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Perception and response of cyclists interacting with autonomous electric vehicles - a virtual reality study[☆]

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A R T I C L E I N F O

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A B S T R A C T

Autonomous electric vehicles (AEVs) will increasingly characterize future motorized traffic in urban areas. These vehicles are often silent and can be driverless. Therefore, understanding the interactions between these vehicles and vulnerable road users (VRUs) is crucial for traffic safety. This study explores the impact of an additional auditory alert system and external human-machine interfaces (eHMIs) on AEVs on cyclists' interaction behavior, comfort, and safety under varying vehicle–signal conditions and environmental noise levels. This study employed immersive Virtual Reality (VR) technology to simulate cycling across 18 traffic scenarios, using a within-subjects design with 40 participants. These scenarios included two vehicle types: autonomous conventional vehicles (ACVs) and autonomous electric vehicles (AEVs), two levels of ambient noise levels (quiet residential areas; noisier streets), and three levels of eHMI signal trigger distances (15, 20, 25 m). Data regarding cycling behavior (e.g., response distance, speed variation, gaze direction) and cyclists' perceptions (e.g., realism, simulator sickness, presence, trust, and perceived safety) were collected through VR and post-experiment questionnaires, respectively. We found that compared to vehicles equipped only with an eHMI, AEVs with auditory alerts significantly enhanced cyclists' perceptions and responses, with cyclists detecting the vehicles earlier and responding faster. Subjective feedback also indicated a stronger sense of safety and comfort, such as smoother deceleration that indicated natural responses and reduced stress. Participants also reported a more comfortable interaction experience with AEVs with auditory alerts. These findings provide evidence that equipping AEVs with additional auditory alerts improves the safety and comfort of cyclists in their interactions with AEVs in urban environments. Therefore, policymakers are advised to consider this when setting regulations for the deployment of AEVs in urban areas.

1. Introduction

With the rapid development of autonomous vehicle (AVs) technology and electric vehicle (EVs) technology, autonomous electric vehicles (AEVs) are emerging as a new trend in the future of transportation. AEVs combine the significant potential of AVs to improve energy efficiency (Bachute and Subhedar, 2021; Fu et al., 2022; Muhammad et al., 2021), optimize traffic flow (Chen et al., 2023; Garg

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et al., 2021; He et al., 2022), and reduce traffic crashes by minimizing human error (Shimanuki et al., 2025). Similarly, EVs offer advantages in reducing carbon emissions and promoting environmental sustainability (Sadek, 2012; Verheijen and Jabben, 2010). However, a major challenge to the widespread adoption of AEVs lies in ensuring the safe interaction between AEVs and other road users, especially vulnerable road users (VRUs) in urban areas.

Despite the promising advancements in autonomous driving technology, there remain substantial challenges in practical applications—particularly in the interaction with vulnerable road users (VRUs). A core issue stems from the potential lack of human drivers in AVs, which eliminates traditional implicit communication cues such as eye contact, hand gestures, or head nods (Rasouli et al., 2017). As a result, VRUs can no longer rely on these subtle signals to infer the vehicle's intentions or anticipate its movements, making interaction more uncertain and potentially unsafe (Rezwana and Lownes, 2024; Rothenbücher et al., 2016). To address this challenge, many researchers have proposed using external human-machine interfaces (eHMIs), which aim to convey vehicle intentions through intuitive signals, such as lights, text, or sounds, to improve the interactions between AVs and VRUs (Feng et al., 2025; Wilbrink et al., 2021). Some studies suggest that eHMIs can help VRUs (e.g., pedestrians and cyclists) better understand vehicle intentions, thereby improving perceived safety and trust in automated vehicles (Dey et al., 2020; Feng et al., 2023). However, current findings on the effectiveness of eHMIs remain mixed. Other studies indicate that their effects may be limited or highly dependent on factors such as interface design, traffic context, environmental conditions, and users' interpretation of the signals (Yang et al., 2024). In recent years, multimodal eHMI systems combining signals such as visual and auditory cues have gained increasing attention and are considered more promising in complex traffic environments (Berge et al., 2023). This is because auditory eHMI signals can partially compensate for the limitations of visual cues, providing VRUs with different types of warning information.

EVs, due to their low-noise characteristics, offer significant advantages in reducing urban noise pollution (Rauf et al., 2024). However, this also introduces new safety challenges for VRUs. Compared to traditional internal combustion engine vehicles, EVs produce significantly less engine noise, especially at low speeds or when stationary, making them harder to be audibly detected in time by VRUs (Parizet et al., 2014). This is particularly problematic in urban areas with high environmental noise or limited visibility, where the low noise of EVs may significantly increase the risk of crashes. In this regard, China's GB/T 37153–2018 standard (Standardization Administration of China, 2018) mentions technical specifications for EVs' noise but does not explicitly require warning sounds or simulated engine noise for low-speed operation. In contrast, several countries, including those in the European Union, the United States, and Canada (European Parliament and Council, 2014), mandate the installation of Acoustic Vehicle Alerting Systems (AVAS) in EVs, which mimic the engine noise of traditional internal combustion engine vehicles, to enhance detectability at low speeds, thereby protecting pedestrians and other road users.

Studying the interactions of AVs and VRUs has gained increased attention (Kopsacheilis and Politis, 2023). However, compared to pedestrian-AV interactions, studies on cyclist-AV interactions are relatively limited. Cyclists have different behavioral and movement features compared to pedestrians; thus the results of pedestrian-AV interaction may not be directly applied to cyclist-AV interactions. For instance, cyclists face greater safety risks due to their higher speeds (Evtyukov et al., 2021). These risks are primarily reflected in less time and distance available to respond in sudden situations. Furthermore, wind noise and tire-road friction may generate additional background noise that masks external auditory cues, making it more difficult for cyclists to detect approaching vehicles or warning signals in time (Stefánsdóttir, 2014). Studies indicate that cyclists typically sustain more severe injuries in collisions with motor vehicles, especially involving large vehicles or at complex intersections (Mackay, 1975; Wisch et al., 2017). Additionally, higher cycling speeds can make it more difficult for automated vehicles to detect and respond to cyclists in time. In addition, due to the lack of non-verbal cues and communication, such as eye contact or hand gestures, cyclists may feel less safe compared to interactions with traditional vehicles controlled by humans (Gaio and Cugurullo, 2024). Recent studies found that cyclists prefer to have confirmation of detection by AVs and prefer communication from the AVs rather than external devices or infrastructure. Studies have found that visual communication methods were the most favored by cyclists (Berge et al., 2022; Berge et al., 2025). On the other hand, the low noise of EVs significantly increases the difficulty of detecting vehicles by cyclists, especially in noisy or highly disturbed urban environments (Liu et al., 2022). This characteristic not only affects cyclists' timely perception of vehicles in the surrounding environment but may also lead to inaccurate judgments about vehicle behavior (Wu et al., 2021). Research suggests that measures such as improving urban infrastructure (e.g., dedicated bike lanes and buffer zones) and equipping EVs with AVAS can effectively reduce such crashes (Stelling-Konczak et al., 2015).

As a combination of AVs and EVs, AEVs inherit both their strengths and weaknesses. On the one hand, like AVs, they lack implicit communication channels such as eye contact or gestures due to the absence of a human driver. On the other hand, like EVs, their low engine noise makes it difficult for road users to detect their approach, especially in urban environments with high ambient noise. In this study, when referring to the experimental comparison, we distinguish between autonomous conventional vehicles (ACVs) and autonomous electric vehicles (AEVs). Here, ACVs refer to autonomous vehicles powered by conventional internal combustion engines, whereas AEVs refer to autonomous electric vehicles. Although the two vehicle types differ in their propulsion systems, the present study focuses specifically on their acoustic difference, particularly the lower engine noise of AEVs, because this may affect cyclists' ability to notice roadside vehicles and initiate timely responses. In recent AV field trials, many AEVs have been equipped with visual eHMIs to communicate their driving intentions to surrounding road users (Forke et al., 2021). This raises an important question: Should AEVs, which are already equipped with visual eHMIs, also incorporate additional AVAS to compensate for their low noise in order to enhance road safety? Although existing research highlights the importance of AVAS and eHMI in improving road safety, studies specifically focusing on interactions between AEVs and cyclists remain insufficient. For example, the combined effects of multimodal signals in high-noise environments on cyclists have yet to be fully explored. Moreover, studies on the perceived safety of cyclists when interacting with ACVs and AEVs are also limited.

To bridge these research gaps, this study investigates the impact of auditory warning signals on cyclists' behavioral responses, perceived safety, trust, and comfort when interacting with AEVs in urban areas. These factors were selected because they capture both objective behavioral adaptation (e.g., response timing and deceleration) and subjective interaction experiences (e.g., perceived safety, trust, and comfort), which are central to evaluating cyclist–vehicle interaction in urban traffic environments. Using virtual reality (VR), this study simulates cyclist–vehicle interactions involving ACVs and AEVs under different environmental noise conditions and vehicle–signal conditions. Objective and subjective measures are used to evaluate the effectiveness of auditory warning signals in AEV interactions across different traffic conditions. The main research question that this study aims to answer is: How effective are auditory warning signals in enhancing cyclist interaction with AEVs under noisy urban conditions? To answer this main research question, the study addresses the following sub-questions:

(1) How do cyclists' perceptual and behavioral responses differ when approaching roadside parked ACVs and AEVs under different warning conditions?

(2) How does increasing environmental noise influence cyclists' attention to and responses to roadside parked ACVs and AEVs?

This paper is structured as follows. Section 2 presents the research methodology, including the experiment design, scenario setup, VR equipment, data collection methods, and participant sampling. Section 3 reports the results of both objective behavioral data collected from the VR experiments and subjective questionnaire feedback. Section 4 discusses the findings in relation to the two sub-research questions, and further reflects on the methodological feasibility, design implications, and societal relevance of the study. Section 5 concludes with the key findings, limitations, and directions for future research.

2. Methodology

2.1. Experiment design

This study employed immersive VR experiments to investigate the effects of environmental noise level, vehicle–signal condition, and eHMI signal trigger distance on cyclists' behavior. A within-subject design approach was adopted to eliminate individual differences for comparison across different scenarios. The main variables that were considered in the experiment and their definitions, including independent variables, intermediate variables, and dependent variables, are presented in Table 1.

This study focused on three primary independent variables and their effects on cyclists' behavior, namely environmental noise level, vehicle–signal condition (a categorical variable with three levels), and eHMI signal trigger distance. These variables were designed to simulate various conditions that cyclists may encounter in real traffic environments and to analyze their impact on cyclists' behavioral and perceptual responses. This study systematically manipulated these three independent variables, generating a total of eighteen experimental scenarios. These scenarios were evenly divided into two levels of environmental noise, representing quieter and noisier ambient sound conditions within the same roadside street context. Within each level, the scenarios were further subdivided into nine distinct conditions determined by variations in the eHMI signal trigger distance (i.e., 15 m, 20 m, 25 m) and vehicle–signal condition (i.e., ACV with visual eHMI, AEV with visual eHMI, and AEV with visual eHMI and additional auditory alert).

The selected eHMI trigger distances were determined based on both a behavioral design reference and pilot testing in the VR simulator. The AASHTO Guide for the Development of Bicycle Facilities assumes a bicyclist perception–reaction time of 2.5 s when determining minimum stopping sight distance (American Association of State Highway and Transportation Officials (AASHTO), 1999). In the pilot sessions, participants typically cycled at approximately 5 m/s in the simulator. On this basis, 15 m was selected as the minimum trigger distance, corresponding to approximately 3 s of advance warning, which is slightly above the 2.5-s reference

Table 1
Main variables and their definitions.

Variable	Definition	Levels and indicators
Independent variables		
Environment noise level	The level of ambient noise in the environment	Quiet residential areas; More noisy streets
Vehicle–signal condition	Vehicle configurations combining vehicle powertrain type and communication modality	ACV with visual eHMI; AEV with visual eHMI; AEV with visual eHMI and additional auditory alert
eHMI signal trigger distance	The distance at which the eHMI signal is activated	Short (15 m); medium (20 m); and long trigger activation distances (25 m)
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–signal condition	Assesses how signal strength and vehicle configuration affect cyclists' responses
Dependent variables		
Response position	The distance between the cyclist and the vehicle at the time of response	Measures how fast the cyclist reacts under different experimental conditions
Response completion position	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 max deceleration applied by the cyclist when responding	Reflects the cyclist's perception of the urgency of the signal
Roadside attention	The direction and duration of the cyclist's head orientation towards the roadside parked vehicles or auditory signal sources	Indicates the cyclist's sensitivity to warning signals and ability to focus on information in complex environments

and still allowed participants sufficient time to perceive the signal and produce a measurable response. The other two distances, 20 m and 25 m, were then added in roughly 1-s increments to represent progressively earlier warning onset.

These vehicle–signal conditions were not intended to represent a fully crossed vehicle-type factor; rather, they were designed to reflect three practically relevant communication configurations. Specifically, the comparison between ACV with visual eHMI and AEV with visual eHMI was intended to examine whether the much lower vehicle noise of AEVs, compared with ACVs, may make them less detectable to cyclists. On this basis, the AEV with visual eHMI and additional auditory alert condition was included to test whether an extra auditory cue could compensate for this potential detectability disadvantage. In each scenario, only one variable was changed, while all other variables remained constant.

The current study included three intermediate variables to help explain how the independent variables influenced cyclists' behavior. The first intermediate variable is noise level, which is jointly determined by environmental noise level (i.e., the surrounding ambient sound conditions) and vehicle–signal condition (i.e., different engine-noise characteristics of ACVs and AEVs). The second intermediate variable is the warning signal, which is determined by the combination of trigger distance and vehicle–signal condition. Specifically, the vehicle–signal condition determines the configuration of visual and/or auditory signals (e.g., ACVs were equipped with visual eHMI only, whereas AEVs were presented either with visual eHMI alone or with visual eHMI plus an additional auditory alert), and the eHMI signal trigger distance determines when the signal is activated. Together, these two factors form the basis for the warning signal that the cyclist receives. In this study, "warning signal" refers to the visual eHMI and, where applicable, the additional auditory alert used to communicate the vehicle's intention to depart from the roadside parking position. The third intermediate variable is cyclists' subjective perception and cognitive processing of their surroundings, including perceived vehicle presence, trust in the signal system, perceived safety, and attention allocation. These intermediate variables were used to interpret the link between signal exposure and behavioral response.

The dependent variables were cyclist's response position, response completion position, maximum deceleration, and roadside attention. These variables were selected to reflect key aspects of cyclists' behavioral adaptation to vehicle-based warning signals, including response onset, response completion, braking intensity, and visual attention allocation. Together, these variables were used to represent the onset, completion, intensity, and attentional characteristics of cyclists' responses to vehicle-based warning signals. Their detailed definitions and processing procedures are provided in Section 2.7.

2.2. Experiment scenario

To investigate how cyclists perceive and respond to vehicle signals in realistic urban conditions, the experimental scenario was designed to replicate a typical Dutch residential/shared street where cyclists and vehicles share the road. The virtual environment was constructed using Unreal Engine and featured a long, straight residential street section with two-way road traffic shared between cyclists and cars, with car parking on the side (see Fig. 1). This simulated road is 1400 m long and 4.5 m wide, representing a standard residential shared road in the Netherlands. The street design reflects a Dutch bicycle-priority residential/shared-street design, characterized by red asphalt and roadside markings indicating a cyclist-oriented traffic environment. In this study, street typology and urban morphology were intentionally held constant across all experimental conditions, rather than treated as independent variables, allowing the analysis could isolate the effects of environmental noise level and vehicle–signal condition.

To make the experimental environment realistic while maintaining experimental control, the virtual road was designed to allow two-way traffic with no intersections, thereby simplifying cyclists' decision-making processes and focusing on testing specific variables. Along the road, a total of 12 parking zones were placed, each 30 m long and containing 10 perpendicular parking spots facing the street. These parking zones were separated by areas with residential buildings ranging from 60 to 80 m in length. These residential

Fig. 1. Illustration of the virtual environment.

areas not only enhanced the realism of the scene but also provided practical conditions for simulating sound signal propagation and environmental noise.

An illustration of one parking zone is shown in Fig. 2. Each parking zone represented an experimental segment, where all vehicles had 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 remained inactive. The eHMIs were only activated and began emitting signals when participants entered the predefined signal trigger distance (see yellow triangle in Fig. 2).

During the experiment, only one idling vehicle in each designated area continuously emitted light and sound signals based on the distance between the cyclist and the vehicle. The volume of the signal received by participants followed natural laws, increasing as the participant approached the vehicle. Specifically, when participants approached the parking area and entered the engine noise area, first the engine noise of the idling vehicle was activated. The loudness of this sound was 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 employed the inverse square attenuation formula (Eq. 1), which is particularly suited for open environments (Epic Games, 2026):

$$L = \frac{L_0}{d^2} \tag{1}$$

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

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

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

This formula ensures that loudness decreases with the square of the distance, simulating the behavior of sound propagation in real life. For example, when the distance doubles, the loudness is reduced to one-quarter of its original value.

During the experiment, participants were instructed to cycle as they would normally do in daily life, without being explicitly required to respond to any specific signals. They cycled from a starting point to an endpoint within the virtual environment, simulating a realistic cycling experience. When participants completed one segment and entered the next, a transition area ensured that participants always entered each experimental segment from the same designated position (i.e., the right side of the road), maintaining consistency in experimental conditions. To guarantee this, a vehicle approached from the opposite direction, prompting participants to ride on the right side of the road (see Fig. 2).

When warning signals were emitted by vehicles, such as the roof-mounted visual eHMI lights shown in Fig. 3 or additional auditory alerts installed on certain vehicles, this indicated that the vehicle was about to depart from its parking position. Participants could choose to continue cycling or, if they perceived the vehicle as a potential hazard, respond by steering away or decelerating to avoid potential danger. The VR system recorded participants' actions, such as slowing down, steering, or maintaining course, to assess how vehicle signaling influenced cyclists' behavior. This response process reflects participants' decision-making and reactive behaviors in

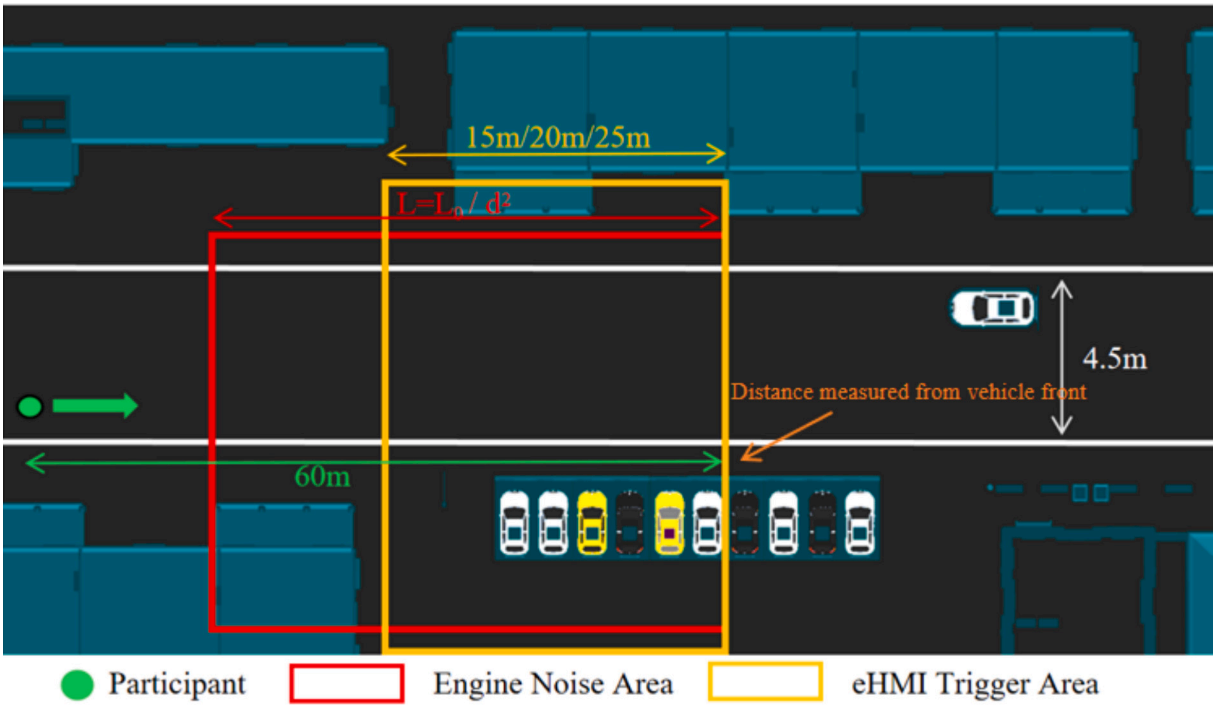

Fig. 2. Top View of the Experimental Scenario.

Fig. 3. Roof-mounted eHMI light signals emitted from the point of view of the cyclist.

unexpected situations.

For an illustrative video of the scenario, see https://youtu.be/zCsNBiGkoi0

2.3. Experimental equipment

The current study used a VR bicycle simulator for the VR experiments (see Fig. 4). The VR bicycle simulator was developed by the Mobility in eXtended Reality Lab at the Faculty of Civil Engineering and Geosciences, Delft University of Technology. The VR bicycle simulator consists of a bicycle mounted on a Tacx Flow Smart rear-wheel resistance trainer and an HTC VIVE Pro Eye VR headset

Fig. 4. A participant using the VR bicycle simulator.

(resolution: 1440 × 1600 pixels per eye, field of view: 110 degrees, refresh rate: 90 Hz). The electromagnetic resistance unit on the rear wheel provides resistance during cycling. The HTC VIVE Pro Eye provided 6-degree-of-freedom (6DoF) head tracking, allowing participants' head position and orientation to be recorded in real time. The bicycle frame was fixed and did not simulate bicycle leaning motion. The HTC VIVE Pro Eye headset (HMD) was connected to a desktop computer running Windows 10, equipped with an Intel Core (TM) i7–8700 CPU, 16GB RAM, an NVIDIA GeForce RTX 2070 graphics card, and a SanDisk SD9SN8W 256GB SSD. All VR operations were performed on this system.

During the experiment, participants wore the HMD device and used the VR bicycle simulator as they would in real life, by pedaling to move forward and using the brakes to slow down or stop within the virtual environment. Directional adjustment was not implemented as natural steering or turning. Instead, participants used the trigger button on the handlebar-mounted controller to initiate a continuous and smooth lateral shift within the virtual environment. Thus, changes in direction were represented as horizontal position adjustments rather than leaning-based or steering-based turning maneuvers.

2.4. *Experimental procedure*

The entire experiment included four main phases: pre-experiment preparation, practice phase, formal experiment, and a post-experiment questionnaire. An overview of the experimental procedure is shown in Fig. 5. The experiment received ethical approval from the Human Research Ethics Committee at Delft University of Technology (ID: 4221).

(1) Pre-experiment preparation:

Upon arriving at the laboratory, participants were first guided to read a detailed instruction document. This document provided an overview of the experiment, including guidance on operating the bicycle simulator (e.g., headset calibration, speed control, and braking), the experimental procedure, potential discomforts, and corresponding safety measures. Participants were also informed about possible temporary motion sickness symptoms associated with VR use and how such discomfort could be addressed. Before the experiment began, all participants read and signed an informed consent form confirming that they understood the purpose, procedure, potential risks, and their right to withdraw from the experiment at any stage without consequences.

(2) Practice phase:

Before starting the formal experiment, participants completed a practice session to familiarize themselves with the VR bicycle simulator and the virtual environment. This practice scenario differed from the formal experimental scenarios and allowed participants to become familiar with basic operations, including pedaling, braking, and lateral movement within the VR setting.

(3) Formal experiment:

At the start of the formal experiment, participants put on the VR headset, were guided to a designated starting point, and began cycling. During the ride, the system presented 18 experimental scenarios in random order. In these scenarios, roadside parked vehicles emitted either visual signals or a combination of visual and auditory alerts to indicate their intention to exit the parking spot. Participants were instructed to respond naturally, for example by slowing down or shifting laterally if they perceived the vehicle as a potential hazard.

(4) Post-experiment questionnaire:

After completing the formal experiment, participants were asked to complete a detailed post-experiment questionnaire. The questionnaire consisted of six sections, including (1) Participant information, (2) face validity questionnaire (Kaptein et al., 1996), (3) Simulator Sickness Questionnaire (Kennedy et al., 1993), (4) Presence Questionnaire (Witmer et al., 2005), (5) Trust in Autonomous Driving Questionnaire (Núñez Velasco et al., 2019), and (6) Perceived Safety Questionnaire. These questions were designed using established instruments and adapted scales to capture both cognitive and perceptual responses of participants.

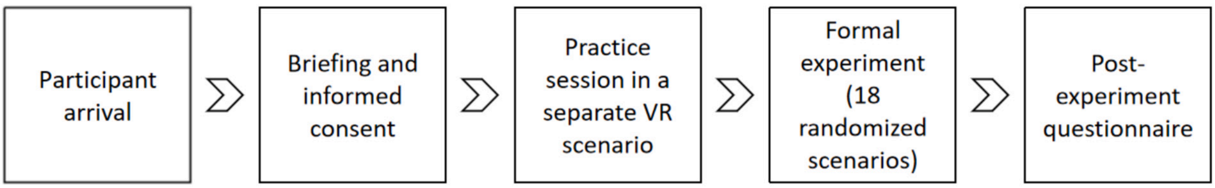

Fig. 5. Overview of the experimental procedure

2.5. Data collection

Two types of data were collected during the experiment, including objective data (i.e., behavioral data obtained through the VR system) and subjective data (i.e., perception data collected through post-experiment questionnaires).

Three types of objective data were collected during the experiment. Participants' cycling trajectory data were recorded at a frame rate of 90 Hz, meaning that position (i.e., coordinate X, Y) and cycling speed data (m/s) were captured 90 times per second and stored. Simultaneously, the Euler angle data from the VR headset worn by the participants were also recorded in sync. The Euler angle data (degrees) captured the direction and orientation of the VR headset in three-dimensional space, including yaw (rotation around the vertical *Z*-axis), pitch (rotation around the lateral Y-axis), and roll (rotation around the longitudinal X-axis).

The post-experiment questionnaire collected participants' subjective evaluations, which were divided into simulator evaluation measures and main subjective outcome measures. The Participant Information section included characteristics such as gender, age, familiarity with video games, familiarity with VR, familiarity with the concept of autonomous driving, and experience interacting with autonomous vehicles. The Face Validity Questionnaire aimed to evaluate whether the simulator met the intended assessment objectives (Kaptein et al., 1996). Participants rated the realism of the virtual environment, virtual objects (e.g., vehicles), motion capabilities, and environmental sound using a 5-point scale. The Simulator Sickness Questionnaire was a standard tool used to assess the level of simulator sickness experienced by participants in the virtual environment (Kennedy et al., 1993). The Presence Questionnaire (Witmer et al., 2005) measured the participants' sense of presence in the virtual environment. These three instruments were included to evaluate the realism, presence, and simulator-related experience of the VR setting.

The main subjective outcome measures focused on participants' evaluations of the vehicle-based warning system, including trust, perceived safety, and comfort, because these constructs capture key aspects of cyclists' interaction experience with vehicle-based warning systems. In particular, trust was assessed using a five-item questionnaire adapted from (Núñez Velasco et al., 2019), perceived safety was measured by participants' rating of the extent to which the warning system enhanced their sense of safety regarding autonomous vehicles, and comfort was assessed through participants' rating of how much the additional auditory signal interfered with daily life. Specifically, trust reflects participants' confidence in the signaling system and vehicle behavior, perceived safety reflects how safe participants felt during the interaction, and comfort reflects the subjective ease and naturalness of the interaction. To improve consistency throughout the manuscript, the item "To what extent does the warning system enhance your sense of safety regarding autonomous vehicles?" is treated as a measure of perceived safety rather than perceived risk.

2.6. Sampling

A total of 41 participants were recruited for the experiment, of whom 40 successfully completed all sessions and were included in the final analysis. Participants were recruited from students and staff at Delft University of Technology through campus posters, resulting in an adult university-affiliated sample. One participant withdrew from the experiment midway due to motion sickness, which is commonly explained by sensory conflict theory as a mismatch between visual input, vestibular input from the inner ear, and proprioceptive information related to body position and movement. Fortunately, the participant fully recovered after drinking water and taking a short rest. Of the 40 participants included in the analysis, 33 were male and 7 were female, with an age range of 23–49 years ($M = 25.54$, $SD = 4.17$).

Participants' familiarity with virtual reality (VR) on a 5-point scale (1 = Never, 5 = Always) was generally low ($M = 2.32$, $SD = 0.90$), indicating that most participants used VR only rarely or sometimes. Similarly, their self-reported familiarity with autonomous driving technology on a 5-point scale (1 = Not at all familiar, 5 = Very familiar) was low ($M = 2.34$, $SD = 1.16$), while their familiarity with electric vehicles was relatively higher ($M = 3.27$, $SD = 1.15$), suggesting a moderate level of understanding.

2.7. Data processing

This section describes how the collected data were processed to derive the dependent variables, followed by the statistical methods used for analysis. The data processing procedures focused on extracting meaningful behavioral indicators from the raw trajectory, speed, and head-orientation data recorded during the VR experiment. The statistical analysis approach is then introduced to examine the effects of experimental conditions on these derived variables.

2.7.1. Derivation of dependent variables

To generate these dependent variables, several additional variables were first derived from the raw trajectory and speed data. The *time variable* was extracted to represent the timestamp of each recorded frame, enabling the calculation of response durations and temporal patterns. The *speed change point* was identified as the location along the trajectory where a significant change in cycling speed occurred, serving as an indicator of the onset of a behavioral response such as braking. The *lowest speed point* captured the moment when participants reached their minimum speed during a response maneuver, which typically marked the completion of the avoidance behavior. Finally, the acceleration/deceleration variable (m/s^2) was computed from the cycling speed time series using the first-order difference formula $a_i = (v_i - v_{i-1})/\Delta t$ to quantify the intensity of participants' reactions to the emitted signals. Because raw bicycle speed data contained short-term fluctuations associated with pedaling dynamics, a filtering procedure was applied to smooth the speed profile before calculating acceleration and deceleration. No interpolation was applied, as the trajectory and speed data had already been recorded at 90 Hz. This variable reflects how sharply participants adjusted their speed in response to potential hazards.

The cyclists' **response position** (meters) is a key variable for evaluating the distance from which they have noticed the vehicle signals and their following response. It represents the distance between the cyclist and the vehicle at the point where the cyclist first initiated a measurable behavioral response, such as decelerating or moving laterally. To accurately identify the reaction time, two criteria were established.

The *first criterion* identifies the reaction point based on speed changes of the cyclists. Within a 1.5-s time window, if the cyclist's initial speed is higher than 2.78 m/s and the longitudinal acceleration becomes lower than -0.015 m/s^2 (Johnson et al., 2014), this indicates intentional braking rather than natural deceleration and this point is marked as the initial reaction point (Huertas-Leyva et al., 2018). The time window is determined based on the average reaction time of cyclists (Martin and Bigazzi, 2025).

The *second criterion* further verifies the accuracy of the reaction point. The system retrospectively examines several preceding data points, searching for a point where the speed is higher than the previous adjacent point. This identifies the moment before deceleration began, improving the temporal accuracy of the reaction marker. To avoid misclassification due to short-term speed fluctuations or sensor noise, a trend consistency check was applied: at least five consecutive data points before and after the candidate point were required to follow a consistent monotonic trend (either increasing or decreasing). If irregular changes were detected (e.g., alternating acceleration and deceleration), the point was excluded. This avoids misidentification caused by insufficient initial deceleration or data noise.

The dual-criterion method, combining significant speed changes with retrospective checks, ensures the precise identification of the reaction point. As shown in Fig. 6, the marked reaction point accurately reflects the participant's initial response to the warning signal.

Response completion position (m) was defined as the position at which the response maneuver was completed. In data processing, the lowest speed point is used as the marker for the completion of the response action. When a participant reaches the minimum speed and then begins to accelerate again, it indicates that the response maneuver is complete and normal cycling has resumed. Therefore, the lowest speed point between the initial reaction point and the signaling vehicle was designated as the response completion position.

Maximum deceleration (m/s^2) is used to quantify the intensity of participants' responses to the warning signals during the response interval. In this study, maximum deceleration was defined as the largest absolute deceleration value within the interval from the reaction point to the response completion point, based on the filtered speed-derived acceleration/deceleration profile. For participants who did not actively react to the warning signal, the maximum deceleration was recorded as N.A.

Roadside attention (degrees) was calculated as the average yaw angle of the VR headset during the interval from signal onset to response completion. The yaw angle represents the horizontal rotation of the headset and was recorded frame by frame, with negative values indicating leftward head movements and positive values indicating rightward movements. The average yaw angle was then computed for the entire response period. If the resulting average was positive, it indicated that the participant's gaze was predominantly directed to the right side, where parked vehicles were located.

2.7.2. Statistical analysis

To examine the effects of experimental conditions on cyclists' behavior, a Linear Mixed-Effects Model (LMM) was constructed separately for the four primary dependent variables: response position, response completion position, maximum deceleration, and roadside attention. LMM is a statistical modeling approach that incorporates both fixed effects and random effects, allowing for the simultaneous consideration of systematic influences of experimental conditions and random variability between participants. It is particularly suitable for analyzing repeated measures data.

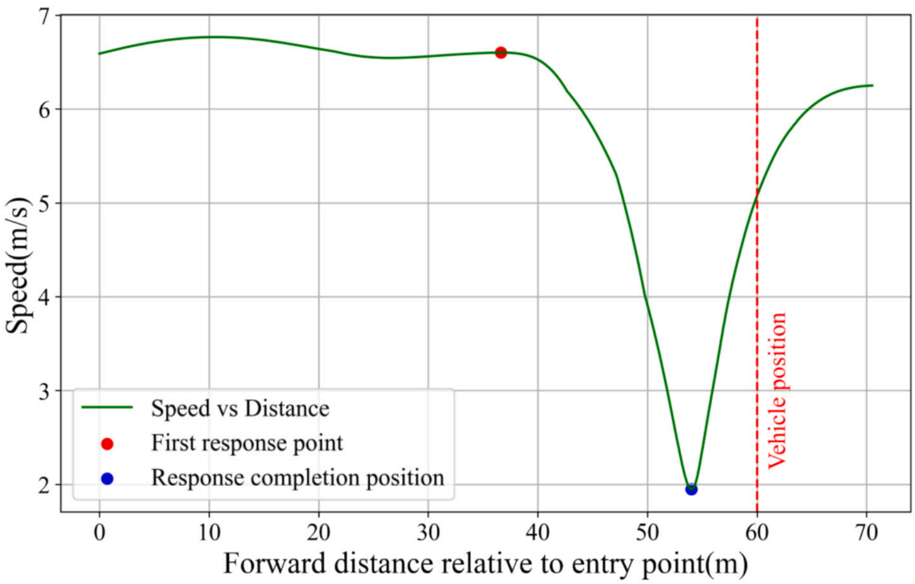

Fig. 6. Speed profile illustrating the point where the cyclist's reaction begins and the response completion position relative to the vehicle position.

Each model included three fixed-effect factors: environmental noise level (quiet vs. noisy), vehicle–signal condition (ACV with visual eHMI, AEV with visual eHMI, and AEV with visual eHMI and additional auditory alert), and signal trigger distance (short, medium, long). Two-way interaction terms between fixed effects were also included to explore potential combined effects. Participant ID was modeled as a random intercept to account for within-subject variability across experimental conditions. During the model fitting process, demographic variables (e.g., age, gender, cycling experience) and subjective measures (e.g., presence, simulator sickness) were also tested, but were excluded from the final models due to lack of statistical significance.

In the LMM analysis, a baseline condition was defined as the combination of a noisy environment, AEV with visual eHMI (without additional auditory alert), and short signal trigger distance. This baseline was selected because it was expected to represent the most challenging condition for cyclists to perceive and respond to the vehicle signal. Specifically, environmental noise may reduce the salience of auditory cues, the absence of additional auditory support may make the vehicle less detectable, and a short signal trigger distance may impose greater time pressure on participants. All model estimates are interpreted relative to this baseline.

The formula for the LMM model is shown in Eq. 2, where Y_{ij} represents the response variable for participant *i*, and scenario *j*, which corresponds to our main target variables (i.e., response position, response completion position, maximum deceleration, and roadside attention). β_0 is the intercept, and β_p, β_{pq} and β_{pqr} represent the fixed effect parameters for each predictor variable, second order interactions, and third order interactions, respectively. The predicting variables $X_{p,ij}, X_{q,ij}$, and $X_{r,ij}$ are assigned a value of 1 when the predictor is present in the scenario and 0 when it is not. μ_i denotes the random effect term (Participant ID) with $\mu_i \sim N\left(0, \sigma_\mu^2\right)$, and ε_{ij} represents the error term with $\varepsilon \sim N\left(0, \sigma^2\right)$. Fixed effects in our model include environmental noise level, vehicle–signal condition, and signal trigger distance, as these factors are predefined experimental conditions that consistently influence all participants. Random effects include individual participant variations, representing differences in participants' responses to experimental stimuli.

$$Y_{ij} = \beta_0 + \sum_{p=1}^{p} \beta_p X_{p,ij} + \sum_{p<q} \beta_{pq} X_{p,ij} X_{q,ij} \sum_{p<q<r} \beta_{pqr} X_{p,ij} X_{q,ij} X_{r,ij} + \mu_i + \varepsilon_{ij} \tag{2}$$

3. Data analysis and results

The Results section is organized into three parts: validation of the VR experimental setup, behavioral responses under different vehicle–signal conditions, and subjective evaluations of vehicle signaling.

3.1. Validation of the VR experimental setup

Before presenting the main behavioral and subjective outcomes, the VR experimental setup was evaluated in terms of perceived realism, simulator sickness, and sense of presence.

3.1.1. Perceived realism of the virtual environment

The Face Validity Questionnaire was used to assess participants' perceived realism in the virtual environment (Kaptein et al., 1996). A Likert scale ranging from 1 to 5 was employed for scoring, where 1 indicates “not realistic at all” and 5 indicates “very realistic.”. This questionnaire included four aspects: the realism of the virtual environment, the realism of virtual objects, the realism of motion capabilities, and the realism of environmental sounds. The results are shown in Table 2.

Among the four evaluation aspects, the realism of environmental sounds received the highest score (M = 3.89, SD = 0.71), indicating that the sounds perceived in the virtual environment closely resembled those in the real world. The realism of motion capabilities received the lowest score (M = 3.11, SD = 0.92). Considering that most participants were frequent cyclists and familiar with the act of cycling, they may have had higher expectations for the realism of cycling in the virtual environment. The overall mean score of the Face Validity Questionnaire was 3.45 (SD = 0.81), which is consistent with previous studies that have used VR to examine cyclist behavior (Huemer et al., 2022). Overall, participants' ratings supported the realism of the current VR bicycle simulator and virtual environment.

3.1.2. Simulation sickness assessment

To measure the extent of simulation sickness experienced by participants in the virtual environment, this study employed the Simulator Sickness Questionnaire (SSQ) (Kennedy et al., 1993). The questionnaire uses a 4-point Likert scale, ranging from 0 (No symptoms) to 3 (Severe symptoms), assessing 16 possible symptoms (e.g., fatigue, eye strain, headache). According to the SSQ standard scoring method, the symptoms are categorized into three main components: Nausea, Oculomotor Disturbance, and

Table 2
Rating of perceived realism in the virtual environment.

Item	Mean	SD
The realism of the virtual environment	3.27	0.79
The realism of the virtual objects	3.54	0.81
The realism of the movement ability	3.11	0.92
The realism of the environment sound	3.89	0.71

Disorientation. The results for these three components are presented in Table 3.

The results indicate that Oculomotor Disturbance received the lowest score, while Disorientation had the highest score. The elevated Disorientation score may be attributed not only to the frequent head movements required during the experiment, but also to the restriction of participants' ability to move laterally in the physical space. This spatial limitation may have intensified sensory mismatch and impaired spatial orientation. The mean total SSQ score was 25.33 (SD = 36.43), with no participants reporting significant discomfort or noticeable symptoms. Based on the SSQ results and participant feedback, this study only exhibited mild or no symptoms of simulation sickness.

3.1.3. Sense of presence in the virtual environment

In this experiment, the feeling of presence was primarily used to assess the immersion and realism experienced by participants in the VR environment. A strong sense of presence helps participants' behaviors closely align with real-world scenarios, thereby enhancing the external validity and generalizability of the experimental results (Fratini, 2024). This study employed the Presence Questionnaire (PQ) (Witmer et al., 2005), which includes four subscales: Involvement, Sensory Fidelity, Immersion, and Interface Quality. Participants rated 19 items using a 5-point Likert scale, ranging from 1 (“not at all”) to 5 (“very much”). The questionnaire results, shown in Table 4, indicated that Immersion and Sensory Fidelity received the highest scores, suggesting that participants experienced a strong sense of immersion and that the visual and auditory stimuli were highly realistic. The overall average score of the PQ questionnaire in this study was 73.23 (SD = 5.63), demonstrating a strong sense of presence.

3.2. Effects of vehicle–signal condition on cyclists' behavioral responses

The effects of environmental noise, vehicle–signal condition, and signal trigger distance on cyclists' behavioral responses were analyzed using Linear Mixed-Effects Models.

3.2.1. Overview of LMM results

To examine the overall effects of experimental conditions on cyclists' behavior, Linear Mixed-Effects Models (LMMs) were applied. The model estimates for the four primary dependent variables—response position, response completion position, maximum deceleration, and roadside attention—are summarized in Table 5.

Table 5 presents the fixed effects and interaction effects of environmental noise level, vehicle–signal condition, and signal trigger distance across all dependent variables. The estimates provide the basis for the detailed analyses reported in the following subsections.

In the following subsections, we explain how the different factors and their interactions affected each dependent variable in detail.

Baseline: AEVs with visual eHMI only + short trigger distance + noisy environment *, **, *** indicate the significant levels of <0.05, <0.01, <0.001, respectively.

3.2.2. Response position

The LMM results show significant main effects of environmental noise, signal trigger distance, and vehicle–signal condition on cyclists' response positions. Specifically, cyclists responded significantly earlier in quiet environments compared to noisy ones ($\beta = -8.098$). Similarly, increasing the signal trigger distance led to earlier reactions, both the middle distance ($\beta = -9.785$) and the long distance ($\beta = -12.848$) compared to the baseline (short trigger distance). Regarding the vehicle–signal condition, AEVs with visual eHMI and additional auditory alert was associated with significantly earlier responses than the baseline condition of AEVs with visual eHMI only ($\beta = -11.346$), enabling them to respond earlier than when interacting with standard AEVs without the alert.

Several significant interaction effects were observed. A significant interaction between quiet environments and middle trigger distances ($\beta = +6.891$, $p = .002$) indicates that although this combination reduced the magnitude of the effect on response position relative to the baseline (short distance in noisy environments), the overall predicted response position still indicated earlier cyclist responses (combined $\beta \approx -11.0$), suggesting earlier cyclist responses.

Similarly, an interaction between quiet environments and AEVs with visual eHMI and additional auditory alert ($\beta = +10.293$, $p < .001$) showed a slightly reduced effect of auditory alerts on response position in low-noise conditions compared to the corresponding baseline condition. Nonetheless, the combined estimate ($\beta \approx -9.15$) still demonstrated a shorter reaction distance compared to the baseline, reinforcing the utility of auditory cues even when ambient noise is low.

Another important interaction was observed between long signal trigger distance and AEVs with visual eHMI and additional auditory alert ($\beta = +9.225$, $p < .001$). Despite the positive interaction term, the total effect remained strongly negative (combined $\beta \approx -14.97$), confirming the benefit of longer lead times in enhancing cyclist reaction.

The interaction between quiet environments and long trigger distances ($\beta = +4.824$, $p = .031$) also remained significant, producing an estimated combined effect of $\beta \approx -16.12$. This finding supports the idea that extending signal lead time in low-noise settings further

Table 3
Result of Simulator Sickness Questionnaire (SSQ).

Item	Mean	SD
Nausea	24.87	28.42
Oculomotor disturbance	18.94	19.76
Disorientation	32.18	37.51

Table 4
Subscales of the Presence Questionnaire (range from 1 - Not at all to 5 - Very much).

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

facilitates early cyclist responses.

Finally, the three-way interaction between quiet environments, long trigger distances, and AEVs with visual eHMI and additional auditory alert was significant ($\beta = -10.489$, $p = .001$). When combined with the corresponding main effects and lower-order interactions, the total estimated effect reached approximately $\beta \approx -13.31$, indicating a shorter predicted reaction distance. This result suggests that, in low-noise urban environments, providing clear and early multimodal alerts may support more effective cyclist responses.

3.2.3. *Response completion position*

The LMM results for cyclists' response completion position are shown in Table 5. Significant main effects were found for environmental noise level, signal trigger distance, and vehicle–signal condition. Specifically, cyclists completed their responses earlier in quiet environments than in noisy environments ($\beta = -4.190$, $p < .001$). Increasing the signal trigger distance also promoted earlier response completion, with both the medium trigger distance ($\beta = -5.760$, $p < .001$) and the long trigger distance ($\beta = -10.293$, $p < .001$) showing significant effects relative to the short trigger distance baseline. Regarding the vehicle–signal condition, the AEV with visual eHMI and additional auditory alert was associated with significantly earlier response completion than the baseline condition of AEV with visual eHMI only ($\beta = -9.804$, $p < .001$), whereas the effect of the ACV with visual eHMI was smaller ($\beta = -1.916$, $p = .033$).

In terms of multi-factor interactions, a significant interaction was first observed between quiet environments and medium signal trigger distances ($\beta = +2.781$, $p = .029$). The main effects were $\beta\_Q = -4.190$ and $\beta\_Distance1 = -5.760$, with a combined estimated effect of $\beta \approx -7.17$. This suggests that while the combination still facilitates earlier responses, the advantage is slightly weaker than the sum of the two main effects alone.

A significant interaction was also found between quiet environments and ACV with visual eHMI ($\beta = +4.409$, $p = .001$). Together with the main effect of $\beta\_VT1 = -1.916$, the total estimated effect is $\beta \approx -1.70$, indicating a slight advancement in behavioral completion, though the effect remains limited.

In addition, the combination of quiet environments and AEV with visual eHMI and additional auditory alert showed one of the stronger two-way interactions ($\beta = +9.579$, $p < .001$). Combined with $\beta\_Q = -4.190$ and $\beta\_VT2 = -9.804$, the total effect was estimated at $\beta \approx -4.41$, indicating that the marginal benefit of auditory alerts is notably reduced under quiet conditions.

Another set of significant interactions was observed between signal trigger distance and AEV with visual eHMI and additional auditory alert. For long distances, the interaction was $\beta = +4.414$, $p = .001$, with corresponding main effects of $\beta\_Distance2 = -10.293$ and $\beta\_VT2 = -9.804$, resulting in a combined effect of $\beta \approx -15.68$. For medium distances, the interaction was $\beta = +4.934$, $p < .001$, yielding a combined effect of $\beta \approx -10.63$. These findings show a strong overall trend, indicating that despite the moderating effect of the interaction terms, the combinations still effectively promote earlier behavioral completion, and that longer signal trigger distances are particularly beneficial in enabling cyclists to respond earlier.

Two notable three-way interactions were observed. First, the quiet environment × medium distance × AEV with visual eHMI and additional auditory alert interaction showed a significant effect ($\beta = -6.323$, $p < .001$). Considering the corresponding main effects (−4.190, −5.760, −9.804) and two-way interactions (+9.579, +2.781, +4.934), the total estimated combined effect was approximately $\beta \approx -8.78$. This indicates that under this combination, cyclists completed their responses farther from the vehicle.

In comparison, the other three-way interaction—quiet environment × long distance × AEV with visual eHMI and additional auditory alert—was also significant ($\beta = -6.512$, $p < .001$). Together with the three main effects (−4.190, −10.293, −9.804) and the three two-way interactions (+1.212, +9.579, +4.934), the total combined effect was approximately $\beta \approx -15.07$. This combination also resulted in a significantly earlier behavioral completion, and the effect was substantially greater than that of the medium distance combination.

3.2.4. *Maximum deceleration*

In terms of main effects, multiple predictors significantly reduced maximum deceleration, including quiet environment ($\beta = -3.484$, $p < .001$), middle trigger distance ($\beta = -2.765$, $p = .002$), long trigger distance ($\beta = -4.568$, $p < .001$), and ACVs with visual eHMI ($\beta = -4.046$, $p < .001$), suggesting smoother deceleration by cyclists under these conditions. While the AEV with visual eHMI and additional auditory alert was not statistically significant ($\beta = -1.043$, $p = .234$), the direction was still favorable.

The interaction effects further revealed how the synergy or attenuation among different contextual factors influenced cyclists' deceleration performance. Although several significant interactions exhibited positive coefficients—indicating a slight reduction in effect compared to the main effects—the combined results across conditions still significantly lowered maximum deceleration, reflecting smoother and more gradual behavioral responses.

Under the combination of a quiet environment and medium signal trigger distance, the interaction term was $\beta = +2.454$ ($p = .048$). With the main effects $\beta = -3.484$ and $\beta = -2.765$, the combined estimated effect was approximately $\beta \approx -3.80$. Similarly, in the context of long signal trigger distances, the interaction term was $\beta = +4.312$ ($p < .001$), yielding a combined estimate of $\beta \approx -3.74$. These findings indicate that in quieter environments, extending the signal trigger distance continued to promote gentler deceleration,

Table 5
The results from the LMM analysis.

Predictors	Explanations	*Response position Estimate (SE)*	*Response completion position Estimate (SE)*	*Maximum deceleration Estimate (SE)*	*Roadside attention Estimate (SE)*
(Intercept)		38.791 (1.187)	54.998 (0.727)	11.791 (0.692)	7.118 (0.501)
β_Q	Quiet environment sound level (vs. noisy)	**−8.098 (1.580)***	**−4.190 (0.901)***	**−3.484 (0.877)***	0.083 (0.656)
$\beta_{Distance\_M}$	Middle signal trigger distance (vs. short)	**−9.785 (1.580)***	**−5.760 (0.901)***	**−2.765 (0.877)****	−0.312 (0.656)
$\beta_{Distance\_L}$	Long signal trigger distance (vs. short)	**−12.848 (1.580)***	**−10.293 (0.901)***	**−4.568 (0.877)***	**−1.686 (0.656)****
β_{VT1}	ACVs with visual eHMI (vs. AEV without warnings)	−2.140 (1.580)	**−1.916 (0.901)*****	**−4.046 (0.877)***	−0.593 (0.656)
β_{VT2}	AEVs with visual eHMI and alert signal (vs. AEV without warnings)	**−11.346 (1.580)***	**−9.804 (0.901)***	−1.043 (0.877)	−1.160 (0.656)
$\beta_{Double1}$	Interaction term (β_Q with $\beta_{Distance\_M}$)	**6.891 (2.235)****	**2.781 (1.274)*****	**2.454 (1.240)*****	−0.685 (0.928)
$\beta_{Double2}$	Interaction term (β_Q with $\beta_{Distance\_L}$)	3.113 (2.235)	1.212 (1.274)	**4.312 (1.240)***	−0.523 (0.928)
$\beta_{Double3}$	Interaction term (β_Q with β_{VT1})	**4.361 (2.235)*****	**4.409 (1.274)***	**3.073 (1.240)*****	**1.818 (0.928)*****
$\beta_{Double4}$	Interaction term (β_Q with β_{VT2})	**10.293 (2.235)***	**9.579 (1.274)***	**3.212 (1.240)****	1.649 (0.928)
$\beta_{Double5}$	Interaction term ($\beta_{Distance\_M}$ with β_{VT1})	1.302 (2.235)	1.456 (1.274)	1.291 (1.240)	−0.042 (0.928)
$\beta_{Double6}$	Interaction term ($\beta_{Distance\_L}$ with β_{VT1})	−3.487 (2.235)	−1.176 (1.274)	**5.423 (1.240)***	1.515 (0.928)
$\beta_{Double7}$	Interaction term ($\beta_{Distance\_M}$ with β_{VT2})	**9.225 (2.235)***	**4.934 (1.274)***	2.318 (1.240)	0.105 (0.928)
$\beta_{Double8}$	Interaction term ($\beta_{Distance\_L}$ with β_{VT2})	**4.824 (2.235)*****	**4.414 (1.274)***	1.782 (1.240)	1.270 (0.928)
$\beta_{Triple1}$	Interaction term (β_Q, $\beta_{Distance\_M}$ with β_{VT1})	−3.843 (3.161)	−3.353 (1.802)	0.135 (1.754)	−0.069 (1.313)
$\beta_{Triple2}$	Interaction term (β_Q, $\beta_{Distance\_L}$ with β_{VT1})	−4.359 (3.161)	−1.362 (1.802)	**−5.469 (1.754)****	−1.623 (1.313)
$\beta_{Triple3}$	Interaction term (β_Q, $\beta_{Distance\_M}$ with β_{VT2})	**−10.489 (3.161)***	**−6.323 (1.802)***	**−3.987 (1.754)*****	0.127 (1.313)
$\beta_{Triple4}$	Interaction term (β_Q, $\beta_{Distance\_L}$ with β_{VT2})	−5.942 (3.161)	**−6.512 (1.802)***	−3.027 (1.754)	−0.674 (1.313)
Random effects		***Var (SD)***	***Var (SD)***	***Var (SD)***	***Var (SD)***
#Participant: intercept	Participant's ID	12.79 (3.577)*	9.835 (3.136)*	7.589 (2.755)*	2.865 (1.693)*
Model performance					
Observations		1440	1440	1440	1440
Marginal R^2		0.239	0.342	0,048	0.034
Conditional R^2		0.325	0.495	0.236	0.172
logLik		−1377.910	−1605.531	−1560.592	−1135.877
AIC		4795.821	3251.065	3160.385	4311.754
BIC		4901.270	3356.510	3265.833	4417.202

although the magnitude of the benefit was somewhat reduced relative to the sum of the individual main effects.

Likewise, when a quiet environment was combined with the ACV with visual eHMI (β = +3.073), or with the AEV with visual eHMI and additional auditory alert (β = +3.212), the interaction effects slightly offset the main effects. However, the overall trends remained positive, with combined β estimates of approximately −4.46 and − 1.31, respectively. These results indicate that in low-noise environments, the benefits of multimodal warnings remain significant.

Notably, the combination of long signal trigger distance and ACVs with visual eHMI yielded an interaction term of $\beta = +5.423$, with a total estimated effect still negative ($\beta \approx -3.19$). This suggests that increasing the available lead time continued to facilitate smoother cyclist deceleration even when the interaction attenuated part of the main effects.

Among all tested conditions, the most significant three-way interaction effect was observed in the combination of quiet environment × long trigger distance × ACV equipped with eHMI ($\beta = -5.469$, $p = .002$). When considered together with the relevant main effects, the total estimated effect was approximately $\beta \approx -4.76$. Although some two-way interactions had positive coefficients that tended to weaken the main effects, the overall effect remained significantly negative. This indicates that in low-noise environments, early multimodal warnings can substantially mitigate cyclists' deceleration responses, thereby potentially supporting smoother and safer riding interactions.

Another significant three-way interaction was found in the combination of quiet environment × medium trigger distance × AEV with visual eHMI and additional auditory alert ($\beta = -3.987$, $p = .023$). When all associated main effects were taken into account, the total estimated effect was approximately $\beta \approx -3.3$. Although this effect was slightly weaker than that of the long-distance condition, it still clearly demonstrates that in quiet environments, moderately early delivery of both visual and auditory cues can effectively guide cyclists to decelerate more smoothly.

3.2.5. Roadside attention

In the analysis of roadside attention, most main and interaction effects did not reach statistical significance, suggesting that cyclists' gaze distribution remained relatively stable across conditions. However, several marginal trends were observed.

Among the main effects, only the "Long Signal Trigger Distance" was statistically significant ($\beta = -1.686$, $p = .010$), indicating that earlier signal triggers promoted stronger forward attention and reduced sideward gaze—an indicator of better task-focused visual concentration.

For interaction effects, only the combination of "Quiet Environment × ACVs with Visual eHMI" reached marginal significance ($\beta = +1.818$, $p = .050$). While this positive coefficient suggests a slight increase in sideward gaze under low-noise conditions with visual interfaces, the overall effect was limited. All other two- and three-way interactions remained non-significant, indicating that cyclists' roadside attention was generally robust across different environmental noise levels, vehicle–signal conditions, and trigger distances.

3.3. Subjective evaluations of vehicle signaling

In addition to the behavioral results, participants' subjective evaluations of vehicle signaling were assessed through questionnaire responses concerning signal noticeability, trust, perceived safety, and comfort.

3.3.1. Self-reported noticeability of vehicle signals

The questionnaire asked participants whether they noticed the different signals emitted by stationary roadside parked vehicles. In total, 5 questions were included and participants needed to rate them on a scale of 1 (not noticeable) to 5 (very noticeable). The results showed an average score of 4.15 (SD = 0.65), indicating that most participants were able to clearly detect these light signals. Meanwhile, when asked to what extent they noticed the auditory signals emitted by vehicles, the average score was 3.54 (SD = 0.99), suggesting that most participants were able to detect the auditory signals. However, the average score for auditory signals was slightly lower than that of light signals. This suggests that light signals, with their strong visual effects, can more effectively attract participants' attention, enabling them to promptly recognize the vehicle's status. This feedback further supports the role of light-based eHMI signals as an essential communication tool for AEVs in traffic environments.

When asked whether they could distinguish between EVs and traditional internal combustion engine vehicles based on engine noise, the average score was 2.83 (SD = 0.79). This indicates that many participants may have found it difficult to differentiate between the two vehicle types based solely on engine noise during the experiment.

3.3.2. Trust in autonomous vehicle signaling

For the trust questionnaire, participants were asked to rate their trust in autonomous vehicles on a scale from 1 (Very low trust) to 5 (Very high trust). In this experiment, the average trust score for vehicles that relied solely on visual signals to convey information was 3.24 (SD = 0.90), indicating a moderate overall rating. The results suggest a moderate level of trust in using only visual signals for communication, indicating that while participants generally found them acceptable, some reservations about their sufficiency remained. However, when asked, "To what extent do you trust an autonomous vehicle that uses multiple signals (e.g., a combination of visual and auditory signals) for interaction?", participants' average score was 3.68 (SD = 0.92), suggesting a higher level of trust in multimodal signaling.

Additionally, all participants were asked to evaluate the effectiveness of AEVs equipped with additional auditory warning systems. When asked, "Does adding auditory warnings effectively enhance road safety?", the average rating was 3.95 (SD = 0.79). For the question, "To what extent does the warning system help you better communicate with autonomous vehicles?", the average score was 3.71 (SD = 0.81). These results suggest that participants generally recognized the value of additional auditory warnings in supporting communication and increasing trust in multimodal vehicle signaling.

At the end of the questionnaire, participants were asked a closed-ended multiple-choice question to evaluate the necessity of adding an auditory warning system to AEVs. The question presented four predefined response options. Only one participant selected "I think the visual signal alone is completely sufficient," indicating that an additional sound signal was unnecessary. Among the remaining participants, 57.5% believed that relying solely on light signals is insufficient and that sound should be added for assistance. Another

40% acknowledged the benefits of light signals but agreed that auditory warnings could further enhance safety.

3.3.3. Perceived safety

For the Perceived Safety questionnaire, participants were asked to answer the question, "To what extent does the warning system enhance your sense of safety regarding autonomous vehicles?" on a scale from 1 (Very low sense of safety) to 5 (Very high sense of safety). The mean score of perceived safety was 3.42 (SD = 0.84), indicating that participants generally felt that the warning system enhanced their sense of safety feeling when interacting with autonomous vehicles.

3.3.4. Comfort

Comfort with the auditory warning system was assessed indirectly through participants' ratings of the extent to which the additional noise signal interfered with their daily life. On a five-point Likert scale (1 = very low interference, 5 = very high interference), the mean score was 3.05 (SD = 1.08), indicating a moderate level of perceived disturbance.

This suggests that while the additional auditory signal introduced a noticeable degree of interference, it was not perceived as excessively intrusive. Combined with the positive evaluations of communication effectiveness and safety enhancement, these findings indicate that the inclusion of auditory support was generally acceptable, although potential trade-offs with user comfort should be considered.

4. Discussion of main findings

4.1. Cyclist perception and response to roadside parked ACVs and AEVs under different warning conditions

To address Sub-Research Question 1 — "How do cyclists' perceptual and behavioral responses differ when approaching roadside parked ACVs and AEVs under different warning conditions?" — this section discusses how different vehicle–signal conditions influence cyclists' perception, trust, and behavioral responses in interaction scenarios with roadside parked vehicles. The experimental results demonstrate clear differences in cyclists' performance across different vehicle–signal conditions, particularly between visual-only AEVs and AEVs supplemented with additional auditory alerts.

When no additional auditory signals were provided, cyclists exhibited delayed reactions and more abrupt deceleration—particularly when interacting with AEVs equipped with visual eHMI only, compared to ACVs with visual eHMI. LMM results indicated that visual-only AEVs, especially in noisy environments or when signals were triggered at short distances, were detected later and required more intensive behavioral adjustments. This was reflected in shorter response distances and higher maximum deceleration. Participants also rated these visual-only conditions lower in terms of trust and perceived safety. Specifically, the mean trust score for vehicles relying solely on visual signals was 3.24 out of 5, indicating only a moderate level of confidence in visual-only communication.

In contrast, the addition of auditory warnings significantly improved both perceptual and behavioral outcomes. Cyclists responded earlier and more smoothly, as indicated by earlier response positions and lower maximum deceleration rates. These effects were particularly evident when signals were triggered at medium or long distances, suggesting that timely auditory input allows cyclists more time to interpret vehicle intent and initiate appropriate responses. Questionnaire data further supported this pattern: AEVs equipped with both visual eHMI and auditory alerts received higher average trust ratings (3.68 vs. 3.24), and 73.2% of participants reported that auditory cues enhanced their ability to detect vehicle movement—especially in complex or noisy environments.

These findings align with existing literature. Previous studies have shown that auditory signals can enhance signal detectability, support decision-making under time pressure, and improve users' sense of safety (Guo et al., 2024; Stankovic et al., 2014). From a theoretical perspective, this pattern can be interpreted through multisensory integration and uncertainty reduction: combining visual and auditory cues increases signal salience, reduces ambiguity regarding vehicle intent, and facilitates faster and more stable behavioral responses. Overall, the presence of auditory support within vehicle–signal conditions enhances cyclists' situational awareness, promotes smoother behavioral adjustments, and strengthens perceived safety. These benefits are particularly important in addressing the near-silent characteristics of electric vehicles and improving cyclist safety in real-world roadside environments.

4.2. Effect of environmental noise

To address Sub-Research Question 2 — "How does increasing environmental noise influence cyclists' attention to and responses to roadside parked ACVs and AEVs?" — this section examines how different noise levels affect cyclists' perception, behavioral responses, and perceived safety and trust under different vehicle–signal conditions. Experimental results indicate that in high-noise environments, cyclists' ability to detect and respond to roadside parked vehicles is significantly reduced, particularly in the absence of auditory warning signals. According to the LMM analysis, participants responded at shorter distances and exhibited higher maximum deceleration rates under noisy conditions, suggesting more delayed and abrupt reactions.

Questionnaire feedback further supported this behavioral pattern. Participants reported lower perceived safety and lower trust in vehicles under noisy conditions, especially when no auditory signals were provided. The reported level of discomfort in such cases was 3.85 (SD = 0.82). Additionally, 65.8% of participants indicated that in noisy traffic environments, visual signals were easily overlooked or misunderstood, particularly when attention was divided.

However, the addition of auditory cues significantly alleviated these negative effects. When AEVs were equipped with both visual and auditory signals, cyclists' behavioral responses remained more stable even in noisy conditions. This highlights the compensatory role of auditory signals in counteracting the masking effects of urban background noise and restoring the salience of vehicle-related warning cues. These findings are consistent with prior research showing that environmental noise can impair signal detection and increase reaction time (Zhou, 2024), posing greater challenges for vulnerable road users who rely on sensory information to make decisions.

From a theoretical perspective, this pattern can be interpreted through perceptual masking and multisensory integration. Environmental noise introduces perceptual masking, reducing the detectability of relevant warning signals, whereas the addition of auditory cues increases signal salience and helps recover effective perception under complex soundscapes. In this context, multimodal warning systems enhance the robustness of cyclist responses by compensating for degraded sensory information.

In summary, increasing levels of environmental noise hinder cyclists' ability to recognize and evaluate roadside parked vehicles under different vehicle–signal conditions. However, these negative effects can be effectively mitigated by multimodal warning systems, particularly those incorporating auditory components, which enhance perceptual salience and reduce uncertainty in noisy environments.

4.3. User experience of the VR bicycle simulator

In addition to the empirical analyses addressing each sub-research question, this section discusses the user experience of the VR bicycle simulator.

The VR bicycle simulator employed in this study demonstrated good feasibility for simulating interactions between cyclists and AEVs in controlled roadside scenarios. Participants consistently reported a high sense of presence and realism, along with low levels of simulator sickness. These findings indicate that the VR setup effectively captured natural behavioral responses while maintaining controlled experimental conditions. Its ability to systematically manipulate variables such as environmental noise and vehicle–signal conditions makes it well-suited for controlled studies in traffic safety and human–vehicle interaction research.

In this study, VR was selected as the experimental platform due to its ability to ensure participant safety while allowing precise control over key variables, including environmental noise, signal trigger distance, and vehicle–signal conditions. This controlled setup enabled the systematic comparison of conditions that would be difficult and potentially unsafe to replicate in real-world cycling environments, particularly those involving potential conflict scenarios.

However, VR-based findings should be interpreted with caution when considering real-world applications. Compared to actual traffic environments, participants in VR may experience lower perceived risk and different attentional demands, which could influence behavioral responses. Therefore, while the present results provide early-stage guidance for the design of multimodal warning systems, further validation through field studies is necessary to assess the transferability of these findings under real-world conditions.

4.4. Implications of the current study

This study highlights the importance of integrating auditory signals into the eHMI design of AEVs, particularly in noisy or complex urban environments. Relying solely on visual cues may be insufficient for timely vehicle detection under certain conditions, whereas the inclusion of auditory elements was associated with improvements in both behavioral performance and subjective evaluations. Future AEV designs should consider implementing environment-adaptive auditory signals in conjunction with visual eHMI elements to enhance communication effectiveness.

At a broader level, facilitating safe and intuitive interactions between AEVs and vulnerable road users is essential for the wider deployment of autonomous driving systems. Enhancing vehicle detectability through multimodal signaling can support safer interactions and strengthen public trust in autonomous technologies. The sound-enhanced eHMI framework proposed in this study provides a practical approach to addressing the low-noise characteristics of electric vehicles and contributes to the development of more user-centered and cyclist-aware interaction design in future urban mobility systems.

5. Conclusion

This study aimed to evaluate whether adding auditory warning signals to autonomous electric vehicles (AEVs) equipped with visual external human–machine interfaces (eHMIs) can help cyclists detect roadside parked vehicles and their movement intention earlier and respond more smoothly, particularly in noisy urban environments. Based on the analysis of the behavioral data from the virtual reality (VR) experiment and questionnaire responses, the findings suggest that integrating auditory warning signals into AEVs with visual eHMI was associated with improvements in cyclists' detectability and behavioral response quality, especially under noisy conditions.

The results indicate that AEVs equipped with auditory alerts helped cyclists perceive vehicle movement earlier, as reflected by earlier response positions and shorter response distances. They also decelerated more naturally and smoothly, as indicated by lower maximum deceleration values, and were better able to manage potentially sudden interactions. The addition of auditory cues can help compensate for the perceptual challenges posed by the low-noise characteristics of electric vehicles. Both objective measures and subjective evaluations, including perceived safety and trust, tended to improve when auditory support was present, particularly at medium to long signal trigger distances and in more complex acoustic environments. The study further suggests that multimodal signaling (visual + auditory) can enhance the detectability of AEVs and the clarity of movement-related cues, especially in situations involving divided attention.

From a methodological perspective, this study supports the feasibility of using immersive VR systems to investigate interactions between cyclists and AEVs. Participants consistently reported strong presence and realism, with minimal simulator sickness, indicating that the VR setup effectively balanced experimental control and ecological validity. Its capacity to systematically manipulate variables such as environmental noise and vehicle–signal conditions (i.e., a categorical variable including autonomous conventional vehicles with visual eHMI, AEVs with visual eHMI, and AEVs with visual eHMI and additional auditory alerts) makes it well suited for behavioral and human–vehicle interaction research.

Practically, the findings support the integration of adaptive auditory alerts into future AEV eHMI designs, particularly for scenarios involving vulnerable road users in noisy or complex traffic conditions. These results provide early-stage empirical support for the development of signaling standards for electric and autonomous vehicles and offer practical guidance for enhancing user trust and supporting acceptable comfort levels, thereby encouraging safer and more intuitive interactions in future urban mobility systems. However, further field validation is still needed before such findings are translated directly into regulatory decisions.

Despite these contributions, several limitations should be acknowledged. First, although VR provides a controlled experimental environment, participants' behavior in virtual settings may not fully reflect real-world responses. In particular, the reduced sense of real-world risk and the potentially lower attentional demands in VR may have influenced participants' responses, further highlighting the need for future field validation to assess the transferability of the observed effects. Future studies should therefore incorporate field experiments to further enhance external validity. Second, this study only tested a single type of auditory signal and did not explore variations in tone, frequency, or volume. Prior research suggests that sound design can produce different psychological and perceptual outcomes (Patterson, 1990); thus, future research should compare various auditory formats. Third, the sample primarily consisted of university students, limiting demographic diversity in age, cycling experience, and mobility level. In addition, the gender distribution in the final sample was imbalanced, which may have limited the representativeness of the findings and their generalizability to broader cyclist populations. Broader participant inclusion with more balanced demographic representation is recommended for improved representativeness. Furthermore, this study examined only the interaction between a single cyclist and a vehicle. Future research should extend this work by investigating cyclist–vehicle interactions in the presence of additional nearby cyclists. Fourth, roadside attention was assessed solely through yaw angle, which may not fully reflect visual attention patterns. Future work could integrate eye-tracking techniques to improve measurement accuracy. Lastly, the experiment focused exclusively on stationary roadside parked vehicles within a single Dutch residential/shared-street context. In addition, street typology and urban morphology were not varied as independent factors in this study. Future studies should systematically vary street typology and urban morphology alongside vehicle-signal conditions and examine more dynamic interaction scenarios such as head-on approaches, overtaking, and turning situations to further understand the effectiveness of auditory alerts under real-world complexity.

CRediT authorship contribution statement

Yixin Sun: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Haneen Farah:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Yan Feng:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author used ChatGPT (OpenAI) in order to improve the clarity, grammar, and coherence of the manuscript. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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