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VIRTUAL REALITY APPLICATION IN TRANSPORTATION SYSTEMS SAFETY ANALYSIS

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Alla mia cara nonna Bruna,

Maestra, cuoca e autista unica.

To my lovely grandmother Bruna,

Unique teacher, cook and car driver.

"I hear and I forget,

I see and I remember,

I do and I understand."

Confucius

Summary

1. Introduction

Road traffic crashes are a leading cause of death across all age groups; this applies, with different percentages, to all road users. Being a global burden, this issue demands urgent attention. In the present PhD project, road users' behavior and their interactions will be analyzed with the aid of virtual reality. A careful investigation will be proposed.

Road users were accordingly inserted in virtual road environments, with virtual simulators. The interaction between road users, infrastructures, and vehicles was investigated.

Overall, this research attempts to answer several questions, as such:

- *Is it possible to improve road safety with virtual reality?*
- *Is it possible to improve road user behavior with virtual reality?*

This thesis has carefully interwoven virtual reality (both non-immersive and immersive), transport and safety, with technology (simulators, visors). The choice of virtual reality is dictated by the many advantages it presents, obviating all the pitfalls related to risk during field tests. A research regarding non-immersive virtual reality for car drivers was conducted at the Transportation Laboratory at the Department of Civil, Environmental and Architectural Engineering at University of Padua. Moreover, a study concerning motorcyclists was instead conducted at the HRT Laboratory of the Department of General Psychology. Eventually, a study with immersive virtual reality was proposed for the vulnerable user *par excellence*, the pedestrian.

The approximately 300 subjects involved were road users, including car drivers, motorcyclists and pedestrians; the road users were of different ages. For studies of drivers and motorcyclists, young adult drivers were expressly selected as this specific age group is at higher risk of being involved in crashes [1] and because of their proneness to be engaged in risky behaviors [2]. For the pedestrian study, the sample of subjects was different. Indeed, children's behavior was investigated, considering that Unicef and the World Health Organization [3] indicated injuries as one of the leading causes of death for those aged 5-24. Evidently, this includes road accidents.

Hence, this work outlined methodologies and techniques for the improvement of road users' behaviors.

This introductory ***Chapter 1*** introduces the matter, providing definitions of the human factor and virtual reality, cornerstones of the entire work.

In recent years, in Italy, the main causes of road accidents were identified as distraction, excessive speed and disrespect of the rules (e.g. precedence). The 2019 ISTAT report [4] illustrated the different types of accidents that occurred. These were frontal collision (~7.8%), frontal-lateral collision (~44.8%), side collision (~16.6%), rear-end collision (~26%), and collision with a stopped vehicle (~4.6%). Spillage was defined as the leading cause of crashes, deaths, and injuries. The same applies to other European countries. Indeed, according to the Bar and Page study [5], lane departure was responsible for more than 40% of accidents. For this reason, it was decided to investigate the lateral control of the vehicle, by designing new Advanced Driver Assistance Systems (ADAS) to monitor this variable. The ADAS are rapidly penetrating American and European vehicle market. However, as some studies pointed out [6], their road safety benefits may be undermined by how drivers change their conduct as they integrate these new technologies to their driving style. This depends on the accuracy of their understanding (i.e., their mental model) of these systems' functionalities [6]. There are only few studies in the literature dealing with drivers' mental models of ADAS, or highlighting the importance of the initial exposure to these technologies, and their potential effects on ADAS effectiveness.

Indeed, once it was observed that lateral control did not change as drivers became more familiar with the driving scenario, an ADAS with visual and auditory feedback was presented to the participants. This will be accordingly outlined in ***Chapter 2***. Half of the participants were not informed about the meaning of the ADAS, the others were directly instructed on the functionalities by reading an information booklet. In following studies, other ADAS with disparate types of visual and auditory feedback will be presented, so as the effects of these systems over time. These technologies, intended to increase safety, have been proposed to participants through an effective learning technique called precision teaching (PT), which will be thus discussed. This technique is an educational technique that allows to repeatedly measure the participants' performance over time to monitor their improvements. PT can be employed in a variety of areas, including road safety.

In the studies presented in the first part of the chapter, participants were indiscriminately assigned a feedback system for lateral control of the vehicle. In the second part, instead, the feedback offered to the subjects was defined according to their driving style. As well-known in the literature, the driving style of drivers can be defined by the acquisition of subjective variables through questionnaires[2], by the acquisition of objective variables or by a combination of them. The here-proposed methodology took into account several driving parameters to evaluate driving style, and focused on differentiating driver's aggressive or defensive style through cluster analysis [7][8][9][10]. The effects of multiple real time coaching programs will be investigated, as well as feedback modalities on driving performance, specifically on the occurrence of elevated gravitational-force event (EGFE).

These programs are commonly known as pay-how-you-drive [59], and are based on the assumption that the more harsh events a driver had, the more unsafe will be their driving [60]. The main idea behind the inquiry is that, by providing effective contingent feedback to drivers on their risky (e.g. harsh event) or safe (smooth event) behavior, the likelihood of hazardous situations may decrease [11]. Two particular cases of risk in this scenario will also be examined to verify the potential positive effects of the technology also on these situations. The first case outlined is the one of drivers overtaking cyclists, as motor vehicle/bicycle interactions are a relevant issue in road safety. The second situation examined is the one of drivers in highway deceleration lanes.

As for two-wheel driving, there are still not many driver assistance systems available that increase safety levels, unlike cars, whose market is constantly expanding. For this reason, ***Chapter 3*** will be devoted to the study of riders' assistance system. Finding over-speeding to be one of the causes of accidents every year, an assistance system indicating speed limit violations during a simulated moped-driving task, in optimal and poor visibility conditions, has been developed. It will be investigated the effectiveness of an alert system providing on-line feedback regarding over-speeding, during a simulated moped-riding task, and the persistence of such a system's effects in a one-month period. To a certain extent, it might be said that the methodologies explored are similar to those of the drivers in the previous chapter (*Chapter* 2).

In 2020 University of Padua funded the SID project "Safety of vulnerable road users: experiments in virtual environment" (2020-2022) proposed by Transportation Laboratory. The need for the Laboratory to open a research section dedicated to the vulnerable users was driven firstly by the data on road accidents reported in the last years by the National Institute of Statistics – ISTAT, and secondly to give space to a neglected area, namely the education of vulnerable road users. In Italy in 2019, according to data published by ISTAT[2], 8 people died every day in road accidents and that at least one of them was indeed a pedestrian. Injuries, includes road accidents, would represent one of the leading causes of death for young people [3]. In Italy only few hours of Road Safety Education are offered during the school years. For this reason, in ***Chapter 4*** a first study involving the most vulnerable road user, the pedestrian, will be presented. The aims of this pilot study are: structuring a procedure creating an immersive virtual road environment and building and testing an immersive virtual road environment. As an application case, an experiment to investigate children's behavior in the street environment was designed. This was possible with the aid of new technologies; it has here to be noted that such technologies are, at least in Italy, rarely used in this area. In this sense, this work proves to be innovative both in its educational objectives, and in the means employed to achieve them.

In ***Chapter 5*** some conclusions will be accordingly outlined, and future developments of the project are thus proposed.

Thanks to the virtual training, with three different devices, it was possible to obtain improvements in behavior and therefore to uncover real benefits of virtual reality in the world of transport safety.

1.1 Human factor [12]

This section will focus on the human factor. Indeed, the study of human factors aims at reducing the probability and the negative consequences (deaths and injuries) of human error. Such a reduction is possible by designing systems (vehicle and infrastructure), based on observation, analysis and model representation of innate human features and individual subjective limits. The purpose is therefore to achieve a design of systems, tasks and environments to ensure maximum efficiency and safety.

1.1.1 Fundamental elements of Transportation systems engineering

One of the goals of the present thesis is to identify the key human factors participating in the interaction between drivers, infrastructure, and vehicles (see Figure 1). The combination of Transportation engineering and human factors is called *positive guidance*; this approach improves safety by providing direct information on how to behave[13].

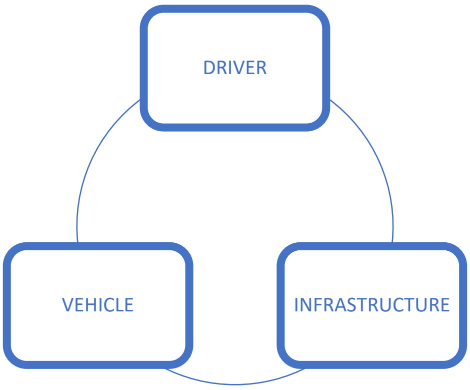


Figure 1: The three fundamental elements of Transportation Systems Engineering.

Drivers are those who ride vehicles and use the infrastructure. They are trained, and if they do not comply with the rules of conduct, they have to resort to coercive measures (fines, penalties, or withdrawal of license). The infrastructures require careful planning dictated by design criteria, changing over time. Infrastructures also change with the variation of traffic conditions and thus need proper and constant maintenance. Vehicles are the means by which drivers move around (they may be new, old, equipped with state-of-the-art devices). Notably, vehicle-infrastructure interaction systems are designed, implemented, and managed intending to minimize the number of crashes. The study is, by implication, interdisciplinary, involving both psychology and physiology, to design efficient and safe systems, tasks and environments.

1.1.2 Potential errors

Hence, the shortcomings of individuals are assessed to minimize the potential errors[14][15]. The subject and the task assigned are also studied. The limitations that they may encounter are:

- Physics;
- Perceptual;
- Cognitive (signal processing).

Reaching the limits can lead to accidents with deaths or injuries, as well as near misses. Not by chance, the primary cause of a road accident is human error. The main causes of error might be summarized so as follows:

- Judgement;
- Distraction and Disengagement;
- Fatigue;
- Overload;
- Violation.

The Judgement errors can be, for example, estimating the speed of approaching vehicles, estimating overtaking width, estimating intersection gap, estimating one’s own speed. Distraction and Disengagement occur both in the vehicle or in the street (e.g. distracted pedestrian). Drivers often occupy their minds with what might be called "internal distraction" or "mind wandering "[16][17].

Talbot et al. [18] argue that an accident is caused by distraction when an external stimulus captures the driver's attention, or even when attention is shifted without the presence of an external stimulus. Fatigue, then, represents the human effort required to perform a demanding activity (=excess work). Fatigue is related to the task. It is a state of mind that the driver equates to drowsiness, fatigue, lack of energy and it is associated with some measure of decreased performance or a physiological indicator.

Overload is a phenomenon caused by the processing of different information to perform multiple tasks simultaneously. The driver relies on a priori knowledge, based on previously

learned patterns.
Violation concerns deliberate violation of control systems or speed limits.

1.1.3 Driving task model

Driving involves several subtasks, the three primary subtasks that are, in turn, performed simultaneously are:

- *Control:* corresponds to keeping the vehicle at the desired speed and aligned with the lane. Lateral position is, for example, a control on the driver about lane alignment;
- *Conduct:* is the interaction with other vehicles (following, overtaking, entering a current, ...) while maintaining a safe distance and following the indications provided by vertical and horizontal signs, or other control systems;
- *Navigation:* involves following a route (from A to B) by reading signs and/or using landmarks (also using the navigator).

Each of these subtasks includes the driver's observation of different sources of information at several decision-making levels. Here, the hierarchy of driving tasks is based on the complexity of the subtask and its priority. It is worth noting that control is the basis for priority, and navigation is the basis for complexity. All in all, a proper driving safe experience requires a harmonious integration of the three subtasks, with the driver's attention shifting from one task to the other, depending on the circumstances. Yet, this intersection of tasks can be achieved only if the workloads of the subtasks are not maximized simultaneously.

1.1.4 Driver skills and limitations

It is necessary to study the capabilities and limitations of the driver during the driving task. These include attention and ability to process information, visual ability, choice of speed, perception and reaction time.
Through the analysis of these skills, it is possible to identify the limitations and problems associated with the task of driving and also to study methodologies to mitigate the risks associated with them.

1.1.4.1 Attention and the ability to process information

It has to be noted that both the attention and the ability to process information are limited. Therefore, criticality and limitations can be created for the driver to best accomplish the subtasks of driving (which are, as previously stated, control, conduct and navigation). Attention can be shifted quickly from one source to another, while one can process only a single source at the time. As a matter of fact, the driver can process only a few pieces of information concerning the overall road scenario, and not all the information simultaneously. When the acceptable load is exceeded, the driver neglects information, on the basis of one's perceived order of importance, ignoring those of lower level. Evidently, this so-called level of importance might be affected by error. It is therefore necessary to recognize which situations lead to an erroneous order of importance. The driver, in some situations, has a high load of information to process and, since he is not able to process it all, the probability of error increases. An example could be the scenario of entering a freeway, in which several pieces of information have to be simultaneously evaluated, namely: gap, speed on the main, type of vehicles, size of the ramp. The driver may therefore be overloaded. Here, the design criteria to increase safety by reducing overload are: presenting information consistently, passing information according to a time sequence for all subtasks, setting speed limits, and maintaining safe distances.

Notably, the driver's attention is not totally consciously-controlled. Indeed, driving emerges as an automated task, for those with some driving experience or, in general, for familiar routes. When a driving task is little challenging, attention will be directed to the unconscious. Clearly, this can lead to critical situations such as accidents, running red lights, etc. In this context, the driver's expectations are derived from previous experiences. The driving task appears easier when one has to process only some additional information. The expectations can be:

- Long-term expectations: the non-habitual driver might apply to the new road environment some previously processed expectations;
- Short-term expectations: the driver is unfamiliar with the road and is expected to maintain consistent behaviors on that stretch of road.

Expectations are benefits that might fuel storage capacity on the driver's part.

1.1.4.2 Visual Ability

Most of the information processed by drivers is visual. Evidently, the rest involves the other senses. Implicit limitations derived from vision are:

- *Visual acuity* [19]: is the ability to visually perceive distinct objects. The minimum value of the angle allowing the distinct vision of two bright points is taken as the measure of acuity. It indicates how well the driver can see the details at distance. It is important for conduct and navigation tasks that require the driver to read signs and identify objects ahead;

- *Visual search* [19]: is the ability to recognize the rapidly changing street scene, to subsequently gather information about it;
- *Contrast sensitivity* [19]: is the ability to detect slight differences in luminance between the object and the background. In other words, it is the ability of the eye to recognize different shades of the same color;
- *Peripheral vision* [19]*:* is the ability to detect objects outside the most accurate area of vision. What might be seen covers an angle of up to 94-104°. The limit of color discrimination and symbol recognition is about 30°. The limit of text recognition is, instead, about 10°. Target identification in peripheral vision also depends on the needs of the driver: when the task is more demanding, the cone of vision is more limited and therefore the driver is more likely to miss peripheral targets;
- *Movement in depth* [19]*:* is the ability to estimate the speed of another vehicle, on the grounds of the rate of change in the visual angle of the vehicle. As the vehicle approaches, the angle increases.

1.1.4.3 Choice of speed

Evidently, the choice of speed is a fundamental aspect within road safety. Here, the limits imposed by law should influence the driver's choice, but they cannot represent the most crucial factor influencing the driver’s speed. On the contrary, the choice should be the result of the elaboration of some information: perceptual signals and/or information coming from the road scenario. If one fully processes the road information, the correct speed might be reached and maintained, even without considering the speed limit signs.

1.1.4.4 Perception and reaction time (PRT)

PRT is required to:

- Detect the target;
- Process the information;
- Decide a response;
- Initiate a reaction.

Overall, PRT is measured from the identification of an object/obstacle that might cause an unexpected maneuver by the driver. In the case of an expected or highly visible object, placed where the driver places spatial attention, only a fraction of a second is required for its identification. In contrast, at night, an object that is at an out-of-sight and in a low-contrast location, takes several seconds to be identified. Failing in recognition could possibly lead to non-braking, i.e., the perception process is not activated. Once the object is perceived, details of the object must be determined to make the best decision. Once it is identified, a decision can be reached about how to react, even without acting yet. Indeed, the choice does not involve any action, it is rather a mental process that determines how the driver responds to a situation. The decision time depends on various factors that make the decision process more complex, for instance when such a decision has to be quickly reached (e.g., the dilemma zone). For example, If the driver is close to a traffic light turning yellow, the driver can comfortably stop without the risk of a rear-end collision or passing the intersection with a red light.

The amount of information is also a parameter to consider; either too much or too little information inevitably affects the matter of decision making. If there is insufficient information, drivers will need additional information, and this requires scene scanning to complete the decision-making process. Otherwise in the case of too much information, the driver may be affected by unnecessary effort resulting in losing time. Increased decision time occurs when the driver must interpret the true nature of unclear information. Once a decision has been made, a reaction is required.

1.1.5 Human Factor in this work

Human Factor is certainly one of the most critical and decisive factors in road safety.

Since human factor is undoubtedly relevant to this work, it will be here studied and then considered to improve the safety of road users.

All the topics covered in the previous paragraphs lead to the correct approach for a road safety design. Consistent design might solve driver limitations by increasing the likelihood of a correct and quick response. Conversely, when information is not received in time, or when an information overload happens, or, again, with unmet expectations, slow responses and errors can occur, with negative consequences for safety.

1.2 Virtual Reality

1.2.1 History

It was in 1938 when Charles Wheatstone managed to create the first *stereoscope*, therefore receiving the Royal Medal from the Royal Society of London (see the Timeline in Figure 2) [20][21]. This was the starting point for a later invention, the so-called stereoscopic 3D TV [22]. Such a technology, with the aid of optical lenses, was later developed and improved in 1848 by David Brewster [23]. Then, about 40 years later, Amariah Lake presented *The*

Haunted Swing [24][25]. The technological progress continued to enormously expand. In the following century, in 1960, a young American researcher Ivan Sutherland created Sketchpad, essential for future interfaces of virtual reality [26]. Two years later, in 1962, Morton Heilig invented *Sensorama,* being the first simulator composed of a stereoscopic color display, odor emitters, fans, a mobile chair and a sound system [27][28]. Soon, he further developed a video camera and carried out five short experiments to demonstrate the potential of its invention. Almost in the same years, Ivan Sutherland described a viewer with interactive graphics and feedback devices and accordingly invented the first head-mounted display called *The Sword of Damocles* [29]. The first flight simulator was instead proposed by Thomas Furness for the Air Force and the General Electric Corporation. In 1972, it was also built a flight simulator with a field of view of 180 degrees, through the use of three screens around the cockpit. In the same years, at the Milwaukee Art Center the first interactive VR platform, Videoplace, was exposed, a creation of Kruger. In '79 McDonnel-Douglas Corporation produced the Vital helmet for military use and the very following year StereoGraphics created the glasses for stereo vision. In 1982 gloves were conceived to monitor hand movements and the first laboratory dedicated to virtual reality, Atari Research, was founded [30].

Figure 2: Virtual reality timeline (Inspired by [31]).

Moreover, in ’85, Scott Fischer developed a head-mounted display "Virtual visual environments display" at a cost of about $2000. Additionally, in the same period, Jerome

Lanier and Thomas Zimmerman founded the Visual Programming Language (VPL) Research, and, from their collaboration, DataGlove and Powerglove were conceived. Worth noting is also that Nintendo launched, in 1995, the console "Virtual Boy" which was, unfortunately, withdrawn from the market due to its lack of color graphics, use convenience and software support. In 2012, the Oculus Rift was presented by Luckey and purchased two years later by Facebook. This was followed by the Samsung Gear VR (2015), the Play Station VR (2016), the Oculus Go (2018) and the Oculus Quest (2019). Subsequently, in the last five years, many companies have designed headsets for virtual reality: HTC, HP, Google, Apple, Amazon, Microsoft Sony, Samsung, etc.

1.2.2 Definitions

Virtual reality might be described as an imaginary world, existing in digital realities and in human minds. In the Webster's New Universal Unabridged Dictionary, the terms “virtual” and “reality” are so defined[32]:

- Virtual is defined as a quality of “being in essence or effect, not in fact";
- Reality as "the state or quality of being real".

Definitions of virtual reality are given in Table 1.

Table 1: Definitions of Virtual Reality.

Definition	Year	Authors
The terms virtual worlds, virtual cockpits, and virtual workstations were used to describe specific projects…. In 1989, Jaron Lanier, CEO of VPL, coined the term virtual reality to bring all of the virtual projects under a single rubric. The term therefore typically refers to three-dimensional realities implemented with stereo viewing goggles and reality gloves.	1991	Kruger [33]
Virtual Reality is an alternate world filled with computer-generated images that respond to human movements. These simulated environments are usually visited with the aid of an expensive data suit which features stereophonic video goggles and fiber-optic data gloves	1992	Greenbaum[34]
VR is a way for human to visualise, manipulate and interact with computers and extremely complex data	1992	Aukstakalnis & Blatner [35]
VR arises from some basic senses of sight, sound, touch and smell that are created by artificial means.	1994	Bjelland & Rlevy [35]
Virtual reality lets you navigate and view a world of three dimensions in real time, with six degrees of freedom. In essence, virtual reality is clone of physical reality	1995	Von Schweber [35]
VR as being a collection of technologies and hi-tech devices e.g. Head Mounted Display HMD, 3D-Stereophonic Audio, Motion Sensors, Cyber Glove etc.	1998	Isdale [35]
an experience .. in which the user is effectively immersed in a responsive virtual world	1999	Brooks [35]
VR is a simulation of a real or imagined environment that can be experienced visually in the three dimensions of width, height and	2002	What Is.com [35]

depth and that may additionally provide an interactive experience visually in full real-time motion with sound and possibly tactile and other forms of feedback		
VR is a high end computer interface that evolves real time simulation and interaction through multiple sensorial channels. These sensorial modalities are visual, auditory, tactile, smell and taste.	2003	Burdea & Coiffet [35]

In this thesis, however, Sutherland's [36] definition will be adopted:
"Don't think of that thing as a screen, think of it as a window, a window through which one looks into a virtual world. The challenge to computer graphics is to make that virtual world look real, sound real, move and respond to interaction in real time, and even feel real".

1.2.3 Key elements of VR

Noticeably, the 4 key elements of virtual reality are [32]:

- The virtual world;
- Immersion;
- Sensory feedback;
- Interactivity.

These 4 elements are below described.

1.2.3.1 The virtual world

Virtual universe can represent both an actual location in the real life and abstract idea, existing on an imaginary level, and even when it is not transposed to a virtual reality system [32]. In other words, it does not need to be actually created to exist. All in all, a computer-generated world might be intended as a written representation of elements that could be eventually exploited to later develop experiments, videogames, simulations. The digital rules assembled to perform, for instance, an experiment, are basically a sort of description, that might or might eventually become concrete. In this sense, a virtual world is metaphorically similar to the process of a movie script used to generate, indeed, a movie, viz. an actual performance of that script.

1.2.3.2 Immersion

Conceivably the most engaging feature of virtual reality is that it allows complete immersion in the fictional experience. For this reason, VR might be defined, perhaps over-simplifying, as an "immersion into an alternative reality or point of view" [32] .

Several times the term "immersion" has been applied incorrectly also instead of presence, below therefore are two definitions to avoid incurring in this mistake: "immersion stands for the objective level of sensory fidelity provided by a virtual reality system, whereas presence is the subjective psychological response of a user experiencing a virtual reality system" [37]. Berkman and Akan in one of their works [37], point out that by some researchers the use of the term "telepresence" is preferred in order to emphasize technology-mediated presence. Steuer [38] defined telepresence as telepresence is defined as the experience of presence in an environment by means of a communication medium."

Broadly speaking, several authors have attempted to define these terms, but as yet there is still no accepted definition, and several divergent definitions can be accordingly found.

These three terms might define so as follows:

- *Immersion:* it is the "sensation of being in an environment" [32], that can be a purely mental state or can be achieved through physical means;
- *Mental immersion*: it is the aim or each media creator, it might be intended as the sense of being deeply involved, and it is connected to the concept suspension of disbelief;
- *Physical immersion*: it is the act of "bodily entering into a medium" or a "synthetic stimulus of the body's senses via the use of technology" [32]; yet, this does not imply that all the senses or the entire body are immersed in the experience. As will be later outlined, it is a pivotal feature of VR.

This notion is inevitably linked to the so-called imaginary reality, which is a reality existing in the human mind. It might be said that whatever might be conceived by human imagination is possible. Indeed, human minds are so powerful that we, whoever "we" happen to be, tend to imagine ourselves within the fictional universe we encounter when reading a novel, or watching a movie. This is also a sign of how much human beings desire to be transposed to a diverse, alternative reality. Such alternative reality might be either a place existing somewhere else, or an ad-hoc crafted, wholly new-invented world. People crave that kind of experience, they subtly look for the emotions evoked by a parallel universe, so that they can escape, even for a few hours, from their real lives. This is exactly the aim of virtual reality.

Since in virtual reality people can transpose their bodies to the computer-generated universe, they are more likely to perceive a deep involvement. The same does not apply to traditional media, which are not as effective as virtual reality in terms of user engagement. Indeed, VR is able to create an active experience, differently from, for example, the passive process of reading a book or watching a comedy. While the latter merely involve a mental, or emotional immersion, virtual reality simultaneously involves both the body and the mind, starting from a physical, sensory immersion. Indeed, the user can act – and interact – *with* the digital world and *in* the digital world. The user therefore becomes so immersed to feel, and actually be, a real part of the virtual world. In this way, direct interaction is established between the user and the medium, as will be discussed in later sections.

1.2.3.3 Sensory feedback

The previous section described how technology enables far-reaching connections with fictional worlds, so that a virtual reality might result extremely vivid, and an intense involvement can be achieved [32]. A simulation of reality, being exceptionally complex, can be so immersive and authentic to come very close to physical reality. This is possible thanks to direct sensory feedback and a wide range of related inventions. It is possible to identify two ways of sensory feedback in the virtual world: participant's actions can affect the world, but also the world can send sensory stimuli to participants. These two way of sensory feedback vary in relation to the implemented VR.

Indeed, VR system is capable of providing direct sensory feedback to the users considering their physical position. That is to say, it can perceive the location and/or orientation of an element existing in the real world, e.g. a part of the user’s body, and then send this information to the virtual world.

Overall, VR is able to track participants’ movements through innovative, disparate technological inventions. In this respect, the visual sense is generally the one receiving feedback. It is here to be noted that, for this feedback to be immediate, a high-speed computer is evidently required.

1.2.3.4 Interactivity

As already outlined, one of the essential elements for virtual reality to be effectively, totally engaging is interactivity [32]. VR is inherently interactive, for it establishes a direct contact and continuous flow of dialogue and information between the virtual world and the physical world, that is, between the user and the computer-generated simulation of reality. The flow of information and feedback might be defined as bi-later, and it is no longer pre-determined nor fixed. A sort of conversion and interconnection is therefore established.

This is concept is deeply rooted in the one of immersion, since the very act of interaction requires a certain degree of immersion. The participant cannot passively consume and receive entertainment by a medium as it happens with traditional media, on the contrary, one has an active, operating role in shaping the experience. In this specific work the road users simulators interact with the subjects that use them. With the car simulator, for example, it is possible to program interactions that the participant will have with the environment (for example: braking vehicle, cyclist to overtake) so as to study then *a posteriori* the behavior of the user in these specific situations. In this work the interactions were always controlled by the researchers.

1.2.4 Types of realities

Reality can be considered as a continuum of virtuality from the real environment to virtual environments. The various forms are wisely explained by the Milgram diagram in Figure 3 [39][40].

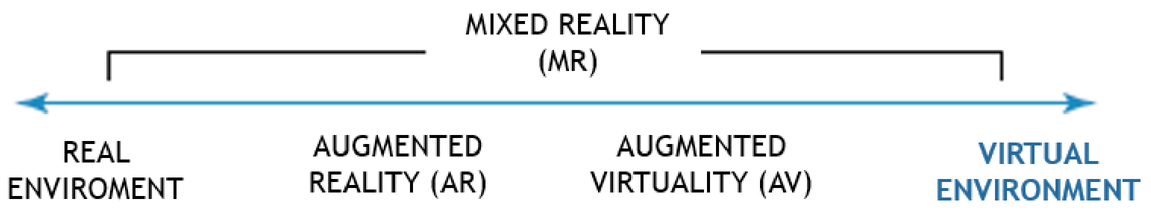


Figure 3: Milgram's Reality Virtuality Continuum.

On the left, real environment is a way to interact directly and use the five senses; on the right, one can find virtual environment, consisting of non-tangible objects created by computers and visible through the use of devices such as monitors, viewers. Virtual environment is a world where nothing perceived is real. Between these two extremes, one might notice mixed reality, that is the combination of virtual and real environments and objects. In "Augmented reality", instead, there is coexistence between virtual and real, with a predominance of reality over added objects. Augmented Virtuality presents increasing virtuality of data, and real data are limited to increasing something already existing, in a completely reconstructed environment. Finally, with the complete replacement of real data, one arrives to VR.

Three types of reality might be distinguished: ***virtual, augmented and mixed*** [20].

Virtual reality is, as previously discussed, a digital environment in which people are immersed and interactions are possible. Augmented reality involves the insertion of digital objects into the real world. Mixed reality involves the presence of a real world and virtual objects in a display. The differences between these three realities are exemplified in Table 2.

Table 2: Differences of realities

Reality	Object	World	Technology
Virtual	Digital	Digital	“Closed” viewers
Mixed	Digital, integrated into the environment	Real	“Open” viewers
Augmented	Digital	Real	“Open” viewers, smarthphone, tablet.

In turn, virtual reality is divided into three categories:

- Immersive virtual reality;
- Semi-immersive virtual reality;
- Non-immersive virtual reality.

In Table 3, differences between these three categories are described [41][42][20].

Table 3: Three virtual reality categories.

Reality	Environment representation
Immersive	Head-mounted display
Semi-immersive	Cave
Non-immersive	Display 2D

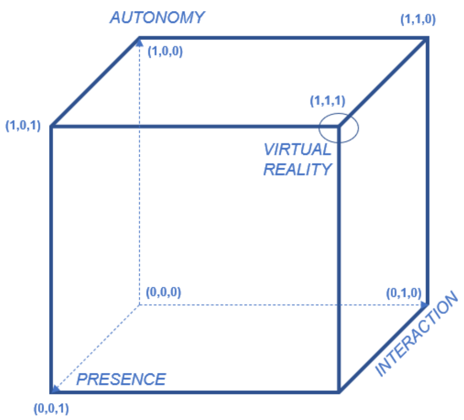


Figure 4: AIP Cube [43].

A virtual reality system, called AIP cube [43], is characterized by three variables (see Figure 4):

- Autonomy: the ability of the system to receive and react to external stimuli, such as actions performed by a user;

- Interaction: describes the extent to which all commands in the system are used;
- Presence: describes the extent to which the system provides haptic feedback.

Each variable can take a value between 0 and 1 and can be represented in a coordinate system with three axes:

- The origin (0,0,0) corresponds to the absence of virtual reality;
- The point (1,1,1) corresponds to the maximum level of virtual reality (maximum autonomy, interaction and presence).

1.2.5 Why VR

The employment of this technology ensures the active use of sensory and motor skills, for the process of learning to be enhanced. This phenomenon is well described by Edgar Dale in 1969 [44] with his "Cone of Experience" (see Figure 5), suggesting that direct experience provides a better basis for the process of understanding [21]. Edgar Dale with this diagram wants to describe how the learning process is a progression of experience.

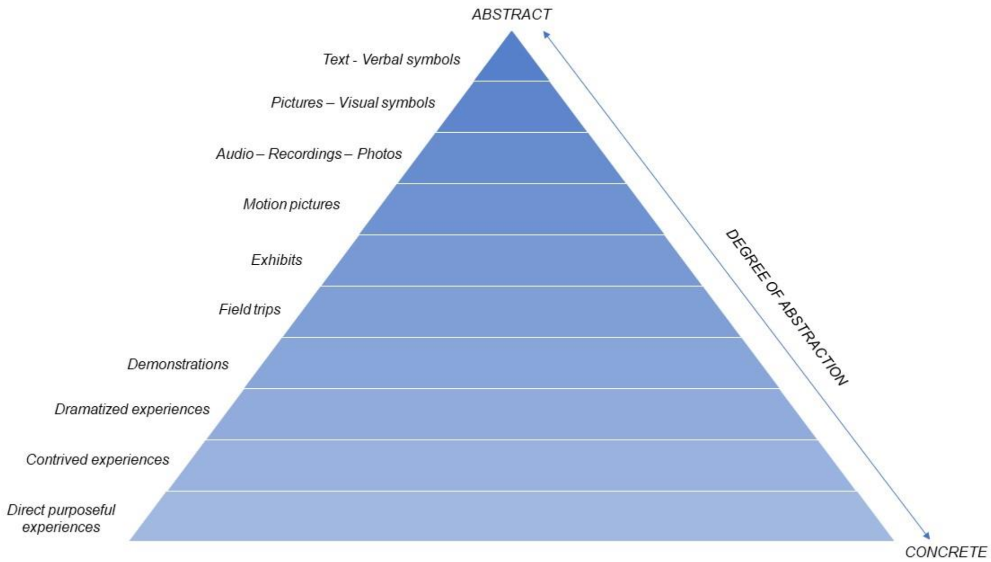


Figure 5: Cone of Experience (Adapted from [21]).

1.2.6 VR applications, advantages and disadvantages

Some of the application areas for VR include: military [45][46], education [47][48], healthcare [49][50], entertainment [51][52], fashion [53][54], heritage [55][56], business [57][58], engineering [59][60], sports [61][62], media [63][64], scientific visualization [65][66], telecommunications [67][68], construction [69][70], cinema [71][72], and programming languages[73][74].

In Table 4 main advantages and disadvantages of VR are presented.

Table 4: Main advantages and disadvantages of VR (Adapted from [59]).

VR advantages	VR disadvantages
Little/no risk	Motion sickness
Safe and controlled area	Eye strain
Realistic scenarios	Fatigue
It can be performed remotely, thus saving time and money	Headaches
It simplifies complex problems/situations	High initial cost
Suitable for different learning styles	Training in VR environment is not always real
Innovative and fun	Need for validation
To be used in a variety of fields	Technical limits
Connections with people	Ethical challenges
Effective communication and learning	
Flexible tool	
Low execution costs	
Multi-modal simulations	
Scene repeatability	
Precise and repeated measurement	
Real-time feedback	
Psychophysiological monitoring	

1.2.7 VR in this work

In this work, virtual reality is used as a means to study road users' behavior and their interactions. Thanks to the use of this technology, it has been possible to propose case studies on problems of road safety, exploiting one of the major advantages that this technology offers: the almost total absence of risk. Overall, non-immersive virtual reality was adopted in the studies of drivers and motorcyclists (in Chapters 2 and 3) and immersive virtual reality was employed in the experiment with pedestrians (in Chapter 4).

2. Virtual reality applications for car drivers

This chapter is entirely devoted to the safety matter of the car driver. A set of studies carried out with driving simulators located at the Transportation Laboratory of the ICEA Department of the University of Padua are accordingly discussed, starting from the description of such driving simulators in the following sections.

The Section 2.1 proposes an innovative Advanced Driver Assistance System (ADAS) based on the integration of training procedure and control equipment monitoring driver’s behavior (lateral control) and providing appropriate feedback. If the control of the vehicle decreases, the values of the investigated variables increase; for this reason, the variables are considered as an indicator of the driver's vehicle’s control and therefore safety. Then the section presents an inquiry aimed at identifying methodologies and solutions for the lateral control of the vehicle [75].

Subsequently, the Section 2.2 examines potential solutions for the reduction of abrupt acceleration and deceleration, once again, as in the previous study, proposing a driving support system to improve driver behavior and increase safety.

Overall, in addition to the analysis of driver behaviors, new technologies (e.g. ADAS) are here proposed and therefore tested, with the purpose of improving driving safety.

Apparatus

The driving simulators employed were produced by the Dutch manufacturer STSoftware®. They are located at the Transportation Laboratory of the ICEA Department of the University of Padua and active since 2010. The laboratory is equipped with two "PC-based" simulators, i.e. composed of one or more PCs.

One of them is static (low fidelity level), while the other is dynamic (medium fidelity level) and therefore able to simulate accelerations, displacements and vibrations that are usually perceived around the cockpit of a vehicle. This effect is achieved through the aid of a movement platform, that enables a more realistic driving experience (Figure 6, Figure 7, Figure 8, Figure 9).

The hardware apparatus of the static driving simulator consists specifically of:

- 3 networked PCs with Intel i5 processor, frequency 3.4 GHz, 2 DDR3 RAM modules of 2 GB each, Nvidia GeForce GTX 760 video card and Microsoft Windows 7 Professional operating system;
- 5 plasma displays of 50 inches with pixel resolution of 1920×1080 (L×H) arranged around the driving position, in particular one in front and two lateral, front and rear, for each side of the cockpit, used to display the driving simulation;

- Operator control display;
- Cockpit equipped with adjustable seat with: seat belt, dashboard with ignition lock, steering wheel, lever for operating direction indicators and turning on lights, five-speed manual gearbox plus reverse, parking brake and pedals with clutch, brake and accelerator;
- 5.1 surround sound system formed by 3 front speakers, 2 at the rear side at driver's head height and 1 subwoofer at the side of the pedals.

The hardware apparatus of the dynamic driving simulator, instead, consists of:

- 3 networked PCs with Intel i7 processor, frequency 3.4 GHz, 2 DDR3 RAM modules of 2 GB each, Nvidia GeForce GTX 760 video card and Microsoft Windows 7 Professional operating system;
- 5 plasma displays of 60 inches with pixel resolution of 1920×1080 (L×H), arranged around the driver's station, namely one in the front and two lateral, front and rear, for each side of the cockpit (> 300° view);
- Display for operator control;
- Kinect camera located above the front display with the function of head tracker, that allows to follow the movement of the driver's head;
- Mobile platform of the Australian manufacturer CKAS®, on which the simulator cockpit is placed, which, by means of it, is able to move with two degrees of freedom along the horizontal longitudinal and transverse axes (X,Y) and therefore to return the inertial sensations of the body;
- Cockpit equipped with adjustable seat with seat belt, dashboard with ignition lock, steering wheel, lever for operating the direction indicators and turning on the lights, five-speed manual gearbox plus reverse, parking brake and pedals with clutch, brake and accelerator;
- 5.1 surround sound system consisting of 3 speakers in the front, 2 in the rear side position at driver's head height and 1 subwoofer at the side of the pedal set.

Figure 6: Static simulator of Transportation Laboratory (STSoftware®).

Figure 7: Dynamic simulator of Transportation Laboratory (STSoftware®).

Figure 8: Cockpit (STSoftware®).

Figure 9: Apparatus (STSoftware®).

The functions for both simulators are divided between three PC (Figure 10) as it follows:

- The main PC ("control 1" or "control 2" according to the used simulator) controls the operator interface ("control terminal"), the management of the traffic simulation, the execution of the scripts, the reproduction of the sounds, the three-dimensional graphic creation (rendering) of the environment in the front monitor ("center") and the kinect camera in the case of the dynamic simulator;

- The second PC ("render A") deals with the graphics in the two front side monitors ("left-1" and "right-1") and with the dynamic simulator of the control of the motion platform;
- The third PC ("render B") deals, in turn, with the graphic rendering of the two monitors placed in the rear lateral position ("left-2" and "right-2").

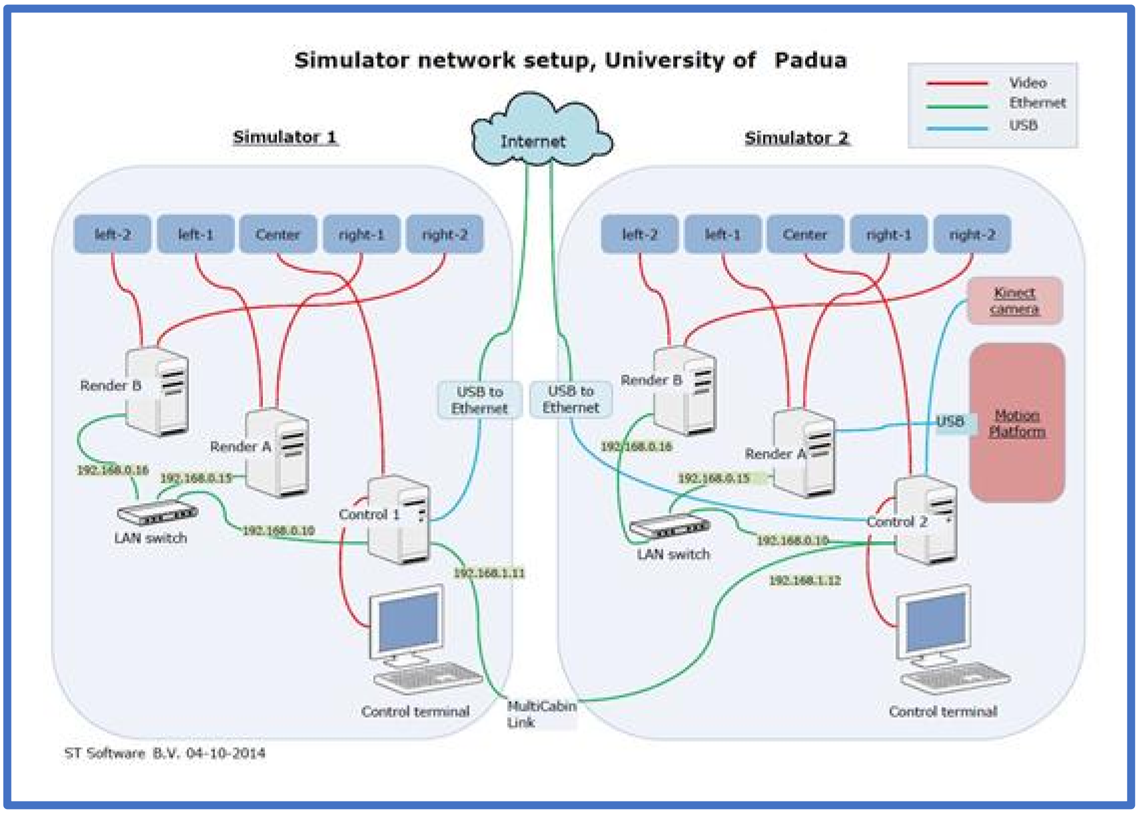


Figure 10: Driving simulator network setup (STSoftware®).

Both simulators are provided with a software package divided in three categories (Figure 11), namely:

1. *Software to design the simulation:*

- stRoadDesign for the creation of the road environments, adopting a graphical user interface (GUI);
- stScenario for the creation of the simulation scenarios with appropriate language of script.

2. *Software for the executive phase of simulation:*

- stControl for simulation control by the operator, using GUI;

- stTraffic for the computation of simulation scenarios;
- stRender for the rendering graphic 3D;
- stSoundEngine for the generation of the sounds.

3. *Software dedicated to the collection and analysis of data resulting from the simulation:*

- stTraffic/stScenario for real-time data processing;
- stDataproc for off-line data processing via GUI.

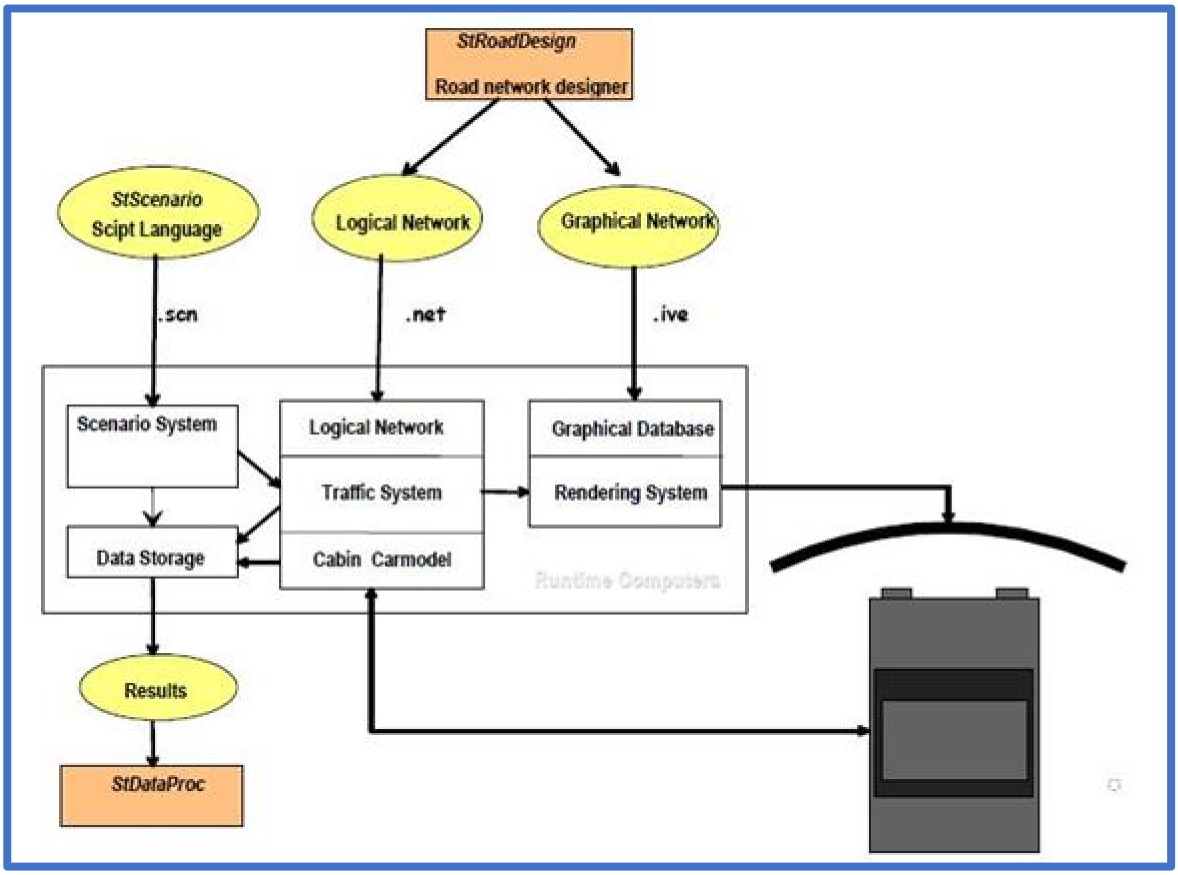


Figure 11: Package of software (STSoftware®).

2.1 Lateral control ADAS

The proposed system is an innovative Advanced Driver Assistance System (ADAS) based on the integration of two main components, namely a set of training procedures rooted in precision teaching, and a control equipment monitoring driver's behavior and providing appropriate feedback. The study had the following objectives:

- To determine whether this precision teaching method had an effect on improving driver's lateral control across consecutive trials;
- To investigate the effect of explicitly informing participants about the driving ability

evaluated by the feedback;

- To compare different combinations of visual and auditory feedback;
- To test if the improvement in driver's lateral control is retained over time.

Standard deviation of lateral position (SDLP) was considered as the main dependent variable to measure the effect of the proposed method on driving behavior.

The idea is to monitor drivers' behavior in real life and, in case they would perform below the standard, train them with a precision teaching implementation in a controlled environment (i.e., the driving simulator), to restore their ability to a satisfactory level.

Multiple driving simulator experiments were thus developed and performed. In particular:

- ***Case study 1*** investigated the effect of regular driving on lateral position measured as standard deviation of lateral position (SDLP). The aim was to observe whether SDLP decreased as drivers became more familiar with the driving scenario. No feedback was provided during this experiment [75] (see Section 2.1.2);
- ***Case study 2*** investigated the effect of precision teaching on driving behavior. The objective was to determine whether repeated driving trials with visual and auditory feedback, providing information regarding drivers' performance, were successful in reducing lateral variability. All participants received the same type of feedback, however, while the first group of participants was being informed about their ability during the trials, the second group was not. [75] (see Section 2.1.3);
- ***Case study 3*** compared the performance of several precision-teaching feedback in reducing lateral variability. Participants were accordingly divided into three groups and each group received a different type of feedback. Participants were, in this case, informed about their ability under evaluation during the trials (see Section 2.1.4);
- ***Case study 4*** investigated whether the effects of this precision teaching technique disappeared over time. Participants from ***Case study 2*** (2.1.3) *and* ***Case study 3*** (2.1.4) were asked to return for a follow-up session one month after their main session [76]. No feedback was provided during this experiment (see Section 2.1.5).

The following paragraphs will offer a detailed description of the above-mentioned experiments. Before proceeding with the description of the studies, the next paragraph will introduce the technique used in these experiments: precision teaching technique.

2.1.1 Precision Teaching technique

The term "precision teaching" refers to a teaching technique grounded in the behavioral analysis theoretical framework [77]. The aim of this method is to enable the learner to perform a given task with higher fluency [78][79], i.e. to provide faster and more accurate responses. Although precision teaching is a flexible teaching method that can be applied to countless disparate tasks [80], it is particularly suitable for structured tasks. These present a clear connection between the stimuli and the response required for each of them, such as the process of learning a foreign lexicon. For this technique to be most effective, the stimuli and the response are not required to be simple, but rather to share a clear connection. The stimulus could be a complex configuration of signals, as in the case of a given configuration of lights and pointers on a control panel. The response can be complex as well, for instance in the execution of a sequence of behaviors, as in operating levers and buttons on a control panel. What is pivotal for efficient precision teaching, is that the rules connecting configurations of stimuli to their response should be clearly defined. This approach attempts at automatizing the learner's reaction, to facilitate one's development of the correct response(s) to a given event automatically, by keeping the intervention of conscious-control processes (voluntary processes based on explicit rules) to the minimum.

Within the driving domain, precision teaching techniques were exploited to instruct drivers about eco-driving practices. In the study conducted by Hibberd et al. [81], participants were asked to use a driving simulator in high and low-density traffic conditions. Information about fuel consumption was provided to them in two ways, that is either visually on a screen, or haptically with a haptic-pedal.

Results indicated that precision teaching adopting either visual or haptic feedback successfully improved fuel efficiency in low-density traffic. Similar findings are to be found in the work of Azzi et al. [82], in which haptic feedback implemented with a precision teaching approach led to potential savings in pollution emission and positive user feedback. Though several researchers have investigated the effect of precision teaching in eco-driving behavior, few of them evaluated the potential benefits of continuous feedback on lateral control and safety. Among these, De Groot et al. [83] investigated whether the use concurrent bandwidth feedback improved learning of the lane-keeping task in a driving simulator. Evidence showed that those drivers who received only off-target feedback had superior retention, compared to those who merely received the on-target feedback.

2.1.2 Case study 1: Does lateral control depend on how familiar the scenario is?[1]

2.1.2.1 Procedure

In ***Case study 1*** participants familiarized with the simulator during a training session. During training, subjects performed a ten-minute driving task and completed a Simulator Sickness Questionnaire to ascertain whether they were subject to simulator sickness [14]. Then, each driver had to perform four consecutive trials without feedback systems.

2.1.2.2 Participants

Twenty-one subjects were involved in ***Case study 1***. Details of participants are presented in Table 5.

Table 5: Participants' gender and age [Adapted from [75]].

Case study	#Part.	Female	Male	Min Age	Max Age	Avg Age
1	21	11	10	20	29	23

They were students, member of University staff and other people with the following features:

- At least 1 year of driving experience;
- At least 5,000 km/year of average driving distance;
- No previous experience with the driving simulator.

All of them were volunteers.

2.1.2.3 Scenario

A two-way road scenario was developed in virtual reality with the 3D software of the driving simulator. The scenario of 10km was composed by a sequence of 56 left and right alternate curves, preceded by a single 200-meters straight road. Each curve presented a radius of 500 meters and was long 350 meters. Carriageway was composed by one lane per direction (width=2.95 meters). The driving route was divided in three sections as a function of the adjacent environment and speed limit in force:

- Rural: speed limit 70km/h, length 2km;
- Urban: speed limit 50km/h, length 2km;
- Rural: speed limit 90km/h, length 6km.

In the opposite direction, low traffic conditions (flow rate of about 300 vehicles/h/lane) were simulated. An average temperature between 20° C and 22° C was maintained in the

[1] The work presented in this Section is part of the following publication:
Rossi, R., Gastaldi, M., Biondi, F., Orsini, F., De Cet, G., Mulatti, C. A driving simulator study exploring the effect of different mental models on adas system effectiveness (2020) Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 12242 LNCS, pp.102-113.

laboratory; moreover, illuminance inside the room was fixed at 4 lx.

2.1.2.4 Feedback system

No feedback system was used in ***Case study 1***.

2.1.2.5 Variables

In each experiment and each trial, a set of variables was recorded by the simulator with its most accurate sampling rate of 50Hz. In the present work, dependent variables were LP and SDLP, both common parameters generally accepted in driving research [85][86]:

- LP has been used to refer to absolute lateral position, in meters:

$$LP = \frac{1}{T}\sum_{j=1}^{T}|x_j| \tag{1}$$

- SDLP indicates the standard deviation of lateral position, in meters:

$$SDLP = \sqrt{\frac{1}{T-1}\sum_{j=1}^{T}(x_j - \bar{x})^2} \tag{2}$$

Where:

- x_j is the lateral position of the vehicle, relative to the axis of the admitted area, at time instant j. x_j=0 when the centerline of the vehicle is exactly on the axis of the admitted area, x_j>0 when it is on the left and x_j<0 when it is on the right;
- T is the total number of records sampled during the experiment, and the time difference between two successive time instants j and j+1 is 0.02 seconds.

SDLP allows to evaluate the lateral variability of the vehicle position, where a value of zero indicates a situation in which the vehicle maintains the same value of lateral position throughout the whole trial. LP identifies the position of the vehicle within the lane, with LP equal to zero corresponding to the situation in which vehicle centerline is on the axis of the admitted area.

Taken singularly, SDLP cannot fully describe the quality of a driver's lateral control. For example, it is possible to maintain a constant value of lateral position (therefore with SDLP close to zero), in a completely incorrect and unsafe position (e.g., with two wheels in the opposite lane). For this reason, in this study also LP was regarded. The feedback system may be considered successful in improving driver's lateral control, only if it reduces both SDLP and LP.

2.1.2.6 Analysis and Results

All data were analyzed using JASP software [87].

To evaluate the learning effect on drivers' lateral control, a series of ANOVA for repeated measures with *Trial* (4 levels: Baseline [Trial 1], Trial 2, Trial 3, Trial 4) as within-subject factor, were performed, one on each dependent variable, namely SDLP and LP. No between-factor was considered.

The ANOVA on the SDLP showed no significant effect of *Trial* with $F(3,60)=1.246$, $p=0.301$, $\eta_p^2=0.059$. The ANOVA on the LP showed no significant effect of *Trial* with $F(3,60)=0.161$, $p=0.922$, $\eta_p^2=0.008$, as in previews works that proved how the reduction in SDLP and LP values across trials cannot be attributed to the participants becoming more familiar with the driving simulator and route ([88][89]).

Figure 12 shows the trends of SDLP and LP for Case study 1.

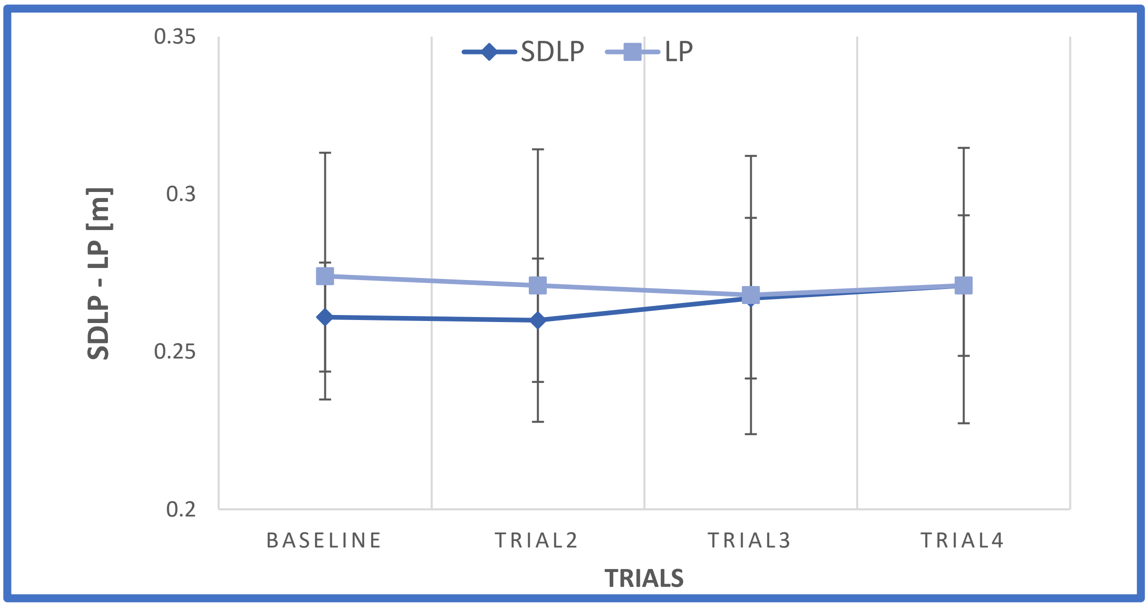


Figure 12: SDLP and LP (both in meters) across trials 1-4 for Case study 1. Error bars represent the standard error. (Adapted from [75]).

2.1.2.7 Conclusion

Results showed that lateral position was not affected by drivers becoming more familiar with the driving simulator and the route.

2.1.3 Case study 2: Has the initial mental model an effect on the learning process? [2]

Advanced driver assistance systems (ADAS) are rapidly penetrating American and European vehicle market. However, as some studies pointed out [6], their road safety benefits may be undermined by how drivers change their behavior as they integrate these new technologies to their driving style, and this depends on the accuracy of their understanding (i.e., their mental model) of these systems' functionalities [6].

In interacting with the environment, with others, and with technology, people tend to form internal, mental models of themselves and, consequently, of the things they are interacting with. These models provide "predictive and explanatory power for understanding the interaction" [90]. In other words, with respect to a technological system, a mental model is what the user believes about the system. It is based on belief and perception, not on concrete facts. It is a model of what the users already know (or better to say, think to know) about the system, initial information and experience both play a crucial role on its development.

There are only few studies in the literature dealing with drivers' mental models of ADAS, or with the importance of the initial exposure to these technologies, and its potential effects on ADAS effectiveness. It has here to be noted that an incorrect driver mental model may compromise the safety benefits of an ADAS, or even produce negative consequences in terms of road safety.

Among these studies, Beggiato and Krems [91] investigated the evolution of mental model, trust and acceptance, in relation to the initial information on an adaptive cruise control system. Indeed, three groups of drivers received three different initial set of information, during a driving simulator experiment, that is, a correct description of the system, an incomplete description and an incorrect description. They concluded that initial information creates an initial mental model, which is updated by real experience with the system and eventually tends to converge to a realistic understanding of system functionalities. However, initial information had an enduring effect on trust and acceptance. Indeed, the more cognitive effort was needed to update the mental model, the lower were trust and acceptance towards the system. In another study, Beggiato et al. [92] analyzed the evolution of the learning process and the development of trust, acceptance and the mental model for interacting with

[2] The work presented in this Section is part of the following publication:
Rossi, R., Gastaldi, M., Biondi, F., Orsini, F., De Cet, G., Mulatti, C. A driving simulator study exploring the effect of different mental models on adas system effectiveness (2020) Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 12242 LNCS, pp.102-113.

an adaptive cruise control system, by requiring drivers to complete multiple on-road driving sessions. Results showed non-linear trends over time, with a steep improvement in the first sessions, and a subsequent stabilization.
McDonald et al.[93] investigated how drivers' knowledge of a technology is influenced by their initial exposure method to the technology. Two traditional learning methods were thus tested. Reading the owner's manual and through a ride-along demonstration, it was illustrated that both of them were able to effectively convey information about the ADAS to the user. A subsequent research [94] showed that the two learning methods had different effects on driver perception of usefulness, apprehension and trust.
Correct mental models will be essential in a future of highly automatized mobility, as underlined by Victor et al. [95], who performed three test-track experiments, by studying intervention response to conflicts in driving highly automated vehicles. They provided evidence of the crucial role of attention reminders to correct the drivers' mental model.
Case Study 2 focused on the effect of the driver mental model on the effectiveness of a lateral control ADAS. The ADAS tested in the driving simulator experiment informed the driver about whether the vehicle was correctly positioned inside the lane or not, with the employment of two visual and one auditory stimuli. Drivers received two different initial exposures to the technology: they were not instructed on the ADAS functionalities, and they therefore had to learn by themselves (not instructed). They were directly instructed on the functionalities by reading an information booklet (instructed). The mean absolute lateral position (LP) and standard deviation of lateral position (SDLP) for each driver were considered as main dependent variables to measure the effectiveness of the ADAS (as in Case study 1). The Case study had the following specific aims:

- To test how the driver's improvement in lateral control evolves over time;
- To test whether the initial mental model has an effect on this learning process.

2.1.3.1 Procedure

In ***Case study 2*** the initial procedure was the same used in *Case study 1*, yet, the feedback system was switched on, after the first trial (control). 28 participants were not informed about the meaning of the stimuli, or about which driving ability it was correlated (experiment condition A). After the experiment, they were asked to fill out a questionnaire and explain the meaning of the feedback. Not all the participants were able to produce a satisfactory response, indeed, 9 out 28 participants did not properly understand the feedback system functionalities. As a matter of fact, 25 additional participants took part in this study; and they were directly instructed on the functionalities by reading an information booklet (experiment condition B).

2.1.3.2 Participants

Fifty-three subjects were involved in ***Case study 2***. Details of participants are presented in Table 6.

Table 6: Participants' gender and age (Adapted from [75]).

Case study 2	#Part.	Female	Male	Min Age	Max Age	Avg Age
A	28	14	14	19	30	23
B	25	10	15	20	30	24

They were students, staff of the University and other people with the following characteristics:

- At least 1 year of driving experience;
- At least 5,000 km/year of average driving distance;
- No previous experience with the driving simulator.

All of them were volunteers.

2.1.3.3 Scenario

Scenario was the same as that used in *Case study 1* (see Section 2.1.2.3).

2.1.3.4 Feedback system

The feedback system monitors vehicle position (centerline) every 10 meters, while following two rules: if the vehicle centerline is out of the admitted area the feedback is negative, otherwise the feedback would be positive. The admitted area was defined according to the Italian Highway Code (Art. 143-1).

The admitted area was developed (see Figure 13) considering the following criteria:

- Driving rule requires the driver maintaining a position reasonably closed to the right border of the lane, the axis of the admitted area was placed 0.25 meters right from the lane axis;
- In the literature SDLP ranges between 0.20-0.30 meters: the admitted area was 0.50 meters width.

Feedback system of *Case study 2* consists in one auditory and two visual feedback:

- Auditory: two tones, high when the vehicle enters the positive feedback zone and low when it enters the negative feedback zone (see Figure 13);

- Visual 1 (score): a display reporting a numeric score (increasing in the case of positive feedback zone and decreasing in the opposite) (see Figure 13 and Figure 14);
- Visual 2 (green bar): a green bar on the windscreen (increasing in the case of positive feedback zone and decreasing in the opposite) (see Figure 13 and Figure 14).

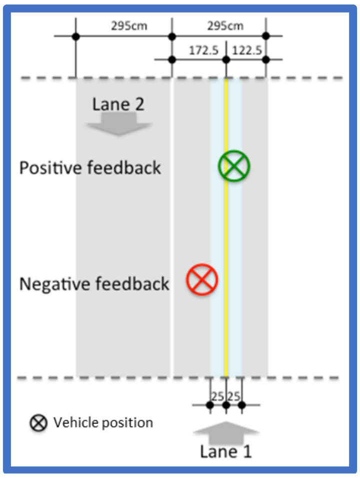


Figure 13: Positive and negative feedback zone [96].

Figure 14: Feedback system Case study 2 [75].

2.1.3.5 Variables

Variables were the same as in *Case study 1* (See Equations (1) and (2), Section 2.1.2.5).

2.1.3.6 Analysis and Results

All data were analyzed using JASP software [87].

To evaluate the effect of the feedback on drivers' lateral control, a series of ANOVA for repeated measures with *Trial* (4 levels: Baseline [Trial 1], Trial 2, Trial 3, Trial 4) as within-subject factor, were performed, one on each dependent variable, namely SDLP and LP, of ***Experiment A*** . No between-factor was considered.

The ANOVA on the SDLP showed a significant effect of *Trial* with $F(3,81)=8.382$, $p<0.001$ $\eta_p^2=0.237$. The ANOVA on the LP showed a significant effect of *Trial* with $F(3,81)=4.012$, $p=0.010$, $\eta_p^2=0.129$. Figure 15 shows the trends of SDLP and LP for Case study 2 – Experiment A. As it can be observed in Figure 15, in absolute terms SDLP decreases from 0.266 m (baseline) to 0.229 m (Trial 4), with a reduction of 37 mm. The post hoc comparisons highlighted a discrepancy between Trial1-Trial2, with $p=0.011$ and Trial1-Trial4, with $p<0.001$. In absolute terms LP decreases from 0.283 m (baseline) to 0.233 m (Trial4), with a reduction of 50 mm. The post hoc comparisons highlighted a discrepancy between Trial1-Trial4, with $p=0.015$.

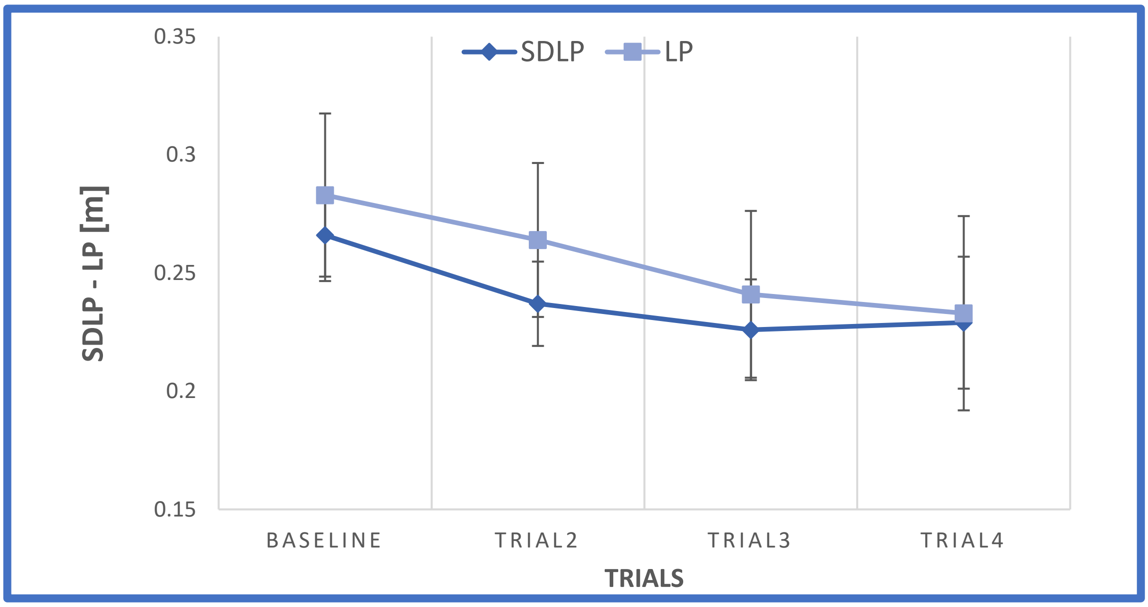


Figure 15: SDLP and LP (both in meters) across trials 1-4 for Case study 2 – Experiment A. Error bars represent the standard error. (Adapted from [75]).

To evaluate the effect of the feedback on drivers' lateral control, a series of ANOVA for repeated measures with *Trial* (4 levels: Baseline [Trial 1], Trial 2, Trial 3, Trial 4) as within-subject factor, were performed, one on each dependent variable, namely SDLP and LP, considering only 19 out 28 participants of ***Experiment A***, called "***aware***", that considers the feedback functionalities. No between-factor was considered.

The ANOVA on the SDLP showed a significant effect of *Trial* with $F(3,54)=30.944$, $p<0.001$ $\eta_p^2=0.632$. The ANOVA on the LP showed a significant effect of *Trial* $F(3,54)=19.513$, $p<0.001$, $\eta_p^2=0.520$. Figure 16 shows the trends of SDLP and LP for Case study 2 – Experiment A "aware". As it can be observed in Figure 16, in absolute terms SDLP decreases from 0.270 m (baseline) to 0.198 m (Trial 4), with a reduction of 72 mm. The post hoc comparisons highlighted a discrepancy between Trial1-Trial2, with $p<0.001$, Trial2-Trial3, with $p=0.028$ and Trial1-Trial4, with $p<0.001$. In absolute terms LP decreases from

0.285 m (baseline) to 0.176 m (Trial4), with a reduction of 109 mm. The post hoc comparisons highlighted a discrepancy between Trial2-Trial3, with p=0.028 and Trial1-Trial4, with $p<0.001$.

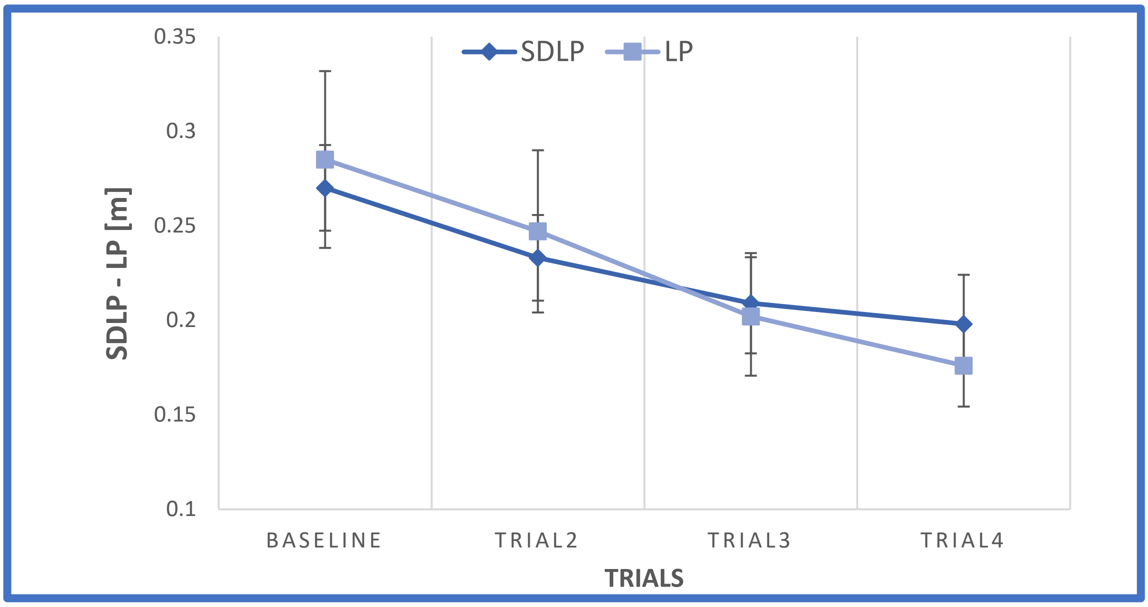


Figure 16: SDLP and LP (both in meters) across trials 1-4 for Case study 2 – Experiment A – "aware" drivers. Error bars represent the standard error. (Adapted from [75]).

To evaluate the effect of the feedback on drivers' lateral control, a series of ANOVA for repeated measures with *Trial* (4 levels: Baseline [Trial 1], Trial 2, Trial 3, Trial 4) as within-subject factor, were performed, one on each dependent variable, namely SDLP and LP, considering only 9 out 28 participants of ***Experiment A***, called "***unaware***", that did not properly understand the feedback functionalities. No between-factor was considered.

The ANOVA on the SDLP showed a significant effect of *Trial* with $F(3,24)=8.114$, $p<0.001$ $\eta_p^2=0.504$. The ANOVA on the LP showed a significant effect of *Trial* $F(3,24)=4.035$, $p=0.019$, $\eta_p^2=0.335$. Figure 17 shows the trends of SDLP and LP for Case study 2 – Experiment A "aware". As it can be observed in Figure 17, in absolute terms SDLP increases from 0.257 m (baseline) to 0.296 m (Trial 4), with an increment of 39mm. The post hoc comparisons highlighted a discrepancy between Trial3-Trial4, with p=0.020 and Trial1-Trial4, with p=0.008. In absolute terms LP increases from 0.280 m (baseline) to 0.353 m (Trial4), with an increment of 73 mm. The post hoc comparisons highlighted a discrepancy between Trial1-Trial4, with p=0.019.

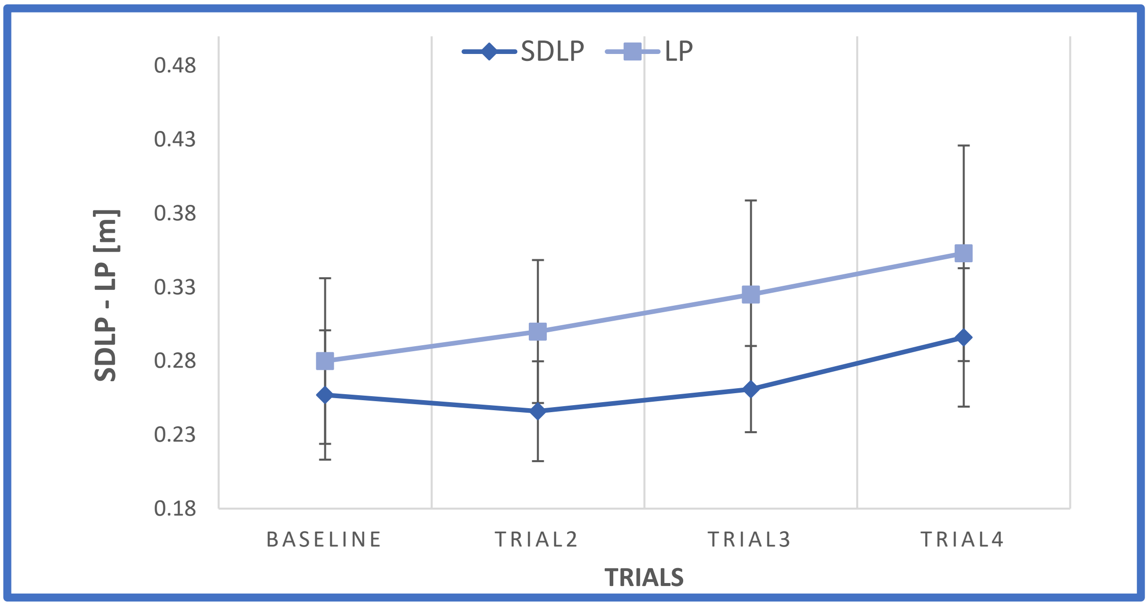


Figure 17: SDLP and LP (both in meters) across trials 1-4 for Case study 2 – Experiment A – "unaware" drivers. Error bars represent the standard error. (Adapted from [75]).

To evaluate the effect of the feedback on drivers' lateral control, a series of ANOVA for repeated measures with *Trial* (4 levels: Baseline [Trial 1], Trial 2, Trial 3, Trial 4) as within-subject factor, were performed, one on each dependent variable, namely SDLP and LP, of ***Experiment B***. No between-factor was considered.

The ANOVA on the SDLP showed a significant effect of *Trial* with $F(3,72)=54.799$, $p<0.001$, $\eta_p^2=0.695$. The ANOVA on the LP showed a significant effect of *Trial* with $F(3,72)=50.744$, $p<0.001$, $\eta_p^2=0.679$. Figure 18 shows the trends of SDLP and LP for Case study 2 – Experiment A. As it can be observed in Figure 18, in absolute terms SDLP decreases from 0.242 m (baseline) to 0.157 m (Trial 4), with a reduction of 85 mm which is a better improvement than in Experiment A. The post hoc comparisons highlighted a discrepancy between Trial1-Trial2, with $p<0.001$ and Trial1-Trial4, with $p<0.001$. In absolute terms LP decreases from 0.259 m (baseline) to 0.147 m (Trial4), with a reduction of 112 mm slightly more than in Experiment A. The post hoc comparisons highlighted a discrepancy between Trial1-Trial2, with $p<0.001$, Trial2-Trial3 with $p=0.021$ and Trial1-Trial4 with $p<0.001$.

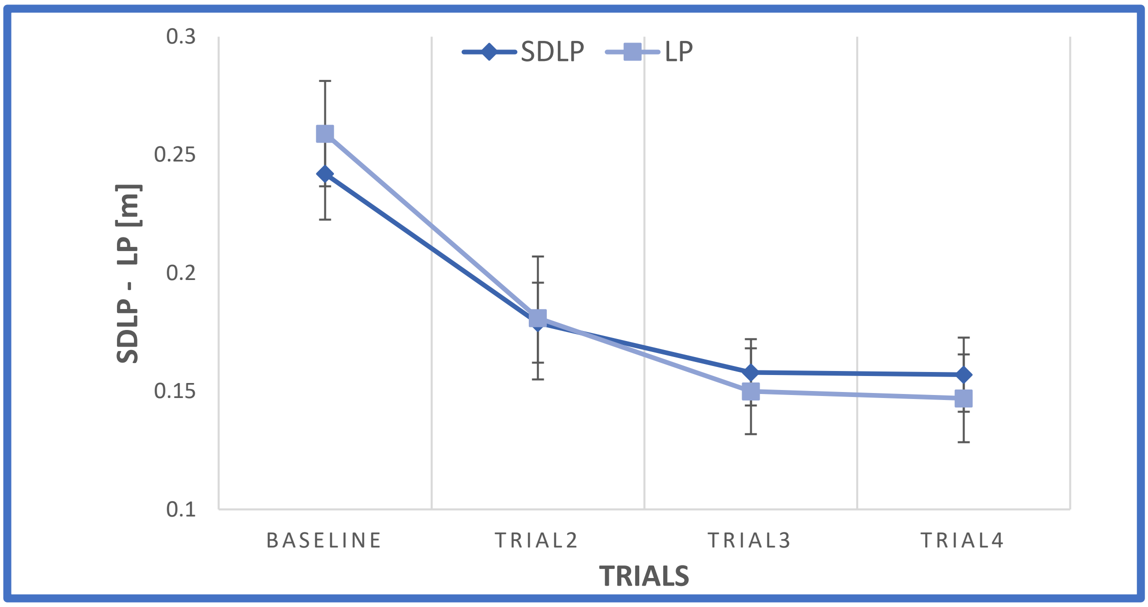


Figure 18: SDLP and LP (both in meters) across trials 1-4 for Case study 2 – Experiment B. Error bars represent the standard error. (Adapted from [75]).

Later, Experiments A and B were compared, in order to investigate the effect of various initial mental models on drivers' lateral control.

A series of mixed-factor ANOVA with *Experiment* (2 levels: A *vs*. B) as between-subject factor and with *Trial* (4 levels: Baseline [Trial 1], Trial 2, Trial 3, Trial 4) as within-subject factor, were performed, one on each dependent variable, namely SDLP and LP. Unaware participants of Experiment A were excluded from this analysis.

The ANOVA on the SDLP showed a significant effect of *Trial* with $F(3,126)=80.379$, $p<0.001$, $\eta_p^2=0.657$ and *Experiment* with $F(1,42)=13.404$, $p<0.001$, $\eta_p^2=0.242$.

The ANOVA on the LP showed a significant effect of *Trial* with $F(3,126)=60.424$, $p<0.001$ $\eta_p^2=0.590$ and *Experiment* with $F(1,42) =7.176$, $p=0.011$, $\eta_p^2=0.146$.

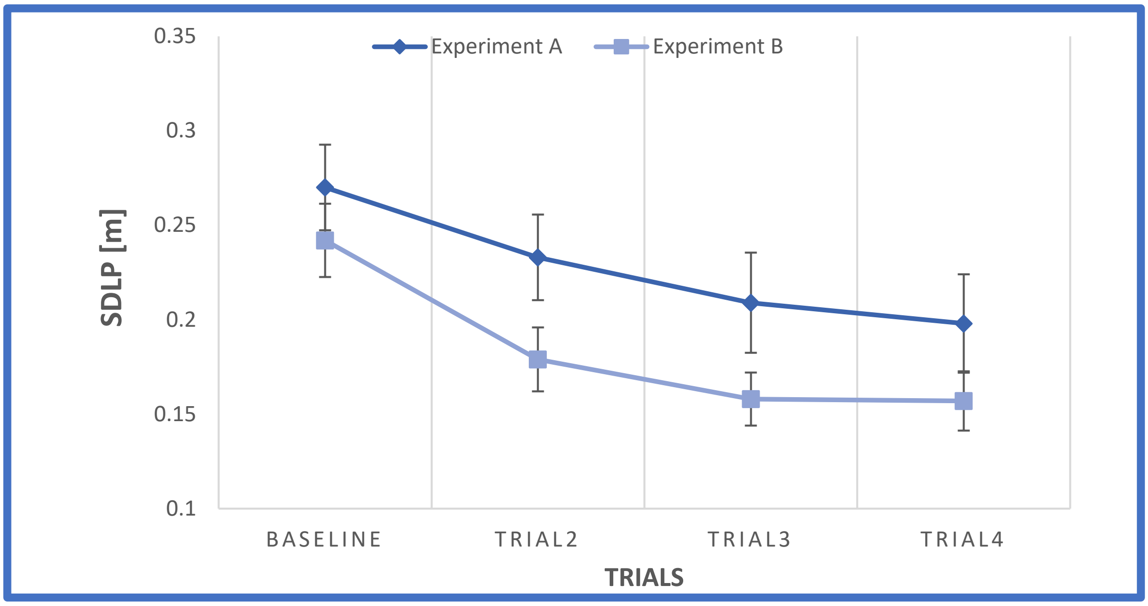


Figure 19: Comparison between Experiments A and B: trend of SDLP across trials 1-4. Error bars represent the standard error. (Adapted from [75]).

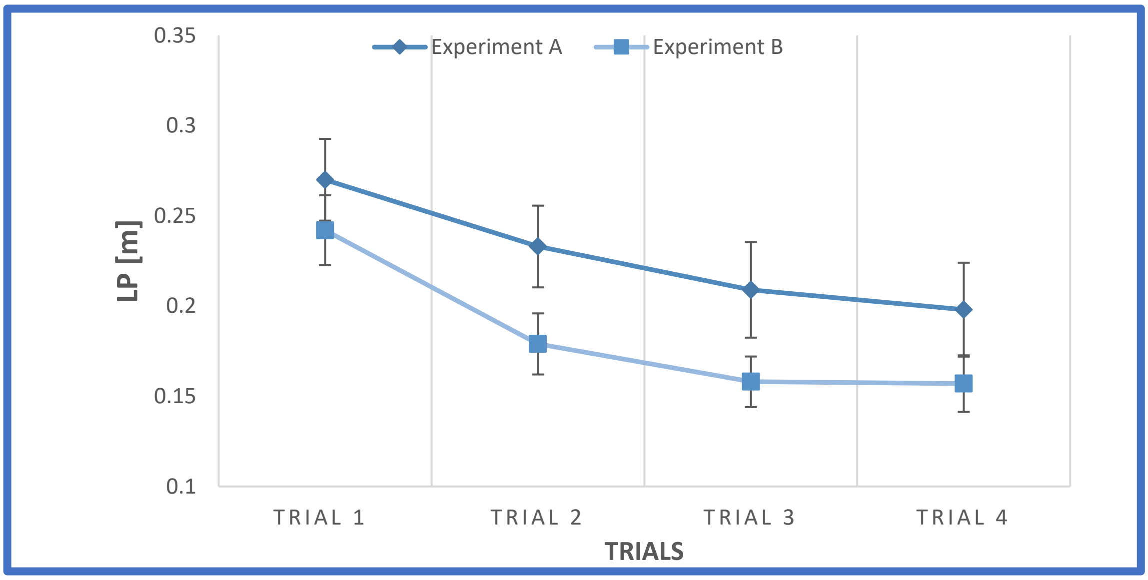


Figure 20: Comparison between Experiments A and B: trend of LP across trials 1-4. Error bars represent the standard error. (Adapted from [75]).

A main effect of experiment can be observed in Figure 19 and Figure 20. It resulted that explicitly instructing subjects on feedback functionalities improved drivers' lateral control, with respect to the SDLP and LP. Values of dependent variables are actually lower, in absolute terms, in Experiment B also during the control trial (i.e., baseline). However, as can be observed in Figure 21 and Figure 22, the differences between Trials 1 of Experiment A and B are not relevant with significance level of α=0.05.

On the other hand, it is interesting to notice that, despite the two factors presented significant effect when considered separately, the same cannot be argued about their interaction. In shorts, the rate at which SDLP and LP decreased in both experiments across trials was similar. The interaction would be significant with a level of α=0.10, and the graphs indicate that the improvement between Trials 1 and 2 is seemingly higher in Experiment B. It can be observed that informing the participants about the feedback by making them read an information booklet, had a positive impact on their performance and led to a considerable improvement. Yet, the same conclusion cannot be drawn about the improvement (in terms of speed) of the learning process, but the analysis suggests a higher reduction of SDLP and LP values between Trials 1 and 2 in Experiment B than in Experiment A.

Figure 21: Comparison between Experiments A and B: trend of SDLP across experiments for each trial. Error bars represent the standard error. (Adapted from [75]).

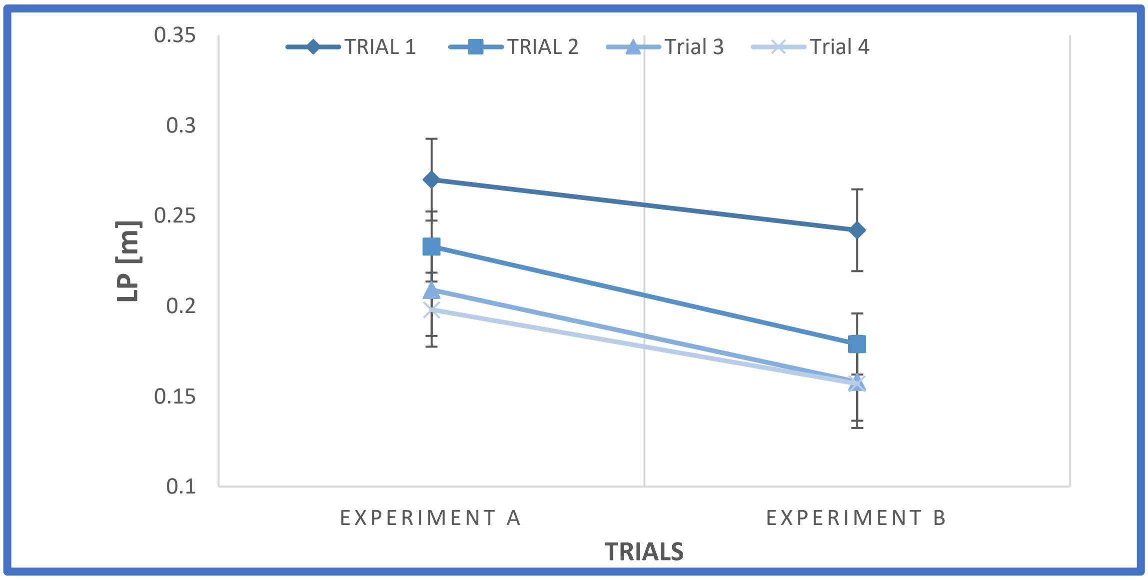


Figure 22: Comparison between Experiments A and B: trend of LP across experiments for each trial. Error bars represent the standard error. (Adapted from [75]).

2.1.3.7 Conclusion

In this Case study the effect of driver mental model on a lateral position control feedback was tested with a driving simulation experiment, with particular focus on feedback effectiveness.

Drivers were accordingly divided into two groups and received two different initial exposures to the system. Members of the former were asked to learn feedback functionalities by themselves, whereas the members of the latter were asked to read an information booklet. Both groups performed multiple successive driving trials. Within the framework of this criteria, this work showed that:

- For both groups feedback effectiveness was validated, with significant improvement of drivers' lateral control across trials. Such improvement was particularly evident in the first trial after control, while further improvements in the following trials were less substantial. This is consistent with the findings of other investigations dealing with different feedback, which observed similar non-linear trends in the learning process across trials [92];
- The initial mental model had an impact on feedback effectiveness. There was a significant difference on the feedback effectiveness, indeed, those reading the information booklet presented a faster and higher improvement in their lateral control.

All in all, this Case study has investigated the value of the drivers' mental model of feedback, underling the noteworthy influence on their effectiveness. Not only inappropriate mental models can undermine the outcome of feedback (e.g., "unaware" subjects in Experiment A), but also different (meaning different initial exposure, though correct) mental models may results in different feedback effectiveness. These findings indicate that, to fully ensure the safety benefits of feedback, it is decisive for drivers to correctly understand their functionalities. In this sense, initial exposure appears as fundamental. This line of research can be further expanded, to investigate other meaningful aspects of feedback that might be influenced by drivers' mental models, such as trust, reliance, acceptance and perception of usefulness. Moreover, other strategies of initial exposure to the technology may be tested, so as the impact of reminding drivers about system functionalities during later trials.

2.1.4 Case study 3: Different types of feedback systems

2.1.4.1 Procedure

In *Case study 3* the procedure was similar the one used in *Case study 2* (see Section 2.1.3.1) , after the first trial (control) the feedback system was switched on and participants were directly instructed on the functionalities by reading an information booklet.

2.1.4.2 Participants

Sixty-five subjects were involved in *Case study 3*. Details of participants are presented in Table 7.

Table 7: Participants' gender and age.

Case study 3	#Part.	Female	Male	Min Age	Max Age	Avg Age
A	19	9	10	20	28	23
B	17	7	10	19	28	23.8
C	29	13	16	19	31	23

They were students, staff of the University and other people with the following characteristics:

- At least 1 year of driving experience;
- At least 5,000 km/year of average driving distance;
- No previous experience with the driving simulator.

All of them were volunteers.

2.1.4.3 Scenario

Scenario was the same as tat used in *Case study 1* (see Section 2.1.2.3).

2.1.4.4 Feedback systems

Feedback system "A" consists in one auditory and two visual feedback:

- Auditory: two tones, high when the vehicle enters the positive feedback zone and low when it enters the negative feedback zone (see Figure 13);
- Visual 1 (score): a display reporting a numeric score (at the end);
- Visual 2 (circle): consisting in a circle, was positioned on the top of the screen, with its center located 18 cm above sight line, and within 10° of the visual field (see Figure 24 and Figure 25), colored in green when the vehicle was within the positive feedback zone and red when it was outside. The circle was positioned inside the near-peripheral visual field; in this way it was far enough from the center of vision, in order not to disturb and distract the driver, but, at the same time, close enough to be

effective. Indeed, in the near-peripheral visual field, people are still able to distinguish basic shapes and colors [97]. In addition to this, positive and negative feedback zones of *Case study 2* - Figure 13 were divided into three sub-zones each (see Figure 23), with the colored circle changing its dimension depending on the sub-zone of the vehicle's location. Circle colors and dimensions, for each zone are summarized in Table 8.

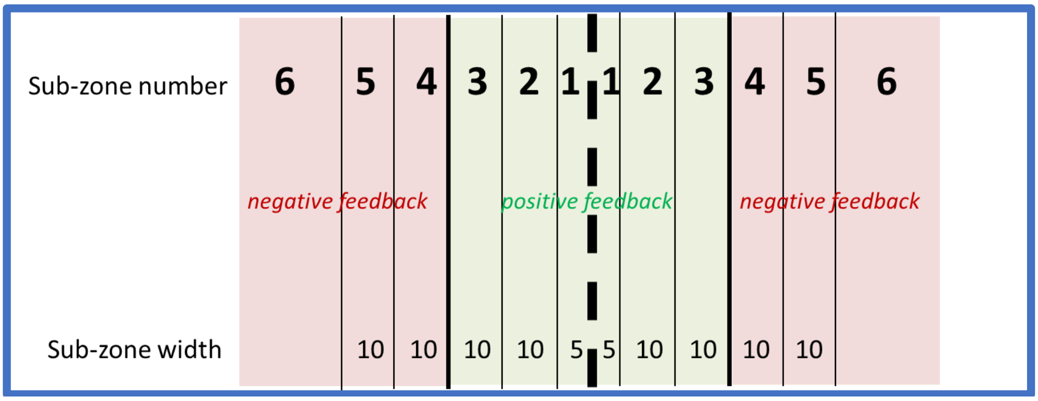


Figure 23: Definition of sub-zones.

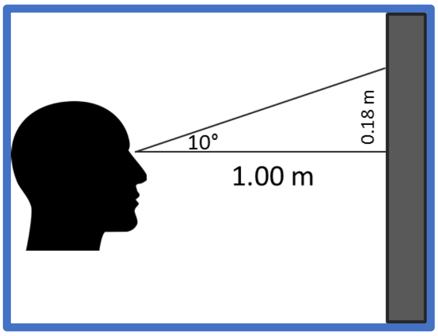


Figure 24: Circle position in feedback systems "A" and "B".

Table 8: Circle color and diameter (in millimeters) in feedback systems "A" and "B".

		Feedback system "A"		Feedback system "B"	
Feedback zone	Sub-zone	Circle color	Circle diameter	Circle color	Circle diameter
Positive	1	green	64	white	64
	2	green	46	20% grey	64
	3	green	28	40% grey	64
Negative	4	red	28	60% grey	64
	5	red	46	80% grey	64
	6	red	64	black	64

Figure 25: Feedback system “A”.

Feedback system “B” consists in one auditory and two visual feedback:

- Auditory: followed the same rules as in Feedback system “A”;
- Visual 1 (score): followed the same rules as in Feedback system “A”;
- Visual 2 (circle): consisted of a circle, positioned as in the system “A”, with its color changing from white to black depending on the sub-zone in which the vehicle was located (see Figure 24, Figure 26 and Table 8). The choice of a black and white contrast, instead of red and green, was motivated by the fact that human near-peripheral vision is more sensitive to changes in luminance than in changes of color tonality [97]. Sub-zones were defined in the same way as in the system “A”. Circle dimension was the same in each sub-zone.

Figure 26: Feedback system “B”.

Feedback system “C” consisted in the auditory feedback used in systems “A” and “B” following the same rules of activation, with no additional visual feedback.

2.1.4.5 Variable

The variable investigated was SDLP (See Equation (1), Section 2.1.2.5).

2.1.4.6 Analysis and Results

All data were analyzed using JASP software [87].

To compare the effectiveness of these feedback systems on lateral control over time, a mixed-factor ANOVA with *Feedback Type* (3 levels: A,B,C) as between-subject factor and *Trial* (4 levels: Baseline [Trial 1], Trial 2, Trial 3, Trial 4) as within-subject factor, was performed, on SDLP. Figure 27 shows the trends of SDLP for each feedback and each trial. The ANOVA on the SDLP showed a significant effect of *Trial* with $F(3,186)=226.37$, $p<0.001$, $\eta_p^2=0.785$. However, neither the feedback type factor nor the interaction between feedback type and trial showed a significant effect. This means that all the feedback systems tested had the same effectiveness and, since all of them contained the same auditory feedback, it can be inferred that none of the visual feedback tested in systems “A” and “B” were able to improve the effectiveness of the auditory-only feedback system (i.e., “C”).

The post hoc comparisons highlighted a discrepancy between Trial1-Trial2 ($p<0.001$), Trial2-Trial3 ($p=0.020$), Tiral3-Trial4 ($p=0.027$) and Trial1-Trial4 ($p<0.001$).

As it can be observed in Figure 27 in absolute terms SDLP:

- For feedback system “A”, decreases from 0.246 m (baseline) to 0.150 m (Trial4), with a reduction of 96 mm;
- For feedback system “B”, decreases from 0.256 m (baseline) to 0.153 m (Trial4), with a reduction of 103 mm;
- For feedback system “C”, decreases from 0.265 m (baseline) to 0.159 m (Trial4), with a reduction of 106 mm.

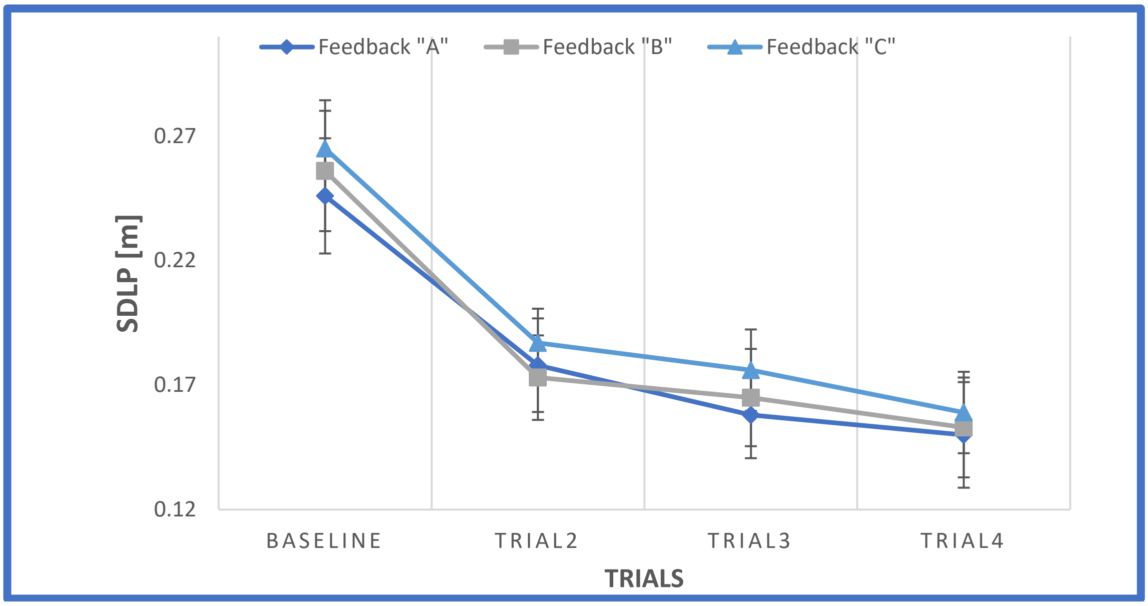


Figure 27: Comparison between feedback systems shows the trend of SDLP across trials, for each feedback system . Error bars represent the standard error.

2.1.4.7 Conclusion

Effects were observed across the above-mentioned three conditions, suggesting that the adoption of the precision teaching technique had a significant effect on the driver lateral control, no matter the characteristics of the feedback.

This is a meaningful conclusion in terms of a potential practical application, since it reduces the complexity of the system. Substantively, the auditory feedback is capable on its own of producing satisfactory results, so that no additional visual feedback is needed. It was demonstrated indeed that a visual feedback would not improve the effectiveness of the system, and, as such, it is unnecessary.

2.1.5 Case study 4: How precision teaching can shape drivers' lateral control over time[3]

Previous *Case study 3* took into account disparate feedback modalities and their subsequent influence on lateral vehicle control [96]. On this basis, the objective of the present ***Case study 4*** is to verify the effects that these feedback systems produce over time on driving behavior.

2.1.5.1 Procedure

After a training of about ten minutes to get familiar with the simulator, the participants were asked to complete the Simulator Sickness Questionnaire [98], to verify that they were not affected by simulator sickness. Then, they performed four driving trials in the simulator: the first, called baseline, did not include any feedback, whereas the other three included one of the feedback systems described below. This procedure was the same as Case study 3.

The final sample included 73 participants, and all of them underwent all the four trials, divided into three groups, so as it follows:

- 29 participants for the auditory feedback system (unimodal);
- 25 participants for the visual (green bar and score) and auditory feedback system (multimodal);
- 19 participants for the visual (red and green dots) and auditory feedback system (multimodal).

About 25% of the participants (*n* = 18; 9 for the auditory feedback system group and 9 for the two multimodal systems groups) agreed to return after one month to be tested again; this time they performed a fifth trial equal to the baseline, again without any feedback. The present work concerns the 18 participants, who have performed all the 5 trials.

2.1.5.2 Participants

18 subjects were involved in *Case study 4*. Details of participants are presented in Table 9.

Table 9: Participants' gender and age.

#Part.	Female	Male	Min Age	Max Age	Avg Age
18	9	9	21	34	23.8

They were students, staff of the University and other people with the following characteristics:

[3] The work presented in this Section is part of the following publication:
Rossi, R., De Cet, G., Gianfranchi, E., Orsini, F., Gastaldi, M. How precision teaching can shape drivers' lateral control over time (2022). Transportation Research Procedia (in press).

- At least 2 year of driving experience;
- At least 1,000 km/year of average driving distance;
- No previous experience with the driving simulator.

All of them were volunteers.

2.1.5.3 Scenario

Scenario was the same as tat used in *Case study 1* (see Section 2.1.2.3).

2.1.5.4 Feedback systems

The unimodal feedback system developed for this experiment was the same of *Case study 3* condition “C” (see Section 2.1.4.4).

Likewise, the multimodal feedback systems in this experiment were the same of *Case study 2 (see* Section 2.1.3.4) and *Case study 3* condition “A” (see Section 2.1.4.4).

For the sake of simplicity, the two multimodal systems were regarded as a whole. The mere potential differences between the unimodal system and the two multimodal systems as a whole were considered.

2.1.5.5 Variables

Several driving variables were recorded by the driving simulator with a 50 Hz sampling rate during each trial of the study, including SDLP (see Equation (1), Section 2.1.2.5) and:

- LS, mean lateral speed, in m/s:

$$\boldsymbol{LS} = \frac{\mathbf{1}}{\boldsymbol{T}}\sum_{\boldsymbol{j}=\mathbf{1}}^{\boldsymbol{T}} \boldsymbol{w_j} \qquad (3)$$

- SDSTEER, the standard deviation of steering angle, in degrees:

$$\boldsymbol{SDSTEER} = \sqrt{\frac{\mathbf{1}}{\boldsymbol{T}-\mathbf{1}}\sum_{\boldsymbol{j}=\mathbf{1}}^{\boldsymbol{T}} (\boldsymbol{\alpha_j} - \overline{\boldsymbol{\alpha}})^2} \qquad (4)$$

Where:

- w_j, the lateral speed of the vehicle, at time instant j;
- α_j, the steering angle of the vehicle, at time instant j; α_j=0 corresponds to no steering, α_j<0 steering to the left, α_j>0 steering to the right;
- T is the total number of records sampled during the experiment, and the time difference between two successive time instants j and j+1 is 0.02 seconds.

2.1.5.6 Analysis and Results

All data were analyzed using JASP software [87].

To evaluate the feedback effect on lateral control over time, a series of mixed-factor ANOVA with *Feedback modality* (2 levels: unimodal *vs*. multimodal) as between-subject factor and *Test* (3 levels: Baseline [Test 1], mean of the three trials with feedback [Test 2], trial performed one month later [Test 3]) as within-subject factor, were performed, one on each dependent variable, namely SDLP, LS, and SDSTEER.

The ANOVA on the SDLP showed a significant effect of *Test* with $F(2,32)=44.955$, $p<0.001$, $\eta_p^2=0.738$, and a significant *Group*×*Test* interaction with $F(2,32)=4.294$ $p=0.022$, $\eta_p^2= 0.212$. The post hoc comparisons highlighted a discrepancy between Test 1-Test 2, with $p < 0.001$, and Test1-Test3, with $p<0.001$. No other sources of variance reached significance.

A slight, not significant, worsening of the variable emerged one month after the administration of the feedback (Test 3) with respect to Test 1, but without returning to the initial value (Figure 28). The trend of the variable for the control group (without feedback) outlined in previous studies is depicted in Figure 28, indicating that the effect on the reduction of the variable, and consequent improvement, is not merely caused by a sense of familiarity with the simulator or with the experimental situation. As it can be observed in Figure 28, in absolute terms SDLP, for Unimodal group, decreases from 0.225 m (baseline) to 0.185 m (1 month later), with a reduction of 40 mm. For Multimodal group, in absolute terms SDLP from 0.269 m (baseline) to 0.192 m (1 month later), with a reduction of 77 mm.

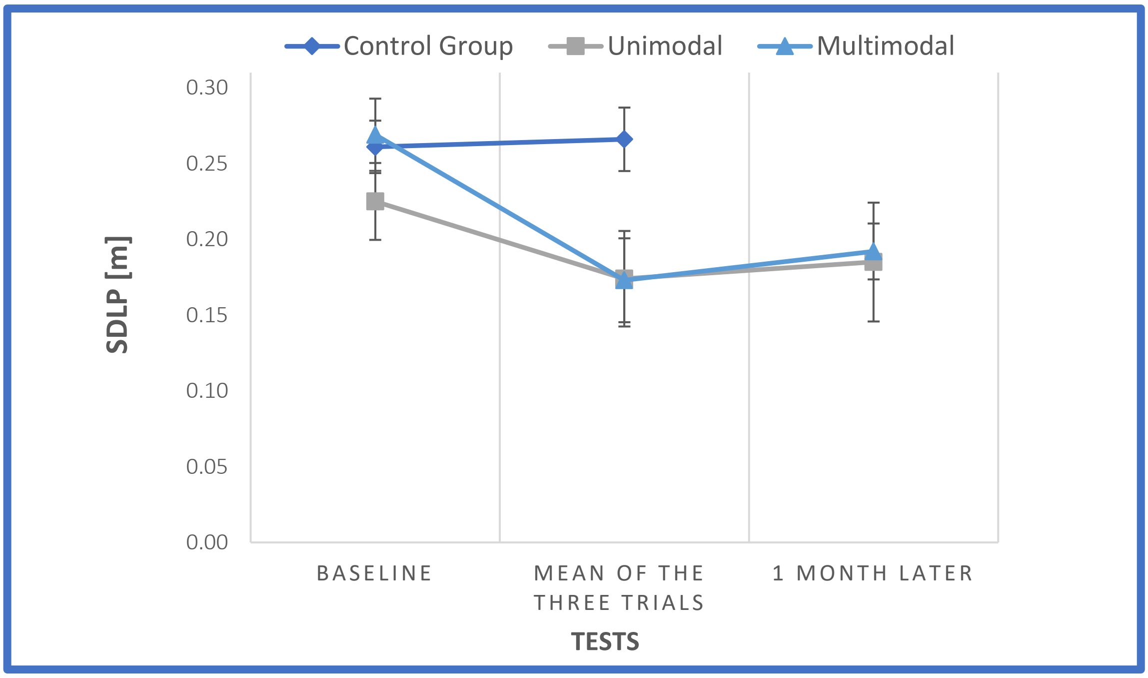


Figure 28: SDLP in m along the three Tests for unimodal and multimodal feedback. The control group results (no feedback) are also reported. Error bars represent the standard error (Adapted from [76]).

The ANOVA on the LS showed a significant effect of *Test* with $F(2,32)=32.328$, $p<0.001$,

η_p^2=0.699. The post hoc comparisons showed a difference between Test1-Test2, with p<0.001, and Test 1-Test 3, with p<0.001.

The trend of the variable for the control group (without feedback) is also shown in Figure 29, indicating that the effect on the reduction of the variable and consequent improvement is not the result of familiarity with the simulator or with the experimental situation. As can be noted in Figure 29, in absolute terms LS, for Unimodal group, decreases from 0.128 m/s (baseline) to 0.1m/s (1 month later), with a reduction of 28 mm/s. For Multimodal group, in absolute terms LS from 0.148 m/s (baseline) to 0.103 m/s (1 month later), with a reduction of 45 mm/s.

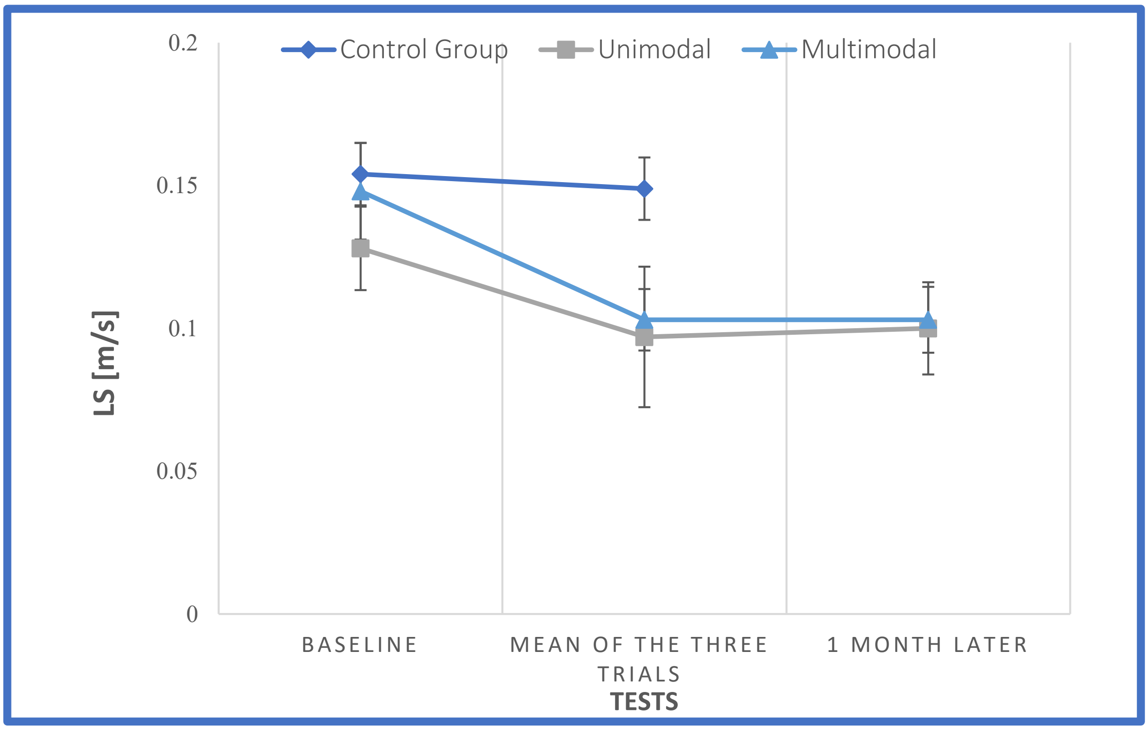


Figure 29: LS in m/s along the three Tests for unimodal and multimodal feedback. The control group results (no feedback) are also reported. Error bars represent the standard error (Adapted from [76]).

The ANOVA on the SDSTEER presented a significant effect of *Test*, with F(2,32)=6.246, p=0.005, η_p^2=0.281. The post hoc comparisons showed a difference between Test 1-Test 2, with p =0.011, and Test 1-Test 3, with p=0.045.

A slight, but not significant, worsening of the variable is to be noted one month after the administration of the feedback, still without returning to the initial value (Figure 30). The trend of the variable for the control group (without feedback) is as well depicted, indicating that the effect on the reduction of the variable and consequent improvement is not due to a simple effect of familiarity with the simulator or with the experimental situation. As can be noted in Figure 30, in absolute terms SDSTEER, for Unimodal group, decreases from 7.978 degree (baseline) to 7.680 degree (1 month later), with a reduction of 0.298 degree. For

Multimodal group, in absolute terms SDSTEER from 8.127 degree (baseline) to 7.504 degree (1 month later), with a reduction of 0.623 degree.

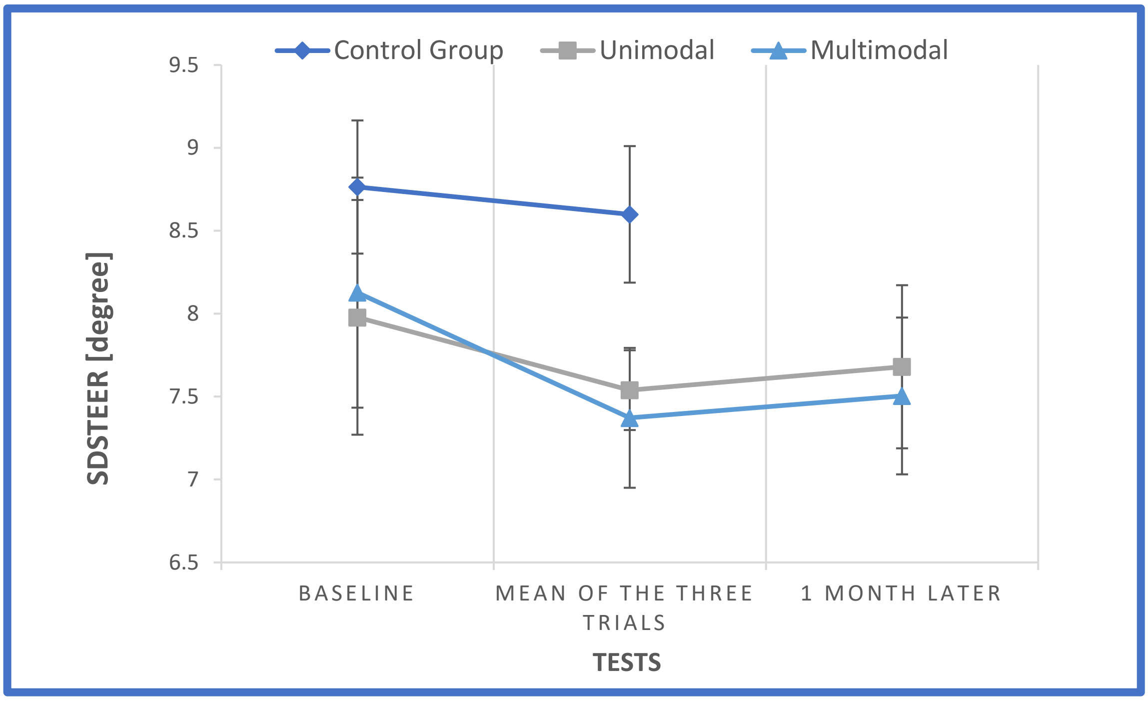


Figure 30: SDSTEER in degrees along the three Tests for unimodal and multimodal feedback. The control group results (no feedback) are also reported. Error bars represent the standard error. To allow better results resolution, the y-axis has been set on a restricted range value (Adapted from [76]).

2.1.5.7 Conclusion

The present Case study reports the results of a driving simulator study aimed at verifying if different feedback systems may have a long-lasting positive effect on the participants' driving behavior in terms of lateral vehicle control. Through the principles of the precision teaching technique, participants' driving behavior along five trials was monitored. To begin with, they drove the simulator without any feedback (baseline). Then, they drove along three trials receiving feedback (either unimodal or multimodal, depending on the group); finally, they were tested again one month later, without receiving any feedback, to verify the stability of the feedback-induced behavior would change over time.

Findings would appear to indicate that, independently from the feedback system employed, the participants' vehicle lateral control (measured in terms of SDLP, LS, and SDSTEER) improved during the three trials with feedback. This implies that all the values in the selected measures of lateral control decreased. This reduction indicates a clear improvement in driving safety. The reduction was still evident in all the variables after one month from the last trial, when the participants drove again the simulator without receiving any feedback.

2.1.6 Conclusion and future developments of Lateral Control ASAS

This study aimed at developing a precision teaching technique, and thus examined its effectiveness in improving the driver’s lateral control. Driving simulator experiments were conducted, feedback systems were tested (Case study 3), and the effect of explicit instructions was investigated (Case study 2). By conducting a follow-up experiment one month after the initial study, the retention effect of the four feedback was evaluated (Case study 4).

Some well-known evidence suggests that feedback effectiveness in inducing driving-related behavior changes is more dependent on feedback contingency (that is, how consistently the delivered feedback corresponds to the participant behavior) than on the type of feedback *per se* [99]. In these case studies it was made sure to administer a consistent feedback each time the participant made an error, independently from the specific feedback system employed. This aspect, along with precision teaching principles, seems to be crucial for ensuring the effectiveness of feedback systems in shaping drivers’ behavior.

What is more, the possibility to maintain the positive effects of feedback over time allows these systems to be even more alluring in terms of educational application (e.g., driving schools).

Taken together, the results imply that the development of complex feedback systems may not be necessary to shape driving behaviors and that perhaps an elementary auditory feedback may be sufficient to achieve some improvement, at least in vehicle later control measures. Given the main limitations of the work, such as the inclusion of a small and well-defined sample (students) and the restricted number of behavioral dependent variables, results so far have been very promising. This approach has the potential to be improved.

For these reasons, the 4 case studies here presented might represent a valuable step towards a future practical application of this system in driver training. On the whole, there are some constructive directions for future research, including:

- Testing the effect of visual feedback separately, to understand their ability to improve driving performance when no auditory feedback is presented;
- Including an analysis of the feedback systems’ effectiveness in relation to road environment (e.g. type of road, presence of on-street parking in an urban), as well as other dependent variables, such as acceleration and deceleration [100], or over-speeding with other means of transport (e.g., moped-riders simulator) [101];
- Investigating drivers' perception of risk in relation to ADAS to assess its goodness.

In fact, according to Wilde's risk homeostatis theory [102], drivers do not always benefit from safety measures by pushing themselves to accept a higher risk because they feel safer;

- Monitoring the perception of feedback systems with visual components with systems such as, for example, eye tracker;
- Evaluating the effect of feedback on driver performance at different time intervals (e.g., immediately after the treatment, after one week, three months, etc);
- Investigating, in the future when most vehicles will have them, the relationship between earlier experiences with ADAS and behavior with the simulator;
- Expanding the sample of subjects both in terms of size and composition, for example including professional drivers or elderly drivers. Such an investigation could also consider participants' social and educational background

All these potential paths of research might be enriched with on-road tests, for this would allow a more straightforward and concrete overview of the results' applicability. While virtual reality is certainly a valuable tool, it is also true that on-road tests are particularly significant and useful.

2.2 Acceleration and deceleration ADAS

In the studies presented in Section 2.1, participants were indiscriminately assigned a feedback system for lateral control of the vehicle. In this section the ADAS offered to the subjects will be defined according to their driving style. As well-known in the literature, the driving style can be defined by:

- The acquisition of *subjective variables* through questionnaires [2];
- The acquisition of *objective variables;*
- The acquisition of a combination of them.

The here-proposed methodology will take into account several driving parameters to evaluate driving style, and will focus on differentiating driver's aggressive or defensive style through cluster analysis. The effects of multiple real time coaching programs will be investigated (***Case study 1***), as well as feedback modalities on driving performance, specifically on the occurrence of elevated gravitational-force event (EGFE). These programs are commonly known as pay-how-you-drive, and are based on the assumption that the more harsh events a driver had, the more unsafe will be their driving. The main idea behind the inquiry is that, by providing effective contingent feedback to drivers on their risky (e.g. harsh event) or safe (smooth event) behavior, the likelihood of hazardous situations may decrease [66]. Two particular cases of risk in this scenario will be examined to verify the potential positive effects of the technology also on these situations:

- ***Subcase study 1:*** outlined drivers overtaking cyclists, as motor vehicle/bicycle interactions are a relevant issue in road safety;
- ***Subcase study 2:*** examined drivers in highway deceleration lanes.

Before proceeding with the description of the studies, the next paragraph will introduce the technique used in these experiments: real time coaching programs.

2.2.1 Real time coaching programs

Thanks to the development of in-vehicle technologies, which can collect real-time vehicle kinematic data (In-Vehicle Data Recorders), motor insurance companies have started to introduce systems aimed at monitoring drivers' behavior, as part of the so-called Pay-How-You-Drive (PHYD) schemes [7]. PHYD are a particular type of usage-based insurance (UBI) schemes, according to which insurance companies charge premiums based on the safety performance of drivers, as an incentive for users to improve their driving style. These systems are promoted by insurance companies, since, evidently, they have an obvious monetary benefit in reducing the number of crashes caused by their clients. At the same time, however, they have several additional advantages, both for the users of the system and the community [103]:

- An incentive for users to adopt safer behavior, reducing the total number of crashes, and ultimately leading to safer roads;
- Users pay according to their behavior on the road, not on other attributes such as socio-demographic characteristics, vehicle type, etc., which do not necessarily reflect the chance of being involved in a crash;
- A reduction in the impact of the cross-subside phenomenon, resulting in more affordable cost of insurance premiums;
- Generally, these systems stimulate users to adopt a smoother driving style, which can also reduce fuel consumption, with even more monetary gain for users and environmental benefits for the community.

Many of these schemes are based on the assumption that the more harsh braking and accelerations drivers experience, the more unsafe will be their driving [104–107]. Following this reasoning, smooth driving is reinforced (e.g., giving discounts on premiums) whereas harsh driving is punished (e.g., incrementing premium prices). Overall, these reward measures seem to have positive effects on road safety [108, 109]. However, investigation of the effectiveness of these interventions is still limited [110, 111].

Generally, this strategy provides some kind of feedback to users. This is usually a delayed ‘after-drive’ feedback, which contains more or less aggregate information about the driver’s performance [112][113][103]. However, some motor insurance companies have recently started offering on-board devices providing real-time feedback to users. They are, in fact, real-time coaching systems, comparable with those proposed in the literature on educational programs. The latter aimed at teaching drivers to avoid speeding [114], keeping a correct position within the lane [89] or eco-driving [81, 115]. In one of the few studies dealing with feedback systems specifically built for UBI schemes, it was observed that drivers can improve their safety performance [116]: in addition, these systems may be more effective than those relying on delayed feedback [117].

To sum up, although there is a large and ever-growing literature on innovative motor insurance schemes. Yet, few researchers have addressed the safety benefits in quantitative and microscopic terms. In addition, the evaluation of real-time coaching systems specifically designed for UBI/PHYD schemes is still a neglected area.

2.2.2 Case study 1: Monitoring and notifying harsh and smooth driving events to improve road safety[4]

Although current traffic legislation has enabled roads to be safer [118], the progress in reducing road deaths has slowed down over the last years [119]. It might be assumed that the driver's incorrect driving speed is conceivably the most influential factor explaining this slackening [120]. Unlike the danger concerning drink-drivers, the thread caused by over-speeding-drivers has not been accepted yet as a major safety issue by society [121]. Thus, actions aimed to mitigate excessive and inappropriate speed behavior, as harsh driving events (i.e., events when more force than normal is applied to the vehicle's brake or throttle system), are in the agenda of a plethora of national and private agencies [122].

A driving speed choice is considered a measure of a driver's disposition to expose oneself to risky situations [123], and it is influenced both by transient (e.g., perceived threat of enforcement) and stable (e.g., personality) features [124]. Several road safety interventions have been developed to support the driver selecting one's driving speed correctly, including traffic-calming measures [125], on-road dynamic speed display signs [126], and vehicle sensors [127]. Notably, one of the most promising interventions is the usage of on-road interactive real time coaching programs [103], previously described.

In the present Case study, an advance-driving simulator was accordingly employed, to investigate the impact of various real time coaching programs and feedback modalities on driving performance.

Based on previous studies [128] it was hypothesized that the effect of feedback would differ depending on driving style.

2.2.2.1 Procedure

The study took place on two different days. On the first day participants completed a 5-minute familiarization driving session to gain confidence with the driving simulator, and then proceeded in performing the first trial. The only instruction they received was to drive as they would normally do in ordinary life and no feedback was provided.

After the first trial, participants were divided into two groups depending on their driving style (defensive vs. aggressive). Before starting the second trial of the experiment, they were again divided into 4 subgroups, considering both driving style and gender.

One month later, participants were asked to return for the second trial. Before starting, they were informed about the presence of feedback during the driving simulation and about its

[4] The work presented in this Section is part of the following publication:
Rossi, R., Tagliabue, M., Gastaldi, M., De Cet, G., Freuli, F., Orsini, F.,Di Stasi, L.L., Vidotto, G. Reducing Elevated Gravitational-Force Events through visual feedback: A simulator study (2021) Transportation Research Procedia, 52, pp. 115-122.

basic functioning. Disparate kinds of feedback were offered to participants, depending on their subgroup. The participants in each subgroup were informed that the feedback depended on their acceleration/deceleration behavior and whether the feedback was activated by correct behavior (positive feedback subgroup) or incorrect behavior (negative feedback subgroup). To avoid any possible effects of confounding factors, including learning or series effects, participants, during the second experimental session, drove a driving scenario similar to the first one, but unfamiliar both in terms of roadside elements (position of trees, hedges, houses, etc.) and in the location of the three events along the track (See Section 2.2.2.3).

2.2.2.2 Participants

One hundred active drivers (49 females, age range 20-33) were recruited.

They were students, member of University staff and other people with the following features:

- At least 1 year of driving experience;
- At least 1,000 km/year of average driving distance;
- No previous experience with the driving simulator;
- Normal or corrected-to-normal vision.

Participants performed two driving trials, the second one taking place one month after the first. Five participants suffered from simulator sickness and therefore could not complete the first trial. 17 of the 95 initial participants, did not participate in the second trial. In the end, data from 78 drivers were available. Details of participants are presented in Table 10.

Table 10: Participants' gender and age.

#Part.	Female	Male	Min Age	Max Age	Avg Age
78	38	40	20	33	24

The final pool of participants, before starting the second experimental session, was divided into 4 subgroups (Table 11).

All participants received monetary compensation for the experiment. Participants were promised to be compensated, depending on evaluation of their behavior, conducted by the real-time coaching program, with a monetary reward ranging between a maximum and minimum value; no further information was provided. In the end, all participants received the maximum possible reward, regardless of their performance.

Table 11: Four subgroups depending of type and modality of the delivered feedback.

Feedback	Cues	Cluster	Participants	Female	Male	Range of age
Contingent positive feedback	visual	Defensive	11	6	5	20-30
		Aggressive	11	5	6	20-33
Contingent negative feedback	visual	Defensive	9	6	3	21-27
		Aggressive	12	5	7	20-30
Contingent positive feedback	auditory	Defensive	9	4	5	20-27
		Aggressive	10	4	6	21-29
Contingent negative feedback	auditory	Defensive	8	4	4	20-27
		Aggressive	8	4	4	23-29

2.2.2.3 Scenario

The driving scenario consists of a route including both urban and non-urban tracks. The route was 11.5 km long with a journey time of about 15 minutes. Along the way, the subjects were faced with a priority intersection, a roundabout and three signalized intersections, two of them leading the participant in the dilemma zone. Three potential risky situations (see Figure 31) were included in the track:

- The driver has to react to a sudden braking of the head vehicle (car-following task);
- The driver meets a cyclist who is riding in the same direction;
- The driver has to react to a sudden merging by a roadside parked vehicle.

Figure 31: Examples of potential hazardous traffic situations presented to the drivers [100].

2.2.2.4 Feedback systems

The real-time coaching program was designed to provide negative or positive feedback after, respectively, harsh or smooth driving events recorded during the experiment. The following definitions of harsh and smooth events were adopted:

- Harsh event: a timeframe longer than 1 second exceeding a deceleration threshold of -0.4g, or an acceleration threshold of 0.3g;

- Smooth event: a timeframe longer than 1 second exceeding a minimum deceleration/acceleration threshold (± 0.075g) without exceeding the deceleration threshold of -0.4g nor the acceleration threshold of 0.3g.

These thresholds were chosen with a sensitivity analysis and were supported by findings of previous studies [129, 130].

Once a harsh or smooth driving event occurred (see Figure 32), participants received one of the following types of feedback, depending on their specific subgroup:

- A contingent positive feedback via auditory cues when a smooth driving event occurred;
- A contingent positive feedback via visual cues when a smooth driving event occurred;
- A contingent negative feedback via auditory cues when a harsh driving event occurred;
- A contingent negative feedback via visual cues when a harsh driving event occurred.

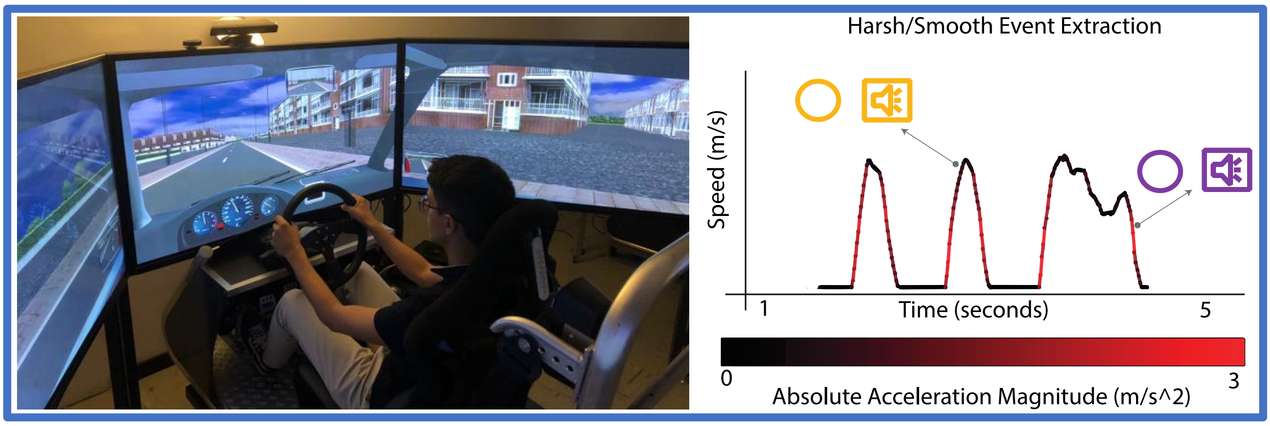


Figure 32: Participants during a trial (on the left). Schematic representation on the way of the provided feedback to the four groups (partially adapted from "eng.uber.com/telematics/") (on the right).

For all types of feedback, the visual/auditory signal was produced immediately after a harsh/smooth event had been recorded. The signal lasted 4 seconds and was presented only once for each event. If multiple events were recorded within the same 4-second time frame, only the first event triggered the signal.

A bright circle on a dark background was selected for the visual cues. A white circle indicated positive feedback, and a purple circle negative feedback. In both cases, the circle was 3 cm in diameter and was located within 13 degrees of the participant's visual field, simulating a device located in the upper part of the windscreen (Figure 33).

For the two auditory cues, two sounds were selected from the International Affective Digitized Sounds database [131]. Both sounds were shortened to 4 seconds. A slot machine sound (#717) was selected as a positive feedback, and a buzzer sound (# 712) as a negative one. According to the normative 9-point rating scale for IADS sounds, the buzzer sound is classified as a stimulus low in pleasantness (1.62) and high in arousal (7.98); the slot machine sound would be a stimulus high in pleasantness (7.32) and medium in arousal (6.44). Thus, the main difference between the two auditory cues was their experienced pleasantness.

The contingent negative feedback with visual cues was developed to resemble a real-time coaching device available on the Italian motor insurance market. The other feedback systems were tested to assess whether a change in the feedback type (negative vs. positive) or how it was presented (visual vs. auditory) affected the effectiveness of the program.

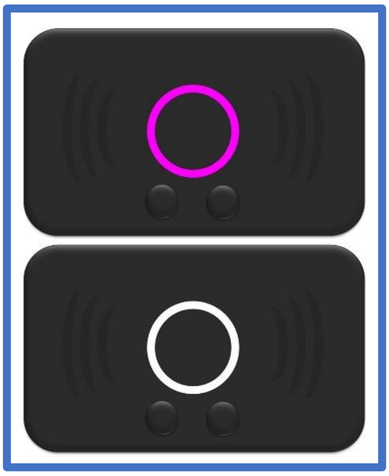


Figure 33: On-board device presenting negative (top) and positive (down) feedback [100].

2.2.2.5 Cluster analysis: defensive and aggressive drivers

A cluster analysis was carried out on 31 driving parameters (see Figure 34 and Table 12), extracted from the simulator with a sampling frequency of 50 Hz. Only data collected during the first trial were used. This analysis aimed at equally distributing participants with different driving styles, as measured through the simulator, in the four feedback subgroups.

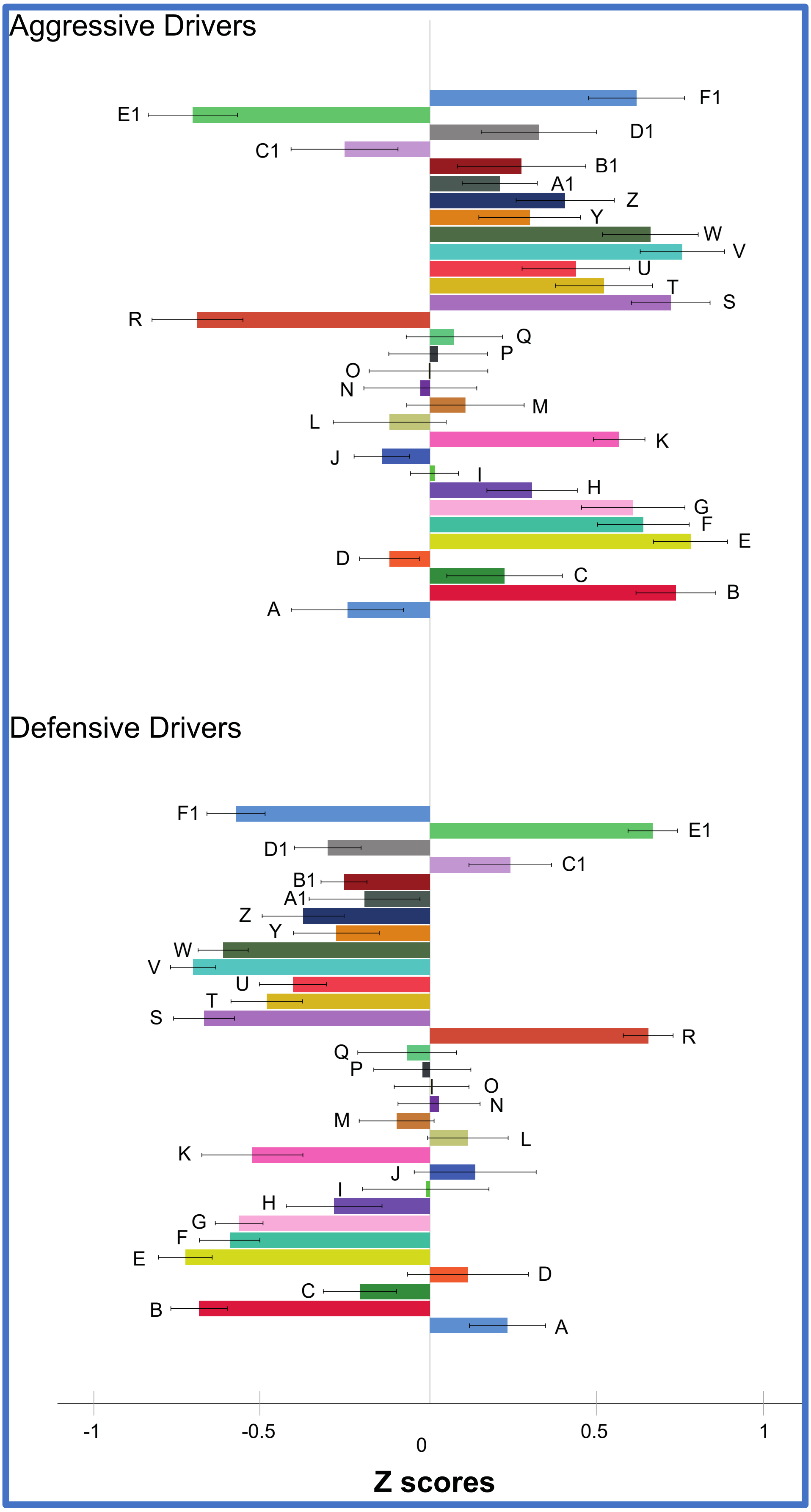


Figure 34: Results of cluster analysis on 31 driving variables [132].

Table 12: Labels and description of the driving parameters used to define the driving styles [132].

Label	Description
A & B	Mean and standard deviation (SD) of the acceleration
C	Maximum acceleration
D	Minimum acceleration value
E & F	Mean and SD of the speed
G	Maximum speed of Main Target
H & I	Mean and SD of the lateral distance (center of front bumper and centerline of the rightmost lane)
J & K	Mean and SD of the lateral speed.
L & M	Mean and SD of the bumper to bumper distance.
N & O	Mean and SD of the time headway, between first lead vehicle in same lane and the main vehicle
P & Q	Mean and SD of the heading of vehicle with respect to the road
R & S	Mean and SD of Time-to-collision between first lead vehicle in same lane and the main vehicle.
T & U	Mean and SD of the Engine RPM (engine revolution per minute) of main vehicle
V & W	Mean and SD of the accelerator pedal position
Y & Z	Mean and SD of the brake pedal position
A1 & B1	Mean and SD of the deviation between the actual vs required steering wheel angle
C1 & D1	Mean and SD of the rotation speed of vehicle longitudinal axis
E1 & F1	Mean and SD of the lateral acceleration of Main vehicle

Following the recommendations of Lucidi et al. [133] and Marengo et al. [134], Ward's method of hierarchical clustering with squared Euclidean distance measures was employed to define the number of clusters, as in Gianfranchi et al. [10][9][8]. The grouping variables were standardized into Z-scores. A K-means cluster analysis was also conducted, to select the most appropriate cluster solution for the sample.

The effect of the real-time coaching program and driver characteristics on overtaking behavior was evaluated with mixed ANOVA model on data collected during Trials 1 and 2. The models were developed considering one Main Factor (Trial), five Between Factors (Gender, Car Usage, Driving style, Feedback type and modality), and their first order interactions. Separate analyses were performed for each of the six continuous dependent variables. η_p^2 quantifies effect size and, as a rule of thumb, indicates a small effect if it is higher than 0.01, a medium effect if it is higher than 0.06 and a large effect if it is higher than 0.14 [135]. Fisher's Least Significant Difference was used for post-hoc tests.

Since the last dependent variable (the overtaking strategy) was categorical, in order to verify the effect of any factor, contingency tables were built, and Chi-square tests were then performed. The ϕ coefficient is a measure of effect size and is equivalent to Pearson's coefficient r [136].

Cluster analysis was performed with IBM SPSS 22 statistical package. Figure 34 displays the outcome after the application of K-means clustering. The inspection of the dendrogram suggested a two-cluster best solution (see Figure 35). The dendrogram is used to get information about the appropriate number of cluster. The tree is sectioned at the height of the maximum jump between levels of distance at which mergers have occurred; doing this operation in this specific case the clusters are two [137].

Cluster 1 included 49 participants (25 females), and Cluster 2 included 46 participants (21 females). In comparison with Cluster 2, the participants of Cluster 1 showed higher, but moderate, standardized mean scores and lower SD scores of acceleration, indicating smooth driving, that is, they had less acceleration and speed peaks, by maintaining lower and smoother speeds. Additionally, they achieved lower mean scores of deviation from lateral position and lower SD scores of lateral speed, higher mean scores and lower SD scores of time to collision, lower scores (both mean and SD) in engine RPM, accelerator pedal position, brake pedal position and steering errors, higher mean scores but lower SD scores in both yaw rate and lateral acceleration. Thus, participants in Cluster 1 were labeled as ‘defensive’ and participants in Cluster 2 as ‘aggressive’.

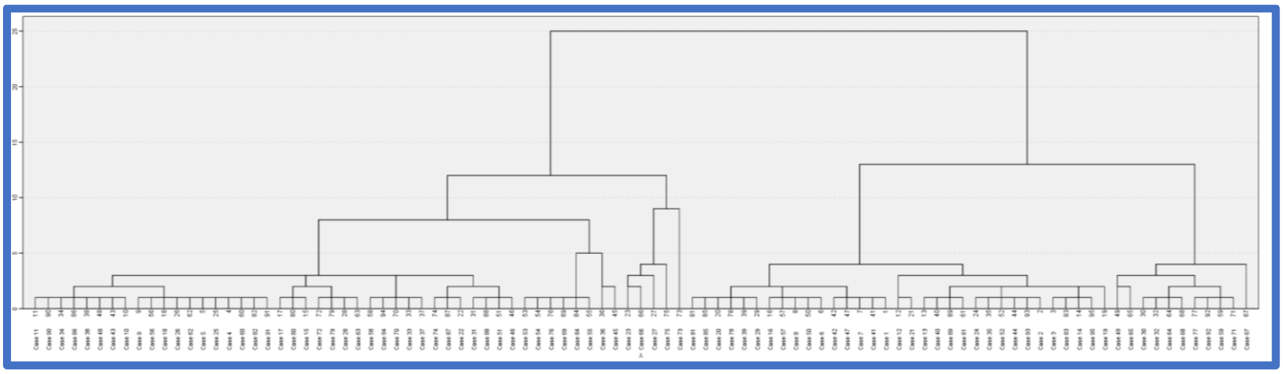


Figure 35: Ward’s method dendrogram; on the x-axis the 95 participants, on the y-axis distance cluster combination with modified scale.

2.2.2.6 Variable

EGFE Number was the investigated variable.

2.2.2.7 Analysis and Results

ANOVA was conducted on the dependent variable Number of EGFE, with Cluster (two levels), Modality (two levels: auditory vs. visual), Feedback type (positive vs. negative), as the between-participants factors and Session (two levels) as the within-participants factor.

Post hoc analyses, using Bonferroni’s correction, were conducted, with α set at 0.05.

In the Analysis of Variance (ANOVA) on the Number of EGFE, the factors Cluster [$F(1,70) = 23.47$, $p<0.001$, $\eta_p^2=0.25$] and Session [$F(1,70)=38.61$, $p<0.001$, $\eta_p^2=0.36$] reached significance. The interaction Cluster X Session was also significant with $F(1,70)=14.06$,

$p<0.001$, $\eta_p^2=0.17$. Defensive drivers showed less EGFE than Aggressive drivers (4.1 vs. 6.5) and, overall, all drivers significantly reduced the Number of EGFE in the second session (6.6 vs. 3.9).

Finally, as depicted in Figure 36, the interaction indicates that, in the first session, Defensive drivers showed less EGFE than aggressive ones ($p < 0.001$), but this difference disappeared in the second session ($p=0.11$). Moreover, Aggressive participants reduced the number of EGFE in the second session ($p<0.001$), whereas Defensive drivers only showed a trend in the same direction ($p=0.09$). No other sources of variance reached significance.

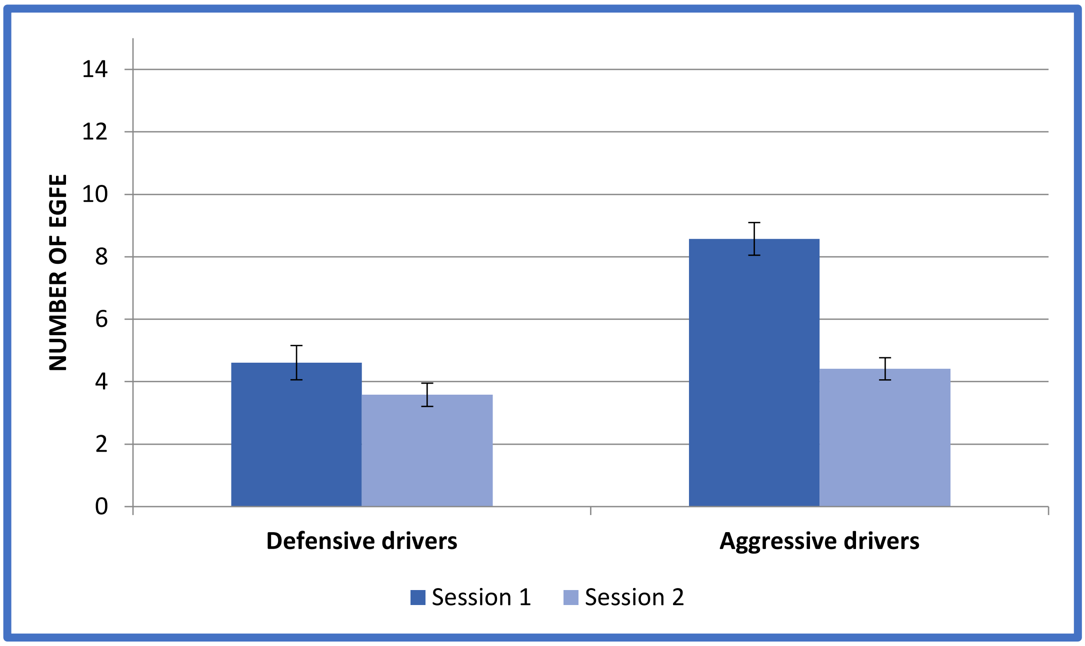


Figure 36: Number of EGFE of Defensive and Aggressive drivers in the two sessions. Error bars represent standard errors.

2.2.2.8 Discussion and Conclusions

The cluster analysis allowed a better categorization of participants on the basis of their driving performance during the first driving simulation session. A clear partition of participants into two strongly different driving style groups were therefore developed. This step was critical, for, as above mentioned, the hypothesis was that the effect of feedback could differ depending on the style of the driver [128].

Indeed, results confirmed the hypothesis, implying that aggressive drivers modify their driving behavior in the second session in the direction of a reduction in EGFE Number, whereas Defensive drivers did not. This last result is not surprising, considering that Defensive drivers had a low Number of EGFE from the beginning of the experiment.

On the contrary, as to the hypothesis concerning different effects of feedback depending on its modality and type (positive vs. negative), the results seemingly indicate an equivalent effectiveness of all kinds of feedback proposed. This result is different from that previously found with lateral vehicle control feedback systems. It might be interesting in the future to see if the modality of the feedback systems (audio, video, or combinations) vary in effectiveness based on the variable they work on. It has here to be noted, however, that the reduced number of participants in each subgroup might represent a limitation to the results.

2.2.3 Subcase study 1: Evaluating the impact of real-time coaching programs on drivers overtaking cyclists[5]

Cycling provides several benefits, both for road users and the environment [138–140]. It is becoming increasingly popular not only in western countries [141, 142], but also in emerging ones [143]. However, this increase in bicycle use raises some safety concerns: in the most recent Road Safety Annual Report issued by the International Transport Forum [144], the trend in cyclists' safety was defined as 'worrying', with the number of fatalities increasing in 13 of the 30 countries analyzed between 2010 and 2017. In the European Union the number of fatalities among cyclists decreased by 1.4% between 2010 and 2016, yet, this decrease was much smaller than that of car users (-20.3%) [145].

The most dangerous collision type is that involving motor vehicles [140] particularly during overtaking maneuvers [146–148]. Road users' behavior and infrastructure characteristics have been shown to be the main factors contributing to motor vehicle-bicycle collisions [149] Many works addressed the problem focusing on cyclists' features: their appearance, their position within the lane and their behavior. In one of the first studies on this topic, Walker [150] discussed the results of both cyclist-related and motor vehicle-related characteristics on overtake proximity. He reached the conclusion that drivers tended to leave more space while passing when the cyclist was closer to the edge of the road, or in absence of a helmet or, again, when appeared to be female. Walker et al. [151] later showed that the cyclist's appearance did not play, in general, a crucial role, since 1–2% of overtakes came within 50 cm of the cyclist, regardless of what the rider was wearing. Cyclists' appearance at night-time emerged as significant by Black et al. [152] with visibility aids resulting in higher passing distances, and by Schwarz et al.[153], who examined the impact of adaptive headlamp features. The effect cyclist's gender was confirmed, inter alia, by Chuang et al. [154], who additionally proved that cyclists' behavior (measured according to wheel angle, speed and speed variation) influenced passing distance.

Llorca et al. [155] analyzed cyclists' perceived risk, stressing the importance of motor vehicle speed and the presence of heavy vehicles; the concerns of cyclists toward heavy vehicles were later considered by Pokorny et al.[156]. The impact of road and traffic features attracted considerable attention, with scholars focusing mainly on lane width, the existence of bicycle lanes, speed limits, and oncoming and/or adjacent traffic [157–161]. Unfortunately, while it is true that findings are not always consistent among these studies, it was demonstrated

[5] The work presented in this Section is part of the following publication:
Rossi, R., Orsini, F., Tagliabue, M., Di Stasi, L.L., De Cet, G., Gastaldi, M. Evaluating the impact of real-time coaching programs on drivers overtaking cyclists (2021) Transportation Research Part F: Traffic Psychology and Behaviour, 78, pp. 74-90.

that lateral passing distance generally tends to increase with wider roads, with the existence of bicycle lanes, with higher speed limits, and without oncoming traffic. Rubie et al. [162] presented a systematic review of how these factors (together with cyclists' factors) could influence lateral passing distances.

Feng et al.[163] investigated several factors with naturalistic data: infrastructural (type of centerline marker, existence of bicycle lanes), traffic (possible oncoming traffic) and driver-related (distraction, use of cellphones). They noted that almost 8% of overtaking maneuvers occurred when the drivers were distracted within five seconds before overtaking cyclists. Therefore, they concluded that shifting the research focus toward drivers' features could provide new insights into the topic.

Another line of research dealt with overtaking strategies, which to some extent may be considered as a driver factor, since the decision of how to perform an overtaking maneuver is ultimately taken by drivers themselves. The concept of overtaking strategies dates back to Matson & Forbes [164]. Subsequently, Dozza et al. [165] adapted this notion to the context of motor vehicles overtaking cyclists, formally defining flying and accelerative maneuvers. In the former, drivers overtake cyclists at a relatively constant speed; in the latter, drivers slow down and follow the cyclist before overtaking.

Bianchi Piccinini et al. [166] used a driving simulator experiment to survey how the presence of oncoming traffic influences the overtaking strategy, eventually demonstrating that it induced more drivers to choose the accelerative one. Moreover, Kovaceva et al. [167] managed to investigate several features, including driver's gender and age, with a naturalistic study, finding no significant impact of such features on passing distances. Still, a significant effect of gender on the chosen overtaking strategy, with females preferring accelerative maneuvers, was observed. In addition to this, Rasch et al. [168] highlighted the aftermath of cyclist position within the lane, resulting in more vehicles opting for an accelerative maneuver when the cyclist is closer to the center of the lane. Farah et al. [169] developed a logistic-regression model to predict the overtaking strategy, using data collected during a driving simulator experiment.

Lastly, in another driving simulator study, Goddard et al.[170] showed how drivers' implicit and explicit attitudes toward cyclists influenced their behavior. Participants with a negative attitude toward cyclists as legitimate road users passed significantly faster, while people with concerns about their knowledge or judgement about overtaking a cyclist passed further and more slowly. The above-mentioned works highlighted the importance of investigating the issue from the driver's perspective, and to establishing overtaking strategy as a relevant indicator to assess the safety of passing maneuvers on cyclists.

As it emerges from this brief review of the literature, there are clearly several works dealing with the problem of drivers overtaking cyclists from a cyclist/infrastructure point-of-view, although more research is certainly needed to investigate the role of drivers' behavior and the related influencial factors.

Further analyses of *Case study 1* (see Section 2.2.2) will be here presented, examining a specific event which occurred in both trials: drivers had the possibility to overtake a cyclist on an urban road. Thus, it was evaluated whether the real-time coaching program influenced drivers' behavior while they were overtaking the cyclist. The coaching program was not designed specifically to address the behavior of drivers overtaking cyclists, but more in general to reduce critical acceleration events, which the literature indicates as valid surrogate measures of dangerous driving [130]. This is of major concrete interest, because it may not always be feasible to develop a real-time program designed to deal with the specific problem of overtaking cyclists, especially in countries where cycling is uncommon, and this events are thus relatively infrequent.

In addition, the effect of several driver characteristics (gender, car usage, driving style) were examined. This is especially relevant for there are many studies in the literature which analyzed motor vehicle, infrastructure and cyclist characteristics, but only a few focusing on driver's characteristics [162].

To sum up, this Subcase study 1 aimed at answering the following questions:

- Do real-time coaching programs have an effect on how drivers overtake cyclists?
- Which drivers' features influence the way in which they overtake cyclists?

2.2.3.1 Procedure

Procedure was the same as that used in *Case study 1* (see Section 2.2.2.1).

2.2.3.2 Participants

Participants were the same as in Case Study 1 (see Section 2.2.2.2).

The analysis focused on the 67 participants (33 females; age range 20-33, mean 24.1, SD=2.73) who overtook the cyclist in both trials.

2.2.3.3 Scenario

Figure 37: virtual environment during overtaking maneuver [132].

The scenario was the same as in Case study 1 (see Section 2.2.2.3). Details of the tract of interest for this Subcase study will be provided below.

After about 5 km from the start of the trial, drivers met a male-looking cyclist on a straight urban road (two-lane, two-way) with a lane width of 3.1 m (Figure 37 and Figure 38). The speed limit on that road segment was 50 km/h and the two lanes were separated by a continuous centerline (which should not be crossed, in accordance with the Italian Highway Code). There was no hard shoulder between the carriageway and the sidewalk. The computer-controlled cyclist started moving when the motor vehicle was 100 m behind it and kept a constant speed of 8 m/s (28.8 km/h), with a constant lateral distance of 0.15 m from the sidewalk. There was no traffic approaching on the opposite lane, nor any other cars in front of the cyclist. If the drivers decided against overtaking, they had to follow the cyclist for about 750 meters; after that, the cyclist would perform a right turn on to a secondary road. Despite the presence of the continuous centerline, the vast majority of drivers (67 out of 78) overtook the cyclist in both trials.

Considering that the car was 1.6 meters wide, drivers could theoretically overtake the cyclist without crossing the centerline, leaving a maximum of 0.75 meters lateral clearance. In practice, although during the experiment a total of 3 drivers recorded a minimum lateral clearance below 0.75 meters, none of them managed to stay on the right of the centerline throughout the overtaking maneuver. Therefore, all the drivers who decided to overtake, crossed the centerline.

Harsh events (=negative feedback) were unlikely to be caused by drivers overtaking the cyclist. Due to the absence of oncoming traffic, drivers had no reason to perform harsh decelerations during the overtaking maneuver and, in fact, no deceleration harsh events were observed during these maneuvers. In the experiment, harsh acceleration events were mainly recorded only when motor vehicles accelerated from a standstill; in fact, only one participant managed to trigger negative feedback during an accelerative maneuver on the cyclist in Trial 2.

Conversely, a number of smooth events (=positive feedback) occurred during overtaking maneuvers past the cyclist during Trial 2. The two subgroups (visual/auditory) who received positive feedback were composed of 34 participants. Sixteen of them performed flying overtakes during which, by definition, accelerations are very low. As expected, none of them managed to trigger positive feedback during the maneuver. The other 18 participants performed accelerative overtakes, and 10 of them received positive feedback.

Noteworthy is that, though users are not explicitly notified about a potentially risky behavior (i.e., performing a flying overtake), the system does not provide contradictory signals to correct behaviors. Others, such as Lane Departure Warning Systems, provide instead negative feedback when drivers leave safer distances while overtaking cyclists.

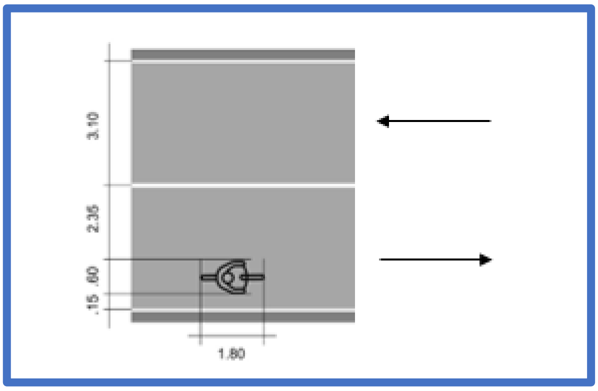


Figure 38: Infrastructure characteristics and cyclist position [132].

2.2.3.4 Feedback systems

Feedback systems were the same as that used in *Case study 1* (see Section2.2.2.4).

2.2.3.5 Variables

In line with recent literature [165, 166], the overtaking maneuver was divided into four phases: 1) approaching; 2) steering away; 3) passing; 4) returning.

Phase 1 starts when the motor vehicle is 100 m behind the cyclist (i.e., when the cyclist starts moving,) and ends when the motor vehicle driver starts to steer away from the collision path; Phase 2 ends when the motor vehicle enters the passing zone; Phase 3 ends when the motor vehicle leaves the passing zone. The passing zone is an area extending 2 m behind and ahead of the cyclist, as in Dozza et al. [165] (see Figure 39).

Drivers were not instructed on how to perform the overtake and were therefore free to choose between flying and accelerative strategies. As defined by Dozza et al. [165], in a flying overtake, drivers pass cyclists keeping a relatively constant speed; while in an accelerative overtake they slow down and follow the cyclist before overtaking.

In this work the following dependent variables were analyzed:

- The time-to-collision (TTC) between motor vehicle and bicycle recorded at the end of Phase 1, i.e., when the motor vehicle leaves the collision path;
- The rear passing distance (RPD), which is the distance between motor vehicle and bicycle at the end of Phase 1, as shown in Figure 39;
- The lateral passing distance (LPD), which is the minimum distance between motor vehicle and bicycle during Phase 3, as shown in Figure 39;
- Passing velocity (V_{Pass}), which is the average speed of the motor vehicle during Phase 3;
- Minimum approaching velocity (V_{Min}), which is the minimum speed recorded in Phase 1 or 2, and, as explained in Farah et al. [169], it may be used as an indicator to identify the overtaking strategy;
- Maximum acceleration (ACC_{Max}), recorded in any phase;
- Overtaking strategy: flying or accelerative.

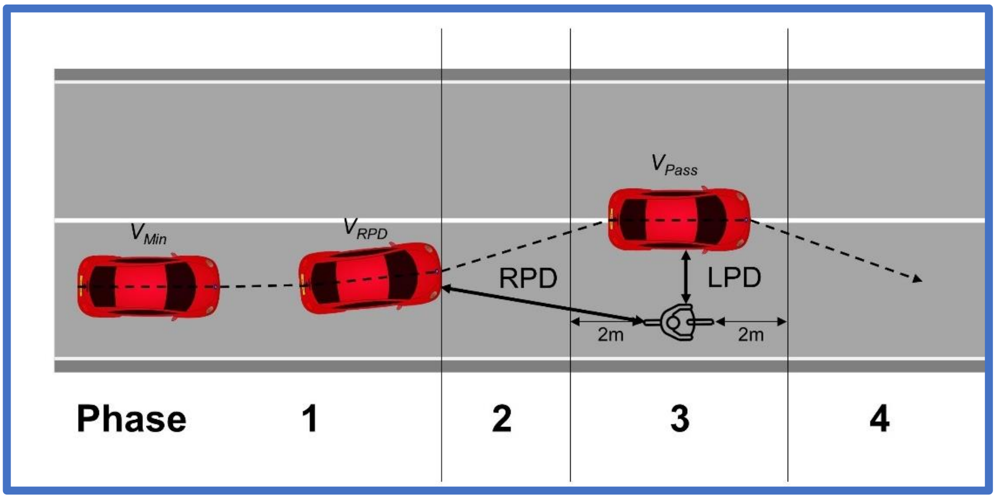


Figure 39: Phases and variables analyzed during overtaking maneuver [132].

Similarly to Kovaceva et al [167], the TTC was computed with the following formula:

$$TTC = \frac{RPD}{V_{RPD} - V_{Cycl}} \tag{5}$$

Where:

- V_{RPD} is motor vehicle speed recorded at the last instant in which driver and cyclist are on a collision course;

- V_{Cycl} is the speed of the cyclist (which was constant in the experiment).

Flying and accelerative maneuvers were defined according to the minimum approaching velocity, as in Farah et al. [169], so that it was possible to cluster the whole set of overtaking maneuvers with a V_{Min} threshold of 45 km/h. This threshold, which was confirmed by qualitative analysis of a selection of drivers' speed profiles, is slightly higher than that of the above-mentioned work. This can be explained by the fact that, in the present case study, the cyclist was faster (28.8 km/h, compared with a speed of 22 km/h in Farah et al. [169]) and drivers were therefore required to slow down less in order to perform an accelerative overtaking maneuver.

Maximum acceleration, which is usually neglected in studies of drivers overtaking cyclists, was investigated in this case study due to its direct connection to the real-time coaching system used in the second trial.

2.2.3.6 Analysis and Results

JASP software [87] and MATLAB were used to perform the analyses.

The analyses examined 67 participants who performed overtakes in both trials. 11 drivers did not perform the overtaking maneuver in at least one of the two trials and were excluded from the analysis. Six of these performed the overtaking maneuver in the first trial but not in the second; three of them performed it in the second trial but not in the first; the remaining two did not overtake in any trial. Their limited number does not allow formal statistical analysis; however, their characteristics are reported in Table 13.

Table 13: Characteristics of participants who did or did not perform the overtaking maneuver in both trials [132].

	Overtaking maneuver	No overtaking maneuver
N	67	11
Average age	24.1	24.9
Number of females (%)	33 (49.3%)	6 (54.5%)
Average driving experience [years]	5.3	6.3
Average car usage [km/year]	9,196	7,318
Number of defensive drivers	31 (46.3%)	6 (63.3%)

Table 14 lists the descriptive statistics of the analyzed variables for each trial. All the mean values of the variables decrease between Trial 1 and Trial 2, in some cases marginally (LPD), in others substantially (RPD, -26.9% and ACC_{Max}, -19.1%). A reduction of V_{Pass}, V_{Min} and ACC_{Max} suggests an improvement in terms of safety; conversely, lower values of TTC, RPD and LPD could be linked to a decrease in safety. TTC, RPD and ACC have the highest coefficients of variation (i.e. ratio between standard deviation and mean) in both trials (~0.6-

0.7), whereas the speed variables have the lowest (~0.13-0.17), indicating much smaller dispersion. Average passing speed is higher than the speed limit in both trials; however, in Trial 2 it is within the 5 km/h tolerance contemplated by the Italian Highway Code. No collisions with the cyclist were recorded during the experiment.

Table 14: Mean values and standard deviation (in parenthesis) of dependent variables in Trial 1 and Trial 2 [132].

	Trial 1	Trial 2
TTC [s]	3.77 (2.85)	3.29 (2.39)
RPD [m]	26.87 (20.65)	19.63 (13.51)
LPD [m]	1.42 (0.39)	1.41 (0.42)
V_{Pass} [km/h]	57.97 (9.87)	54.22 (7.52)
V_{Min} [km/h]	47.51 (7.21)	45.41 (7.08)
ACC_{Max} [m/s^2]	1.15 (0.67)	0.93 (0.56)

Mixed ANOVAs were carried out to assess the effect of *Trial* (Main Factor, MF), between factors (BF):

- *Driver gender* – female (N=33) vs. male (N=34);
- *Car usage* – 5,000 or less km per year (N=25) vs. more than 5,000 km per year (N=42);
- *Driving style* – defensive (N=31) vs. aggressive (N=36);
- *Feedback type* – positive (N=34) vs. negative (N=33);
- *Feedback modality* – auditory (N=31) vs. visual (N=36).

and their first order interactions on TTC, RPD, LPD, V_{Pass}, V_{Min} and ACC_{Max}.

TTC was not affected by Trial, $F(1,61)=1.0$, $p=0.325$, $\eta_p^2=0.02$, nor by Gender, Usage, Driving style and Feedback type/modality, or by their interactions.

RPD differed significantly across trials, $F(1,61)=7.8$, $p=0.007$, $\eta_p^2=0.11$, but with no significant BF nor any interaction. As can be observed drivers tend to perform the overtaking maneuver with lower RPD in Trial 2.

As regards **LPD**, no effect of Trial was found, $F(1,61)=1.0$, $p=0.320$, $\eta_p^2=0.02$.

Gender was marginally significant, $F(1,61)=4.0$, $p=0.051$, $\eta_p^2=0.06$, with female drivers showing a tendency of leaving more lateral clearance in both trials (Figure 40a).

While Usage was not significant, its interaction with Trial was ($F(1,61)=9.1$, $p=0.004$, $\eta_p^2=0.13$): less frequent car users (with less than 5,000 km/year) tended to reduce their LPD in Trial 2, whereas frequent car users did not (Figure 40b).

Clustered driving style was significant, $F(1,61)=10.6$, $p=0.002$, $\eta_p^2=0.15$, with aggressive drivers keeping a larger lateral margin while overtaking; however, no significant interaction was found, indicating that the effect of driving style was maintained throughout the two trials (Figure 40c).

Feedback type/modality showed no significant effect.

Post-hoc tests on Trial 1 were carried out to assess the effect of driver characteristics on LPD, prior to the feedback. These tests revealed a considerable discrepancy between female and male drivers, $t(61)=2.17$, $p=0.034$, aggressive and defensive drivers, $t(61)=2.86$, $p=0.006$, and frequent and less frequent car users, $t(61)=2.41$, $p=0.019$. Female, aggressive and less frequent car users left a much larger LPD while overtaking the cyclist (see Figure 40a-c)).

Trial was significant for $\mathbf{V_{Pass}}$, $F(1,61)=8.4$, $p=0.005$, $\eta_p^2=0.12$, with a reduction of almost 4 km/h in the second trial. Cluster was significant, $F(1,61)=36.0$, $p<0.001$, $\eta_p^2=0.37$, with a very large effect size, as well as the interaction Trial*Cluster, $F(1,61)=7.1$, $p=0.010$, $\eta_p^2=0.10$. As Figure 40d illustrates, the real-time coaching was significantly effective only for aggressive drivers, who reduced their speed by about 7 km/h, whereas defensive drivers maintained their relatively low passing speed also in Trial 2. Post-hoc test confirmed that aggressive drivers had a significantly higher V_{Pass} in Trial 1, $t(61)=5.84$, $p<0.001$.

No other BF nor interaction reached significance.

Similar trends were observed for $\mathbf{V_{Min}}$, with a significant effect of Trial, $F(1,61)=4.2$, $p=0.045$, $\eta_p^2=.06$ and Cluster, $F(1,61)=25.5$, $p<0.001$, $\eta_p^2=0.30$. Interaction with Cluster was not significant, $F(1,61)=2.5$, $p=0.117$, $\eta_p^2=0.04$, but a tendency comparable to that of V_{Pass} can be noted (see Figure 40e) In absolute terms, aggressive drivers reduced their minimum approaching speed by about 3.5 km/h, suggesting that some of them changed from a flying to an accelerative strategy. Post-hoc tests highlighted a substantially higher V_{Min} for aggressive drivers in Trial 1, $t(61)=5.11$, $p<0.001$.

No other BF nor interaction reached significance.

As expected, since the real-time coaching program is related to acceleration/deceleration events, $\mathbf{ACC_{Max}}$ was influenced by Trial, with MF resulting significant, $F(1,61)=4.2$, $p=0.046$, $\eta_p^2=0.06$.

Gender was also significant, $F(1,61)=7.7$, $p=0.007$, $\eta_p^2=0.11$, but without interaction: in both trials female drivers tended to accelerate more abruptly than males, when overtaking the cyclist. Cluster was significant, $F(1,61)=5.1$, $p=0.028$, $\eta_p^2=0.08$. As can be observed in Figure 40f, the real-time coaching was effective only for aggressive drivers, in line with what observed for EGFEs by Rossi et al. [100]. Post-hoc tests confirmed significant higher values of ACC_{Max} for aggressive drivers, $t(61)=2.45$, $p=0.017$, but not for female drivers, $t(61)=1.85$, $p=0.069$ in Trial 1. No other BF nor interaction reached significance.

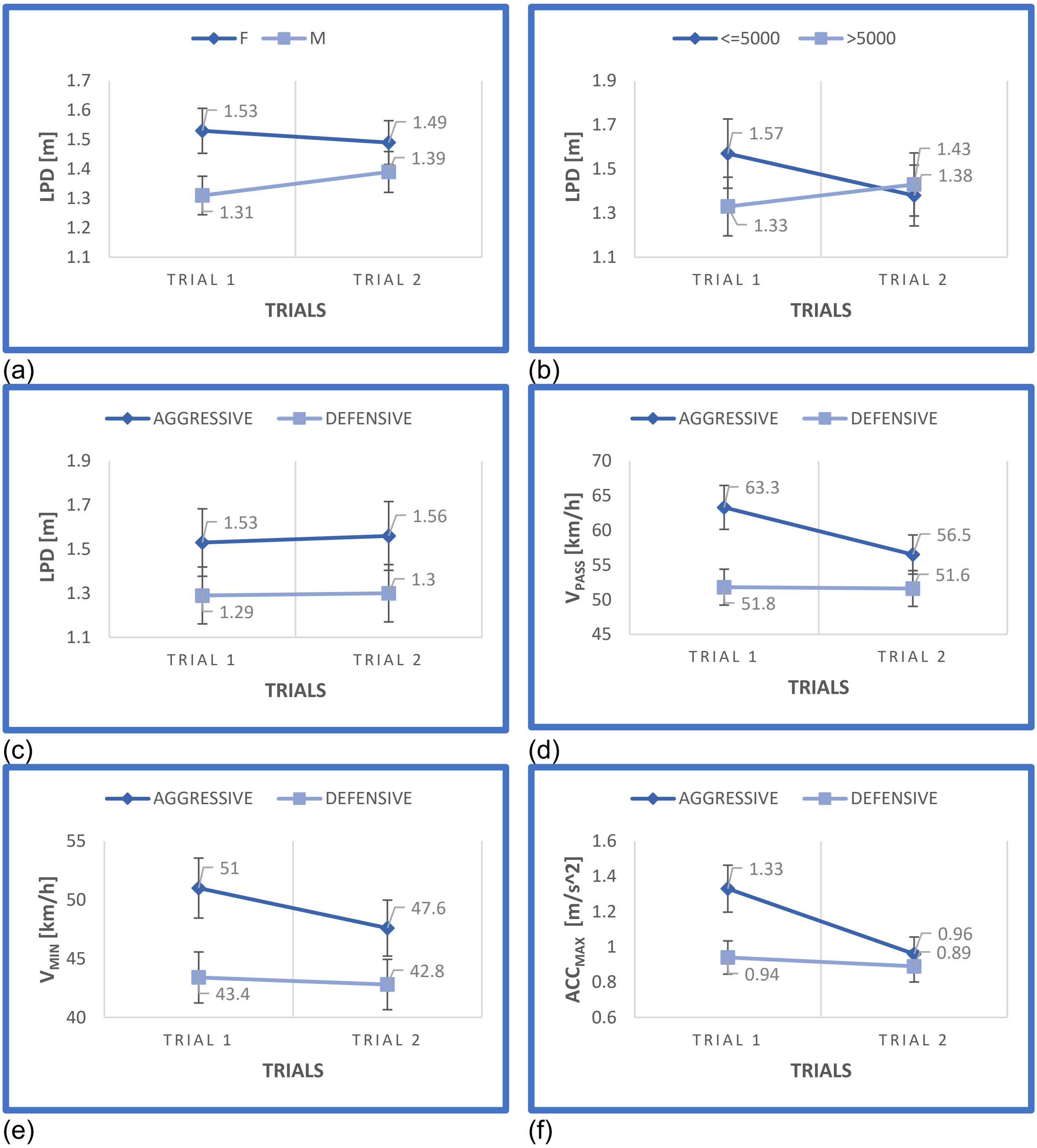


Figure 40: Mixed ANOVA. Error bars represent the standard error. Effects of: (a) BF Gender on LPD; (b) BF Usage on LPD; (c) BF Cluster on LPD; (d) BF Cluster on V_{Pass}; (e) BF Cluster on V_{Min}; (f) BF Cluster on ACC_{Max} (Adapted from [132]).

As regards **overtaking strategy,** contingency tables were drawn, initially with a mere analysis of effect of Trial, and then searching for any additional effects.

Trial 2 showed a tendency toward the reduction of flying maneuvers (Table 15), as they decreased from 64.2% of the total to only 49.3%, despite a marginally significant difference, χ^2 (1,N=134)=3.04, p=0.081, ϕ=.15.

Taking into account the effect of Gender (Table 16), male drivers did not exhibit any significant alteration in their overtake strategy: although flying overtakes decreases from 61.8% in Trial 1 to 52.9% in Trial 2, this change was far from significance, as χ^2 (1,N=68)=0.54, p=0.462, ϕ=0.09. Conversely, female drivers reduced flying overtakes from 66.7% to 45.5%, very close to significance: χ^2 (1,N=66)=3.0, p=0.083, ϕ=0.21.

A much clearer pattern emerged considering the effect of Driving Style (Table 17), as defensive drivers maintained their strategy (from 29.0% to 25.8%), whereas many aggressive drivers changed to the accelerative strategy, reducing their flying overtakes from 94.4% of the total down to 69.4%, with χ^2 (1,N=72)=7.6, p=0.006, ϕ=0.33.

Considering Trial 1 alone, in order to assess the effect of Driving Style on overtaking strategy, without the presence of feedback, aggressive drivers were essentially more prone to prefer the flying strategy to defensive ones, χ^2 (1,N=67)=31.0, p<0.001, ϕ=0.68.

Table 15: Contingency table to investigate the effect of Trial on the chosen overtaking strategy [132].

	Trial 1	Trial 2	Total
Accelerative strategy	24	34	58
Flying strategy	43	33	76
Total	67	67	134

Table 16: Contingency table to investigate the effect of Trial and Gender on the chosen overtaking strategy [132].

		Trial 1	Trial 2	Total
Female drivers	Accelerative strategy	11	18	29
	Flying strategy	22	15	37
Male drivers	Accelerative strategy	13	16	29
	Flying strategy	21	18	39
Total		67	67	134

Table 17: Contingency table to investigate the effect of Trial and Driving Style on the chosen overtaking strategy [132].

		Trial 1	Trial 2	Total
Aggressive drivers	Accelerative strategy	2	11	13
	Flying strategy	34	25	59
Defensive drivers	Accelerative strategy	22	23	45
	Flying strategy	9	8	17
Total		67	67	134

2.2.3.7 Discussion and Conclusion

This work examined the effect of a motor insurance real-time coaching program on drivers' behavior while overtaking cyclists.

Despite a continuous centerline which, according to the Italian Highway Code, should not be crossed, the vast majority of participants (67 out of 78, i.e., 85.6%) performed the overtaking maneuver and crossed the continuous centerline. Unsurprisingly, this result is consistent with findings from real-world data: in the study of Feng et al. [147].

Broadly speaking, it was observed that motor vehicles crossed a continuous centerline in 89% of overtaking maneuvers on cyclists, when there was no oncoming traffic and no bike lane or shoulder. The presence of a continuous centerline may have had a reducing influence on LPD in this experiment, since in Feng et al. [147] drivers were found to cross the centerline to a greater extent with the dashed line, than with the continuous centerline, with no oncoming traffic and bike lanes/shoulders.

In examining Trial 1, it is thought-provoking to notice the significant effect of driving style (aggressive vs. defensive) on several dependent variables, i.e.: LPD, V_{Pass}, V_{Min} and ACC_{Max}. Although the two clusters were defined with highly aggregated variables collected throughout the trial (and not specifically during the overtaking maneuver), they could correctly identify two groups of drivers who showed different behaviors during overtaking, in that aggressive drivers gave more lateral space to the cyclist, but overtaking at a much higher relative speed than defensive drivers. This behavior can also be seen in real driving, regardless of driving style, at higher speed corresponds greater attention that must be paid during overtaking maneuver. In general, aggressive drivers preferred a flying strategy, and defensive drivers the accelerative one. According to previous works, the accelerative overtaking strategy is considered safer than the flying one, since speeds are lower, drivers have better control of interaction with a possible oncoming vehicle, and they allow larger clearances to cyclists [165, 169].

Two other factors revealed a significant effect on LPD in Trial 1: driver gender and car usage, with female drivers and drivers who use the car for less than 5,000 km/year giving more lateral space to the cyclist. As there was no oncoming traffic, this behavior may be considered safer than that of male drivers and those who use the car for more than 5,000 km/h.

The tendency of female drivers to leave more lateral clearance to cyclists was also observed by Goddard et al. [170] , who illustrated that women had a lower likelihood of performing close passes (within one meter of the cyclist). On the other hand, these findings are different from those of Kovaceva et al. [167], who did not observe any significant effect of gender on LPD and, conversely, did find a significant effect on overtaking strategy (female drivers preferred the accelerative); the latter effect was also observed by Rasch et al. [168]. These differences may be due to the limited sample sizes of the studies or to drivers' cultural differences. In general, however, this work is consistent with the aforementioned studies in linking female drivers to safer behaviors. As regards the factor 'car usage', Goddard et al. [170] showed that people who drive more frequently were more likely to have negative implicit attitude toward cyclists, although this did not prove to be a relevant aspect in passing safety.

As said, the main focus was to evaluate the effect of a motor insurance real-time coaching device on how drivers overtake cyclists. Since the device is closely related to accelerations (it warns drivers in real-time about correct/incorrect accelerations, as explained in 2.1.4), it promotes a cautious driving style. No wonder that, thanks to the presence of the on-board device, drivers reduced their maximum acceleration during the passing maneuver.

Interestingly, this was not the only aftermath. It should be noted that the flying strategy is the smoothest way for a driver to overtake a cyclist, since the whole maneuver may theoretically be performed with zero acceleration and constant speed. However, the real-time coaching system had the opposite effect and basically increased the number of accelerative maneuvers (especially for aggressive drivers). By implication, this indicates that the presence of the device induced drivers to behave more cautiously, in general, regardless of accelerations, and that drivers kept lower speeds both before and during the passing maneuver. Moreover, this is paramount not only for cyclists' safety, but also for their comfort since, as shown by Llorca et al. [155], motor vehicle speed has an extensive impact on perceived risk.

A reduction in RPD was also observed: taken singularly, this would not be positive, in terms of safety; however, thanks to the reduced speeds, TTC did not decrease.

Clustered driving behavior was a significant 'between factor' for several dependent variables, with significant interactions with MF Trial, in line with results reported by Rossi et al. [100]: real-time coaching is more effective for aggressive drivers, because there is more margin for improving their driving style. Instead, defensive drivers, already presented satisfactory behavior in Trial 1 and, therefore, they improved less.

The tested program was a general-purpose coaching program, i.e., not designed specifically to address the problem of drivers overtaking cyclists. The results appear extremely relevant for real-world applications, because it might be impractical to develop dedicated programs for specific situations such as car drivers overtaking cyclists.

Although the program tested improves the overall safety of overtaking maneuvers, there is still substantial margin for improvement, especially in increasing relative distances from cyclists (RPD and LPD) and TTC.

The coaching program could be improved by examining not only kinematic variables of a motor vehicle, e.g., its acceleration, but also information on nearby vehicles and objects, including relative distances and TTC. Evidently, this would require more substantially sophisticated technologies, such as video, radar or lidar sensors; however, considering that a growing amount of motor vehicles are currently equipped with such technologies, this could be viable in the relatively near future.

Two main conclusions can be accordingly drawn from this investigation:

- The presence of an on-board real-time coaching program can ameliorate the safety of maneuvers in passing cyclists. Though the tested feedback system is quite elementary (it is activated when crossing some fixed acceleration/deceleration thresholds), the results indicate not only that this can reduce the number of EGFEs, but also that it can generally induce drivers to behave more safely on road, and this has surely great practical interest;
- Drivers' characteristics influence overtaking behavior, as aggressive drivers prefer the flying strategy and overtake at higher speeds. Female drivers and drivers with low car usage tend to be safer while overtaking, giving more lateral space to cyclists. This suggests that considering these characteristics is quite relevant and that other factors should also be analyzed in the future.

Unfortunately, this study presents some limitations, which will be addressed more deeply in future research.

Firstly, this inquiry focused on subjects from a single age group (18-30 years), all living in the same country (Italy). Ideally, further tests should be performed to assess whether there are significant effects of age and/or culture. Bicycle usage would also be worth studying (i.e., if drivers are also cyclists themselves), as this may influence both driving behaviors [171] and drivers' attitudes toward cyclists [170].

In addition, since the experiment was designed to include only one overtaking per trial, it was not possible to address any specific cyclist, road or traffic-related factors, such as: cyclist appearance, centerline marking, or oncoming traffic. In this sense, it is compelling to envisage an extension of this study in the future, with multiple overtakes per trial, in order to analyze these factors.

Other types of real-time coaching programs could also be tested, for example providing feedback with alternative modalities (e.g., tactile), combinations of modalities, or feedback depending on different variables (e.g., relative distances to other vehicles).
Another noteworthy aspect to be investigated is the long-term effect of feedback, e.g., how drivers behave once they become familiar with the presence of the on-board device, or if the effects of the coaching program are retained after feedback has been removed. In addition, a long-term approach could be applied to develop a more realistic monetary incentive system.
Lastly, this study did not consider possible interactions between cyclist and driver behaviors. Hence, these aspects could be expanded and discussed with connected driving and bicycle simulators in future research.

2.2.4 Subcase study 2: Highway Deceleration Lane Safety: Effects of Real-Time Coaching Programs on Driving Behavior[6]

Undoubtedly, highway deceleration lanes and exit ramps are a relevant concern in road safety. Despite accounting for a negligible amount of total freeway mileages, they are significantly more risky than freeway mainline sections. As a matter of fact, in the United States, a National Cooperative Research Program (NCHRP) report showed an average rate of 0.68 crashes per million miles travelled by vehicles on deceleration lanes, 20% higher than that of freeway mainline sections near the exit ramp, and three times higher than that on acceleration lanes [172].

Despite this, few researchers have addressed the issue, and their research dates back to the 60s of the last century [173]. The vast majority of the studies focused on finding relationships between geometric/traffic features of the deceleration lanes and crash rates [174–177]. Their main goal was to help practitioners to design safer infrastructures. The main geometric features which were proved to have an impact on deceleration lane safety are: deceleration lane length, deceleration lane type, and number of deceleration lanes. The conclusions from these studies, however, were quite inconsistent. A recent meta-analysis [178], revealed that, although significant risks associated with geometric features were observed, the meta-estimates were not significant, stressing the need for further research on the topic.

A different approach was applied by Calvi et al. [179], who discussed the impact of traffic volume on deceleration lane safety with a driving simulator study involving 30 participants. Contrarily to previous crash-based studies, the focus switched to microscopic aspects of the phenomenon, i.e., the behavior of drivers on the deceleration lane: to evaluate safety, they considered vehicle speeds, deceleration, and trajectories. The results showed a significant effect of traffic volume on vehicle speed, deceleration rate, and trajectory, and highlighted some relevant issues, such as that drivers tended to decelerate before diverging, and that speeds in the deceleration lane were significantly higher than the design speed. Subsequently, the authors applied the same driving-simulator-based approach to investigate the effect of the deceleration lane type, comparing parallel and tapered designs [180], and observed significant differences in the speeds of diverging drivers, with greater interference with the through traffic on the tapered lane. Moreover, another work focused on

[6] The work presented in this Section is part of the following publication:
Orsini, F.; Tagliabue, M.; De Cet, G.; Gastaldi, M.; Rossi, R. Highway Deceleration Lane Safety: Effects of Real-Time Coaching Programs on Driving Behavior (2021). Sustainability, 13, 9089

evaluating the effects of the number of exit lanes [181]: the two-lane exit layout seemed to provide improved performance over the single-lane one, by limiting the interference of the diverging drivers with the through traffic. Their driving simulator approach was later successfully validated by comparing speed and trajectory data collected both in the field and with a simulator experiment [182]. As in the majority of studies in the literature, their declared end goal was to provide guidance for safer infrastructure design.

A driver-behavior-focused approach was followed also by Lyu et al. [183], who carried out a naturalistic experiment involving 46 participants on a typical highway deceleration lane in Wuhan. Lyu et al. [179] studied drivers' speed, deceleration rate, and trajectories; in addition, they investigated vehicle lateral control during the diverging maneuver. The aim of their work was to investigate the effect of some sociodemographic characteristics (i.e., gender, occupation, experience) on drivers' behavior, presenting several significant effects. In particular, male drivers presented earlier entries in the deceleration lane in comparison with female drivers; moreover, before entering the deceleration lane, experienced and professional drivers performed the last lane change as early as possible; in addition, the vehicles' speed while entering the exit ramp exceeded significantly the speed limit. Their approach introduced a crucial novelty in this line of research, switching the focus from infrastructural/traffic characteristics to drivers' characteristics.

From this analysis of the literature, it is possible to observe that only few studies investigated the safety of highway deceleration lanes by focusing on the driving behavior of road users. What is more, to the best knowledge, none of them investigated in-vehicle countermeasures aimed at improving the safety of exiting maneuvers in highways.

The present Subcase study 2 concerned a specific part of the trials of Case study 1, namely the maneuver of exiting the highway using the deceleration lane in particular, and investigated whether the real-time coaching program had an impact on participants' behavior during such maneuver.

It is worth noting that the coaching program was not specifically developed to address the behavior of drivers exiting the highway, but, more generally, to reduce the number of critical braking/acceleration events, which are considered as valid surrogates for dangerous driving [130]. Since the development of a specific real-time programs to deal with each specific maneuver on the road (e.g., overtaking a cyclist or exiting a highway) is not feasible, it would be pragmatically stimulating to assess whether a general-purpose real-time coaching program can actually increase safety in different scenarios.

2.2.4.1 Procedure

Procedure was the same as that used in *Case study 1* (see Section 2.2.2.1).

2.2.4.2 Participants

Participants were the same as in Case Study 1 (see Section 2.2.2.2). Hence, the final sample included 74 drivers (37 males and 37 females, age range 20-33; mean=24, SD=2.80).

2.2.4.3 Scenario

The scenario was the same as in Case study 1 (see Section 2.2.2.3). Details of the tract of interest for this Subcase study will be provided below.

After about 6.5 km from the start of the trial, drivers entered a two-lane highway. The lanes were 3.60 meters wide and there was a 3.00-meter-wide hard shoulder on the right. After 2.6 km, drivers were required to perform an exit maneuver. The first traffic sign, indicating participants to exit the highway, was located 1.2 km before the deceleration lane. The deceleration lane was 3.60 meters wide and 300 meters long, including a 100-meter taper, with a parallel layout (Figure 41 and Figure 42). The lane was followed by a smooth curve with a 500 m radius. The posted speed limit on the highway was 100 km/h, and there was about 1,200 vehicles/lane/hour computer-controlled traffic. The speed of the computer-controlled vehicles was between 90 and 110 km/h.

Figure 41: 3D driving simulator scenario [184].

2.2.4.4 Feedback systems

Feedback systems were the same as that used in *Case study 1* (see Section 2.2.2.4).

2.2.4.5 Variables

Several dependent variables were analyzed in this Subcase study. They can be classified into four broad categories, i.e., speed, deceleration, trajectory, and lateral control variables.

The variables were chosen in line with the existing literature investigating driving behavior on deceleration lanes [179, 183].

The distance *D* was considered to the end of the deceleration lane as a spatial reference. The deceleration lane was therefore located between *D* = 300 m and *D* = 0 m (Figure 2). A preliminary analysis showed, consistently with previous works, that some participants started decelerating before the beginning of the deceleration lane. Still, no participant started to decelerate earlier than *D* = 500 m.

Speed variables:

- *V_MEAN* [km/h]. The average speed on the highway, calculated from *D*=2300 m to *D*=1300 m, therefore before the first traffic sign indicating the highway exit;
- *ΔV1* [km/h]. Speed change at the beginning of the deceleration lane, calculated as the difference between the speed at *D*=300 m and *V_MEAN*;
- *ΔV2* [km/h]. Speed change when entering the deceleration lane, calculated as the difference between the speed recorded when the vehicle's center of gravity (COG) entered the deceleration lane and *V_MEAN*.
- *ΔV3* [km/h]. Speed change at the end of the deceleration lane, calculated as the difference between the speed at *D* = 0 m and *V_MEAN*.

Deceleration variables:

- *DEC_MEAN* [m/s^2]. Average deceleration between *D*=500 m and *D*=0 m;
- *DEC_MAX* [m/s^2]. Maximum deceleration between *D*=500 m and *D*=0 m.

Trajectory variables:

- *E* [m], "exit point", defined as the point in the space between *D*=300 m and *D*=0 m where the vehicle's COG enters the deceleration lane;
- *A* [m], "start-of-deceleration point", defined as the point in the space between *D*=500 m and *D*=0 m where the driver first fully raises the foot from the gas pedal[7].

Lateral control variables:

- *LATACC* [m/s^2]. Average lateral acceleration between *D*=300 m and *D*=0 m;
- *SDSA* [degrees]. Standard deviation of steering angle between *D*=300 m and *D*=0 m.

[7] Note that, in principle, A is different from the point where the vehicle actually starts decreasing its speed; moreover, drivers can decelerate even without fully removing the foot from the gas pedal. A was defined in such way to avoid ambiguity in the definition of the deceleration phase, and to be consistent with previous literature [179].

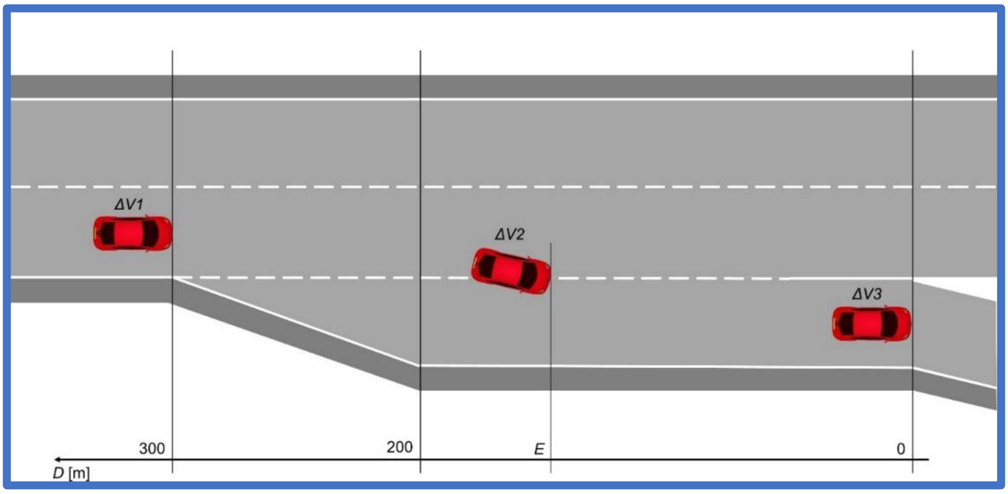


Figure 42: Speed/trajectory variables and geometric features of the deceleration lane [184].

2.2.4.6 Analysis and Results

Mixed ANOVA models were applied to investigate the impact of the real-time coaching program on the exiting maneuver, using data collected in both trials. The work considered one main factor (Trial), three between-participant factors (Driving style, Feedback valence, and Feedback modality), and their interactions. Each dependent variable was investigated with separate analysis. Effect size was quantified with $\eta_p{}^2$ which, as a rule of thumb, indicates a small effect if it is higher than 0.01, a medium effect if it is higher than 0.06, and a large effect if it is higher than 0.14 [135]. Post hoc tests were carried out with Fisher's Least Significant Difference procedure.

JASP software [87] and MATLAB were used to perform the analyses.

Table 18 presents descriptive statistics for the 74 participants who performed the exit maneuver from the highway in both trials. Mean values indicate a reduction in the average speed on the highway in Trial 2, and an even higher reduction in the other speed indexes in the deceleration lane. Mean and maximum deceleration tend to be lower (in absolute value) in Trial 2, whereas the exit and the start of deceleration spots appear to be farther away from the end of the deceleration lane. Average lateral acceleration and standard deviation of the steering angle are lower in Trial 2, suggesting higher lateral control of the vehicle. Except for some speed variables, standard deviations are lower in Trial 2, indicating more consistent behavior among the participants. It is worth mentioning here that only the data from 62 participants were available for the variable *A* in Trial 1 and 66 in Trial 2, since the other participants did not fully remove their foot from the gas pedal during the maneuver.

Furthermore, it has to be noted that, in absolute terms, the mean and maximum deceleration values are essentially low, compared to those of previous works on deceleration lanes (e.g.,[179]). In the present experiment, the lane was not designed to necessarily induce harsh decelerations, and, indeed, it was relatively long, and followed by a smooth curve.

Figure 43 displays the trajectories of the individual vehicles' COG in both trials, showing that virtually all participants approached the exit from the right lane, and most of them entered the deceleration lane within its first third (i.e., within the taper) - but with notable exceptions.

Table 18: Mean values and standard deviation (in parentheses) of dependent variables in Trial 1 and Trial 2 [184].

	Trial 1	Trial 2
V_MEAN [km/h]	92.33 (7.89)	87.59 (8.03)
ΔV1 [km/h]	-1.40 (7.88)	-2.59 (7.59)
ΔV2 [km/h]	-2.11 (8.01)	-4.84 (8.27)
ΔV3 [km/h]	-14.29 (8.55)	-17.01 (9.42)
DEC_MEAN [m/s^2]	-0.46 (0.22)	-0.41 (0.16)
DEC_MAX [m/s^2]	-1.05 (0.34)	-0.95 (0.28)
E [m]	222.08 (43.93)	227.38 (33.33)
A [m]	189.16 (133.67)	211.64 (124.45)
LATACC [m/s^2]	0.22 (0.07)	0.18 (0.06)
SDSA [°]	4.04 (1.71)	3.45 (1.25)

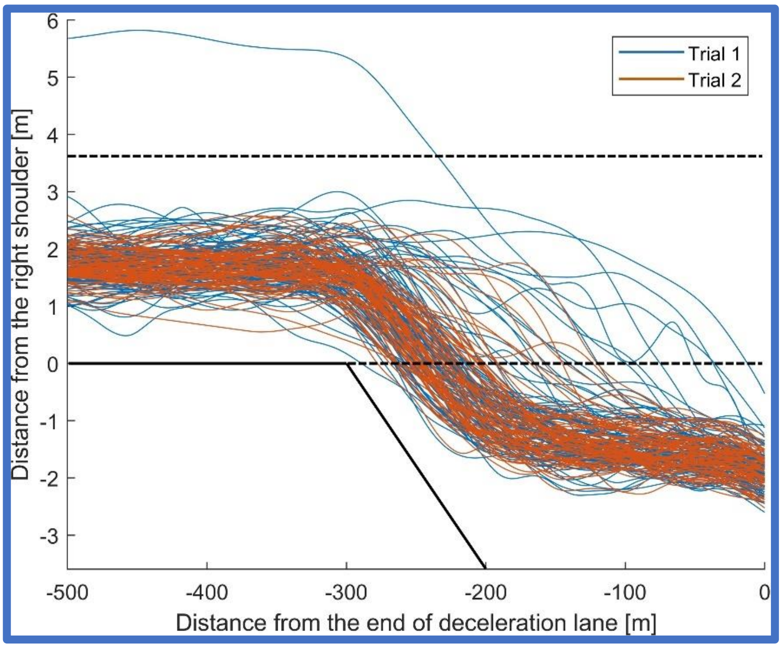


Figure 43: Individual vehicle's COG trajectories in each Trial [184].

Mixed ANOVAs were carried out to assess the effect of *Trial* (Main Factor), and the between-participant factors:

- *Cluster* – aggressive (*N*=38) vs. defensive (*N*=36);
- *Feedback valence* – negative (*N*=35) vs. positive (*N*=39);
- *Feedback modality* – visual (*N*=41) vs. auditory (*N*=33).

besides their interactions on the variables.

A significant effect of Trial on ***V_MEAN*** was observed, $F(1,66) = 29.23$, $p < 0.001$, $\eta_p^2 = 0.31$: participants reduced their average speed in Trial 2 by almost 5 km/h. Aggressive drivers had, on average, higher speed than defensive drivers in both trials, as the effect of Cluster was also significant, $F(1,66)=36.20$, $p < 0.001$, $\eta_p^2=0.35$. Interaction was not significant, meaning that both clusters were affected in the same way by the main factor Trial (Figure 44a). Feedback valence and modality showed no significant effect.
Trial and Cluster had no significant effect on ***ΔV1***, but their interaction was yet significant, $F(1,66) = 6.87$, $p=0.011$, $\eta_p^2 =0.09$. This can be observed in Figure 44b, whereby, in Trial 2, defensive drivers had a much higher speed reduction (about 4km/h) at the beginning of the deceleration lane than in Trial 1, contrarily to aggressive ones. This was also confirmed by post hoc tests, which showed a significant difference for defensive drivers, $t(66)=2.54$, $p=0.013$, contrarily to the aggressive ones, $p=0.246$.
As regards ***ΔV2***, Trial has a significant effect, $F(1,66)=5.51$, $p=0.022$, $\eta_p^2 =0.08$, as well as Cluster, $F(1,66)=6.65$, $p =0.012$, $\eta_p^2 =0.09$, but not their interaction, with both aggressive and defensive drivers reducing their speed more when entering the deceleration lane in Trial 2 than in Trial 1, and with defensive drivers reducing their speed more than aggressive ones in both trials (Figure 44c). A similar trend is to be observed at the end of the deceleration lane (variable ***ΔV3***, Figure 44d) with significant effect of Trial, $F(1,66)=7.29$, $p=0.009$, $\eta_p^2=0.10$, and Cluster $F(1,66)=10.56$, $p=0.002$, $\eta_p^2=0.14$.
As in the case of *V_MEAN*, feedback valence and modality showed no significant effect on any of the three speed-change variables investigated.

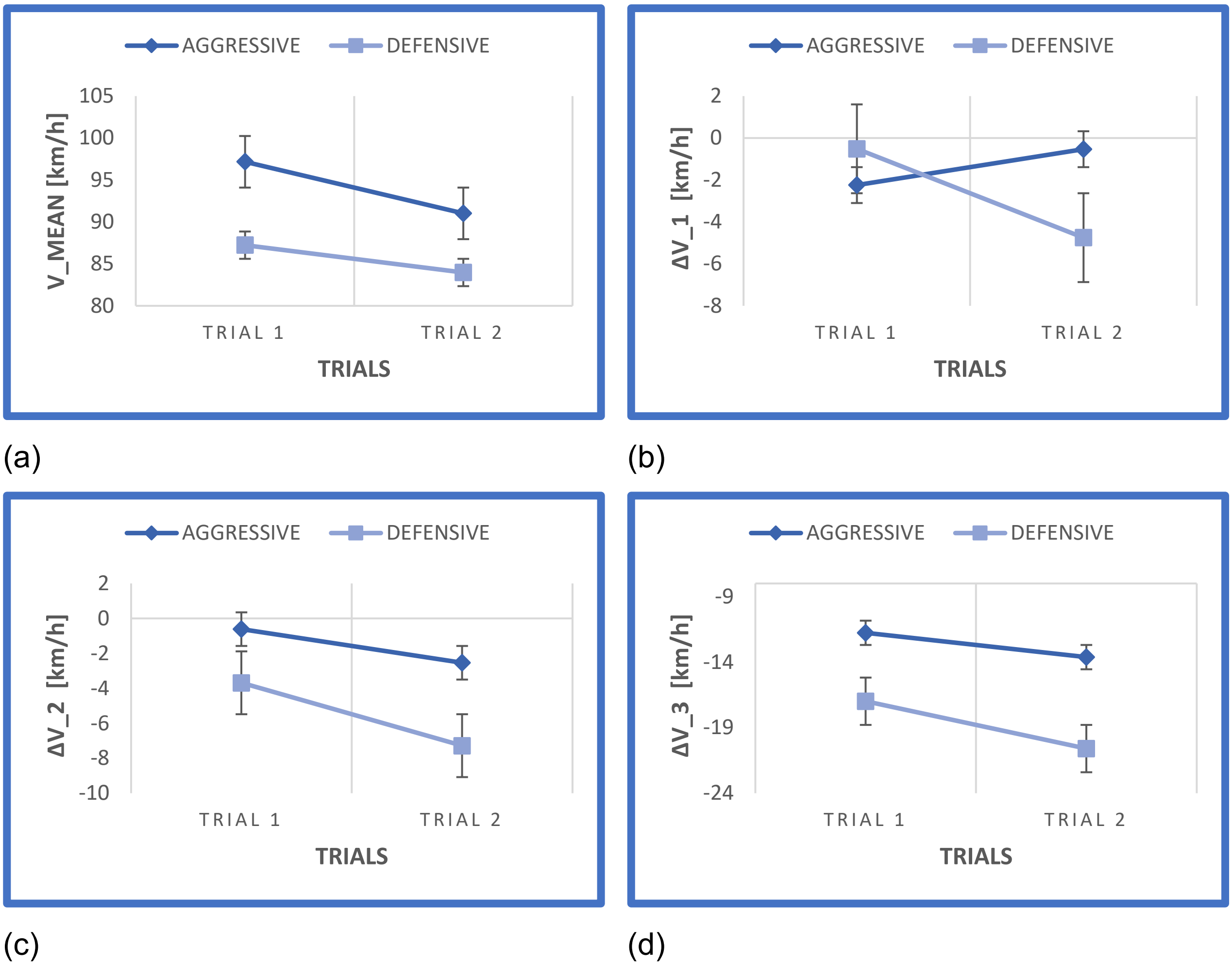
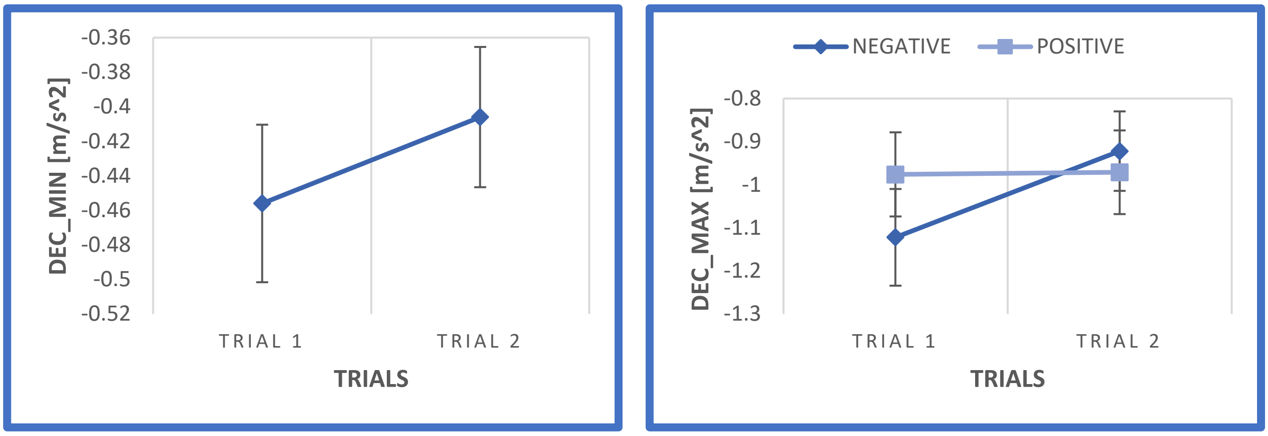


Figure 44: Mixed ANOVA results. Error bars represent the standard error. Trial and Cluster effects on: (a) mean speed in the highway; (b) speed change at the beginning of the lane; (c) speed change at the exit point; (d) speed change at the end of the lane (Adapted from [184]).

The main factor Trial was not significant on ***DEC_MEAN***, $F(1,66)=2.75$, $p = .102$, $\eta_p^2 = 0.04$, although a tendency of participants to reduce (in absolute value) their mean deceleration in Trial 2 can be noticed in Figure 45a. No significant effect was reported for any of the between-participant factors.

A more evident and significant effect of Trial was found analyzing ***DEC_MAX***, $F(1,66)= 5.18$, $p=0.026$, $\eta_p^2=0.07$: participants reduced, on average, their maximum deceleration from -1.05 m/s^2 to -0.95 m/s^2 (Figure 45b). A significant interaction between Trial and Feedback valence was also observed, $F(1,66)=5.04$, $p=0.028$, $\eta_p^2=0.07$. It revealed that the participants who received a negative feedback were able to significantly reduce their maximum deceleration, as confirmed by the post-hoc test, $t(66)=-3.07$, $p=0.003$, contrarily to those who received the positive feedback, $p=0.827$.

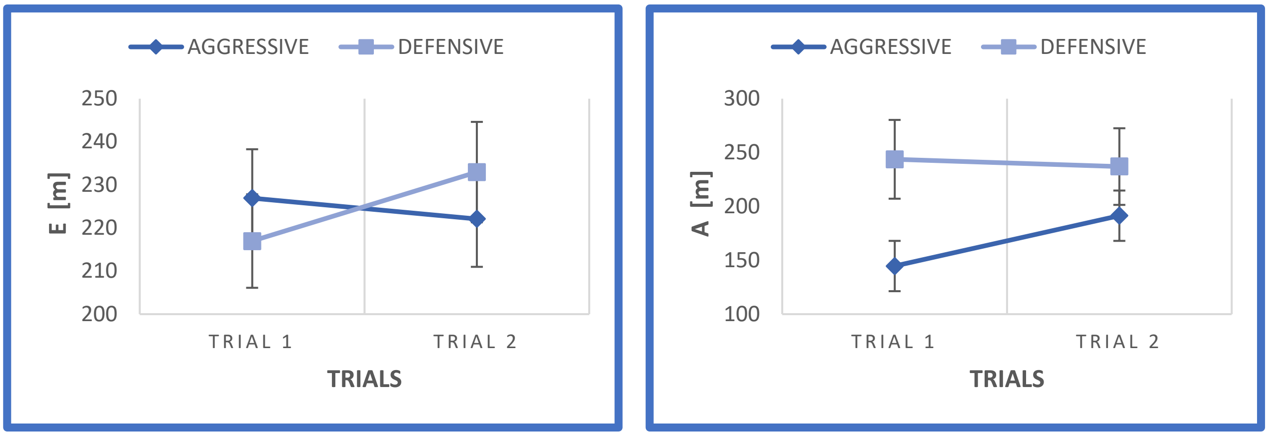
No significant effect was reported for any of the between-participant factors, nor for any other interaction.



(a) (b)

Figure 45: Mixed ANOVA results. Error bars represent the standard error. (a) Trial effect on mean deceleration; (b) Trial and Feedback valence effects on maximum deceleration (Adapted from [184]).

No significant main factor effect was found for variable ***E***: on average, drivers tended to enter the deceleration lane around the same point in both trials. However, an intriguing interaction Trial*Cluster was found significant, $F(1,66)=6.45$, $p=0.013$, $\eta_p^2=0.09$. As can be observed in Figure 46a, defensive drivers tended to enter the lane significantly earlier in Trial 2, the post hoc tests resulting significant, $t(66)=2.77$, $p=0.007$. In absolute terms, they entered the lane about 16 meters earlier in Trial 2. Conversely, aggressive drivers did not significantly change their behavior, $t(66)=0.83$, $p=0.411$. As regards the variable ***A***, Trial was found not significant, and neither its interaction with Cluster. Factor Cluster, however, was itself significant, $F(1,47)=7.34$, $p=0.009$, $\eta_p^2=0.14$, with defensive drivers raising the foot from the gas pedal much earlier (about 70 meters on average) than the aggressive ones, in both trials (Figure 46b). The analysis of this variable was performed on the 55 participants who released the gas pedal in both trials; the others kept the foot on the pedal for the whole maneuver in one or both trials.

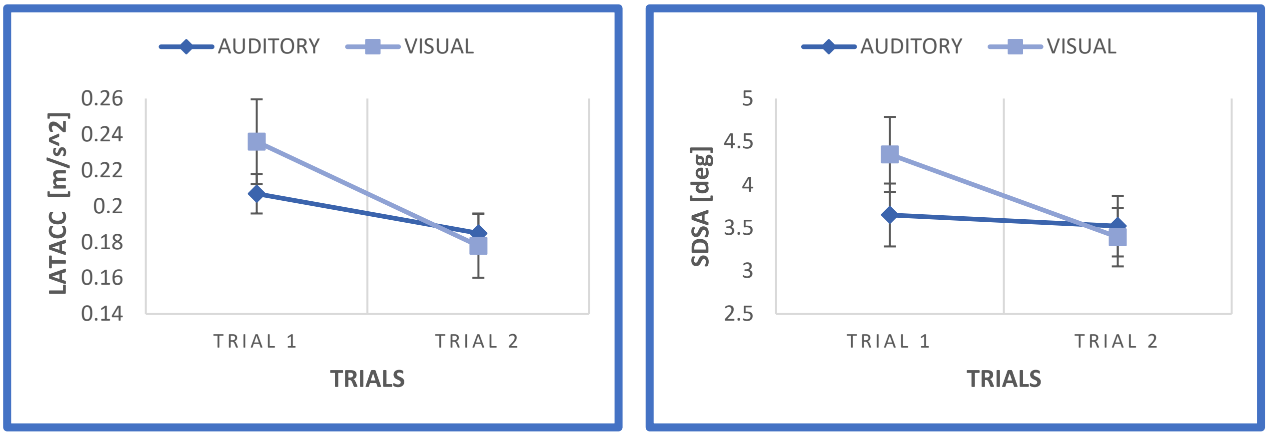


(a) (b)

Figure 46: Mixed ANOVA results. Error bars represent the standard error. Trial and Cluster effects on: (a) exit point E; (b) start-of-deceleration point A (Adapted from [184]).

Trial had a significant effect on ***LATACC***, $F(1,66)$ 19.37, p <0.001, η_p^2 = 0.23 with a relevant reduction of mean lateral acceleration in the second trial. There was also a significant interaction between Trial and Feedback modality, $F(1,66)$=4.54, p=0.037, η_p^2=0.06, with the visual feedback seemingly more effective than the auditory one (Figure 47a). Indeed, post hoc tests demonstrated that the visual feedback group significantly reduced their *LATACC* values in Trial 2, $t(66)$=4.93, p<0.001, whereas the auditory feedback group did not, p=0.134.

Similar results were coherently found analyzing ***SDSA***, with significant effects of Trial, $F(1,66)$=7.25, p =0.009, η_p^2 = 0.10, and interaction Trial*Feedback modality, $F(1,66)$ = 4.24, p = .043, η_p^2=0.06 (Figure 47b). Again, the visual feedback group was able to improve lateral control, $t(66)$ = 3.58, p < .001, whereas the auditory feedback group did not, p = .673. However, in this case, post hoc tests also displayed a significant difference between the two feedback groups in the first trial, $t(66)$=2.10, p=0.040. This suggests that the effect could be at least partially explained by the random difference in behavior of the two groups during the baseline trial.



(a) (b)

Figure 47: Mixed ANOVA results. Error bars represent the standard error. Trial and Feedback modality effects on: (a) mean lateral acceleration (LATACC); (b) standard deviation of steering angle (SDSA) (Adapted from [184]).

2.2.4.7 Discussion and Conclusions

This Subcase study investigated the impact of a motor insurance real-time coaching program on drivers' behavior on highway deceleration lanes. The evidence from this *Subcase study* suggests that real-time coaching program have a meaningful effect on participants' driving behavior, influencing respectively their speed, deceleration, trajectory, and lateral control.

Drivers tended, in general, to behave more cautiously in Trial 2 (with feedback). This is confirmed by the fact that the average speed in the highway section decreased, on average, by almost 5 km/h. Since the driver's "base" speed was lower in Trial 2, it might be assumed that the speeds in the deceleration lane were also reduced in that trial. For this reason, instead of examining in absolute terms the speeds at the beginning, entry point, and end of the deceleration lane, it was decided to investigate the speed-changes at those points. This allowed an isolation of reduction in speed, which was directly caused by the real-time coaching program. This effect was significant at the entry point (*ΔV2*) and at the end (*ΔV3*) of the lane. These two variables are particularly relevant in terms of safety, as one of the main issues of deceleration lanes is that drivers tend to exceed the design speeds used to determine the length of the lane and the radius of the ramp curve [179, 185, 186]. As regards the speed change at the beginning of the lane (*ΔV1*), the effect of the feedback appears evident only for the defensive drivers, as will be further discussed.

Since the feedback system is directly linked to drivers' acceleration/braking, it is not surprising that participants decelerated more smoothly in Trial 2. In particular, the improvement was more evident on the maximum deceleration values than on the mean values, coherently to what was observed in the entire simulation path, where participants significantly reduced the number of elevated gravitational-force events [100]. Note that this reduction in the deceleration values of Trial 2 occurred despite an increase in the speed reduction, meaning that drivers decelerated with less intensity but for a longer time, i.e., in a smoother way. Certainly, smoother driving is advantageable in terms of safety; whereas harsh decelerations are dangerous, due to an increasing probability of loss of vehicle control and a reduction of the time for other road users to respond to the drivers' behavior [130]. In addition, it is also worth noting that this significant reduction was observed despite the maximum deceleration value being relatively low even in Trial 1, due to the geometric characteristics of the deceleration lane. Further research could investigate how program effectiveness on deceleration variables is influenced by lane geometry.

The program had a much more limited impact on vehicles' trajectories, as it was not found significant, except for an interaction with the factor Cluster on variable *E*. Therefore, on average, drivers tended to start decelerating and entering the deceleration lane in the same points in both trials. However, by analyzing individual vehicle trajectories, it is possible to observe that in Trial 2 the behavior is much more consistent among the participants and that there are fewer outliers: in Trial 1 seven of seventy-four drivers entered the deceleration lane with $E < 100$ m, whereas in Trial 2 all of them did it with $E > 100$ m.

One of the most crucial effects of the program involved lateral control, which significantly improved in Trial 2, considering both *LATACC* and *SDSA*. To some extent, this can be observed in qualitative terms in Figure, where the trajectories in Trial 2 show generally less oscillations. This, again, represents a further positive aftermath on road safety.

A significant effect of participants' driving style was detected on speed and trajectory variables. Previous studies underlined that the same real-time coaching program was more effective for aggressive drivers, mainly because there is more space for improvement [100, 132].

As regards speed variables, however, the improvement is similar for both driver categories (except in the case of *ΔV1*), meaning, on the one hand, that all users can benefit from it, and, on the other hand, that aggressive drivers are unable to reach defensive drivers' performance.

The analysis of trajectory variables deserves a more in-depth discussion, as, actually, the defensive drivers' behavior is not the optimal one in terms of safety. As can be seen in Figure 6a, in Trial 1, defensive drivers tended to start their deceleration earlier than aggressive drivers, while entering the deceleration lane at approximately the same spot. This implies that the majority of defensive drivers adopted a potentially dangerous (and also operationally disruptive – see [187]) exit strategy, which consists in starting the deceleration before entering the deceleration lane. Such behavior was observed also in [179]. Twenty-three out of 36 defensive drivers (63.8%) were characterized by this behavior; conversely, only 12 out of 38 aggressive drivers adopted it (31.6%).

By entering the deceleration lane earlier in Trial 2, some defensive drivers switched exit strategy, reducing to 18 (i.e., 50%) the number of defensive drivers decelerating before entering the deceleration lane.

This change in exit strategy is potentially linked to the decrease in approaching speed. Here, defensive drivers reached the beginning of the deceleration lane (see the analysis of variable *ΔV1*) with a significantly lower speed in Trial 2, allowing them to perform the exiting maneuver comfortably, even without starting the deceleration beforehand. This did not happen to aggressive drivers, who, consequently, did not significantly modify their trajectory in Trial 2.

It has been suggested in the literature that multimodal feedback are more effective than either visual or auditory feedback, whereas, considering the two modes separately, results are not conclusive [188–190]. For this reason, Feedback Modality variable was included in the experimental design. The results of the present study did not show relevant differences between auditory and visual modalities, with the notable exception of lateral control, where the visual feedback produced an improvement in performance and the auditory did not. However, this may have actually been caused by a random difference in the two groups in Trial 1, combined with a ceiling effect, which prevented the participants in the auditory feedback group to improve their performance in the second trial.

Feedback valence (positive or negative) did not display any significant effect on most of the dependent variables, as observed in previous studies on this driving simulator experiment [100, 132]. This apparently disagree with the findings of Harbeck et al. [191], who implied that rewards have greater impact on behavioral changes, especially for young drivers. It is nonetheless possible that the present study involved a ceiling effect, caused by the attributes of the feedback sounds: their symbolic meaning may have amplified their effect, disguising differences in their impacts. For one variable, *DEC_MAX*, a significant interaction between Feedback valence and Trial was actually found, as only participants who received a negative feedback could improve their performance in Trial 2. However, as in the case of the feedback modality effect on lateral control discussed above, this may be at least partially explained by a random difference in the two groups in Trial 1. Further research is required to confirm these findings.

The present work revealed that the tested real-time coaching programs were able to significantly improve the safety of the exit maneuver from the highway, with participants reducing their speed both approaching and using the deceleration lane, decelerating more smoothly and with higher lateral control. These findings have a potentially relevant practical interest, because they suggest that it is possible to improve the driving behavior with a very simple general-purpose feedback system, which only depends on some fixed acceleration/deceleration threshold. They also indicate that developing real-time coaching systems, primarily aimed at increasing the smoothness of driving style, could also produce additional benefits in specific and seemingly unrelated situations, as also shown in previous works [132].

Yet, there are some limitations which might be addressed in future research, in order to generalize the conclusions and the practical implications of the present work. The main shortfall is that only a single exit maneuver per trial was performed, and this partially limited the investigation in a variety of features that can potentially modulate the feedback effect, such as, geometric and traffic features. In particular, the deceleration lane was designed in a “safe” way, since it was relatively long, and it was followed by a smooth curve. In the future, one promising application of this project could be an analysis of the program’s effectiveness on deceleration lanes which require higher speed reduction.

The kinematic realism of the simulator was validated in several scenarios. However, an individual analysis of the realism of vehicle deceleration in the present case could be of interest.

2.3 Conclusions and future developments of Acceleration and deceleration ADAS

Based on modern insurance schemes known as Pay-how-you-drive, the purpose was the one of developing an on-road interactive real time coaching program, able to reduce harsh driving events. The methodology take into account several driving parameters to evaluate driving style, and focuses on differentiating driver’s aggressive or defensive style through cluster analysis [7][8] [9] [10]). The main idea behind the inquiry is that, by providing effective contingent feedback to drivers on their risky (e.g. harsh event) or safe (smooth event) behavior, the likelihood of hazardous situations may decrease[11].

Here, with an advance-driving simulator, it was underlined the effectiveness of different contingent feedback program to modulate aggressive driving style. It has been demonstrated that a series of short (4 seconds) contingent feedback (independently of being a positive or negative feedback) was sufficient to achieve a significant drop of harsh events during a virtual driving test. The modality applied to deliver the feedback (auditory or visual) achieved was similar in its effects. These findings lend support to the idea that the presence of a contingent feedback program might help drivers to modulate their driving style. While Defensive drivers kept their driving style, Aggressive driver reduced the presence of harsh events.

It can be argued that the present results could have been influenced by a sort of order effect, since the order in which the two driving tasks were administered (without and with the feedback) was unbalanced. For the purposes of the present work, it was necessary to have a baseline (without feedback) to identify the spontaneous driving style of the participants and to assess whether their driving style modulates the effect of the feedback.

This issue remains open to further investigation; however, it could not be solved by simply counterbalancing the order of the trials in a second group of participants, since providing the driving task with the feedback first, would rise the same problem, i.e., the confounding between the effect of the feedback on the second trial (first group) and the learning effect that could occur in the second trial (second group) would not be prevented. This confounding effect could be disentangled by collecting twice the data recorded for the first trials, carrying out the cluster analysis and then splitting participants into two groups, one performing the tasks as in the present study and the other performing two trials, both without feedback. In this latter case, the comparison between trial 2 with and without feedback may assure to keep the effect of the feedback separate from a possible learning effect. Note that carrying out one overall cluster analysis would be crucial to gather comparable data from the two hypothesized task-order conditions.

Finally, there are still some compelling directions for future research.

For example, it would be intriguing to verify if the reduction in EGFE number would persist along the time for aggressive drivers, and to test if combing feedback (positive and negative) within the same on-road interactive real time coaching program would benefit road safety.

Furthermore, this approach could be valid regardless of type of the operated vehicle. Thus, future studies (see Section 3) using riding simulator might include the presence of performance feedback (positive and negative) to improve drivers' speed management on the road (e.g.[192]). Moreover it might be interesting to see if the modality of the feedback systems (auditory, visual, or combinations) vary in effectiveness based on the variable they work on

Although future research is reasonably required before a similar contingent feedback program could be implemented in the real world, including the limited attentional resources of the driver [193], these results still illustrate that such a solution could be effective, complementing the existing punitive system of fines[194].

3. Virtual reality application for motorcyclists

This chapter is entirely devoted to the subject of motorcyclists[8]. A study carried out with the Honda Riding Trainer (HRT) simulator of the General Psychology Department of University of Padua, will be presented [101]. The present study presents an inquiry aimed at identifying methodologies for the reduction of over speeding in moped-riders, to increase road safety. An ADAS signaling speed limit violations is accordingly presented. As a matter of fact, over speeding is considered one of the main causes of road crashes and, as such, it demands urgent attention.

3.1 Introduction

Currently, extreme attention is being paid to the role of risky driving behaviors in road crash occurrence. In this respect, the efforts are dedicated to the reduction of road fatalities worldwide. Over speeding remains one of the main causes (among others) of road accidents. In all the countries involved in the Road Safety Annual Report 2019 [144], speeding seemingly contributed from 15% up to 35% of fatal crashes in 2018. In Italy, according to the Italian National Institute of Statistics, speeding caused 10.2% of road accidents in 2018 and tuned out to be the main contributing factor in 10.3% of injury crashes and 18.5% of fatal crashes in 2017 [144].

In the act of driving, speed is one of those elements totally governed by drivers. That is to say, speed, representing a crucial aspect of risky driving behavior, is subject to human choice. As such, it might be influenced and modified in disparate ways. For this reason, Lucidi et al.[195] underlined the significance of educational interventions on drivers' attitudes. Indeed, being a choice, speed is something that can be corrected and repaired, far more than other features in risky driving. Additionally, Lucidi et al. [196], in the light of the "personality-attitudes" approach of Ulleberg and Rundmo [197], demonstrated that personality features influence actions, i.e., driving aberrant behaviors, both directly and indirectly through attitudes. In their studies, they replicated a previous inquiry on different subtypes of drivers, based on personality traits [9], either in adolescent moped drivers [196] or in young, adult, and old car drivers [195]. Starting from the assumption of attitudes being less fixed, and more easily modifiable than psyche and temperament, they identified interventions on attitudes as the most effective technique [195].

[8] The work presented in this Section is part of the following publication:
Tagliabue M., Rossi R., Gastaldi M., De Cet G, Freuli F., Orsini F., Di Stasi L. L., Vidotto G. (2021) Visual Feedback Effectiveness in Reducing Over Speeding of Moped-Riders. Frontiers in Psychology, vol 12, pp 572.

Another way to reduce risky behaviors such as over speeding, is by acting directly on actions that need to be corrected, by means of driving assistance systems providing on-line feedback. This would induce drivers to modify their behavior (behavioral perspective). Despite the great variety of advanced driving assistance systems developed and tested on cars, less effort has been devoted to powered two-wheeler (PTW) riders [198] [192][199]. This is even more surprising, considering that riders are more prone to several outcomes when involved in a crash, and they are among the most vulnerable category of road users in 2018, in all the IRTAD countries, except United States [144].

Acknowledging the role of over speeding in road crash occurrence [144], systems based on speed detection (among others) could be fruitfully applied to PTWs, and virtual reality - i.e., simulated riding - might represent an effective tool for investigation.

Notably, Bayly et al. [200] declared that only 6 among 35 in-vehicle systems aimed to improve road safety are specifically implemented in motorcycles. Such technologies deviate from a protection (in case of collision) approach to collision prevention. That is to say, they enable a proactive attitude to road safety, instead of a retroactive.

Moreover, the role of feedback in reducing crash risk is pivotal, not only for an immediate information provided in risky situations, but also as to avoid crashes. Indeed, studies also demonstrated that some feedback systems lead the driver to behave in a safer way, reducing the overall probability of risks. These behavioral changes may still be evident 1 month later, even if the feedback is no longer presented [100].

Overall, such investigations are generally based on driving simulators, so that drivers can be immersed in risky contexts, while being in the safe environment of virtual reality. Moreover, this allows to test the persistence over time of the benefits acquired, demonstrating that the effects of such training may be evident 1 year after the training and are influenced, in turn, by the on-road experience [201]. Furthermore, simulators result as key tools for properly investigating potentialities of in-vehicle systems, since they allow all the variables involved to be manipulated, to realize fine-graded testing of the prototypes and to show which setting provides better effects [88] [89].

That being said, studies intended to improve motorcyclists' safety should follow two essential paths. Firstly, they should investigate motorcyclist behavior, and then identify the features of risky driving. Secondly, future research might investigate how this information can be employed to induce safer riding behaviors, providing the know-how about optimal implementation of these technologies for motorcycles[198].

3.2 Aims of the study

For the above-mentioned reasons, the aim of the present study was to investigate:

- The effectiveness of an alert system providing an on-line feedback on over speeding, during a simulated moped-riding task;
- The persistence of its effect in a one-month period, starting from the consideration of the role that speed control plays in crash prevention.

However, the focus was not on aspects related to automatic speed control systems, the central core was rather an investigation on how to lead motorcyclists to follow strategies of speed adjustment and reduction. Furthermore, these strategies' benefits and their continuity over time were examined. To this purpose, a virtual moped-riding condition was realized, by means of the Honda Riding Trainer (HRT) simulator, in which the system provided visual feedback about over speeding. In particular, the feedback consisted of a red horizontal rectangle appearing when a speed limit was exceeded. The goal was the one to test different impact of this feedback procedure, depending on the riding style of the participants. Moreover, a further crucial aspect was considered, i.e., the optimal position in which feedback should be displayed, to maximize its effectiveness. As to the latter aspect, three locations were accordingly selected, that should be usually monitored during a riding task, namely the speedometer and the two side-view mirrors. In this way, needless interferences of visual scanning were eliminated.

Firstly, it was hypothesized that the visual feedback was effective in reducing driving speed. Secondly, it was hypothesized that the above-mentioned impact would be more relevant in those people with a risky driving style. Thirdly, the effects of the feedback procedure were expected to be evident after one month too, when the feedback was no longer available. Finally, as to the feedback position, effects due to attentive processes were expected. Indeed, if it true that attentional mechanisms are crucial for feedback processing, the feedback should be better detected when presented in a central position (which does not require lateral shifts of attention). Broadly speaking, studies presented disparate attitudes in risk prevention regarding moped riding. Different methods were proposed in the case of risk being straight ahead or in lateral positions [202]. Moreover, it is well known that horizontal attentional shifting is asymmetrical, with an advantage of shifts toward the right visual hemi-field, due to the lateralization of the attentional brain control system [203][204]. Thus, greater effects for the right feedback position were predicted.

3.3 Procedure

Three riding sessions were carried out one month apart from each other (see Figure 48 – Table 19). Each session proposed two routes of main urban roads, so that participants had to drive in six disparate routes, in the three sessions. The six routes were divided in different sessions considering their complexity to make homogeneous the overall difficulty of each session.

Table 19: Session description.

<table>
<tr><th>Session</th><th>Routes</th><th>Daylight condition</th><th>Feedback</th><th>Condition name</th><th>Instruction</th></tr>
<tr><td rowspan="2">1</td><td>route of urban road 1</td><td rowspan="2">optimal daylight conditions (without fog)</td><td rowspan="2">No</td><td rowspan="2">preFeedback/NoFog</td><td rowspan="2">ride respecting the limit indicated by the traffic signals</td></tr>
<tr><td>route of urban road 2</td></tr>
<tr><td rowspan="2">2</td><td>route of urban road 3</td><td rowspan="2">Fog</td><td rowspan="2">Yes</td><td rowspan="2">Feedback/Fog</td><td rowspan="2">ride respecting a lower speed limit of 30 km/h</td></tr>
<tr><td>route of urban road 4</td></tr>
<tr><td rowspan="2">3</td><td>route of urban road 5</td><td>Fog</td><td rowspan="2">No</td><td>postFeedback/Fog</td><td>ride respecting a lower speed limit of 30 km/h</td></tr>
<tr><td>route of urban road 6</td><td>optimal daylight conditions (without fog)</td><td>postFeedback/NoFog</td><td>ride respecting the limit indicated by the traffic signals</td></tr>
</table>

During the last session, half participants firstly performed the with-fog route, and secondly the without-fog route. On the contrary, the left half experienced the routes in a opposite order.

Once the first session was finished, people were divided according to two riding style groups, Defensive vs. Aggressive. This was possible with a cluster analysis based on 18 variables presented in the simulator. This process is similar to that described and carried out previously for the identification of driving style. Then, participants were assigned to three groups of 25 participants, in which gender, riding style, and annual mileage were balanced. Each group was assigned to one of the three experimental conditions (a,b,c), depending on the position of the visual feedback. Feedback position, riding style groups, gender, means and standard deviations of age for each condition are reported in Table 20.

Figure 48: Experiment procedure.

Table 20: Means and standard deviations of age for each group (Adapted from [101]).

Condition	Feedback position	Riding style groups	Gender	Mean age	St. dv.
Condition a	Feedback on the lower edge of the left side-view mirror	Defensive	7 females 7 males	23.86	2.96
		Aggressive	5 females 6 males	23.82	4.07
Condition b	Feedback on the lower edge of the speedometer	Defensive	7 females 7 males	24.79	3.21
		Aggressive	6 females 5 males	23.91	1.51
Condition c	Feedback on the lower edge of the right side-view mirror	Defensive	8 females 6 males	24.50	2.44
		Aggressive	5 females 6 males	23.82	2.40

3.4 Simulator

The HRT simulator is a moped-riding simulator precisely developed for training skills. It has been proved to be effective in training risk perception and anticipation. On the one hand, this allowed to record correlations between personality features and decision-making abilities, on the other hand, it allowed to examine the simulated driving performance [9][8][10]. What is more, correlation between simulated riding and different degrees of road exposure and experience have been outlines [205]. The device presented a handlebar (comparable to the one of authentic motorcycles), a motorcycle chassis, and the foot clutch pedal. All these were linked to a Pentium 4 PC and LCD monitor (1024*768 resolution). The perspective of side mirrors was displayed in the screen, while the lateral was offered by a button. The span between the participant and the display was roughly 80 cm (horizontal angle 27.2° and vertical angle 21.7°; as in Figure 49).

Figure 49: The HRT simulator with an example of risky scene before and during the crash [101].

3.5 Participants

75 subjects were recruited. Details of participants are presented in Table 21.

Table 21: Participants' gender and age.

#Part.	Female	Male	Avg Age
75	38	37	24.15

They were students, member of University staff and other people with the following features:

- At least 1 year of driving experience;
- At least 1,000 km/year of average driving distance;
- No previous experience with the driving simulator;
- Normal or corrected to normal vision.

All participants were paid for participating in the experiment.

3.6 Scenario

The simulator included several scenarios in main (urban with high traffic density) and secondary (urban with medium traffic density) roads, in which typical risky scenes were presented, for riders to be familiar with unexpected potentially hazardous road situations (see Figure 49). The virtual system was automatically fixed on “moped”. Driving elements were then collected in a log document, as well as the judgment of risky situations, ranging from 1 (totally safe performance) to 4 (crash occurrence).

3.7 Feedback systems

The visual feedback presented a red horizontal rectangle, being 7.3 cm long (equivalent to the side-view mirrors) and 1.8 cm wide. It was displayed in three divergent locations according to the group, that is along the lower line of the left side-view mirror, in the speedometer, and in the right mirror.

3.8 Variables, Analysis and Results

All the investigations was carried out with IBM SPSS 22 statistical package. After the first session, a hierarchical cluster analysis was performed, applying the Ward’s method with squared Euclidean distance, with the 18 riding parameters. This preliminary analysis underlined the presence of two clusters. Then, on the Z-scores of the driving parameters, a K-means clustering method was applied, to extract the best clustering solution.

To test the before-mentioned hypotheses, two ANOVAs were carried out on the percentage of over speeding with reference to the 30-km/h limit and to the limits indicated by the traffic signals, respectively, both with two between-participant factors, i.e., Cluster (2 levels: Defensive vs. Aggressive) and Feedback position (three levels: left, center, and right), and Visibility condition (four levels: preFeedback/NoFog, Feedback/Fog, postFeedback/Fog, and postFeedback/NoFog) as the within-participant factor.

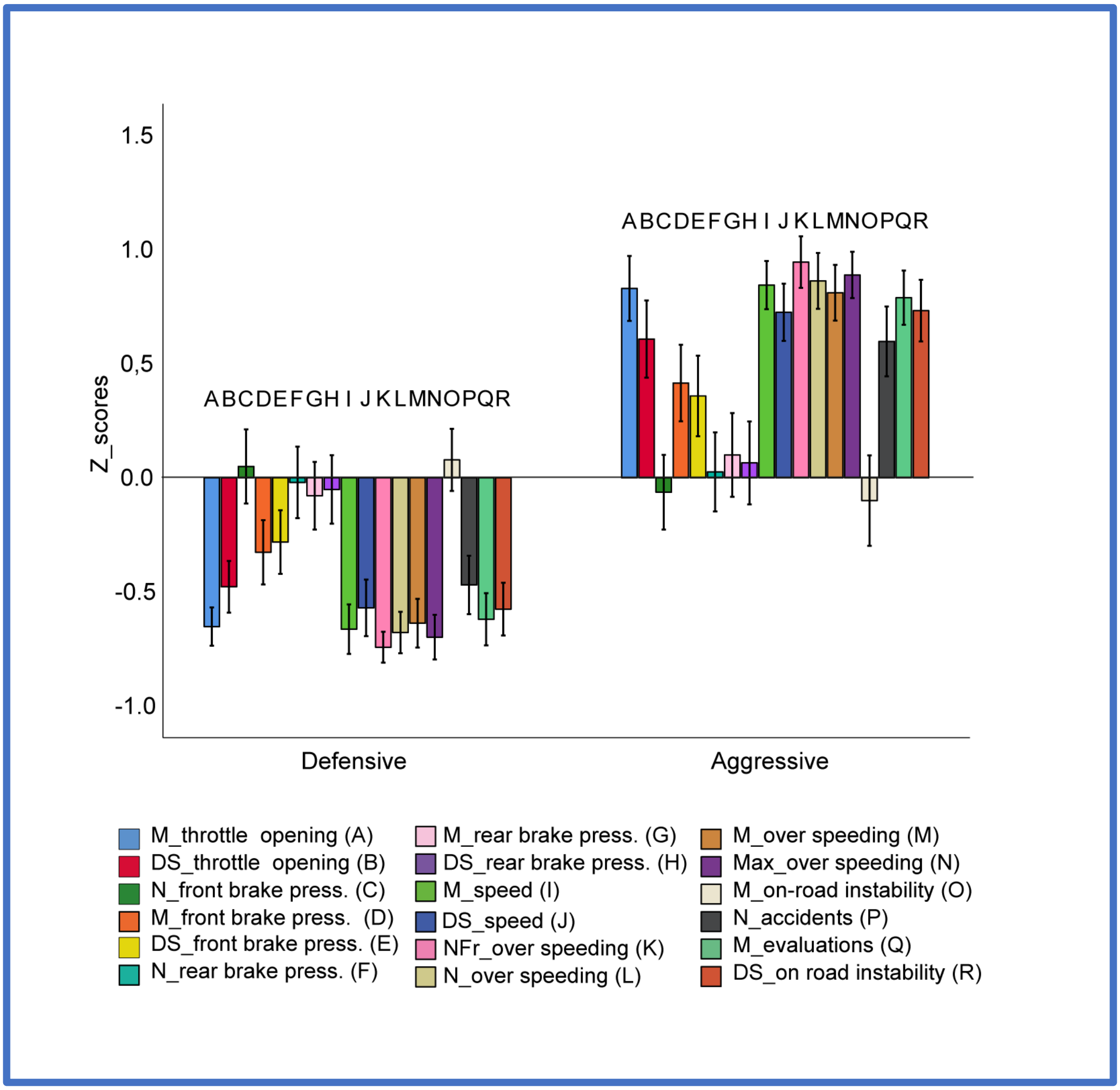


Figure 50: Patterns of Z-scores of the 18 HRT indexes in the two clusters. Legend: mean and standard deviation of the throttle opening (A and B respectively); number, mean, and standard deviation of brakes with the front brake (C, D, E); number, mean, and standard deviation of brakes with the rear brake (F, G, H); mean and standard deviation of speed (I and J); time spent over the speed limit (K); number, mean, and the highest value of over speeding (L, M, N); mean (O) and standard deviation (R) of on-road instability; number of accidents (P) and evaluation score (Q). Vertical bars represent standard errors [101].

The final solution of the cluster analysis underlined the presence of two clusters with different riding patterns. The inspection of the dendrogram suggested a two-cluster best solution (see Figure 51) [137].

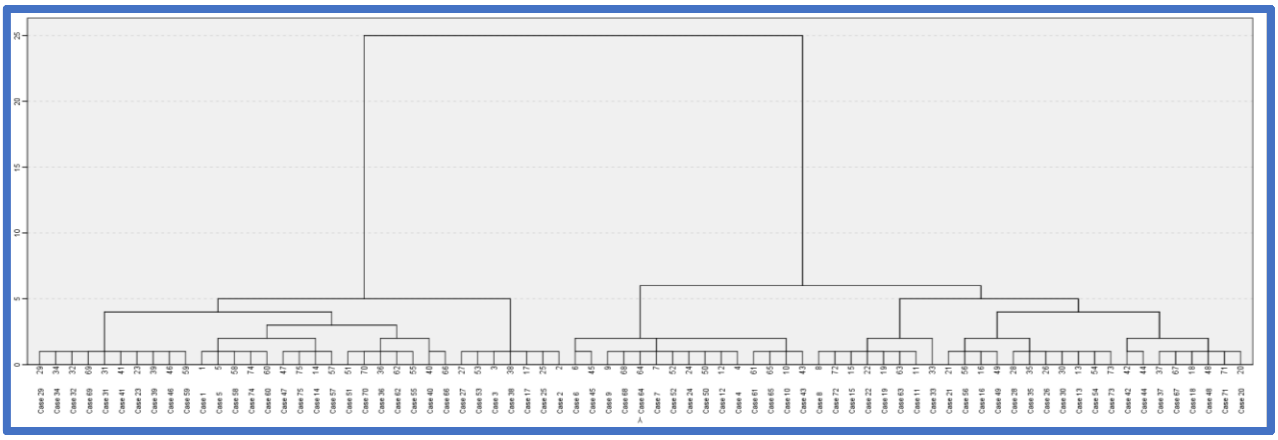


Figure 51: Ward's method dendrogram; on the x-axis the 75 participants, on the y-axis distance cluster combination with modified scale.

The first cluster, the "Defensive" one, encompassed 42 participants (22 females and 20 males; annual mileage 8257), while the second, the "Aggressive", involved 33 people (16 females and 17 males; annual mileage 9473). The Figure 50 displays the mean Z-scores of the HRT indexes for the two clusters. As it might be noticed, the Defensive cluster presents overall better performance evaluations, supported by lower number of accidents, speed, and acceleration rate, than the Aggressive cluster.

Two participants were discarded since they withdrew before the third session (1 female - Defensive, Condition b and 1 male - Aggressive, Condition a).

The initial ANOVA regarding the breaking the 30 km/h speed limit, the factors Cluster and Visibility condition reached significance with $F(1,67)=60.60$, $p<0.001$, $\eta_p^2=0.47$ and $F(3,201)=110.93$, $p<0.001$, $\eta_p^2=0.62$, respectively. People classified as aggressive riders presented a higher proportion of over speeding than defensive ones (12.89% vs. 23.70%). What is more, in the preFeedback/NoFog context, over speeding resulted higher (30.4%) than in the other visibility conditions. In the two Fog visibility contexts, the percentages of over speeding were comparable (9.4 and 12.2%), and lower than that in the postFeedback/NoFog condition (21.1%). No other source of variance or interaction outlined significance.

The second ANOVA involved violations of the speed limits, the factors Cluster, Visibility condition and the interaction Cluster X Visibility condition reached significance with $F(1,67)=74.66$, $p<0.001$, $\eta_p^2=0.53$, $F(3,201)=125.44$, $p<0.001$, $\eta_p^2=0.65$,

and $F(3,201)=42.76$, $p<0.001$, $\eta_p^2=0.39$, respectively. Defensive riders manifested less speeding violations than Aggressive riders (1.38% vs. 5.73%). In the fog conditions, participants presented the same percentage of speeding violations (0.66 vs. 0.90), but less speeding violations than in the NoFog conditions. In the latter case, violations were less in the post-F condition (4.29% vs. 8.39%). Finally, the interaction indicated that the reduction in the percentage of speeding violations in the postFeedback/NoFog condition is significant only in the Aggressive rider group (see Figure 52). No other source of variance or interaction reached significance.

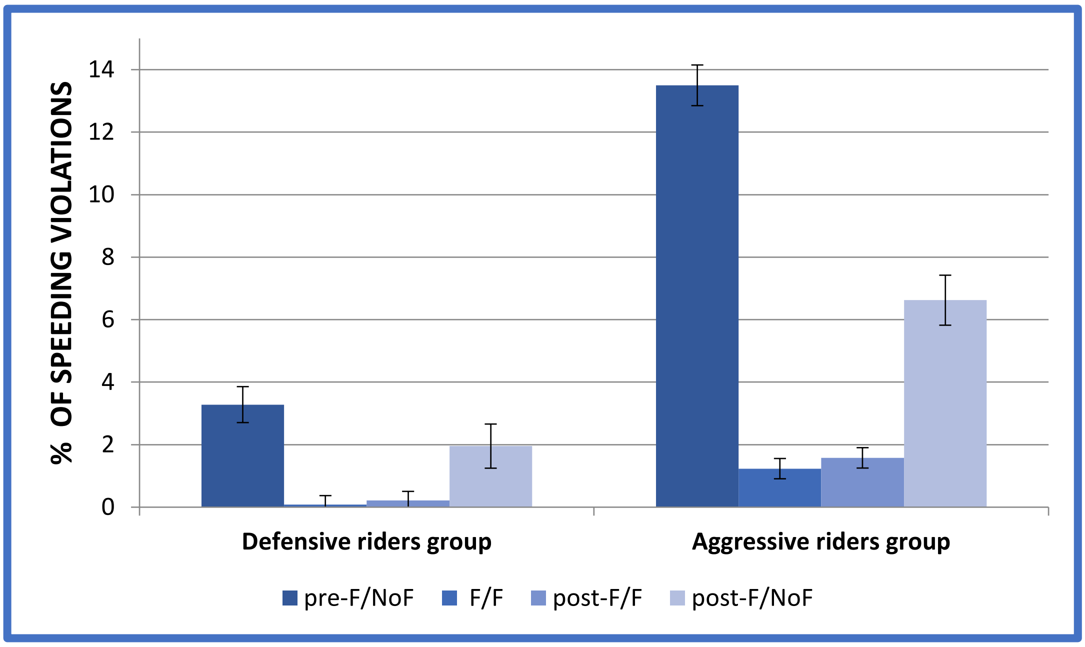


Figure 52:% of speeding violations of Defensive and Aggressive riders in the 4 visibility conditions. Vertical bars represent standard errors (Adapted from [101]).

3.9 Discussion

The results of the inquiry on the lower speed limit violations indicated that the feedback appears to be effective in reducing speed under poor (and partially under optimal) visibility conditions after one month. The evidence indicates feedback as leading to a cautious riding behavior, both while it is still provided and when it is no longer offered. This seems to intimate an extreme effectiveness of the feedback, since the behavior modifications observed are quickly acquired in a 12–15min session and persist over time, so as to manifest also when visibility conditions are optimal.

Regarding feedback position, this does not influence the overall performance. Considering the mechanisms controlling attentive shifting, a different degree of feedback effectiveness was expected, dependently on the feedback position. The fact that this prediction has not been confirmed seems to indicate that the processes underlying feedback detection do not increase the attention needed for the task. This may be due to the positions chosen, since all the three positions are typically salient while riding. In other words, riding (as driving in general) always requires to monitor the speedometer and the side-view mirrors.

3.10 Conclusion and future developments

The present study considered the significance of visual feedback in the field of dangerous driving behaviors, including over speeding. Overall, it has highlighted that a mere visual feedback discretely indicating when a certain speed is exceeded, generally induces behavioral modifications, that tend to persist over time. Such a signal is different from the speedometer, since the latter provides a continuous flow of information.

Moreover, this also seems to induce safer behaviors in riders with an aggressive riding style. In other words, thanks to feedback systems aimed at reducing speed in low-visibility conditions, Aggressive riders are less prone toward speeding violations, even in optimal visibility conditions, and even when the feedback is removed.

One potential limit of the inquiry lies in the interpretation feedback's impact. Indeed, it can be argued that the more cautious riding behavior of the last session, when the feedback is not delivered, might be due to participants having developed better speed-control strategies. This might be caused by their expectations or beliefs about experimental goals. Note that this effect should not be considered as a contextual learning effect related to the specific characteristics of the routes, since the administered routes were disparate in all the conditions. Conversely, participants could have realized that their speed was monitored. However, this alternative explanation might regard the last session, with poor visibility conditions, but it does not apply to the NoFog condition. In fact, participants were never asked to follow speed limits lower than that those in traffic signals, in favorable daylight conditions.

It is quite thought-provoking the idea of testing the duration of feedback's effects over longer periods of time. This could indeed provide intuitions about the way in which assistant systems may be more successful, and it can further suggest valuable insights for educational interventions in the promotion of safe driving.

In the present study, driving simulation has proved to be an efficient instrument for encouraging the development of assistance systems able to improve road safety in PTW-riders. As a final remark, it is worthy to emphasize that, to effectively tackle road safety issues, multiple approaches should be simultaneously employed. This is indeed consistent with the recommendation of the European Commission. As previously highlighted, educational programs aimed at reducing aberrant driving behavior should be developed in several directions: from the intervention on attitudes toward traffic safety [195], to trainings pointing to directly modify behaviors, but also through in-vehicle systems supporting speed management.

There are some constructive directions for future research including:

- Testing the effect of different feedback systems (e.g. auditory);
- Evaluating the effect of feedback on motorcyclists performance at different time intervals (e.g., after one week, three months, one year etc);
- Including an analysis of the feedback systems’ effectiveness in relation to road environment (e.g. rural and urban type of road), as well as other dependent variables, such as acceleration and deceleration [100];
- Monitoring the perception of feedback systems with visual components with systems such as, for example, eye-trackers;
- Expanding the sample of subjects both in terms of size and composition, for example including elderly motorcyclists. Such an investigation could also consider participants’ social and educational background

All these potential paths of research might be enriched with on-road tests, for this would allow a more straightforward and concrete overview of the results’ applicability.

4. Virtual reality application for pedestrians[9]

Human beings face the matter of transportation and mobility from their early childhood. Starting with first hand-held walks, children slowly develop the skill of walking, in the same way they will eventually learn to drive. While it is true that children, teenagers and adults are taught how to perform these tasks, no sufficient attention is yet given to the issue of mobility and its many possibilities, such as road rules and road safety. For this reason, this chapter seeks at giving space to a neglected area, namely the education of vulnerable road users. Specifically, it focuses on the most vulnerable road user *par excellence*, which therefore requires special attention: the pedestrian.

4.1 Introduction

Vulnerable road users are essentially pedestrians, cyclists and motorcyclists. They are regarded as vulnerable due to the two drawbacks they face in potential accidents [19]: (a) except helmets, they do not have any protective shield in case of collision and (b) their mass, being significantly lower than the one of cars and trucks, is a major disadvantage in eventual crashes. This is why their probability of being injured or killed in an accident is much higher than, for example, a car driver. Pedestrians and cyclists as a category encompass an extremely heterogeneous range of age. This allows the range of cognitive, visual and motor skills of the samples to be broadened.

The need for the Transportation Laboratory to open a research section dedicated to the vulnerable non-motorized users is also driven by the data on road accidents reported in the last years in the annual report of the National Institute of Statistics – ISTAT.

In Italy in 2019, according to data published by ISTAT[4], road accidents were more than 450 per day. It was indicated that 8 people died every day in road accidents and that at least one of them was indeed a pedestrian. According to the report "Levels & Trends in Child Mortality 2020" by Unicef and the World Health Organization [3], injuries would represent one of the leading causes of death for people aged 5-24. Clearly, this includes road accidents.

Noticeably, there are several studies in the literature examining children's behavior in the road environment as pedestrians. The reaction times of these young road users are influenced by disparate factors [206], such as gender, age and context's complexity.

In a study [207] conducted in Osijek, Croatia, children's reaction times were collected in the

[9] The work presented in this Section is part of the following paper submitted to "1st International Conference on eXtended Reality (XR SALENTO 2022)": De Cet, G., Baldassa, A., Tagliabue, M., Rossi, R., Vianello, C., Gastaldi, M. The application of immersive virtual reality for children's road education: validation of a pedestrian crossing scenario.

laboratory and accordingly measured, both with a computer and in real traffic conditions. The data collected were compared with those of a group of adults who also took part in the research. Eventually, the results outlined that the reaction times of the two groups were divergent, with higher reaction times for children. Thanks to the employment of a neural network, a model for the prediction of reaction times of children in real traffic conditions was thus developed.

Moreover, in a school in Mehriz, Iran, an inquiry investigated how an active educational intervention might affect road crossing behavior [208]. Children's behaviors were observed respectively before, 1 week after, and 6 months after this intervention in three situations: looking for vehicles on the road, being cautious of hazards, and crossing from safe places. Results showed that after both 1 week and 6 months, behaviors significantly improved in terms of safety.

A further study, proposed by Barton et al.[209], also demonstrated how simple interventions can change children's conduct and safety on the road. This latter project proposed a method for skill-based training to increase the number of safe pedestrian attitudes. Again, after training, young road users presented safer behaviors.

Virtual reality, inter alia, was also applied as a methodology to educate and train children to harmlessly cross the street. Indeed, McComas et al. [210] indicated that, through VR trials, children's caution increased. To reach this conclusion, they observed their behavior before and after administration. As a matter of fact, what was acquired in the virtual world was transferred to the real world.

In Italy, few hours of Road Safety Education are offered during the school years. However, while this is an essential first step, students are unlikely to give attention to the topic until they obtain a driving license. Also for this reason, and those previously stated, a study has been designed and implemented with the “pedestrian” simulator of the Transportation Laboratory.

It has here to be said that one goal of the Sustainable Development, within SDG 11, is the one of improving road safety by 2030. In this respect, the present project happens to be an opportunity to raise awareness about this crucial issue among young people. By creating a culture of safe and sustainable mobility, it will be possible to have careful road users, aware of changes, innovations in transport modes and services, as well as environmental issues.

4.2 Aims of the study

The present study is part of the wider SID project on “Safety of vulnerable road users:

experiments in virtual environment" (2020-2022), funded by the University of Padua. This research embodies an opportunity to address the issue of mobility, with the aid of new technologies. At the moment such technologies are, at least in Italy, rarely used in this area. In this sense, this work proves to be innovative both in its educational objectives, and in the means employed to achieve them. The goals of this project include:

- Structuring a procedure for the creation of an immersive virtual road environment;
- Creating and testing an immersive virtual road environment;
- Identifying effective strategies to spread the culture of road safety (such as strategies for teaching children to cross roads safely, with the repeatability and risk-free advantages of virtual reality);
- Developing a procedure for the validation of virtual reality as a tool to prevent road accidents;
- Collecting data to design safer real-world infrastructures (e.g., traffic light cycle outside a school).

The present research aims at achieving the first two of the above-mentioned goals. Specifically, this work aims to validate immersive VR pedestrian crossing scenarios through the observation of children's behavior for future use of the tool for road safety educational purposes in.

4.3 Procedure

Broadly speaking, the experiment examines children's behavior in a road environment. In the first part of the inquiry, participants were asked a series of general questions about mobility (e.g.: By what means do you go to school? How much do you walk per week?), and a questionnaire was administered to investigate their conduct as pedestrians [211]. In the second part, participants, wearing the headset, were asked to cross the street in a virtual street environment (see Figure 53 and Figure 54). During the experiment the subjects moved in the virtual environment in the area of the crosswalk; a wide aisle -to carry out the experiments- was chosen in order to guarantee safe movements for the participants (see Figure 53); boundaries were also drawn with the simulator software.

Figure 53: Experiments setting.

4.4 Simulator

The Pedestrian simulation device is a compact/portable wearable system produced by HP® (see Figure 54). The apparatus is equipped with a backpack PC (HP Backpack VR G2) and a Reverb headset (HP Reverb VR Headset G2), delivering an immersive, comfortable, and compatible experience. The resolution is 2160 x 2160 LCD panels per eye, and full RGB stripe. The headset also includes Valve speakers, and sit off the ear by 10mm. The simulation device allows a natural free-roam VR experience and the analysis of pedestrian behavior in road hazard situations. The strong point of this simulator is its compactness, the absence of cables as a connection to a fixed PC in the room allows a natural movement of the participants [11]. Not being a wireless device is also obviated the problem of latency, one of the causes of simulator sickness.

Figure 54: Pedestrian simulator of Transportation Laboratory.

4.5 Participants

46 subjects were recruited. Details of participants are presented in Table 22.

Table 22: Participants' gender and age.

#Part.	Female	Male	Avg Age
46	28	18	12.04

They were:

- Middle school students;
- Aged between 11 and 13 years;
- No previous experience with the simulator;
- All of them were volunteers.

No participants dropped out of the study due to simulator sickness.

4.6 Scenario

Figure 55: One-way crosswalk in virtual environment. On the left without traffic light, on the right with traffic light.

Figure 56: Two-ways crosswalks in virtual environment. On the left without traffic light, on the right with traffic light.

After a careful analysis of the literature, an immersive road environment was designed and implemented, thanks to Unity® software. In this first work the study of the interaction of the pedestrian with other users was not foreseen, for this reason other road users were not present in the simulation. The environment was shaped considering realistic elements' dimensions. The guidelines for the design of crosswalks in Italy recommend a speed not exceeding 1 m/s in the design phase in order to include those with a slower gait. During design phase this parameter has been taken as reference.

The scenario consisted of 2 trainings and 14 trials (see Table 23), the trainings presenting two crosswalks (1 one-way and 1 two-way).

The 14 trials were then equally divided into one-way (see Figure 55) and two-way (see Figure 56). The following experimental situations were presented: no traffic light, presence of green traffic light, presence of red traffic light, presence of traffic light with a steady yellow light, presence of traffic light that was off, presence of traffic light with a yellow light that came on in the middle of the crossing, and presence of traffic light with a yellow light that came on once the participant stepped off the curb. The trials were introduced in random order.

Participants were subdivided into two groups, counterbalanced by gender. The first one performed the 1-way training and trials first (see Figure 57), whereas the second group the 2-way training and trials first (see Figure 58). Both Group 1 and Group 2 consisted of 14 females and 9 males.

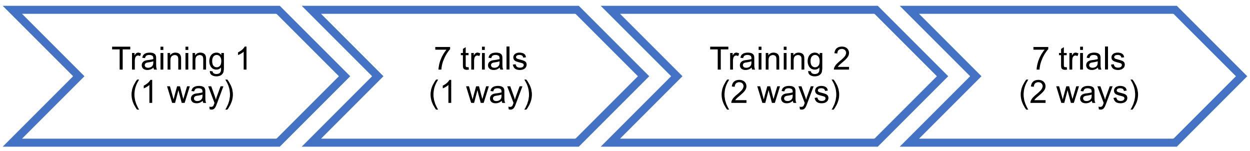


Figure 57: Sequence for group 1.

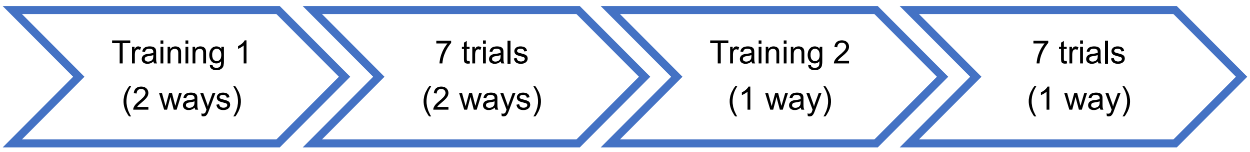


Figure 58: Sequence for group 2.

Table 23: Description of trainings and trials of the experiment.

Type	Ways	Traffic Light
Training	1	No
Trial	1	No
Trial	1	Turned off
Trial	1	Green
Trial	1	Red
Trial	1	Steady yellow light
Trial	1	Yellow light that came on in the middle of the crossing
Trial	1	Yellow light that came on once the participant stepped off the curb
Training	2	No
Trial	2	No
Trial	2	Turned off
Trial	2	Green
Trial	2	Red
Trial	2	Steady yellow light
Trial	2	Yellow light that came on in the middle of the crossing
Trial	2	Yellow light that came on once the participant stepped off the curb

4.7 Variables

Considering the trials (1 way - 2 ways) with the red light, the variables investigated were:

- The reaction time (s) from the moment of the light turning green to when the subject steps off the curb;
- The average speed (m/s) of crossing with the red light (for subjects who have crossed red light).

4.8 Analysis and Results

In this study, the behavior of children when facing a red light was examined. Data were analyzed with the aid of JASP Software [87].

With reference to the trials with red light off the 46 participants:

- 31 participants waited for the green light to cross, in both trials (1-way-2-way);
- 11 crossed both times (2-way-1-way) with the red light;
- 1 participant crossed a single time on a red light;
- 3 participants were off the curb when the light was red (for this reason, RTs could not be calculated as defined).

The first analysis performed aims to investigate whether the behavior the user had during the experiment was consistent with the conduct as pedestrian stated during the administered surveys. For this reason, the focus was on the particular case of the red light. Was their behavior consistent with their initial claims about crossing the road even with red light? In order to determine if this relationship exists a contingency analysis was carried out between the two categorical variables. The 42 participants were categorized into those who claimed in the self-report that they crossed on red (11) and those who reported that they never did (31). χ^2 statistic with continuity correction ($\chi^2(1)=8.144$, $p<0.004$) suggested that there was a significant association between behavior and self report questionnaire answer. Since the data set was a small sample and the table in one cell has an expected count of less than 5, continuity correction was applied to prevent overestimation of statistical significance [212]. This result showed that the children's behavior during the experiment was consistent with their behavior in real life for the road crossing scenario.

The reaction time of the 31 participants that waited for the green light to cross was calculated. A one-way ANOVA was performed. The response variable was RT, ways (1-2) and group (1-2) as factors. No main effects of ways ($p=0.897$), group ($p=0.267$) and interaction ($p=0.952$) were found. A repeated measure ANOVA was performed on RTs, with Trials (1st and 2sd trial with red light) as the within-participants factor. No significant effect was found ($p=0.196$). This result indicates that there is no learning factor between the two trials due to familiarity.

The average crossing speed of the 11 participants crossing both trials with a red light, was calculated. A one-way ANOVA was then performed. The response variable was speed, and ways (1-2) was factor. No main effect of ways ($p=0.454$) emerged. The mean speed outlined was 1.05m/s. Overall, this indicates that there is no difference in crossing speed between the one-way and the two-way situations. Comparing with the average walking speed while crossing from the study by Deb et al. [213] under no-traffic conditions (1.096 m/s) the one sample t-test test showed no significant difference in speed compared to those recorded in this study ($t(21)=-1.148$, $p=0.264$).

4.9 Conclusions and future developments

In the present work, a procedure for an immersive virtual road environment was created. Subsequently such a virtual environment was tested, to validate immersive VR pedestrian crossing scenarios through the observation of children’s behavior for future use of the tool for road safety educational purposes. Among the conditions proposed, the inquiry specifically focused on the case of a red traffic light. The reaction times of the subjects presented no discrepancy considering different tests' order (Group 1 vs Group 2), nor in different types of crossing (1 way vs 2 ways). Hopefully, this investigation might be a starting point for future instrumentation validation.

Regarding the 11 subjects crossing at red lights in both ways (1-way and 2-way), their behavior was consistent with their initial claims about crossing the road even with red light. Yet, evidence of the average speed in red light crossings is, to say the least, alarming. Indeed, no significant difference was outlined between the average speed values for one-way and two-way crossings. This could indicate a lack of risk perception in the case of a two-way crossing participants did not increase their speed; this invites reflection.

Future developments to achieve the several above-mentioned goals, might include:

- Comparison of results in virtual environment, with those measured in real environment;
- Comparison of pedestrian movements in virtual and real road environments;
- Comparison of RTs results with model to predict them;
- Further validation of the instrumentation;
- Presentation of results to the students involved and consequent reflections about road safety;
- Involvement of other schools to spread the culture of road safety through experiences with virtual reality (a new "Road Education");
- The addition of eye-tracking instrumentations and the study of head movement;
- Analysis of road user interaction;
- Design of new experiments enhancing the effective learning of correct pedestrian behavior in a dynamic and entertaining way.

5. Conclusions and future developments

In this thesis road users' behavior and their interactions were analyzed with the aid of virtual reality. Some case studies including three different road users (car drivers, motorcyclists and pedestrians) and 300 subjects were accordingly presented. Overall, this work attempted to answer the two issues already outlined in Chapter 1. The first concerned the possibility to ***improve road safety with virtual reality***, while the second one investigated the potential ***improvement of road user behavior with virtual reality***.

To answer these questions, several experiments were conducted at the Transportation Laboratory at the Department of Civil, Environmental and Architectural Engineering and at the HRT Laboratory of the Department of General Psychology of University of Padua both with non-immersive and immersive virtual reality instrumentation.

It has to be noted that, as was previously illustrated, virtual reality is a widely used tool in many disparate fields (whether in research and not). Thanks to it, it has been possible to ***improve road safety*** by implementing and testing ADAS both on cars and motorcycles. It was possible to insert the subjects in contexts with almost no risk, in controlled and repeatable situations. Moreover, with the aid of different software, realistic road scenarios were created. The advantages that this technology presents are far more substantial than the negligible problems encountered (a few cases of simulator sickness).

Through learning techniques such as precision teaching and programs commonly known as pay-how-you-drive, it was possible to ***improve road user behavior***.

In most of the studies presented here, crucial answers might be inferred regarding the two research questions (see Table 24).

Table 24: Research questions answers. Future developments are in italics.

Chapter	Section	Road User	How improve road safety	How improve road user behavior	Acting on…		
					Vehicle	Infrastructure	Road user
2	322.1	Driver	ADAS	Precision Teaching	X		X
2	2.2	Driver	ADAS	pay-how-you-drive	X		X
3	3	Motorcyclist	ADAS	pay-how-you-drive	X		X
4	0	Pedestrian	*Traffic Light*	*Road Education*		X	X

5.1 Main findings

This thesis, employing virtual reality simulators in the road environment, allows to highlight the benefits that this technology can bring within the field of road safety. What is more, it significantly contributes to outline the countless possibilities of its use in the sector, also in light of previously presented results.

Firstly, from the studies of Chapter 2 – Section 2.1, it was possible to stress how crucial it is to have a proper understanding of an ADAS for its correct functioning. In other words, it was illustrated to what extent an adequate understanding of ADAS is pivotal to benefit from all its advantages. Through the implementation of several ADAS for the lateral control of the vehicle and the administration with PT technique, it was overall investigated how many considerable benefits they produce. Since lateral control is a variable of particular interest in terms of safety, because of its many implications and effects, the results obtained from these technologies are encouraging for the mitigation of road risk and, consequently, of accidents. The results proposed (see Section 2.1.6), by underlining the benefits of these technologies over time, confirm that this is a legitimate approach both in terms of ADAS design and in the use of learning techniques.

Secondly, considering the studies in ***Chapters 2*** and ***3*** – Sections 2.2 and 3, it might be argued that for both car and motorcycle drivers with aggressive driving style, the presentation of feedback to reduce elevated gravitational-force event (EGFE) and speed limit violations, produces a significant reduction of these variables. The results obtained are again relevant in terms of road safety: thanks to the methodologies tested in this work it is possible to design programs to correct the behavior of the most aggressive, and by implication most dangerous, road users. With respect to motorcyclists, it was also demonstrated that the benefits of these systems persist over time. Notably, this is in line with the experiments of lateral control.

It can therefore be concluded that knowing the driving assistance systems in vehicles, with appropriate techniques, one can benefit from such systems in terms of risk reduction; even over time.

Finally, as far as the study of pedestrians is concerned, this thesis represents one of the first works in Italy of road safety education of children with virtual reality. The present inquiry, indeed, being part of a broader project dedicated to vulnerable users, investigated children's behavior in the street environment. In this sense, this study proved to be innovative both in its educational objectives, and in the means employed to achieve them. Overall, it produced a procedure for the creation of an immersive virtual road environment, that was subsequently tested.

This first project outlined results in line with those already found in the literature, that will certainly need to be further investigated in the future.

5.2 Future research and practical implications

This thesis has presented several projects involving virtual reality employed to increase road safety, producing positive results in terms of risk mitigation.

First, it might be concluded that virtual reality brings benefits both in terms of road safety (acting on the infrastructure and vehicles) and in terms of improving user behavior (acting on the human factor).

Evidently, there are numerous aspects that might be further investigated in the future. With regard to experiments with the simulator of cars and motorcycles, it could be interesting to:

- Evaluate the effect of feedback/ADAS on driver performance at different time intervals (e.g., immediately after the treatment, after one week, three months, etc);
- Create educational programs aimed at reducing aberrant driving behaviors;
- Test different types of feedback to complete experimental conditions (for example providing in precision teaching experiments only a visual feedback, while for the motorcycles implementing an auditory feedback);
- Extend the participant sample to commercial drivers, who could benefit the most from effective implementation of the precision teaching technique or pay-how-you-drive method;
- Further tests could be performed to assess whether there are significant changes in effects according to age and/or culture (the experiments were conducted on samples of certain age groups and of Italian nationality);
- Interactions between users will be extensively investigated (e.g. vehicle-bike interaction from the cyclist's perspective with the new simulator being installed at the lab).

With regard to experiments with immersive reality for pedestrians, a preliminary study was here presented, allowing to improve road safety both with interventions concerning infrastructure design (such as traffic light cycle outside a school building) and with road education programs. It was stated by the participants that through this test they were able to notice many aspects of walking on the street they did not notice before. Moreover, they claimed that the new, virtual world really offered them a realistic, authentic experience. The future developments of this work will lead to those of the broader research project in which it is placed (see Section 4.2), aiming to spread the culture of road safety through experiences with virtual reality. Techniques that promote learning, as in the case of cars and motorcycles, will be investigated in the future. Broadly speaking, this study is intended to be a steppingstone for this new line of research, which will continue over the next few months with the validation of the instrumentation.

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Figure

Table

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