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Effect of eHMI-equipped automated vehicles on pedestrian crossing behavior and safety: A focus on blind spot scenarios

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ABSTRACT

Blind spot collisions are a critical and often overlooked threat to pedestrian safety, frequently resulting in severe injuries. This study investigates the impact of automated vehicles equipped with external human–machine interfaces (eHMIs) on pedestrian crossing behavior and safety, focusing on scenarios where AVs create mutual blind spots between pedestrians and adjacent traffic. A virtual reality experiment with 51 participants simulated crossing situations in front of yielding trucks with obstructed pedestrian visibility, featuring three eHMIs: 'Walk,' 'Don't Walk,' and 'Caution! Blind Spots'. Vehicles within the truck's blind spot exhibited proactive and reactive braking behaviors toward pedestrians. The results indicate that eHMI designs based on color, text, and symbols enhance pedestrian understanding. However, the 'Walk' eHMI, which ignores blind spot risks, may lead to dangerous crossing behaviors. In contrast, the 'Don't Walk' eHMI effectively reduced unsafe crossing behaviors, though yielding trucks sometimes caused pedestrian confusion. The 'Caution! Blind Spots' eHMI increased alertness but was not significantly more effective than the direct 'Don't Walk' instruction. This study provides empirical evidence for integrating dynamic environmental perception and hazard warnings into eHMI designs to raise road users' awareness of blind spots. The findings emphasize the importance of comprehensive strategies, including policy-making, education, and VR-based training, to ensure the effective deployment and public understanding of eHMIs in blind spot environments.

1. Introduction

1.1. Pedestrian-vehicle interaction safety in the blind spot

Blind spot collisions are more common than one might think, often resulting in serious injuries and fatalities to vulnerable road users (VRUs; e.g., pedestrians and cyclists). These incidents occur when road users, due to obstructed views or limited perception, fail to detect other vehicles, pedestrians, or obstacles in their blind spots, resulting in continued movement and eventual crashes. The Federal Highway Administration (FHWA) reports 840,000 blind spot-related incidents in the US annually, with over 300 deaths and tens of thousands of injuries. Similarly, the European Union reports around 400 annual fatalities in such accidents, the majority of which involve VRUs (European Union, 2007). These data underscore that blind spot collisions have become a critical issue in traffic safety, particularly concerning pedestrian protection.

With the increasing variety of vehicles and the complexity of road environments, the types of blind spot collisions have expanded, involving diverse vehicle types (e.g., large trucks, buses, small sedans), driving modes (manual, automated), and pedestrian interactions. Blind spot scenarios are also varied: for example, during turns, drivers may overlook pedestrians or cyclists in blind spots, particularly around the front and inner wheels of large vehicles, where collisions are more likely (Tomasch and Smit, 2023). Reversing maneuvers can obscure lower rear-view areas, risking collisions with unseen individuals or objects

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(Suhr and Jung, 2017). lane changes can place adjacent vehicles in a side blind spot, increasing the risk of side collisions (Cicchino, 2018). Additionally, a specific type of 'bidirectional blind spot' occurs when a vehicle obstructs the view between pedestrians and adjacent vehicles traveling in the same direction, leaving both parties in each other's blind spots (see Fig. 1) (Lu et al., 2024).

Among these blind spots, bidirectional blind spots should warrant particular attention but have not received sufficient focus. Compared to other types, bidirectional blind spots are more concealed and unpredictable, making them difficult to mitigate through conventional means. Blind spots of drivers during turning, reversing, and lane changing are generally caused by own vehicle structure, and their risks are significantly reduced with advanced driver assistance systems (ADAS). These systems include blind spot monitoring (BSM), which alerts drivers to vehicles, vulnerable road users, and obstacles in their blind spots (Mueller and Cicchino, 2022; Tomasch and Smit, 2023), and automatic emergency braking system for pedestrians (AEB-P), which initiates braking when the vehicle's sensors detect an imminent collision with a pedestrian (Abdel-Aty et al., 2022; Herman et al., 2022). More advanced automated vehicles (AVs) combine radar, sonar, cameras, and Light Detection and Ranging (LiDAR) to detect surrounding road users or objects (Rasshofer and Gresser, 2005; Sivaraman and Trivedi, 2013; Van Brummelen et al., 2018; Carballo et al., 2020). However, these sensors have limitations; they cannot penetrate metallic objects, leading to occlusions in perception, as illustrated in Fig. 1(b) (Etinger et al., 2014). While AVs can communicate with each other to extend perception, human-driven vehicles, which do not share information, remain a challenge. Infrastructure solutions like roadside cameras can assist AVs in detecting pedestrians (Zhu et al., 2021), but relying heavily on such roadside equipment limits widespread application. Therefore, bidirectional blind spots caused by vehicle obstruction remains an unavoidable and critical challenge.

Simultaneously, the continuous growth of urban logistics and public transportation has increased the prevalence of large vehicles on roads heavily used by pedestrians (Kechagias et al., 2020). This has significantly heightened the risk of collisions in bidirectional blind spot scenarios, where delayed reactions from vehicles often result in severe harm to pedestrians. Furthermore, autonomous trucks are widely regarded as having immense potential, with their market projected to reach $179.9 billion by 2035 (MarketsandMarkets, 2024). Autonomous buses have already been gradually integrated into urban transportation systems (Mouratidis and Cobeña Serrano, 2021). However, these vehicles face the same challenges posed by bidirectional blind spots due to their high and opaque vehicle bodies.

Currently, enhancing public awareness of blind spot dangers is the main measure aimed at improving blind spot safety (Tomasch and Smit, 2023). However, the effectiveness of this approach may not meet expectations, as merely raising awareness does not directly alter pedestrian behavior patterns. There is a clear need for reliable countermeasures, and research in this area remains limited. This study aims to address these gaps in current knowledge by providing pedestrian-vehicle interactive information pertinent to blind spots.

1.2. Pedestrian-AV interaction and eHMIs

As AVs begin to enter public roads, they will increasingly interact with human road users like pedestrians. Today, pedestrians and drivers often communicate using explicit signals (e.g., hand gestures, eye contact) or implicit cues (e.g., vehicle movement) to negotiate crossing decisions, especially in scenarios where formal traffic rules do not apply (Rodríguez Palmeiro et al., 2018; Zhao et al., 2023). In the future, with no driver present, AVs will likely rely on external human–machine interfaces (eHMIs) to facilitate these interactions.

eHMIs serve as a crucial communication bridge between pedestrians and AVs, with the goal of transmitting messages swiftly and accurately to pedestrians. Currently, most eHMI research focuses on small vehicles. eHMI design involves two key dimensions: message contents and communication modalities. The content of eHMIs includes various aspects, such as vehicle state (e.g., driving autonomously or manually), motion information (e.g., deceleration), situational state (e.g., pedestrian detected), vehicle intentions (e.g., yielding), advice to pedestrians (e.g., 'Walk'), etc. (Dey et al., 2020; Faas et al., 2020; Mahadevan et al., 2018; Woodman et al., 2019). Research indicates that pedestrian advisory information is more effective in interaction processes than vehicle information alone (Ackermann et al., 2019b). The interface designs for 'Walk' and 'Don't Walk' signals are particularly representative.

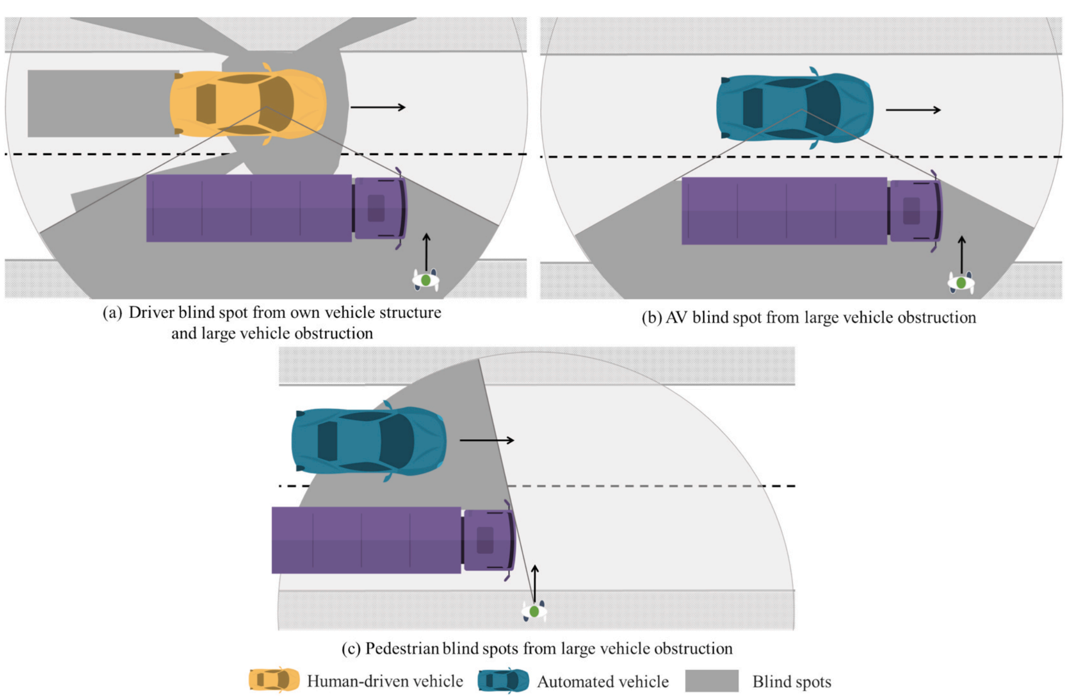


Fig. 1. Blind spots for different road users.

The communication modalities of eHMIs predominantly involve visual elements like text, symbols, and lighting, with some auditory elements, including both verbal and non-verbal cues (Ackermann et al., 2019a, 2019b; Bazilinskyy et al., 2019; Dey et al., 2020; Rettenmaier et al., 2020). Past research has suggested that symbol-based eHMIs based on a universal pedestrian signal ensure familiarity, comprehensibility, and visibility from a distance (Ackermann et al., 2019b; Rettenmaier et al., 2020). Textual advice provides unambiguous information, although readability diminishes at greater distances (Ackermann et al., 2019a; Bazilinskyy et al., 2019). Furthermore, research suggests that using consistent colors in text messages enhances the effectiveness of communication (Bazilinskyy et al., 2019). However, most current eHMI designs rely on a single communication channel (Löcken et al., 2019).

Research on eHMIs for large vehicles remains limited. Colley et al. (2020) examined scenarios where trucks partially parked along the street obstruct pedestrians' views and employed an 'Auditory + Text + Arrows' eHMI design. The findings demonstrated direct pedestrian advisory information—such as 'Caution'—are more effective in pedestrian-vehicle interactions. In terms of communication modality, existing studies on eHMIs for large vehicles primarily rely on LED light strips (Benderius et al., 2018; Oehl et al., 2022; Zheng et al., 2024; Lau et al., 2022a, Lau et al., 2024a, Lau et al., 2024c, Lau et al., 2024b). Moreover, the effectiveness and safety of eHMIs in complex traffic environments remain uncertain. Consider a scenario: if a truck yields and signals 'Walk' eHMI and a pedestrian starts crossing, an approaching vehicle from an adjacent lane hidden in the truck's blind spot could pose a serious accident risk. This underscores the limited research on eHMIs for large vehicles and the neglect of blind-spot scenarios in existing studies. Overall, studies by Oehl et al. (2022) and Lau et al. (2022b, Lau et al. (2024a),Lau et al. (2024c), Lau et al., 2024b) indicate that eHMIs could improve pedestrians' understanding of AV intention, perceived safety, trust, and comfort, which may facilitate their crossing decisions. However, they also point out that there is no "one-size-fits-all" solution for eHMI design. Designs developed for small vehicles may not be directly applicable to large vehicles. Therefore, it is essential to integrate the advantages of various eHMI interfaces developed for small vehicles to design integrated visual communication forms. Its applicability to large vehicles, particularly in blind spot scenarios, warrants further exploration.

1.3. Study aim

In light of the above, this study aims to explore the impact of eHMI-equipped AVs on pedestrian crossing behavior and safety, focusing on scenarios where AVs create mutual blind spots between pedestrians and adjacent traffic. To achieve this, three visually integrated eHMIs were designed using a combination of text and symbols. 'Walk' eHMI aligns with AV deceleration and yielding behavior without considering blind spots. 'Don't Walk' eHMI indicates pedestrians not to cross. 'Caution! Blind Spots' eHMI alerts pedestrians to blind spot risks. This study has two primary objectives: first, to understand pedestrians' perception of these eHMIs, and second, to investigate how these eHMIs influence pedestrian crossing behavior and safety. We propose the following hypotheses:

- AVs displaying eHMI based solely on their dynamic states (e.g., 'Walk' eHMI) negatively impact pedestrian crossing behavior and safety.
- AVs displaying eHMI based on surrounding risks enhance pedestrian safety, with risk alerts (e.g., 'Caution! Blind Spots' eHMI) being more effective than crossing advice (e.g., 'Don't Walk' eHMI).

To test these hypotheses, a virtual reality (VR) experiment was designed. Participants were asked to cross in front of a yielding truck platoon with limited visibility. The lead truck displayed one of the three eHMIs, while vehicles without eHMI served as control conditions. Adjacent lane vehicles within the blind spot exhibited both proactive and reactive braking responses. Following the experiment, interviews were conducted to gather insights and interpretations on the eHMI designs and crossing decisions, providing a comprehensive understanding of the pedestrian decision-making process.

2. Method

2.1. Participants

Participants were randomly recruited from Southeast University (China). Initially, 55 participants took part, but after excluding those with motion sickness, the final sample included 36 males and 15 females, aged 19 to 31 (M = 23.49, SD = 3.04) years old. All participants met motion capture requirements, with no mobility restrictions. They reported normal or corrected-to-normal vision and hearing. Participants' self-reports indicate that 83.8% walk more than 30 min daily, with 70.3% walking for work or school commuting. Additionally, 78.4% follow AV developments or work/study in AV-related fields, reflecting a certain level of background knowledge relevant to the experiment. However, 89.2% are unaware of eHMIs, indicating that this concept was relatively novel to most participants. Participation was voluntary with no monetary reward.

2.2. Apparatus

This study involved enhancing the CARLA autonomous driving simulation software to create a virtual reality pedestrian simulator. CARLA, developed using Unreal Engine, allows convenient control over vehicles and agents via its API in Python or C++, offering realistic vehicle dynamics, sensor data generation, and dynamic environmental settings (Dosovitskiy et al., 2017). This pedestrian simulator used a high-fidelity HTC VIVE Pro 2 setup, featuring a head-mounted display (4896 × 2448 pixels), handheld controllers, and infrared trackers. Four VIVE base stations tracked the head-mounted display's position. For improved immersion, the sound of the real world was suppressed, and engine noises of approaching vehicles in terms of distance and speed were played through headphones. The simulator ran on a high-performance desktop with Intel® Core™ i9-12900K CPU processor (3.00 GHz), 64 GB RAM, an NVIDIA GeForce RTX 4090 graphic card with 24 GB VRAM, and a Windows 11 Enterprise operating system, maintaining a simulation refresh rate of 60 Hz.

Participants interacted within a virtual environment simulating a one-way, two-lane road with a 6.5m cross-section, as depicted in Fig. 2 (a). No signalized crosswalk was included to increase the ambiguity of the traffic scenario. As shown in Table 1, the scenario included two vehicle types: trucks and small sedans (hatchback). Participants' visibility was impacted by the trucks. They could move freely within a designated 10 × 3m area, marked with blue squares indicating start, waiting, and target positions.

Body movement data were collected using a motion capture system with four HTC VIVE wireless trackers, a head-mounted display, and two handheld controllers, positioned on hands, abdomen, chest, and ankles, as shown in Fig. 2(b). The data were sampled at 20 Hz. Before motion data collection, a calibration routine was carried out carefully for every participant. An internally developed software synchronized and stored real-time motion data.

2.3. Experimental design and conditions

The scenario design was inspired by Lobjois and Cavallo (2007). It involves four vehicles (numbered in Fig. 3) approaching a pedestrian waiting at the curb, allowing control of time gaps between the two vehicles. Following road traffic safety regulations for urban environments in China, the vehicles' initial speeds were set to 30km/h. As shown in

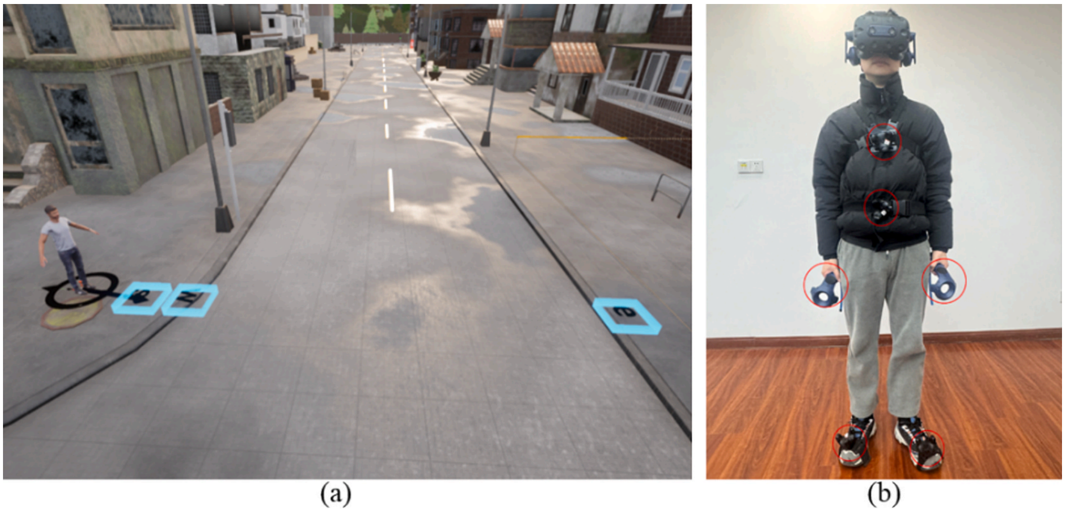
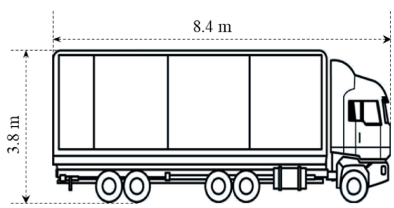
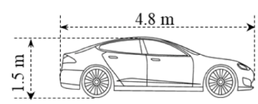
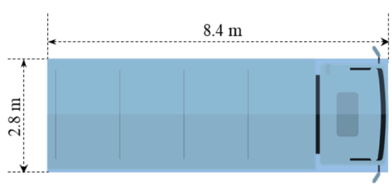
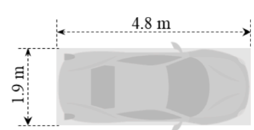


Fig. 2. (a) Virtual traffic environment. (b) Positions of wireless trackers on the body locations.

Table 1
Size information of the truck and the hatchback in Carla.

	Truck	Small sedan (hatchback)
Side View		
Simplified Shape		

: The effective shape of the truck as a visual obstacle in the two-dimensional space;
: The effective shape of the sedan as an object in the two-dimensional space.

Fig. 3(a), the first vehicle in the near lane (Vehicle 1) is a non-yielding sedan, followed by two trucks (Vehicles 2 and 3). The initial time gap between the first and second vehicles (Vehicles 1 and 2) is 4.5s (37.5m). This time gap was determined based on a small pilot study involving 8 participants, where over 90% of participants crossed at 7s gaps, but none at 3s or less. The third vehicle (Vehicle 3) maintains a constant distance of 5m from the second vehicle (Vehicle 2) to block the pedestrian's view of the sedan in the far lane (Vehicle 4). As shown in Fig. 3(b), the second vehicle in the near lane (Vehicle 2) decelerates at 27.5m (3s) from the crossing position and stops at 2.5m. The third vehicle (Vehicle 3) decelerated in synchronization with the second vehicle (Vehicle 2).

The virtual reality experiment employed a 3×4 repeated measures design with two independent variables: 3 types of braking responses and 4 types of eHMI communication strategies. Each combination of braking response and eHMI condition was presented twice to each participant, resulting in a total of 24 trials per participant (see Table 2). The first variable, the braking response of the sedan in the far lane, included:1) proactive braking, 2) reactive braking, and 3) no-vehicle baseline. Proactive braking of the far-lane sedan occurs at the moment the near-lane truck begins to yield, with a deceleration rate of 1.5 m/s2. This allows the sedan to stop 2.5m from the pedestrian, 1s after the truck has completely stopped. Reactive braking simulates an AEB-P system, shown in Fig. 4. The system's sensor is mounted at the center front of the sedan and continuously monitors a 180-degree horizontal visibility (i.e., a fan-shaped area extending 90 degrees to each side). The sensor's detection criteria specify that when a pedestrian steps into the roadway and maintains a speed greater than 1 m/s for 0.3 s, the system interprets this as an intent to cross and immediately initiates emergency braking. If the pedestrian waits at the curb, braking is not activated. Notably, the sensor's visibility can be obstructed by a nearby truck in the adjacent lane, potentially limiting its ability to detect pedestrians. The experiment assumes no delay in the AV's response, allowing the sedan to stop precisely 0.5 m from the pedestrian. Although this may exceed actual braking capabilities (with deceleration rates exceeding 10 m/s2), it reduces the psychological burden on participants from virtual collisions.

The second variable, the eHMI communication strategy of the near-lane truck, included: 1) No eHMI (baseline), 2) 'Walk' eHMI, 3) 'Don't Walk' eHMI, and 4) 'Caution! Blind Spots' eHMI. In the baseline condition, the AV starts braking at 27.5m from the pedestrian without additional communication, and pedestrians infer the vehicle's intention from its deceleration alone. A 1 × 0.3m LED display was integrated into the truck's radiator grille, a position found suitable for communication

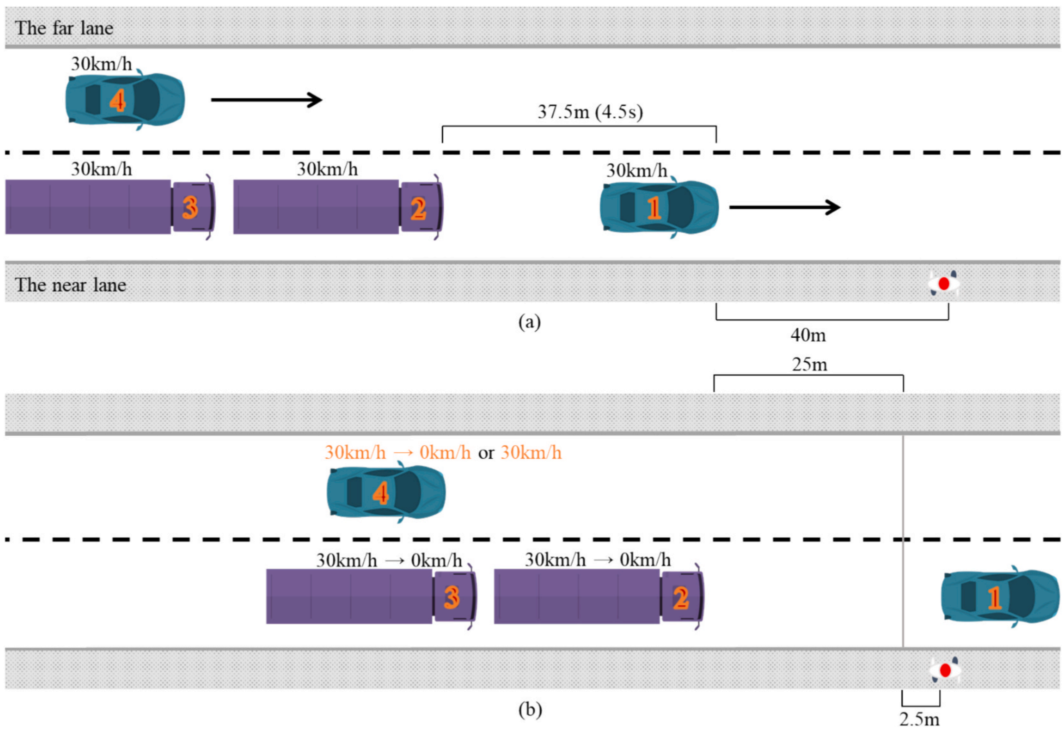


Fig. 3. Illustration of the scenario.

Table 2
Experimental conditions: 3 braking responses × 4 eHMI conditions, with 2 repetitions per condition.

Braking response	eHMI	Repetitions	Sequence
Proactive braking	No eHMI	2	Randomized
	Walk	2	
	Don't Walk	2	
	Caution! Blind Spots	2	
Reactive braking	No eHMI	2	
	Walk	2	
	Don't Walk	2	
	Caution! Blind Spots	2	
No-vehicle	No eHMI	2	
	Walk	2	
	Don't Walk	2	
	Caution! Blind Spots	2	

devices in previous research (Eisma et al., 2019; Bindschädel et al., 2021). The three eHMI designs are shown in Fig. 5. The 'Walk' eHMI signals to pedestrians that it is safe to cross, based on the vehicle slowing down to yield. Conversely, the 'Don't Walk' eHMI instructs pedestrians not to cross, even if the vehicle is decelerating. In this study, the 'Don't Walk' signal is intended to remind pedestrians of the risks associated with blind spots. This warning design is currently a popular format for eHMIs (Zhao et al., 2024) and was chosen to evaluate its effectiveness in scenarios involving blind spots. The 'Caution! Blind Spots' eHMI alerts pedestrians to potential risks within blind spots, mirroring conventional traffic signs commonly found on large vehicles. All these eHMI options use familiar texts and symbols for quick recognition and understanding. The eHMI display of the truck begins when the first sedan passes the

Fig. 5. Three eHMI designs.

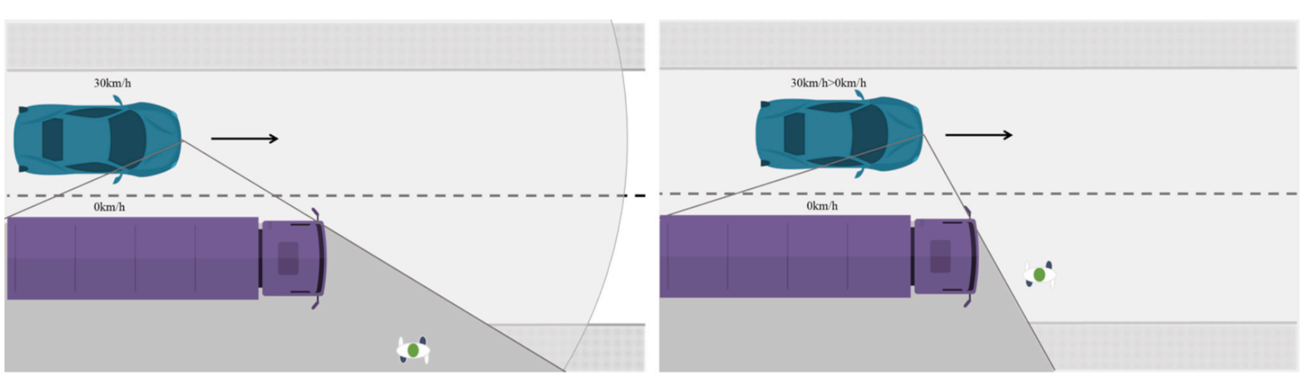


Fig. 4. Illustration of reactive braking.

crossing position and turns off 2s after the truck stops.

2.4. Procedure

The subjects participated individually. Upon arrival, they were briefed on the study's objective and procedure and familiarized with the VR pedestrian simulator. The first part of the study involved a VR experiment where participants, standing on a pavement, faced AVs approaching exclusively from the left side without driver intervention. Without prior information about eHMI, they were instructed to cross the road whenever they felt safe after the first vehicle passed the crossing position. Upon reaching the target location, they rate their subjective safety feelings on a virtual board. After signing the consent form and completing calibration, they conducted practice trials crossing in front of stationary vehicles until they felt comfortable. Each participant then experienced 24 randomized trials. Throughout the experiment, participants were instructed to minimize interaction with the experimenter for sufficient immersion.

The second part of the study involved completing the following questionnaires: demographic information, the Misery Scale (MISC) to assess discomfort levels during the experiment (Bos et al., 2005), the Igroup Presence Questionnaire (IPQ) to evaluate the realism of the VR experiment (Schubert et al., 2001), and eHMI questionnaires regarding trust and user experience. Participants were also interviewed to further explain their behavior during the experiment. Altogether, the experiment lasted approximately 1 h with about 40min dedicated to the introduction and the VR component, followed by 20min for the follow-up questionnaires and interviews.

2.5. Dependent variables and materials

Crossing initiation time (CIT): CIT is widely used as an objective measure of pedestrian crossing behavior (Bindschädel et al., 2022; Lee et al., 2022; Zhao et al., 2024). Participants' CIT was calculated by subtracting the time when the first vehicle passed the crossing position from the time when the pedestrian stepped off the curb. This calculation was performed using a histogram-based thresholding algorithm as suggested by Bindschädel et al. (2022).

Subjective safety: After each trial, participants rated their subjective safety feelings on a 7-point scale from -3 to $+3$ by answering the question: "How safe did you feel while crossing the road? (Not at all – Very)." To enhance immersion, this single-item scale was presented on a virtual board on the opposite side of the road. Participants selected their answers using handheld controllers. After answering, the button lit up, providing instant visual feedback (Bindschädel et al., 2021).

User experience and trust in eHMI: Trust is a multidimensional concept consisting of cognitive, that is, knowledge-based, and affective, that is, emotion-based, components (Lee et al., 2015). Each 7-point Likert scale has three items: credible, reliable, safe (cognitive trust, Cronbach's $\alpha =$ 0.82 to 0.91) and friendly, likable, positive (affective trust, Cronbach's α=0.90 to 0.93) (Faas et al., 2020). User experience covers pragmatic and hedonic attributes when interacting with a product. Pragmatic attributes are paramount for user experience in the context of pedestrian-AV interaction. Thus, we measured user experience with the dimension "pragmatic quality" of the short version of the User Experience Questionnaire (UEQ-S; Schrepp et al., 2017). The 7-point Likert scale entails four semantic differentials: obstructive – supportive, complicated – simple, inefficient – efficient, and confusing – clear. Reliability was acceptable, with Cronbach's $\alpha = 0.78$ to 0.82.

MISC and IPQ: To ensure the discomfort did not affect the VR experiment's validity, participants rated their wellbeing on the single-item Misery Scale (MISC) (Bos et al., 2005) ranging on a Likert scale ranging from 0 (no problems) to 10 (vomiting). The Igroup Presence Questionnaire (IPQ) (Schubert et al., 2001) was used to assess participants' sense of presence and behavior in the virtual environment. The IPQ includes 14 items and comprises the three subscales of spatial presence, involvement, and experienced realism. Participants responded to each item on different 7-point Likert scales ranging from 0 to 6.

Structured interview: After the questionnaires, a short-structured interview followed. The post-experiment interviews gathered insights into three key areas: the changes in participants' attention to vehicle blind spots before and after the experiment, their understanding of three eHMIs and how these eHMIs influenced their road-crossing behavior and safety, and their feedback on the effectiveness, necessity, and potential improvements for these eHMIs.

2.6. Statistical analysis

Analyses were conducted using Python with the statsmodels module. To examine the impact of eHMI and braking response on pedestrian safety, linear mixed models (LMM) were used. LMM is particularly well-suited for analyzing hierarchically structured data, where measurements are nested within different levels (Nezlek, 2008). In this study, CIT and subjective safety served as the dependent variables. Two-level models were constructed, with participants as the second-level variable and experimental trials as the first-level variable.

The model testing process was conducted in several phases. Initially, a null model was computed to evaluate the variability of the dependent variables across participants, with random intercepts allowed for each participant. The intraclass correlation coefficient (ICC) derived from the null model indicated the extent of variability among participants, where a high ICC suggests significant differences across participants (Nezlek, 2008). Based on the findings of Maas and Hox (2005), the final sample size of $N = 51$ was considered sufficient for accurate estimation of regression coefficients.

CIT and subjective safety were assessed for homogeneity of variance and normal distribution. The results indicated that the assumptions of normality were not met. To address this, the Yeo-Johnson transformation was applied to the variables (Yeo, 2000). Since the LMM results for the transformed variables were consistent with those for the non-transformed variables, the analysis demonstrated robustness against violations of the normality assumption. Therefore, the LMM results for the non-transformed variables are reported for ease of interpretation.

3. Results

3.1. Crossing initiation time

Table 3 shows descriptive statistics for CIT and subjective safety by eHMI and braking response. For further analysis, LMMs were used due to the hierarchical data structure. All null models were significant with $p < .001$, indicating that participants significantly differed in their CIT. The ICC for CIT was 0.472, suggesting considerable individual differences. To investigate their effect on CIT, eHMI and braking response

Table 3
Descriptive statistics for CIT and subjective safety.

		CIT[s]		Subjective safety	
Braking response	**eHMI**	**Mean**	**SD**	**Mean**	**SD**
Proactive braking	No eHMI	5.77	2.62	0.83	1.50
	Walk	3.70	2.30	0.59	1.77
	Don't Walk	6.59	2.67	1.44	1.51
	Caution! Blind Spots	5.12	2.93	1.19	1.11
Reactive braking	No eHMI	5.41	2.87	−0.73	1.48
	Walk	3.82	2.51	−0.23	2.01
	Don't Walk	6.59	2.81	1.12	1.53
	Caution! Blind Spots	5.59	2.47	0.52	1.48
No-vehicle	No eHMI	5.72	2.54	1.15	1.54
	Walk	3.73	2.65	1.77	137
	Don't Walk	6.46	2.37	1.38	1.51
	Caution! Blind Spots	5.61	2.74	1.76	1.13

were used as independent variables at level 1. Since the LMMs with interaction terms provided a better fit to the data, the results of LMMs considering interactions are reported. The results are displayed in Table 4. A significant effect for eHMI was found, indicating variations in CIT depending on the eHMI condition. Specifically, participants showed significantly decreased CIT for the 'Walk' eHMI compared to not having an eHMI present ($\beta = -0.72$, $t(1173) = -4.88$, $p < 0.001$). Additionally, the 'Don't Walk' eHMI was associated with significantly higher CIT compared to no eHMI ($\beta = 0.27$, $t(1173) = 2.22$, $p = 0.027$). The 'Caution! Blind Spots' eHMI did not show a significant difference in CIT compared to no eHMI ($\beta = -0.04$, $t(1173) = -0.37$, $p = 0.723$). Braking response and its interactions with eHMI had no significant effects on CIT across all conditions. Post-hoc multiple comparisons using Tukey HSD test with Holm correction revealed significant differences between the eHMIs at $p < 0.05$, except for a non-significant difference between the baseline and the 'Caution! Blind Spots' eHMI. For braking response and the interaction terms involving eHMI and braking response, no significant main effects were found.

3.2. Subjective safety

The null model results indicate substantial individual differences in subjective safety. An ICC of 0.254 suggests moderate variability between participants. The full model, incorporating eHMI and braking response as independent variables, shows that eHMI significantly influences subjective safety. Results indicate higher safety with the 'Caution! Blind Spots' eHMI ($\beta = 0.35$, $t(1173) = 2.56$, $p = 0.011$), while the 'Walk' eHMI also indicated a marginally significant positive effect ($\beta = 0.36$, $t(1173) = 1.95$, $p = 0.052$). The 'Don't Walk' eHMI did not significantly alter safety perceptions compared to no eHMI ($\beta = 0.14$, $t(1173) = 0.92$, $p = 0.371$). Braking responses revealed significant differences, with reactive responses substantially decreasing subjective safety ($\beta = -1.11$, $t(1173) = -5.98$, $p < 0.001$). Proactive responses showed no significant effect ($\beta = -0.19$, $t(1173) = -1.36$, $p = 0.173$). Significant interaction effects were observed. For example, proactive braking in the 'Walk' eHMI negatively affected subjective safety ($\beta = -0.50$, $t(1173) = -2.17$, $p = 0.031$). Reactive braking in the 'Don't Walk' eHMI also had a significant positive effect ($\beta = 0.95$, $t(1173) = 3.97$, $p < 0.001$). Post-hoc multiple comparisons using Tukey HSD tests for eHMI confirmed significant differences between most eHMIs at $p < 0.05$, except between the 'Walk' and 'Don't Walk' eHMI. For braking response, Tukey HSD tests revealed significant differences across all braking response levels, with reactive response consistently perceived as less safe.

3.3. User experience and trust in eHMI

Table 5 displays descriptive results of user experience and trust in eHMI. Pragmatic aspects of user experience are particularly relevant for the evaluation of communication concepts of AVs. According to the guidelines of Hinderks et al. (2019), all eHMI types received very positive evaluations with overall pragmatic quality scores exceeding 0.8. For cognitive trust, the 'Caution! Blind Spots' eHMI had the highest trust ($M = 1.85$, $SD = 0.92$). For affective trust, it also had the highest trust ($M = 1.77$, $SD = 1.01$). The Walk eHMI had noticeably lower cognitive trust ($M = 0.65$, $SD = 1.46$).

3.4. MISC and IPQ scale

The descriptive statistics of the MISC scale ($M = 1.16$, $SD = 0.73$) indicated low discomfort during the virtual reality experiment, similar to Zhao et al. (2024). The IPQ results showed general presence ($M = 4.26$, $SD = 1.29$), spatial presence ($M = 4.09$, $SD = 0.81$), involvement ($M = 4.06$, $SD = 0.94$), and experienced realism ($M = 2.68$, $SD = 0.79$), comparable to Bindschädel et al. (2022). Overall, participants exhibited a high sense of immersion.

3.5. Qualitative analysis

In this study, post-experiment interviews were conducted with all

Table 5
Descriptive results of User experience and trust in eHMI.

		Walk eHMI		**DON' Walk eHMI**		**Caution! Blind Spots eHMI**	
Negative	**Positive**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
obstructive	supportive	1.60	1.17	1.81	1.29	1.51	1.39
complicated	easy	2.03	0.90	2.08	0.98	1.41	1.50
inefficient	efficient	1.49	1.39	1.57	1.64	1.41	1.28
confusing	clear	1.87	1.40	2.08	1.16	1.73	1.28
Pragmatic Quality		1.74	0.96	1.89	1.04	1.51	1.10
Cognitive trust		0.65	1.46	1.61	1.15	1.85	0.92
Affective trust		1.34	1.54	1.23	1.39	1.77	1.01

Note: The range of the scales is between −3 (horribly bad) and + 3 (extremely good).

Table 4
Linear Mixed Models for CIT and subjective safety.

	CIT[s]				Subjective safety			
Variables	β	SE	t	p	β	SE	t	p
Level 1 main effects								
eHMI[a]								
Walk	−0.72	0.15	−4.88	<0.001	0.36	0.19	1.95	0.052
Don't Walk	0.27	0.12	2.22	0.027	0.14	0.15	0.9	0.371
Caution! Blind Spots	−0.04	0.11	−0.37	0.723	0.35	0.14	2.56	0.011
Braking response[b]								
Proactive	0.02	0.11	0.17	0.862	−0.19	0.14	−1.36	0.173
Reactive	−0.11	0.15	−0.76	0.447	−1.11	0.19	−5.98	<0.001
Level 1 interactions								
Proactive * Walk	−0.03	0.18	−0.16	0.872	−0.50	0.23	−2.17	0.031
Proactive * Don't Walk	0.03	0.16	0.18	0.854	0.22	0.2	1.08	0.279
Proactive* Caution! Blind Spots	−0.20	0.18	−1.11	0.269	−0.14	0.22	−0.64	0.521
Reactive * Walk	0.15	0.20	0.72	0.473	−0.07	0.25	−0.27	0.790
Reactive * Don't Walk	0.16	0.19	0.84	0.399	0.95	0.24	3.97	<0.001
Reactive * Caution! Blind Spots	0.11	0.18	0.58	0.565	0.38	0.23	1.65	0.100
Statistics								
AIC	2535.4				2957.6			
BIC	2606.9				3029.1			
Log Likelihood	−1253.7				−1464.8			
ICC	0.472				0.254			

Note: Standardized regression coefficients are given. [a] Reference category is categorical variable no eHMI. [b] Reference category is categorical variable no vehicle.

participants to explore their awareness of vehicle blind spots, interpretation of eHMIs, levels of trust, and suggestions for improvement. Each interview lasted approximately 10 min, focusing on their behavioral decisions and responses to different eHMIs. The interview questions were partially adapted from Zhao et al. (2024), with a detailed list provided in Appendix A. Two independent coders conducted a thematic analysis following the methodology outlined by Berends and Johnston (2005) and collaboratively developed a coding scheme. The coders then independently coded the data, and inter-coder reliability was assessed using Cohen's Kappa coefficient, resulting in a score of 0.81 ($p < 0.001$), indicating a high level of agreement.

3.5.1. Pedestrian awareness and response to blind spots

In this study, 77% of participants reported being aware of vehicle blind spots in their daily lives, and 20% specifically mentioned paying special attention to blind spots when crossing the road. For instance, one participant noted, "*I am very conscious of my safety when crossing the road. Whenever there is a vehicle blind spot, I slow down, move closer, and ensure no vehicles are coming before continuing.*" Additionally, three participants mentioned that when their view is obstructed by a truck, they prefer to let the truck pass first to ensure safety.

In contrast, 23% of participants admitted they generally do not pay attention to vehicle blind spots and did not initially notice potential vehicles in blind spots during the experiment. One participant recalled, "*At first, I did not notice the blind spot, but when a vehicle suddenly sped through, I realized its presence.*" Two others shared similar experiences: "*Initially, I didn't notice the blind spot until a vehicle suddenly appeared and startled me.*"

While 31% of participants claimed they usually pay attention to vehicle blind spots, they did not promptly notice vehicles in the blind spots during the early stages of the experiment. However, those who reported being particularly attentive to blind spots in their daily lives demonstrated strong awareness during the experiment's initial phase. One participant stated, "*When you see this kind of scene, you think there might be invisible vehicles next to the truck.*" *Another participant mentioned, "Because the truck was parked close to the sidewalk, the blind spot was large. So when I approached, I cautiously leaned forward to check if there were any cars in the other lane before crossing.*"

Most participants indicated that they would be more cautious about potential dangers from vehicle blind spots in the future, except for one participant who remarked, "*I don't think my response to blind spots has changed much because I've always waited and paid attention when encountering a blind spot.*"

Regarding future behavioral adjustments, 29% of participants mentioned they would rely on eHMIs to assess blind spot situations. One participant pointed out, "*Early on, whenever I saw text on the truck, I waited for it to stop before crossing. Later, I used color and distance cues from the text to judge whether to proceed, while also paying attention to smaller vehicles in the blind spot.*" Another participant expressed, "*I realized that vehicles could provide blind spot information, so when I saw a green sign, I walked directly; when I saw a yellow sign, I hesitated, and when I saw a red sign, I stopped.*" Additionally, one participant noted, "*As the experiment progressed, I found the information on the signs more reliable, though some signs were still inaccurate.*"

On the other hand, 17% of participants preferred to personally check the blind spot, finding that eHMI information could be inaccurate. One participant commented, "*At first, the alerts were often incorrect, so I stopped relying on them and just crossed normally because it's a matter of safety.*" Another shared a similar sentiment: "*Initially, I followed the signs on the truck, but a few times, the sign indicated it was safe to cross, and then a car suddenly appeared. Other times, the sign said not to cross, but there were no vehicles. So I decided it was better to check the blind spot myself.*"

3.5.2. Pedestrian interpretation and trust in three eHMIs

The study revealed significant differences in pedestrians' understanding and trust in the three eHMIs. Participants generally perceived the green 'Walk' eHMI as indicating that it was safe to cross. However, approximately half of the participants believed that the 'Walk' eHMI was displayed because there were no vehicles in the blind spot. Initially, some participants exhibited a high level of trust in the 'Walk' eHMI, believing it clearly communicated safety. For instance, one participant stated, "*When the truck signals that it's safe to cross, I feel confident moving forward.*" However, as the experiment progressed, some participants began to question the signal's accuracy, particularly when vehicles appeared despite the 'Walk' eHMI. This led to a gradual erosion of trust: "*At first, I would cross as soon as I saw the green light, but after being hit, I no longer trust it.*"

The red 'Don't Walk' eHMI was widely understood as a clear directive to stop, prompting pedestrians to exercise greater caution. However, about half of the participants believed that the 'Don't Walk' eHMI was triggered by the presence of vehicles in the blind spot. One participant mentioned, "When I see the red and yellow lights, I stop and wait for the vehicle to come to a complete stop before crossing." Yet, a few participants expressed confusion, feeling that the signal was overly authoritative and might lead to misleading situations: "The 'Don't Walk' signal feels too forceful to me, and I am skeptical about it."

The yellow 'Caution! Blind Spots' eHMI was generally perceived by participants as a reminder to stay alert when crossing. However, there were varying interpretations of this signal's specific meaning. Some participants saw the yellow signal as indicating potential danger: "The yellow signal suggests there might be risks in the vehicle's blind spot, which helps in assessing the environment." Others desired more explicit guidance from the signal: "The yellow signal should align more closely with red or green, providing a clearer indication."

3.5.3. Pedestrian understanding processes and suggestions for eHMI

Overall, most participants responded positively to the three eHMI signals, finding the designs relatable to everyday life and easy to understand. However, a few participants expressed concerns about specific aspects of the designs. For instance, one participant mentioned that the meaning of the 'Caution! Blind Spots' eHMI was unclear, while another felt that the 'Don't Walk' eHMI sounded too commanding.

The majority of participants easily understood the meanings they believed the eHMI signals conveyed. Specifically, 37% of participants understood the signals immediately, 51% needed to see them a second time. As one participant noted, "*After comparing the three signals following the first round, I better understood their meanings.*" Another 12% of participants said they fully understood the signals' meanings only halfway through the experiment, after each signal had appeared approximately three times.

Color played a crucial role in helping pedestrians interpret and distinguish the signals, with 57% of participants highlighting its importance. Five participants specifically noted that the eHMI colors being similar to traffic lights made the signals easier to understand. One participant observed, "*The colors are obvious, just like traffic lights.*" However, some participants relied more on the text than on the color, stating, "*The color didn't add much meaning for me; I mainly focused on the text.*" Additionally, three participants mentioned using a combination of color, symbols, and text to understand the signals. One participant commented, "*I look at the colors from a distance and focus on the text and symbols when I'm closer.*".

In discussing the improvement of eHMI design, participants proposed several key suggestions focused on enhancing the accuracy and reliability of the eHMIs. One participant recommended adding a proximity distance display when a vehicle approaches a blind spot, stating that "*the current signals only provide qualitative information; adding quantitative data could increase trust in the signals.*" Additionally, some participants advocated for simplifying the signal design by using basic color blocks: "*green for go, red for stop, and yellow for caution,*" which would help pedestrians quickly grasp the meaning of the signals. Another participant emphasized the need for clear indicators of whether a vehicle is in autonomous mode, arguing that "*there should be a sign* *indicating the vehicle is autonomous, as people might be more cautious around self-driving cars.*" Moreover, one participant suggested that "*Signals should comprehensively reflect the safety of the traffic environment, not just the behavior of the truck alone.*" Finally, some participants highlighted the importance of public education: "*If these signals are to be used, it's necessary to educate the public on what they mean.*"

4. Discussion

This study explores pedestrian behavior and safety when interacting with eHMI-equipped AVs in blind spot scenarios. To achieve this, we designed and evaluated three types of eHMIs—'Walk,' 'Don't Walk,' and 'Caution! Blind Spots'—each incorporating elements of color, text, and symbols. The 'Walk' eHMI suggests that pedestrians can cross, while the 'Don't Walk' and 'Caution! Blind Spots' eHMIs instruct them to wait, with the latter specifically indicating potential risks. The effectiveness of these eHMIs was assessed across various scenarios, focusing on pedestrian understanding of the signals and their impact on crossing behavior. Additionally, the study uncovered cognitive processes and potential misunderstandings that may occur during interactions with eHMIs. Furthermore, this study underscores the importance of eHMIs in improving pedestrian safety around large vehicles and offers insights for future eHMI design improvements.

Firstly, this study provides an analysis of how pedestrians understand eHMI and the potential misunderstandings that may arise. To ensure the signals were easy to understand, all eHMIs were designed based on familiar traffic signals, supplemented with additional text (Norman, 1981). The study results showed that approximately 90% of participants were able to grasp the meaning of the eHMIs after just one to three interactions. Additionally, the UEQ-S evaluation indicated high ratings for these eHMIs in terms of pragmatic quality, suggesting that the designs were highly intuitive. However, it is important to note that some participants partially misunderstood the meanings of the 'Walk' and 'Don't Walk' eHMIs. Eisele and Petzoldt (2022) found that people tend to quickly form interpretations of eHMIs and stick to them, even if those interpretations are incorrect. In our study, about half of the pedestrians mistakenly thought the 'Walk' and 'Don't Walk' eHMIs indicated whether a vehicle was present in the blind spot. This misunderstanding likely stems from their initial experience in a scenario involving blind spots. Notably, two participants were confident that they understood the meaning of the 'Walk' eHMI and believed they would not be further influenced, yet their misunderstanding led to situations where vehicles were unable to brake in time. Similar behavior patterns were observed in a previous study, which highlighted the potential risks of such misunderstandings leading to traffic conflicts (Madigan et al., 2019).

Qualitative results revealed more about participants' understanding processes of eHMI. Over half of the participants were able to quickly recognize and understand the eHMI signals through their use of color, with more than 20% noting the similarity to traffic lights. Although some studies have warned about potential misunderstandings associated with green signals (Bazilinskyy et al., 2019; Dey et al., 2020), our eHMI design effectively minimized confusion between yielding and non-yielding signals by incorporating text and symbols alongside the green and red colors. Words like 'Walk,' in particular, were found to be highly intuitive for participants, enhancing the clarity of the signals. However, directional issues may still arise, especially in scenarios involving multiple pedestrians, necessitating further research to determine whether these signals are effective for all users (Zhao et al., 2024). Thus, while the current design, which combines color, symbols, and text, has successfully reduced some misunderstandings, it has not entirely eliminated them. Future research should explore more context-sensitive eHMI designs that can better adapt to various traffic environments and pedestrian dynamics. Additionally, as many researchers have suggested, public education on AVs and eHMIs remains crucial. By increasing public awareness and understanding of eHMI signals, misunderstandings can be reduced, thereby enhancing overall traffic safety (Dey et al., 2020).

The study then tested the first hypothesis, which proposed that eHMIs reflecting only the vehicle's yielding dynamics might negatively impact pedestrian crossing behavior in blind spot scenarios. While the 'Walk' eHMI is generally believed to enhance pedestrian trust and safety (Bazilinskyy et al., 2019), our findings revealed that when vehicles suddenly appeared from blind spots, this signal significantly decreased participants' trust and subjective safety—more so than when no eHMI was present. This negative effect can be explained by cognitive dissonance: participants expected to cross safely after seeing the 'Walk' signal, but when the actual situation contradicted this expectation, they experienced intense emotional discomfort. According to Expectancy Violation Theory (EVT) (Burgoon, 2015), when reality fails to meet expectations, individuals often feel uneasy and fearful, which was reported by over 60% of participants in this scenario. Lau et al. (2024b) noted that explicit communication signals should be well-coordinated with the vehicle kinematics. Furthermore, both our study and previous research found that 'Walk' eHMIs can encourage pedestrians to initiate crossing earlier (Bindschädel et al., 2021), but this might increase the risk of them overlooking potential risks. For instance, some participants expressed trust in the 'Walk' eHMI and were willing to cross immediately upon seeing the signal, even when they recognized potential dangers. One participant specifically noted that despite being aware of the risks, they would instinctively start crossing when seeing the 'Walk' signal. This suggests that the relationship between trust and behavior is complex, particularly in blind spot scenarios, where trust might paradoxically lead to unsafe actions. Therefore, caution is necessary when designing 'Walk' eHMIs. Future designs should ensure that these signals not only accurately reflect the vehicle's yielding intention but also convey a comprehensive assessment of the overall safety of the traffic environment.

The second hypothesis proposed that eHMIs accounting for surrounding dangers could enhance pedestrian crossing safety. The results supported this hypothesis, showing that the 'Don't Walk' eHMI significantly reduced late or unsafe crossings. This finding aligns with previous research, which indicated that such eHMIs are particularly effective in scenarios involving non-yielding vehicles (Zhao et al., 2023). However, our study also found that even when vehicles yielded, the 'Don't Walk' eHMI caused hesitation among some pedestrians, accompanied by a decrease in subjective safety and trust. This hesitation stemmed from confusion between the vehicle's deceleration and the 'Don't Walk' signal, with some participants even questioning whether the vehicle was malfunctioning. Despite this confusion, most participants chose to follow the eHMI's instruction, considering the brief wait to be acceptable. When vehicles in blind spots suddenly braked, participants' subjective safety and trust increased, as the eHMI accurately reflected the real danger. Nevertheless, 6% of participants ignored the 'Don't Walk' eHMI, a figure lower than the 26% reported in previous studies (Zhao et al., 2023). Interviews revealed that these participants perceived the eHMI warning as a command and trusted that the AV would eventually yield. An additional finding was that when the 'Don't Walk' eHMI genuinely indicated danger, these participants quickly corrected their behavior. This suggests that exposing pedestrians to similar scenarios could help reduce risky behaviors and improve adherence to eHMI instructions. However, replicating such situations frequently in the real world is impractical, indicating that VR could serve as a safe and effective alternative for enhancing pedestrian understanding and compliance with eHMI signals.

The 'Don't Walk' eHMI is valuable not only in blind spot and non-yielding scenarios but also in other situations. For instance, Zhao et al. (2024) suggest that warning eHMIs can effectively reduce potential dangers when a vehicle malfunctions. Therefore, it is worth exploring whether the 'Don't Walk' eHMI could serve as a universal signal in various risky situations. As a universal indicator, the advantage of the 'Don't Walk' eHMI lies in its intuitiveness and broad applicability, consistently conveying danger across different contexts and helping pedestrians make cautious decisions. However, this uniformity could also present limitations. For example, even when pedestrians have the legal right-of-way, the eHMI might still warn them not to cross in blind spot situations. Future research should investigate its effectiveness and pedestrian acceptance across different contexts.

The ‘Caution! Blind Spots’ eHMI is designed to specifically address the risks associated with blind spots by directly warning pedestrians of potential dangers. We hypothesized that this form of risk warning would be more effective than simple instructions. Qualitative results showed that the ‘Caution! Blind Spots’ eHMI increased participants’ awareness of vehicles in blind spots, with some feeling safer due to their heightened attention to potential dangers. However, quantitative analysis revealed no significant difference in effectiveness between the ‘Caution! Blind Spots’ eHMI and the ‘Don’t Walk’ instruction. Additionally, 23% of participants perceived the functions of the ‘Caution! Blind Spots’ and ‘Don’t Walk’ signals to be similar, preferring the clarity and simplicity of the latter. This debate over the effectiveness of danger warnings versus direct instructions is reflected in previous studies. Some research suggests that direct instructions are more effective due to their straightforward communication, while others argue that providing background information can enhance understanding and judgment, thereby improving safety (Ackermann et al., 2019b). Therefore, eHMI design should strike a balance between delivering direct instructions and offering contextual details, quickly conveying commands while also explaining the reasons behind potential dangers to improve understanding and predictive ability.

This study focuses on the application of eHMIs in addressing blind-spot challenges associated with large vehicles, such as trucks. While previous research primarily targeted smaller vehicles, studies by Oehl et al. (2022) and Lau et al. (2022b, Lau et al. (2024a), Lau et al. (2024c), Lau et al., 2024b) demonstrate that well-designed eHMIs can enhance pedestrians’ perceived safety and emotional evaluation of large vehicles. This study confirms these findings and further shows that eHMI designs integrating color, text, and symbols significantly improve pedestrians’ understanding of large vehicle behavior. Existing research has established that pedestrians perceive vehicles of varying sizes differently, with large vehicles often being associated with greater perceived risk (Petzoldt, 2014). Through interviews and quantitative analysis, this study highlights differences in pedestrians’ awareness of blind spots when interacting with large vehicles. 20% of participants exhibited heightened vigilance toward blind spots, adopting more cautious behavior, while 23% displayed little to no awareness of blind-spot risks during the initial phase of the experiment and in real-world contexts. This indicates that not all pedestrians are sufficiently sensitive to the potential hazards posed by large vehicles. For less-vigilant pedestrians, eHMI can enhance risk perception by providing clear and timely warnings. Supporting this conclusion, Fabricius et al. (2022) further emphasizes that eHMIs are more critical for large vehicles than for smaller ones, as pedestrians are more prone to misjudging the speed and distance of large vehicles. By delivering explicit cues, eHMIs improve pedestrians’ understanding of vehicle kinematics, reducing the likelihood of sudden accelerations or decelerations of large vehicles. In this study, the majority of participants expressed support for equipping large vehicles with eHMIs. Notably, around 30% reported that they would rely directly on eHMIs to assess blind-spot conditions. These findings underscore the necessity of implementing eHMIs on large vehicles to improve pedestrian safety and interaction efficiency.

In eHMI implementation, placing the interface at the truck’s radiator grille is often effective as it is prominent and easily noticeable by pedestrians (Benderius et al., 2018). However, due to the large blind spots of these vehicles, pedestrians may adjust their behavior based on surrounding cues (Fabricius et al., 2022), and the message at the grille may not always be visible during the entire interaction. In practice, many blind spot warning signs are also located on the vehicle’s side. Colley et al. (2020) has shown that placing the eHMI on truck’s side improves pedestrians’ perceived safety and trust when the truck remains partially on the street, blocking sidewalks. Additionally, Zheng et al. (2024) suggests that larger eHMIs on large vehicles could increase visibility from a greater distance. Given the size of large vehicles and the impact of their blind spots on pedestrian behavior, the design of eHMI placement and its effectiveness in enhancing safety require further investigation.

4.1. Enhancing eHMI effectiveness in blind spots: strategies, policies, and education

In light of the above discussion, to enhance the effectiveness and safety of eHMI systems in blind spot scenarios, it is essential to adopt a comprehensive strategy that integrates design, policy, and education. eHMI design should prioritize clarity, consistency, and adaptability to different vehicle types and traffic environments. For instance, standard eHMI signals could include ‘Walk’ eHMI with green text/symbols for safe crossing, and ‘Don’t Walk’ eHMI with red text/symbols for unsafe conditions. Establishing clear guidelines for when to activate, deactivate, or switch between these signals is crucial. To ensure accurate ‘Walk’ and ‘Don’t Walk’ eHMIs, the vehicle requires precise environmental assessment, coordinated through perception, prediction, and decision-making processes. Any error in these stages could lead to incorrect signals (e.g., mistakenly showing ‘Walk’ or ‘Don’t Walk’ eHMIs), posing potential risks to pedestrians. A ‘Caution’ yellow eHMI can be added to indicate when the vehicle assessment is uncertain, prompting pedestrians to proceed carefully and reducing potential misinterpretation. Special vehicles that obstruct views, such as trucks, may require signals that alternate between blind spot warnings and standard indications to ensure pedestrians are adequately informed. Furthermore, AVs in blind spots can share real-time data for accurate eHMI signals.

Policymakers and AV developers must work together to establish long-term strategies that ensure safety and consistency in eHMI information. These strategies should emphasize strict adherence to eHMI instructions to reduce confusion and improve overall traffic safety. In complex traffic environments, pedestrians may encounter unforeseen risks, such as vehicles that do not slow down in blind spots or emergency vehicles that are unable to brake in time. Given that it is impractical to design eHMI instructions for every possible situation, a unified ‘Don’t Walk’ signal is essential to indicate when crossing is unsafe. This signal should be supported by auditory warnings to address cases where pedestrians may ignore visual instructions, thereby enhancing overall safety.

Public education is equally critical to the success of eHMI systems. To eliminate confusion and ensure that pedestrians correctly respond to eHMI signals, educational efforts must be synchronized with the broader promotion of AV technology. VR presents a significant opportunity in this regard, as it can safely simulate dangerous scenarios like blind spots, helping to increase pedestrian awareness and adherence to eHMI signals in real-life situations. By integrating VR into public education campaigns, it is possible to create more immersive and impactful learning experiences that reinforce the correct responses to eHMI signals.

To implement these strategies effectively, a preliminary system, as outlined in Table 6, is proposed. This system is an early-stage, simplified approach aimed at enhancing road safety, particularly in blind spot scenarios. While this proposal lays a foundational framework, further evaluation and real-world testing are essential to confirm its effectiveness and refine the design.

4.2. Limitations and future research

While this study provides valuable insights into pedestrian-vehicle interactions within blind spot scenarios, several limitations must be acknowledged. First, the sample predominantly comprised young males from a university setting, which may not accurately represent other pedestrian groups, such as the elderly. Both of these groups may exhibit different behaviors and reactions due to factors such as slower reaction

Table 6
eHMI display system in blind spots.

Signal Type	Display Method	Signal Meaning
Green eHMI	Green text: 'Walk' + animated pedestrian icon	The surrounding environment is safe, pedestrians can cross.
Red eHMI	Red text: 'Don't Walk' + static pedestrian icon	Potential danger in the surrounding environment, pedestrians should not cross.
Yellow eHMI	Yellow text: 'Caution' + exclamation mark icon	No collision risk, but system in uncertain state, use caution to avoid misunderstanding.
Blind Spot eHMI	Red text: 'Blind Spot' + vehicle and exclamation mark icon	Alternates with red eHMI to indicate blind spot danger.
Signal Switching Interval		
As the vehicle enters the interaction area, the system checks traffic conditions every 0.5 s, updating signals in real-time. The interaction area boundaries and signal update frequency can be adjusted as needed.		
Signal Display Logic		
1. No other vehicles in the blind spot • Ego vehicle can yield: display Green eHMI (safe to cross). • Ego vehicle cannot yield: display Red eHMI (wait). 2. AV in the blind spot • Both ego vehicle and AV can yield: display Green eHMI. • Either cannot yield: display Red eHMI + Blind Spot eHMI. 3. Human-driven vehicle in the blind spot • Ego vehicle can yield and human-driven vehicle is yielding: display Green eHMI. • Either cannot yield: display Red eHMI + Blind Spot eHMI. 4. Uncertain conditions • None of the above conditions are met: display Yellow eHMI.		
Audio warning		
If pedestrians ignore the red eHMI, the vehicle issues an audio warning: 'Danger! Don't Walk, please step back!'		

times, reduced sensory acuity, and limited experience with AVs (Rasouli and Tsotsos, 2020). Future research should strive to include a more diverse population that encompasses a broader age range and varying levels of familiarity with AV technology. This will ensure that findings are more generalizable and applicable to real-world pedestrian populations.

Additionally, the study's focus on a large truck as the sole vehicle type for creating blind spots limits the generalizability of eHMI applications. While trucks effectively obscure pedestrian visibility, they are not the only vehicles that pose such risks. Other common vehicles, like SUVs, vans, and buses, also create significant blind spots and are frequently encountered in urban environments. Pedestrians might react more cautiously around large trucks due to their imposing size and familiarity with the associated risks, whereas smaller vehicles like SUVs and vans might not elicit the same level of caution, potentially leading to riskier crossing decisions (Bindschädel et al., 2022). As Lau et al. (2022) observed, pedestrians' perception and behavior vary when interacting with differently sized vehicles. Future research should therefore broaden the application of eHMI across various vehicle sizes to understand their impact on pedestrian behavior fully when forming blind spots. For instance, it remains to be seen whether the effectiveness of eHMI in alerting pedestrians to blind spot risks on smaller vehicles could match that of larger vehicles.

Another significant limitation is the use of a simulated VR environment, which, while offering controlled conditions, may not perfectly replicate the complexities and unpredictability of real-world traffic. In particular, participants performed crossing tasks at the same location repeatedly, potentially making the scenarios more predictable than real-life situations. To enhance the ecological validity of future research, it would be beneficial to introduce more varied and dynamic traffic scenarios within the VR environment to better mimic real-world conditions. Despite this, the controlled environment allows for standardized scenarios and precise variable manipulation, facilitating isolated analysis. It also enables the study of pedestrian-AV interaction given the limited presence of AVs in real traffic, reducing the risk associated with interacting with emerging AV technology (Deb et al., 2018).

Finally, although the eHMI designed in this study significantly reduces misunderstandings, instances of misunderstanding or choosing not to comply with the eHMI still exist. However, follow-up experiments have not yet been conducted to assess the impact of these behaviors on traffic safety. While we suggested that auditory warnings could be a solution to address non-compliance or other risky situations, this approach was not tested in the current study. Future research should explore the effectiveness of combined visual and auditory eHMI signals, particularly in scenarios where pedestrians may be distracted or choose not to comply with the eHMI. Additionally, discussions around the ethical and liability issues of AVs altering VRUs perception of risks—particularly when these risks are not directly caused by the AV itself—should be continued. This is critical to ensure that AVs communicate risks effectively without shifting undue responsibility onto pedestrians or other VRUs.

5. Conclusion

This study explored pedestrian behavior and safety when interacting with AVs equipped with eHMIs in blind spot scenarios, emphasizing the importance of designing eHMIs that are clear, consistent, and reliable. The findings show that eHMIs using color, text, and symbols can enhance pedestrian understanding. The study also uncovers a hidden danger: 'Walk' eHMIs that fail to account for blind spot risks can inadvertently lead pedestrians into hazardous situations. The 'Don't Walk' eHMI effectively reduced unsafe crossing behaviors, even when vehicles yielded, although some participants experienced confusion. Additionally, the 'Caution! Blind Spots' eHMI heightened pedestrian alertness, but its effectiveness was not significantly greater than direct 'Don't Walk' instructions.

This study provides empirical evidence that eHMIs conveying only the state of AVs without considering environmental factors pose substantial risks in blind spot scenarios. Future eHMI designs should integrate dynamic environmental perception and hazard warning functions to enhance pedestrian safety. Furthermore, the study highlights the heterogeneity in pedestrian responses, suggesting that eHMI designs need to be adaptable to different traffic environments and pedestrian groups to ensure broad societal acceptance of autonomous driving technology. Finally, the use of VR in this study demonstrated that it can effectively simulate realistic scenarios, making aggressive pedestrians more aware of the dangers of their behavior, thereby encouraging safer crossing decisions. This finding offers a new perspective on the application of VR in traffic safety research and underscores its potential as a tool for educating and training pedestrians in safe interaction with AVs.

CRediT authorship contribution statement

Xu Chen: Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Xiaomeng Li:** Writing – review & editing, Conceptualization. **Yuxuan Hou:** Writing – review & editing, Investigation. **Wenzhang Yang:** Writing – review & editing, Formal analysis. **Changyin Dong:** Writing – review & editing, Funding acquisition, Formal analysis. **Hao Wang:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization.

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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Appendix A. Interview questions

1. In your daily life, do you pay attention to vehicle blind spots when crossing the road?
2. At the beginning of the experiment, were you aware of the possibility of vehicles appearing in blind spots?
3. Now, after the experiment, how would you approach a situation involving a vehicle's blind spot?
4. How do you understand the meanings of the 'Walk', 'Don't Walk', and 'Caution! Blind Spots' signals? How long did it take you to get used to these signals?
5. Did these signals influence your decision-making? If so, in what way? Has this influence changed over time?
6. Do you think these three signals are useful and necessary? Are they sufficient for interacting with pedestrians?
7. What is your opinion on the overall design of the signals (visibility, timing, etc.)?
8. Do you see any other issues with these signals? What suggestions do you have for improvement?

Data availability

The authors do not have permission to share data.

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