Evaluating the Need for Additional Noise in Autonomous Electric Vehicles: A Virtual Reality-Based Study

A virtual reality research for analyzing the safety and comfort of cyclists interacting with autonomous electric vehicles: Is an additional noise needed?

Master Thesis

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A virtual reality research for analyzing the safety and comfort of cyclists interacting with autonomous electric vehicles

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Preface

This study, titled "A Virtual Reality Research for Analyzing the Safety and Comfort of Cyclists Interacting with Autonomous Electric Vehicles: Is an Additional Noise Needed?" has been completed as the final project for my Master's degree in Transport and Planning at Delft University of Technology.

I would like to extend my heartfelt gratitude to Haneen Farah for guiding me in defining the specific direction of my research and for always making time to offer advice and assistance throughout the process. I am also deeply grateful to Yan Feng, my daily supervisor, for the regular face-to-face meetings that provided invaluable support and allowed me to plan each step effectively. Their contributions were instrumental to both my experiment and my thesis. The insights they provided helped me gradually understand the nature of academic research, and their meticulous attention to detail greatly enhanced my writing by addressing logical and structural aspects of my work.

A special acknowledgment goes to Zhenlin Xu for his invaluable assistance during the modeling phase with Unreal Engine, where he helped me overcome numerous technical challenges. I also want to thank Yiman Bao, Yining Chen, Honghao Zhao, and others who generously dedicated their time to participate in my experiment during the summer. Without their involvement, this research would not have been possible.

Lastly, I hope that this study contributes meaningfully to the field of traffic safety in autonomous driving, facilitating the safer and more comfortable integration of autonomous vehicles into future road systems.

Yixin Sun
Delft, November 2024

Summary

Introduction:

In recent years, the advancement of autonomous driving and electric vehicle technology has significantly impacted urban mobility. Although these vehicles promise a cleaner and safer transportation system, new challenges remain in understanding their interactions with vulnerable road users, such as cyclists.

According to the 2014 EU legislation, electric vehicles (EVs) are required to install Acoustic Vehicle Alerting Systems (AVAS) to convey information to other road users through sound signals, ensuring their safety. At the same time, autonomous vehicles (AVs) are also recommended to be equipped with external Human-Machine Interface (eHMI) systems to promote better interaction with other road users. However, for the specific category of autonomous electric vehicles (AEVs), the continued requirement for both AVAS and eHMI systems may appear redundant in terms of functional deployment and inefficient in terms of resource use. Therefore, it remains unclear whether AEVs can rely solely on visual eHMI to communicate with road users, thus eliminating the need for AVAS, or if a simple sound signal can replace AVAS. This study aims to investigate how an additional auditory alert system in AEVs equipped with visual eHMI affects the objective and subjective safety of cyclists.

Against this background, I conducted research at the Mobility in eXtended Reality Lab at Delft University of Technology to explore whether additional warning sound systems are necessary in AEVs to enhance the safety and comfort of cyclists. The study emphasizes the importance of using immersive virtual reality (VR) technology to simulate real traffic environments for precise behavioral analysis.

Research gap and research questions:

Existing research has thoroughly demonstrated the need for adding AVAS systems to electric vehicles when driving at low speeds to ensure they can be detected in a timely manner by other vulnerable road users. In the field of autonomous driving, eHMI has also been considered effective in many studies for communicating information to other road users and reducing the rate of traffic accidents(Wu et al., 2024). Although existing studies have explored pedestrian safety and interactions with autonomous vehicles, research specifically focusing on interactions between AEVs and cyclists remains limited. Cyclists face unique risks due to their higher speeds and to, on some types of roads, sharing the space with vehicles. The quieter engine noise of AEVs at low speeds makes them harder to detect compared to conventional vehicles, and the absence of human driver control may further exacerbate the risks faced by cyclists. This study aims to fill this gap by posing the following main question: How does an additional auditory alert system in autonomous electric vehicles equipped with visual eHMI affect cyclists' behavior, comfort, and safety under different types of idling vehicles and environmental noise?

To answer the main research question the following sub-questions were defined:

- In the absence of additional auditory alerts, is there a difference in cyclists' perception abilities and behavior between autonomous vehicles (AVs) and autonomous electric vehicles (AEVs) equipped with the same electronic human-machine interface (eHMI) system?
- How does the additional auditory alert system to AVs and AEVs affect cyclists' perception abilities and behavior ?

- Does the environmental noise level of an area influence the perception abilities of cyclists towards different types of vehicles equipped with the same eHMI system?

Research Methods:

A controlled experimental approach was adopted in this research, using VR technology to create an immersive environment that simulates real traffic conditions. This allowed to study the impact of different variables on the interaction between cyclists and AEVs in various scenarios. In this experiment, a simulated test environment was created using Unreal Engine, focusing on observing participants (acting as cyclists) as they responded to different variables. These variables included different levels of environmental noise, the warning distance of sound signals emitted by autonomous vehicles, and the autonomous vehicles themselves.

Data was collected in two forms: one objective dataset containing participants' time, speed, and position, and another subjective dataset obtained through post-experiment questionnaires, reflecting participants' perceptions of trust, safety, and comfort. The participants consisted of 40 individuals with diverse ages ranging between 23 to 49 years old, from both genders (32 male; 8 female), and cycling experiences. Data was collected using a within-subject design to minimize individual differences and ensure robust results. The dual approach of analyzing subjective survey data and objective data using Linear Mixed Model (LMM) analysis provided a comprehensive understanding of cyclists' perceptions and behaviors under different auditory and visual conditions.

Results:

The research results indicate that cyclists' comfort and feeling of safety vary significantly depending on the auditory and visual cues provided by AEVs. Based on the objective behavioral data collected from participants and the subjective feedback from questionnaires, AEVs equipped with additional alert systems and visual eHMI showed significant advantages in terms of safety and comfort compared to those equipped only with visual eHMI.

In terms of safety, the results of the Linear Mixed Model (LMM) analysis indicate that AEVs equipped with an additional alert system consistently showed significant effects across various scenarios. Specifically, participants were able to notice these vehicles earlier and respond more quickly when encountering AEVs with the additional alert system. This demonstrates that adding extra auditory signals can help participants detect potential hazards earlier, providing them with more time and distance to react, thereby effectively reducing traffic risks. The questionnaire results further supported this finding, showing that participants agreed that AEVs with the additional alert system gave them a stronger sense of safety after the experiment.

In terms of comfort, the results of the LMM analysis show that AEVs equipped with an additional alert system allowed participants to respond in a less abrupt manner compared to those without the system. This was particularly evident in the smoother deceleration observed when interacting with AEVs equipped with the additional alert system, as opposed to the more abrupt deceleration associated with other vehicles. This indicates that participants were better able to assess the situation and make more natural and comfortable responses based on their own judgment, thus avoiding the stress or discomfort caused by sudden reactions.

Conclusions and Implications:

The research concluded that equipping AEVs with additional auditory warning systems plays an important role in enhancing the safety and comfort of cyclists. This measure can mitigate the traffic safety risks associated with AEVs in busy urban environments. This study provides valuable insights for the future optimization and development of autonomous driving technology, further proving the critical role of sound warning systems in enhancing road safety and improving the overall user experience. Therefore, adding the sound signal to AEV with eHMI is not redundant, but have an added value. These findings are significant for policymakers, vehicle manufacturers, and urban planners in designing safe transportation systems that cater to all road users. Future research should further explore the effectiveness of different types of warning sounds and the interactions between AEVs and vulnerable road users under various real traffic conditions to optimize the sound warning systems.

Contents

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Introduction

1.1 Research Background

As technology progressed, it was expected that autonomous vehicles (AVs), with their advanced sensors and algorithms, would reduce human driving errors and lower traffic accident rates (Muhammad et al., 2021; Fu et al., 2022; Bachute & Subhedar, 2021). They offered convenience to mobility-impaired groups such as the elderly and disabled, making travel easier (Harper et al., 2016). Additionally, AVs improved road usage efficiency and reduced traffic congestion through more orderly and dense driving patterns, thereby optimizing overall traffic flow (Garg et al., 2021; He et al., 2022; Chen et al., 2023). Meanwhile, as people increasingly focused on environmental protection and sustainable development, concerns rose about the rapid increase in car ownership and the resultant vehicle exhaust pollution's impact on the environment. In this context, Electric Vehicles (EVs) gradually entered the automotive market. As new energy vehicles, EVs used electricity instead of traditional fossil fuels, effectively reducing the environmental impact of vehicle emissions. Moreover, EVs, by using electric motors instead of internal combustion engines, significantly addressed the issue of car noise during peak urban traffic periods (Verheijen & Jabben, 2010; Sadek, 2012). However, EVs still faced many challenges, such as insufficient battery range compared to traditional cars, preventing long-distance travel (Greaves, Backman, & Ellison, 2014), a lack of charging infrastructure making it difficult to find charging stations (Funke, Sprei, Gnann, & Plötz, 2019; Gnann et al., 2018), and safety concerns from other road users due to EVs' low noise, making them harder to detect (Pallas et al., 2015; Hoogeveen, 2015).

When AVs and EVs were practically implemented, considerations of their safety interactions with other road users became a focal point. In the electric vehicle field, engine noise had been a key concern (Pallas et al., 2015). The noise produced by a car primarily comprised tire friction noise, aerodynamic noise, and engine noise. At low speeds, engine noise was the main source, while at high speeds, friction and aerodynamic noises became predominant (Kim et al., 2013). Electric vehicles, compared to traditional cars, used electric motors instead of internal combustion engines, eliminating noise caused by combustion and mechanical movement in internal combustion engines. This made them much quieter at low speeds than traditional cars (Parizet et al., 2014). The significantly lower noise levels at low speeds made them less noticeable to other road users in urban areas, potentially creating safety issues (Pallas et al., 2015). In response, countries worldwide introduced related legislations. The European Parliament approved a regulation in April 2014 requiring all new electric and hybrid electric vehicles to be fitted with an AVAS (Regulation (EU) No 540/2014).

In addition to the noise issues of EVs, the introduction of AVs also faced challenges in communicating with other road users. In this field, the application of external Human-Machine Interfaces (eHMI) significantly improved the safety interactions between autonomous vehicles and other road users (de Winter & Dodou, 2022; Lim, Kim, Shin, & Yu, 2024). With the help of eHMI, other road users could more intuitively understand the behavior of autonomous vehicles (Othersen et al., 2018; Alhawiti et al., 2024). Numerous experiments showed that autonomous vehicles equipped with eHMI were perceived as safer (Ackermans et al., 2020; Sadeghian et al., 2020). Furthermore, research found that autonomous vehicles equipped with eHMI provided pedestrians with a sense of safety and trust similar to that of human-driven vehicles (Faas et al., 2020; Joisten et al., 2020).

The eHMI system communicates with road users through various types of signals, such as text, patterns, light signals, and sound signals, providing them with more intuitive information so that they can make quick and accurate judgments (de Clercq et al., 2019). This improves the visibility and interactivity of autonomous electric vehicles in complex traffic situations (Chauhan et al., 2023; Hensch et al., 2019). Meanwhile, the AVAS system primarily adds noise to ensure that drivers can hear the vehicle approaching at low speeds, similar to traditional combustion engines, where pedestrians are warned by the engine's presence (Fabra-Rodriguez et al., 2021). It is important to note that concerns have been raised about the lack of differentiation between the functions of these two systems, which could lead to unnecessary resource consumption and potentially cause road users to receive multiple or redundant signals from different driver assistance systems, thereby extending reaction times and increasing potential safety issues.

For all vulnerable road users, cyclists were not only a popular mode of transportation but also a group that deserved special attention due to their vulnerability (Kareem, 2003). However, compared to pedestrians, cyclists were often overlooked, although everyone's safety was equally important. Because bicycles moved at higher speeds, cyclists had less time to react and make decisions when faced with sudden situations than pedestrians (Evtyukov, S. et al., 2021). Additionally, when cycling at high speeds, wind noise could cause cyclists to miss auditory signals from other road users (such as cars accelerating/decelerating, or tire friction on the road), which placed them in unsafe situations (Stefánsdóttir, 2014). Therefore, given the popularity of cycling and the safety risks they faced, research results targeted at pedestrians could not be directly applied to cyclists, and more attention needed to be given to ensuring cyclists' safety.

Some studies published in 2023 proposed and validated that using eHMI in autonomous vehicles could replace driver information, and artificial sounds could compensate for the engine noise in electric vehicles, playing important roles in pedestrian safety perception (Fass, S. M., & Baumann, M. 2021). In 2021, a predictive model for a Mechanical Acoustic Vehicle Alerting System (MAVAS) was introduced to improve the detectability of electric vehicles while complying with European standards (Fabra-Rodriguez, M. et al., 2021). Additionally, research in 2023 summarized various eHMI systems related to bicycles and cyclists, explaining different modes of information interaction and their carriers (Berge, S. H. et al., 2023). However, despite significant progress in understanding eHMI systems, research on whether autonomous electric vehicles should be equipped with AVAS systems remained limited, highlighting a gap that needed to be addressed.

1.2 Problem Definition

Although previous research made significant progress in exploring how eHMI enhanced the interaction safety between cyclists and AVs (Berge et al., 2022, 2023; Carmona et al., 2021), and studies also focused on improving the detectability of EVs (Fabra-Rodriguez, M. et al., 2021), there remained a research gap: whether AEVs needed to be equipped with an Acoustic Vehicle Alerting System (AVAS). Most current studies focused solely on EVs or AVs individually, without fully addressing the unique challenges posed by the combination of these two technologies. This was particularly important in urban environments, where safety concerns were more pronounced, and the need for a tailored AVAS system for AEVs had not been thoroughly investigated.

The direct aim of this study was to determine whether AEVs needed to be equipped with an additional sound warning system to ensure the safety and comfort of cyclists. To achieve this, the study used virtual reality technology to simulate experiments in a realistic urban environment, ensuring controlled experimental conditions and participant safety.

Through experiments and surveys, this study collected both subjective and objective data and applied a Linear Mixed Model (LMM) to conduct a step-by-step analysis of key target variables, examining the differences in the effects of vehicle noise, environmental noise, and the activation distance of eHMI on cyclists. Based on the collected experimental data, the study further explored whether AEVs should be equipped with an AVAS system and its potential impact on cyclist safety.

1.3 Research Objective

To more comprehensively explore whether it is necessary to equip AEVs with an AVAS, this study aims to analyze in depth the functional overlap between the eHMI and AVAS systems and their potential impact, examining whether AVAS can be omitted on AEVs already equipped with visual signal eHMI. The goal of this research is to evaluate whether it is possible to optimize system configurations to reduce resource waste and lower production costs without compromising road safety. Current electric vehicle regulations require vehicles to be equipped with an AVAS system to ensure that they can be detected by other road users in low-noise environments through audio signals, while autonomous vehicles rely on the eHMI system to communicate with pedestrians, cyclists, and other road users. However, with the convergence of autonomous driving technology and electric vehicles, AEVs, as an emerging mode of transportation, a question arises of whether an AVAS is needed when the AVs have also eHMIs, or if that would be redundant.

Thus, this research will carry out a VR experiments (especially with special audio signals) to demonstrate if the AVAS system is redundant when an eHMI system is present in an AV or a simple alarm signal would produce the same safety effect. The intention of this research is to support the development and manufacturing of AEVs based on scientific data and evidence base, both for regulators and manufacturer that need to find the best trade-off between traffic safety and costs. This research will contribute to the development of this emerging technology.

1.4 Research Question

Main research question:

How does an additional auditory alert system in autonomous electric vehicles equipped with visual eHMI affect cyclists' behavior, comfort, and safety under the influence of different types of idling vehicles and environmental noise?

Sub-questions:

(1) In the absence of additional auditory alerts, is there a difference in cyclists' perception abilities and behavior between autonomous vehicles (AVs) and autonomous electric vehicles (AEVs) equipped with the same electronic human-machine interface (eHMI) system?

(2) How does the additional auditory alert system to AVs and AEVs affect cyclists' perception abilities and behavior ?

(3) Does the environmental noise level of an area influence the perception abilities of cyclists towards different types of vehicles equipped with the same eHMI system?

1.5 Research method

The interactions between cyclists and autonomous vehicles (AVs and AEVs) equipped with visual eHMI were studied in a virtual reality environment under different levels of environmental noise and with/without an additional auditory alert system. This study aimed to understand how additional auditory alerts impacted cyclists' attention, perception, and safety when identifying and judging changes in their environment. VR was chosen over real-life experiments because it allowed for an in-depth investigation of reactions and behaviors in complex traffic environments while ensuring participant safety (Ali et al., 2020; Alhawiti et al., 2024). Additionally, VR enabled the simulation of realistic scenarios under controlled experimental conditions (Katrakazas et al., 2015; Tatler et al., 2019), providing deeper insights into how these alert systems enhanced cyclists' safety and comfort.

This study used the Unreal Engine to create a realistic virtual experimental space to achieve this goal. The virtual environment included city streets (i.e., the experimental roads, which were detailed in section 3.2 Virtual Environment), vehicles, buildings, and environmental sound effects. To create an authentic auditory experience, different audio files were carefully selected from multiple sources, including idle sounds of electric and traditional fuel vehicles, urban background noise, and warning signals, and were integrated into the environment. These sounds were configured in the VR simulation to ensure that the auditory experience closely matched real-world conditions.

The experiment was conducted in the MXR lab, which is equipped with high-performance computers, HTC VIVE Pro Eye VR headsets, and a newly developed virtual reality cycling simulator from the MXR lab, providing a fully immersive experience. Using these tools, participants could enter the virtual world, cycle, and experience multiple simulated scenarios.

For the experiment, I recruited between 30 and 40 participants, representing diverse age, gender, and cycling experience characteristics to ensure the generalisability of the experimental findings. Real-time trajectory data — cycling paths and speed adjustments from participants were collected during the experiment. This data allowed us to assess the impact of additional auditory warning systems on cyclists' ability to detect vehicles as well as their perceptions of safety.

After finishing the experiment, each participant was asked to fill out a detailed questionnaire, which was used to collect qualitative data. This questionnaire included the participants' subjective preferences regarding additional auditory warning systems, their safety feelings during the experiment, and their acceptance of this new system, which might be used in future autonomous electric vehicles. These qualitative results provided valuable information to better understand the potential impact of auditory warning systems in real-world applications and public acceptance.

This research aimed to propose that the outcomes of this holistic research endeavor would partly be used to establish the scientific evidence required for designing and implementing assisted/autonomous electric vehicles, with an emphasis on external auditory warning systems to improve road safety. It was believed that this research would not only help improve current regulations regarding automotive safety but also facilitate the broader adoption and development of autonomous driving technologies.

1.6 Experiment conceptual framework

The conceptual model of this project is shown in the figure. The main target of the study is to explore whether it is necessary to add an additional auditory alert system to AEVs that are already equipped with visual eHMI to enhance the safety of cyclists during interactions with AEVs. Among the potential variables that may affect the information interaction between cyclists and AEVs, I selected environmental noise level, signal trigger distance, and vehicle type as the main variables. The specific experimental design is described in the methodology section (Section 3). The subjective and objective results collected from the virtual reality experiment and the questionnaire will be evaluated in terms of safety and comfort to address our research question.

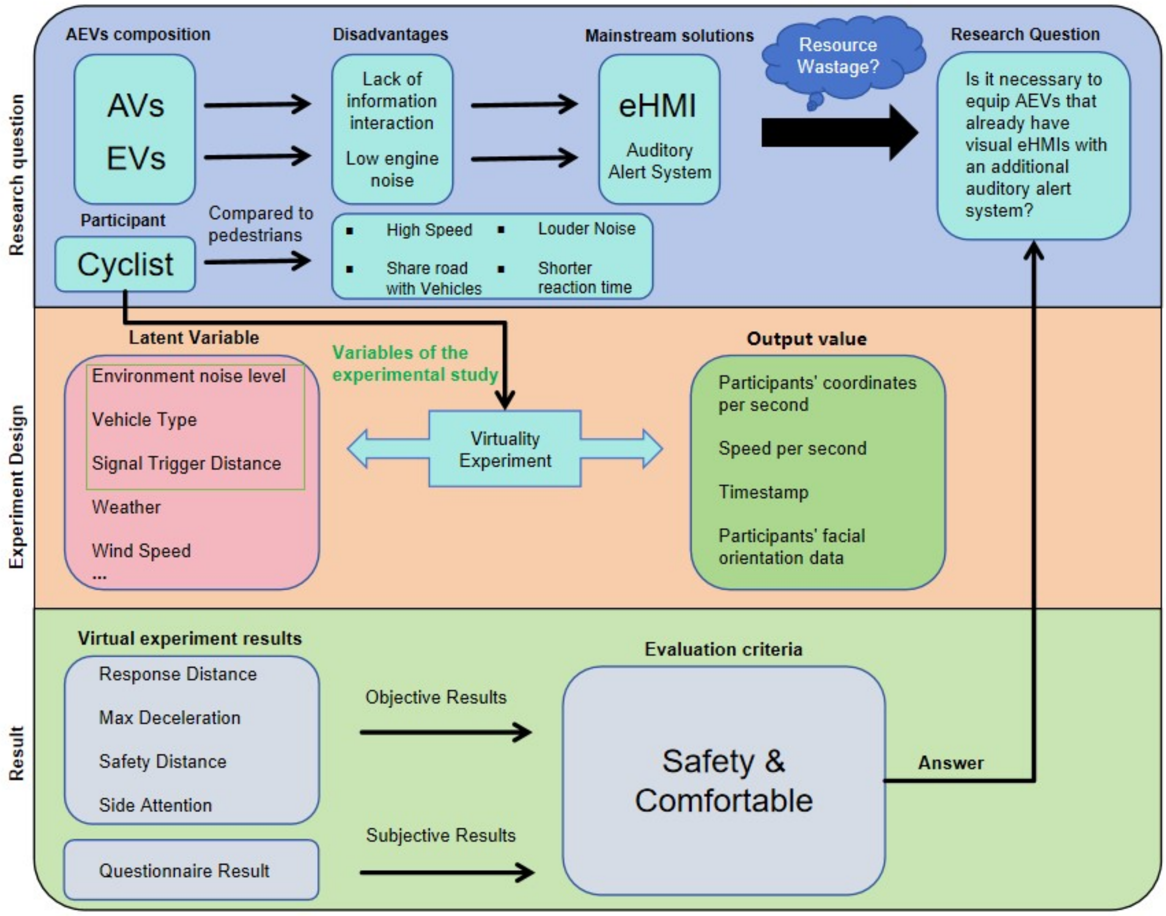

Figure 1 Experiment conceptual framework

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Literature Review

Autonomous Electric Vehicles (AEVs) represent the integration of Autonomous Vehicles (AVs) technology and Electric Vehicles (EVs) technology. Although both AVs and EVs technologies are advancing rapidly, and there is extensive research on each individually, comprehensive studies on AEVs—particularly focusing on how to ensure they can effectively communicate with other road users in traffic environments while maintaining safety — remain limited. Ensuring safety while combining these two advanced technologies presents unique challenges. Research specifically focusing on AEVs is relatively scarce, likely because they involve the integration of two cutting-edge fields. However, given the potential safety and operational benefits that AEVs offer by combining the features of both AVs and EVs, understanding the specific research gaps and challenges related to traffic safety in these areas is crucial for the successful implementation and broader adoption of AEVs.

The literature review in this chapter aims to provide a comprehensive understanding of the impact of the integration of AVs and EVs technologies (AEVs) on cyclist safety. Section 2.1 begins by examining the unique challenges cyclists face as vulnerable road users in urban environments. Sections 2.2 and 2.3 then analyze the current state of AVs and EVs in terms of traffic safety. Following this, Section 2.4 discusses the role of eHMI in enhancing communication between AVs and other road users, emphasizing their potential to bridge communication gaps. Sections 2.5 and 2.6 address specific safety considerations related to AVs and EVs concerning cyclist safety, focusing on their advantages and limitations. Finally, Section 2.7 summarizes the main findings and highlights key research gaps.

2.1 Introduction to Cyclist safety

In the field of urban traffic safety research, the interaction between motor vehicles and vulnerable road users, such as pedestrians and cyclists, is often the primary focus. Numerous researchers have explored the urban traffic safety issues of these groups from various perspectives. For example, by analyzing factors such as urban road layouts, population density, national policies, and non-motorized vehicle infrastructure (Passoli et al., 2024; Mukherjee & Mitra, 2022; Maghanga, Onkware, & Wasike, 2024), they have proposed several optimization strategies to reduce the occurrence of traffic accidents. These strategies include reducing vehicle speeds, creating dedicated zones for cyclists and pedestrians, and raising public awareness through traffic safety education (Eric Dumbaugh & Li, 2010; Pucher & Dijkstra, 2000).

Among vulnerable road users, cyclists face more severe safety risks compared to pedestrians. This is because cyclists typically travel at higher speeds, which results in shorter reaction times and less decision-making space. Additionally, the risk of collision increases with higher speeds, and injuries tend to be more severe. During cycling, factors such as wind noise and friction sounds from the bike can also affect cyclists' attention, making them face more challenges in complex urban road environments (Billot-Grasset, Amoros, & Hours, 2016). Moreover, cyclists tend to sustain more serious injuries in collisions with vehicles compared to pedestrians (Wisch et al., 2017; Mackay, 1975). Studies have shown that in such accidents, cyclists often fall after being thrown off their bicycles, and during the slide, they are prone to severe injuries such as fractures or head trauma (Mackay, 1994). In contrast, pedestrian injuries are typically caused by head impact with the ground, whereas cyclist injuries often result from falling off the bike, leading to greater bodily harm (Mesimäki & Luoma, 2021).

In addition, several studies have highlighted the risks cyclists face in interactions with motor vehicles. A study by Macioszek and Granà (2022) emphasized that key factors affecting the severity of injuries sustained by cyclists in road accidents include the driver's age, alcohol consumption, vehicle speed, and the type of vehicle involved. The research revealed that larger vehicles, such as trucks, significantly increase the risk of severe injuries. Environmental factors, such as poor visibility, road conditions, and cyclists' speed, further exacerbate the potential for injury. Since cyclists are unprotected vulnerable road users, these factors considerably heighten the likelihood of injury in collisions. The study underscores the need for improving urban infrastructure and implementing policy measures to address these risks and ensure the safety of cyclists on the road.

Johnsson et al. (2021) focused on cyclist-motor vehicle interactions at intersections, particularly looking at surrogate measures of safety such as minimum time to collision (MTTC) and post-encroachment time (PET). Their study found that the proximity of cyclists to motor vehicles in terms of space and time significantly correlates with the likelihood of crashes. Specifically, environments where motor vehicles turn left or right across cyclists' paths, especially at intersections with simultaneous green lights for cyclists and vehicles, increase the risk of collision(Johnsson, Laureshyn, & D'Agostino, 2021).

Furthermore, their analysis revealed that the use of larger vehicles, like trucks, coupled with complex intersection designs without clear separations for cyclists, significantly heightens crash severity. Johnsson et al. emphasized the need for better traffic signal designs, such as separate phases for cyclists and vehicles, to reduce the frequency of these dangerous interactions

Overall, cyclists, as vulnerable road users, face safety risks not only in interactions with motor vehicles but also in potential conflicts with pedestrians and other road users (Muslim & Antona-Makoshi, 2022). Therefore, future urban traffic planning and policy-making should prioritize the safety needs of cyclists. Optimizing infrastructure and enhancing traffic safety education will help reduce the risk of injury for cyclists in traffic accidents.

2.2 Autonomous Vehicles (AVs) and Safety

In the field of autonomous driving, there are five levels of automation as defined by the Society of Automotive Engineers (SAE). Level 1 is driver assistance, where the vehicle can control either steering or acceleration/deceleration, but not both simultaneously. Level 2 is partial automation, where the vehicle can control both steering and speed, but the driver must remain attentive and monitor the driving environment at all times. Level 3 is conditional automation, where the vehicle can manage all driving tasks under specific conditions; however, the driver needs to be ready to take over when prompted by the system. Level 4 is high automation, where the vehicle can operate fully autonomously within designated areas without driver intervention, though certain situations or areas may still require manual control. Finally, Level 5 is full automation, where the vehicle can independently handle all driving tasks in all environments, entirely without human intervention. This research will focus on Level 5 autonomous vehicles.

Autonomous vehicles, as a new mode of transportation, have gradually become a focal point due to their multiple potential benefits. For instance, autonomous vehicles can effectively reduce human errors, shorten travel times, and lower carbon emissions, bringing a range of advantages to urban transportation systems (Olayode et al., 2023). Through precise algorithms and sensor technology, these vehicles can more effectively plan routes and reduce traffic congestion, especially during peak hours (Katrakazas et al., 2015). This efficient traffic management not only saves time but can also significantly reduce carbon emissions caused by vehicle idling, thereby improving air quality and mitigating climate change (Alexander-Kearns et al., 2016). Moreover, autonomous vehicles offer great potential for reducing traffic accidents. Studies show that most traffic accidents are caused by human errors, such as distracted driving, drunk driving, or fatigue (Easa et al., 2020). By eliminating these factors, autonomous driving technology is expected to significantly lower the frequency of traffic accidents. However, despite the promise these technologies hold for the future of urban transportation, ensuring safe interactions between autonomous vehicles and other road users (such as pedestrians, cyclists, and conventional vehicle drivers) remains a major challenge before widespread adoption.

Several major accidents have raised concerns about autonomous driving technology. In 2016, a Tesla vehicle in Autopilot mode was involved in a fatal accident in Florida. The driver, overly relied on the Autopilot system, failed to take corrective action and collided with a trailer truck crossing the highway, resulting in the driver's unfortunate death (Banks, Plant, & Stanton, 2016). Similarly, in 2018, an Uber autonomous vehicle struck and killed a pedestrian in Arizona. This accident revealed the shortcomings of the technology in complex environments, particularly the system's ability to handle unpredictable factors like pedestrians and non-motorized road users (Stilgoe, 2021).

The primary causes of these accidents are as follows: First, current autonomous driving systems still rely on human supervision, but drivers often develop an over-reliance on the automated systems, neglecting potential hazards on the road. Second, autonomous vehicles exhibit technological deficiencies when dealing with complex road scenarios, such as nighttime pedestrians or sudden obstacles. To address these issues, stricter regulations and testing standards must be established to ensure the safety of autonomous vehicles in real-world traffic environments. Additionally, improving human-machine interaction systems and increasing redundant safety mechanisms, such as external human-machine interfaces (eHMI), are crucial measures to enhance safety (Stilgoe, 2021).

To tackle this challenge, the industry has widely adopted the solution of equipping autonomous vehicles with eHMI to achieve optimal communication and interaction between these vehicles and pedestrians, cyclists, drivers, and other road users. eHMI use visual, auditory, and even tactile methods to convey the vehicle's status and intentions to other road users, thereby enhancing non-verbal communication (Grimm et al., 2012). These interfaces can display text, light signals, or sounds to inform nearby pedestrians and cyclists whether the vehicle intends to turn, stop, or continue moving. This interactive mechanism not only helps reduce the likelihood of traffic conflicts but also increases other road users' trust in autonomous vehicles.

Numerous studies have pointed out that eHMI offer significant advantages in terms of safety, as they compensate for the lack of information typically provided by a human driver(Othersen et al., 2018; Alhawiti et al., 2024; Dey et al., 2020; Faas et al., 2020). By conveying the vehicle's status, intentions, and actions to the external environment, road users can better anticipate the vehicle's movements, leading to a stronger sense of safety and trust — this aspect is also emphasized in Hillis' research.(Grimm et al., 2012; Hillis et al., 2016). Through this system, autonomous vehicles communicate their intentions to road users in an intuitive manner, reducing the likelihood of traffic conflicts and thereby improving overall traffic safety.

2.3 Electric Vehicles (EVs) and Safety

EVs, as a vital part of new energy transportation, exhibit significant advantages over traditional fuel-powered vehicles in many aspects. First, EVs use electric motors instead of internal combustion engines, making a considerable contribution to reducing carbon emissions. Their high energy conversion efficiency allows EVs to utilize electrical resources more effectively, thus decreasing reliance on fossil fuels. This advantage not only plays an essential role in helping reduce global greenhouse gas emissions but also provides strong support for mitigating global climate change (Rauf et al., 2024). As EVs become more widely adopted, urban air quality has also improved. Traditional fuel-powered vehicles emit large amounts of harmful gases, such as nitrogen dioxide (NO2) and particulate matter (PM2.5), which are major causes of urban air pollution (Wakamatsu, Morikawa, &

Ito, 2013; Ramacher & Karl, 2020; Kumar & Joseph, 2006). In contrast, EVs produce no tailpipe emissions during operation, reducing their negative impact on air quality. Moreover, the noise level of EVs is significantly lower than that of conventional vehicles, especially at low speeds or when idling, which substantially decreases noise pollution in cities and improves the quality of life for residents.

However, despite the numerous environmental and energy-related advantages of EVs, they also face certain challenges. First is the issue of range. Although battery technology is continually advancing, the range of many EVs remains limited during long-distance driving, particularly in extreme weather conditions when battery performance may degrade. This poses significant limitations for EVs in long-distance travel and in remote areas (Thiel et al., 2022). Additionally, EVs charging times are generally longer compared to refueling with gasoline. Even though fast-charging technology has seen improvements, charging still takes more time than refueling, which can be inconvenient in daily use. Furthermore, with the increasing number of EVs, the significant growth in electricity demand places higher demands on urban infrastructure, such as the power grid. If the grid and other infrastructure are not upgraded in a timely manner, there could be issues with power shortages. Another challenge that should not be overlooked is the lifespan and recycling of batteries. While EVs batteries perform well in the early stages, their performance declines over time. Moreover, the production and disposal of batteries pose potential environmental concerns, especially as battery recycling technologies are not yet fully developed. A large number of discarded batteries could pose threats to ecosystems (Haram et al., 2021).

On the other hand, aside from the limitations of EVs themselves, they have also raised some concerns in the field of urban traffic safety. While EVs help reduce urban noise pollution, they have introduced new safety risks, particularly for vulnerable road users (Parizet et al., 2014). Due to the extremely low noise levels of EVs, especially when traveling at low speeds, pedestrians and cyclists in noisy urban environments may find it difficult to detect the approaching vehicles, thereby increasing the risk of accidents (Liu et al., 2018). Vulnerable road users, such as the elderly, children, and individuals with visual or hearing impairments, often rely on auditory signals to perceive the proximity of vehicles. The low noise characteristic of EVs makes it harder for these groups to detect the vehicles, leading to a failure to react in time (Tabone et al., 2021). At night or in busy traffic environments, the lack of noise cues may result in pedestrians and cyclists being unaware of the presence of an EV, further increasing the risk of collisions. This is especially concerning for groups with slower reaction times, such as children, the elderly, or pets, who may overlook the approach of an EVs while crossing the street, potentially leading to accidents (Petrarulo, 2021).

To address this issue, many countries have begun requiring EVs to emit artificially generated sounds, such as warning tones, when driving at low speeds to alert pedestrians and cyclists. These sounds mimic the engine noise of traditional fuel-powered vehicles, helping road users better perceive the approach of EVs and reduce potential safety risks (Regulation (EU) No 540/2014). However, despite the gradual implementation of such measures, the safety risks posed by the low noise of EVs still require further research and technological optimization to ensure that vulnerable road users can more effectively detect and respond to the presence of EVs. Additionally, the acceleration performance of EVs presents another potential safety risk. Due to the immediate torque response of electric motors, EVs can accelerate rapidly, especially in urban traffic environments. If pedestrians and cyclists are unaware of the EV's acceleration, they may struggle to react in time, leading to potential traffic accidents (ACRS, 2024).

Therefore, while EVs offer significant advantages in environmental protection and energy use, their unique low-noise characteristics and acceleration performance have also introduced new safety challenges, particularly for vulnerable road users. For example, a 2020 study by Pardo and his colleagues provided experimental evidence that due to the low-noise nature of EVs and their potential risks to traffic safety, drivers must pay closer attention to the surrounding traffic environment when driving EVs (Pardo-Ferreira et al., 2020). His research highlighted the safety issues posed by nearly silent cars, especially when pedestrians and other road users may have difficulty hearing the relatively quiet EVs.

In 2018, Karaaslan and his colleagues expanded this research area by using Agent-Based Modeling (ABM) and employing AnyLogic software for micro-traffic simulation. The study aimed to investigate the impact of electric vehicles and hybrid electric vehicles on pedestrian traffic safety at low speeds by conducting experiments in a new three-dimensional simulation environment designed to mimic real urban intersections. He found that the nearly silent operation of electric vehicles makes it more difficult for pedestrians to hear the approach of cars, thereby increasing the likelihood of collision accidents (Karaaslan et al., 2018). This study again emphasizes the very real possibility that electric vehicles, due to their almost silent operation at speeds below approximately 20-25 miles per hour, could pose a danger to traffic safety.

To address the issue of EVs being hard to detect, the AVAS has come into the spotlight. AVAS is an acoustic warning system designed for electric and hybrid vehicles, aimed at improving the detectability of vehicles when they are traveling at low speeds, particularly when the sound of the vehicle is minimal as it approaches other road users. As EVs produce almost no noise at low speeds, AVAS generates artificial sounds to alert nearby road users, such as pedestrians and cyclists, particularly those with visual impairments, thereby enhancing their awareness of the approaching vehicle. Several experiments have shown that this system can provide additional safety alerts for pedestrians in quieter environments, though it demonstrates certain limitations in noisier settings (Fiebig, 2020; Berge & Haukland, 2019).

2.4 External Human-Machine Interface (eHMI)

The eHMI is a technology used to facilitate communication between AVs and road users, such as pedestrians, cyclists, and other vehicles. Since autonomous vehicles lack the traditional gestures, eye contact, or verbal cues provided by human drivers, eHMI conveys the vehicle's intentions through visual, auditory, or tactile signals. These signals inform road users of the vehicle's actions, such as whether it is about to start, stop, turn, or yield. The goal of eHMI is to enhance road safety, especially in situations where human interaction is absent. By offering intuitive communication methods, eHMI helps pedestrians and other vulnerable road users understand the behavior of autonomous vehicles, reducing the likelihood of traffic accidents and increasing trust in autonomous driving technology.

According to the literature review, current eHMI systems can generally be categorized into several types: first, text-based systems, which convey the vehicle’s status or instructions through text on screens or display panels, such as “Please go ahead” or “Vehicle started”; second, visual light signal systems, which use changes in light patterns to communicate information; third, auditory signal systems, which use alarms or beeps to attract the attention of road users; and finally, tactile signal systems, which interact with sensors installed in road users' devices, such as pedestrians' or cyclists' equipment, providing vibrations or other haptic feedback to alert them to the presence or intentions of the vehicle (Berge S.H. et al., 2023; Deb et al., 2018; Lee et al., 2019; Colley et al., 2019).

Among these, visual light signals are the most common system and the most extensively researched area. Vehicle warning systems that rely on visual light signals can be further divided into the following types: one involves projecting information directly onto the road surface through lights or projections to display the vehicle's behavioral intentions or road conditions; another uses screens installed on the vehicle to display patterns or symbols to help pedestrians and other road users understand the vehicle's next action; a third type uses light strips with flashing or different colored lights to indicate the vehicle’s status through changes in frequency or color, such as stopping, starting, or turning (Lee et al., 2022; Feng, Xu, Farah, & van Arem, 2023). However, despite the widespread application and research on visual light signal systems, most existing studies have focused primarily on this area, neglecting other forms of eHMI signals, such as auditory signals or tactile signals (Dey et al., 2020; Liu, H. et al., 2024; Bazilinskyy et al., 2019; Hillis et al., 2016).

In recent years, several studies have explored the impact of eHMI on pedestrian safety and awareness in various contexts. Liu and his colleagues conducted an experimental study and found that eHMI with voice signals attracted more attention from pedestrians compared to text or graphic signals, particularly when using Automated Personal Mobility Vehicles (APMV). Voice signals demonstrated clear advantages in drawing attention (Liu et al., 2024). However, the limitation of this study was that it only examined pedestrian behavior in a closed environment, without considering the impact of external environmental noise on auditory perception. Additionally, it did not explore the safety concerns of other vulnerable road users, such as cyclists. Meanwhile, Haimerl and his colleagues found that sound signals in multi-modal eHMI serve as important safety cues for pedestrians with intellectual disabilities, helping them better assess whether it is safe to cross the street under traffic stress (Haimerl et al., 2022). This highlights the crucial role of sound signals in enhancing pedestrian decision-making. Similarly, Kreißig and his colleagues expanded research on eHMI by examining the impact of different types of eHMI on pedestrian awareness during the automatic parking of electric cargo bikes (Kreißig et al., 2023). The results showed that visual signals performed better in building pedestrian trust, but auditory signals also played an important role when visual cues were absent. Although auditory eHMI were found to be less effective than visual eHMI, they still significantly improved pedestrian awareness and safety compared to the absence of eHMI. Overall, these studies demonstrate that both visual and auditory signals are essential for enhancing pedestrian safety in various scenarios, though the impact on other vulnerable road users, such as cyclists, requires further investigation.

2.5 Cyclist Interactions with AVs

In discussing the interaction between cyclists and AVs, the study by Berge et al. provides critical insights. The research systematically analyzes various interaction scenarios between cyclists and AVs in urban traffic through a literature review, expert interviews, and surveys (Berge et al., 2024). The study found that several high-risk scenarios exist in the interactions between AVs and cyclists, particularly during right-turn maneuvers, "dooring" incidents (when cyclists collide with a car door), and vehicle merging situations. These scenarios present a higher probability of accidents. Experts highlighted that AVs face significant technical challenges in detecting cyclists, especially when dealing with complex actions such as merging and turning. These challenges arise because AVs have not yet fully adapted to dynamic road environments and the behavior patterns of non-motorized vehicles. Additionally, the study pointed to a potential safety risk known as "phantom braking," where AVs may suddenly brake due to sensor misinterpretation, which not only poses a risk to vehicle occupants but also increases the likelihood of collisions with cyclists. To address these risks, the study recommends the implementation of more proactive safety systems and eHMI, allowing AVs to communicate more effectively with cyclists and reduce unnecessary traffic conflicts. These findings offer important guidance for the development of autonomous driving technology, emphasizing that AVs must pay greater attention to the safety needs of cyclists, particularly in road-sharing environments.

Apart from safety, cyclists' comfort in their interactions with AVs is also a critical research topic. As autonomous driving technology gradually advances, the comfort of cyclists during their travels has become an important factor that must be considered in traffic design (Botello et al., 2019). Gaio and his colleagues' research delves into the impact of AVs on cyclists' attitudes, particularly focusing on their sense of safety and comfort when interacting with AVs. Through on-site interviews and focus group discussions conducted in four "living labs" across three countries, the study gathered direct experiences and perceptions from cyclists regarding AVs. The results indicate that cyclists generally feel uneasy when interacting with AVs, particularly due to the lack of non-verbal communication (such as eye contact and gestures) with the driver, which leads to a diminished ability to predict AVs behavior, thereby reducing their sense of safety. In some cases, this unease surpasses that experienced during interactions with traditional vehicles, highlighting the need for improvements in comfort and trust in autonomous driving technology (Gaio & Cugurullo, 2024).

Furthermore, the study also highlighted that cyclists' sense of safety and comfort is closely related to the surrounding traffic conditions and infrastructure design. Participants emphasized that dedicated cycling infrastructure, such as separate bike lanes and clear traffic signage, is crucial to ensuring the safety and comfort of cyclists. In the absence of such infrastructure, cyclists often feel more vulnerable, especially in situations where they must share the road with motor vehicles. Gaio and his colleagues' research further pointed out that the introduction of autonomous vehicles could exacerbate the power imbalance between cyclists and motor vehicles, leading to the further marginalization of cyclists in traffic.

To address these issues, the study recommends that regulatory authorities closely monitor the communication gap between autonomous vehicles and cyclists, and develop more effective communication mechanisms and technologies. For example, optimizing eHMI systems so that they not only convey the vehicle's intended actions but also adjust in real-time to interact with different road users. Additionally, improvements in urban design are equally important. Dedicated cycling infrastructure and clear traffic management policies can significantly enhance cyclists' sense of safety and comfort. The design of future urban transportation systems must balance technological development with the actual needs of cyclists to ensure that the safe implementation of autonomous driving technology does not compromise the rights of vulnerable road users (Gaio & Cugurullo, 2024).

2.6 Cyclist Interactions with Electric Vehicles

The interaction between electric vehicles and cyclists is also a key focus in traffic safety research. Compared to pedestrians, cyclists have more difficulty noticing vehicles that are in low-speed or idling states, making them more prone to accidents. Liu and his colleagues conducted a study on electric vehicle accidents in Norway and identified several key factors contributing to the occurrence of such accidents.(Liu et al., 2022) First, the almost silent operation of electric vehicles makes it more difficult for pedestrians and cyclists to detect their approach, especially when they are traveling at low speeds. This quietness increases the risk of accidents. Second, electric vehicle accidents often occur in urban areas and at road intersections, where there are usually more pedestrians and cyclists, leading to an increased risk of interactions with these vulnerable road users. Additionally, most electric vehicle accidents occur on low- and medium-speed roads (below 80 km/h), primarily during weekday peak hours, particularly in the morning and evening rush hours, which is closely related to the usage pattern of electric vehicles for short-distance commuting. The study also found that collisions between electric vehicles and cyclists or pedestrians are more frequent, with nearly one-third of accidents involving these vulnerable road users.

To address these issues, Liu and his colleagues proposed a series of effective measures. First, electric vehicles can be equipped with sound alert systems to improve their audibility at low speeds, thereby alerting pedestrians and cyclists. This measure has already been implemented in the European Union, requiring new electric vehicles to be fitted with an AVAS. Second, improving urban infrastructure is crucial, such as creating safer pedestrian and cyclist pathways in busy areas and at intersections, installing traffic lights, speed bumps, and signs to enhance the visibility of road users. Additionally, increasing traffic safety education for electric vehicle drivers, cyclists, and pedestrians is essential to raise awareness of potential traffic risks, particularly emphasizing the dangers posed by the quiet operation of electric vehicles. Moreover, when designing roads, the installation of central medians can be considered to significantly reduce the severity of collisions, as studies have shown that medians greatly reduce the occurrence of head-on collisions. Finally, the ongoing collection and in-depth analysis of electric vehicle accident data will help identify potential safety issues and trends. As electric vehicle adoption increases, researchers need to regularly update the data to make timely adjustments to traffic safety strategies (Liu et al., 2022).

Stelling-Konczak and his colleagues' study also explored how the use of electronic devices affects cyclists' safety, as well as the impact of the quietness of hybrid and electric vehicles on cyclists. Using a literature review and accident data analysis, the study found that listening to music or making phone calls while cycling significantly reduces cyclists' auditory perception, increases self-reported accident risk, and affects cycling performance. Additionally, hybrid and electric vehicles are very quiet when traveling at low speeds, making it harder for cyclists to detect their presence, especially in noisy traffic environments. Although there is no direct evidence that the quietness of electric vehicles leads to a higher accident rate for cyclists, the data show that collisions between electric vehicles and cyclists occur more frequently compared to collisions with pedestrians. The study emphasizes that cyclists rely on auditory cues in low-visibility situations, and the lack of sound alerts increases safety risks (Stelling-Konczak et al., 2015).

2.7 Summary of Key Findings and Research Gaps

Key Findings:

- AEVs combine the advantages of AVs and EVs, potentially reducing human error and emissions while improving traffic flow.
- Cyclist Safety: Cyclists face higher risks than pedestrians, primarily due to speed, visibility, and limited reaction time, especially when interacting in mixed traffic environments and high-density areas.
- Safety Issues for Cyclists with AVs: Although AVs show potential for reducing human errors and enhancing road safety, they still face challenges in recognizing and safely interacting with cyclists, especially in complex urban settings.
- Safety Concerns with EVs: EVs' near-silent operation at low speeds poses potential risks for vulnerable road users who rely on auditory cues.
- External Human-Machine Interface: eHMI has shown potential to improve communication between AVs and vulnerable road users, though the effectiveness varies across signal types (visual, auditory, etc.).

Research Gaps:

- Limited research on AEVs interactions with diverse road users (especially cyclists) in traffic environments.

- A lack of in-depth studies on combining eHMI with AVAS to improve cyclist safety and comfort in AEVs.

- Absence of experimental testing to evaluate the effectiveness of multi-sensory eHMI under different traffic and environmental noise conditions.

- Few studies address the long-term impact of AEVs on cyclist behavior, trust, and perceived safety, especially in mixed traffic environments.

3

Methodolgy

This section summarized the research methodology, detailing the conceptual model of the experiment, the experimental scenario design, the equipment used, and the experimental procedure. Section 3.1 first described the conceptual model of the experimental design. Section 3.2 provided a detailed explanation of how the virtual experimental environment was established. Sections 3.3 offered specific descriptions of the equipment used in the experiment. Section 3.4 introduced the experimental process.

3.1 Experimental Design

This study employs immersive virtual reality experiments to investigate the effects of autonomous vehicle types, environmental noise, and eHMI trigger distance on cyclist behavior. A within-subject design approach was used in the study to remove the effects of individual differences, where each participant experiences all experimental conditions or treatments. This means that the performance of each participant will be measured and compared under different conditions.

The main variables involved in this experiment (independent, dependent, and intermediary variables) and their relationships are shown in Figure 3.1. In this figure, yellow represents independent variables, blue represents intermediary variables, and green represents dependent variables. I selected three main independent variables to investigate their influence on cyclist behavior: environmental noise level, vehicle type, and signal trigger distance. These independent variables were chosen to represent different conditions that cyclists might encounter in real traffic environments, with the aim of exploring their impact on cyclist safety. The figure also includes two intermediary variables: noise and warning signals, which represent how the independent variables influence cyclist behavior through certain mechanisms. Specifically, different environmental noise levels and vehicle types affect the level of noise, while signal trigger distance affects the range of the warning signal. These intermediary variables further influence multiple dependent variables, which are the measured outcomes in the experiment: reaction distance, maximum deceleration, safety distance, and lateral attention.

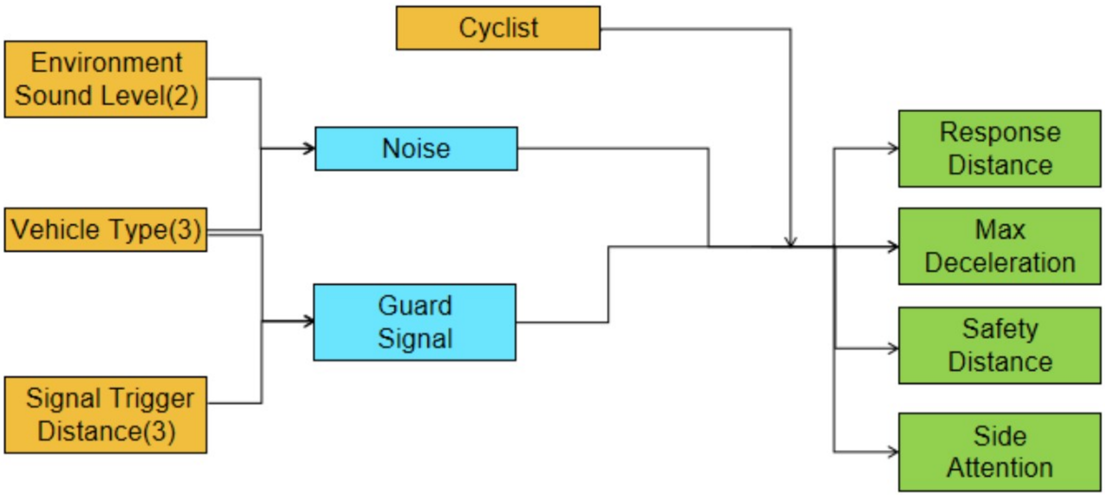

Figure 3.1. Variable relation Map

Table 3.1. Main variables included in the experiment

Variable	Definition	Brief Indication
Independent Variables		
Environment Sound Level	The level of ambient noise in the environment	Compares quiet residential areas with noisy streets to observe cyclists' reactions under varying noise conditions
Vehicle Type	Different types of vehicles used in the study	Includes AVs with eHMI, AEVs with eHMI, and AEVs with eHMI and additional auditory alerts to test safety impacts
Signal Trigger Distance	The distance at which the eHMI signal is activated	Tests short, medium, and long activation distances to assess their effect on cyclists' awareness and reactions
Intermediary Variables		
Noise	Combines ambient noise level and idle engine noise from vehicles	Simulates real-world road environments with varying background noise levels to test cyclist perception
Warning Signal	Determined by the combination of trigger distance and vehicle type	Assesses how signal strength and vehicle configuration affect cyclists' responses
Dependent Variables		
Reaction Distance	The distance between the cyclist and the vehicle at the time of response	Measures the cyclist's reaction speed under different experimental conditions
Safety Distance	The distance between the cyclist and the vehicle when the cyclist completes their response	Measures the cyclist's complete response behavior under different conditions
Max Deceleration	The strength of deceleration applied by the cyclist when responding	Reflects the cyclist's perception of the urgency of the signal
Side Attention	The level of attention the cyclist pays to auditory signals in the environment	Indicates the cyclist's sensitivity to warning signals and ability to focus on information in complex environments

The main variables in this experiment and their definitions are shown in Table 3.1. For a more detailed description, see Appendix A. In this study, by systematically manipulating three independent variables using the controlled variable method, a total of 18 different experimental scenarios were generated. These 18 scenarios are divided into two main levels, each corresponding to a different environmental noise level. Specifically, one level of scenarios is set in a quiet residential area, while the other level is set in a busy street environment. Within each level, the scenarios are further subdivided into 9 different conditions, which are determined by varying the warning signal trigger distances and vehicle types.

This carefully designed combination of scenarios allows for comprehensive data collection and analysis under 18 different conditions, enabling an in-depth exploration of the impact of each independent variable on participants' behavior and reactions. During the experiment, participants will ride from the starting point to the endpoint, simulating a real cycling experience. If participants perceive a warning signal emitted by a vehicle(The light signals emitted by the roof-mounted visual eHMI and the additional warning sound signals installed on some vehicles), they will be required to execute an evasive maneuver, such as changing direction or reducing speed, to avoid potential hazards. This reaction process reflects participants' decision-making abilities and response behaviors when faced with sudden situations.

In each scenario, only one variable is changed while all other variables remain constant. This controlled variable method allows for the precise evaluation of the effect of a single variable on the experimental outcomes. Since all other parameters in the virtual environment are consistent, the impact of each variable can be independently analyzed. This approach not only enhances the reliability and validity of the experimental results but also reduces the interference of external factors on the outcomes, enabling a more accurate understanding of the role and significance of each variable under different conditions.

Table 3.2. Two different level based on the Environment Sound Level

Quiet Residential area	Very busy Streets
54 dB	68 dB

Table 3.3. Experiment scenario for each sound level

Vehicle Type	Additional Signal Trigger distance
AVs with eHMI	15 m
AEVs with eHMI	15 m
AEVs with eHMI and Additional alert	15 m
AVs with eHMI	20 m
AEVs with eHMI	20 m
AEVs with eHMI and Additional alert	20 m
AVs with eHMI	25 m
AEVs with eHMI	25 m
AEVs with eHMI and Additional alert	25 m

3.2 Virtual Environment

To ensure the scientific rigor and precision of this experiment, I adopted a controlled experimental method, which allows us to isolate and systematically compare the impact of each variable on participants' attitudes toward cycling safety, both subjectively and objectively, as well as their cycling behavior. The advantage of using a controlled experiment is that it minimizes external interference, enabling us to focus on comparing the specific effects of different factors on cyclists' behavior and safety perception. For this purpose, I set up 18 test sections within the experiment, each representing a specific test scenario. These scenarios encompass various combinations of variables, allowing us to explore in depth the influence of factors such as vehicle type, environmental noise levels, and signal trigger distances on cyclists.

The advantage of choosing a virtual reality (VR) experiment lies in its ability to replicate real-world scenes and environments to the greatest extent possible, while also precisely controlling various potential influencing factors that are difficult to quantify in the real world. By using VR technology, I can eliminate random external environmental interference, thereby ensuring the reliability and repeatability of experimental data. Additionally, the VR environment provides a safe platform for participants, allowing them to simulate real cycling scenarios and respond accordingly without facing actual traffic risks. This approach offers a high degree of flexibility and safety for conducting the experiment(Rizzo et al., 2009; Guo et al., 2018; Howie & Gilardi, 2021; Newman et al., 2022).

The virtual environment used in this study was constructed using Unreal Engine and is designed as a long, straight road shared by both bicycles and cars. The road is 1400 meters long and 4.5 meters wide, representing a standard two-lane shared road. To make the experimental environment as realistic as possible, this virtual road is designed for two-way traffic with no intersections, simplifying cyclists' decision-making processes and focusing on testing the impact of specific variables.

Along this road, 12 parking zones are set up, each 30 meters long, with vehicles parked perpendicularly to the road, facing the street. The parking zones are separated by residential areas ranging from 60 to 80 meters in length. These residential areas not only enhance the realism of the scene but also provide practical conditions for simulating the propagation of sound signals and environmental noise, as shown in Figure 3.1.

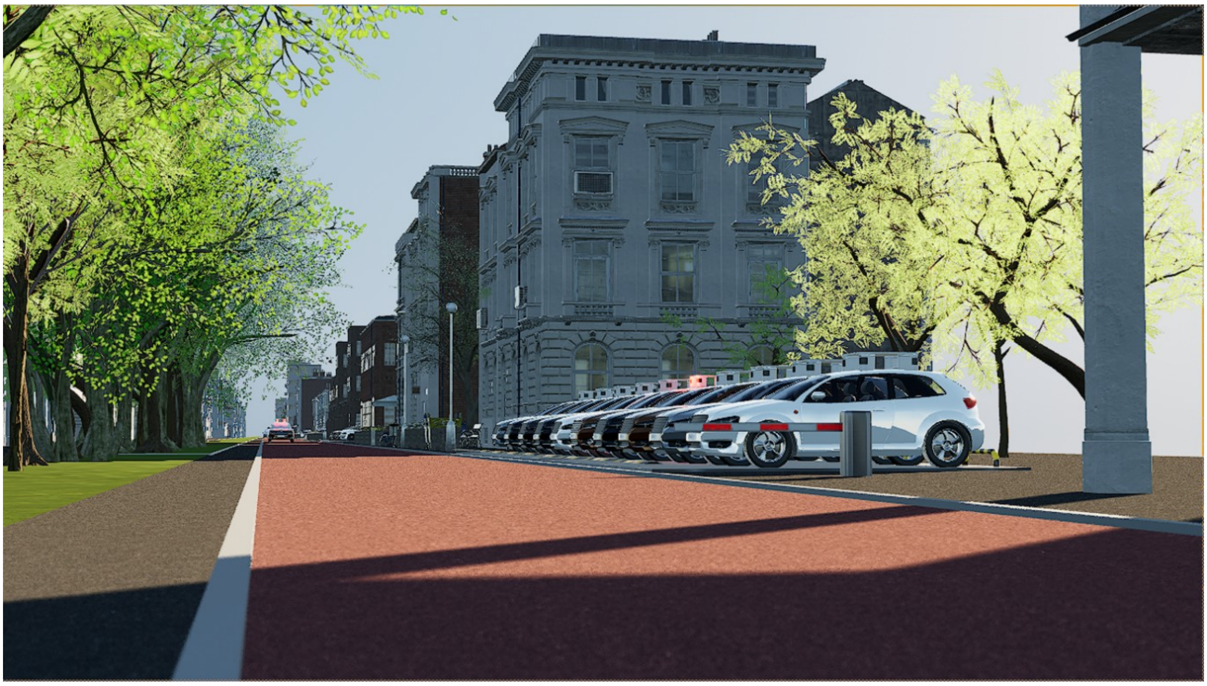

Figure 3.2. Experiment environment setting

The shapes of the parking areas are shown in Figure 3.2. Each parking area represents an experimental section. Upon completing one section and entering the next, there is a transition area to guide participants back to a designated position, ensuring that each experiment controls for participants entering the experimental area from the same location. In this area, a vehicle will drive in the opposite direction to encourage participants to ride on the right side of the road. In each experimental section's parking area, 10 cars are evenly distributed, all with the same shape but different colors to provide visual diversity and realism. At the beginning of the experiment, the eHMI signal lights on these vehicles remain inactive. These devices only activate and start emitting signals when participants enter the predefined signal trigger distance. The experimental setup ensures that in each scenario, when participants enter the parking area, only one of the 10 cars is in an idling state. This vehicle emits continuous light and sound signals based on the distance between the participant and the idling vehicle upon entering the designated zone. The sound of the signal received by the participants follows natural laws, increasing in volume as the participants approach the vehicle.

Specifically, when participants approach the parking area and enter the signal trigger range, they will first notice the engine noise of the idling vehicle. The loudness of this sound is designed to account for the characteristics of sound propagation and attenuation in a real environment. To realistically simulate the perception of sound approaching from a distance, Unreal Engine uses an inverse square attenuation formula, which is particularly suited for open environments.

$$L = \frac{L_0}{d^2}$$

L (dB):represents the perceived loudness at a distance d.

L_0 (dB):is the reference loudness near the sound source (typically the loudness at the source).

d (m):is the distance between the sound source and the listener.

This formula ensures that the loudness decreases with the square of the distance, simulating the behavior of sound in real life. For example, when the distance doubles, the loudness decreases to one-quarter of the original value. In Unreal Engine, this formula is essential for maintaining the realism of sound in open environments, where sound naturally spreads over a larger area. By using this setup, the realism of the experiment and the participants' sense of immersion will be enhanced. When participants continue to move forward and enter the preset signal trigger zone, the eHMI signal lights on top of the idling vehicle will be activated and start emitting light signals.

Figure 3.3. Parking area setting draft

In order to ensure the accuracy of the experimental data and reduce the possibility of the participants forming habitual reactions due to repeated attempts, I randomly set 3 interference zones in 12 parking spaces. Data from these interference regions will not be included in the final analysis to avoid interfering with the experimental results. In these interference zones, I set up two specific scenarios: in some cases, certain vehicles would not trigger any signals, and subjects would drive by without receiving any visual or auditory cues. In other cases, certain vehicles will leave the parking space immediately after the signal. This setup is designed for disrupting the participants' expected responses so that they do not act on the same pattern through the whole experiment, which can avoid the formation of habitual responses. In this case, this design can not only helps to avoid the influence of "learning effect" on the experimental results, but also increase the authenticity and complexity of the virtual experimental environment, and finally improves the accuracy of the simulation of real driving scenarios.

In addition, to further increase the general realism of the experimental situation multiple finer objects and features were added in the virtual setting. The road was dotted with residential buildings, potted trees, streetlamps and parked cars on both sides. These details both deepen the visual of the scene and give participants more information about the environment, these settings can make the participants naturally immerse themselves in the virtual environment.

During the experiment, participants wore head-mounted display (HMD) virtual reality equipment and experienced the experiment from a first-person perspective. Through the HMD devices, participants were able to cycle in a nearly realistic street scene. The participants' perspective was presented through a virtual camera, and they moved within the scenario using a custom-made bicycle simulator.

This design aims to allow participants to conduct the experiment more naturally, while also striving to achieve a reasonable degree of similarity between the experimental conditions and real-world scenarios. Although simulations are simplifications of reality, setting up a realistic scenario can still make the responses and behaviors of participants resemble what they might do in the real world, thereby increasing the external validity of your study. By taking this approach, the experiment data will not only show the behavior of participants in a virtual environment, but it can also offer some insights into analyzing and predicting their behavior in real-world contexts. In essence, this experiment, with its detailed setup, will yield invaluable data and insights for optimizing eHMI strategies in AEVs.

3.3 Experimental Equipment

In this experiment, a bicycle simulator (described in Section 3.4) and two HTC VIVE Pro Eye Head-Mounted Display (HMD) virtual reality devices (resolution: 1440 × 1600 pixels/eye, 110 FOV, 90Hz refresh rate) were used (as shown in Figure 3.4). This setup was implemented so that one device could serve as a backup during the experiment. The HTC devices were connected to a Windows 10 desktop computer equipped with an Intel Core (TM) i7-8700 CPU, 16GB RAM, NVIDIA GeForce RTX 2070 graphics card, and a SanDisk SD9SN8W 256GB SSD. The HMDs were run on a Windows 10 desktop computer powered by an Intel Core (TM) i7-10700F CPU, 16GB 2933MHz RAM, and an NVIDIA GeForce RTX 3060 GPU. Virtual reality technology has been widely accepted by many scholars, and HMDs, as a type of VR device, play a crucial role in immersive experiments. However, since HMD devices come into direct contact with the face, a lack of cleanliness could lead to hygiene and comfort issues. Therefore, in this experiment, a system of alternating between the two devices was adopted.

Figure 3.4. HTC VIVE Pro Eye

Keep operating the above mentioned method then it ensures that the equipment is cleaned fully and disinfected after its each use. Not only does this method serve as a very direct disinfection aid for the gadgets (important because of Covid-19 pandemic is just over), it also helps maintain the equipment in optimal condition. Participants performing the experiment while wearing the HMD VR devices, usually cycling in the virtual environment, make physical effort that may lead to sweating as well. Sweat can accumulate which will alter the comfort of the equipment and may cause them to feel uncomfortable, in turn making it difficult for participants to concentrate on the experiment. To this end, the device will be kept clean and dry for every individual use.

Another benefit of alternating equipment use is that it allows for more optimal utilization. First, this ensures that all participants can conduct the experiment with the equipment in its best condition, avoiding any discomfort caused by hygiene issues. Additionally, while one set of equipment is in use, another can be cleaned or replaced, thereby reducing downtime during the experiment. This not only makes the experimental process more convenient but also provides participants with a more comfortable and safe experience.

On the other hand, in this study, a newly developed virtual reality (VR) cycling simulator from the Mobility in eXtended Reality Lab at the Faculty of Civil Engineering and Geosciences at Delft University of Technology was also utilized. The simulator consists of a bicycle mounted on a Tacx Flow Smart rear-wheel resistance trainer and a virtual reality headset (HTC VIVE Pro Eye).The electromagnetic resistance unit on the rear wheel provides resistance during cycling. During the experiment, participants only need to wear the HMD, and by using the cycling simulator as they normally would—by pedaling the pedals or pressing the brakes—they can move forward or stop in the virtual environment.

However, the simulator cannot simulate the tilting or pitching motions of a real bicycle, allowing only forward motion and lacking steering capabilities. To address this limitation, a VIVE controller was attached to the handlebars of the bicycle, allowing participants to make lateral movements by pressing buttons on the controller, partially fulfilling the need for left and right directional adjustments. Before the experiment, participants will be informed that by pressing the trigger buttons on both handles of the VIVE controller, they can translate their position 5 cm in the corresponding direction in the virtual environment. Holding down the trigger button will continuously move them in that direction until the button is released. Although this setup does not fully replicate the real-world cycling experience, it allows participants to make basic directional changes in the virtual environment. See Figure 3.5.

Figure 3.5. Bicycle Simulator

3.4 Experimental Procedure

The experiment consists of four stages:

(1) **Pre-experiment Preparation:** Upon arriving at the laboratory, participants will first be guided to read a detailed instruction document. This document is intended to provide participants with a comprehensive overview of the experiment, including a user guide for the HMD device used in the experiment, the overall experimental procedure, and the potential discomforts along with the corresponding safety measures. The document also explains in detail the possible temporary effects of motion sickness induced by the virtual reality equipment and how to manage these potential discomforts. The purpose of this step is to ensure that participants have a thorough understanding of the experimental process and are able to correctly use the equipment. Additionally, to protect participants' rights, all participants are required to read and sign an informed consent form before the experiment begins. This consent form confirms that participants are fully aware of all relevant information about the experiment, including its purpose, procedures, potential risks, and their right to withdraw from the experiment at any stage. The experiment staff will particularly emphasize that participants have the unconditional right to withdraw from the experiment at any time, whether due to physical discomfort, psychological stress, or any other reason, ensuring that they feel comfortable and safe throughout the entire process.

(2) **Practice:** Before entering the formal experiment, participants will need to undergo a practice session with the equipment to familiarize themselves with the use of the HMD VR device and the experimental procedure. This phase is an essential part of the experiment as it helps participants gradually adapt to the virtual reality environment, reducing the likelihood of operational errors or anxiety during the formal experiment. Participants will wear the head-mounted display and use the bicycle simulator provided by the laboratory to practice in a specially designed preset virtual scenario. As shown in Figure 3.6, the practice scenario requires participants to ride from point A

to point B, perform a lane change at point B, and then continue riding to point C. This practice session not only helps participants become familiar with navigating within the virtual environment but also allows them to master the specific operational techniques of the experimental equipment, such as how to control cycling speed and direction using the simulator and how to react within the virtual environment.

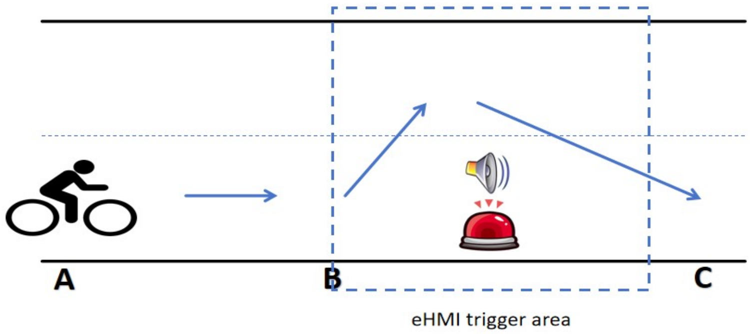

Figure 3.6. Practice Field

(3) **Formal Experiment:** At the start of the formal experiment, participants will be guided to a predetermined starting point, where they will wear the HMD VR device and prepare to begin cycling. Once the experiment begins, participants will follow the system's instructions to ride along the virtual road until they reach the endpoint. During the ride, the system will randomly present the designed scenarios, including different types of autonomous vehicles. These vehicles may emit warning signals, indicating that they are about to take certain actions. When participants detect these signals, they will need to naturally adjust their cycling behavior, such as slightly changing direction or reducing speed, to safely navigate through the simulated traffic situations.The experimental system(Unreal Engine) will continuously record various data from participants, including their cycling trajectory, speed, and other key behavioral indicators.

(4) **Post-experiment Questionnaire:** After the formal experiment concludes, participants will be guided to a computer in the laboratory to complete a detailed post-experiment questionnaire. This questionnaire is designed to gather participants' subjective experiences with the AEVs they encountered during the experiment, with a particular focus on their impressions and feedback regarding vehicles equipped with additional auditory warning systems.

4

Data Analysis

In this chapter, a detailed description will be provided of the types of data collected during the experiment, the data processing methods, the analysis techniques used, and the results derived from these analyses. This section aims to lay a solid foundation for the subsequent discussion and conclusions.

4.1 Experiment Data collection

During the experiment, participants' cycling trajectory data will be recorded frame by frame and stored in CSV files as coordinates and velocity data. Simultaneously, the Euler angle data from the HMD VR device worn by the participants will also be recorded in sync. These Euler angles capture the orientation and posture of the head-mounted VR device in three-dimensional space, including the yaw angle (rotation around the vertical Z-axis), pitch angle (rotation around the lateral Y-axis), and roll angle (rotation around the longitudinal X-axis). The types of data recorded in their original form are listed in Table 4.1. This data is crucial for analyzing the participants' gaze direction and attention distribution within the virtual environment.

Table 4.1. The types of data directly recorded through the experiment

Data Type	Unit
Location	m
Longitudinal Velocity	m/s
Yaw / Pitch / Roll Angle	Degrees (°)

By analyzing the coordinate data and its changes, it is possible to calculate the time taken between two points by determining the coordinates and speed. Once the time data is computed, further analysis of the trajectory data can yield key information, such as the distance between the participant and the target vehicle when the participant first notices the vehicle and initiates an evasive maneuver, as well as the final distance between them after the evasive action is completed. These distance metrics are vital for assessing the detectability of vehicle signals and the participant's reaction speed.

By combining speed and time data, a deeper analysis of the intensity of the participant's avoid action can be conducted. Observing the magnitude of speed changes and the time intervals can reveal whether the participant decelerates gradually and smoothly avoids the vehicle or performs a last-minute emergency maneuver. The types of data obtained after processing are listed in Table 4.2. These details provide valuable insights into the participant's decision-making process and reaction strategies.

Table 4.2. The types of data obtained through processing

Data Type	Unit
Time	s
Speed change Point	m
Lowest Speed Point	m
Acceleration/Deceleration	m/s^2

Meanwhile, the Euler angle data from the HMD VR device provides information about the participant's head orientation and posture during the experiment. Analyzing this data allows for an assessment of the participant's attention to different directions, particularly the roadside environment. This information is essential for understanding the distribution of the participant's attention and their ability to perceive and respond to the surrounding environment under different experimental conditions. Through comprehensive analysis of this multi-dimensional data, the experiment can yield profound insights into the observed phenomena, providing robust support for the optimization of autonomous driving technology and human-machine interface design.

4.2 Questionnaire Data Collection

The subjective experience data of the participants were collected through a questionnaire completed after the virtual reality experiment. This questionnaire was based on survey designs used in similar virtual reality experiments (Feng, Xu, Farah, & van Arem, 2023). The questionnaire consists of six sections: (1) participant information, (2) face validity questionnaire, (3) simulator sickness questionnaire, (4) presence questionnaire, (5) trust in autonomous driving questionnaire, and (6) perceived behavior questionnaire. The participant information section includes characteristics such as gender, age, familiarity with computer games, familiarity with VR, familiarity with the concept of autonomous vehicles, and experience interacting with autonomous vehicles. The face validity questionnaire measures whether the simulator assessed what it was intended to assess (Kaptein, Theeuwes, & van der Horst, 1996). In the face validity questionnaire, the realism of the virtual environment, virtual objects (such as vehicles), motion capability, and environmental sound are rated on a 5-point scale. The simulator sickness questionnaire is a standard tool for assessing the level of simulator sickness experienced by participants in virtual environments (Kennedy, Lane, Berbaum, & Lilienthal, 1993). The presence questionnaire (Witmer, Jerome, & Singer, 2005) measures the sense of presence in the virtual environment. Based on the work of Nuñez Velasco, Farah, van Arem, and Hagenzieker (2019), a trust in autonomous driving questionnaire was used, consisting of five questions. Finally, a perceived behavior questionnaire, also consisting of five questions, was used to assess participants' attitudes toward the additional warning sound system for AEVs. The six sections of the questionnaire can be broadly categorized into the following three parts.

4.2.1 Participant Demographic Questionnaire

This section focuses on collecting demographic data about the experiment participants. The survey includes not only basic information such as age and gender but also more specific background details such as cycling frequency and the participants' experience with video games and related types of vehicles.

Regarding cycling frequency, the questionnaire measures participants' cycling habits through multiple options. Participants will be asked to select the number of days they typically ride per week, with options ranging from "less than one day" to "every day." This data helps to understand participants' real-life cycling frequency, providing better context for interpreting their performance in the experiment.

Additionally, the questionnaire explores participants' familiarity with video games and the autonomous vehicles involved in the experiment. Participants will self-assess their experience in these areas using a five-point Likert scale, with options ranging from "very unfamiliar" to "very familiar." This approach allows for a nuanced understanding of participants' backgrounds, helping to distinguish different levels of familiarity with the virtual environment and autonomous driving technology.

By collecting this detailed background data, the study can more thoroughly analyze the differences in performance among participants with varying characteristics. This not only aids in controlling for variables but also provides important reference points for subsequent data analysis, making the research findings more scientifically robust and persuasive.

4.2.2 Presence Questionnaire

Including a presence analysis in the questionnaire is intended to systematically evaluate participants' sense of immersion and realism within the virtual reality (VR) environment. This analysis is crucial in VR research because the sense of presence directly affects the validity and reliability of experimental results. Presence, or the feeling of "being there," refers to the extent to which participants feel immersed in the virtual environment, serving as an important measure of the environment's realism.

In VR experiments, the strength of presence can significantly impact participants' psychological and behavioral responses. If participants experience a strong sense of presence in the VR environment, their behavior and decision-making are often more reflective of how they would act in the real world, thereby enhancing the external validity and generalizability of the experimental data. Conversely, if the sense of presence is weak, participants may be more aware that they are in a virtual environment, leading to behaviors that differ from what would be expected in real-life situations, which could affect the interpretation and application of the experimental results.

This section of the questionnaire is designed with multiple dimensions to allow participants to evaluate their sense of presence during the VR experiment from various perspectives. The questions cover several aspects, including overall feelings about the virtual environment, perception of sound effects, and whether the behavior of the controlled virtual characters met their expectations. To ensure precision and consistency in evaluations, the questionnaire employs a five-point Likert scale, with options ranging from "strongly agree" to "strongly disagree." The Likert scale allows for capturing nuanced differences in participants' attitudes toward the VR environment, rather than simply a binary agree or disagree response. Additionally, the Likert scale is easy to understand and use, simplifying the questionnaire completion process and improving the efficiency of data collection.

Through the presence analysis in the questionnaire, the study can provide an important reference framework for assessing the impact of the virtual environment on participants' behavior. This allows the research to not only explain behavioral patterns observed in the data but also to evaluate whether the design of the virtual environment successfully simulated real-world situations.

4.2.3 Subjective Experience Questionnaire

This section of the questionnaire is designed around the core research questions, aiming to directly collect participants' perceptions and feelings about different types of vehicles after the experiment.

These questions include whether participants noticed the engine noise emitted by vehicles in idle mode and whether they could distinguish the difference between the engine noise of electric vehicles and conventional cars. Additionally, the questionnaire directly asks for participants' opinions on the eHMI system, particularly whether they believe it is necessary to add auditory warning signals when the vehicle is already equipped with strong visual cues, such as light signals.

These questions provide direct insight into participants' subjective attitudes toward the need for warning sounds in AEVs. Participants' perceptions of different types of noise and their evaluations of the eHMI system will offer valuable qualitative data for the study. This data can reveal the actual effectiveness of light signals and auditory warnings in enhancing vehicle detectability, as well as their relative importance in different noise environments. By analyzing this feedback, the research can better understand participants' safety needs, thereby providing more targeted recommendations for the future design of autonomous driving technology.

4.3 Participants

A total of 41 participants took part in the experiment, with 40 successfully completing the entire experimental process. One participant opted to withdraw from the experiment midway due to physical discomfort. The reason for this participant's withdrawal was due to experiencing discomfort with the VR equipment, presenting typical symptoms of VR-induced motion sickness. VR motion sickness is a common issue encountered when using virtual reality technology and is typically caused by a mismatch between visual input and the body's actual sensory experiences, leading to confused signals in the brain. Symptoms include dizziness, nausea, sweating, eye strain, and headaches. These reactions may be related to technical limitations of VR devices, such as latency and low refresh rates, or a lack of prior experience using VR. Fortunately, after drinking water and taking a brief rest, the participant fully recovered.

4.4 Data Processing and Filtering

This section provides a detailed explanation of how the data collected during the experiment was processed, as well as how the target experimental variables were extracted and calculated.

The collected data was pre-processed to extract the necessary values for the experimental variables. This step was crucial for ensuring the data was in a format suitable for analysis. In this experiment, four core variables were primarily focused on, each representing participants' reactions and behavioral characteristics under different experimental conditions. By analyzing these variables, a deeper understanding can be gained of how participants respond to the signals of AEVs in various traffic scenarios and make safety-related decisions. The four core variables are summarized in Table 4.3 below for clarity.

The first variable is the position where participants first react. This variable provides a clear indication of the distance at which participants initially notice the vehicle and begin to react during the experiment. By analyzing participants' reaction distances, the effectiveness of vehicle signals can be assessed, and insights can be gained into the participants' ability to detect approaching vehicles under different warning conditions (e.g., light signals, sound signals). Changes in reaction distance can directly reveal the role of warning signals in vehicle perception and provide valuable feedback for optimizing warning systems.

Table 4.3. Brief Overview of Core Variables in the Experiment

Variable	Unit	Definition (How it was measured)	Brief indication
Position where participants first react	m	The location at which participants first notice the vehicle and begin to react.	Indicates participants' initial detection of the vehicle and their reaction distance.
Position where the avoidance maneuver is completed	m	The distance at which participants first notice the vehicle and begin to react.	Indicates the distance participants used to complete the avoidance maneuver.
Maximum Deceleration	m/s	The highest deceleration rate observed during the avoidance maneuver.	Measures the urgency and intensity of the participants' avoidance actions.
Euler Angle Data	Degrees (°)	The yaw angles recorded by the VR headset during the experiment.	Assesses participants' attention distribution.

The second variable is the position where the avoidance maneuver is completed, which indicates the specific location where participants finish their avoidance action under different scenarios. By analyzing the avoidance position, researchers can combine it with the reaction start position to calculate the distance participants used to perform the avoidance maneuver. This helps assess participants' ability to respond to different experiment scenarios and reveals their level of control over the situation. If the avoidance is completed at a closer position with a shorter distance, it suggests that participants reacted quickly in an emergency. In contrast, if the avoidance position is farther away with a longer distance, it typically indicates that participants, after receiving sufficient warning information, confidently completed the maneuver based on their own experience. This variable is crucial for understanding participants' trust and sense of safety in the autonomous driving system.

The third variable is the maximum deceleration during the avoidance maneuver, which directly measures the urgency of participants' actions when avoiding the vehicle. When participants perceive potential danger, they often instinctively perform a sharp deceleration to ensure safety. Conversely, if participants have better control over the situation, they tend to decelerate more smoothly, maintaining a lower deceleration rate. By analyzing the maximum deceleration, researchers can gauge the level of danger participants felt during the experiment and the urgency of their avoidance actions. This data helps to understand the role of different warning signals in participants' decision-making processes.

The fourth variable is the Euler angle data from the participants' headsets, which tracks head rotation (including yaw, pitch, and roll). By analyzing the recorded Euler angles (including yaw, pitch, and roll) during the experiment, it is possible to assess the participants' attention distribution and focus within the virtual environment. These data help determine whether participants noticed roadside vehicle signals in a timely manner and their directional response when facing warning signals. This variable is highly valuable for evaluating the impact of different signaling systems on participants' visual attention.

During the data processing phase, in order to extract the aforementioned variables, the raw data first undergo a series of pre-processing operations. Although participants' behavior data were recorded on a frame-by-frame basis, the frame rate during the experiment was not fixed, resulting in slight differences in the time intervals between recorded frames. Therefore, the first step is to calculate the time data for each frame by computing the differences in distance and speed between each pair of recorded data points. Subsequently, the acceleration data are derived from the changes in speed and time, leading to a complete dataset that encompasses all the key response variables.

In this experiment, the experimental data was filtered using low-pass filtering techniques to reduce noise and highlight the main trends in the data. This method effectively smoothed out minor fluctuations during participants' cycling, allowing for clearer identification of key reaction points and behaviors. Detailed information on the filtering process and its implementation can be found in Appendix B.

In the process of collecting experimental data, apart from the typical deceleration behavior, special cases such as lateral avoidance and missed responses to warning signals were observed. These behaviors are of significant research value for understanding participant reactions under specific conditions and have been retained for further analysis. For details on the classification and processing of these special data sets, please refer to Appendix C.

4.5 Method of getting core variable

4.5.1 Position of cyclists' reactions

The reaction position(m) is an important target variable used to evaluate when participants notice the vehicle signal and react accordingly. This variable represents the distance participants travel from the moment they start receiving the information conveyed by the vehicle's eHMI to the point where they actually react by slowing down or making a lateral movement. A larger value indicates that participants reacted closer to the vehicle, meaning they reacted later. Given the large amount of data generated in the experiment, manually identifying the reaction position for each data set is impractical and time-consuming. Therefore, an autonomous standard is needed to enable batch processing and analysis of the data through a computer.

To achieve this, two main criteria were established for selecting the reaction position to ensure accurate identification of the reaction time. The first criterion was based on changes in the participants' speed to determine whether they reacted. Specifically, the system began at a pre-designated target point and set a time window. Within this time window, if the participant's speed decreased by more than a specified threshold, this speed change was considered significant, and the point was identified as the starting point of deceleration, or the reaction point. In other words, if the participant's speed dropped beyond the preset standard within the given time frame, it signified that they had begun to react at that point. For the time window, a 1.5-second interval was chosen in the experiment, based on the average reaction time for cyclists, which is approximately 0.8 seconds. Therefore, a 1.5-second observation period was selected to effectively capture the speed changes from the moment the signal was activated to when participants reacted. The system then identified the first point that met this condition as the initial reaction point.

The second criterion was designed to further validate the accuracy of the identified reaction point. Whenever the system found a reaction point based on the first criterion, it checked several preceding data points to verify whether the speed at the previous point was greater than the current point. If there was a point before the initial reaction point where the speed was higher, this earlier point was marked as the new reaction point. This process was repeated until a data point was found where the speed of the previous point was not greater than the current point. At this point, the system confirmed the location as the final reaction point.

The purpose of the second criterion was to address a potential situation where participants may have started to react, but their initial speed reduction was not significant enough for the system to capture it using the first criterion. For instance, participants might have begun decelerating, but the early deceleration was too subtle to meet the threshold set in the first criterion. In such cases, the system might have incorrectly identified a later point as the reaction point. By adding the second criterion, this issue was effectively avoided, ensuring the accuracy of the reaction point, and preventing the omission of the actual reaction time due to less dramatic initial speed changes.

By applying these two criteria in combination, the system was able to more precisely identify the reaction position of participants during the experiment, ensuring the accuracy and reliability of data analysis. As shown in Figure 4.1, the reaction point identified using the two criteria was located at the point where the speed began to significantly decrease. This validated the effectiveness of the two-step filtering method, ensuring not only the precise identification of the reaction point but also the elimination of irrelevant data fluctuations that could interfere with the experimental results. Therefore, the reaction point indicated in Figure 4.1 accurately reflected the moment and position where the participant first reacted to the vehicle's warning signal during the experiment, providing a solid foundation for subsequent data analysis and experimental conclusions.

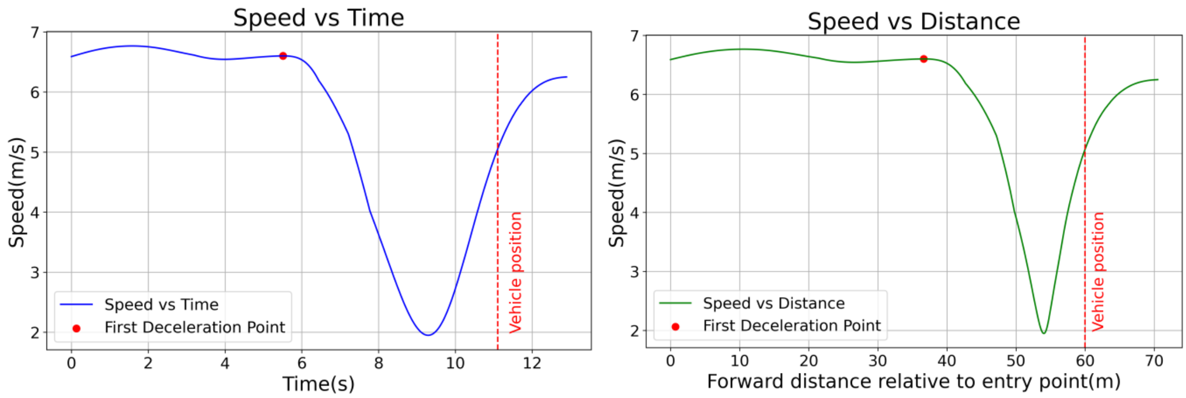

Figure 4.1 The finding point where the avoidance action begins

When determining the reaction start position for special data sets, different processing methods need to be established. First, for participants who exhibited no response, identifying the reaction start position is relatively straightforward. Since these participants did not show any deceleration or avoidance behavior, the system will set their avoidance reaction start position at the location of the vehicle. This indicates that the participants only became aware of the vehicle when they were at the same location as the vehicle. In other words, they failed to timely notice the vehicle's warning signal during the experiment and did not make an effective avoidance response.

However, for data sets involving lateral avoidance behavior, identifying the reaction start position becomes much more complex. The behavior patterns of these participants could include first decelerating and then changing lanes when they judged the situation to still be critical, or they might perform a lateral avoidance first, and then decide whether to decelerate based on their control of the situation. Due to these varied response combinations, identifying the exact start point of the avoidance behavior becomes more challenging.

To accurately pinpoint the start of the lateral avoidance behavior, a comprehensive analysis of two key events—lateral movement and deceleration—must be conducted. Specifically, the system will compare the location where the first lateral movement occurred with the location where deceleration began, determining which of the two is farther from the vehicle. The farther location indicates the earliest point where the participant began to react, and this is considered the start of the avoidance behavior. The system will mark this earliest reaction point as the start of the avoidance action.

This method takes into account the diverse response strategies participants may adopt in different scenarios. For example, some participants might choose to immediately move laterally after detecting the vehicle to maintain a safe distance, while others might opt to decelerate first, observe the situation, and decide whether to change lanes based on the vehicle's actions. By analyzing both lateral movement and deceleration together, this approach provides a more comprehensive understanding of participants' response patterns, ensuring that the identification of the avoidance start point is both accurate and reflective of the actual experimental conditions.

This processing method not only improves the precision of data analysis but also provides richer behavioral patterns for further analysis and research, thereby offering deeper insights into participants' decision-making processes and safety responses under different traffic conditions.

4.5.2 Position of Avoidance Completion

The completion position of the avoidance action(m) is a critical target variable in the experiment, recorded as the distance between the point at which the participant begins receiving the vehicle's signal and the point where they complete the avoidance action. Therefore, the larger this value, the closer the participant is to the vehicle emitting the signal when they finish the avoidance action. This variable is significant because it can be used to measure the participant's total reaction time, thereby assessing their efficiency in responding to sudden situations. By analyzing this data, researchers can gain a deeper understanding of participants' decision-making processes, especially regarding how they perform avoidance actions under different traffic conditions. Additionally, the completion position of the avoidance action can reveal different behavioral patterns, such as distinguishing between quick deceleration and gradual deceleration, which reflect the participant’s driving style and risk perception ability.

The position where the avoidance action is completed can also be used to evaluate the participant’s control over the experimental environment. If the avoidance completion positions are similar across multiple data sets, this may indicate that the participant has developed strong control over the experimental scenario and the vehicle’s behavior. They may feel confident in performing the avoidance action at a location that suits their judgment of safety, rather than reacting immediately. This behavior typically indicates that participants are more confident in choosing when to perform the avoidance rather than responding quickly in an emergency.

In terms of data processing, identifying the position where the avoidance action is completed is relatively straightforward. For participants who decelerate to avoid the vehicle, the point where the avoidance action is completed is marked by the lowest speed recorded. When participants reach their lowest speed and subsequently begin to accelerate, it indicates that the avoidance action has been completed, and the participant has resumed normal cycling. Therefore, in data analysis, the system selects the lowest speed point between the reaction start point and the position of the signaling vehicle as the position where the avoidance action is completed.

For data sets where participants exhibit lateral avoidance behavior without any significant deceleration, a different approach is used. In such cases, the system directly selects the first point with the greatest lateral movement between the avoidance start position and the signaling vehicle. This point represents the furthest distance from the vehicle achieved through lateral movement. No further lane changes suggest that the participant perceives this distance as safe, and thus this point is considered the completion position for lateral avoidance.

However, for participants who exhibit both deceleration and lateral avoidance behavior, the situation is more complex. For these data sets, the system compares the lowest speed point with the point of greatest lateral movement to determine which is closer to the vehicle. By comparing these two points, the system can accurately identify the final position where the avoidance action is completed.

Finally, for participants who do not perform any avoidance action, the completion position is set to the same point as the reaction start position, which is the location of the vehicle. This indicates that the participant only noticed the vehicle upon reaching it and did not take any effective avoidance action. Such data highlight situations where participants either ignored or failed to respond promptly to the warning signals, providing valuable insights for improving the signaling systems of autonomous vehicles.

4.5.3 Maximum Deceleration

Maximum deceleration(m/s^2), as a critical observed variable in the experiment, reflects the peak deceleration exhibited by participants during the period from reacting to the signal until the completion of the response action. The larger the value, the greater the deceleration, meaning the participant's speed decreases more rapidly over a given period of time. This variable provides a direct measure of participants' perception of safety in the current environment. When faced with an emergency situation, individuals instinctively decelerate to ensure their safety. Therefore, the maximum deceleration value quantitatively represents participants' perception of the urgency of the situation and their attitude towards potential risks.

In the data processing phase, for those participants who performed lateral avoid action without significant deceleration, the maximum deceleration is set to 0. This is because, in the bicycle simulator, forward speed is calculated by reading the wheel's rotational speed, which naturally generates acceleration and deceleration variations. However, due to the limitations of the simulator, lateral movement is controlled by buttons attached to the handlebars, which trigger fixed-speed movement without any changes in acceleration. Therefore, for participants who performed lateral evasions, the maximum deceleration is recorded as 0.

Additionally, since there are only 42 data sets of lateral avoid action without deceleration, the sample size is relatively small and insufficient for separate analysis. To ensure the continuity of data analysis, I assigned a maximum deceleration of 0 to these data sets and incorporated them into the broader analysis model. Comparative tests revealed no significant changes in the effect sizes of the variables after including these data. The integration of these data into the analysis did not affect the significance or interpretation of the other variables in the model. Thus, combining these lateral evasion data with the rest is feasible without negatively impacting the overall results. A detailed comparison of this analysis is presented in the appendix.

For participants who exhibited significant deceleration during the response action, their maximum deceleration was recorded in the same manner as for standard deceleration data sets. The system tracked their deceleration curve and identified the highest deceleration value throughout the avoidance process. This value is crucial for assessing the level of perceived danger and urgency experienced by the participants during the maneuver.

Finally, for participants who did not exhibit any response action, the maximum deceleration was also recorded as 0, indicating that no deceleration occurred during the experiment. By analyzing these combined data sets, I can gain deeper insights into how participants respond to vehicle warning signals under different experimental conditions, as well as how different signal types and activation distances influence their evasive behaviors. Maximum deceleration, as a key variable, helps to better evaluate the effectiveness of the Alert signal systems in AEVs in enhancing road safety.

4.5.4 Roadside Attention

The variable Roadside Attention(°) serves as an important metric in the study, effectively reflecting the extent to which participants focus on the right side of the road between the moment they begin receiving signals and when they complete an avoidance maneuver. This data is derived by calculating the average yaw angle from the Euler angles of the VR headset. The yaw angle indicates the horizontal rotation of the headset, which aligns with the study's goal of tracking the direction of participants' head movements. The average yaw angle reveals how frequently participants focused on roadside information during the experiment. If participants consistently monitored roadside signals, the average yaw angle would be relatively high, indicating that their attention was more frequently directed toward the side of the road rather than straight ahead.

For participants who displayed significant attention to roadside signals, the yaw angle data would show higher values, indicating that their head was frequently turned toward the roadside. This could suggest that participants were actively searching for and responding to roadside signals or visual cues, which is important for evaluating safe driving behaviors. Conversely, if the yaw angle values are lower, it would suggest that participants were primarily focused on the road ahead, potentially overlooking key roadside signals or cues.

For special data sets, such as those in which participants executed lateral avoidance actions or did not perform any avoidance actions, the method of calculating roadside attention remains unchanged. Regardless of the avoidance strategy employed by participants, their degree of attention to roadside information can still be measured through the average yaw angle. This consistent method of calculation ensures a comprehensive analysis across all data sets, allowing for an accurate assessment of participants' attention to roadside signals, regardless of their specific avoidance behavior.

Measuring roadside attention not only provides valuable insights into participants' attention distribution but also helps evaluate the effectiveness of roadside signals in capturing attention. This can inform further improvements in road safety and the design of signal systems.

5

Results

In this chapter, I analyze the experimental data I have collected. The data collected from the experiment is divided into subjective attitude data, gathered through questionnaires and presented in Section 5.1, and objective behavioral data, collected through the virtual reality experiment and presented in Section 5.2.

5.1 Questionnaires Data Analysis Results

In this section, I will present and analyze the data collected from the survey, summarizing valuable insights and findings. To clearly convey the results of the analysis, this chapter will be divided into three subsections. The first subsection covers the demographic data of the participants, which will help us understand the basic background characteristics of the subjects. Next, I will analyze the participants' sense of presence during the experiment, exploring their feelings of immersion and realism within the virtual reality environment. Finally, I will examine participants' direct feedback and impressions of the experiment, including their subjective evaluations of the different signal systems and AEVs. These analyses will provide a deeper understanding of participants' reaction patterns and attitudes, supporting the conclusions drawn from the experiment.

5.1.1 Demographic Results

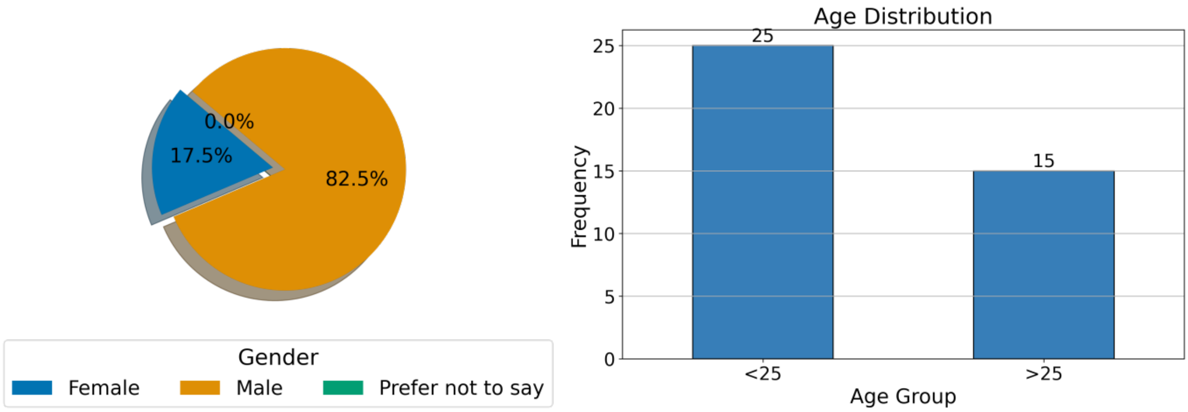

Figure 5.1. Age and Gender distribution

In this study, information was collected from 40 participants, covering aspects such as gender, age, and their experience with virtual reality (VR) devices and computer games. The gender and age distribution of the participants is shown in Figure 5.1. Among the participants, 33 were male and 7 were female. In terms of age, the majority of participants were concentrated in two main groups: 25 participants were under 25 years old, and 15 participants were over 25 years old.

Regarding familiarity with computer games, the distribution of responses was relatively even. Specifically, 24.4% of participants reported being very familiar with computer games, another 24.4% said they were somewhat familiar, 17.1% claimed to be quite familiar, and 24.4% indicated they were moderately familiar. Only 9.8% of participants stated they were completely unfamiliar with computer games. This distribution suggests that most participants had a reasonable level of familiarity with computer games, which may imply stronger adaptability to virtual environments.

As for their experience with VR devices, the participants showed varying levels of exposure. The data in Figure 5.2 revealed that 39.0% of participants occasionally used VR devices, while 36.6% said they rarely used them, and 19.5% had never used VR devices before. Only 2.4% of participants reported using VR devices frequently, and another 2.4% stated they always used them. This information helps us better understand participants' ability to adapt to and interact with the virtual reality environment during the experiment.

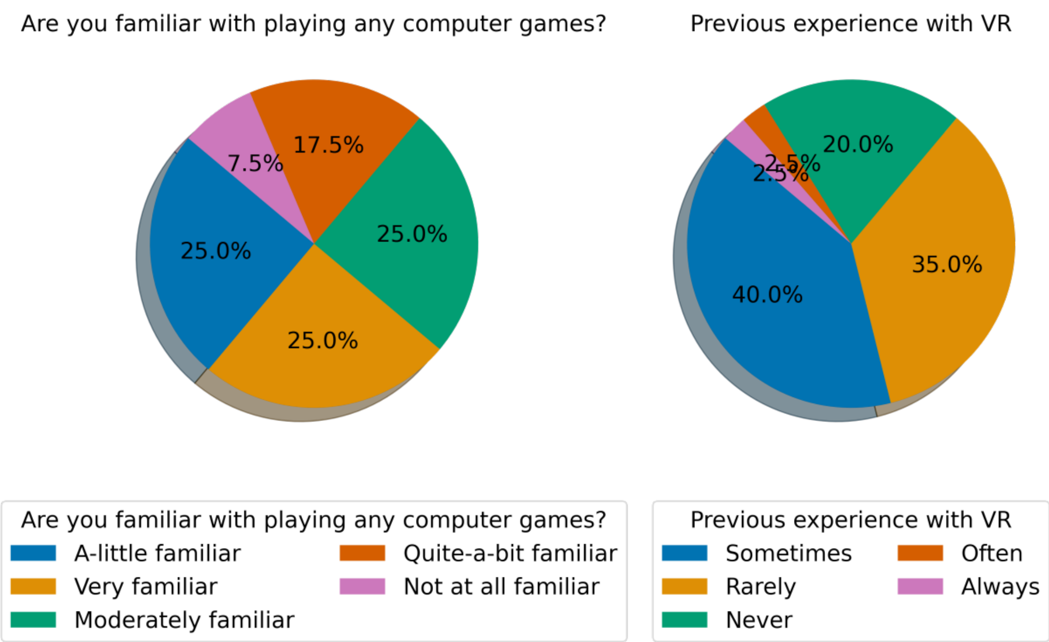

Figure 5.2. Statistics on Computer Game Experience and VR Device Usage

In the experiment, in addition to observing participants' reactions to different signals, special attention was given to whether they could distinguish between the engine noise of conventional vehicles and electric vehicles. To better understand this, participants' experience with electric vehicles was thoroughly analyzed. Understanding their familiarity with the concept of electric vehicles and their actual experience driving or riding in them helps us gain insights into how their responses during the experiment correlate with their knowledge of electric vehicles.

As shown in Figure 5.3, there is a wide variation in participants' familiarity with the concept of electric vehicles. 29.3% of participants reported that they were somewhat familiar with the concept of electric vehicles, while 26.8% said they had a moderate understanding of it. Additionally, 22.0% of participants considered themselves quite familiar with the concept, and 19.5% indicated they were very familiar with the technology and concept of electric vehicles. Only 2.4% of participants stated they were completely unfamiliar with the concept. This data suggests that as electric vehicles have gradually become more widespread, the related knowledge has been well disseminated, with most people having at least some understanding of the concept.

However, despite the high level of familiarity with the concept, participants’ actual experience with electric vehicles is relatively limited. The data shows that 39.0% of participants reported that they rarely drive or ride in electric vehicles, while 26.8% said they occasionally use them. Additionally, 22.0% had never driven or ridden in an electric vehicle, and only 12.2% frequently use electric vehicles. This indicates that while electric vehicle technology has been broadly introduced and is in practical use, the proportion of individuals in the 20 to 30 age group who have frequent experience with electric vehicles remains relatively small. Most people are still at the stage of limited exposure or occasional use.

This data highlights that although electric vehicle concepts are well-known, actual user experience is still not as widespread. For participants, the gap between conceptual familiarity and real-world experience might influence their ability to distinguish between conventional and electric vehicle engine noises during the experiment. Those with greater familiarity and experience with electric vehicles may find it easier to perceive these noise differences, while those with limited experience may struggle to make accurate distinctions.

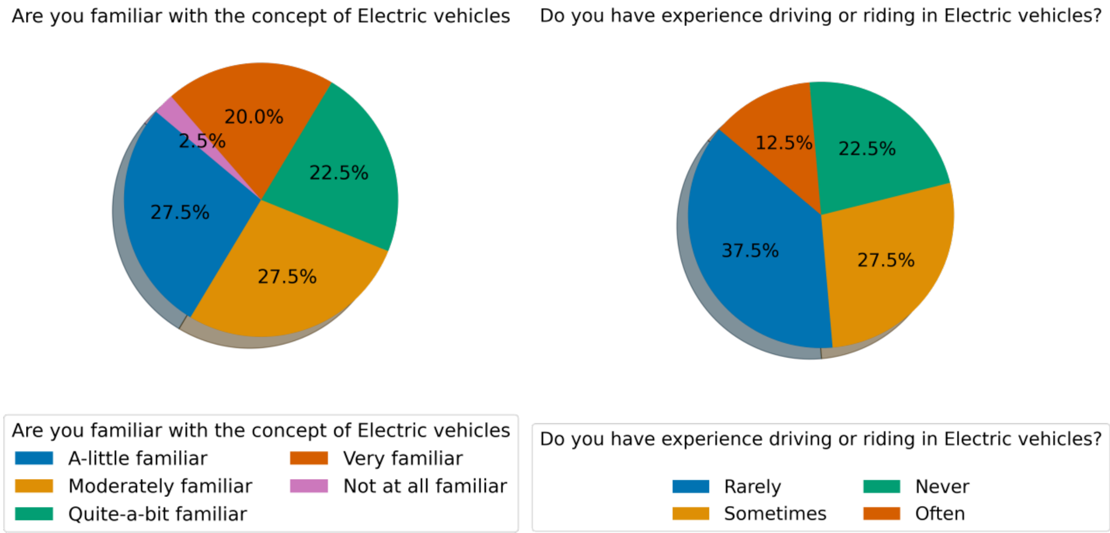

Figure 5.3. Familiarity with the Concept of Electric Vehicles and Experience in Using Them

The primary objective of this experiment is to evaluate the safety and comfort of adding an additional alert system to AEVs. Therefore, analyzing participants' familiarity with autonomous vehicles and their practical experience with them is crucial for interpreting their behavioral responses during the experiment. Generally, participants who are familiar with or have had exposure to autonomous vehicles tend to exhibit more pronounced behavioral tendencies, as they already have formed opinions and attitudes toward the safety and technological features of autonomous vehicles.

Figure 5.4 shows the participants' familiarity with the concept of autonomous vehicles. According to the results, 41.5% of the participants reported having some level of understanding of autonomous vehicles, while 24.4% indicated that they were completely unfamiliar with the concept. Additionally, 17.1% of the participants stated they had a moderate level of knowledge about autonomous vehicles, 9.8% said they were fairly familiar, and only 7.3% indicated they were very familiar with this emerging technology. This suggests that while autonomous vehicles have gradually entered the public consciousness in recent years, most people still have only a surface-level understanding or are entirely unfamiliar with the concept.

In terms of practical experience, the data reveals an even greater scarcity. A total of 90.2% of participants had never driven or ridden in an autonomous vehicle, 4.9% reported occasionally having the opportunity to do so, and another 4.9% said they sometimes used autonomous vehicles. Clearly, most participants have very limited experience with autonomous vehicles, which aligns with the current reality that autonomous vehicles are not yet widely deployed. At this stage, autonomous vehicles are still largely in the development and testing phases, with limited opportunities for the public to interact with them.

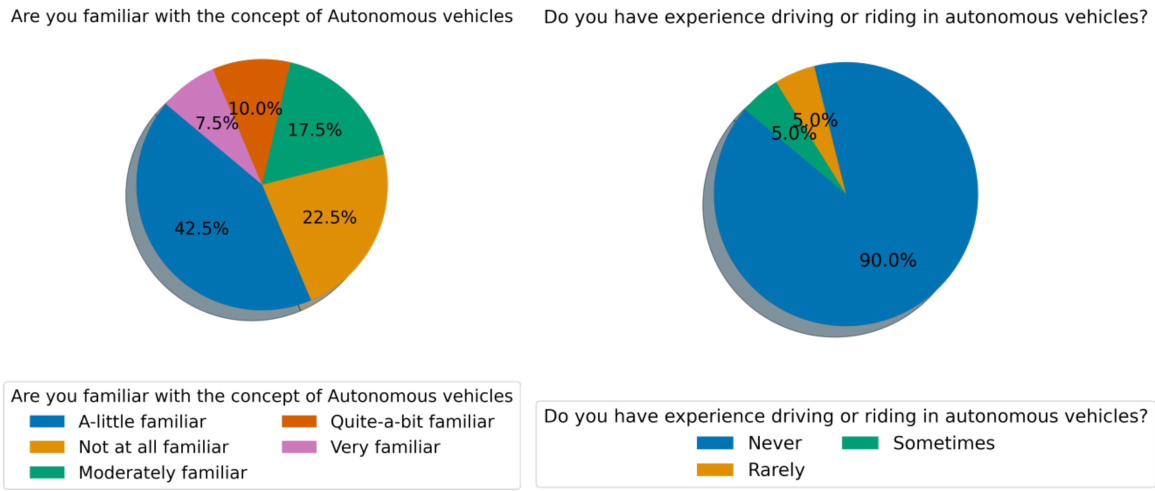

Figure 5.4. Familiarity with the Concept of Autonomous Vehicles and Experience in Using Them

5.1.2 Presence Analysis

In this experiment, presence analysis is primarily used to assess the immersion and realism experienced by participants in the virtual reality environment. This analysis is crucial to the validity of the experiment, as a strong sense of presence allows participants to behave more similarly to how they would in real-life situations, thereby enhancing the external validity and generalizability of the experimental results. If participants experience weak presence in the virtual environment, they may become more aware that they are in a simulated setting, which could affect their behavioral patterns and decision-making processes. This could result in a disconnection between the experimental results and real-world conditions, ultimately impacting the accuracy and applicability of the experiment's conclusions.

In this experiment, a specific questionnaire was used to gather participants' feedback on their visual and auditory experiences in the virtual environment, as well as their overall sense of presence. The study adopted the Presence Questionnaire (PQ) (Witmer, Jerome, & Singer, 2005) to measure participants' sense of presence. This questionnaire consists of four subscales: involvement, sensory fidelity, immersion, and interface quality. Participants rated 19 items using a 5-point Likert scale. The results of the PQ survey are shown in Table 5.1. Both the immersion and sensory fidelity subscales had the highest scores, indicating that participants experienced a strong sense of immersion and that the sensory stimuli, such as visual and auditory aspects in the virtual environment, closely resembled those in the real world. The average total score of the PQ in this study was 73.225 (SD = 5.63), indicating a strong sense of presence in the study.

Table 5.1. Subscales of PQ(range from 1 to 5)

	Involvement	*Sensory fidelity*	*Immersion*	*Interface quality*
Mean	3.85	3.98	3.98	2.81
SD	0.29	0.1	0.19	0.63

According to the statistical analysis of responses to certain questions, more than 70% of participants indicated that the objects in the virtual environment realistically replicated those in the real world. This suggests that the visual aspects of the experimental design were effective, as the object modeling and details provided participants with a strong sense of realism, allowing them to fully engage with the experimental environment.

In addition to the visual experience, participants were also asked to evaluate whether their behavior in the virtual world matched their expectations and whether their interactions with the environment felt natural. Most participants reported that their interactions in the virtual environment were smooth and natural, and that they were able to freely control their actions and reactions. This fluidity and responsiveness are key factors in enhancing immersion, helping participants focus more on the experiment and reduce their awareness of the virtual setting. Auditory feedback also played a significant role in enhancing immersion; well-designed sound effects further increased the realism of the virtual environment, allowing participants to adapt to the simulated scenarios more quickly.

Overall, participants' feedback indicated that their experience in the virtual environment largely matched their expectations of the real world, with most reporting a strong sense of presence. This provides important support for the validity of the experimental results, ensuring that the collected data reflects the behavioral traits and reaction patterns participants would likely exhibit in real-life scenarios. The full questionnaire will be presented in the appendix for further analysis and reference.

5.1.3 Direct perceptions

In the survey, I used a 1-5 scale to measure and record participants' direct feedback following the experiment, particularly regarding whether they noticed the light signals emitted by idling vehicles on the roadside. The average score for this question was 4.15 (SD = 0.65), indicating that most participants were able to clearly detect these light signals. This suggests that the light signals were highly effective in conveying the vehicle's intentions. The strong visual effect of the light signals quickly caught participants' attention, allowing them to promptly respond to the vehicle’s status. This feedback further confirms the role of light signals as an important communication tool in traffic environments.

Meanwhile, for the question on the noticeability of sound signals, the average score was 3.54 (SD = 0.99), indicating that most participants also acknowledged the effectiveness of sound signals. However, compared to light signals, sound signals were perceived as slightly less effective. While sound signals performed well in quieter environments, some participants noted that their distinguishability decreased in noisier street environments. This result suggests that, although sound signals can provide additional warning functionality, relying solely on sound signals may not be sufficient in complex traffic scenarios.

Regarding the distinction between electric vehicles and traditional internal combustion engine vehicles, the average score of 2.83 (SD = 0.79) indicates that many participants found it difficult to differentiate between the two based on engine noise when the vehicles were idling. This suggests that the low-noise characteristic of electric vehicles is not always easily perceptible, especially in more complex environments.

Additionally, participants' trust in autonomous vehicles that rely solely on light signals to convey information had an average score of 3.24 (SD = 0.90), generally rated as moderate. This reflects some skepticism regarding the effectiveness and safety of using light signals as the sole communication method. Most participants felt that relying solely on light signals might not be sufficient to handle complex driving environments, especially in busy urban traffic (with an average score of 3.88, SD = 0.49 on the question of whether it is insufficient for complex environments). They generally believed that combining multiple signals (such as light and sound) could offer a more comprehensive and reliable way for autonomous vehicles to interact with other road users, thereby enhancing overall safety (average score of 3.68, SD = 0.92).

On the other hand, I conducted a detailed survey of participants who experienced AEVs equipped with an alert system, aiming to assess their attitudes towards this new feature. On the question of whether adding sound alerts could effectively improve road safety, the average score was 3.95 (SD = 0.79), indicating that most participants agreed that the addition of sound alerts could significantly enhance road safety, helping other road users detect the approach of autonomous vehicles in a timely manner. However, on the question of whether sound alerts would contribute to noise pollution, the average score was 2.72 (SD = 1.07), with the highest standard deviation among all the questions, reflecting a wide range of opinions among participants. Some participants expressed concerns that widespread use of sound alerts could increase urban noise pollution, especially in busy street environments. Therefore, while improving vehicle detectability, avoiding excessive noise pollution has emerged as a topic that requires further research and improvement.

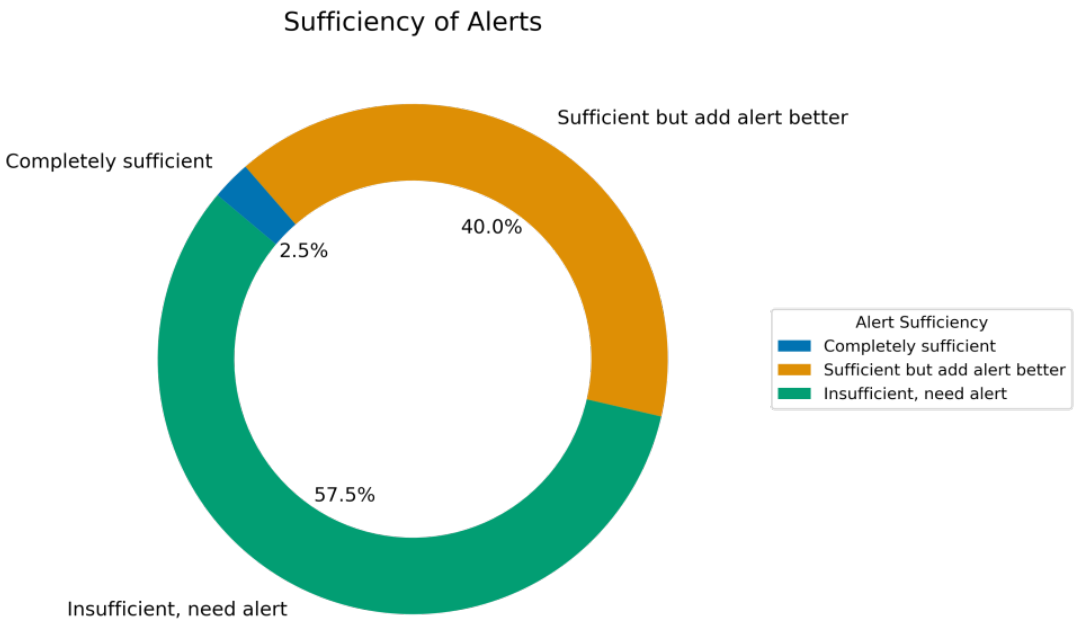

Figure 5.5 Participants' Opinions on the Necessity of the Additional Alert Signal System

At the end of the survey, I directly asked participants for their subjective feedback on the alert signal system after completing the experiment. As shown in Figure 5.5, only one participant felt that it was unnecessary to add an audible alert system to autonomous vehicles. Among the remaining participants, 60% believed that relying solely on light signals was insufficient to ensure safe interactions between vehicles and other road users, while 40% indicated that light signals could effectively support the operation of autonomous vehicles but also agreed that adding audible alerts would further enhance safety. Overall, participants generally felt that, while light signals were somewhat effective, the addition of sound alerts could significantly improve the subjective sense of safety and comfort for cyclists and pedestrians, especially in complex urban traffic environments.

Based on the subjective feedback, the addition of an alert signal system is still considered highly necessary. This enhancement would not only increase the visibility and warning effectiveness of autonomous vehicles in various scenarios but also boost the safety perception and trust in autonomous driving technology among road users. These survey results provide valuable insights for future design and optimization of autonomous driving systems, indicating that a combination of multiple signaling methods (such as light and sound signals) can better facilitate safe interactions between autonomous vehicles and other road users.

5.2 Analysis Results of VR Experiment Data

In this section, an in-depth analysis of the four main target variables(Reaction position,Avoidance finish position,Max Deceleration and Roadside Attention) from the experiment was conducted. The analysis model used is the Linear Mixed Model (LMM). LMM is a statistical model that combines fixed effects and random effects, allowing the consideration of both systematic influences and random variations in the data. Fixed effects describe factors that have the same influence on all observational units, which are typically the experimental variables pre-set to observe their changing effects. Random effects, on the other hand, account for factors that influence observational units differently, usually reflecting minor unnoticed differences in the experiment or variations in participants' behavior.

In this experiment, three main independent variables were designed, each consisting of two, three, and three different settings, resulting in a total of 18 experimental condition combinations. The "noisy environment," "AEVs without Visual eHMI and alert system," and "close signal trigger distance" were chosen as the baseline group. In LMM analysis, the baseline group serves as a reference point for all experimental conditions, with other conditions being compared to the baseline in terms of their effects.

These three conditions were selected as the baseline because the initial hypothesis suggests that this combination of independent variables (i.e., noisy environment, AEVs without an alert system, and short signal trigger distance) is likely the most challenging for participants to perceive vehicle warning signals. This assumption is based on the consideration that noise in the environment might interfere with sound signals, AEVs without an alert system may lack sufficient visual and auditory cues, and the short signal trigger distance may put participants under greater pressure to react in a shorter timeframe, thus affecting their ability to respond promptly to vehicle signals.

$$Y = \beta_0 + \beta_{11}X_{11} + \beta_{21}X_{21} + ... + \beta_{32}X_{32} + \beta_{double}X_{11}X_{21} + ... + \beta_{Triple}X_{11}X_{21}X_{31} + Zb + \epsilon$$

The formula for the LMM model is shown in the figure above, where Y represents the response variable, which is our main target variable. $\beta 0$ is the intercept, and βn are the fixed effect parameters for each predictor variable. These parameters combine with the predictor variable xn, taking a value of 1 when this predictor variable is present in the scenario and 0 when it is absent. βdouble and βtriple represent the interaction effect parameters for two and three predictor variables, respectively. Zb is the random effects term, and ε represents the error term.

5.2.1 The longitudinal position of the reaction

In the main effect analysis, five key variables were studied: AVs, AEVs equipped with an Alert system, medium and long-range signal trigger distances, and quiet environments. The analysis results showed that only AVs did not display significant differences, while AEVs equipped with the Alert system, long-range signal triggers, and quiet environments significantly affected participants' responses. This suggests that warning systems and quiet environments can effectively enhance participants' perception of and reaction to vehicles. In contrast, AVs performed relatively weaker compared to the baseline group (AEVs without the Alert system), indicating that the difference in engine noise is not as noticeable in noisy environments.

Table 5.2. Significance Evaluation of Longitudinal Reaction Points and Their Standardized Coefficients

Predictors	**Explanations**	***EsL***	***SE***	***CI***	***p***
(Intercept)		38.791	1.187	[36.465,41.117]	<0.001
β_Q	Quiet Environment Sound Level(Ref: Noisy level)	**-8.098**	**1.580**	**[-11.195,-5.000]**	**<0.001**
$\beta_{Distance1}$	Middle Signal Trigger Distance(Ref: Short Distance)	**-9.785**	**1.580**	**[-12.882,-6.688]**	**<0.001**
$\beta_{Distance2}$	Long Signal Trigger Distance(Ref: Short Distance)	**-12.848**	**1.580**	**[-15.945,-9.751]**	**<0.001**
β_{VT1}	Vehicle Type:AVs with Visual eHMI (Ref: AEVs with Visual eHMI)	-2.140	1.580	[-5.237,0.957]	0.176
β_{VT2}	Vehicle Type:AEVs with Visual eHMI and Alert signal (Ref: AEVs with Visual eHMI)	**-11.346**	**1.580**	**[-14.443,-8.248]**	**<0.001**
$\beta_{Double1}$	Interaction term(β_Q with $\beta_{Distance1}$)	**6.891**	**2.235**	**[2.510,11.271]**	**0.002**
$\beta_{Double2}$	Interaction term(β_Q with $\beta_{Distance2}$)	3.113	2.235	[-1.267,7.494]	0.164
$\beta_{Double3}$	Interaction term(β_Q with β_{VT1})	**4.361**	**2.235**	**[-0.019,8.742]**	**0.051**
$\beta_{Double4}$	Interaction term(β_Q with β_{VT2})	**10.293**	**2.235**	**[5.913,14.674]**	**<0.001**
$\beta_{Double5}$	Interaction term($\beta_{Distance1}$ with β_{VT1})	1.302	2.235	[-3.078,5.682]	0.560
$\beta_{Double6}$	Interaction term($\beta_{Distance2}$ with β_{VT1})	-3.487	2.235	[-7.867,0.893]	0.119
$\beta_{Double7}$	Interaction term($\beta_{Distance1}$ with β_{VT2})	**9.225**	**2.235**	**[4.845,13.605]**	**<0.001**
$\beta_{Double8}$	Interaction term($\beta_{Distance2}$ with β_{VT2})	**4.824**	**2.235**	**[0.444,9.205]**	**0.031**
$\beta_{Triple1}$	Interaction term(β_Q , $\beta_{Distance1}$ with β_{VT1})	-3.843	3.161	[-10.038,2.352]	0.224
$\beta_{Triple2}$	Interaction term(β_Q , $\beta_{Distance2}$ with β_{VT1})	-4.359	3.161	[-10.553,1.836]	0.168
$\beta_{Triple3}$	Interaction term(β_Q , $\beta_{Distance1}$ with β_{VT2})	**-10.489**	**3.161**	**[-16.684,-4.295]**	**0.001**
$\beta_{Triple4}$	Interaction term(β_Q , $\beta_{Distance2}$ with β_{VT2})	-5.942	3.161	[-12.136,0.253]	0.060
Random effects		***Var***	***SD***	***p***	
#Participant: Intercept	Participant's ID	12.79	3.577	<0.001	
Model Performance					
Observations		1440			
Marginal R^2		0.239			
Conditional R^2		0.325			
logLik		-1377.910			
AIC		4795.821			
BIC		4901.270			

*The zero reference point is 0, representing the moment when participants enter the experimental area and begin receiving the signal.

Further analysis revealed that the combination of quiet environments and vehicle types had a significant effect on participants' response distance (p = 0.051). Although the main effect of AVs was not significant, this indicates that in quiet environments, AV engine noise was more noticeable, prompting participants to react more quickly.

Regarding signal trigger distances, the combination of a quiet environment and medium-range signals showed significant differences, while the combination with long-range signals did not. This could be because long-range warning signals provided participants with more time, allowing them to choose the appropriate moment to perform avoidance actions rather than reacting immediately. In other words, a longer warning distance may give participants a sense of having ample reaction time, which could delay their decision to avoid.

Additionally, the combination of AVs and signal trigger distance did not show significant differences, but the combination of AEVs with the Alert system and various distances exhibited significant effects. This may be due to the fact that, at medium and long distances, the additional sound warning signals helped participants detect the distant light signals earlier and respond more effectively. In particular, under long-range warning signal conditions, sound signals become especially important as they assist participants in better noticing and locating the light signals.

This significant effect is not only observed in two-variable combinations but also in the interaction effects of three variables. Multi-variable interaction analysis further confirms that AEVs equipped with warning systems demonstrated significant comprehensive advantages in quiet environments and under varying signal distances.

From the standardized main effect coefficients, it is evident that changes in warning distance have a clear impact on the position where participants react. However, given the small difference between medium distance (M) and long distance (L), it can be inferred that the effect of warning distance may only be more pronounced within a certain range. There is a significant difference between AEVs and AEVs equipped with the Alert system, while the difference between AVs and these vehicles is minimal. This indicates that the differences in engine noise types did not have a significant impact on the participants' reaction positions, while the additional alert signal played a crucial role. This may be because the alert signal is more likely to capture the participants' attention, prompting them to react more quickly.

The combination of quiet environments and vehicle types generally shows a positive effect, but after considering the main effects, the overall impact on the target variable still presents as a negative effect. This may be because in quiet environments, participants can more easily detect the presence of vehicles through engine noise at the same distance and locate the vehicle earlier. Consequently, they may feel more confident in reacting at a distance they consider safe rather than taking immediate action. This leads to a certain delay in the reaction point, but overall, participants are still able to respond more promptly due to earlier detection of the signal.

For AEVs equipped with the Alert system, the interaction effect with medium and long signal trigger distances shows significant differences, whereas AVs do not exhibit this effect. This could be because in noisy environments, the sound signals from the Alert system are more easily received by participants, helping them better judge the distance between themselves and the vehicle. This allows them to more safely and confidently choose the position at which to react.

The three-variable interaction effects are mostly negative. After combining the main effects and interaction effects, the overall impact on the target variable remains negative. However, significant interaction effects are observed only when the vehicle is an AEV equipped with the Alert system. In quiet environments, when more noticeable sound alerts are combined with longer warning distances, participants react earlier. This is reasonable because when considering these factors individually, they all have negative effects—each variable enables participants to notice the vehicle's position earlier. The earlier the vehicle is noticed, the earlier the reaction.

5.2.2 Position of Avoidance Completion

First, the significance analysis shows that all main effects have statistically significant impacts on the completion position of avoidance behavior. In the two-way interaction effects, the interaction between signal trigger distance and AVs did not show significant differences. However, the interaction between signal trigger distance and AEVs equipped with the Alert system did show significance. This difference may be due to the Alert system's auditory warning signals, which prompt participants to quickly notice approaching vehicles and take avoidance action. This phenomenon also appears in the three-way interaction effects, further confirming the important role that auditory warning signals play in triggering participants' responses.

Table 5.3. Significance evaluation of the Longitudinal Position of Avoidance completion and its standardized coefficients

Predictors	Explanations	*EsL*	*SE*	*CI*	*p*
(Intercept)		54.998	0.727	[53.572,56.423]	<0.001
β_Q	Quiet Environment Sound Level(Ref: Noisy level)	**-4.190**	**0.901**	**[-5.956,-2.424]**	**<0.001**
$\beta_{Distance1}$	Middle Signal Trigger Distance(Ref: Short Distance)	**-5.760**	**0.901**	**[-7.526,-3.994]**	**<0.001**
$\beta_{Distance2}$	Long Signal Trigger Distance(Ref: Short Distance)	**-10.293**	**0.901**	**[-12.059,-8.527]**	**<0.001**
β_{VT1}	Vehicle Type:AVs with Visual eHMI (Ref: AEVs with Visual eHMI)	**-1.916**	**0.901**	**[-3.682,-0.150]**	**0.033**
β_{VT2}	Vehicle Type:AEVs with Visual eHMI and Alert signal (Ref: AEVs with Visual eHMI)	**-9.804**	**0.901**	**[-11.570,-8.038]**	**<0.001**
$\beta_{Double1}$	Interaction term(β_Q with $\beta_{Distance1}$)	**2.781**	**1.274**	**[0.283,5.279]**	**0.029**
$\beta_{Double2}$	Interaction term(β_Q with $\beta_{Distance2}$)	1.212	1.274	[-1.286,3.710]	0.342
$\beta_{Double3}$	Interaction term(β_Q with β_{VT1})	**4.409**	**1.274**	**[1.911,6.907]**	**0.001**
$\beta_{Double4}$	Interaction term(β_Q with β_{VT2})	**9.579**	**1.274**	**[7.082,12.077]**	**<0.001**
$\beta_{Double5}$	Interaction term($\beta_{Distance1}$ with β_{VT1})	1.456	1.274	[-1.042,3.954]	0.253
$\beta_{Double6}$	Interaction term($\beta_{Distance2}$ with β_{VT1})	-1.176	1.274	[-3.673,1.322]	0.356
$\beta_{Double7}$	Interaction term($\beta_{Distance1}$ with β_{VT2})	**4.934**	**1.274**	**[2.436,7.431]**	**<0.001**
$\beta_{Double8}$	Interaction term($\beta_{Distance2}$ with β_{VT2})	**4.414**	**1.274**	**[1.916,6.912]**	**0.001**
$\beta_{Triple1}$	Interaction term(β_Q , $\beta_{Distance1}$ with β_{VT1})	-3.353	1.802	[-6.885,0.179]	0.063
$\beta_{Triple2}$	Interaction term(β_Q , $\beta_{Distance2}$ with β_{VT1})	-1.362	1.802	[-4.894,2.171]	0.450
$\beta_{Triple3}$	Interaction term(β_Q , $\beta_{Distance1}$ with β_{VT2})	**-6.323**	**1.802**	**[-9.855,-2.791]**	**<0.001**
$\beta_{Triple4}$	Interaction term(β_Q , $\beta_{Distance2}$ with β_{VT2})	**-6.512**	**1.802**	**[-10.044,-2.980]**	**<0.001**
Random effects		*Var*	*SD*	*p*	
#Participant: Intercept	Participant's ID	9.835	3.136	<0.001	
Model Performance					
Observations		1440			
Marginal R^2		0.342			
Conditional R^2		0.495			
logLik		-1605.531			
AIC		3251.065			
BIC		3356.510			

Additionally, the interaction effects between a quiet environment and all vehicle types showed significance, indicating that a quiet environment had a notable influence on the completion point of avoidance behavior. However, it is worth noting that the combination of a quiet environment and medium-distance signal triggers showed significance, while the combination with long-distance signal triggers did not. This may be because, in a quiet environment, long-distance warning signals allow participants to notice approaching vehicles earlier, giving them ample time and space to assess the situation. As a result, they feel confident in completing the avoidance maneuver at an appropriate moment rather than acting immediately, thus not showing significant differences with the long-distance signal.

In contrast, participants in the medium-distance signal trigger condition, without the extended reaction time offered by long-distance signals, may feel more urgency when the signal is activated, leading them to complete the avoidance maneuver earlier, which results in significant differences. This analysis suggests that in a quiet environment, medium-distance signal triggers have a more direct impact on participants' avoidance behavior, while long-distance signals provide more flexibility, allowing participants to perform avoidance actions with greater confidence and comfort, which may explain the lack of significant differences.

The analysis of the standardized main effect coefficients shows that a longer warning distance indeed prompts participants to complete avoidance actions earlier. Similarly, AEVs equipped with alert signals are more effective in prompting participants to take early evasive actions compared to AEVs without alert systems. This indicates that the introduction of alert signals significantly improves participants' awareness, enabling them to detect the approaching vehicle earlier and respond in a timely manner.

The interaction effects between variables present a more complex pattern. In most of the two-variable interactions, the effects are positive. However, when the main effects and interaction effects are applied simultaneously to the target variable, the results still show a negative effect. This suggests that, while the combined interaction effects do accelerate the completion of avoidance action, the degree of acceleration is not as pronounced as the sum of the individual main effects would predict. In other words, although the warning signals and specific experimental conditions promote earlier avoidance behavior, the combined impact is not as significant as initially expected.

In the combination of quiet environments and vehicle types, the distance at which participants complete avoidance action is significantly reduced. Notably, the effect of AEVs equipped with alert signals is more pronounced than that of standard AVs. This could be because in a quiet environment, participants are more likely to detect the vehicle's engine sound, allowing them to more accurately determine the vehicle's position. This auditory signal provides a sense of safety, giving participants the confidence to complete the avoidance maneuver at a location they deem appropriate, rather than taking action too early or too late.

Additionally, the interaction effect between warning distance and AEVs equipped with alert systems shows a significant positive effect. This may be due to the fact that, in noisy environments, engine noise can be obscured by ambient sounds, while the loud alert signal remains distinct, helping participants to better locate the vehicle. This confidence in determining the vehicle's position explains why the effect coefficients for both medium and long warning distances are quite similar.

The three-variable interaction effects are generally negative. Even after accounting for both the main effects and two-variable interaction effects, the overall impact on the target variable remains negative. However, significant effects primarily occur in the combination of AEVs equipped with alert systems. This indicates that when a quiet environment, a longer warning distance, and a more noticeable alert signal are combined, participants complete avoidance actions even earlier. This is because these variables are more prominent compared to the control group, allowing participants to gain a better understanding of the situation earlier, which prompts them to take action and complete the avoidance maneuver sooner.

5.2.3 Maximum Deceleration

In the significance analysis, the evaluation of the main effects shows that only the AEVs with warning signals did not exhibit significant differences, while all other variables demonstrated significant effects. In terms of two-way interaction effects, the quiet environment, in combination with warning distance and vehicle type, displayed significant differences, indicating that compared to a noisy environment, a quiet setting can significantly enhance participants' ability to perceive vehicle signals. However, in the interaction between distance and vehicle type, only the combination of long distance and AVs showed significant effects, suggesting that longer warning distances can more effectively capture participants' attention under certain conditions.

In the analysis of multi-variable interaction effects, the combination of AVs and long warning distances in a quiet environment showed significant effects, as did the combination of AEVs with Alert systems and medium warning distances. This indicates that different signal types and trigger distances have varying impacts on participants' maximum deceleration in a quiet environment.

Table 5.4. Significance evaluation of the maximum deceleration and its standardized coefficients

Predictors	Explanations	EsL	SE	CI	p
(Intercept)		11.791	0.692	[10.434,13.148]	<0.001
β_Q	Quiet Environment Sound Level(Ref: Noisy level)	**-3.484**	**0.877**	**[-5.203,-1.765]**	**<0.001**
$\beta_{Distance1}$	Middle Signal Trigger Distance(Ref: Short Distance)	**-2.765**	**0.877**	**[-4.484,-1.046]**	**0.002**
$\beta_{Distance2}$	Long Signal Trigger Distance(Ref: Short Distance)	**-4.568**	**0.877**	**[-6.286,-2.849]**	**<0.001**
β_{VT1}	Vehicle Type:AVs with Visual eHMI (Ref: AEVs with Visual eHMI)	**-4.046**	**0.877**	**[-5.765,-2.327]**	**<0.001**
β_{VT2}	Vehicle Type:AEVs with Visual eHMI and Alert signal (Ref: AEVs with Visual eHMI)	-1.043	0.877	[-2.762,0.676]	0.234
$\beta_{Double1}$	Interaction term(β_Q with $\beta_{Distance1}$)	**2.454**	**1.240**	**[0.023,4.884]**	**0.048**
$\beta_{Double2}$	Interaction term(β_Q with $\beta_{Distance2}$)	**4.312**	**1.240**	**[1.881,6.743]**	**0.001**
$\beta_{Double3}$	Interaction term(β_Q with β_{VT1})	**3.073**	**1.240**	**[0.643,5.504]**	**0.013**
$\beta_{Double4}$	Interaction term(β_Q with β_{VT2})	**3.212**	**1.240**	**[0.781,5.643]**	**0.010**
$\beta_{Double5}$	Interaction term($\beta_{Distance1}$ with β_{VT1})	1.291	1.240	[-1.140,3.722]	0.298
$\beta_{Double6}$	Interaction term($\beta_{Distance2}$ with β_{VT1})	**5.423**	**1.240**	**[2.992,7.854]**	**<0.001**
$\beta_{Double7}$	Interaction term($\beta_{Distance1}$ with β_{VT2})	2.318	1.240	[-0.113,4.749]	0.062
$\beta_{Double8}$	Interaction term($\beta_{Distance2}$ with β_{VT2})	1.782	1.240	[-0.648,4.213]	0.151
$\beta_{Triple1}$	Interaction term(β_Q , $\beta_{Distance1}$ with β_{VT1})	0.135	1.754	[-3.303,3.573]	0.939
$\beta_{Triple2}$	Interaction term(β_Q , $\beta_{Distance2}$ with β_{VT1})	**-5.469**	**1.754**	**[-8.907.-2.031]**	**0.002**
$\beta_{Triple3}$	Interaction term(β_Q , $\beta_{Distance1}$ with β_{VT2})	**-3.987**	**1.754**	**[-7.425,-0.550]**	**0.023**
$\beta_{Triple4}$	Interaction term(β_Q , $\beta_{Distance2}$ with β_{VT2})	-3.027	1.754	[-6.465,0.411]	0.084
Random effects		*Var*	*SD*	*p*	
#Participant: Intercept	Participant's ID	7.589	2.755	<0.001	
Model Performance					
Observations		1440			
Marginal R^2		0,048			
Conditional R^2		0.236			
logLik		-1560.592			
AIC		3160.385			
BIC		3265.833			

From the standardized coefficients of the main effects, it can be observed that a quiet environment, longer warning distances, and more prominent engine noise all contribute to a decrease in participants' maximum deceleration. This implies that their deceleration behavior becomes more gradual and less abrupt, suggesting that participants are able to make more controlled and less hasty avoid actions under these conditions, reducing the likelihood of emergency braking.

In the two-way interaction effects, although many combinations showed positive effects, when the main effect coefficients were included in the overall analysis, the maximum deceleration still showed a decreasing trend. This suggests that while interaction effects may weaken some of the impacts of the main effects, the overall trend remains a reduction in maximum deceleration. Particularly in quiet environments, the interaction between vehicle type and trigger distance shows positive coefficients, likely because sudden signals in quiet settings can induce a momentary sense of urgency, leading to more abrupt initial reactions to ensure safety.

In the three-way interaction effects, almost all combinations exhibited negative effects. Upon observing these interactions, it becomes clear that longer warning distances indeed facilitate more gradual evasive actions. However, the type of warning signal also plays a crucial role—it is not simply a matter of longer distances leading to smoother deceleration. For instance, AEVs with warning signals showed smoother deceleration at medium distances compared to long distances. This may be because, in a quiet environment, participants are closer to the vehicle at medium distances and can hear the engine noise earlier, allowing them to prepare sooner, resulting in less abrupt deceleration. Conversely, long distances might provide too much time and space, causing participants to lower their guard.

In conclusion, while longer warning distances and a quiet environment help participants detect vehicle signals earlier and prompt them to make more gradual avoid actions, the specific deceleration behavior also depends on the combination of warning signal types and distances. In some cases, medium warning distances may encourage more controlled reactions rather than relying solely on long-distance warning signals.

5.2.4 Roadside Attention

In the evaluation of the significance of road-side attention, most main effects did not show significant differences. However, the AEVs equipped with alert signals showed a notable trend toward significance compared to other vehicles, though the P-value of 0.077 is still greater than the 0.05 threshold for statistical significance. Meanwhile, long-distance warning signals were found to be significant, and the effect was negative. As for multivariable interactions, most did not show significance, with the exception of the combination of AVs and a quiet environment, which demonstrated a significant interaction.

Table 5.5. Significance evaluation of roadside attention and its standardized coefficients

Predictors	**Explanations**	***EsL***	***SE***	***CI***	***p***
(Intercept)		7.118	0.501	[6.136,8.100]	<0.001
β_Q	Quiet Environment Sound Level(Ref: Noisy level)	0.083	0.656	[-1.203,1.369]	0.899
$\beta_{Distance1}$	Middle Signal Trigger Distance(Ref: Short Distance)	-0.312	0.656	[-1.598,0.974]	0.634
$\beta_{Distance2}$	Long Signal Trigger Distance(Ref: Short Distance)	**-1.686**	**0.656**	**[-2.973,-0.400]**	**0.010**
β_{VT1}	Vehicle Type:AVs with Visual eHMI (Ref: AEVs with Visual eHMI)	-0.593	0.656	[-1.879,0.694]	0.366
β_{VT2}	Vehicle Type:AEVs with Visual eHMI and Alert signal (Ref: AEVs with Visual eHMI)	-1.160	0.656	[-2.446,0.126]	0.077
$\beta_{Double1}$	Interaction term(β_Q with $\beta_{Distance1}$)	-0.685	0.928	[-2.504,1.135]	0.461
$\beta_{Double2}$	Interaction term(β_Q with $\beta_{Distance2}$)	-0.523	0.928	[-2.342,1.296]	0.573
$\beta_{Double3}$	Interaction term(β_Q with β_{VT1})	**1.818**	**0.928**	**[-0.002,3.637]**	**0.050**
$\beta_{Double4}$	Interaction term(β_Q with β_{VT2})	1.649	0.928	[-0.170.3.468]	0.076
$\beta_{Double5}$	Interaction term($\beta_{Distance1}$ with β_{VT1})	-0.042	0.928	[-1.861,1.778]	0.964
$\beta_{Double6}$	Interaction term($\beta_{Distance2}$ with β_{VT1})	1.515	0.928	[-0.304,3.335]	0.103
$\beta_{Double7}$	Interaction term($\beta_{Distance1}$ with β_{VT2})	0.105	0.928	[-1.715,1.924]	0.910
$\beta_{Double8}$	Interaction term($\beta_{Distance2}$ with β_{VT2})	1.270	0.928	[-0.549,3.089]	0.171
$\beta_{Triple1}$	Interaction term(β_Q , $\beta_{Distance1}$ with β_{VT1})	-0.069	1.313	[-2.642,2.504]	0.958
$\beta_{Triple2}$	Interaction term(β_Q , $\beta_{Distance2}$ with β_{VT1})	-1.623	1.313	[-4.196,0.950]	0.216
$\beta_{Triple3}$	Interaction term(β_Q , $\beta_{Distance1}$ with β_{VT2})	0.127	1.313	[-2.445,2.700]	0.923
$\beta_{Triple4}$	Interaction term(β_Q , $\beta_{Distance2}$ with β_{VT2})	-0.674	1.313	[-3.247,1.898]	0.607
Random effects		***Var***	***SD***	***p***	
#Participant: Intercept	Participant's ID	2.865	1.693	<0.001	
Model Performance					
Observations		1440			
Marginal R^2		0.034			
Conditional R^2		0.172			
logLik		-1135.877			
AIC		4311.754			
BIC		4417.202			

The long-distance warning signal showed both significance and a negative effect, indicating that when participants noticed the vehicle's signal from a greater distance, they were less likely to continuously or significantly turn their heads to monitor the signaling vehicle. This is because they had already gathered enough information from a distance, allowing them to focus more on the road ahead and use peripheral vision, rather than fully turning their heads to follow the vehicle. This behavior suggests that when signals are detected early, participants' attention to the vehicle decreases, and they focus more on the road's overall conditions. This is considered a safety enhancement, as participants are both aware of the signaling vehicle and able to focus on the road without being overly distracted by the signaling vehicle.

Additionally, the combination of AVs and a quiet environment showed significance when compared to the baseline group, and the interaction remained positive after adjusting for the main effects. This suggests that in closer proximity, participants in a quiet environment were able to detect the vehicle's engine noise earlier, but the absence of visual signals caused them to maintain their attention on the roadside, searching for potential warning signals. This continued attention resulted in increased road-side focus, particularly in scenarios where AVs were not equipped with additional alert signals. Consequently, participants' visual attention was more heavily concentrated on identifying the signal source in such conditions.

6

Discussion and Conclusions

In this chapter, the main research findings will be discussed. First, Section 6.1 will revisit the research question and explain the importance of conducting this study. Section 6.2 will summarize the main results presented in Chapter 5 and positioning the study results within the literature. Finally, Section 6.3 will address the limitations of this research and future research directions.

6.1 Recap of Problem Statement and Research Importance

With the rapid development of autonomous driving and EVs technologies, AEVs are emerging as a critical component of future transportation systems. AEVs not only offer significant advantages such as reducing carbon emissions, improving energy efficiency, and optimizing traffic flow, but they are also seen as a potential solution to many of the transportation and environmental challenges faced by modern society. However, despite their immense potential, the safe interaction between AEVs and other road users remains a key challenge that must be addressed for their widespread adoption and use.

Currently, one of the widely adopted industry solutions is to equip autonomous vehicles with external Human-Machine Interfaces (eHMI), which use visual signals to communicate non-verbally with pedestrians, cyclists, and other road users. These visual cues help others on the road to better understand the intentions of the autonomous vehicle, thereby reducing the risk of accidents. However, because AEVs, like most electric vehicles, produce little engine noise, especially when traveling at low speeds or idling, they may be difficult to detect by sound alone. As a result, the question of whether AEVs should be equipped with Acoustic Vehicle Alerting Systems (AVAS) to provide additional auditory warnings and compensate for this lack of noise remains unresolved. Currently, there is insufficient research support in both industry and academia to definitively answer this question.

To address this key issue, the present study used Virtual Reality (VR) technology to simulate interaction scenarios between AEVs and cyclists, focusing specifically on whether additional auditory warning systems (AVAS) could enhance cyclists' ability to perceive vehicles and improve their sense of safety. An experiment was designed within the virtual reality environment, incorporating different combinations of environmental noise levels, signal trigger distances, and vehicle types. The goal was to systematically analyze experimental data to assess the impact of auditory warning systems on the interaction between AEVs and road users.

The central research question is: In situations where autonomous electric vehicles are already equipped with eHMI systems, is an additional auditory warning system still necessary to ensure road safety? Through comprehensive analysis of the experimental data, this study aims to provide scientific evidence for policymakers, traffic management authorities, and vehicle manufacturers. The goal is to help them strike the optimal balance between ensuring the safety of road users and reducing the cost of implementing this technology.

6.2 Summary of main results

6.2.1 Safety Aspect

Through the analysis of experimental data and survey responses, it is clear that the acoustic alert system significantly enhances cyclists' ability to perceive approaching vehicles. Firstly, the experimental results indicate that AEVs equipped with acoustic alert signals perform exceptionally well, especially in noisy environments. Compared to vehicles that rely solely on visual signals, the acoustic alert system effectively compensates for the low engine noise of electric vehicles, particularly when triggered at medium to long distances. This was strongly validated through data analysis, specifically in the evaluation of maximum deceleration and reaction points, where the acoustic alert system enabled cyclists to detect vehicles earlier and react in advance. This not only reduced reaction time but also significantly lowered the sense of urgency and stress participants experienced when faced with sudden situations.

Survey feedback corroborates these findings, with 73.2% of participants clearly stated that the acoustic alert system helped them perceive approaching vehicles more effectively, particularly in complex traffic conditions where visual signals alone may not fully ensure safety (In the questionnaire, all participants gave a score of 3.24 to vehicles that used only light signals in noisy environments, while vehicles with an additional alert system received a score of 3.88. This is a significant difference). This feedback aligns closely with the experimental data. Although 40% of participants believed that visual signals were sufficient in scenarios without the complex lighting and sound interference typical of urban areas, nearly all participants expressed a preference for the inclusion of an acoustic alert to enhance perception and safety. This demonstrates that, from a subjective standpoint, the acoustic alert system not only enhances participants' sense of security but also improves their ability to control the environment and recognize potential hazards.

Overall, the acoustic alert system consistently enabled participants to notice vehicles earlier and provided them with more ample reaction time and distance under various experimental conditions, representing an improvement in safety. It effectively compensates for the low noise levels of electric vehicles, ensuring that vehicles are more easily perceived by other road users, especially in noisy urban environments. Therefore, the integration of an acoustic alert system in future transportation systems has the potential to significantly enhance overall road safety.

6.2.2 Comfort Aspect

From the perspective of comfort, the acoustic alert system also plays a significant role, particularly in enhancing participants' comfort during the avoidance process. Experimental data shows that AEVs equipped with alert signals not only prompted cyclists to initiate avoidance behaviors earlier but also significantly improved the smoothness of their avoidance actions. The analysis of maximum deceleration reveals that the acoustic alert signals allowed cyclists to perform smoother avoidance actions, avoiding the stress and anxiety associated with abrupt braking. This smoother response indicates that participants, when aware of the vehicle's presence, were able to react in a more composed and natural manner, rather than becoming highly tense due to the sudden appearance of a signal.

This experimental outcome aligns with the subjective feedback collected from the surveys. Many participants noted that the sound signals not only increased the perceptibility of the vehicle but also reduced their mental burden when interacting with autonomous vehicles, making the overall driving experience more comfortable. This suggests that the acoustic alert system not only enhances the visibility of vehicles in traffic but also significantly boosts participants' confidence, allowing them to interact with autonomous vehicles in a more composed and relaxed manner.

Furthermore, the analysis of roadside attention further supports this conclusion. The experimental data indicates that longer warning distances showed a significant advantage over medium warning distances. The results suggest that participants were able to gather information about the vehicle's status from a distance, thereby reducing the need for frequent head-turning. This implies that the acoustic alert system may allow participants to detect potential hazards earlier and more quickly, enabling them to focus on the road ahead without frequently shifting their gaze.This more natural behavior effectively reduced participants' anxiety, enhancing the smoothness and comfort of their driving experience. Participants in the survey commonly reported that sound signals not only increased their sense of security but also alleviated their anxiety when facing autonomous vehicles, significantly improving overall driving comfort.

6.2.3 Answering the research questions

This study aims to explore how an additional auditory alert system affects the interaction between cyclists and AEVs equipped with a visual eHMI in a virtual reality environment, focusing particularly on its impact on cyclists' perceived safety and comfort. The central research question is to determine whether this auditory alert system can enhance both the objective and subjective road safety and comfort of cyclists. To answer the central research question, three sub-questions were defined to delve deeper into specific aspects of this interaction. In the previous chapters, a series of data analyses and discussions were conducted, and several conclusions were drawn. Now, a summary will be provided to answer the sub-research questions and the central research question that were set out at the beginning of this study.

Sub-question 1: In the absence of additional auditory alerts, is there a difference in cyclists' perception abilities and behavior between autonomous vehicles (AVs) and autonomous electric vehicles (AEVs) equipped with the same electronic human-machine interface (eHMI) system?

The research results show that in the absence of an auditory alert system, cyclists' perception abilities toward AEVs are significantly lower than those toward AVs. Due to the low engine noise of AEVs, cyclists found it more difficult to detect the approaching vehicle in noisy environments, leading to longer reaction times. Although visual eHMI signals provide some assistance, the lack of auditory cues makes AEVs less perceivable than AVs, resulting in slower response speeds.

Sub-question 2: How does the additional auditory alert system to AVs and AEVs affect cyclists' perception abilities and behavior ?

The auditory alert system significantly enhanced both the safety and comfort of cyclists. Objective data showed that the auditory signals reduced reaction times and lowered maximum deceleration, enabling cyclists to complete avoidance actions in a smoother manner. Subjective feedback also indicated that participants were satisfied with the presence of the auditory signals, believing that it not only improved their awareness of the approaching vehicle but also alleviated psychological stress, making their cycling experience more relaxed and comfortable.

Sub-question 3: Does the environmental noise level of an area influence the perception abilities of cyclists towards different types of vehicles equipped with the same eHMI system?

The study demonstrated that environment noise levels significantly impact cyclists' perception abilities. In noisy environments, AEVs, due to their low noise characteristics, are harder for cyclists to detect quickly, and the effectiveness of visual eHMI signals is also reduced. However, when an auditory alert system is introduced, the negative impact of noise on perception abilities is effectively mitigated. The auditory signals enable cyclists to more accurately judge the vehicle's position and movement. Therefore, the auditory alert system proves especially effective in high-noise environments.

Main research question: How does an additional auditory alert system in autonomous electric vehicles equipped with visual eHMI affect cyclists' behavior, comfort, and safety under the influence of different types of idling vehicles and environmental noise?

The research results indicate that the auditory alert system significantly enhances cyclists' perceived safety. Objective data show that the auditory signal improves cyclists' reaction time, prompting them to complete avoidance actions earlier, particularly in noisy environments where the sound signal compensates for the low noise levels of electric vehicles. Moreover, the subjective feedback from the survey supports this, with participants expressing a clear preference for the auditory signal, noting that it greatly improved their awareness of the vehicle and made them feel safer in complex traffic situations. Therefore, the study concludes that the auditory alert system is an effective tool for improving the safety of interactions between AEVs and cyclists.

Based on the answer of the research questions, it is clear that the auditory alert system significantly enhances the safety and comfort of cyclists when interacting with AEVs. From a safety perspective, the experimental data show that auditory signals significantly reduce cyclists' reaction time, prompting them to notice potential hazards earlier and complete avoidance actions sooner. The increased reaction distance is considered an effective factor in reducing the likelihood of accidents. This finding is further supported by survey feedback, where over 60% of participants indicated that relying solely on visual signals is insufficient to ensure complete road safety, especially in noisy urban environments. The additional auditory signals complemented the visual eHMI, improving cyclists' perception of approaching vehicles and enhancing safety in complex traffic scenarios.

In terms of comfort, the auditory alert system not only increases vehicle detectability but also allows cyclists to execute avoid actions more smoothly and naturally, alleviating the psychological strain caused by sudden reactions. The data demonstrate that the inclusion of auditory alerts reduces cyclists' maximum deceleration, allowing them to respond more smoothly. The survey feedback corroborates these findings, with participants expressing that auditory alerts made them feel more at ease and significantly improved their overall cycling experience.

6.2.4 Positioning the study results within the literature

Currently, in the literature on interactions between AEVs and other vulnerable road users, most studies focus primarily on pedestrian interactions with AEVs. However, research on cyclists, who are also vulnerable and often have to share the road with vehicles, remains relatively limited.

In the existing literature, significant progress has been made regarding the interaction between AEVs and road users. Wessel et al. (2022) investigated how the sound characteristics of electric vehicles during acceleration affect pedestrians' estimation of time-to-collision (TTC). Their experiment, conducted using virtual reality technology, tested pedestrians' TTC judgments in scenarios where electric vehicles were either equipped with or without acoustic vehicle alerting systems (AVAS). The results indicated that due to the low noise levels of electric vehicles, pedestrians often overestimated the TTC, which increased the risk of road accidents. While the introduction of AVAS improved this judgment, it was still less effective than for internal combustion engine vehicles (ICEVs). This research highlights the critical role of sound signals in enhancing traffic safety perception, especially in the absence of such signals, where pedestrian reactions were slower compared to traditional vehicles.

In contrast, the present study showed that sound warning signals not only effectively enhanced cyclists' ability to perceive the approaching vehicle but also significantly reduced reaction times, prompting them to complete avoidance actions earlier, particularly in noisy environments. Although both studies emphasize the positive impact of sound warning systems on safety, there are some differences in their conclusions. Wessel et al. found that electric vehicles equipped with AVAS were less effective than ICEVs in terms of pedestrian safety, whereas this study demonstrated that additional sound signals could effectively compensate for the shortcomings of low-noise vehicles in complex environments. This discrepancy may stem from key differences in experimental design: Wessel's experiment focused on pedestrians estimating TTC during vehicle acceleration, whereas this study examined scenarios in which cyclists actively approached stationary vehicles. Additionally, Wessel et al. concentrated on the effects of different AVAS loudness levels, while this study employed a beeper as the warning signal. The differences in signal types, as well as the types and sound level of environmental noise, may explain the variation in conclusions.

Bindschädel et al., (2023) conducted a real-world experiment exploring the effectiveness of AVs communicating with pedestrians through eHMI and acoustic signals. The study revealed that the combination of acoustic signals and eHMI significantly improved pedestrians' decision-making when crossing the street and increased their sense of safety. This finding aligns with the results of the present experiment, particularly regarding the effectiveness of sound warning systems in noisy environments. Although Bindschädel's study used a real-world setting while the current research relied on virtual reality technology, both studies demonstrate that sound signals are crucial tools for enhancing interactions between AVs and pedestrians or cyclists. This further supports the role of sound signals in improving safety and perception.

Similarly, Liu et al., (2024) explored the impact of multimodal eHMI (MUI) with emotional voice prompts on the interaction between autonomous personal mobility vehicles (APMV) and pedestrians. Through passenger experiments in real-world environments, the study found that eHMI with voice prompts significantly enhanced passengers' understanding and quality of interaction with pedestrians. While this study focused on the effectiveness of emotional voice prompts and the current experiment used a simpler beeper warning signal, both studies reached the conclusion that sound signals significantly improve users' sense of safety and driving experience.

Additionally, Shen et al.,(2020), through simulation modeling concluded that the low noise characteristic of electric vehicles increases the risk to pedestrians at low speeds. Although the experimental methods differ, this finding is highly consistent with the conclusions of the current study, both indicating that the low noise of electric vehicles can make it difficult for road users to respond promptly, thus increasing the risk of accidents. This study further validated through virtual reality experiments that sound warning systems can significantly improve cyclists' awareness of approaching vehicles. Especially in noisy urban environments, the addition of sound warnings effectively compensates for the perceptual limitations caused by electric vehicles' low noise.

By comparing the aforementioned studies, it can be concluded that while the methodologies and experimental designs differ, all suggest that incorporating sound warning systems in autonomous electric vehicles plays a crucial role in improving road safety. Sound signals not only significantly enhance pedestrians' and cyclists' ability to perceive vehicles but also improve their sense of safety and comfort, with their effectiveness being particularly prominent in complex traffic environments.

6.3 Research Limitations and Future Research

Despite several important findings in this stusy, there are some limitations that need further exploration. First, while the use of virtual reality (VR) technology provided numerous advantages, such as offering a safe and controlled environment to simulate real road scenarios, it also has inherent limitations. Participants' behaviors in a virtual environment may not fully align with how they would act in reality. Though VR technology can effectively simulate driving situations, there may still be differences in perception and action feedback compared to real-world experiences, especially in complex traffic scenarios. Participants' psychological responses and decision-making might be constrained by the VR equipment. Thus, conclusions drawn from VR experiments need to be validated through rigorous real-world control experiments to confirm that findings from virtual environments are applicable to actual settings.

Secondly, the choice of signal type in this experiment may have influenced the generalizability of the study's results. This research used a beeping sound as a substitute for a sound warning signal but did not explore more diverse acoustic signals, such as different loudness levels or frequencies. This limitation restricts the generalizability of the findings and does not fully assess how other types of sound signals may impact cyclists' perception and reactions. Following the findings from previous research, Wessel's experiment thoroughly evaluated the effects of different sound levels and frequencies, resulting in findings that differ from those in this study. Therefore, future research could benefit from comparing various types of sound warning signals to better understand the effectiveness of warning systems across different environments and signal forms.

Third, the background of the participants may have influenced the results. The participants in this study were primarily recruited from a campus setting, meaning the sample largely consisted of students and young adults who had prior experience with virtual reality and computer games. This may have led to a higher level of adaptability to the experimental environment, which could mean that the findings do not fully reflect the behavior of older or less technologically experienced drivers and cyclists. To increase the generalizability of the results, future research should consider including a more diverse group of participants to verify whether the findings apply to road users from different backgrounds.

Fourth, the limitations of the cycling simulator also have potential impacts on this study. Since the simulator's handlebars are fixed, participants could only control lateral movement using buttons, which differs from the body tilting and handling involved in real cycling. These limitations may affect participants' behavior, especially in complex traffic scenarios, as the simulator may not fully reflect real-world operations and reactions. Moreover, the cycling simulator cannot simulate real-world variations in terrain elevation, or environmental factors like wind and rain. For transparency, it is important to acknowledge these limitations and address them in future research. Improvements could include using more realistic simulators or conducting comparative tests on real roads to verify the reliability and applicability of the study's findings.

Fifth, the measurement method for the mean yaw angle used in this study has certain limitations in terms of accuracy. Although the average yaw angle provides valuable insights into participants' head movements, its validity as the sole measure of "roadside attention" should be approached with caution. The yaw angle only reflects the direction of the participants' head and does not ensure that their visual focus is always on roadside information. Factors such as peripheral vision, eye movements, or brief distractions may affect attention allocation, which cannot be captured solely by the yaw angle. Additionally, the accuracy of the VR headset in tracking the yaw angle may be influenced by device lag or calibration errors, potentially introducing some bias into the data. Future research could incorporate eye-tracking technology or other behavioral indicators to improve the reliability of this measurement method.

Additionally, the design of the experimental scenarios may have limited the study's conclusions. Although the research simulated different signal scenarios in both noisy urban and quiet environments, the experiment was conducted on a single road or under specific conditions. Real-world traffic situations can be much more complex, involving multiple vehicles, pedestrians, and other road users interacting simultaneously. Therefore, the experimental setup does not cover all potential real-world situations. Future research could benefit from incorporating more complex experimental settings to further validate the effectiveness of sound warning systems in a broader range of traffic environments.

Lastly, the chosen signal trigger distances in the experiment may have had an impact on the results. This study used specific trigger distances to test the effectiveness of the sound warning system, but in real-world scenarios, trigger distances may vary due to factors such as vehicle speed, road conditions, and ambient noise. Thus, future studies should consider testing the warning system over a wider range of trigger distances to further enhance the applicability of the conclusions.

In future research, I will continue to validate the conclusions of the current study by addressing some of its limitations. First, I will investigate the types of sounds used in sound alert systems, as studies have shown that different warning sounds can have varying effects on individuals (Patterson, 1990). Therefore, replacing the buzzer sound used in this experiment with different types of sounds and verifying their effects would be a promising direction for future research. Additionally, adjusting the vehicles from an idle stationary state to moving vehicles is another key aspect for future investigation. In this study, the vehicles were stationary, but to apply the current findings to real-world scenarios, it is essential to study the interactions between moving vehicles and other road users. These interactions should not only include face-to-face encounters but also situations such as overtaking, turning, and various real-world scenarios.

7

Study Implications

I believe the findings of this study have significant implications for the design and regulation of future autonomous vehicles. Both subjective and objective results indicate that the presence of auditory information enhances other road users' perception of the road environment and makes them feel safer on a subjective level. Therefore, ensuring that AEVs are equipped with an additional alert system can bridge the perceptual gap caused by the low-noise characteristic of electric vehicles. This is particularly crucial in noisy environments, where auditory information is essential for detecting approaching vehicles. This study provides evidence supporting the integration of comprehensive eHMI systems (combining visual and auditory elements) to enhance the safety and comfort of all road users, especially cyclists.

Additionally, this study utilized a virtual experimental environment. It provides an opportunity for more researchers to go beyond merely using virtual reality experiments to study human behavior and instead incorporate a wider variety of vehicles into the virtual world. The experimental parameters and environmental settings in this study were based on extensive references to existing literature, making them suitable for continued use in more in-depth research. As mentioned earlier, further investigations into different types of sound signals and various vehicle behavior patterns, which were not implemented in this study, can also be developed based on the experimental environment established here.

Furthermore, from a long-term perspective, the study highlights the potential broad societal benefits of equipping AEVs with sound alert systems. Improving the safety and comfort of cyclists can encourage more sustainable transportation choices, fostering urban mobility solutions that align with environmental goals. By ensuring safe interactions between AEVs and non-motorized road users, the promotion and adoption of AEV technology can be advocated to a certain extent.

In conclusion, this study has demonstrated the important role of integrating sound alert systems with visual eHMI into AEVs in addressing the safety and comfort challenges faced by cyclists. The combination of experimental data and participant feedback provides strong support for the practical significance of sound alert systems. Although this is only a small step toward enhancing safety in the field of AEVs, continuous and in-depth research will help establish reasonable regulations that meet the safety needs of all road users while ensuring the effectiveness of autonomous driving solutions, thereby accelerating the integration of AEV technology into daily life.

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Appendix

Appendix A. Main Variables in experiment

For the three main independent variables in this experiment, these variables are the factors actively controlled in the experiment, aimed at studying how they affect cyclists' behavioral responses in different situations. By selecting these specific independent variables, the experiment can explore their potential impact on road safety under diverse traffic conditions.

First, the environmental sound level, as one of the independent variables, includes two levels: quiet residential areas and busy streets. This setup is designed to compare participants' responses under different environmental noise conditions. Specifically, in a quiet residential environment, people have more opportunities to hear the audible warning sounds emitted by vehicles. On the other hand, in a busy street environment, the background noise might make it harder for participants to detect warning signals, which could result in differences in their reaction speed and behavior when approaching vehicles. By comparing the experimental results under these two environmental conditions, a better understanding can be gained of how environmental noise affects public safety perception, reaction time, and decision-making behavior.

The second independent variable was the type of vehicle. The study used three selected vehicle configurations in order to represent common types of AVs which presently and/or potentially could be find on the roadway in future, i.e., 1) AVs with eHMI; 2) AEVs with eHMI; and 3) AEVs with both addition alert signals and eHMI. The three configurations allow an investigation into how the different vehicle type affect participants' perception, trust and behaviors across scenarios—specifically if AEVs with additional alert signals provide better safety assurances.

The third independent factor indicates the trigger distance of the eHMI signals, including short, medium, long-distance conditions. This variable is designed to assess the impact of different trigger distances on participants' responses, particularly whether their perception of approaching vehicles and their reaction behaviors vary with the trigger distance of the signals. Through comparison of these three trigger distance boundary conditions, the objective is to further investigate the role of signal trigger distance in improving road safety, particularly in a complex traffic environment, and establish the optimal trigger distance for signal activation thereby leading to providing cyclist with sufficient time allowance for safety avoidance.

The two mediating variables in the experiment are as follows. The first is "Noise," which combines different levels of environmental noise with the engine noise emitted by various types of vehicles in idle mode. The variation in noise levels simulates diverse real-world road environments, ranging from quiet residential areas to busy streets, allowing an assessment of participants' perception and reaction abilities under these varying noise backgrounds. The second is "Warning Signal," which is determined by the combination of different warning signal trigger distances and vehicle types. This design enables the experiment to explore how participants' responses are affected by different warning signal strengths and vehicle configurations.

The dependent variables include: (1) the distance between the participant and the signaling vehicle at the moment of reaction, used to measure participants' reaction speed; (2) the intensity of deceleration, indicating how forcefully participants reduce their speed in emergency situations, reflecting their perception of potential danger; (3) participants' attentiveness to sound signals, which relates to their sensitivity to warning signals and their ability to focus on information in complex environments; and (4) the distance between the participant and the signaling vehicle when stopping, reflecting participants' perception of safe space after completing the evasive maneuver. By collecting and analyzing these dependent variables, a more detailed understanding of how the independent variables specifically affect participants' behavior can be obtained.

Appendix B. Data Filtering

After the initial processing of the experimental data, plotting the participants' behavioral data reveals that the results based on the raw experimental data contain a wealth of details. These details provide more comprehensive information, offering a clearer picture of the participants' reactions and behavior Apatterns during the experiment. However, the abundance of details also presents significant challenges for subsequent data analysis, especially when trying to identify trends or extract key variables. The complexity of the data can obscure important analytical objectives.

As shown in Figure 1, which displays the speed-time and speed-distance graphs based on the raw experimental data, each frame's detailed information is preserved, but the graphs also highlight the data's volatility and noise. For example, variations in speed and distance during participants' cycling may be influenced by multiple factors, leading to irregular fluctuations in the data. While these fluctuations reflect the actual conditions of the experiment, they can obscure the precise points of key reactions (such as participants' initial reactions or deceleration behavior), thus increasing the difficulty of extracting core variables. Because these fluctuations and noise may mask the exact timing or magnitude of critical behaviors, further data processing is necessary to smooth the data and accurately identify key reaction points and behaviors.

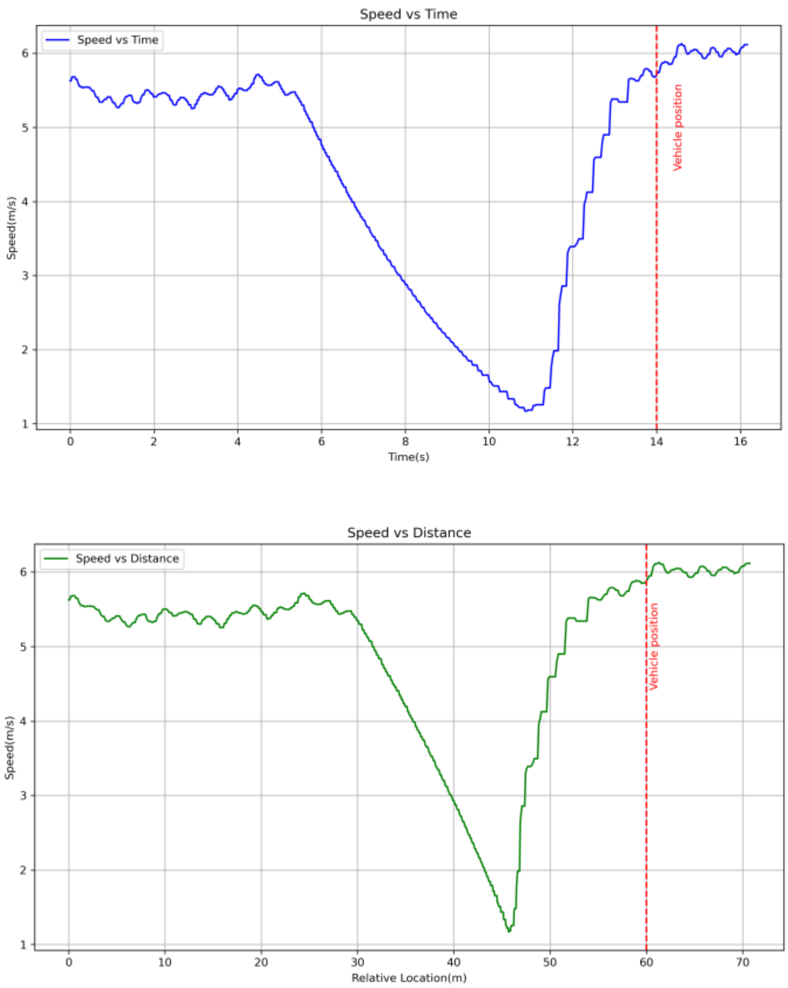


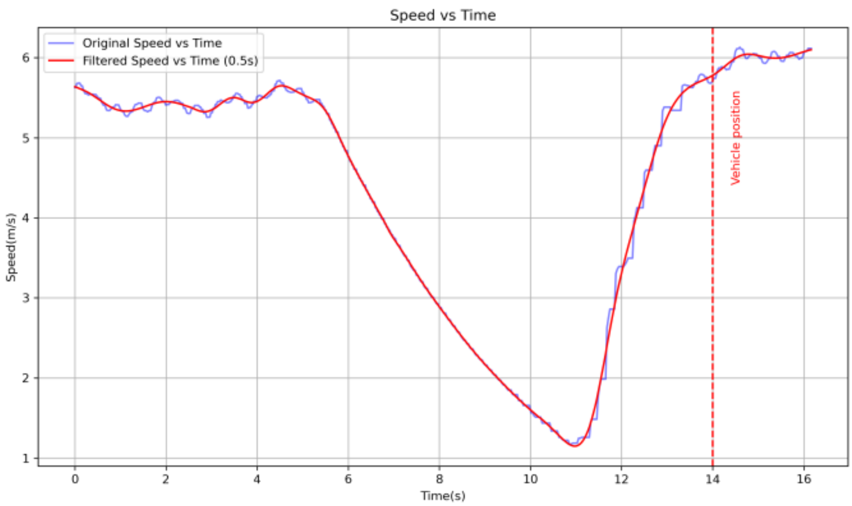
Figure 1 Speed-Time Graph and Speed-Distance Graph Based on Raw Data

As shown in Figure 1, participants generated significant trends of peaks and troughs during cycling, but there were also many small-amplitude fluctuations. These minor fluctuations were caused by the pedaling action during cycling: each time participants pressed the pedals, a noticeable acceleration occurred, leading to the formation of peaks. Between the first and second pedal strokes, the bicycle gradually decelerated due to friction and air resistance, resulting in troughs. These fine fluctuations provided detailed information about the dynamics of cycling, showing how the power output changed throughout the process. However, during data analysis, these small fluctuations are not the primary focus and may complicate the analysis process.

For instance, when attempting to identify the exact moment participants reacted using algorithms or code, these small fluctuations could interfere with the accuracy of the analysis. The system might incorrectly identify one of these minor fluctuations as the point of reaction, leading to inaccurate data analysis results. Therefore, to ensure data accuracy and simplify the analysis process, it is necessary to optimize these small fluctuations to avoid their interference with subsequent analysis.

In the field of data analysis, when there are many small fluctuations or noise in the data, smoothing or filtering techniques are typically applied to reduce interference and highlight the overall trend. In this experiment, low-pass filtering was chosen as the primary data processing method. Low-pass filtering is a classic signal processing technique that allows low-frequency signals to pass through while blocking or attenuating high-frequency noise components. By applying this technique, the data can be effectively smoothed, eliminating rapid changes and noise while preserving the major trends and key patterns.

Specifically, in the data processing for this experiment, low-pass filtering was applied to smooth the cycling speed and distance data, reducing the fine fluctuations caused by participants' pedaling actions. This process not only aids in more accurately identifying the moments when participants reacted but also makes the data easier to interpret, providing a clearer foundation for subsequent variable analysis. As shown in Figure 2, after applying low-pass filtering, the small fluctuations in the data are significantly reduced, and the overall trend becomes smoother. This greatly facilitates further analysis, allowing researchers to focus on the primary trends and reaction points without being disturbed by minor noise.



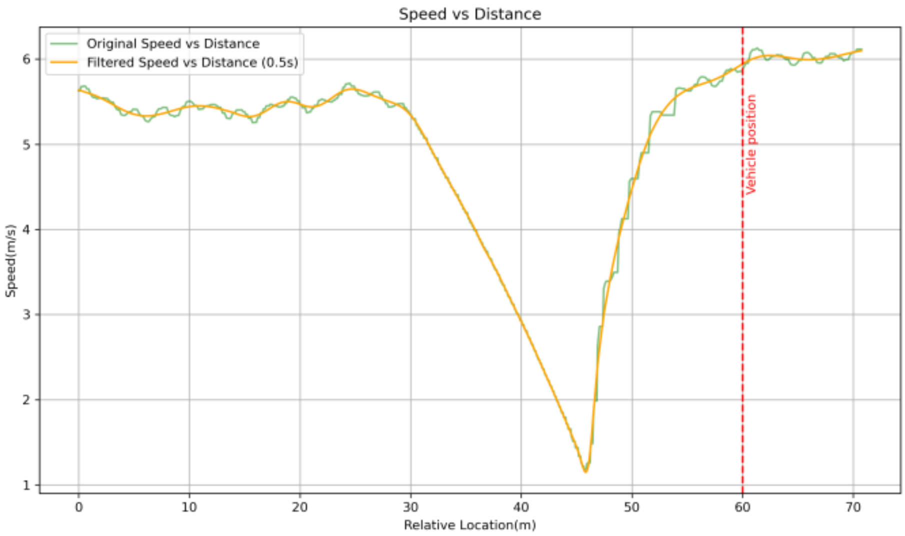


Figure 2 Speed-Time Graph and Speed-Distance Graph after Low-Pass Filtering

As shown in Figure 2, compared to the image generated from the raw data, the graph processed with low-pass filtering appears significantly smoother. The distracting fluctuations, which are irrelevant to the core data analysis, have been effectively smoothed out and eliminated. This smoothing allows the primary trends and key data points to stand out more clearly, making the data easier to interpret.

Appendix C. Classification of Atypical Behavior Data

In the process of collecting experimental data, in addition to the typical deceleration avoidance behavior, there were some special data sets. Since the experiment allowed participants to choose their avoidance strategy based on their own judgment and preferences, some participants opted for lateral movement to avoid roadside vehicles, rather than deceleration. Additionally, in certain situations, due to factors such as lack of attention or insufficiently clear signals, participants failed to notice the vehicle emitting the warning signal in time and did not perform any avoidance actions. Although these data differ from typical avoidance behavior, they still represent participants' real reactions in specific conditions during the experiment and have significant research value. Therefore, these data should not be ignored but should be retained and included in the analysis. However, the processing of these data differs from that of typical deceleration avoidance data and cannot be handled in the same way.

For example, for participants who performed lateral movement to avoid vehicles, the conventional method of "finding the deceleration start point" cannot be used to determine the onset of their avoidance behavior. In these cases, lateral movement data require special treatment to correctly capture the key points and behavioral characteristics of participants' avoidance actions. This section will discuss in detail how to classify these data sets and provide a framework for the subsequent analysis of special data. Specific methods for extracting the target variables from these special data sets will be explained in the following chapters.

First, for the data sets involving lateral avoidance behavior, it is necessary to identify and extract them. As shown in Figure 1, the way participants entered each scenario was carefully designed: they were required to enter the scene from a position 1.2 meters to the right of the center line of a 4.5-meter-wide road. This design ensured that the participants' initial position remained relatively fixed and reduced lateral movement at the start of the experiment. However, even though the bicycle simulator itself did not have built-in lateral movement functionality, an additional handle was provided to enable lateral movement. Some participants, out of curiosity or interest in testing the equipment, might have attempted lateral movement. Therefore, it is necessary to distinguish between normal movements and actual avoidance actions.

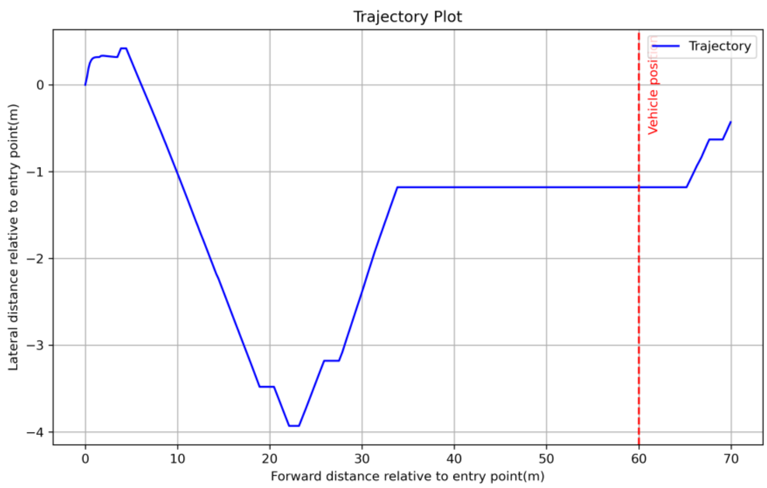


Figure 1 Example of the trajectory plot for lateral avoidance data

To determine whether participants genuinely performed lateral avoidance actions, a criterion was established: when participants crossed the centerline of the road in the experimental scene, moving from the right half to the left half, it was considered that they had engaged in lateral avoidance behavior. To prevent participants from changing lanes arbitrarily and thus affecting the validity of the experimental data, vehicles were introduced in the opposite lane as part of the experimental design. This ensured that participants could not remain in the left lane for extended periods. Based on this, if a participant moved from the right side of the road to the left side during the experiment, it can be assumed that they performed a lateral avoidance maneuver in response to the situation. This identification criterion ensures the accuracy of the data, allowing lateral avoidance behavior to be effectively captured and analyzed.

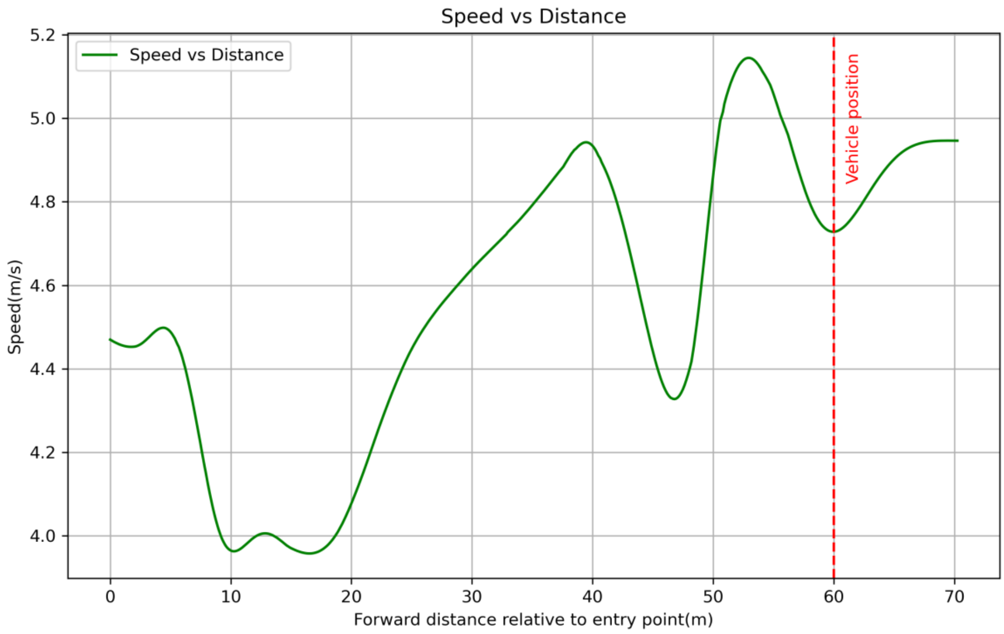


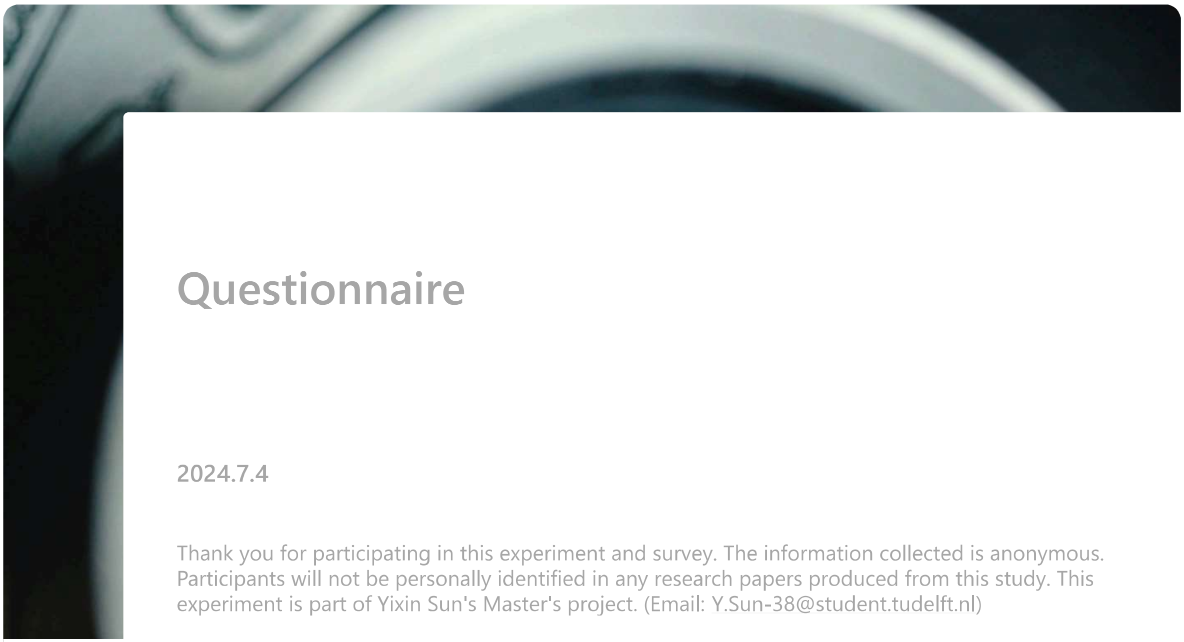
Figure 2 Example of the speed-distance plot for data with no avoidance behavior

Similarly, for the data sets where no avoidance behavior was performed, as shown in Figure 2, the filtering process is relatively simpler. These data typically show that participants neither exhibited significant deceleration nor performed any lateral movement or lane change. In such cases, it can reasonably be inferred that the participants either did not notice the vehicle emitting the warning signal in the scene or did not perceive it as a potential danger requiring avoidance.

Specifically, the filtering criterion is set as follows: when a data set shows no significant deceleration and no lateral movement to the other side of the lane, it is classified as a scenario where the participant did not react. The term "significant deceleration" refers to the moment the participant begins to react, as recorded during the experiment and detailed in section 4.5.3. If no clear deceleration is detected at or near that point, it can be assumed that the participant did not respond to the vehicle's signal in time.

This data filtering standard allows us to distinguish between data sets where participants did not react to the vehicle signals and those where avoidance behavior was performed. Such data also hold significant research value, as they can reveal potential issues with the effectiveness of the vehicle's warning signals under certain conditions, or indicate that participants did not adequately notice the signals in specific environments. Analyzing these data can help further optimize the warning systems of autonomous vehicles, ensuring that signals are more effective at capturing the attention of road users and prompting them to take appropriate avoidance actions in complex traffic environments.

Appendix D. Questionnaire



Questionnaire

2024.7.4

Thank you for participating in this experiment and survey. The information collected is anonymous. Participants will not be personally identified in any research papers produced from this study. This experiment is part of Yixin Sun's Master's project. (Email: Y.Sun-38@student.tudelft.nl)

* Required

Part 1. Participant's characteristic

1. Participant's ID (Fill in by the researcher) *

2. Your Gender *

- ◯ Male
- ◯ Female
- ◯ Prefer not to say

3. Your Age *

4. Previous experience with VR *

- Never
- Rarely
- Sometimes
- Often
- Always

5. How often do you usually ride a bicycle *

- Every day
- 4 to 5 days a week
- 2 to 3 days a week
- Less than one day a week

6. Are you familiar with playing any computer games? *

- Not at all familiar
- A-little familiar
- Moderately familiar
- Quite-a-bit familiar
- Very familiar

7. Are you familiar with the concept of Autonomous vehicles *

- Not at all familiar
- A-little familiar
- Moderately familiar
- Quite-a-bit familiar
- Very familiar

8. Do you have experience driving or riding in autonomous vehicles? *

- ◯ Never
- ◯ Rarely
- ◯ Sometimes
- ◯ Often
- ◯ Always

9. Are you familiar with the concept of Electric vehicles *

- ◯ Not at all familiar
- ◯ A-little familiar
- ◯ Moderately familiar
- ◯ Quite-a-bit familiar
- ◯ Very familiar

10. Do you have experience driving or riding in Electric vehicles? *

- ◯ Never
- ◯ Rarely
- ◯ Sometimes
- ◯ Often
- ◯ Always

Part 2. Virtual environment realism

11. Realism of the virtual environment *

	Unrealistic	Not at all realistic	Normal
Evaluate the realism of the virtual environment	○	○	○
Evaluate the realism of the virtual objects (e.g., vehicles)	○	○	○
Evaluate the realism of the Environmental Audio	○	○	○
Evaluate the realism of the Vehicle Audio	○	○	○
Evaluate the realism of visual experience about the movement abilities	○	○	○

Part 3. Simulator Sickness Check

12. How much each symptom below is affecting you right now *

	None	Slight	Moderate
General discomfort	◯	◯	◯
Fatigue	◯	◯	◯
Headache	◯	◯	◯
Eye strain	◯	◯	◯
Difficulty focusing	◯	◯	◯
Increased salivation	◯	◯	◯
Sweating	◯	◯	◯
Nausea	◯	◯	◯
Difficulty concentrating	◯	◯	◯
Fullness of the head	◯	◯	◯
Blurred vision	◯	◯	◯
Dizziness with eyes open	◯	◯	◯
Dizziness with eyes closed	◯	◯	◯
Vertigo	◯	◯	◯
Stomach awareness	◯	◯	◯
Burping	◯	◯	◯

Part 4. Presence analysis

13. Presence Check *

	Not at all	Low	somewhat
How much were you able to control events	◯	◯	◯
How responsive was the environment to actions that you initiated (or performed)?	◯	◯	◯
How natural did your interactions with the environment seem?	◯	◯	◯
How much did the visual aspects of the environment involve you?	◯	◯	◯
How much did the auditory aspects of the environment involve you?	◯	◯	◯
How natural was the mechanism which controlled movement through the environment?	◯	◯	◯
How much did your experience in the virtual environment seem consistent with your real-world experience ?	◯	◯	◯
Were you able to anticipate what would happen next in response to the actions that you performed?	◯	◯	◯
How well could you identify sounds?	◯	◯	◯
How well could you localise sounds?	◯	◯	◯
How compelling was your sense of moving around inside the virtual environment?	◯	◯	◯
How involved were you in the virtual environment experience?	◯	◯	◯

How much

How much delay did you experience between your actions and expected outcomes?

Pa perception

How quickly did you adjust to the virtual environment

14. previous experiment *

	Very Low	Low	Mid
How much do you notice the light signals emitted by the vehicle?	○	○	○
How much do you notice the sound signals emitted by the vehicle?	○	○	○
How much difference do you notice between electric and conventional vehicles when idling?	○	○	○
Evaluate your perception of safety regarding autonomous vehicles operating without human intervention	○	○	○
Evaluate your level of trust in autonomous vehicles that communicate information using only light signals	○	○	○
Was the information provided through different senses in the virtual environment (e.g., vision, hearing) consistent?	○	○	○

environment?

15. Additional Noise System Evaluation in previous experiment *

	Very Low	Low	Mid
To what extent can you notice a signaling vehicle among those parked by the roadside without additional noise?	○	○	○
To what extent does additional noise increase your sense of safety regarding autonomous vehicles?	○	○	○
How much does noise impact your awareness of autonomous vehicles in a noisy environment?	○	○	○
If brought into reality, to what extent do you think the additional noise signals would interfere with your daily life?	○	○	○
To what extent do you think a noise system helps vehicles communicate better with pedestrians?	○	○	○

16. After the experiment, do you think it is sufficient for autonomous electric vehicles to communicate with the general public on the road using only visual signals (e.g., lights, images, text) in reality? *

- ○ I think it is completely sufficient.
- ○ I think it is sufficient, but adding sound might be helpful.
- ○ I think it is insufficient; sound should be added for assistance.
- ○ I think it is insufficient, but sound does not help.