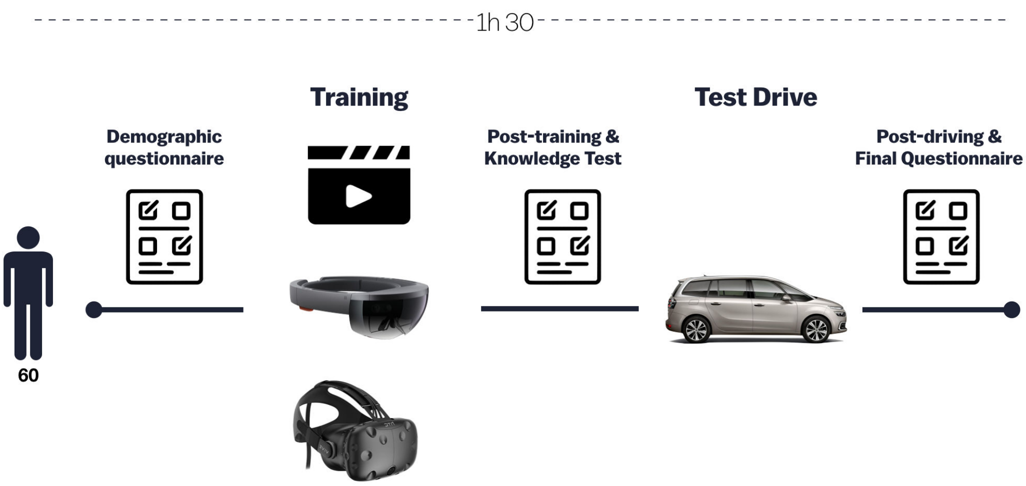


Figure 6.9: The protocol of the user study

6.4.1 The training

The learning phase included a common video for the three modalities (displayed according to the system) in which the following information was given: the purpose of the training was explained and the main characteristics of the Level 3 autonomous driving were introduced; afterward, the 5 states of the car were presented along with the icon and the visual-auditory alerts representative of each state. In addition to the video, the AR and VR groups included simple simulated driving scenarios in which the trainee could practice the activation and the deactivation of the automated driving system and experience two TORs (roadwork and exit from the highway).

As in the previous user study, we implemented the training content in a more traditional modality. For this study we chose an on-board video tutorial.

The on-board Video tutorial

The training based on the on-board video tutorial consisted in simply displaying the informative video on the central screen of the car. This condition represented the baseline for the study. The training provided the participants with the bare essential knowledge needed to interact with the car. This training provided the lowest level of interaction: in fact, the localization of the "Autonomous driving button" was the only active part. Also, it represents, at the time of writing, the most commonly implemented informative modality in cars; in fact, car companies are more and more providing embedded manuals in the form of electronic documents and videos to allow their customers to get easier access to the information about their car.

To summarize, the main differences between the three conditions were related to the coherence between the training and the operational environment (real vehicle vs 3D model of the car) and the presentation of driving situations in which the trainee could practice activation/deactivation of the autonomous system and experience TORs.

6.4.2 The target vehicle

The vehicle used for the test drive was a Citroën Grand C4 Picasso, suitably modified for the experiment. The car was a right-handed driving vehicle with automatic transmission to which fully functional steering wheel, pedals and gear shift were added on the left-hand (Figure 6.10). To detect the presence of the hands and the foot on the steering wheel and the pedals respectively, these controls were equipped with force sensors. In agreement with the Level-3 definition by SAE SAE [2018] the vehicle had 5 possible states which are described in Figure 4.2. ing, the vehicle respected the speed limit, adapting the speed in order to maintain the safety distance from the preceding car; however, the vehicle did not perform overtaking or lane changes.

The Human-Machine Interface inside the car included an on-board computer with two screens, a sound system and the Autonomous Driving button. The two screens (behind the steering wheel, and in the central console), were used to display information about the car and to provide the possibility, during the autonomous driving, to

Figure 6.10: The vehicle used for the test drive with the participant's control interface on the left and the pilot wizard's controls n the right. The two seats were separated by a panel.

perform secondary activities such as watching a movie and playing games. The Autonomous Driving button was placed in the central console near the gear shift. When the Autonomous Driving mode was available, the driver could push the button to activate it. All the car's state changes were notified to the driver with visual-auditory alerts which consisted of displaying an icon on the screens and playing a sound and a vocal message.

6.4.3 The Wizard of Oz setup

To validate the effectiveness of a training program, it is important to assess to what extent trainees are able to transfer skills acquired from the training environment to the real case. With this purpose, and to satisfy security and liability requirements, the presented study proposes the implementation of the Wizard of Oz protocol to simulate autonomous driving in order to make drivers believe that they were actually interacting with an automated system.

The experimental setup included the presence of two *Wizards* in the car: (1) the *pilot wizard* who drove the car when the *Autonomous Driving Mode* was active and (2) the *Interaction Wizard* who performed the sensing part, analyzed the driving environment and sent appropriate notification to the participant.

The participants were told that since they were driving a prototype, a test engineer (the *pilot wizard*) was legally required to sit on the passenger seat to ensure the correct functioning of the car and to intervene in case of emergency. To hide the pilot's controls and to help participants believe that the car was actually autonomous, a panel was placed between the two seats. The panel did not cover the entire height, so the participant could still have a partial view of the right side. The participants were in charge of the driving task only when the vehicle was in *manual mode*, but they could take over the control at any time.

6.4.3.1 The Pilot Wizard

The Pilot Wizard was in charge of the driving task when the vehicle was in *autonomous mode*. From the display placed behind his steering wheel, he could know the current state of the car and if the participant was touching the steering wheel or the pedal. When the car was in manual mode, he completely stopped to control the car, but he was always ready to intervene in case of emergency. Prior to the study, he was adequately trained to behave as a Level-3 automated driving system.

6.4.3.2 The Interaction Wizard

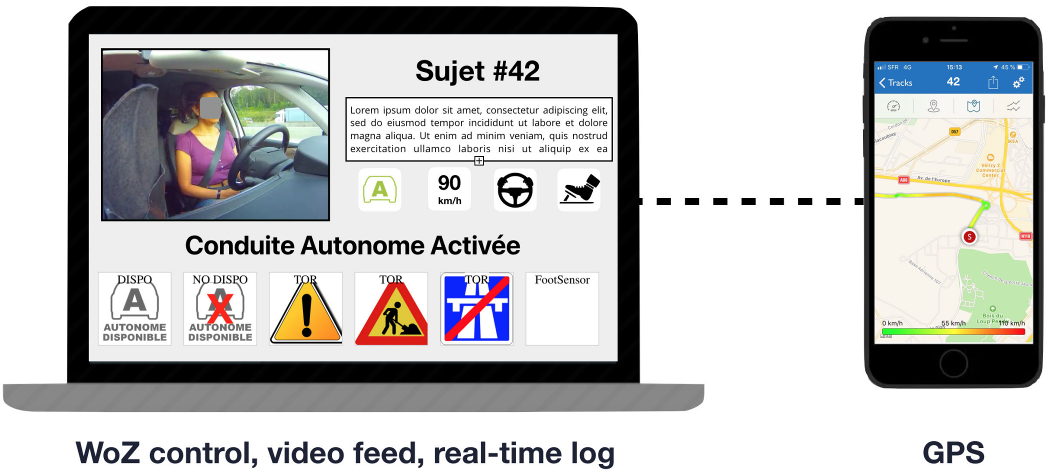


Figure 6.11: The Wizard Of CAN

The Interaction Wizard sat in the back seat of the car. He was in charge of analyzing the driving environment and controlling the HMI and the state of the car from a laptop connected to the car 6.11. Moreover, he talked to the participants and logged valuable information during the test drive.

The HMI was controlled by software running on a computer placed in the trunk. The computer provided a wireless access point and a server with a webpage providing a user interface from which the *Interaction Wizard* could update the state of the car could be updated and send TORs.

6.4.4 The test drive

After the training, all the participants performed a test drive on a public road. The aim of the test drive was to assess how people interacted with the vehicle in a real life driving scenario.

The participants were informed about the presence of the *Pilot Wizard*, who was required to ensure the correct functioning of the car and about the itinerary of the test drive, which was already stored in the GPS system of the car. The experimenters clarified that the test drive was not part of the training; for this reason, to interact

Figure 6.12: The test drive: a participant makes a phone call while the car is in autonomous mode; in the background, the *interaction wizard*

with the car, the participants had to rely on the knowledge learned during the training beforehand.

As instructed, during the automated driving, the participants were free to perform non-driving related activities. On the on-board computer they could choose between watching a movie or playing some games. Moreover, they were allowed to use their own phone to do what they wished. Sleeping was not allowed. As the vehicle did not perform lane changes, the driver was also free to take-over in order to overtake another vehicle.

All the test drives were performed during daylight. The weather during the test drive varied from clear to cloudy (slight rain in one case); however, this study does not take into account the weather variable.

6.4.4.1 The driving scenario

The participants drove for about 25 kilometers on a public freeway (dual carriageway with central barrier). The stretch of road used for the test drive is known for heavy traffic in particular time slots and, unfortunately, for accidents (mostly collisions with no serious consequences). Moreover, during the weeks in which this test took place, roadwork was scheduled and carried out in a short stretch of road. The road works caused a narrowing of the carriageway that a Level 3 ADS could not handle. All these features were relevant to the study, in particular because the participants could face all the three types of TOR presented during the training.

For the participants who did not have any experience with automatic gearboxes, a familiarization route of 4 kilometers in manual mode was added to the itinerary.

At the beginning the participants were required to drive in manual mode in order to reach the entrance of the freeway. Once in the freeway the *Interaction Wizard* sent the notification "Autonomous Driving Available" to the car and from that moment the participant could activate the autonomous driving by pushing the appropriate button.

The itinerary included 3 planned TORs.

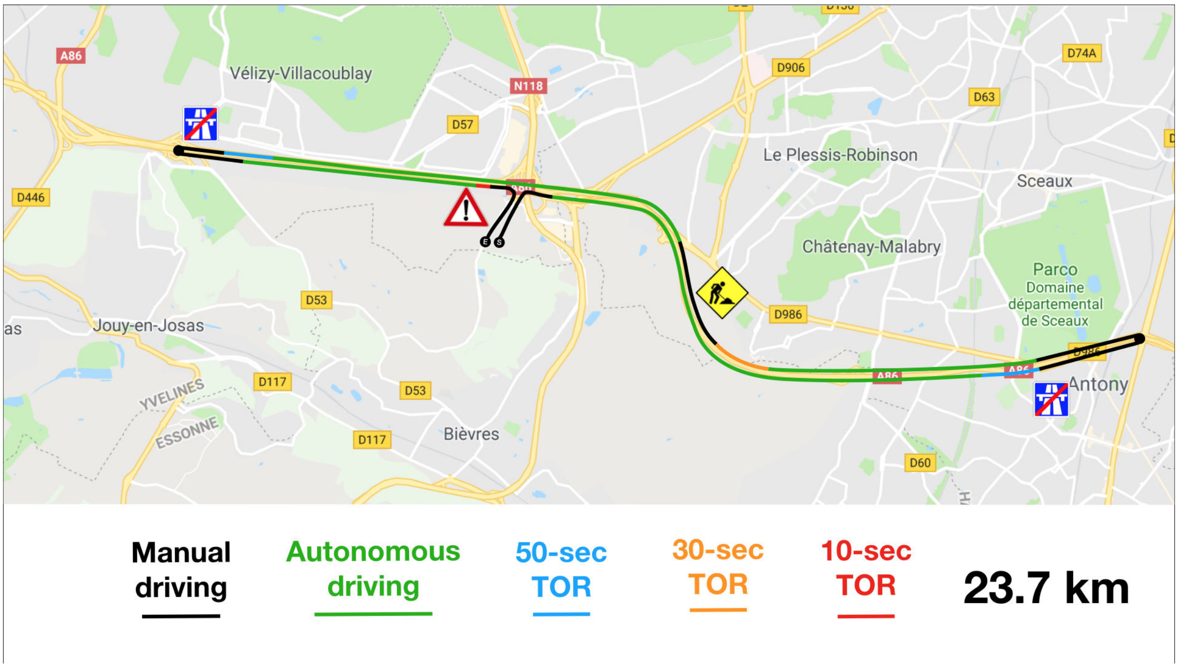


Figure 6.13: The default test drive itinerary on the public freeway.

The first TOR was a 50-second "End of the autonomy zone" TOR launched after about 7 kilometers. The drivers were required to take-over, exit from the freeway, and re-enter in the opposite direction after a roundabout. Afterwards, they could re-activate the Autonomous Driving. After 5 kilometers, a 30-second "Roadwork" TOR was launched. The TOR was justified from the temporary road marking, and the narrowing of the carriageway due to the presence of traffic cones (which however did not require a lane change). After 5.5 kilometers, a 50-second "End of the autonomy zone" TOR was launched. Before definitely exiting the freeway to end the test drive, a 10-second TOR was launched, for no apparent reason to the driver. The itinerary is illustrated in **??**. In addition to these requests to intervene, supplementary urgent 10-second TORs could be sent in case of emergency. This happened, for example, in presence of heavy traffic on the entrance ramps, signaled accidents on the road, or stationary cars in the lane. Moreover, because of too intense traffic or blocked roads, in few cases it was necessary to make small changes to the itinerary.

TOR	Urgency	Predictability	Criticality	Drivers' Response
End of autonomy zone	50 sec	High	Low	Simple
Roadwork	30 sec	Medium	Medium	Simple
Non-planned	10 sec	Low	High	Simple/Complex

Table 6.1: Take-Over Requests according to Gold et al. [2017] taxonomy

6.4.5 Participants

A panel of sixty volunteers (N = 60) was recruited by a company specialized in hiring consumer tests participants. The participants, 29 men and 31 women, were aged

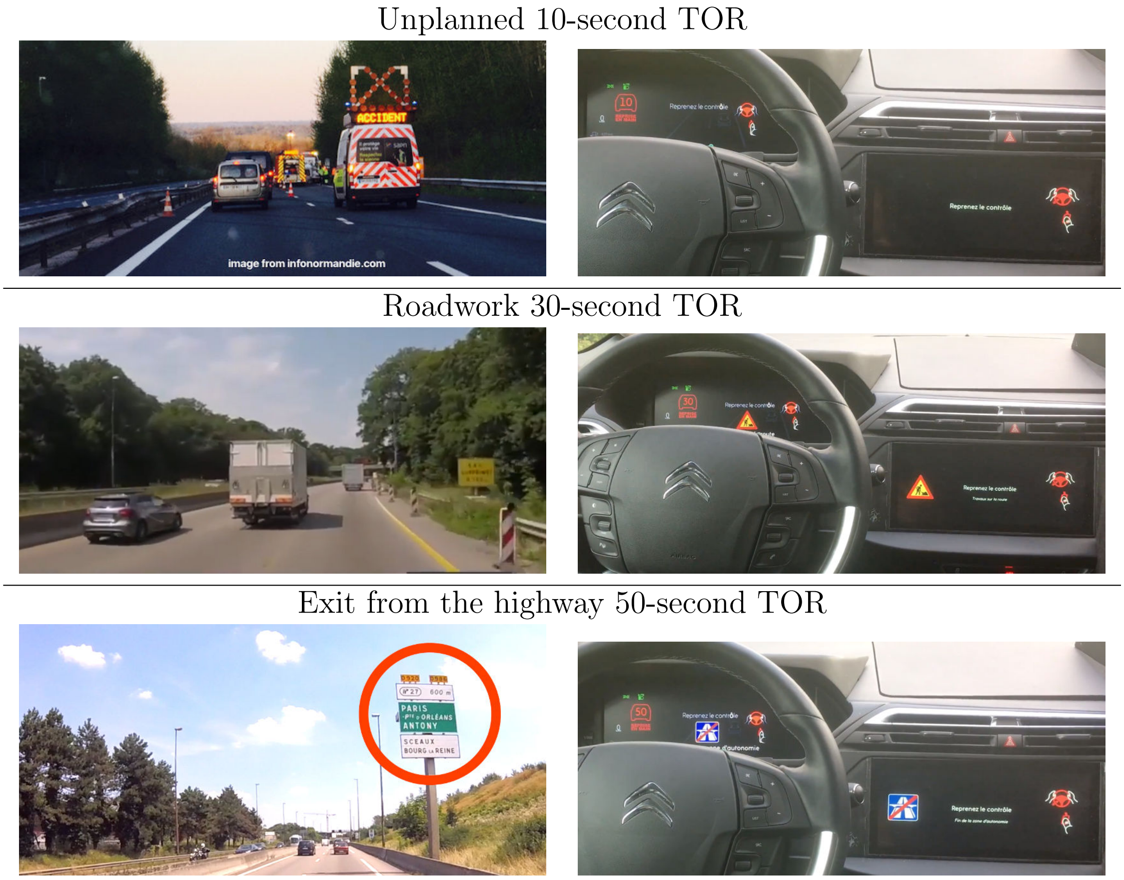


Figure 6.14: The three categories of TOR

Table 6.2: Demographic features distributed across the different systems

System	**Gender** (F/M)	**Age** y (SD)	**Age Group** <36 / [36,56] / > 56	**Car with Cruise Control?** Yes (no use) / No
Video	10/10	46.3 (15.1)	7/6/7	15(9) / 5
AR	10/10	46.7 (14.4)	6/7/7	13(7) / 7
VR	11/9	45.8 (13.3)	7/6/7	11(2) / 9
Total	31/29	46.2 (14)	20/19/21	39(18) / 21

between 25 and 73 (mean age 46.2, SD 14) and they had a valid driving license and no previous experiences with autonomous cars. However, some of them had previously used some automated driving functions such as Cruise Control and Lane Keeping Assistance. In detail, 35% of participants regularly used the Cruise Control function in their car, 35% had the function but s/he did not use it, 30% did not have the function in the car. The panel was divided into three homogeneous groups of 20 participants, equally distributed in gender and age groups (less than 36 years old, between 36 and 56, more than 56 years old). Each group was trained with one of the systems previously described. Details of the demographic features are reported in Table 6.2. At the end of the experiment, each participant was rewarded with a 45 euro voucher.

6.5 Results

All the participants completed the study (no dropout occurred during the training or the test drive). To evaluate how the training and the test drive affected participants' impression of and opinion about autonomous driving, they filled out the same set of questions three times: at the beginning of the study (with no prior knowledge of autonomous driving), after the training and after the test drive.

After the training phase, the participants answered a post-hoc questionnaire to evaluate the training phase, and a Knowledge Test which required them to classify autonomous driving scenarios, identify interfaces in the car, and explain activation and deactivation procedure of the system. In addition, after the test drive, the participants filled out a questionnaire for evaluating to what extent the training helped them in having a successful on-road experience.

It is known that the exposure to VR systems, and in particular immersive headsets, can produce a feeling of sickness in some users. Limiting its occurrence is crucial for any VR application. To evaluate the simulator sickness produced by the Virtual Reality simulator, the VR group filled the Simulator Sickness Questionnaire (SSQ) Kennedy et al. [1993].

Drivers' take-over performance was evaluated with the reaction time, defined as the elapsed time from TOR until the driver takes back control. This measure has been used and validated as a performance metric in all the take-over studies. Since the prototype used in the test drive was not equipped with sensors (such as lasers or radars), it was not possible to evaluate other well-known metrics such as the position in the lane and the time to collision from a vehicle ahead.

In addition to these measures, two cameras inside the car recorded the drivers' behavior and a live log annotated by the *Interaction Wizard* during the test drive. All the data was synchronously collected and anonymously stored according to the local privacy policy. If not differently specified, all the variables were tested for group difference using ANOVAs for continuous normally distributed data and the Kruskal-Wallis test for categorical, ordinal and non-normally distributed data; Fisher's LSD was used for pairwise comparison. A significant level of 5% was chosen for all the tests.

6.5.1 Objective measures

6.5.1.1 Knowledge Test

The maximum score possible of the Knowledge Test (KT) was 13. Summarizing the answers of the KT (Video $= 8, AR = 10, VR = 9, p < 0.05$) a significant difference was observed in the scores of the AR and Video group. This difference was mainly due to the questions concerning driving scenarios understanding (Video $= 6, AR = 12, VR = 10$) and the explanation of take-over procedure (Video $= 7, AR = 17, VR = 14, p < 0.05$).

Concerning the icons of each state, the hardest to identify were the ones indicating the availability of the autonomous mode and emergency stop (19 correct and 41 wrong answer).

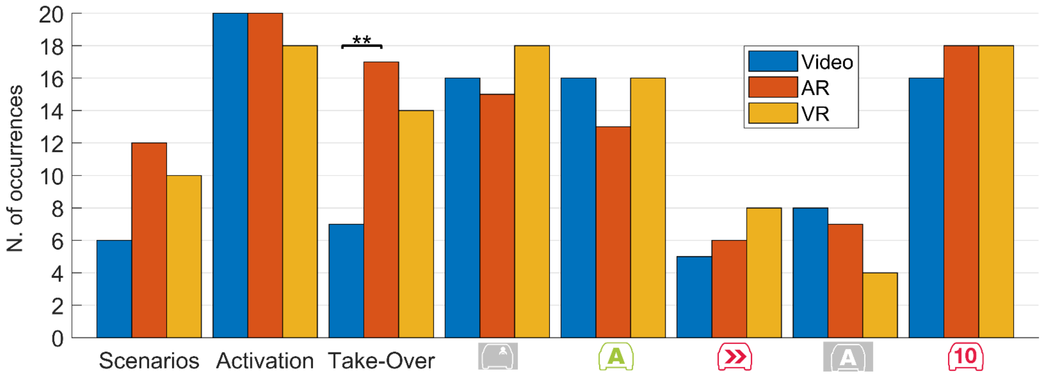


Figure 6.15: Correct answers to the Knowledge Test for each training system

6.5.1.2 Reaction Time

In total, 234 TORs were correctly computed, including 128 TOR of 50 seconds, 51 TORs of 30 seconds and 55 TORs of 10 seconds. Although in the test drive there were some fixed predetermined situations (exit from the highway and roadwork), unplanned circumstances required participants to take-over: this did not ensure the same number nor order of TORs for all the subjects.

VR training produced the lowest reaction times in all the three types of TOR, but only for what concerns the urgent 10-second TORs, this difference is significative ($rt_{Video10} = 3.07s$, $rt_{AR10} = 3.12s$, $rt_{VR10} = 2.08s$; $H_{(2,52)} = 9.04$, $p < .05$).

A result in agreement with related work in the field is that the reaction time depends on the time budget (Figure 6.16): the more time given to the driver to take over, the slower the reaction ($rt_{TOR10} = 3.43s$, $rt_{TOR30} = 4.69s$, $rt_{TOR50} = 5.49s$, $p < 0.001$). However, it can be observed that even when the available time budget triples (TOR 30) or quintuples (TOR 50), drivers reacted very quickly anyway. If the difference between the 3 types of TOR is considered negligible ($rt_{TOR10} = 2.50s$, $rt_{TOR30} = 3.83$, $rt_{TOR50} = 4.46s$; $H_{(2,231)} = 28.8$, $p < .001$), it is possible to average all the reaction times to have a more general view (Fig.6.18, solid lines). In this case, a significant difference can be observed, but only between VR and Video ($rt_{Video} = 4.50s$, $rt_{AR} = 4.04$, $rt_{VR} = 3.47s$, $H_{(2,231)} = 8.31$, $p < .05$). Since the training groups were also equilibrated in terms of age, a 2-way ANOVA was performed with the age groups and the training conditions: it can be noted that the oldest group benefits from the AR training in a statistically significant way ($rt_{AG3Video} = 6.72s$, $rt_{AG3AR} = 4.37s$, $rt_{AG3VR} = 6.31s$, $F_{(4,225)} = 3.18, p < .05$). On the other hand, VR training seems to be more effective for the youngest groups. If only the first TOR is taken into consideration (Fig.6.18, dashed lines), the participants trained with the Video tutorial reacted around 2 seconds slower than the VR and the AR groups, but not in a significant way ($rt_{1stVideo} = 8.2s$, $rt_{1stAR} = 6.1s$, $rt_{1stVR} = 5.8s$, ns). In particular, the highest reaction time to the first TOR was observed for the third group of age trained with the Video tutorial.

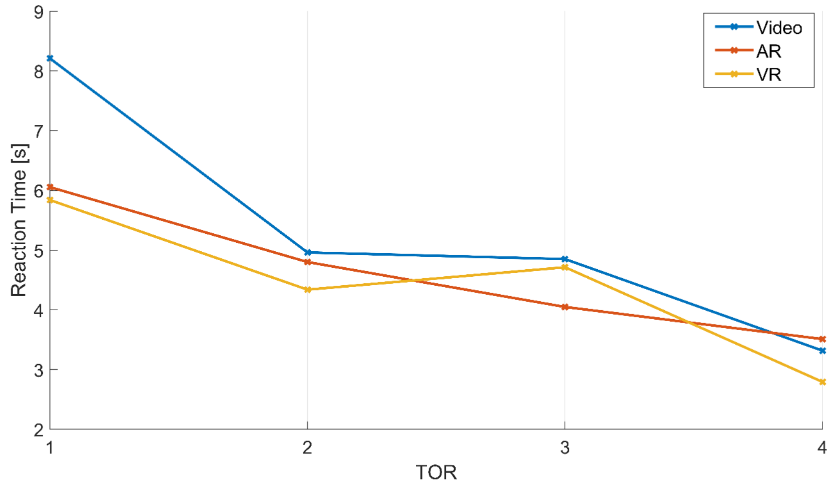


Figure 6.16: The reaction time in the first 4 TORs.

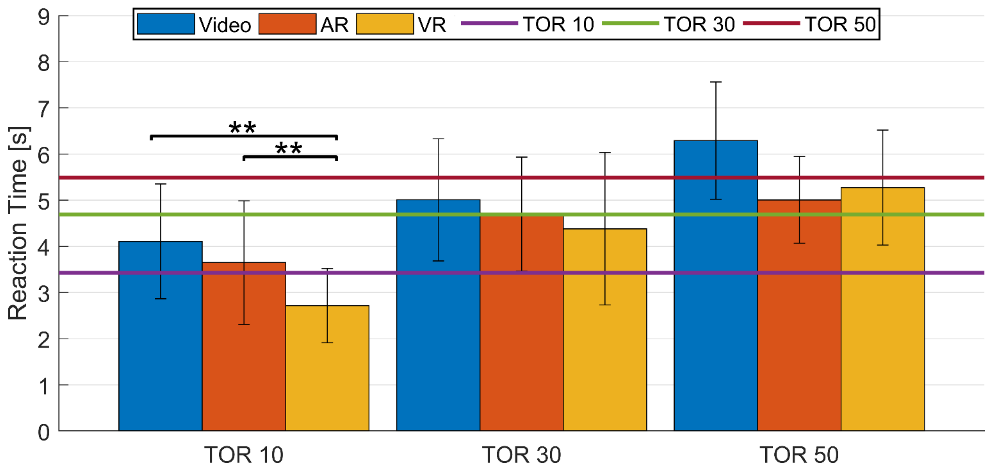


Figure 6.17: The reaction time according to the TOR type and the training system. In solid lines are the means.

6.5.2 Self-reported measures

6.5.2.1 Training evaluation

The training part was evaluated by the participants with a 5-point likert scale survey about perceived usefulness, easiness of understanding and familiarity. The results reported in Figure 6.19 show that there are no significant differences for questions related to the training in general (usefulness and necessity of training). However, when it comes to questions specific to the training system, VR seems to be preferred in terms of familiarity with the vehicle, easiness of understanding, and readiness to drive, in particular for the third age group.

6.5.2.2 Perceived trust and usefulness of autonomous driving

The participants were asked to indicate their level of agreement (on a 5-point Likert scale) with a set of sentences about the concept of autonomous driving. They filled out

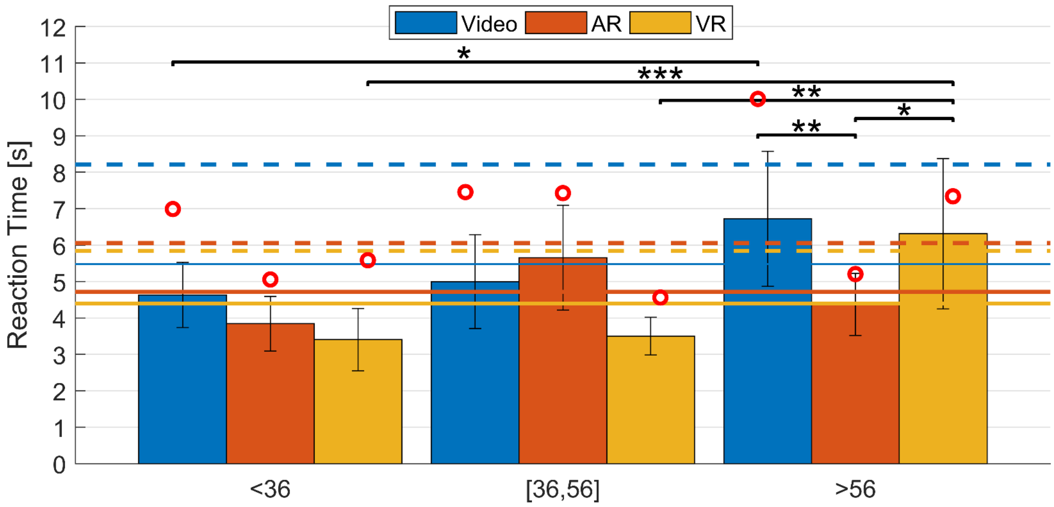


Figure 6.18: Take Over reaction time (RT) according to group age and training system. Red dots are the RTs of the first TOR for each group. In dashed lines, the mean of the RT to the first TOR. In solid lines the mean of the RT to all the TORs.

the same questionnaire three times: before the training, after the training and after the test drive. The questions were grouped in three categories (Fig.6.20): (i) trust in automation, (ii) perceived usefulness of the autonomous driving, (iii) willingness to perform a NDRT. A first outcome is that there was a statistically significant increment in the three sets of questions for all the training conditions and that for no single question was there a decrease in the score. In particular, the higher increment was noticed in questions related to secondary activities ("I can imagine myself doing other tasks than driving") and trust on the driving decision made by the vehicle after the test drive.

In addition, the participants evaluated on a 5-score Likert scale to what extent the training helped them interact with the vehicle in the various situations (activation, take-over, recognizing alerts) during the test drive ($Video = 4.6, AR = 4.7, VR = 4.6; ns$).

6.5.2.3 VR Simulator Sickness

In order to validate the results for the VR group, the SSQ was filled out by the involved participants. 50% of them reported 0 for all the symptoms. On a maximum possible total score of 78.54, the mean was 5.0, which represents the limit for negligible symptoms in the categorization of score proposed by Kennedy et al. [1993].

Table 6.3: Results of the Simulator Sickness Questionnaire. The maximum possible score for the subscales is 200.34 [N], 158.18 [O], 292.32 [D], 235.62 [TS]

Subscale	Mean	Median	SD	Min	Max
[N]ausea	4.3	0	7.2	0	19.1
[O]culomotor	4.5	0	7.9	0	30.3
[D]isorientation	4.2	0	10.2	0	41.7
Total Score [TS]	5.0	1.9	7.5	0	26.2

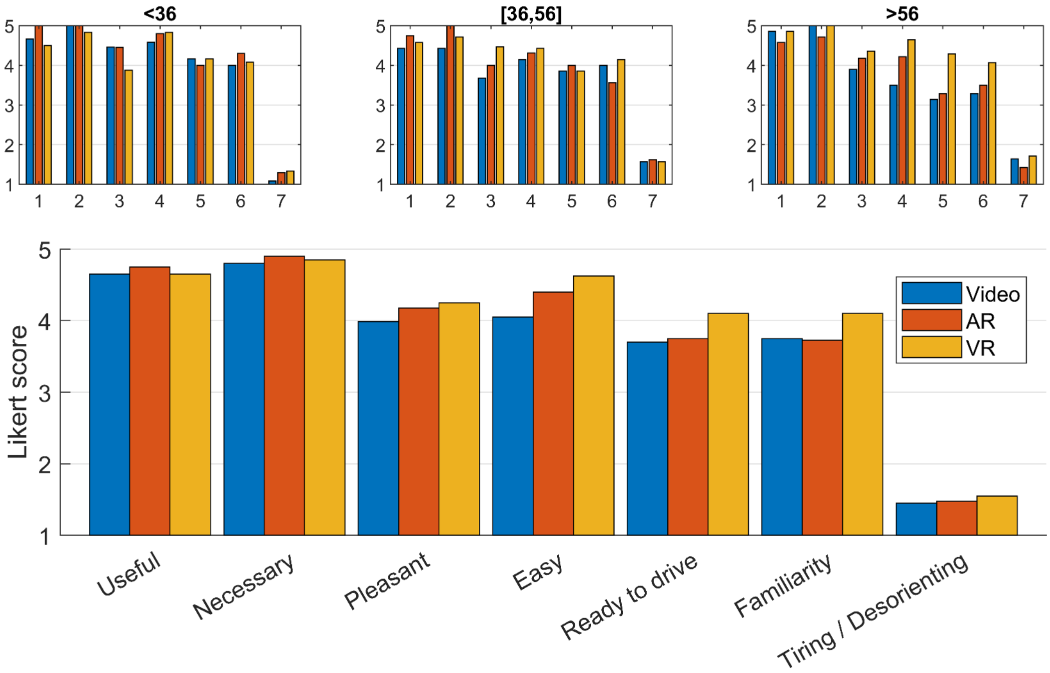


Figure 6.19: The results of the questionnaire for the training phase evaluation

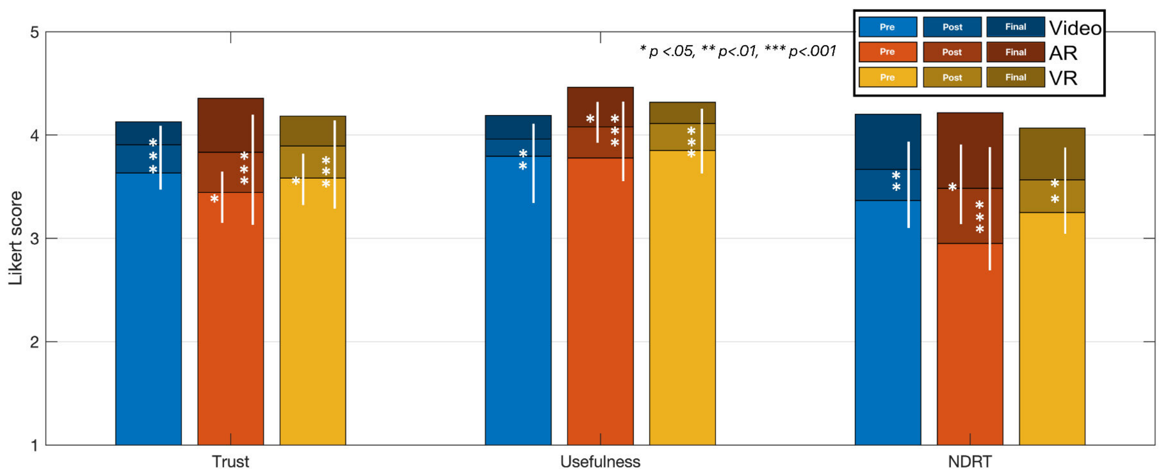


Figure 6.20: Likert responses to the pre, post and final questionnaire about perceived trust and usefulness of autonomous driving and willingness to perform a secondary activity during autonomous driving.

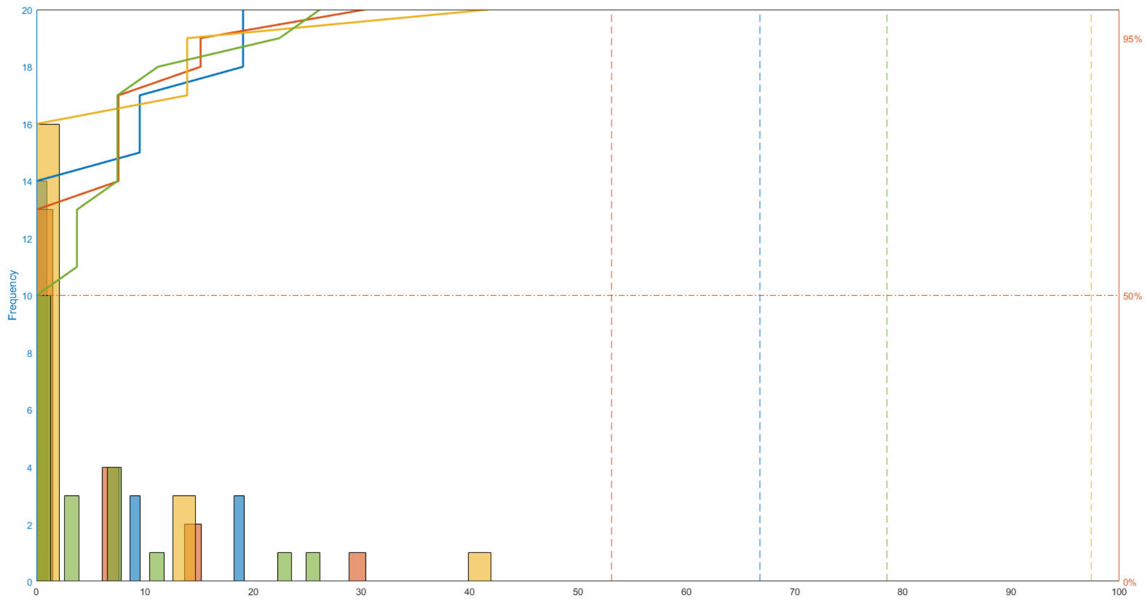


Figure 6.21: Results of SSQ scores (Nausea, Oculomotor, Disorientation subscales and Total) for the VR group with the percentile graph. The vertical dotted lines represent the value of SSQ if all the symptoms were reported as “slight” on that subscale.

6.6 Discussion

A first important outcome of this study is that the Wizard-of-Oz protocol represents a robust and effective research methodology that allows for an assessment of the general public's interaction with autonomous vehicles in real driving scenarios. All the sixty participants in this study, in fact, orally reported that they were convinced to be in an actual autonomous car: in other words, no subject realized that the car was actually driven by a human pilot.

The three training programs proposed in this study were designed to make drivers ready to operate their vehicle by providing general understanding of the autonomous system, the rules of use, and by supporting the know-how to interact with it.

All the trained participants transferred the training to the real scenario: during the test drive they were able to correctly activate the autonomous driving and safely take over in all the situations in the given time, without the need to perform an "emergency stop". The AR and the Video training both took place in the real vehicle and, in addition, the AR and the VR training included the presentation of simulated driving scenarios in which the drivers could practice the interaction with the system and Take-Over Requests. We suppose that this difference may have influenced results of the Knowledge Test (KT), in which a gap between the Video Tutorial and the other systems was observed especially for what concerns the description of the take over procedure.

For what concerns take-over time, the participants trained with VR reacted faster to the TORs than those trained with the Video in a significant way. If we consider only the first TOR, the VR and AR groups reacted about 2 seconds faster than the Video group, but this difference was not statistically significant. However, there is not a strong evidence, and we do not have sufficient elements to make a strong claim, if these results are due to the characteristics of immersion or to the practice of a TOR during the training. The role of the first TOR is crucial for the purpose of this study since a first bad takeover may be already dangerous or compromise future uses of the system. A difference between AR and the other training systems can be observed by taking into account also the age groups: in this case, while for the first two age groups the reaction time was comparable among all the training systems, older participants trained with Augmented Reality reacted faster with respect to the others and in a time comparable to younger groups. The outcomes of this study about take over time are in line with related work in the field in which it is proven that subjects who execute a take-over during the training performed better in the test drive [Hergeth et al., 2017].

It has to be said that the participants were not obliged, only invited, to perform a secondary task: this might not guarantee the same level of distraction for all the subjects at the moment of the TOR. The results about objective measures suggest that the different age groups would benefit from different training systems. In terms of reaction time, if VR seems to be more convenient for young and middle-aged drivers, older people would take more advantage from the AR training.

This hypothesis may be verified by conducting a within-subject study to explore preferences about the training programs. A learning (or ceiling) effect can be as well observed in all the groups between the first reaction time and the final mean, in agreement with results of the previous user study (Chapter 5).

The results for the identification of icons were ambiguous: the manual, TOR and Autonomous Active icons were easily identifiable, but the emergency stop and the Autonomous Available were not. We assume that this difference is due to two main reasons: a flaw in designing the Autonomous Driving icons (subjects got confused about the green and the white one) and an incomplete explanation of the Emergency Stop state.

In general, the participants judged the training programs useful and necessary for the purpose of using the automated system. The VR system however produced better results in terms of easiness of understanding, readiness to drive and familiarity with the vehicle; this can be explained by the fact that this training provided a higher sense of immersion and isolation, which may have allowed the participants to better familiarize themselves with the car and the driving situations they would face. In addition, the simplified cockpit of the virtual car and the bare virtual environment may have helped users focus their attention on the interfaces relevant to the training. The VR system received good scores in particular from the third age group; although this sounds in contrast with the objective results, it may underline a difficult for older drivers to transfer the training skills from the virtual environment to the real scenario. This aspect requires further investigation in future work.

Self-reported measures pointed out also the importance of the test drive for what concerns trust in automation, perceived usefulness and willingness to perform a secondary activity. This result was expected since, thanks to the implementation of the WoZ protocol, the functioning of the automated system was ideal. Analyzing the Pre-Post-Final questionnaire, it is important to mention that although the participants had already high expectations for the autonomous system, the experience allowed them to improve their opinion. Also, as some participants admitted, the presence of the experimenters in the vehicle during the test drive reassured and helped them in having a pleasant driving experience.

In addition, during an informal exchange about the training phase after the test drive, 63% of participants stated that no additional training sessions were necessary to drive the real vehicle; one participant stated that s/he could have performed the test drive with only the information about the location of the autonomous driving button. On the other hand, some participants suggested including the test drive with an expert as part of the training.

It would have been interesting to have a group of participants not trained at all and evaluate the ability to take-over without any prior information. However, for security reasons, this would have required performing the test drive in a simulator or on a track.

From our experience we can conclude that using the WoZ protocol for test drives in real driving scenarios provide robust ecological validity (participants can behave in a more naturalistic way), at the expense of a much lower control over the events on the road which brings to a more difficult reproducibility and assessment of objective driving measures.

Analysis based on video data showed that most of the participants became more comfortable after the first TOR, probably because they realized that they were able to easily take-over when required. However, the opposite behavior was as well observed in few participants: they were confident during the first autonomous driving zone, but became less confident after the first TOR.

6.6.1 Comparison with the previous user study

In Table 6.4 we report a summary of results of this study and the presented in Chapter 5.

	User Manual	Fixed-base	HMD	Video	AR	HMD+Hands	
Test Drive	High-end fixed base simulator			Real Driving with WoZ			
N. of users	20	20	20	20	20	20	
Reaction Time [s]	7,36	3,8	3,34	8,21	6,06	5,84	First TOR
	5,51	3,23	3,15	6,07	5,00	4,97	First 3 TORs
	3,96			5,35			
Training Evaluation [1-5]	3,95	4,0	4,3	4,21	4,31	4,43	
SSQ	-	-	21,32	-	-	5,0	

Table 6.4: Measures comparison between the two user studies

Although the training content was similar between the two user studies, the training protocols was substantially different: *learning-by-driving* (first study presented in Chapter 5), and *learn-then-drive* (second user study, presented in this Chapter). In addition, the test drive in the previous study was conducted in a high-end fixed-base driving simulation while in this one the participants drove in a predefined real driving itinerary on public roads. Also, the time buffer in the two studies was different (two 10-second and a 5-second TORs in the first study, two 50-second, one 30-second and one 10-second TORs in this user study) as well as the number of TORs (always three in the first study, from two to six in the second one).

It is possible to observe that, despite these methodological differences, we obtained similar results in terms of reaction time (the only driving-related performance variable that we could measure in real driving due to the experimental limitations), in accordance with the results in the literature [Zhang et al., 2018]. For what concerns the reaction time relative to the first TOR, we can observe that participants trained with video and user manual (thus simple training without practice) reacted slower than those trained with VR and AR systems who experienced TORs in simulated driving scenarios. Also these results agree with the findings in the literature [Hergeth et al., 2017]. In the first user study the general lower reaction time to the first TOR with respect to this study, could have been caused by the time budget accorded to the driver (10s, 50s) and the severity of the consequences of a wrong reaction.

With regard to the evaluation of the training, we can observe that in both studies, and for all the training systems, the scores were very positive. The slight improvement between the second study is due to the modification made to the training program according to the remarks collected at the end of the first study.

Concerning Simulator Sickness in the VR-HMD case, the participants reported less symptoms with respect to the first user study in which they were, in any case, tolerable. We think that the decrease of the SSQ is due to three main reasons: first, the time spent in operating the virtual vehicle on the road was lower; second, the separation between the training environment and the driving environment allowed users to focus on one specific activity at time; third, the addition of the display of the user's tracked hands reduced the occurrence of visuo-manipulation sensorimotor incoherences.

6.7 Concluding remarks

We conducted an experimental study on a public road aimed at comparing three programs for the drivers' training of conditionally automated cars (SAE Level-3). The application of the Wizard of Oz protocol played a central role in this study; it allowed us to assess transfer of training to the real circumstances and to evaluate driver behavior during an authentic driving experience, satisfying current safety and liability requirements.

Results show that participants trained with Virtual Reality and Augmented Reality had generally a better understanding of the take over procedure and better performance in term of reaction time during the test drive, with respect to participants trained with the video tutorial. In particular, the take-over time to the first request to intervene emerges to be about 2 seconds faster, even if not in a significant way. Difference within AR and VR can be observed only if the age group is taken into consideration: in this case, while young and middle-ages participants ($<$ 56 years old) benefits more of the VR training, older participants show better reaction time if trained with AR.

Nevertheless, even simple and non-interactive training programs (such as the on-board video tutorial) help drivers in localizing the interfaces and recognizing the alerts. the training is necessary to have a better understanding of the system capabilities and limitations and to increase people perception of trust and usefulness in the automated vehicle.

These results offer the insight that specific immersion conditions should be considered according to the age groups. For this reason, further within-subject studies are necessary to explore user preferences with regard to the training programs. Longer test drives should be conducted in order to validate the current results.

Chapter 7

Discussion and Conclusion

Veggano ora quanta sia la forza della verità, mentre l'istessa esperienza che pareva nel primo aspetto mostrare una cosa, meglio considerata ci assicura del contrario.
(*See now the power of truth; the same experiment which at first glance seemed to show one thing, when more carefully examined, assures us of the contrary.*

Galileo Galilei

Contents

7.1 Introduction

At Level 3 of automation (conditional automation), the Automated Driving System completely performs the driving task; the human driver does not have to monitor the system nor the driving environment, but is expected to resume the driving task within a reasonable amount of time after being prompted by the automated driving system with a Request to Intervene. This interaction with the automated vehicles is crucial as the human driver is required to respond to system limitation in potentially dangerous situations.

While autonomous driving technology advances very quickly and allows for testing prototypes on real roads, the role of the drivers during automation is still far from being precisely defined.

The bibliography review (Chapter 2) showed that interaction with AVs is an essential research question characterized by a strong multidisciplinary interest. Human factors experts are mainly studying the behavioral questions related to the problem of out-of-the-loop drivers; User experience designers and ergonomists are designing intuitive and adequate HMI; engineers are developing algorithms to anticipate unexpected situations on the road and to detect and predict the state of the driver during automation.

All this work is primarily focused on a specific objective: ensuring a safe transition of control between the automated driving system and the human driver.

A still little explored subject concerns how human drivers will be taught in using the system and interacting with the novel interfaces. On this topic, human factors research [Kyriakidis et al., 2017] agrees on the fact that current driver training programs should be redesigned in order to instruct drivers on how to use automation; familiarizing drivers with the vehicle before the first ride is considered crucial for the correct understanding and use of the automated system and, in turn, for road safety in general.

Promising results can be inferred from closely related domains, first among all, aviation and interaction between the pilot and the aircraft cockpit. However, the target audience for the training is different: pilots training targets professionals who undertake extensive theoretical and practical training; drivers training must address a more general public with heterogeneous cultural background, age range and willingness to learn.

It is not yet clear whether the training will be provided by driving schools or it will be the responsibility of the manufacturer ensuring that the necessary knowledge for operating this kind of vehicle is acquired. In both cases, designing appropriate training programs and assessing whether or not a human driver is able to correctly operate automated systems becomes a crucial problem.

Results summary

In this context, we addressed the problem of familiarizing drivers with the automated driving system using Mixed Reality. The familiarization consisted in providing future

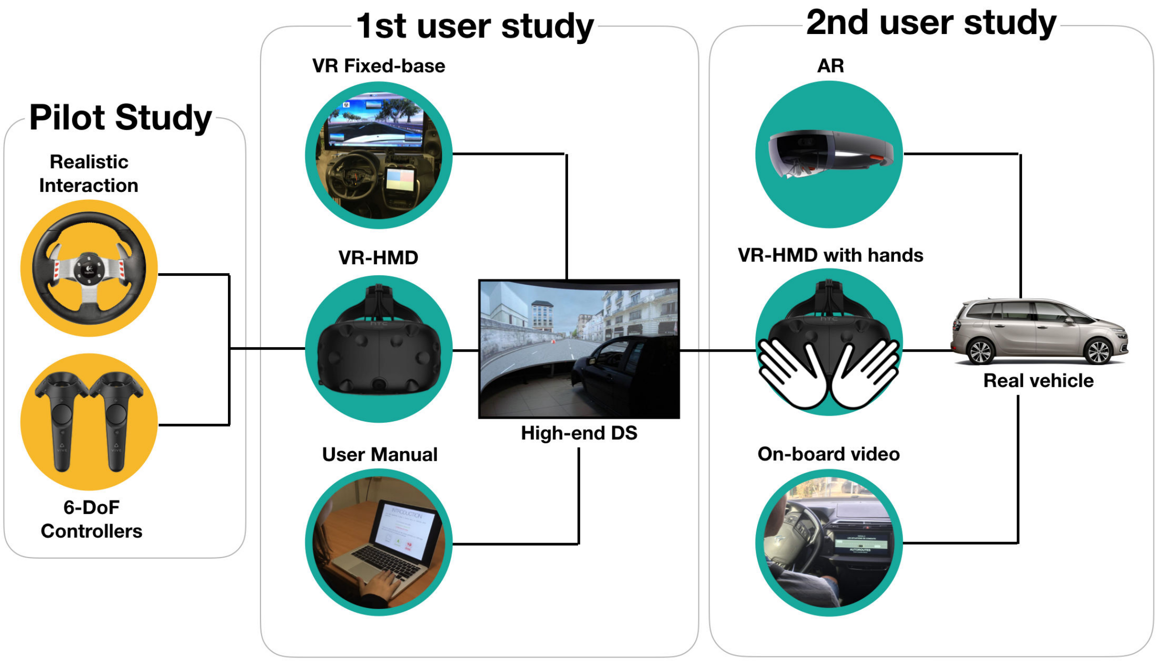


Figure 7.1: Plan of the thesis

drivers of conditionally automated vehicles with information about automated system's capabilities and limits, the role of the human driver in automation and the actions to perform when their intervention was required during transition of control.

In particular we explored the role of immersion along the Mixed Reality continuum, investigating the impact of visualization and manipulation space and the correspondence between the virtual and the real world. For industrial constraints, we restricted the possible choice to *light* systems (portable, cost-effective, accessible) and we took into account the limitations that this choice entailed and the sensori-motor conflicts that may be caused by these systems.

For what concerns the design of the training program, we based the learning needs on the Rasmussen's Skill, Rules, Knowledge (SRK) model, by defining training requirements for each level. We subsequently implemented the training program both in Virtual Reality (Fixed-base simulator, VR-HMD) and Augmented Reality HMDs.

With the objective of providing the users with the possibility to practice the acquired knowledge and rules and experience what it is like "to drive" a L3 conditional automated car (where *driving* is not only limited to the actual control of the vehicle, but also includes the execution of secondary activities) we designed and developed a Driving and On-board Activity Simulator and we empirically evaluated the manipulation interfaces in the VR case.

Two user studies, which involved 120 participants in total, were conducted with the aim of evaluating the effectiveness of the training systems. Participants training was evaluated according to self-reported measures of trust and awareness of automation and objective driving-related measures of take-over quality (e.g. take-over time, maximum distance from lane center, time to collision from an obstacle ahead, etc). To do so, the user studies included test drives performed in a high-end driving simulator and a real vehicle on public roads.

From the training point of view, results of our research are in agreement with the literature in the field that does not take into account the question of immersion [Boelhouwer et al., 2019; Hergeth et al., 2017; Payre et al., 2017b]: training is a *condicio sine qua non* to ensure road safety in automated driving.

In particular, our research shows that Mixed Reality systems are valid tools for familiarizing drivers with conditionally automated systems. They are effective for the acquisition of general knowledge relative to the system including the localization and identification of HMI and for the understanding of the role of the driver in automation. In addition, the simulated practice of simple driving scenarios further facilitate the acquisition of motor skills relative to transfer of control. Hence, Mixed Reality systems should be considered as a support tool during the handover process of a new vehicle. According to the target audience, some MR systems may be preferred to others for their characteristics of isolation from the real world.

In the following sections we summarize the research approach that led to the identification of the training systems, the design and implementation of the training content and the evaluation of the training effectiveness, and we discuss the findings of our research.

7.2 Immersion

Define the characteristics of the training system(s) and analyze their entailed limitations

The necessity to allow a driver to practice safety-critical driving scenarios without risk for them and other road users leads to the need of *alternatives* to reality. One of the possibility explored in this thesis is Mixed Reality.

Along the entire Mixed Reality spectrum we identified combinations of visualization and manipulation spaces to design *light* systems that met both the training objectives (familiarization with the automated system, interaction with the HMI, practice of driving scenarios) and the industrial constraints (cost-effectiveness, target audience, portability and physical footprint). In particular, the light systems designated for our analysis were a Virtual Reality System including an HMD, a steering wheel and pedals, the same system equipped with finger-tracking device, and an Augmented Reality HMD which, by definition, required a real cockpit to augment. A fixed-base VR simulator was also included in the analysis for its characteristics of immersion and for the availability in driving schools.

Choices made in the visualization and manipulation spaces, two of the components we used to define immersion in Mixed Reality, affect the possibility to see and interact with the real world, alter the perception of the user's body and imply a number of sensorimotor conflicts causing observation (e.g. in fixed-base simulator), manipulation (e.g. in VR-HMD without hands) and navigation (e.g. fixed-base, VR-HMD and AR) incoherences. These characteristics were evaluated and preventive measures for the occurrence of conflicts were taken into account in order to design systems and environments that are effective and not disruptive for the user.

	AR	Fixed-base	VR-HMD	VR-HMD + hands
Perception of the body	Visual Proprioceptive (real)	Visual Proprioceptive (real)	Visual - (virtual)	Visual Proprioceptive (virtual)
Virtual Environment	FOV : 35 FOR : 360 POV : Tracked 60 FPS -	FOV : 47 FOR : 47 POV : Fix 60 FPS -	FOV : 110 FOR : 360 POV : tracked 90 FPS Scale of 1:1	FOV : 110 FOR : 360 POV : tracked 90 FPS Scale of 1:1
Visual Realism of the cockpit	Real cockpit	Real cockpit	Virtual Cockpit	Virtual cockpit
Manipulation	Co-localized	Co-localized	Co-localized	Co-localized
Sound	Real cabin + Spatial 3D (speakers)	Virtual 2D (screen speaker)	Virtual spatial 3D (headphones)	Virtual spatial 3D (headphones)

Figure 7.2: The characteristics of immersion of the four studied systems

A preliminary pilot study was performed to empirically evaluate the manipulation interface (natural interaction vs controller-based) of the light VR system. One of the objectives was to understand the extent to which we could push the boundary of system *lightness* and interface abstraction. In other words, *can we do without the steering wheel when it comes to simulate the driving task?* Although there was no significant difference in the driving related measures, the self-reported questionnaire stated in favor of natural interfaces in terms of comfort, ease of use and adaptation.

In the first user study (presented in Chapter 5) the effectiveness of the light VR training system was compared to a fixed-base simulator and a control group trained with a user manual. In the second user study (presented in Chapter 6), starting from the result of the first one, we compared the effectiveness of the AR-HMD system and a VR-HMD system with improved body perception with respect to an embedded video tutorial.

The results of the two experimental studies showed that training using interactive digital methods is necessary to have a better understanding of the automated driving system capabilities and limitations and to increase user's perception of usefulness and trust in the automated vehicle and willingness to perform a secondary activity during automation.

Concerning measurements during test drives, both the user studies showed that the training system affected take-over time. In detail, the participants trained with systems that allowed to experience Requests to Intervene during the training phase (VR, Fixed-base and AR) were able to take over faster than those who did not performed an RtI (user manual and on-board video). This behavior was mainly observed for the first take-over; in the subsequent TORs a *learning effect* brought the take-over time to an asymptotical value. Between the light VR system and the Fixed-base simulator we did not find any significant difference in terms of objective measures, while between AR and VR the differences concern the age groups: older participants benefits of training in the real environment augmented with digital content, rather than a completely virtual environment. After the take-over, the training system did not significantly influence the driving performance (in the lane keeping task and in the evasive maneuver).

Limitations

The limited differences found in the pilot study (presented in Chapter 4) in which we compared realistic and controller-based interaction made us question if having as independent variables single components of immersion (e.g. FOV, manipulation interface, realism of the cockpit) was the right approach for evaluating the role of immersion on training in large population. Thus, we assumed that to elicit greater difference in learning, we had to evaluate systems as an *ensemble* of features. These considerations led us to adopt, in the subsequent experimental studies, an *holistic* approach in which the independent variable were the systems considered as wholes (with proper characteristics) rather than the single aspects of immersion. If on the one hand this allowed us to address the research question in a more comprehensive and ecologically valid way (from training novice drivers to driving in real scenarios), on the other hand it limited us in the possibility of evaluating the role of individual characteristics of the systems taken into account.

Another possible limitation is that positive self-reported feedback from participants about Mixed Reality training may have been due to the novelty of the Mixed Reality systems, the fact that the experience may be interpreted as a game and its application to automated driving may have generated an unconscious bias towards perceived utility and acceptability. Mixed Reality experts and frequent users of immersive experiences should be put into the loop for a rigorous validation of the learning environments and the simulator.

Results about Simulator Sickness in VR were promising in both user studies, but should be handled with care considering the short duration of the Virtual Reality experience. Longer experiments in VR should be considered and users with specific motion sickness predisposition should be included in the panel.

Considering Augmented Reality, the limitations of the selected headset made hard displaying augmented information of the real world in a large field of view. For this reason, HMD with larger FOV should be considered in order to exploit the full potential of AR to bring more easily the attention of the user to specific region of the space. Also, the manipulation space in AR should be improved implementing hands detection to enable interaction with virtual objects in addition to real ones.

7.3 Training Content

Design a training protocol on the basis of the choices made in terms of content and systems.

Once the training objectives have been established and the characteristics of the *light* systems identified, we were able to address the design of the training programs, implemented in the light Mixed Reality systems previously identified. To formally define the training requirements, we used the Rasmussen's SRK model which has proven to be an effective way to describe and evaluate specific aspects of training at various Skill, Rule and Knowledge level.

Using SRK as a guideline, we implemented the training programs in two environments: a Driving and Onboard Activities Simulator and a learning environment.

The learning environment was used to acclimatize the users with the training system and to present the *knowledge* part of the training by means of videos that illustrated general information about Level-3 and drivers' role during automation.

The On-board Activities and Driving Simulator allowed the drivers to be immersed in a conditionally automated car where they could experience the onboard activities typical of this level of automation: manual driving, automated driving, secondary activities and take-over. The simulator therefore included some typical driving scenarios (highway, traffic jam) and both safety-critical and non-critical take-over scenarios (e.g. accident, system failure, roadwork and so on). The user thus could safely practice the interaction with the onboard equipment and novel driving situations and the actions to perform when their intervention was required.

The user studies we performed helped us in shaping and adjusting the content of the training according to empirical observations. Most notably, the learning strategy in the Virtual Learning Environment evolved between the two user studies: the first version of the VLE (used in the user study presented in Chapter 5) was inspired by what happens in traditional car handover or what would happen in the real case: a trainer/car dealer provides information about the control or the functionalities of the car during a driving session. The first version of the VLE reproduced this concept, and therefore the learning content was provided to the user while they were driving. This *learning-by-driving* approach, however, showed its disadvantages in terms of mental workload: drivers may have been too focused on the control of the virtual car (steering and acceleration) to easily process training information about take-over procedure. For this reason, the next version of the VLE (used in the user study presented in Chapter 6) separated the environment where the *rules* were learned from the driving environment were the *skills* were practiced: this *context switch* helped the participants in focusing their attention first in the acquisition of rules, and subsequently to the driving environment for the application of the acquired skills in the driving situations. Also, this approach allowed us to implement driving scenarios with different complexity and this contributed in improving users adaptation.

Limitations
The training was designed to give a general understanding of the system, but its content may not have been in the best possible form; further work on the content should be performed by including ergonomists, UX experts, technical writers and media creators such as video editors and UX designers. An important question that needs to be further addressed concerns the mandatory information a human driver must be provided before operating an automated vehicle.

Although the HMI (visual pictograms and auditory alerts) used for the user studies was validated with a study of a partner institution (VeDeCom, [Bueno et al., 2016]), its clarity, intuitiveness and effectiveness should be further investigated. Also, additional interaction modes (e.g. vocal commands, gesture recognition) should be considered for experimentation as well as other feedback channels (e.g. haptics, cabin light).

7.4 Training Evaluation

Evaluate training effectiveness and assess the transfer of skill to the driving scenario.

The efficacy of the training was assessed in two between-subjects user studies with sixty participants each one. In order to compare the effectiveness of the proposed training systems, we implemented the training content also in two other more traditional systems that we used as control groups: a user manual displayed on a laptop, and an on-board video tutorial. Thus, the two user studies evaluated six different training systems in total, three for each study.

The experimental activity was conducted with the aim of producing ecologically valid results in order to maximize the extent to which the findings of the research could be generalized to real-life settings.

The participants were evaluated during a test drive in which they were asked to behave as they would normally have done in the real situation; to further preserve the ecological validity, participants were also free to perform naturalistic secondary tasks (e.g. videos, games, monitoring of the driving environment) during autonomous driving. In particular in the first user study the test drive was performed in a high-end driving simulator, while in the second user study it was performed on public roads using the Wizard-of-Oz methodology and an actual vehicle.

We proposed to evaluate the training effectiveness and the learning outcome in both studies with self-reported (questionnaires, auto-evaluation, etc) and objective measures (knowledge assessment tests, driving-related measures) chosen after a review of the literature.

The results about first take-over and importance of prior experience are in agreement with the literature Hergeth et al. [2017]. However, the meaning of take-over time needs further investigation. One of the hypothesis is that, since take-over time depends on how long it takes for the driver to reestablish the driving context, a training program which includes the practice in driving scenarios may favor the process of bringing the driver back into-the-loop. To confirm this hypothesis, more specific and experimental controlled user studies (out of the scope of this thesis) should be conducted. Also, the fact that after the second Request to Intervene, take-over time reaches a steady state may denote that the test drive itself had as well a learning effects on drivers.

The absence of significant differences in the driving related measures suggests that, although these metrics could be useful to assess driving performance and driver behavior after a take-over request, they are not very suitable to compare training effectiveness. Evaluating driving and interaction skills in automated cars remains a complex task because the concept of being well trained to drive or operate vehicles with this level of automation is multidimensional and it involves, as we presented, behaviors at skills, rules and knowledge levels.

Limitations

During the test drives the budget time for RtI was arbitrarily chosen and it may not reflect the actual time interval in the real vehicle. Due to the experimental settings, protocol and objective, the time of automated driving before a RtI may have been way shorter than in real driving scenarios. Also, the number of RtI during the test drive was generally higher than the real scenario.

Both test drives presented some limitations. The simulated test drive in the high-end driving simulator had high, but still limited ecological validity due to the nature of simulation itself (e.g. surrounding environment, perception of danger and so on). The Wizard-of-Oz test drive, instead, allowed to assess training effectiveness in the real driving scenario. If on one hand, the WoZ test drive provided higher ecological validity because participants could behave in a more naturalistic way, it is also important to point out that there was a much lower experimental control over the events on the road, and thus it would be harder to ensure reproducibility and validity of objective driving measures. In addition, there is also a limitation in the type of measure that can be assessed. While in simulation there is a complete and precise knowledge of all the actors (i.e. ego vehicle, traffic vehicles, road sign) involved, in the real case the knowledge and the quality of information relative to the exterior of the vehicle depends on the equipment of the car. Even a fully equipped prototype, which may be very expensive to build and not very adapted for testing purposes, would not be able to deliver the same information of a simulator. Information coming from a simulator is also much easier to process than raw CAN data from a vehicle. Thus, test drives should be conducted to take into account parameters that have been considered relevant and significant in order to obtain a measure of take-over performance and quality.

Also, it is important to underline that since the Wizard-of-Oz vehicle was driven by an experienced pilot, the findings should not be generalized to driver's behavior in actual automated cars; in particular we remind that some participants were reassured by the presence of the experimenters inside the car and that they would have not performed the test drive alone. Further research should be conducted to ensure the validity of WoZ protocol for automated driving: for example a comparison of behavior between real and simulated driving, or a sort of Turing test with an actual automated car and a Wizard-of-Oz prototype.

7.5 Open questions and perspectives

To assess user's readiness to operate the automated system we performed test drives. An important challenge to address concerns the evaluation of users during the training itself (without test-drives). This is considered of crucial importance because, as discussed, it may be plausible that the test drive had a learning effect as well.

Therefore, also the training content should be improved and a possibility is to design it as a more structured *serious game* in which the type of information is adapted to the user's skill and the complexity increases as the user progresses in the game. Gamification may also improve users' motivation and involvement, which may foster the learning and skills acquisition process. Designing a serious game however would require a heterogeneous team consisting of programmers, game designers, artists, testers and domain experts.

A major challenge for future work will be to identify a set of metrics that may allow the characterization of user's performance during the training itself rather than a simulated test drives. In other words, at the end of the training it should be possible to tell if a user is ready or not (i.e. has acquired the necessary skills) to operate a conditionally automated car by applying machine learning algorithms to markers related, for example, to attention, situation awareness, gaze behavior and driver's state.

A further perspective concerns the question of skill maintenance over time and generalization to various driving scenarios. In other words, research should be focused in answering to questions such as *"Is only one training session sufficient? Are the drivers able to operate the system, even not just after the training? Will drivers lose driving or operational skills because of lack of practice?"*

Also, although the training was conceived with the aim to teach drivers how to operate the vehicle, it is possible to assume that the content of the training program would be useful also for familiarizing car dealers with the novel functionality of the car. The increasing complexity of car equipment and the variety of optional features could make insufficient the training courses that the car dealers have to regularly attend in order to be updated. In this case, the training content should be focused in fostering declarative knowledge rather than operational skills or driving performance.

7.6 Epilogue

Mixed Reality is a valid tool for familiarizing drivers with conditionally automated vehicles. MR systems are effective for the acquisition of general knowledge relative to the system including the localization and identification of the HMI and for understanding the role of the driver in automation. In addition, the simulated practice of simple driving scenarios further facilitates the acquisition of motor skills relative to transfer of control. Hence, Mixed Reality systems should be considered as a support tool during the handover process of a new automated vehicle. According to the target audience and the technological limitations, some MR systems may be preferred to others for their characteristics of isolation from the real world.

Appendices

Appendix A

Scientific Production

The research work performed during this PhD thesis have been presented to the scientific community in the following forms of journal articles, conference papers, posters and oral presentations.

Journal articles

- Sportillo D, Paljic A, and Ojeda L. ”Get ready for automated driving using Virtual Reality.” *Accident Analysis & Prevention* 118 (2018): 102-113.

International conference papers

- Sportillo D, Paljic A, and Ojeda L. ”On-Road Evaluation of Autonomous Driving Training”. *14th ACM/IEEE International Conference on Human Robot Interaction* (2019).
- Sportillo D, Paljic A, Boukhris M, Fuchs P, Ojeda L, Roussarie V. ”An immersive Virtual Reality system for semi-autonomous driving simulation: a comparison between realistic and 6-DoF controller-based interaction”. In Proceedings of the *9th International Conference on Computer and Automation Engineering* 2017 Feb 18 (pp. 6-10). ACM.

Poster presentation

- Sportillo D, Paljic A, Boukhris M, Fuchs P, Ojeda L, Roussarie V. ”Light Virtual Reality systems for the training of conditionally automated vehicle drivers”. *IEEE VR 2018*
- Sportillo D, Paljic A, Boukhris M, Fuchs P, Ojeda L, Partipilo G, Roussarie V. ”Learn how to operate semi-autonomous vehicles with Extended Reality”. *1st International Workshop on Virtual, Augmented and Mixed Reality for Human-Robot Interaction - HRI 2018*

Appendix B

Questionnaires

B.1 The role of immersion in VR-based training

Questionnaire A

* Required

1. **How often do you drive a car in these conditions?**
Mark only one oval per row.

	Rarely	Once a month	Once a week	2/5 days a week	Everyday
City					
Routes Nationales					
Highways					
Fluid traffic					
Heavy traffic					

2. **Do you use the Cruise Control?**
Mark only one oval.

- Yes
- I have it, but I don't use it
- I don't have it in my car

3. **Have you already used a driving simulator?**
Mark only one oval.

- Yes
- No

4. **What is your familiarity with Virtual Reality?**
Mark only one oval.

- I don't know what it is
- I know the concept, but I have never tried
- I have already tried once or twice
- I often use it in my private or professional life

5. **Do you play video games?**
Mark only one oval.

	1	2	3	4	5	
Never						I am an intense gamer

Questionnaire B

Do you agree with the following statements?

6. **I think that a semi-autonomous car will be useful in my everyday life**
Mark only one oval.

	1	2	3	4	5	
Not agree at all	◯	◯	◯	◯	◯	Totally agree

7. **I think that a semi-autonomous car will be useful for the society, from the point of view of the road safety**
Mark only one oval.

	1	2	3	4	5	
Not agree at all	◯	◯	◯	◯	◯	Totally agree

8. **I think that a semi-autonomous car will be useful for the society, from the environmental point of view**
Mark only one oval.

	1	2	3	4	5	
Not agree at all	◯	◯	◯	◯	◯	Totally agree

9. **I think that the semi-autonomous car can make my travels more enjoyable**
Mark only one oval.

	1	2	3	4	5	
Not agree at all	◯	◯	◯	◯	◯	Totally agree

10. **The semi-autonomous car can reduce the risk of accidents**
Mark only one oval.

	1	2	3	4	5	
Not agree at all	◯	◯	◯	◯	◯	Totally agree

11. **I think I would feel safe in a semi-autonomous car**
Mark only one oval.

	1	2	3	4	5	
Not agree at all	◯	◯	◯	◯	◯	Totally agree

12. **I see myself doing other tasks than driving in a semi-autonomous car**
Mark only one oval.

	1	2	3	4	5	
Not agree at all	◯	◯	◯	◯	◯	Totally agree

13. **In the current state of my knowledge, I have confidence in the decisions that the semi-autonomous car would take in my place**
Mark only one oval.

	1	2	3	4	5	
Not agree at all	⬭	⬭	⬭	⬭	⬭	Totally agree

Skip to question 14.

Questionnaire C

Your impressions after the training phase:

14. **The training phase was:**
Mark only one oval per row.

	Not at all	Slightly	Moderately	Very	Extremely
Useful	⬭	⬭	⬭	⬭	⬭
Enjoyable	⬭	⬭	⬭	⬭	⬭
Realistic	⬭	⬭	⬭	⬭	⬭
Effective	⬭	⬭	⬭	⬭	⬭
Innovative	⬭	⬭	⬭	⬭	⬭
Easy	⬭	⬭	⬭	⬭	⬭
Pleasant	⬭	⬭	⬭	⬭	⬭
Hard to understand	⬭	⬭	⬭	⬭	⬭
Disorientating	⬭	⬭	⬭	⬭	⬭
Annoying	⬭	⬭	⬭	⬭	⬭

15. **To what extent did the training teach you how to interact with a semi-autonomous car?**
Mark only one oval.

	1	2	3	4	5	
Not at all	⬭	⬭	⬭	⬭	⬭	A lot

16. **How ready do you feel to drive a semi-autonomous car?**
Mark only one oval.

	1	2	3	4	5	
I am not ready	⬭	⬭	⬭	⬭	⬭	I am ready

Questionnaire D

Post Training (Light VR, Fixed-base)

17. **To what extent was the simulator physically realistic?**
Mark only one oval.

	1	2	3	4	5	
Not at all	⬭	⬭	⬭	⬭	⬭	A lot

18. **How do you evaluate the physical comfort of the training?**
Mark only one oval.

	1	2	3	4	5	
Not at all comfortable	⬭	⬭	⬭	⬭	⬭	Very comfortable

19. **How much did you feel in a real driving situation?**
Mark only one oval.

	1	2	3	4	5	
Not at all	⬭	⬭	⬭	⬭	⬭	A lot

20. **To what extent the experience in the virtual environment has it been compatible with your real-world experiences?**
Mark only one oval.

	1	2	3	4	5	
Not at all	⬭	⬭	⬭	⬭	⬭	A lot

Questionnaire F

21. **To what extent did the training help you prepare for the following situations?**
Mark only one oval per row.

	Not at all	Slightly	Moderately	Very	Extremely
Obstacle on the road	⬭	⬭	⬭	⬭	⬭
Loss of marking	⬭	⬭	⬭	⬭	⬭
Sensor failure	⬭	⬭	⬭	⬭	⬭

22. **How ready do you feel to drive a semi-autonomous car?** *
Mark only one oval.

	1	2	3	4	5	
I am not ready	⬭	⬭	⬭	⬭	⬭	I am ready

23. **How many training sessions identical to today's would be necessary for you to feel ready (put 0 if you indicated that you feel ready)**

____

24. **Do you think you have understood how to activate the automated driving?**
Mark only one oval.

	1	2	3	4	5	
Not at all	⬭	⬭	⬭	⬭	⬭	Totally

25. **Do you think you have understood how to activate the manual driving?**
Mark only one oval.

	1	2	3	4	5	
Not at all	⬭	⬭	⬭	⬭	⬭	Totally

26. **In the simulator, do you think you have understood the situation that provoked the take-over request?**
Mark only one oval.

	1	2	3	4	5	
Not at all	⬭	⬭	⬭	⬭	⬭	Clearly

B.2 On-Road Evaluation of VR and AR training

Formulaire Initial

* Required

1. **ID** *

2. **Date** *

Example: December 15 11:03 AM

3. **Système** *

Mark only one oval.

- ◯ Réalité Virtuelle
- ◯ Réalité Augmentée
- ◯ Video

Habitudes de conduite

4. **Vous conduisez une voiture dans ces conditions :** *

Mark only one oval per row.

	Rarement	Une fois par mois	Une fois par semaine	2 à 5 jours / semaine	Tous les jours
Ville	◯	◯	◯	◯	◯
Route	◯	◯	◯	◯	◯
Autoroute	◯	◯	◯	◯	◯
Circulation Fluide	◯	◯	◯	◯	◯
Circulation Embouteillée	◯	◯	◯	◯	◯

5. **Utilisez-vous la fonction régulateur de vitesse quand vous conduisez ?** *

Mark only one oval.

- ◯ Oui
- ◯ J'ai la fonction sur mon véhicule mais je ne l'utilise pas
- ◯ Je n'ai pas cette fonction sur mon véhicule

6. **Quelle est votre familiarité avec la** *

Mark only one oval per row.

	Je ne sais pas ce que c'est	Je connais le concept mais je n'ai jamais essayé	J'ai déjà essayé une fois ou deux	Je l'utilise souvent dans ma vie privée ou professionnelle
Réalité Virtuelle	◯	◯	◯	◯
Réalité Augmentée	◯	◯	◯	◯

7. **En cas de problème avec des dispositifs technologiques (téléphone, ordinateur,...), quelle est la démarche principale pour le résoudre ?** *
Mark only one oval.

- Par vous même : vous consultez des forum en ligne pour trouver la solution; vous utilisez le manuel utilisateur;
- Vous cherchez dans votre entourage quelqu'un d'expert qui vous donne un coup de main / conseil
- Vous vous adressez à un professionnel / réparateur

Etes-vous d'accord ou pas d'accord avec les propositions suivantes?

8. **La voiture semi-autonome...** *
Mark only one oval per row.

	1 = Pas du tout d'accord	2	3	4	5 = Tout à fait d'accord
serait utile dans ma vie courante.					
serait utile pour la société, du point de vue de la sécurité routière.					
serait utile pour la société, du point de vue de l'environnement.					
peut rendre mes déplacements plus agréables					
peut réduire mes temps de déplacement.					

9. **Je me sentirais en sécurité dans une voiture semi-autonome** *
Mark only one oval.

	1	2	3	4	5	
Pas du tout						Tout à fait

10. **Je m'imagine faire d'autres tâches que la conduite dans une voiture semi-autonome** *
Mark only one oval.

	1	2	3	4	5	
Pas du tout						Tout à fait

11. **J'ai confiance dans les décisions de conduite que la voiture semi-autonome prendrait à ma place** *
Mark only one oval.

	1	2	3	4	5	
Pas du tout						Tout à fait

Etes-vous d'accord ou pas d'accord avec les propositions suivantes?

12. **La conduite autonome...** *
Mark only one oval per row.

	1 = Pas du tout	2	3	4	5 = Tout à fait
diminue mes problèmes pendant la conduite	⬭	⬭	⬭	⬭	⬭
me permet de gérer des activités utiles pendant la conduite	⬭	⬭	⬭	⬭	⬭
me donne du temps que j'aurais perdu pendant la conduite manuelle.	⬭	⬭	⬭	⬭	⬭
augmente la sécurité routière.	⬭	⬭	⬭	⬭	⬭
empêche les infractions au code de la route.	⬭	⬭	⬭	⬭	⬭
aide le conducteur à détecter les dangers à temps	⬭	⬭	⬭	⬭	⬭
contribue à réduire le risque d'accident	⬭	⬭	⬭	⬭	⬭
interfère avec la détection des dangers (distraction)	⬭	⬭	⬭	⬭	⬭

13. **Je conduis de manière plus sûre que la conduite autonome.** *
Mark only one oval.

	1	2	3	4	5	
Pas du tout	⬭	⬭	⬭	⬭	⬭	Tout à fait

14. **En termes de sécurité, on a plus à perdre qu'à gagner avec la conduite autonome.** *
Mark only one oval.

	1	2	3	4	5	
Pas du tout	⬭	⬭	⬭	⬭	⬭	Tout à fait

Formulaire après formation

* Required

1. **ID** *

Vos impressions après la phase de formation :

2. **La phase de formation vous a semblé :** *

Mark only one oval per row.

	Pas du tout	Pas beaucoup	Un peu	Beaucoup	Très
Utile	◯	◯	◯	◯	◯
Nécessaire	◯	◯	◯	◯	◯
Amusante	◯	◯	◯	◯	◯
Efficace	◯	◯	◯	◯	◯
Innovante	◯	◯	◯	◯	◯
Engageante	◯	◯	◯	◯	◯
Facile	◯	◯	◯	◯	◯
Agréable	◯	◯	◯	◯	◯
Difficile à comprendre	◯	◯	◯	◯	◯
Désorientante	◯	◯	◯	◯	◯
Pénible	◯	◯	◯	◯	◯
Fatigante	◯	◯	◯	◯	◯

3. **Dans quelle mesure la formation vous a-t-elle appris à interagir avec une voiture semi-autonome ?** *

Mark only one oval.

	1	2	3	4	5	
Pas du tout	◯	◯	◯	◯	◯	Beaucoup

4. **Dans quelles conditions la conduite autonome est autorisée? (plusieurs réponses possibles)** *
Check all that apply.

- [ ] Option 1
- [ ] Option 3

- [ ] Option 2
- [ ] Option 4

- [ ] Option 5

5. **Quelle action devez vous faire pour activer la conduite autonome ?** *

6. **Quelle action devez vous faire pour désactiver la conduite autonome ?** *

7. **Indiquez la signification du pictogramme** *

8. **Indiquez la signification du pictogramme** *

9. **Indiquez la signification du pictogramme** *

10. **Indiquez la signification du pictogramme** *

11. **Indiquez la signification du pictogramme** *

12. **À quel point vous sentez-vous prêt à conduire une voiture semi-autonome?** *
Mark only one oval.

	1	2	3	4	5	
Je ne suis pas du tout prêt(e)	⬭	⬭	⬭	⬭	⬭	Je suis prêt(e)

13. **À quel point vous sentez-vous familier avec le véhicule?** *
Mark only one oval.

	1	2	3	4	5	
Pas du tout	⬭	⬭	⬭	⬭	⬭	Très

Etes-vous d'accord ou pas d'accord avec les propositions suivantes?

14. **La voiture semi-autonome ...**
Mark only one oval per row.

	1 = Pas du tout	2	3	4	5 = Tout à fait
serait utile dans ma vie courante.					
serait utile pour la société, du point de vue de la sécurité routière.					
serait utile pour la société, du point de vue de l'environnement.					
peut rendre mes déplacements plus agréables					
peut réduire mes temps de déplacement.					

15. **Je me sentirais en sécurité dans une voiture semi-autonome**
Mark only one oval.

	1	2	3	4	5	
Pas du tout						Tout à fait

16. **Je m'imagine faire d'autres tâches que la conduite dans une voiture semi-autonome**
Mark only one oval.

	1	2	3	4	5	
Pas du tout						Tout à fait

17. **J'ai confiance dans les décisions de conduite que la voiture semi-autonome prendrait à ma place**
Mark only one oval.

	1	2	3	4	5	
Pas du tout						Tout à fait

Etes-vous d'accord ou pas d'accord avec les propositions suivantes?

18. **La conduite autonome...**
Mark only one oval per row.

	1 = pas du tout	2	3	4	5 = tout à fait
diminue mes problèmes pendant la conduite	◯	◯	◯	◯	◯
me permet de gérer des activités utiles pendant la conduite	◯	◯	◯	◯	◯
me donne du temps que j'aurais perdu pendant la conduite manuelle.	◯	◯	◯	◯	◯
augmente la sécurité routière.	◯	◯	◯	◯	◯
empêche les infractions au code de la route.	◯	◯	◯	◯	◯
aide le conducteur à détecter les dangers à temps	◯	◯	◯	◯	◯
contribue à réduire le risque d'accident	◯	◯	◯	◯	◯
interfère avec la détection des dangers (distraction)	◯	◯	◯	◯	◯

19. **Je conduis de manière plus sûre que la conduite autonome.**
Mark only one oval.

	1	2	3	4	5	
Pas du tout	◯	◯	◯	◯	◯	Tout à fait

20. **En termes de sécurité, on a plus à perdre qu'à gagner avec la conduite autonome.**
Mark only one oval.

	1	2	3	4	5	
Pas du tout	◯	◯	◯	◯	◯	Tout à fait

Formulaire après conduite

* Required

1. **ID** *

____

Etes-vous d'accord ou pas d'accord avec les propositions suivantes?

2. **La voiture semi-autonome ...** *

Mark only one oval per row.

	1 = Pas du tout	2	3	4	5 = Tout à fait
serait utile dans ma vie courante.	⬭	⬭	⬭	⬭	⬭
serait utile pour la société, du point de vue de la sécurité routière.	⬭	⬭	⬭	⬭	⬭
serait utile pour la société, du point de vue de l'environnement.	⬭	⬭	⬭	⬭	⬭
peut rendre mes déplacements plus agréables	⬭	⬭	⬭	⬭	⬭
peut réduire mes temps de déplacement.	⬭	⬭	⬭	⬭	⬭

3. **Je me sentirais en sécurité dans une voiture semi-autonome** *

Mark only one oval.

	1	2	3	4	5	
Pas du tout	⬭	⬭	⬭	⬭	⬭	Tout à fait

4. **Je m'imagine faire d'autres tâches que la conduite dans une voiture semi-autonome** *

Mark only one oval.

	1	2	3	4	5	
Pas du tout	⬭	⬭	⬭	⬭	⬭	Tout à fait

5. **J'ai confiance dans les décisions de conduite que la voiture semi-autonome prendrait à ma place** *

Mark only one oval.

	1	2	3	4	5	
Pas du tout	⬭	⬭	⬭	⬭	⬭	Tout à fait

Etes-vous d'accord ou pas d'accord avec les propositions suivantes?

6. **La conduite autonome...** *
Mark only one oval per row.

	1 = pas du tout	2	3	4	5 = tout à fait
diminue mes problèmes pendant la conduite	⬭	⬭	⬭	⬭	⬭
me permet de gérer des activités utiles pendant la conduite	⬭	⬭	⬭	⬭	⬭
me donne du temps que j'aurais perdu pendant la conduite manuelle.	⬭	⬭	⬭	⬭	⬭
augmente la sécurité routière.	⬭	⬭	⬭	⬭	⬭
empêche les infractions au code de la route.	⬭	⬭	⬭	⬭	⬭
aide le conducteur à détecter les dangers à temps	⬭	⬭	⬭	⬭	⬭
contribue à réduire le risque d'accident	⬭	⬭	⬭	⬭	⬭
interfère avec la détection des dangers (distraction)	⬭	⬭	⬭	⬭	⬭

7. **Je conduis de manière plus sûre que la conduite autonome.** *
Mark only one oval.

	1	2	3	4	5	
pas du tout d'accord	⬭	⬭	⬭	⬭	⬭	tout à fait d'accord

8. **En termes de sécurité, on a plus à perdre qu'à gagner avec la conduite autonome.** *
Mark only one oval.

	1	2	3	4	5	
pas du tout d'accord	⬭	⬭	⬭	⬭	⬭	tout à fait d'accord

Etes-vous d'accord ou pas d'accord avec les propositions suivantes?

Les questions concernent le véhicule que vous avez conduit.

9. *

Mark only one oval per row.

	1 = Pas du tout	2	3	4	5 = Tout à fait
Le véhicule est trompeur					
Le véhicule se comporte d'une manière suspecte					
Je me méfie de l'intention, de l'action ou des résultats du véhicule					
Je me méfie du système de conduite autonome					
Les actions du véhicule auront un résultat nuisible ou préjudiciable					
Je suis confiant dans le véhicule					
Le véhicule me donne sécurité					
Le véhicule a l'intégrité					
Le véhicule est fiable					
Le véhicule est digne de confiance					
Je peux faire confiance au véhicule					
Je suis familier avec le véhicule					

10. **J'aimerais bien avoir ce système dans ma prochaine voiture**

Mark only one oval.

	1	2	3	4	5	
Pas du tout						Tout à fait

11. **Si j'avais ce système je l'utiliserais dès que possible, seul en voiture**

Mark only one oval.

	1	2	3	4	5	
Pas du tout						Tout à fait

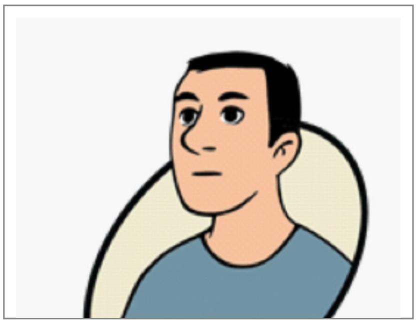
12. **Si j'avais ce système je l'utiliserais dès que possible, avec ma famille y compris des enfants.**

Mark only one oval.

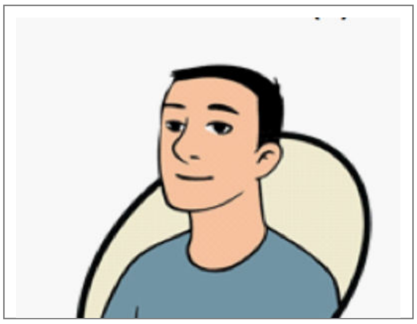
	1	2	3	4	5	
Pas du tout						Tout à fait

Questionnaire Final

13. **Dans ce tableau, sont représentés 9 personnages ressentant tous des humeurs différentes. Sélectionnez le personnage qui représente au mieux votre état actuel.** *
Mark only one oval.



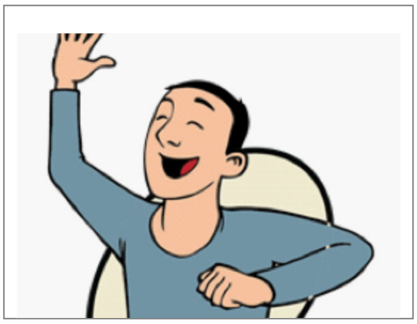
Neutre



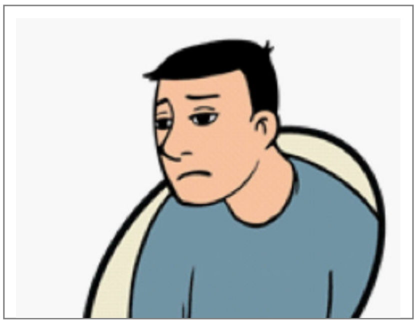
Calme, serein(e)

Relaxé(e), détendu(e)

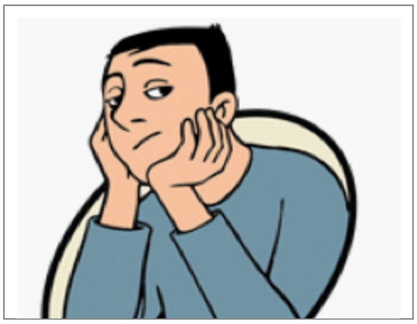
Content(e), joyeux(se)



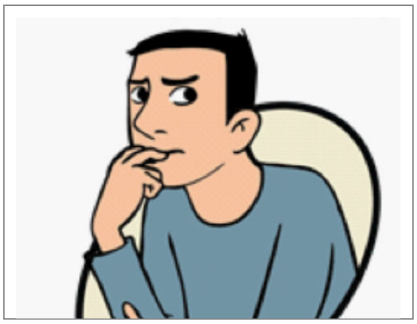
Enthousiaste, gai(e)



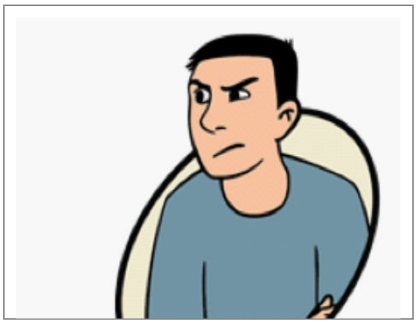
Triste, maussade



Ennuyé(e), fatigué(e)



Nerveux(se), tendu(e)



Irrité(e), énervé(e)

14. **À quel point la formation avant la conduite a-t-elle aidée à:** *

Mark only one oval per row.

	Pas du tout	Pas beaucoup	Un peu	Beaucoup	Très
Activer le mode autonome					
Reprendre le contrôle					
Reconnaître les alertes visuelles relatives à la conduite autonome					
Reconnaître les alertes sonores relatives à la conduite autonome					
Interagir, en général, avec la voiture					

15. **À quel point vous sentez-vous prêt à conduire une voiture semi-autonome ?** *

Mark only one oval.

	1	2	3	4	5	
Je ne suis pas du tout prêt						Je suis prêt

16. **Combien de séances de formation identiques à celle d'aujourd'hui seraient nécessaires selon vous pour que vous vous sentiez prêt (mettez 0 si vous avez indiqué que vous vous sentez prêt)** *

17. **Pensez-vous avoir regardé les rétroviseurs lors des phases de reprise de contrôle, après demande du système ? ***
Mark only one oval.

	1	2	3	4	5	
Non, pas du tout	⬭	⬭	⬭	⬭	⬭	Oui, à chaque fois ou presque

18. **Pensez-vous avoir utilisé le clignotant pour signaler votre changement de voie ? ***
Mark only one oval.

	1	2	3	4	5	
Non, pas du tout	⬭	⬭	⬭	⬭	⬭	Oui, à chaque fois ou presque

19. **Dans la phase de conduite, avez-vous pu comprendre la nature de la situation sur la route qui a provoqué la demande de reprise en main ***
Mark only one oval.

	1	2	3	4	5	
Non, pas du tout	⬭	⬭	⬭	⬭	⬭	Oui, clairement

20. **Avez-vous des suggestions ou des remarques?**

____
____
____
____
____

Merci de votre participation

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Appendix C

Résumé en Français

Chapitre 1 : Introduction

L'augmentation de l'automatisation et de la complexité des voitures peuvent transformer des conducteurs expérimentés en novices lorsqu'il s'agit d'interagir avec le véhicule. C'est pourquoi, avant d'utiliser un véhicule automatisé pour la première fois, il est nécessaire de bien familiariser les conducteurs avec le système afin d'apprendre les bonnes pratiques pour interagir en toute sécurité avec l'équipement du véhicule. Pour cette raison, il est nécessaire de permettre aux futurs conducteurs de maîtriser le véhicule, de comprendre les capacités et les limites du système et de leur permettre de vivre, dans un environnement sûr, diverses situations de conduite critiques et imprévues. Dans ce contexte, les technologies de Réalité Mixte et la simulation peuvent représenter des outils précieux à cette fin. En outre, des systèmes de réalité mixte légers (en termes de portabilité, d'accessibilité, de coût) permettraient de déployer facilement de tels programmes de formation dans les auto-écoles, les concessions automobiles ou même chez les clients. L'objectif de cette recherche est d'explorer si les systèmes de réalité mixte légers peuvent favoriser l'acquisition de compétences dans le contexte de voitures conditionnellement automatisées.

Les principaux objectifs de la thèse sont les suivants :

1. Définir les caractéristiques des systèmes de formation et analyser leurs limites.
2. Concevoir un protocole de formation sur la base des choix effectués en termes de contenu et de systèmes
3. Évaluer l'efficacité de la formation et évaluer le transfert des compétences dans un scénario de conduite.

Chapitre 2: Automatisation de la conduite

Les véhicules autonomes sont généralement classés en fonction du niveau d'automatisation qu'ils offrent, des capacités du système et du rôle du conducteur humain. Dans ce manuscrit, on adopt la taxonomie proposée par SAE International, dans laquelle 6 niveaux d'automatisation sont identifiés, de 0 (où le conducteur humain effectue la totalité de la tâche de conduite) à 5 (où la tâche de conduite est effectuée par le système de conduite automatique). Une distinction importante est faite entre les trois premiers niveaux (0-2) d'automatisation, dans lesquels c'est le conducteur humain qui surveille l'environnement de conduite, et les trois derniers niveaux (3-5), dans lesquels c'est le système de conduite automatisé qui s'occupe de la surveillance. Les cibles de cette thèse sont les VA de niveau 3. Cette catégorie de véhicules automatisés soulève des questions intéressantes et très stimulantes, qui sont analysées dans ce chapitre avec un focus particulier sur l'interaction entre le conducteur humain et le système.

Chapitre 3: Conception de la formation en réalité mixte pour les conducteur de voitures autonomes

Se familiariser en conduisant dans une situation de circulation réelle a beaucoup d'inconvénients. Premièrement, il serait dangereux pour le conducteur lui-même et pour les autres usagers de la route. Deuxièmement, il serait difficile de généraliser ou de diversifier le scénario de conduite, car il dépendrait de la situation réelle du trafic. Enfin, il est exigeant en termes de temps, de coût et de disponibilité du personnel et des formateurs. Pour ces raisons, il est nécessaire d'explorer des alternatives pour immerger le conducteur dans des environnements de conduite sans risque. L'une des possibilités est donnée par les environnements basés sur la Réalité Mixte. Dans ce chapitre, pour atteindre notre objectif, on définit ce qu'un système de Réalité Mixte devrait fournir en termes d'immersion en analysant ses caractéristiques de visualisation et de manipulation et on examine les bonnes pratiques pour éviter les conflits possibles qu'un utilisateur peut rencontrer en raison de la perception modifiée de l'environnement. Par la suite, on présente comment la RM a été utilisée à des fins de formation et comment les utilisateurs peuvent être évalués en fonction de leur capacité à transférer leurs compétences dans leur environnement réel.

Chapitre 4: Plateforme d'expérimentation

Dans ce chapitre, on décrit comment on a posé les bases des études expérimentales. A partir de l'analyse du contexte et de l'état de l'art présentés aux chapitres 2 et 3, on présentera les contributions qui ont menés à la conception et au développement d'une première plate-forme expérimentale. On commence par définir les caractéristiques d'un véhicule cible conditionnellement automatisé de niveau 3 et les exigences de formation pour familiariser les conducteurs avec celui-ci. Ensuite, on décrit comment les caractéristiques du véhicule ont été implémentées dans un simulateur de conduite et d'activités à bord et comment le choix de l'interface de manipulation a été justifié par une étude expérimentale. Par la suite, on présente comment ce simulateur a été implémenté comme environnement de pratique dans le programme de formation et comment ce dernier a été intégré dans le système de formation.

Chapitre 5: Le rôle de l'immersion dans la formation en réalité virtuelle

Dans cette première étude expérimentale on compare le système de RV léger présenté dans le chapitre précédent avec l'une des solutions largement utilisées dans les auto-écoles pour permettre aux futurs conducteurs de pratiquer les scénarios routiers : les simulateurs statiques. Ce type de système diffère du système léger de RV que nous proposons en termes de visualisation et de manipulation. L'objectif de cette étude est d'évaluer si cette différence joue un rôle significatif dans l'acquisition de compétences opérationnelles pour les véhicules conditionnellement automatisés. Nous focalisons notre analyse de l'immersion sur les caractéristiques de visualisation et de manipulation que les systèmes fournissent. Le simulateur statique et le système léger de RV avaient des interfaces de manipulation similaires et des caractéristiques de visualisation différentes. Nous analyserons en détail ces systèmes.

Chapitre 6: Évaluation sur route de la formation en Réalité Virtuelle et Réalité Augmentée

Les axes d'amélioration ressortis de l'étude précédente peuvent être résumés selon l'immersion, le contenu de la formation et l'évaluation de la formation. Partant de ces orientations, on présente dans ce chapitre la deuxième étude expérimentale dans laquelle nous avons comparé l'efficacité de la formation basée sur la RV et la RA et évalué le transfert de la formation à une situation réelle de conduite en effectuant un essai routier sur route publique. Comme (au moment de la rédaction du présent rapport) en Europe, les voitures automatisées de niveau 3 ne sont pas encore autorisées sur la voie publique sans permis spécial, l'essai routier a été effectué en appliquant le protocole Wizard-of-Oz (WoZ) : il a fait croire aux participants que le véhicule était conduit par un système de conduite automatisé alors que c'était un conducteur humain qui en assurait le contrôle. A notre connaissance, il s'agit de la première étude WoZ sur la conduite autonome sur route publique avec des participants inexpérimentés et inconscients.

Chapitre 7: Discussion et conclusion

Dans cette thèse on a abordé le problème de la familiarisation des conducteurs avec les véhicules autonomes de niveau 3 à l'aide de la réalité mixte. La familiarisation consistait à fournir aux futurs conducteurs de véhicules à automatisation conditionnelle de l'information sur les capacités et les limites du système automatisé, le rôle du conducteur humain dans l'automatisation et les consignes à suivre lorsque leur intervention était nécessaire pendant la transition du contrôle. Notamment, on a exploré le rôle de l'immersion dans le continuum de la réalité mixte, en étudiant l'impact de l'espace de visualisation et de manipulation et la correspondance entre le monde virtuel et le monde réel. On a mis en place un programme de formation en Réalité Virtuelle (simulateur statique, casque de RV) et en Réalité Augmentée. Deux études expérimentales, auxquelles ont participé 120 participants au total, ont été menées dans le but d'évaluer l'efficacité des systèmes de formation. En particulier, la recherche montre que les systèmes de réalité mixte sont des outils valables pour familiariser les conducteurs avec les systèmes automatisés sous conditions. Ils sont efficaces pour l'acquisition de connaissances générales relatives au système, y compris la localisation et l'identification des IHM et pour la compréhension du rôle du conducteur dans l'automatisation. De plus, la pratique simulée de scénarios de conduite simples facilite davantage l'acquisition des habiletés motrices relatives au transfert de contrôle. Par conséquent, les systèmes de Réalité Mixte doivent être considérés comme un outil d'aide lors du processus de mise en main d'un nouveau véhicule. Selon le public cible, certains systèmes de RM peuvent être préférés à d'autres pour leurs caractéristiques d'isolement du monde réel. Dans ce chapitre, on résume l'approche de recherche qui a mené à l'identification des systèmes de formation, à la conception et à la mise en œuvre du contenu de formation et à l'évaluation de l'efficacité de la formation, et on discute les résultats de notre recherche.

Chapter 8

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RÉSUMÉ

L'automatisation de la conduite est un processus en cours qui est en train de changer radicalement la façon dont les gens voyagent et passent du temps dans leur voiture pendant leurs déplacements. Les véhicules conditionnellement automatisés libèrent les conducteurs humains de la surveillance et de la supervision du système et de l'environnement de conduite, leur permettant d'effectuer des activités secondaires pendant la conduite, mais requièrent qu'ils puissent reprendre la tâche de conduite si nécessaire. Pour les conducteurs, il est essentiel de comprendre les capacités et les limites du système, d'en reconnaître les notifications et d'interagir de manière adéquate avec le véhicule pour assurer leur propre sécurité et celle des autres usagers de la route. À cause de la diversité des situations de conduite que le conducteur peut rencontrer, les programmes traditionnels de formation peuvent ne pas être suffisants pour assurer une compréhension efficace de l'interaction entre le conducteur humain et le véhicule pendant les transitions de contrôle. Il est donc nécessaire de permettre aux conducteurs de vivre ces situations avant leur première utilisation du véhicule. Dans ce contexte, la Réalité Mixte constitue un outil d'apprentissage et d'évaluation des compétences potentiellement efficace qui permettrait aux conducteurs de se familiariser avec le véhicule automatisé et d'interagir avec le nouvel équipement dans un environnement sans risque. Si jusqu'à il y a quelques années, les plates-formes de Réalité Mixte étaient destinées à un public de niche, la démocratisation et la diffusion à grande échelle des dispositifs immersifs ont rendu leur adoption plus accessible en termes de coût, de facilité de mise en œuvre et de configuration.
L'objectif de cette thèse est d'étudier le rôle de la réalité mixte dans l'acquisition de compétences pour l'interaction d'un conducteur avec un véhicule conditionnellement automatisé. En particulier, nous avons exploré le rôle de l'immersion dans le continuum de la réalité mixte en étudiant différentes combinaisons d'espaces de visualisation et de manipulation et la correspondance entre le monde virtuel et le monde réel. Du fait des contraintes industrielles, nous avons limité les candidats possibles à des systèmes légers portables, peu chers et facilement accessibles; et avons analysé l'impact des incohérences sensorimotrices que ces systèmes peuvent provoquer sur la réalisation des activités dans l'environnement virtuel. À partir de ces analyses, nous avons conçu un programme de formation visant l'acquisition des compétences, des règles et des connaissances nécessaires à l'utilisation d'un véhicule conditionnellement automatisé. Nous avons proposé des scénarios routiers simulés de plus en plus complexes pour permettre aux apprenants d'interagir avec ce type de véhicules dans différentes situations de conduite.
Des études expérimentales ont été menées afin de déterminer l'impact de l'immersion sur l'apprentissage, la pertinence du programme de formation conçu et, à plus grande échelle, de valider l'efficacité de l'ensemble des plateformes de formation par des mesures subjectives et objectives. Le transfert de competences de l'environnement de formation à la situation réelle a été évalué par des essais sur simulateurs de conduite haut de gamme et sur des véhicules réels sur la voie publique.

MOTS CLÉS

Réalité Mixte, Formation, Conduite Autonome

ABSTRACT

Driving automation is an ongoing process that is radically changing how people travel and spend time in their cars during journeys. Conditionally automated vehicles free human drivers from the monitoring and supervision of the system and driving environment, allowing them to perform secondary activities during automated driving, but requiring them to resume the driving task if necessary. For the drivers, understanding the system's capabilities and limits, recognizing the system's notifications, and interacting with the vehicle in the appropriate way is crucial to ensuring their own safety and that of other road users. Because of the variety of unfamiliar driving situations that the driver may encounter, traditional handover and training programs may not be sufficient to ensure an effective understanding of the interaction between the human driver and the vehicle during transitions of control. Thus, there is the need to let drivers experience these situations before their first ride. In this context, Mixed Reality provides potentially valuable learning and skill assessment tools which would allow drivers to familiarize themselves with the automated vehicle and interact with the novel equipment involved in a risk-free environment. If until a few years ago these platforms were destined to a niche audience, the democratization and the large-scale spread of immersive devices since then has made their adoption more accessible in terms of cost, ease of implementation, and setup. The objective of this thesis is to investigate the role of Mixed Reality in the acquisition of competences needed for a driver's interaction with a conditionally automated vehicle. In particular, we explored the role of immersion along the Mixed Reality continuum by investigating different combinations of visualization and manipulation spaces and the correspondence between the virtual and the real world. For industrial constraints, we restricted the possible candidates to *light* systems that are portable, cost-effective and accessible; we thus analyzed the impact of the sensorimotor incoherences that these systems may cause on the execution of tasks in the virtual environment. Starting from these analyses, we designed a training program aimed at the acquisition of skills, rules and knowledge necessary to operate a conditionally automated vehicle. In addition, we proposed simulated road scenarios with increasing complexity to suggest what it feels like to be a driver at this level of automation in different driving situations. Experimental user studies were conducted in order to determine the impact of immersion on learning and the pertinence of the designed training program and, on a larger scale, to validate the effectiveness of the entire training platform with self-reported and objective measures. Furthermore, the transfer of skills from the training environment to the real situation was assessed with test drives using both high-end driving simulators and actual vehicles on public roads.

KEYWORDS

Mixed Reality, Training, Autonomous Driving