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ORIGINAL ARTICLE

Assessing the impact of cinematic virtual reality simulations on young drivers: behavior and physiological responses

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Abstract

Road safety is still a critical concern for all countries of the world since most of the reports state that traffic fatalities remain very high. Despite the reduction of fatal situations while driving, traffic collisions, especially due to unsafe behaviors, are the leading cause of death among young individuals. Governments use safety campaigns to promote safer driving, but traditional methods such as videos conveyed through 2D screens may have a limited impact. Cinematic Virtual Reality (CVR), with its immersive features, could offer a more effective way to deliver road safety messages. This study proposes a between-subject design to explore how CVR influences attitudes, behaviors, and physiological responses related to traffic safety. A sample of 95 young participants, split into two groups, watched either a fear-based or a positive-based 360° CVR video. They completed the Attitudes Towards Traffic Safety (ATTS) and Driving Behavior Questionnaire (DBQ) at different stages (before and after CVR experience and in follow-up condition), as well as a User Experience Questionnaire (UEQ) and a Virtual Reality Sickness Questionnaire (VRSQ). ECG data were collected during the CVR experience to assess physiological response. The results demonstrate that CVR significantly impacts safety attitudes and behavior, with a statistically stronger effect observed in the fear-based approach. Furthermore, CVR markedly impacts users' physiological responses, as evidenced by ECG analysis. Physiological data underscore CVR's effectiveness in engaging users and reveal that responses vary significantly based on the nature of the immersive experience, highlighting CVR's potential as a targeted intervention tool for traffic safety education.

Keywords Cinematic virtual reality · Risky driving · Young drivers · Physiological response · Road safety · Educational intervention

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1 Introduction

According to the Global Status Report on Road Safety, an estimated 1.19 million fatalities were caused by road traffic accidents in 2021. These fatalities, along with the injuries resulting from such accidents, persist as significant global health and development challenges. As of 2019, road traffic collisions remain the leading cause of death for individuals aged 5 to 29 and are the 12th leading cause of death across all age groups. Two-thirds of road traffic fatalities occur among individuals of working age (18–59 years), resulting in substantial health, social, and economic impacts worldwide. Furthermore, the World Health Organization (WHO) reports that young drivers are particularly vulnerable, facing a 24% higher risk of being involved in road traffic accidents, underscoring the need for targeted interventions in this demographic (World Health Organization 2023).

In recent years, due to enhanced safety campaign methods and policies, the number of road traffic accidents has been steadily declining, as shown in Fig. 1, reflecting significant progress in mitigating traffic-related risks. However, it is important to highlight that the pronounced drop in 2020 is largely attributable to pandemic-related mobility restrictions rather than road safety campaign methods. Between 2021 and 2022, traffic volumes slowly rebounded, and road fatalities increased by about 3% (European Commission 2023) as the reduced number of vehicles on the streets led to increased boredom while driving, and speeding was perceived as less risky (Soltani et al. 2024; Tucker and Marsh 2021). Nevertheless, EU road-safety reports indicate that pre-pandemic progress has been largely maintained: compared with 2019, road-traffic deaths in 2022 were still approximately 10% lower (European Commission 2023). Results published in March 2025 further confirm this trend, showing a 3% decrease in road fatalities in 2024 compared to the previous year (EU 2024). However, while these improvements are positive, they remain insufficiently rapid, and the number of fatalities remains critically high, exceeding the targets set for the 2030 safety goals (see Fig. 1) (Road safety statistics 2024).

Statistical data and previous studies have shown that risky behaviors lead to an increase in the probability of being involved in a traffic accident, even a fatal one (European regional status report on road safety 2019). Among young drivers, such behaviors are particularly prevalent, with speeding and distracted driving identified as primary contributors to road traffic accidents (European Transport Safety Council (ETSC) 2016).

Thus, the assessment of a driver's behavior can be a valuable tool in preventing potentially dangerous situations. Human behaviors and attitudes towards specific situations are explained by the theory of reasoned action and planned behavior (Ajzen 1985). This theory provides a solid framework for predicting and understanding how people's intention to perform a certain behavior is closely related to their attitude towards that behavior (Chada et al. 2023). An important application of this theory in the field of road safety emerges from a study conducted by Iversen and Rundmo (Iversen and Rundmo 2004), who analysed the behaviors of over 2600 Norwegian drivers. The results of this study show a direct correlation between the wrong attitudes of drivers and their tendency to be involved in imminent or actual traffic collisions. In light of this, it is evident that appropriate measures can be considered to change the driver behavior, fostering greater responsibility and safer driving practices (Evans 1996).

European governments have taken various measures to change and improve driving behaviors by investing in

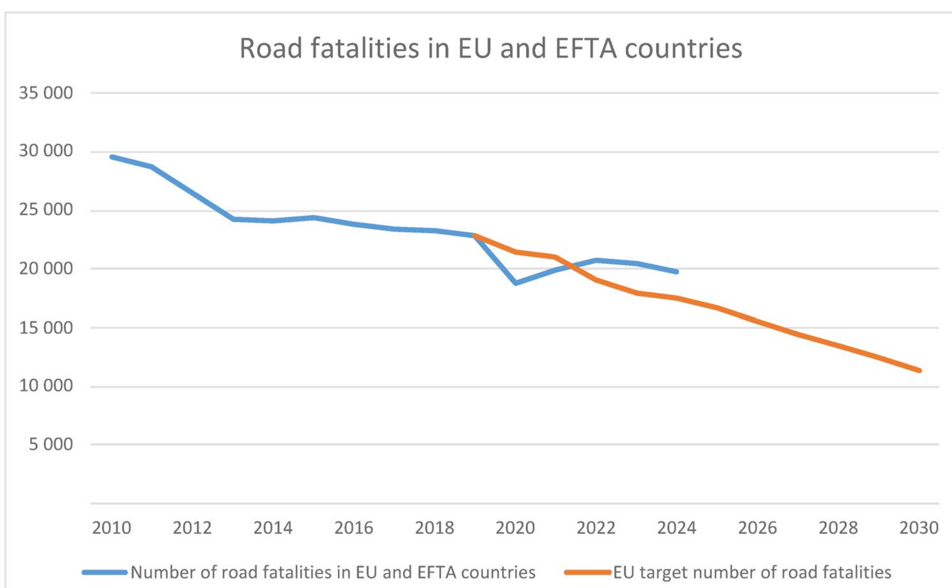


Fig. 1 Number of road fatalities in EU and EFTA countries between 2010 and 2024 (blue line) and EU target number of road fatalities up to 2030 (orange line). *Source* European Road Safety Observatory, Mobility & Transport – Road Safety, European Commission. (https://transport.ec.europa.eu/background/road-safety-statistics-2024_en)

awareness campaigns and projects. These initiatives often employ multimedia content to depict the severe consequences of inappropriate driving behavior, such as fatalities and serious injuries, relying on the theory of "fear-arousing" (Lewis et al. 2007a; Tay and Watson 2002). This approach aims to evoke a sense of fear in users, thereby prompting a change in their attitude and behavior through increased risk awareness.

Several theories in the literature support the concept that the attitude towards a certain behavior develops strongly in the initial phase of learning a task. Experiences, rewards, role models, and the perception of self-efficacy during these early stages contribute significantly to shaping a person's future approach (Skinner 2005; Kolb xxxx). Consequently, educational institutions often implement methods to improve attitudes towards driving behavior in order to positively influence future drivers at a young age. In the UK, for example, the "Safe Drive, Stay Alive" campaign has been funded to raise awareness by involving individuals directly affected by road accidents, to educate young people about the risks and real consequences of collisions (European Transport Safety Council (ETSC) 2016). The aim was to illustrate and educate children about the negative consequences of a collision. Similarly, in Italy, a road safety campaign was launched in July 2023 by the National Police in collaboration with the company 'Autostrade per l'Italia'. This campaign, which employed various media, including television, radio, and online videos, had two main objectives. The first was to raise public awareness of the high number of road fatalities in a single year, while the second was to raise awareness of correct driving behavior. Nevertheless, there is no statistically significant evidence that these campaigns alone have a positive effect on driving behavior (European Transport Safety Council (ETSC) 2016).

There are a few studies in the literature that evaluate the effectiveness of fear-based interventions in altering and improving driving behavior, particularly with regard to their long-term effects. Some studies suggest that such interventions may be ineffective or even counterproductive in certain contexts (Cutello et al. 2021; Blondé and Girandola 2019). According to the theory of "fear-patterning," behavioral modification cannot be based solely on the arousal of fear; effective change requires a reduction in fear in addition to the original fear stimulus (Algie 2011). This approach not only captures individual attention more effectively but also increases engagement by encouraging users to re-evaluate potentially overlooked or underestimated situations (Lewis et al. 2007b). An alternative method employs multimedia content to promote safe driving behavior through positive messaging, which is referred to as a positive-based approach (Cutello et al. 2021). In contrast to the fear-based approach, multimedia materials are used here to emphasize positive behaviors and their beneficial outcomes, such as ensuring one's own safety and that of other road users, thereby promoting a constructive attitude towards road safety.

Consequently, the type of content presented to users—whether fear-based or positive-based—could significantly influence drivers' attitudes and behavior. Furthermore, it is plausible to hypothesize that the way in which the content is delivered (i.e., the display technology with which users view these materials) could also be critical in shaping behavioral outcomes. Traditionally, 2D displays such as TVs, PC monitors, or smartphones have been used for behavioral interventions. However, these technologies have inherent limitations that could hinder the user's immersion (Wenk et al. 2023), potentially reducing the effectiveness of the conveyed messages (Chirico et al. 2017). In recent years, technological advances and the wider availability of Virtual Reality (VR) and Cinematic Virtual Reality (CVR) tools at lower costs have enabled more immersive and effective methods of content delivery that overcome the limitations of 2D displays. VR and CVR technologies, which utilize head-mounted displays (HMDs), offer a high level of immersion and are particularly attractive to young users.

VR and CVR differ in their technical approaches. While VR is based on the creation of virtual environments (VEs) using 3D models and graphics engines, and the user is completely immersed in a synthetic world, CVR uses 360° video and spatial audio captured with panoramic cameras. CVR technology facilitates the development of immersive and realistic virtual experiences while eliminating or minimizing the effort of modeling 3D assets and integrating them into a graphics engine (Manghisi et al. 2022; Matay and Bayar 2023). Thanks to its simple implementation, CVR could enable faster scaling of road safety campaign methods and increase their reach and impact.

Consequently, CVR has been explored as a promising tool for road safety education (Barić et al. 2020; Baptie et al. 2021; Evangelista et al. 2024a). However, the implementation of this new technology requires a thorough scientific evaluation in several dimensions. In addition to evaluating the different effects of fear-based and positive-based approaches, it is also important to assess potential negative effects, such as simulation sickness. Objective, quantitative tools are needed to assess these factors. In addition to traditional user questionnaires, innovative methods, such as physiological monitoring, can be used to assess the impact of immersive experiences on users, providing a more comprehensive understanding of their effects.

Scientific literature has shown that the acquisition of physiological parameters, such as heart rate (HR), electrocardiogram (ECG), and galvanic skin response (GSR), allows the derivation of quantitative data on users' psycho-physiological states within synthetic environments. Several studies highlight a direct correlation between these physiological markers and the stress level triggered by certain situations (Morra et al. 2019; Halbig and Latoschik 2021; Kim et al. 2021; Giannakakis et al. 2022; Rahma et al. 2022).

However, there remains limited evidence on the effectiveness of using different CVR approaches in influencing long-term attitudes and behaviors, as well as on potential physiological effects such as simulation sickness.

This study, which expands on previous preliminary findings (Giglio et al. 2025), addresses these gaps by developing a CVR platform designed to assess the impact of both fear-based and positive-based content on young drivers' attitudes and behaviors, focusing on the following research questions (RQ):

RQ1. Can CVR technology effectively promote a positive attitude and behavior when driving, including in the context of follow-up assessments?
RQ2. Which approach (fear-based vs. positive-based) exerts a stronger influence on young drivers' attitudes towards road safety?
RQ3. Which of the two experiences best retains its impact over time?
RQ4. What is the influence of CVR technology on user experience (UX) and physiological state?
RQ5. Which approach (fear-based vs. positive-based) has the greatest impact on the user's physiological state?

The study is conducted as part of the "Secure Roads 360 (SR360)" project, funded by the National Institute for Industrial Accidents Insurance (INAIL), which aims to enhance road safety, particularly among young drivers.

To provide a comprehensive evaluation, the study employs both subjective assessments, through validated questionnaires such as the Attitude Towards Traffic Safety (ATTS) (Iversen and Rundmo 2004), and Driving Behavior Questionnaire (DBQ) (Af Wåhlberg et al. 2011; Reason et al. 1990), and objective physiological measurements, including ECG data, to monitor the physiological responses of the participants. Preliminary findings indicate that fear-based content significantly enhances driving attitudes and behaviors, with effects persisting at follow-up. Additionally, UX assessments suggest improvements for better user interaction, while VR sickness metrics reveal higher physical discomfort among participants in the positive-based group. The outcomes related to the physiological measurements enable the authors to consider the CVR technology as a potentially effective tool for influencing the psycho-physiological state of individuals, particularly with regard to stress induction. In addition, the analysis of the acquired ECG signals underlines the ability of CVR to effectively engage users and shows that physiological responses vary greatly depending on the type of immersive experience.

This study's methodology provides a dual approach to measuring the effects of immersive experiences, offering new insights into the role of CVR in road safety campaigns.

2 State of art

2.1 Educational interventions in VR to improve driving behaviors and safety

As previously highlighted, road safety remains a critical issue, prompting governments and institutions to look for effective solutions to reduce the high incidence of traffic-related fatalities. Alongside conventional approaches, VR has proven to be a promising tool as it better engages users and creates safe immersive experiences. These environments allow users to experience various scenarios, including dangerous ones, without real-life risks, thus providing a valuable means of skill acquisition and risk awareness (Barić et al. 2020; Evangelista et al. 2024b; De Lorenzis et al. 2023). In particular, VR enables drivers to understand the dangers associated with risky driving behavior through simulated, consequence-free experiences.

A broad spectrum of VR applications has been reported in the scientific literature, ranging from education (Marougkas et al. 2023; Pellas et al. 2020), to health research (Dastan et al. 2022; Adeghe et al. 2024), to industrial training (Evangelista et al. 2025), and more. Specifically, VR has been investigated as an effective tool for modelling risk attitudes and influencing behavioral intentions in road safety campaigns (Vankov and Jankovszky 2021; Kalatian and Farooq 2022; Xia et al. 2024), with a focus on achieving a sustainable impact over time.

There are different VR modalities, each offering unique hardware and software features that affect the UX differently. Non-immersive virtual simulators, or desktop VR, are notable for accurately replicating vehicle interiors, including cockpits and dashboards, on wide-field screens. Desktop VR has been extensively used to assess driving behavior in synthetic urban environments that simulate risk scenarios and effectively minimize physical risk to participants. For example, Branzi et al. (2017) validated the use of a driving simulator by replicating a real urban road near Florence to evaluate speed behavior and comparing the results with those from the real world. The outcomes showed that the simulator reliably predicted drivers' responses to various road situations, such as roundabouts, pedestrian crossings, and bends, thus providing a robust tool for testing urban safety interventions. Similarly, Vasiljevic et al. (2018) developed

VR-based training scenarios to address risky behaviors such as speeding and misuse of seat belts. Their intervention, which included three simulation sessions with immersive visual, audio, and vibration feedback, produced measurable changes in drivers' attitudes towards road safety, highlighting the effectiveness of VR in modifying unsafe behaviors. The development of models that combine the cognitive and emotional aspects of drivers allows researchers to find ways to predict driving behavior more accurately (Wang et al. 2024). In this context, it has been found that drivers' actions are not only characterized by cognitive limitations but by a combination of these limitations with fluctuating emotional states. It can therefore be assumed that desktop VR can be a reliable tool for predicting and positively influencing driving behaviors by increasing users' awareness of the risk involved in road traffic.

Immersive virtual reality (IVR) technology, instead, offers a fully immersive experience by utilizing HMDs that allow the user to interact with synthetic environments in a way that feels realistically detached from the physical world. This enhanced sense of presence, as described by Malone and Brunken (Malone and Brünken 2021), enables users to better perceive and respond to potential threats. Comparisons between IVR and desktop VR have demonstrated that participants in fully immersive environments recognize road hazards and risks in road traffic earlier and with greater efficiency. The HMD's wide field of view is considered an innovative tool for evaluating driving performance and understanding driver behavior in relation to hazard anticipation (Pai Mangalore et al. 2019). IVR has also been employed to teach drivers the correct behavior in certain traffic situations, often with the help of serious games that utilize HMDs to promote safe driving practices (Kirytopoulos et al. 2024). For example, Kirytopoulos et al. (2024) developed a VR-based serious game designed to train drivers in safe behavior when passing through road tunnels, where emergency management and compliance with safety regulations are critical. Their system exposed participants to various realistic scenarios such as congestion, fire hazards, and lane closures, providing immediate feedback and corrective instructions. Results showed that the VR tool improved awareness of tunnel-specific risks and helped drivers internalize the correct behavioral patterns required in emergency conditions. In addition, Mao et al. (2023) used IVR to investigate how different driving styles affect danger perception, showing that individuals with riskier driving habits had significantly lower hazard awareness. Thus, VR technology primarily provides interactive training environments in which participants actively control the vehicle and respond to dynamic traffic events, allowing for the reproduction of motor actions, hazard perception, and decision-making processes.

By contrast, CVR focuses on passive yet highly immersive exposure to 360° video scenarios, where the mechanism of influence is psychological identification with the protagonists and the emotional salience of the depicted events. Although its application in road safety education remains limited, studies suggest that CVR can effectively modify risky behaviors by exposing users to both safe and hazardous driving situations (Baptie et al. 2021; Ma 2022). For example, Barić et al. (2020) evaluated a 360° video-based educational intervention on level crossing safety among learner drivers in Croatia. The program combined lectures with immersive VR exposure to both safe and risky crossing scenarios and showed that such interventions significantly influenced attitudes towards rule compliance and reduced intentions to engage in dangerous crossing behaviors. Effectiveness evaluations often compare traditional viewing methods (e.g., tablets or 2D screens) with CVR delivered via HMDs. Findings suggest that viewing 360° videos in CVR reduces users' tendency towards unsafe driving behavior, primarily due to their psychological identification with the protagonists of the traumatic scenarios depicted. A study by Cutello et al. (2021) further compared the effects of watching safe and traumatic videos with 2D displays and via HMDs, concluding that positive messaging delivered through CVR had a stronger, longer-lasting influence on driving behaviors, particularly in follow-up assessments.

2.2 Physiological responses as indicators of psychophysical state

In recent years, scientific interest in defining and analyzing individual psycho-physical states using measurable physiological parameters has increased significantly. At the same time, commercially available devices have been introduced that enable the acquisition of such parameters and allow a non-clinical and accessible assessment of a person's psychophysical state. Key physiological metrics include ECG signals, respiratory rate, skin conductivity, blood pressure, eye-tracking, and electroencephalographic (EEG) activity (Charles and Nixon 2019). Among these, ECG is widely studied for the assessment of psychological states due to its non-invasive nature. It is usually recorded with medical electrodes attached to the user's body (e.g., Shimmer 3, BioSignalPlux) (Evangelista et al. 2024b; Pourmohammadi and Maleki 2020; Li et al. 2022). Moreover, commercial wearable devices (e.g., thoracic belts, smartwatches, wristbands) have also been validated for reliable ECG acquisition (Sedighi Maman et al. 2020; Villani et al. 2020; Mach et al. 2022; Mehler et al. 2009; Nixon and Charles 2017; Besson et al. 2020).

A primary objective in these acquisition systems is to enable heart rate variability (HRV) analysis across time and frequency domains. HRV analysis is based on the assessment of RR interval variability, which is defined as the time intervals between successive heartbeats. HRV is recognized as a reliable indicator of stress levels (Dishman et al. 2000; Rajendra Acharya et al. 2006). Research demonstrates a direct relationship between HRV and task complexity; high HRV values are associated with a relaxed state, whereas reduced HRV often correlates with increased task complexity and resultant stress (Nixon and Charles 2017; Tiwari et al. 2021; Veltman and Gaillard 1998; Kim et al. 2018a).

The accessibility of physiological measures has spurred substantial research on the integration of these metrics with VR technologies across diverse applications. In psychology, physiological parameters have been essential for evaluating the effectiveness of VR in reducing stress triggered by certain scenarios. They provide objective data on perceived stress reduction through cardiac activity analysis (Kim et al. 2021; Shiban et al. 2017). In VEs' design, physiological data integration has been shown to enhance realism and immersion, enabling dynamic responses to users' emotional and physical states, thereby deepening the immersive experience (Blum et al. 2019). Such integrations have made VR more effective for targeted psychological interventions and interactive experiences. Furthermore, a growing body of research has investigated the role of VR video games in influencing both physical and psychological states (Rodríguez-Fuentes et al. xxxx), particularly in the context of stress management (Ishaque et al. 2020). These studies employ objective parameters (e.g., heart rate) to objectively evaluate the psycho-physiological state during VR interaction. Notably, one of the most influential applications of VR is in training and education, where physiological metrics aid in assessing cognitive workload and stress during task performance. For instance, Clifford et al. (2021) utilized VR to train aerial firefighters, demonstrating that HRV analysis could differentiate stress levels and distinguish between novice and experienced participants, with the latter showing better control in managing stress.

In the context of driver safety, physiological metrics have shown their effectiveness in evaluating driving risks in controlled VR simulations. Desktop VR technology, combined with physiological sensors, facilitates the simulation of various driving scenarios, enabling the analysis of potentially dangerous user behaviors. Among the promising tools for assessing cognitive responses and attention levels during driving, there are EEG devices, which have demonstrated significant potential in monitoring attention levels and cognitive responses under varying road conditions (Blasiis et al. 2021; EEG-Based Assessment of Driver Cognitive Responses in a Dynamic Virtual-Reality Driving Environment xxxx). In the context of autonomous vehicles, EEG has also gained attention as an important parameter for studying road users' perceptions, attitudes, and preferences (Anciaes et al. 2024). Studies also show that this parameter, when coupled with IVR, can evaluate the impact of variables such as correlated color temperature on driving performance, with physiological metrics effectively capturing fluctuations in driver attention and behavior (Li et al. 2021). Additionally, eye-tracking metrics, including pupil diameter, blink frequency, and duration, have been used to monitor changes in driver behavior, revealing a direct correlation with reduced concentration or variations in vehicle speed (Niu et al. 2024; Wang et al. 2023; Blasiis et al. 2020). Moreover, HRV data gathered via ECG in VR simulators have been used to assess driver alertness under diverse visibility conditions and driving scenarios (Gruden et al. 2019; Deniaud et al. 2015). Furthermore, the galvanic skin response (GSR) has emerged as a key indicator of physiological stress, assessing how various traffic modes influence the stress responses of different road users, including pedestrians, cyclists, and e-scooter riders, within IVR environments (Su et al. 2025; Nazemi et al. 2024). These findings are essential for understanding the dynamics of road users and are crucial for addressing planning and safety management challenges, particularly in the growing context of micromobility.

Despite these advancements, a literature review reveals a clear gap in studies evaluating psycho-physical responses in CVR environments using physiological parameters. To date, there are a few studies that have quantitatively analyzed the effects of IVR on driving behavior, especially in the context of CVR. In particular, there is a lack of studies on the long-term impacts of VR-based interventions on users' attitudes and behavior, as well as detailed assessments of physiological responses over extended periods.

This study aims to address these gaps by exploring the potential of CVR technology to induce attitudinal and behavioral change in drivers. Specifically, a pre- and post-CVR experience assessment was conducted, along with a follow-up evaluation using validated questionnaires. Given current technological capabilities to objectively assess psycho-physical states, this study further hypothesizes that the effects of CVR on these states can be quantitatively evaluated through physiological data, providing new insights into the effectiveness of IVR experiences in improving driver safety. Additionally, the study examines the differential effects of a fear-based versus a positive-based approach on both safe driving attitudes and physiological responses, seeking to determine how each approach uniquely influences driver engagement in safety-oriented behavior.

3 Materials and methods

This section describes in detail the experimental procedure, the methods, and the subjective and objective measures utilized in the study. The results are presented and discussed in the following sections.

3.1 Participants

A total of 100 volunteers, 55 males and 45 females, aged 18 to 22 years (M = 19.82, SD = 1.67), were recruited for this study. Among them, 38 were high school students from the city of Bari, and the remaining participants were undergraduate students of the Polytechnic University of Bari. To be eligible to take part, participants had to have a valid driving license (for motorbikes or cars) that was issued no more than five years previously and be no older than 24 years old. In this way, the inclusion criteria are aligned with (Report-Novice and drivers. xxxx), in which a definition of novice drivers is provided. Participants were randomly assigned to one of two groups of 50 individuals each. The first group was exposed to a fear-based CVR experience, while the second group viewed a positive-based CVR experience. The experimental design aimed to collect physiological data from participants; however, occasional data loss occurred due to technical issues with the recording devices. As a result, the final sample size was 95 participants, 52 males and 43 females. There were 48 people in the positive-based group and 47 in the fear-based group.

3.2 Measures

3.2.1 Attitude and behavior evaluation

In order to investigate research questions RQ1, RQ2, and RQ3, the participants' attitudes and driving behavior were quantitatively assessed using the ATTS Questionnaire and the DBQ.

The ATTS questionnaire, developed by Iversen and Rundmo (2004), is a validated instrument for measuring drivers' attitudes towards traffic violations and speeding. It consists of 16 items, including both positively and negatively framed statements. Participants rated their agreement with each item using a 5-point Likert scale. Higher overall scores reflect greater adherence to road safety norms.

The DBQ, originally developed by Reason et al. (1990), is widely used in research to analyze drivers' self-assessments of their driving behavior. This study employed the 50-item version, which categorizes responses into two primary domains: errors and violations. Errors are unintentional actions, often resulting from incorrect judgments or rapid shifts in planned actions, typically due to inaccurate information processing. Violations, by contrast, reflect a conscious disregard for road traffic regulations and include behaviors associated with potentially severe or fatal outcomes. Responses were rated on a 6-point Likert scale (from 0 = "never" to 5 = "almost always"), where higher scores indicate a greater frequency of risky behaviors.

3.2.2 UX evaluation

To address RQ4, UX was assessed through self-report measures. Specifically, the Virtual Reality Sickness Questionnaire (VRSQ) and the User Experience Questionnaire (UEQ) were administered. Details regarding these instruments are provided in the following sections.

The VRSQ, validated by Kim et al. (2018b), assesses symptoms of discomfort potentially induced by IVR experiences, which can disorient users and cause sensory detachment from the real environment. The VRSQ items are divided into two categories: oculomotor symptoms and disorientation symptoms. Scores are reported on a 0–100 scale, with higher scores indicating more severe symptoms of VR-induced discomfort.

The UEQ (Analysis Tool and n.d. 2024) consists of 26 items divided across six scales: attractiveness, perspicuity, efficiency, dependability, stimulation, and novelty, which evaluate both pragmatic and hedonic qualities of a system (Schrepp et al. 2017). For each item, participants rate their experience by selecting between pairs of contrasting adjectives, reflecting their immediate impression of the task.

3.2.3 Physiological parameters evaluation

To address RQ4 and RQ5, the study investigates the effects of CVR on participants' physiological responses during the experimental conditions by recording and analyzing their ECG signals. According to the relevant literature, physiological signals, with the most prominent being heart rate, are regulated by the Autonomic Nervous System (ANS) and its sympathetic (SNS) and parasympathetic (PNS) divisions. The heart rate variability parameters are valuable indicators in evaluating arousal or stress conditions, which are manifested mainly by increased sympathetic activity (Giannakakis et al. 2022). There are specific HRV parameters that are consistently identified as significant in stress-related literature, such as HR_m, SDNN, and LF/HF (e.g., LF/HF presents increased values under stress conditions compared to neutral ones (Tiwari et al. 2021; Tao et al. 2019)).

The ECG was recorded by a sensor placed on the chest during the experimental conditions with a sampling frequency of 1 kHz. The signals were then subsampled to a sampling frequency of 200 Hz to improve processing and memory performance. The preprocessing phase included noise removal, detrending (by subtracting the time series polynomial fit of order 60), and ectopic heartbeat fix (using the rule of percentage change of 70% over the averaged previous 5 heartbeats). The whole preprocessing phase is described in a previous work (Giannakakis et al. 2019).

The R peaks were detected using a custom parametric peak detection algorithm leading to the extraction of the RR intervals (RRI). After the RRI extraction, the heart activity was evaluated through HRV parameters. The HRV parameters investigated in this study are divided into time, frequency, and nonlinear domain as follows:

- Time Domain: HR_m, SDNN, HR_{std}, RMSSD, NN50, pNN50
- Frequency Domain: Total power, VLF_{norm}, LF_{norm}, HF_{norm}, LF/HF, LF peak, HF peak
- Non linear: DFA α_1, DFA α_2, Approximate Entropy (ApEn)

The temporal HRV parameters were directly computed from RRI, which is the gold standard for cardiology. The spectral HRV parameters were estimated from the spectral transformation of the RRI time series according to the (Heart and rate variability Standards of measurement, physiological interpretation, and clinical use. xxxx). Besides, the nonlinear measures detrended fluctuation analysis (DFA) components (α_1, α_2) and Approximate entropy were estimated, which are quite robust and promising features in HRV analysis. Machine learning algorithms (such as KNN, NVB, SVM of different kernels, and decision trees) were utilized to distinguish the two experimental phases (rest, test) as well as populations (positive-based and fear-based) based on HRV parameters, evaluating the system's classification performance in terms of accuracy, sensitivity, and specificity.

3.3 CVR 360 film and hardware

The study employed two 360° videos, each lasting six minutes, provided by the Leicestershire Fire & Rescue Service (UK). The first video is fear-based, while the second is positive-based. Both videos were filmed using a 360° camera mounted on the front passenger seat of a standard vehicle and were implemented in a CVR application developed with the Unity engine. The use of the passenger perspective offers some advantages. An external perspective (Baptie et al. 2021; Sagberg et al. 2019) enables the observation of driver behaviors that may otherwise be challenging to detect. This viewpoint allows for a clearer identification of potentially unsafe or improper actions.

The fear-based video depicts a young male driver operating a vehicle at high speed with two female passengers in the back seat. Throughout the video, the driver is frequently distracted by the improper use of his mobile phone. After multiple instances of deviating from the intended trajectory, he ultimately loses control of the car, resulting in a serious traffic accident with severe injuries and fatalities. The video concludes with rescue and emergency operations aimed at assisting the victims, aiming to evoke a strong sense of fear and anxiety in the CVR viewer.

In contrast, the positive-based video features the same vehicle and characters but presents a scenario in which the driver adheres to traffic laws, avoiding distractions from the smartphone and engaging safely with the other passengers. This video concludes with the passengers reaching their destination safely, designed to convey a message of responsible driving and traffic safety.

The CVR experiences were administered using a Meta Quest 2 HMD. The participants' ECG signals were acquired by using the BioSignalPlux Research Kit (BioSignalPlux Research Kit n.d 2024) with a setup of 16-bit resolution and a sampling rate of 1000 Hz.

3.4 Procedure

In this study, a between-subjects experimental design was employed.

3.4.1 Pre-experimental phase (pre-test)

Prior to the CVR experience, researchers explained the experimental procedures to participants, who then completed informed consent forms in accordance with the Helsinki Declaration. Participants also provided demographic information and completed the ATTS and the DBQ, establishing a baseline for subsequent comparisons. Participants were then randomly assigned to either the fear-based or the positive-based CVR group.

To ensure initial group homogeneity, baseline ATTS and DBQ scores were analyzed. For ATTS scores, normality was confirmed, and an independent samples T-test revealed no significant differences between groups ($t(98)=1.316$; $p=0.191$, 95% CI [−0.996;4.916]), where CI stands for Confidence Interval. Regarding the DBQ scores, these were initially non-normally distributed and therefore log-transformed to meet normality criteria. This transformation permitted a subsequent T-test, which also showed no significant difference between groups ($t(98)=-1.157$; $p=0.250$, 95% CI [−0.147;0.389]). Therefore, randomization successfully produced homogeneous groups with respect to driving attitudes and behaviors.

3.4.2 CVR experience phase

Participants were invited to return on a subsequent day to complete the CVR experience. To avoid any physiological signal alterations, they were instructed to sleep adequately. They were also told to abstain from caffeine and alcohol, and to avoid smoking before the experiment (Digiesi et al. 2020). During this session, a single-lead ECG was recorded with three Ag/AgCl electrodes placed on the chest. Electrodes placement followed BioSignalPlux guidelines.

Participants answered the VRSQ, wore an HMD, and were immersed in a neutral VE (Meta's virtual home room) for approximately five minutes to establish a reliable baseline ECG reading (Giannakakis et al. 2022; Digiesi et al. 2020; Yin et al. 2018). This resting phase helped mitigate motion artifacts from body movements on the acquired ECG signal, enabling a more accurate comparison of physiological responses across experimental phases.

After the baseline recording, participants proceeded to the CVR experience by viewing the 360° videos corresponding to their assigned group (see Fig. 2). Upon completion of the video (post-test), participants again completed the ATTS, VRSQ, and UEQ to enable comparison of post-experience results with baseline measures.

3.4.3 Follow-up phase

Two weeks post-CVR experience, participants returned for a follow-up assessment. They completed the DBQ and ATTS questionnaires once more to assess the sustained impact of the CVR intervention on driving attitudes and behaviors.

4 Results

4.1 Overview

Statistical analyses were conducted on ATTS, DBQ, VRSQ, and UEQ scores across different experimental phases, along with physiological responses recorded during the relaxation and test phases. Analyses were performed using IBM SPSS Statistics 20. All estimates reported in the following subsections are with 95% CIs. In the analysis, M stands for "mean", SE stands for "Standard Error", while "r" refers to the rank-biserial correlation value.

4.2 Attitudes toward traffic safety (ATTS)

The ATTS questionnaire was administered to assess participants' attitudes towards road safety across three time points: pre-test, post-test, and follow-up. The respective ATTS score for each participant was calculated, and the scores obtained in the three time periods for both groups were compared, as shown in Fig. 3.

For the fear-based group, a Friedman test was conducted due to non-normal distribution, revealing significant differences among the three time points ($\chi^2(2) = 15.71$, $p < 0.001$, Kendall's W = 0.16). Pairwise comparisons (Table 1) indicated statistically significant changes from the pre-test to

Fig. 2 On the left side: participant during the experimental phase, wearing the HMD and BioSignalPlux; on the right side: scenes captured from the two 360° videos (top right picture from positive-based video; bottom right picture from fear-based video)

Fig. 3 Boxplots of the ATTS score collected for both groups in the three time periods

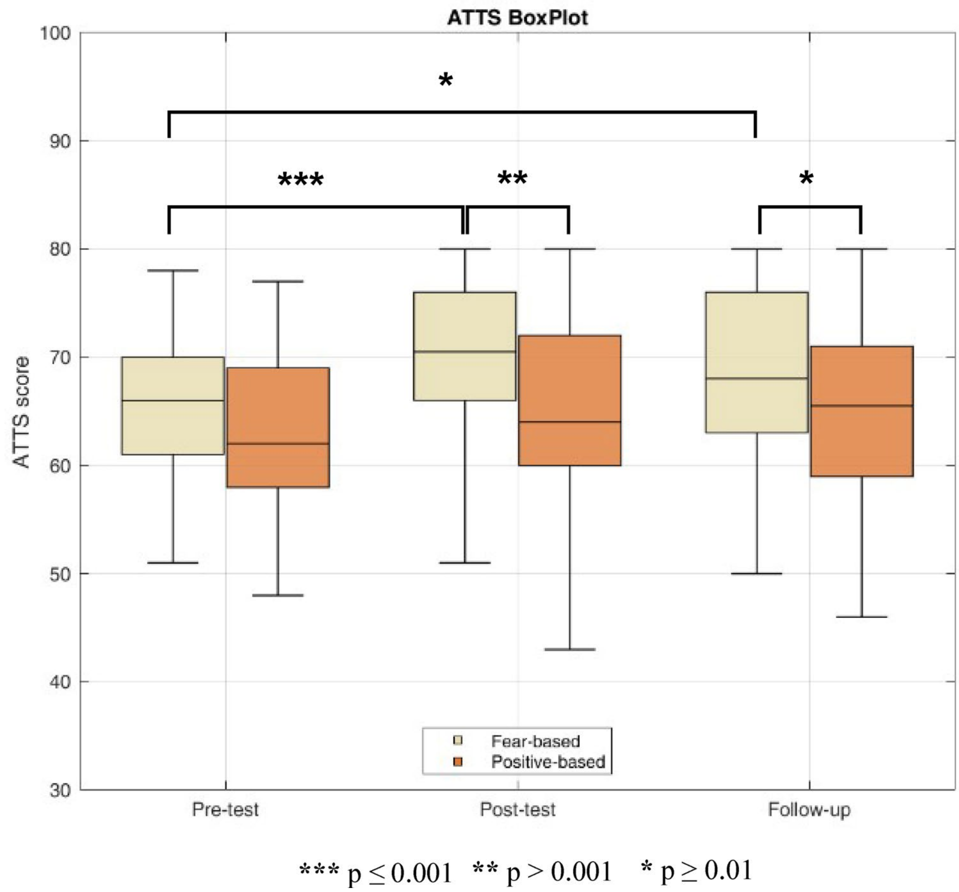


Table 1 Pairwise comparison and related *p*-values for the ATTS score of the fear-based group

	ATTS score		
	Compared temporal condition	*p*-value	diff
Fear-based group	Pre-test vs. post-test	**0.001**	↑
	Pre-test vs. follow-up	**0.018**	↑
	Post-test vs. follow-up	1.000	ns

In bold, statistically significant results

the post-test ($p=0.001$, M = −5.180, SE = 1.08, 95% CI [−7.86; −2.50]) and from pre-test to follow-up ($p=0.018$, M = −3.30, SE = 1.30, 95% CI [−6.53; −0.07]).

For the positive-based group, the normality was confirmed ($p>0.05$), and Levene's test verified homoscedasticity (F(2,147) = 0.720, $p=0.488$). However, due to a violation of sphericity (Mauchly's test, $\chi^2(2)=37.31$, $p<0.001$), a Greenhouse–Geisser correction was applied, revealing no significant differences across the three time points ($p=0.192$).

For the between-group comparisons, the post-test scores were compared using a Mann–Whitney U test, as normality was not met even after log transformation, revealing a significant difference (U = 824.5, $p=0.003$, r = 0.340, 95% CI [0.126; 0.524]). At follow-up, normality and homoscedasticity assumptions were met, and an independent samples t-test found a significant difference between groups (t(93) = 2.195, $p=0.031$, M = 3,427, SE = 1.561, 95% CI [0.329; 6,524]).

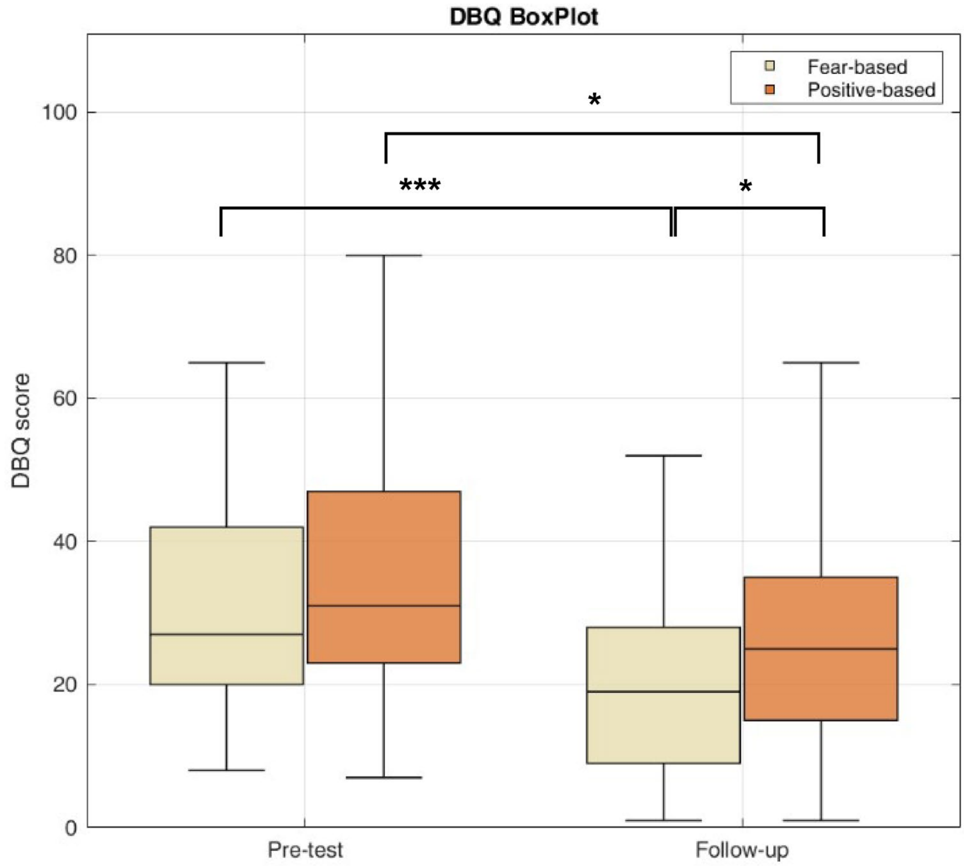
4.3 Risky driving behaviors (DBQ)

The DBQ questionnaire was administered at the pre-test and during the follow-up to evaluate self-reported risky driving behaviors. For each participant, the DBQ score was calculated, and then the scores obtained in the two time periods for both groups were compared. The results are shown in Fig. 4.

For the fear-based group, the DBQ scores were log-transformed for normality, but homoscedasticity was not met (Levene's test, F(1,93) = 8.576, $p=0.004$). Therefore, Welch's ANOVA was used, revealing a statistically significant difference between the pre-test and follow-up (F(1,79.03) = 12.53, $p=0.001$, M = 0.218, SE = 0.061, 95% CI [0.097, 0.339]).

For the positive-based group, the non-normal distribution required the use of the Wilcoxon signed-rank test, identifying a significant change in scores between the pre-test and follow-up (Z = 2.412, $p=0.016$, r = 0.396, 95% CI [0.097, 0.629]).

Table 2 resumes these analyses.



*** p ≤ 0.001 * p ≥ 0.01

Fig. 4 Boxplot of the DBQ score collected for both groups during the pre-test and follow-up phases

Table 2 Statistical analysis and related p-values for the DBQ Score of both groups

	DBQ score			
	Compared temporal conditions		Test statistics	diff
Fear-based group	Pre-test vs. Follow-up	Welch's ANOVA	$\mathbf{p=0.001}$	↓
Positive-based group	Pre-test vs. Follow-up	Wilcoxon Signed Rank	$\mathbf{p=0.016}$	↓

In bold, statistically significant results

To compare the follow-up results between the two groups, a Mann–Whitney U test was applied to the non-normally distributed follow-up scores, revealing a significant difference between groups (U = 962.5, $p=0.047$, r = −0.234, 95% CI [-0.436;-0.010]). To better improve this analysis, since the p-value does not show a strong significant effect, a linear mixed-effects model analysis was carried out, including time (pre-test vs follow-up) and group (fear-based vs positive-based) as fixed effects and a random intercept for participants. Estimated marginal means and Bonferroni-adjusted pairwise contrasts are reported below. There was a clear main effect of time. For instance, the DBQ scores decreased from pre-test (M = 33.37, SE = 1.66; 95% CI [30.09, 36.65]) to follow-up (M = 24.11, SE = 1.66; 95% CI [20.83, 27.39]), $F(1, 93) = 17.28$, $p < 0.001$. The mean change was −9.26 points (SE = 2.23; 95% CI [−13.68, −4.84]), indicating a statistically and practically meaningful improvement over time. The main effect of the group was also observed. In detail, across time periods, the positive-based group showed higher DBQ scores than the fear-based group (positive-based: M = 31.26, SE = 1.75; 95% CI [27.80, 34.73] vs fear-based: M = 26.22, SE = 1.75; 95% CI [22.76, 29.69]), $F(1, 93) = 4.17$, $p = 0.044$. The estimated between-group difference was 5.04 points (SE = 2.47; 95% CI [0.14, 9.94]). The interaction between group and time conditions was not relevant (F(1,93) = 0.149, $p = 0.700$). Both groups improved from pre-test condition to follow-up (fear-based: 31.28 → 21.16, Δ = −10.12; positive-based: 35.46 → 27.06, Δ = −8.40), yielding a broadly parallel pattern of change and no compelling evidence that the magnitude of improvement differed by group. Furthermore, the estimated marginal effects analysis (M = 28.740, SE = 1.235) showed a 95% CI [26.290, 31.190], reinforcing the reliability of the findings.

4.4 User experience (UX) evaluation: VRSQ and UEQ

The results of the VRSQ were compared to assess the UX of the participants. It was administered to both test groups before and after the CVR experience. For each participant, a VRSQ score was defined ranging from 0 to 100, and a statistical analysis was carried out on these values. Firstly, the Shapiro–Wilk test was applied, finding that the data of both groups did not follow a normal distribution ($p<0.05$). Thus, the Wilcoxon Signed-rank test for paired samples allowed us to reject the null hypothesis of equality of the medians before and after the CVR experience only for the positive-based Z=-3.056, $p=0.002$, r=−0.599, 95% CI [−0.794, −0.292]) group and not for the fear-based one (Z=−1.442, $p=0.149$, r=−0.298, 95% CI [−0.603, −0.084]), as shown in Table 3.

Furthermore, the UEQ analysis tool, available online, was employed to evaluate the responses obtained from the related questionnaire, focusing on six key dimensions (attractiveness, perspicuity, efficiency, dependability, stimulation, and novelty). This tool enabled the authors to assess the overall quality of the UX as perceived by the participants in the experiment. According to Schrepp (xxxx), these six dimensions are divided into two classes, called pragmatic quality, which encompasses perspicuity, efficiency, and dependability, and hedonic quality, which includes stimulation and novelty. These two classes were computed for both groups of this study.

To examine differences in pragmatic quality, the Shapiro–Wilk test was first carried out to verify the normality of the data distribution. Results confirmed that the data met the normality assumption ($p>0.05$). Consequently, a T-test for independent samples was performed, revealing a statistically significant increase in pragmatic quality for the fear-based group compared to the positive-based one (t(93)=2.569, $p=0.012$, 95% CI [0.073; 0.572]).

For the hedonic quality analysis, the Shapiro–Wilk test indicated that the data did not follow a normal distribution, even after the application of a Box-Cox transformation. As a result, the non-parametric Mann–Whitney U test was employed. This analysis did not find statistically significant differences in hedonic quality between the fear-based and positive-based groups (U=1.199, $p=0.596$, r=−0.063, 95% CI [−0.288; 0.169]). A graph summarizing the results is shown in Fig. 5.

4.5 Physiological parameters evaluation

The HRV analysis was performed as described in Sect. 3.2.3 to address RQ4. The aim was to assess whether the use of CVR affects the participants' physiological response significantly by comparing the rest and the test phases.

For all the parameters, the features' normal distribution was checked, and then the appropriate statistical test was applied. Firstly, it was investigated whether each group (positive-based, fear-based) presented differences between the rest and test phases utilizing the T-Student test or the Wilcoxon signed-rank test. The results are shown in Table 4 (a, b), and in Fig. 6.

It can be observed that there is a statistically significant increase in test HRm values both for positive-based (t-test: t(47)= −3.707, $p=0.001$, d=−0.535, 95% CI [−0.835, −0.230]) and fear-based (t-test: t(46)= −3.173, $p=0.003$, d=−0.463, 95% CI [−0.762, −0.159]) groups in comparison to the relative rest phase. Regarding the frequency domain, a statistically significant increase has been observed for the LF/HF parameters while comparing, by using the Wilcoxon signed-rank test, the test and rest phases of only the fear-based group (Z=−0.297, $p=0.015$, r=−0.410, 95% CI [−0.643, −0.106]). Moreover, for the DFA α1 and DFA α2 values of the positive-based group, a significant increase has been observed. For both of the parameters the T-Student test was applied and regarding the first one the following results were obtained (t(47)= −5.048, $p=0.000$, d=−0.729, 95% CI [−1.044, −0.407]) while for the DFA α2 these ones (t(47)= −3.976, $p=0.000$, d=−0.574, 95% CI [−0.877, −0,266]). On the contrary, a statistically significant reduction has been observed in the test SDNN value only for the fear-based group in comparison to the rest phase (Z=2.730, $p=0.002$, r=0.457, 95% CI[−0.346, 0.281]). A significant reduction has been highlighted by the RMSSD parameter both for positive-based (t-test: t(47)=3.368, $p=0.002$, d=0.486, 95% CI [0.184, 0.783] and fear-based (Wilcoxon signed rank: Z=3–111, $p=0.001$, r=0.521, 95% CI [0.245, 0.719]) groups in relation to the rest phase. In addition, a significant reduction (using the Wilcoxon signed rank test) has been noted for the NN50 parameter for the positive-based (Z=5.201, $p=0.000$, r=0.871, 95% CI[0.766, 0.931]) and for the fear-based group (Z=4.164, $p=0.000$, r=0.698, 95% CI [0.489, 0.831]) as well as for the pNN50 parameter. In detail, carrying out the Wilcoxon signed-rank

Table 3 Statistical analysis and related *p*-values for VRSQ scores of both groups

	VRSQ scores								
	Pre-test			Post-test			Test statistics		diff
	Mean	Median	SD	Mean	Median	SD			
Fear-based group	6.86	4.17	8.38	8.51	7.50	9.28	Wilcoxon signed rank	$p=0.149$	ns
Positive-based group	5.56	4.17	6.67	9.05	7.50	9.71	Wilcoxon signed rank	$\mathbf{p=0.002}$	↑

In bold, statistically significant results

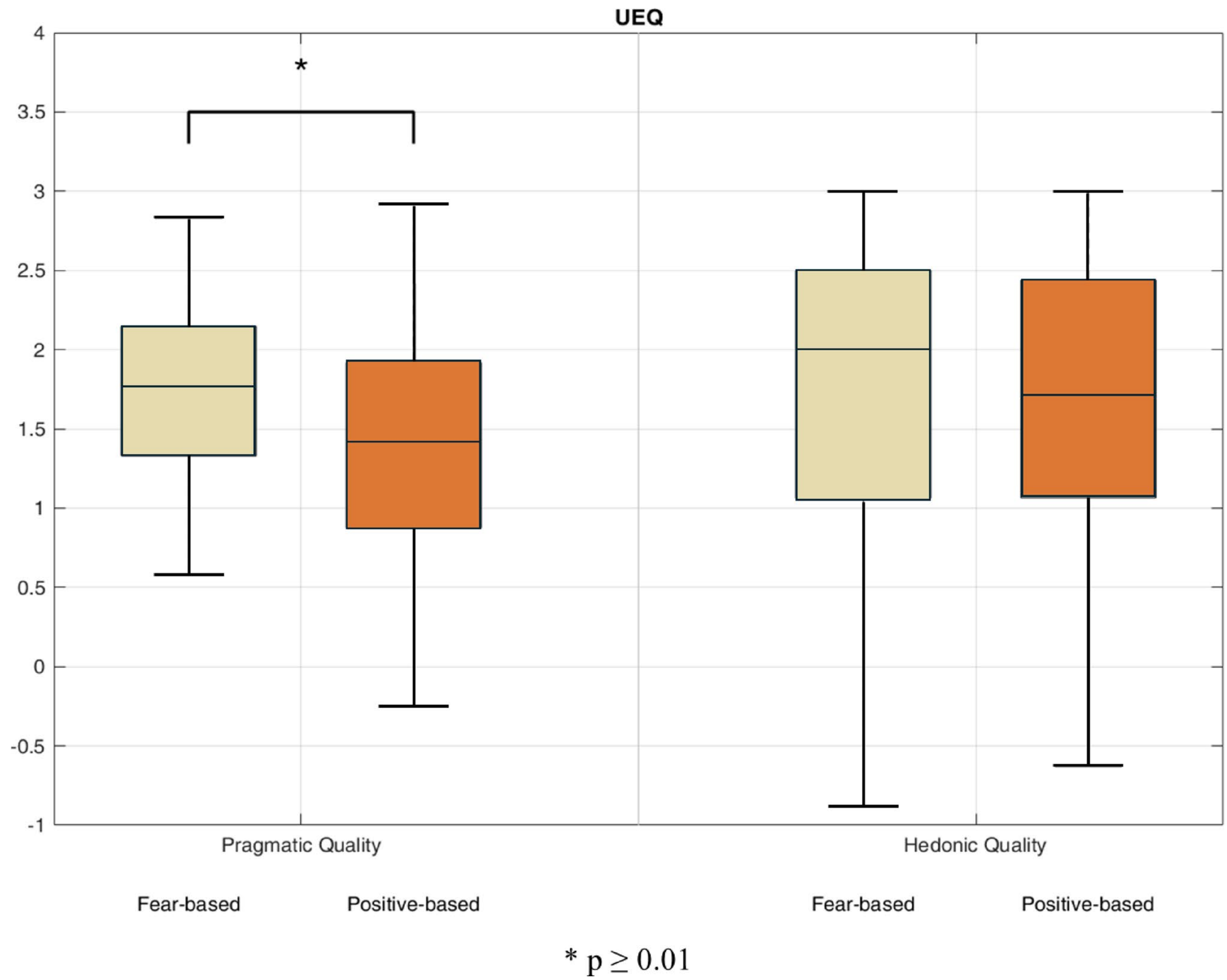


Fig. 5 Comparison of pragmatic and hedonic qualities between the groups

test, the positive-based group showed the following results (Z=3.508, p=0.000, r=0.582, 95% CI [0.327, 0.757]) while the fear-based one these results (Z=4.127, p=0.000, r=0.691, 95% CI [0.480, 0.827]). Finally, a significant decrease was noted in the ApEn values of the fear-based group (Wilcoxon signed-rank test: Z=2.824, p=0.012, r=0.478, 95% CI [0.187, 0.692]).

To answer RQ5, the values of the physiological parameters of both groups (positive-based and fear-based), obtained only during the test phase, were compared. To have a common reference and to eliminate the great inter-subject variability, an estimation of the differential features in relation to the rest phase for each subject was calculated. Using this approach and the Mann–Whitney test, the statistical results of Table 5 were obtained.

It can be observed that during the test experimental phase, the fear-based group presents statistically significant reduced SDNN (U=1425, z=1.996, p=0.046, r=−0.263, 95% CI [−0.465, −0.036]), HR_{std} (U=1456, z=2.22, p=0.026, r=−0.291, 95% CI[−0.488, −0.066]), DFA α_1 (U=1499, z=2.53, p=0.011, r=−0.330, 95% CI [−0.520, −0.109]), DFA α_2 (U=1647, z=3.62, p<0.001, r=−0.461, 95% CI [−0.624, −0.259]) and increased LF/HF (U=883, z=1.97, p=0.049, r=0.217, 95% CI [−0.013, 0.425]).

To evaluate the relevance of each feature, we performed the minimum Redundancy Maximal Relevance (mRMR) algorithm (Ding and Peng 2011) which evaluated and ranked the features according to their relevance to the investigated problem. The results are shown in Fig. 7. After the mRMR application, an iterative process was performed, adding one of each ranked feature and retaining the subset with the minimum misclassification error. With this procedure, all features were considered significant for the subsequent classification procedure.

Then, the system's classification performance of the differential HRV parameters between the positive-based

Table 4 a) HRV parameters statistical results of the positive-based group between the 2 experimental conditions (rest vs test); b) HRV parameters statistical results of the fear-based group between the 2 experimental conditions (rest vs test)

a)

HRV feature	rest	test	p-value	diff
HRm	79.051	80.810	**0.001**	↑
SDNN	0.06	0.06	0.863	ns
HRstd	6.1	7.5	0.233	ns
RMSSD	0.0	0.0	**0.002**	↓
NN50	74	43	**0.000**	↓
pNN50	18.3	13.6	**0.000**	↓
peakVLF	0.0	0.0	0.286	ns
peakLF	0.09	0.08	0.781	ns
peakHF	0.21	0.17	0.692	ns
VLF (%)	0.10	0.08	**0.037**	↓
LF (%)	0.61	0.61	0.313	ns
HF (%)	0.25	0.27	0.924	ns
LF/HF	2.52	2.24	0.822	ns
DFA α1	0.84	0.91	**0.000**	↑
DFA α2	1.100	1.140	**0.000**	↑
ApEn	0.002	0.001	0.089	ns

b)

HRV feature	rest	test	p-value	diff
HRm	73.327	75.594	**0.003**	↑
SDNN	0.06	0.06	**0.002**	↓
HRstd	6.9	6.3	0.073	ns
RMSSD	0.0	0.0	**0.001**	↓
NN50	71	56	**0.000**	↓
pNN50	18.6	15.0	**0.000**	↓
peakVLF	0.0	0.0	0.275	ns
peakLF	0.10	0.08	0.079	ns
peakHF	0.20	0.21	0.299	ns
VLF (%)	0.10	0.10	0.993	ns
LF (%)	0.55	0.62	0.070	ns
HF (%)	0.32	0.24	**0.038**	↓
LF/HF	1.85	2.66	**0.015**	↑
DFA α1	0.83	0.83	0.086	ns
DFA α2	1.092	1.071	0.094	ns
ApEn	0.009	0.003	**0.012**	↓

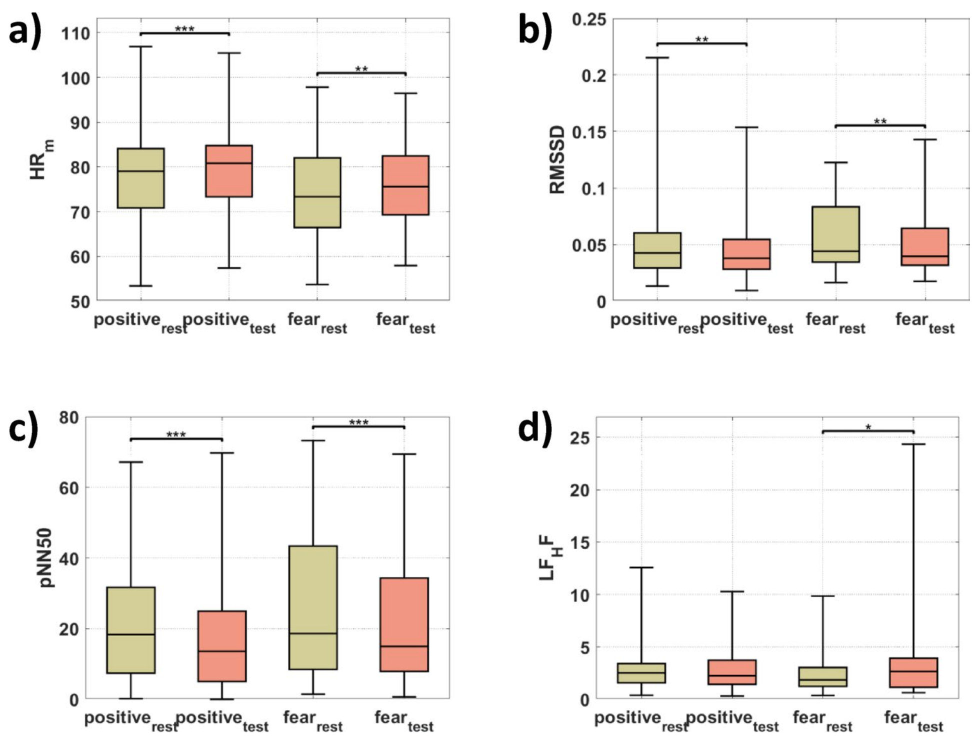


Fig. 6 Box plots of the most relevant results for the rest-test phases comparison of both groups. In detail: **a** graph of the HRm; **b** graph of RMSSD; **c** graph of pNN50; **d** graph of the LF/HF ratio. *** $p<0.001$; ** $p\geq0.001$; * $p\geq0.01$

Table 5 HRV differential parameters statistical results of the test experimental phase (positive-based vs fear-based groups).

HRV feature	Positive	Fear	p-value	Diff
HR_m	1.048	1.239	0.772	ns
SDNN	0.00	−0.01	**0.046**	↓
HR_{std}	0.8	−0.4	**0.026**	↓
RMSSD	0.0	0.0	0.991	ns
NN50	−29	−16	**0.009**	↑
pNN50	−2.9	−3.9	0.789	ns
$peak_{VLF}$	0.0	0.0	0.137	ns
$peak_{LF}$	0.00	−0.01	0.141	ns
$peak_{HF}$	0.00	0.01	0.283	ns
VLF (%)	−0.02	0.00	0.165	ns
LF (%)	0.02	0.03	0.457	ns
HF (%)	−0.01	−0.04	0.130	ns
LF/HF	0.19	0.44	**0.049**	↑
DFA α_1	0.07	0.02	**0.011**	↓
DFA α_2	0.037	−0.011	**0.000**	↓
ApEn	0.000	−0.001	0.369	ns

In bold, statistically significant results.

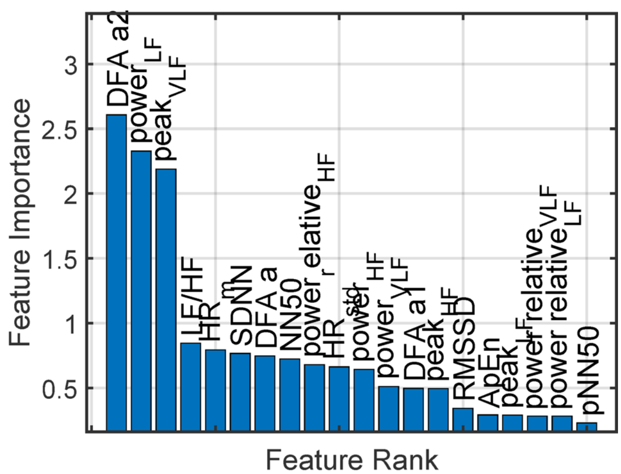


Fig. 7 HRV Features ranking according to the mRMR algorithm

Table 6 Classification performance results between the positive and fear-based groups in the test experimental phase using differential HRV parameters.

	Accuracy (%)	Sensitivity (%)	Specificity (%)
KNN	78.8	76.5	81.0
NVB	78.9	79.0	79.0
LDA	**90.6**	**89.0**	**92.0**
SVM linear	89.5	87.5	91.5
SVM quadratic	89.9	93.0	87.0
SVM cubic	85.2	91.5	79.0
SVM gaussian	84.0	89.5	78.5
Ens. decision trees	82.0	87.5	77.0

In bold, the best classifier.

and fear-based groups in the test experimental phase was evaluated in terms of tenfold cross-validation classification accuracy. Towards this, the classifiers Naive Bayes (NVB), Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), SVM linear, SVM quadratic, SVM cubic, SVM Gaussian, and ensemble bagged trees were utilized. The results are presented in Table 6.

It can be observed that the LDA achieved the highest classification accuracy of 90.6% between the 2 groups (positive-based vs fear-based).

5 Discussion

The results obtained during the experimental campaign were aimed at answering the RQs defined in the introduction section. The discussion will first examine the impact of the CVR on drivers' attitudes and behavior, followed by an analysis of which of the two experiences had a greater impact on the participants. Finally, the effects on self-evaluation of UX and physiological responses are analysed to determine which CVR approach (i.e., fear-based or positive-based) had the strongest impact. Section analyses the results related to RQ1, RQ2, and RQ3 in detail, while Sect. 5.2 focuses on the results related to RQ4 and RQ5. It should emphasize that all these results refer to young drivers. A brief mention of the limitations of the study is provided in Sect. 5.3.

5.1 Attitudes towards traffic safety and behavioral analysis

Regarding RQ1, results suggest that CVR technology could be *an effective tool for influencing positive driving attitudes and behaviors, and such an influence persists during the follow-up investigation.*

The analysis of ATTS and DBQ scores provided statistically significant evidence that participants were significantly influenced by the immersive experience of watching 360° videos with CVR technology. This result supports the experimental findings in the existing scientific literature, which hypothesize that CVR, thanks to the first-person perspective, allows users to perceive their experience as active participants and/or protagonists (Tong et al. 2021; MacQuarrie et al. 2017; Aitamurto et al. 2018; Szita et al. 2018), thus promoting emotional engagement. This immersive engagement is crucial as it enhances the sense of presence—a psychological state in which the individual is physically present in the VE, rather than merely observing it (Witmer and Singer 1998; Kraft et al. 2023). Furthermore, the immersive qualities of CVR also play an important role in fostering empathy (Schutte and Stilinović 2017), a multicomponent positive characteristic with both cognitive and affective dimensions (Davis 1983). The affective aspects of empathy include experiencing another's feelings and having an appropriate emotional response to their situation (Batchelder et al. 2017), while the cognitive aspects involve understanding another person's perspective. In this experiment, CVR's ability to immerse individuals in a first-person perspective allowed users to make deep connections with the experiences of other vehicle occupants, enabling them to simulate emotional and cognitive responses as if they were their own. All these aspects could have contributed to an increased awareness of the consequences of risky driving behavior, thereby influencing participants' responses, leading to an increase in ATTS scores, which measure attitudinal shifts, and a reduction in DBQ scores, associated with risky driving behaviors. These changes were observed consistently across both participant groups immediately following the CVR experience. Such findings underscore the potential of immersive technologies not only to engage users but also to positively influence their attitudes and behaviors in ways that can be beneficial for applications such as driver training, behavioral interventions, and risk awareness programs. The impact of CVR on these parameters thus suggests that immersive video content could play an important role in modifying both attitudes and behavioral responses.

Regarding RQ2 and RQ3, the obtained results reinforce the scientific basis of the literature by demonstrating the greater effectiveness of the fear-based approach compared to the positive one. Both the ATTS and the DBQ scores confirm these statements. In particular, the ATTS scores show statistically significant differences between the two approaches in the post-test condition, as well as in the follow-up one, with a higher score of the fear-based group compared to the positive one. Regarding the DBQ questionnaire, the fear-based group obtained a lower score compared to the positive one in the follow-up condition, with a statistically significant difference with respect to the pre-test condition. These results are in contrast with the portion of the literature findings (Cutello et al. 2021; Yaoshan et al. 2011) showing that the fear-based approach fails to decrease risky behaviors while driving. The findings of this study, instead, suggest that the fear-based approach in CVR significantly influences attitudes toward traffic regulations and promotes safer driving behaviors. Notably, these effects persist in a two-week follow-up assessment, underscoring the CVR intervention's potential for lasting impact. This enduring effect could be partially explained by the role of episodic memory (Baddeley 2001), a key component of long-term memory that enables individuals to recall specific events, including the emotions and sensory details associated with them. By immersing participants in a first-person perspective, CVR creates highly vivid and emotionally charged experiences, particularly in scenarios involving life-threatening outcomes such as road traffic accidents. These experiences are more likely to be encoded as episodic memories, which include not only the sensory and contextual details of the scenario but also the associated fear and heightened awareness of the consequences of risky driving. Such intense and immersive experiences could have prompted participants to engage in a process of critical reflection on how their driving behaviors could lead to similar situations in real life, further reinforcing their awareness and motivation to adopt safer driving habits. Indeed, research on episodic memory highlights its ability to influence future decision-making by allowing individuals to mentally "revisit" past experiences and integrate them into their behavior (Baddeley 2001; McLelland et al. 2015). The outcomes of this study are also consistent with previous research in this area, emphasizing the effectiveness of fear-based media in capturing attention and heightening awareness of the dangers associated with unsafe driving (Lewis et al. 2007a). Such an approach seems to have a strong influence on behavioral intentions and promotes sustained positive changes in driving practices (Yaoshan et al. 2011).

5.2 User experience and impact on physiological state

With regard to RQ4, the study provides interesting results on the impact of the CVR experiences on the reaction and physiological state of the users. Only the VRSQ scores of the positive-based group demonstrated statistically significant levels of simulation sickness induced by the CVR experience. In contrast, the fear-based group showed no statistically significant symptoms. It is possible to hypothesize that this difference in results may be related to the differences in the dynamism of the visual in the two experiences.

In the positive-based video, participants are exposed to a calm, uneventful car journey, during which they adopt the role of a passive passenger. The car remains in motion throughout the entire video, in contrast to the fear-based video, where the vehicle comes to a stop due to the accident. This continuous movement in the positive-based scenario prolongs the exposure to visual motion cues. This prolonged dynamic visual input may create a stronger difference between what participants see and their physical sensations of stillness, potentially increasing the likelihood of simulation sickness. Conversely, in the fear-based video, the stationary perspective during the rescue operations could lessen sensory conflicts and the onset of simulation sickness symptoms, despite the emotionally intense content. The different levels of immersion and engagement elicited by each type of video content appear to influence participants' susceptibility to VR-induced sickness, highlighting the importance of content type in designing CVR experiences.

Alongside the VRSQ, the RQ4 was also examined by analyzing the results of the UEQ, specifically in terms of both pragmatic and hedonic aspects of the UX. The findings indicated that the pragmatic quality of the experience was significantly influenced by the type of intervention implemented. More specifically, the analysis suggested that participants perceived the fear-based approach as more useful compared to the other interventions. This could be attributed to the higher emotional impact related to the fear-based scenario in the CVR experience. The more intense and potentially alarming situation could have activated threat-related cognitive pathways, as also reflected in the physiological responses presented in the following paragraphs, triggering and increasing a sense of risk awareness. It led to prompting users to significantly reconsider their behaviors while driving. This aligns with previous research, which has demonstrated that fear-based interventions can enhance users' perception by increasing their engagement with safety-related behavior (Lewis et al. 2007a; Tay and Watson 2002). On the other hand, the analysis of hedonic quality revealed no significant differences between the two 360° video interventions. Participants in both groups perceived the emotional appeal of the experiences similarly. This lack of variance in hedonic quality could stem from the inherent design characteristics of the two interventions. Despite their contrasting emotional tones—fear-based versus positive-based —the core design elements of both treatments were likely equally effective in generating interest in the new technology. It is important to highlight that 45.26% of participants, as evidenced in the demographic questionnaire results, were novices to CVR technology and its applications, which may have contributed to a more neutral or generalized response to the emotional appeal of the interventions.

The acquisition and analysis of participants' ECG signals enable a deeper investigation of RQ4; furthermore, it provides a means to answer RQ5 by determining which of the two CVR experiences —fear-based or positive-based— exerts a more pronounced physiological impact on the study's participants.

The comparative analysis between the rest phase and the test phase indicates that the CVR experience yields statistically significant effects on individuals' physiological responses for both groups. As illustrated in Fig. 6a–d, examining key ECG-extracted features across both the time and frequency domains reveals substantial. More in detail, it is possible to see that for both groups there is an increment of the HRm parameter as well as the LF/HF one for the fear-based group during the test condition. In addition, it can be observed a reduction in RMSSD and pNN50 values. All these trends correspond to an increased level of stressful conditions for the participants. These significant variations in physiological features confirm that exposure to 360° videos within CVR environments can induce a notable shift in users' physiological states, showing elevated stress levels in comparison to the baseline condition.

This finding aligns with prior research (Deniaud et al. 2015; Wiederhold et al. 2001), which suggests that the level of immersion in VEs directly correlates with physiological responses. This research supports the claim that increased sensory immersion in CVR environments enhances physiological arousal, highlighting the influence of varying emotional content (e.g., fear-based versus positive-based stimuli) on user experiences and physiological indicators.

Indeed, the fear-based experience shows a more impactful effect on participants' physiological responses when compared to a positive-based approach. As illustrated in Table 4 (b), several HRV parameters obtained for the fear-based group—including SDNN, HR_{std}, DFA α_1, and DFA α_2—display significant reductions. Additionally, there is a marked increase in other parameters, such as NN50 and the LF/HF ratio. These outcomes underscore statistically significant differences from the positive-based condition, highlighting elevated stress levels induced by the fear-based stimuli and their consequent impact on participants' physiological and psychological state throughout the CVR experience. These results align with the existing scientific understanding that HRV metrics can be considered as reliable indicators of arousal and stress. For example, reductions in SDNN and DFA α1, as well as an increase in LF/HF ratio, are related to physiological responses associated with stress activation in both laboratory and real-world settings (Kim et al. 2021; Heart and rate variability Standards of measurement, physiological interpretation, and clinical use. xxxx). The LF/HF ratio actually represents the balance between sympathetic and parasympathetic activity, and when it increases, there is a sympathetic dominance during stress responses. Moreover, DFA parameters are also stress and autonomic dysregulation indicators. Lower DFA values correspond to a breakdown in complex heart rate dynamics commonly linked to stress states (Shaffer and Ginsberg 2017). The features used lead to a best-yielded classification accuracy of 90.6% which introduces a good data separability between the 2 groups. These findings suggest that fear-based stimuli significantly affect autonomic functioning and stress responses, likely due to the heightened sense of presence and emotional engagement elicited by CVR environments (Chirico et al. 2017). The elevated physiological stress response observed in the fear-based group could also account for their improved attitudes and behaviors toward traffic safety. Therefore, experiencing a highly realistic scenario from a first-person perspective appears to induce a controlled emotional impact.

Finally, the use of CVR technology demonstrates a capacity to modulate physiological responses in alignment with the nature of the experienced scenario. It can be used as an effective tool for evoking autonomic reactions comparable to those encountered in real-life high-stress or threatening situations, making it a valuable instrument for education and behavioral intervention in contexts such as traffic safety.

5.3 Limitations and future improvements

The present study has several limitations that should be considered in future research. Firstly, the participant sample was restricted to high school students from Bari and undergraduate students from the Polytechnic University of Bari. In future studies, the authors intend to expand the sample pool by including participants from diverse cultural and educational backgrounds to enhance the generalizability of the findings. In addition, the evaluation of driving attitudes and behaviors relied only on self-reported questionnaires. To more accurately assess risky driving behaviors, future studies should incorporate real-world driving sessions over extended periods to evaluate whether CVR's impact on behavior is retained over time. Additionally, to make the effectiveness of CVR technology reliable, future experimental designs should include a control group that receives the same messages via non-immersive platforms, such as desktops or smartphones, to facilitate a direct comparison of immersive and non-immersive methods. Moreover, HRV analysis, while valuable, is not the only physiological measure available for assessing stress responses. As suggested in the scientific literature (Giannakakis et al. 2022), other objective measures, such as skin conductance through GSR or eye-tracking during task engagement, can offer further insights into physiological and emotional responses. Integrating these additional metrics with HRV could provide a more reliable and comprehensive understanding of participants' engagement levels and stress reactions throughout the CVR experience.

6 Conclusions

The education of younger generations on traffic safety regulations and responsible driving behaviors is a crucial priority for modern societies committed to reducing the high incidence of road traffic accidents. Addressing this issue requires innovative approaches that effectively engage novice drivers and foster adherence to road safety norms.

This study explores the potential of immersive technologies, with a particular focus on CVR, as a transformative tool for enhancing attitudes and behaviors aligned with traffic regulations. By leveraging immersive 360° video experiences that simulate the outcomes of risky driving behaviors, this research evaluates the comparative effectiveness of fear-based and positive-based scenarios in improving road safety awareness. Specifically, the key findings of this study can be summarized as follows:

- behavioral improvements, thanks to data collected through validated tools such as the ATTS and DBQ that reveal a statistically significant positive shift in participants' respect for traffic laws after exposure to CVR scenarios;
- fear-based approach superiority since it demonstrated more effectiveness than the positive-based one, as evidenced by its sustained impact on participants' attitudes even two weeks after the intervention, according to the follow-up analysis;
- positive evaluation of the UX since participants generally indicated satisfaction with the CVR experience, even though the positive-based group showed side effects of simulation sickness related to the use of a HMD device.
- significant variations in physiological responses, highlighting the capacity of CVR to elicit distinct emotional and physical reactions. These results suggest a strong correlation between the type of immersive scenario and the user's physiological engagement.

Overall, the study demonstrates the substantial potential of CVR technology as an educational tool for promoting safer driving behaviors among young drivers. By simulating the real-life consequences of unsafe driving practices within a controlled and risk-free environment, CVR provides an impactful means of fostering traffic law adherence. Furthermore, the observed influence of CVR on both psychological and physiological responses underscores its value as an innovative and effective strategy for inclusion in driver safety education programs.

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Data availability Data will be made available on reasonable request.

Declarations

Conflict of interest The authors declare no competing interests.

Ethical approval All procedures followed were in accordance with the ethical standards of the responsible committee on human experimentation of the Polytechnic University of Bari (Italy) and with the Helsinki Declaration of 1975 (in its most recently amended version).

Informed consent Informed consent was obtained from all individual participants involved in the study.

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