Building Pedestrians' Trust and Awareness while Interacting with Automated Vehicles: A Solution through e-HMI Designs

by

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Dedication

I dedicate this thesis to my beloved parents, Amal and Jamil, who have been my pillars of support and source of inspiration. Without their endless sacrifices, unconditional love and constant encouragement, this journey would not have been possible. I further dedicate this work to my brother, Ahmad, for his constant support and unfaltering belief in my capabilities. I would also like to dedicate this work to the soul of my beloved Godfather Dr. Assaad Zebian for inspiring me and pushing me to strive for competence since childhood.

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Abstract

The introduction of high-level automated vehicles (AVs) into the current transportation system is expected to enhance road safety, including that of vulnerable road users (VRUs). However, one challenge to their deployment is the lack of typical communication cues exchanged between human drivers and pedestrians. One potential solution to replace those human-to-human cues is the development of external human-machine interfaces (e-HMIs). Although several researchers have introduced e-HMI concepts, there remains a deficit in guidance for optimizing these designs. In designing effective and efficient e-HMIs, it is important to incorporate people's needs by considering all stakeholders and reaching out to a representative sample. Moreover, while establishing appropriate levels of trust among pedestrians upon their interaction with AVs is crucial, there has been scant research into the potentially adverse effects of varying trust levels. A multitude of factors—including pedestrians' demographics, behaviors, and familiarity with AVs, AVs' driving styles, and crossing locations—contribute to the spectrum of trust in AVs. This spectrum ranges from overtrust to distrust, each posing distinct implications for pedestrian safety and mobility. To mitigate risks associated with such trust levels, it is vital to engineer e-HMIs that facilitate safe and efficient interactions.

To bridge the identified research gaps, this dissertation provides a novel, structured approach to crafting safe and effective e-HMIs, utilizing a three-phase framework: (1)Formulation, (2)Derivation, and (3)Validation.

In the Formulation phase, the study conducts an in-depth analysis of historical vehicle-pedestrian crash data. The analysis revealed an increased risk associated with straight-moving vehicles to pedestrians at intersections, highlighting the growing vulnerability of older pedestrians in recent years. By quantifying these factors, the study identifies key pre-crash variables essential to developing AV-pedestrian use cases.

During the Derivation phase, the work seeks to understand user needs through participatory design, engaging both experts in the domain and a cross-section of the general public via surveys. Findings indicated that pedestrians' e-HMI preferred features were heavily shaped by their current interactions with human-driven vehicles (HDVs), and these preferences were influenced by their personal attitudes and demographics. Expert feedback also unearthed distinct preferences and highlighted specific challenges tied to certain e-HMIs.

In the Validation phase, the research embraces textual and symbolic e-HMI prototypes informed by earlier survey insights. These prototypes' influence on pedestrians' trust, situation awareness, and cognitive workload was assessed in a virtual reality setup. Through collecting and analyzing self-reported, behavioral, and physiological measures, the results underscore the potential for symbolic e-HMIs to mitigate pedestrian distrust and frustration, while also bringing attention to potential unintended consequences.

This dissertation presents an extensive approach to improving pedestrian safety and mobility, through applying an integrated data-driven and user-centered e-HMI design process. Consequently, it advances our comprehension of pedestrian requirements when engaging with AVs, enabling the derivation of more precise potential interaction scenarios, and paving the way for more customized e-HMI configurations. This work informs the development of novel e-HMI guidelines aimed at fostering optimal—not merely maximal—levels of pedestrian trust in AVs at both controlled and uncontrolled crossing locations. By fine-tuning the level of trust, the study enhances the public's receptivity towards AVs. Moreover, the outlined framework holds potential for wider application, including developing and evaluating HMI solutions across various industries. The anticipated outcome is a more seamless integration of automated systems into daily life, predicated on human-centered design principles prioritizing both safety and trust.

Chapter 1 Introduction

1.1 Problem statement

Pedestrian safety has become an increasing societal concern, especially with the increase in the number of pedestrian fatalities upon being involved in vehicle-pedestrian crashes. In 2021, pedestrian fatalities increased by 13% as compared to 2020 (NHTSA, 2023). A significant contributor to these crashes is human errors, primarily those committed by human drivers (WHO, 2018). In this regard, driver errors such as distracted driving, failure to yield, and impaired driving have been shown to play a substantial role in endangering pedestrian safety (Harrison and Fillmore, 2011; Pope et al., 2017).

Experts argue that advances in vehicle automation, including high-level automated vehicles (AVs), could drastically reduce fatalities by eliminating human errors (Combs et al., 2019; Detwiller & Gabler, 2017; Utriainen, 2021). Beyond improving pedestrian and overall traffic safety, the widespread use of high-level AVs offers additional societal benefits including an eco-friendlier transportation system and an improved quality of life (Fagnant & Kockelman, 2015; Haboucha et al., 2017; KPMG, 2012).

As vehicle automation progresses, the role of human drivers in managing and operating the vehicle is gradually decreasing. In driving automation Level 0, the driver has full control over the vehicle. By Level 3, the vehicle manages most driving tasks, but the driver must be ready to intervene when necessary. At Level 5, the vehicle independently handles all driving tasks without any human intervention (SAE J3016, 2020).

However, this reduction in driver involvement introduces new challenges, particularly concerning AV-pedestrian interactions. In the absence of the human driver or in the presence of an inattentive driver, pedestrians lose informal communication cues, such as eye contact, that they typically rely on while interacting with human-driven vehicles (HDVs). To address this, new human-machine interfaces (HMIs) external to AVs, known as e-HMIs, are being developed to replace those cues. However, there is a lack of consensus among researchers regarding the necessary attributes for the design of an efficient and effective external HMI (e-HMI) (Dey et al., 2020).

While the majority of the general public have not interacted with AVs yet, it is substantial to develop a comprehensive understanding of people' needs in designing favorable e-HMI solutions. Therefore, it is crucial to involve all stakeholders including the different expert entities and the public, ensure sample representativeness, and examine the impact of existing communication patterns on future communication needs.

Moreover, it is necessary to develop e-HMI solutions that support pedestrians' information processing model in terms of their situation awareness, workload, and trust levels. On one hand, e-HMIs are potential means to improve pedestrians' awareness and trust levels while interacting with AVs especially at ambiguous crossing locations, where the right of way (ROW) is unclear (Habibovic et al., 2018). However, these e-HMIs can make pedestrians less aware of the potential risk imposed by surrounding traffic, which triggers unsafe crossing behavior as a result of overtrust (Habibovic et al., 2018; Palmeiro et al., 2018; Tabone et al., 2021). Thus, it is important to design for scalable e-HMIs that calibrate trust levels.

On the other hand, inefficient crossing scenarios may occur due to pedestrians' distrust in AVs resulting from their non-conservative driving performance, which leads to pedestrians' hesitant and delayed crossing behavior (Hudson et al., 2018; Jayaraman et al., 2019. Limited studies have explored this particular case of pedestrians' distrust, and it is crucial to examine this topic further, especially in the presence of both vehicular e-HMIs and infrastructure-based e-HMIs (in the form of traffic signals) to enhance pedestrians' trust. However, the presence of different sources of cues highlights the significance of determining the vehicular e-HMI cue configuration that reduces pedestrians' workload.

1.2 Research objectives

The objective of this research is to enhance the safety and mobility of pedestrians in the presence of AVs. More specifically, this research work is designed to enhance pedestrians' trust and awareness of the overall traffic environment while interacting with AVs under dynamic conditions through the design of safe and effective e-HMIs. To achieve the research goal, a multistep data-driven and user-centered method is employed. The first step involved analyzing pedestrian crash data to identify the contributing factors, the critical case scenarios, and safety patterns of pedestrians' interaction with HDVs over recent years. This step was informed by the absence of a comprehensive library on AV-pedestrian interaction scenarios enabling the development of more customized e-HMI designs and its evaluation under more tailored scenarios. Then, we conducted an extensive literature review to acquire knowledge about current pedestrians' communication cues with HDVs, existing e-HMI prototype solutions evaluated by other researchers, pedestrians' trust in AVs, and candidate conflicting interaction scenarios. The thorough review indicated a lack of consensus among researchers regarding the necessary attributes for the design of an efficient and effective e-HMI. Therefore, in the second step, we conducted two studies to gather user needs from experts and the general public to extract their requirements and preferences for an e-HMI design that aids their interaction with AVs. In the third step, we evaluated e-HMI prototypes derived from user needs in a virtual reality (VR) environment. We gathered various subjective, objective, and psychological measurements to assess the impact of proposed e-HMI solutions on pedestrians' information processing stages, especially their situation awareness, workload, and trust levels while interacting with AVs. Specifically, we identified design solutions capable of calibrating pedestrians' trust in AVs to minimize potential distrust and overtrust in ambiguous (e.g., midblock location) and unambiguous (e.g., signalized location) crossing scenarios due to limited studies examining pedestrians' unfavorable levels of trust and situational awareness in the presence of e-HMIs.

The proposed research work aims to achieve the following objectives:

1. Investigate the contributing factors to pedestrians' severe injuries during crashes with vehicles at intersections, in order to better understand their interaction with HDVs over the years and to infer factors dictating riskier encounters and potential AV-pedestrian evaluation scenarios.

2. Gather a comprehensive list of user needs, preferences, and expectations towards AVs and e-HMI technology, by surveying end-users (non-motorized vulnerable road users (VRUs) and their advocates), installers and maintainers (industry and government), planners (planning agencies), and facilitators (academic and research institutions).

3. Analyze differences in user needs among pedestrians, based on their attributes (age group, gender), knowledge of AVs, behavior, and existing interaction patterns with HDVs.

4. Develop e-HMI prototypes that meet user needs and evaluate their efficiency (in terms of pedestrians' mobility) and effectiveness (in terms of pedestrians' safety) under dynamic traffic conditions in a VR environment to promote pedestrians' safety, trust and situation awareness.

5. Monitor and compare the influence of different e-HMI prototype solutions on pedestrians' situation awareness, workload, and trust levels, with the goal of improving these measures.

The dissertation covers six different chapters structured as follows:

In **Chapter 1**, we introduced the problem statement and the accompanying research objectives.

In **Chapter 2**, we presented a thorough literature review on safety-critical interactions between pedestrians and vehicles, existing e-HMI design concepts and their evaluation, pedestrians' information processing, and pedestrians' trust in AVs, contributing factors, unfavorable levels, and assessment methods. We also highlighted the research contribution of this work and the theoretical framework developed.

In **Chapter 3**, we analyzed pedestrian-involved crashes at intersections to understand safety-critical scenarios and examine e-HMIs' potential contribution to mitigating adverse effects of lacking human-human communication cues.

In **Chapter 4**, we conducted two surveys, one to the general public and another to experts, to elicit user needs for the development of safe and efficient e-HMIs.

In **Chapter 5**, we conducted a virtual reality experiment to examine the impact of different e-HMI prototypes on calibrating pedestrians' trust, situation awareness and workload.

In **Chapter 6**, we provided a summary of resulting findings from previous chapters and discuss future research directions.

Chapter 2 Research background

2.1 Vehicular-pedestrian crashes

Many studies have been conducted to identify contributing factors related to pedestrian crashes. Lefler and Gabler (2004) found that the pedestrian fatality rate when struck by light trucks and vans (LTV) was two to three times greater than the fatality rate when struck by passenger cars. Oh et al. (2005) conducted a study to identify significant factors related to the probability of pedestrian fatalities in South Korea, with the conclusion that impact speed at a crash was the most significant factor. Tarko and Azam (2011) found that the most dangerous pedestrian behavior was road crossing between intersections (i.e., jaywalking while not using crosswalks). By examining six years of pedestrian crashes from 2002 to 2007 in San Francisco, Jang et al. (2013) reported that the three most significant risk factors that were associated with increased severity of pedestrian crashes were pedestrians' alcohol involvement, their cell phone use, and their age (either below 15 years or above 65 years). Another study found that both children and older pedestrians visiting emergency rooms in the U.S. were found to be involved in riskier injuries from crashes than younger and middle-aged cohorts (Chakravarthy et al., 2007). Distracted driving, failing to respect right of way, and speeding were other risk factors associated with pedestrians' injury levels in Spain as reported by Casado-Sanz et al. (2019). In addition, roadway factors such as road infrastructure, land use, and transit supply characteristics can also cause more severe injury consequences for pedestrians (Mukherjee & Mitra, 2019). More severe pedestrian injuries were reported to be from the crashes that occurred in urban areas, on six-lane roadways and/ or on roadways with speed limits of 40 mph and 50 mph in Ohio than from the crashes at rural locations, on roadways with several lanes other than six, and/or on roadways with other speed limits (Mukherjee & Mitra, 2019). Similarly, environmental conditions, especially dark light situations, were correlated with more severe injury consequences to pedestrians (Billah et al., 2021).

2.2 External human-machine interfaces (E-HMIs)

E-HMIs have been considered as a promising method to replace the traditional communication patterns usually exchanged between pedestrians and drivers of HDVs, and many efforts have been paid to design particular e-HMIs to display and transmit important messages to pedestrians (Dey et al., 2020).

2.2.1 E-HMI design concepts

A variety of e-HMI design concepts have been proposed since 2016. These concepts have employed different modes of communication: visual (Bockle et al., 2017; Dey et al., 2018; Fridman et al., 2019), audio (Deb et al., 2018; Mahadevan et al., 2018), haptic (Mahadevan et al., 2018), and multimodal (Mahadevan et al., 2018). Some studies have indicated that multimodal communication can be more effective than single modality communication (Forke et al., 2021), although this concept is limited by current regulations. In its turn, the visual modality encompassed several types of cues: textual, symbolic, anthropometric, and light-based (Ackermann et al., 2019; Chang et al., 2018; Deb et al., 2018), which can be displayed either dynamically or statically (Othersen et al., 2018). Likewise, two main different auditory cues have been tested: speech and abstract cues (Deb et al., 2018). The proposed concepts have communicated different types of messages: (1) AV's status depicting if the AV is in automated driving mode (e.g., "Self-driving mode") (Joisten et al., 2020; Palmeiro et al., 2018), (2) AV's awareness of surrounding environment (Dey et al., 2018, Mahadevan et al., 2018), (3) AV's intent describing the vehicle's operating state ("Yielding", "Beginning to drive") (Bockle et al., 2017; Dey et al., 2018; Habibovic et al., 2018; Othersen et al., 2018), (4) advice communicating to the pedestrians some form of instructions (e.g., "Safe to cross", "Not safe to cross) (Ackermann et al., 2019; Bazilinskyy et al., 2019; De Clercq et al., 2019; Fridman et al. 2019; Hudson et al., 2018), and (5) kinematics such as the time to cross (Dey et al., 2018). In addition to that, the explored e-HMIs have been assigned to different install-locations: (1) on the AV, including several positions like windshield (Fridman et al., 2019; Mahadevan et al., 2018), radiator grille (Chang et al., 2018; De Clercq et al., 2019; Song et al., 2018), and hood (Palmeiro et al., 2018), (2) on infrastructure elements (Mahadevan et al., 2018), (3) on road projection (Takamatsu et al., 2014), and (4) on the VRU through devices attached to VRUs such as wearables and phones (Mahadevan et al., 2018). To implement these concepts, different technologies and tools have been used: LED displays (Ackermann et al., 2019;

Fridman et al., 2019), headlights (De Clercq et al., 2019), and LED light strips (Weber et al., 2019), and laser projections (Mercedes-Benz, 2020).

Several researchers have presented some concerns associated with the different e-HMI concepts. Visual e-HMIs may be limited in adverse light and weather conditions which impair visibility and readability (Ackermann et al., 2019). Furthermore, implementing on-road projections in real-life scenarios may not be feasible due to constraints in real-time visibility (Fridman et al., 2019). Such concerns, added to the need to account for people with visual limitations when presenting visual cues, encouraged Mahadevan et al. (2018) to examine other e-HMI modalities. Mahadevan et al. (2018) and Ackermann et al. (2019) were also concerned about the use of audio feedback delivered through the AV itself, as it may be affected by surrounding noises, disruptions, and distance-related problems. Other concerns were related to the type of communicated information, in particular, advice information. First, using advisory e-HMIs may result in incorrect interpretations of the traffic situation as it can mislead pedestrians into assuming that other vehicles will also stop, solely based on the fact that the host AV has come to a stop (Metayer & Coeugnet, 2021; Andersson et al., 2017). Habibovic et al. (2018) considered the potential of advisory e-HMIs being hazardous to pedestrians; there may be other road users such as HDVs posing a risk to pedestrians, which the host AV may not be aware of.

2.2.2 E-HMI evaluation

A wide range of studies have evaluated the different e-HMI concepts mentioned before. These studies employed different measurements to conduct this assessment, including objective measures like decision times, error rates, frequency of crossings, and willingness to crossing, and subjective measures like satisfaction, effectiveness, comprehensibility, usefulness, comfort, trust, and perceived safety.

Numerous studies have assessed the importance of e-HMIs in AV-VRU interactions, by comparing its presence to the absence of an e-HMI. According to Stadler et al. (2019) explicit e-HMIs are essential to compensate for the communication between pedestrians and drivers as the presence of explicit e-HMIs resulted in lower reaction time, was more effective as translated through less error rate, and more satisfactory compared to no e-HMI. Similarly, Hollander et al. (2019) concluded to e-HMIs enhancing the perceived safety of pedestrians towards AVs as the presence of e-HMIs resulted in shorter crossing decision times as compared to no e-HMIs. In

Othersen et al. (2018), the introduction of various displays led to shorter crossing initiation times and more frequent crossings before the AV came to a complete stop, as compared to situations when such displays were not present. In a similar manner, Faas et al. (2020) reported participants' significantly greater safety, trust, experience ratings and higher intelligence and transparency relative to the baseline condition of no e-HMI.

Other studies have compared different e-HMI concepts to determine the one that best optimizes pedestrians' safety, efficiency, and experience. Based on Faas et al. (2020), Status+Intent e-HMI was valued more than Status+Awareness and Status+Intent+Awareness in terms of participants' subjective ratings and was deemed most effective based on participants' responses to interviews. In De Clercq et al's (2019) work, textual displays were regarded as the least ambiguous compared to brake lights, smileys and symbols. Chang et al. (2018) shared similar results such that textual displays were most effective in conveying the car's intention, leading to fewer errors in participants' crossing decisions. By comparing different types of auditory messages, participants preferred verbal messages over music and horn sounds, while horn sounds recorded the longest crossing time preceding the no e-HMI scenario (Deb et al., 2018). Among the very few studies that considered different e-HMI install-locations, Mahadevan et al. (2018) devised participants' preference for e-HMIs installed on AVs and infrastructure at the same time in their car study and for e-HMIs installed on three locations concurrently (AVs, infrastructure and VRUs) in their segway study. When it comes to comparing e-HMI technologies, projections and LED displays scored significantly higher recognizability, unambiguousness, and interaction than LED light strips (Ackermann et al., 2019).

Nevertheless, it is noteworthy to mention that most of the reviewed research on the interaction of pedestrians with AVs and accompanying e-HMIs was on a one-to-one basis; that is, one pedestrian and one AV. This underscores the need for further studies examining the interaction between multiple pedestrians and multiple AVs at a time. For example, more research into the development of scalable e-HMIs is necessary so that communication messages can be correctly received by target pedestrians. Similarly, it is important to account for the impact of multiple e-HMIs corresponding to several AVs on a pedestrian's information processing.

2.2.3 Collection of e-HMI-related user needs and preferences

Several researchers have looked into existing interactions to comprehend the needs for vehicle automation. In their interaction with HDVs, pedestrians rely on different forms of communication which are indispensable for a safe and efficient commute. This communication is usually established by interpreting: (1) vehicle dynamics and (2) cues exchanged with the driver. In regard to vehicle dynamics, pedestrians are usually influenced by vehicle sound, vehicle speed (Pawar et al., 2015; Sucha, 2014), vehicle acceleration or deceleration (Sucha, 2014; Risser, 1985), distance gap (Oxley et al., 2005; Yannis et aal., 2013), and time to arrival (Moore, 1953; Petzoldt, 2014). Nevertheless, several other cues directly elicited from the driver or indirectly through the vehicle show greater influence. Eye contact is one of the widely used ways to communicate with drivers. In Rasouli et al. (2017), eye contact with drivers depicted through pedestrians looking at the direction of incoming vehicles accounted for 90% of the total communication events. Aside from indicating the drivers' awareness of the pedestrian, eye contact was also depicted as a sign of high likelihood that the driver stops for the pedestrian (Ren et al., 2016). Other behaviors depicted coming from the driver are hand waving, and nodding (Sucha, 2014, Sucha et al., 2017). In addition to these, drivers might utilize vehicle specific cues such as headlight flashing (Sucha, 2014) and beeping horns (Nathanael et al., 2018).

This communication framework is being studied to dictate e-HMI design aspects. In attempt to better understand pedestrians' preferences for e-HMI concepts, some survey-based and semi-structured interview studies were directed to VRUs or experts to capture their preferences towards the different e-HMI technologies. The results of these studies provide valuable insights into the design of effective and efficient e-HMIs for AVs to ensure safe and seamless interaction with VRUs. For example, in Zandi et al. (2020), participants from various countries reached the conclusion that the "Intent" messages of e-HMIs were more significant than "Status" messages. Bazilinskyy et al. (2019) conducted a large-scale survey on e-HMIs, receiving 1,770 responses regarding the clarity of 28 e-HMIs developed by the industry and 2,000 responses regarding the impact of e-HMI text and color. The results indicated that textual e-HMI messages were the most comprehensible to VRUs, with the "Walk" message being particularly clear when displayed in green. In another study utilizing an online-recruitment methodology, 200 participants viewed augmented real-world photos with 30 e-HMIs and made crossing decisions based on the visual cues. Different visual elements were evaluated, including the location of the e-HMI on the AV, the content of the textual message (e.g., “Go” versus “Walk”), type of icon, and light color. Merat et al. (2018) sought to determine which external travel information was perceived as most important by VRUs. Their study found that VRUs preferred receiving information about the AV’s behavior, while also showing an interest in being aware of their detection by the AV.

This literature emphasizes the importance of considering both vehicle dynamics and driver cues in the design of e-HMIs.

Despite these insights, the literature reveals certain gaps and inconsistencies that need to be addressed.

Some studies have limited their scope to specific demographics, which may not fully capture the diversity of pedestrian experiences and preferences. Additionally, while some cues are consistently preferred across studies, others might be associated with variability in their perceived effectiveness, suggesting that context and individual differences play significant roles. Moreover, it is important to acknowledge that despite pedestrian preferences, there exist other concerns related to some e-HMI design solutions such as feasibility, adaptation, and regulatory and safety standards. These cannot be captured by reaching out to the general public but by reaching out to experts in the field.

Moreover, the relationship between current HDV-to-pedestrian cues and e-HMI preferences is critical for designing effective e-HMIs. Pedestrians have already developed a sense of trust and understanding of the traditional cues, such as speed adjustments, engine sounds, and driver gestures. Integrating these familiar cues into e-HMI designs can bridge the gap between HDVs and AVs, making the transition smoother for pedestrians. However, it is essential to recognize that despite the alignment of e-HMI preferences with traditional cues, there might still be unresolved concerns. Some e-HMIs might not fully capture the complexity of human interactions. Additionally, the familiarity and thus the effectiveness of these cues can vary based on individual, cultural and regional differences, which necessitates a comprehensive approach to e-HMI design.

Integrating the findings from various studies, it becomes clear that a multifaceted approach including a participatory design process and influence analysis to e-HMI design is necessary.

2.3 Pedestrians’ information processing model

Pedestrians’ information processing model is composed of three stages: situation awareness, decision making, and decision execution as shown in Figure 1 (Endsley et al., 2017). Situation awareness involves the comprehension of the current situation at hand, and based on that information, predicting what might occur in the future (Endsley, 1988). It involves three levels: (1) perception of elements in the environment which includes the primary acquisition of surrounding information in its unprocessed form, (2) comprehension of current situation which involves the integration and synthesis of the information to generate a comprehension, and (3) prediction of future status which is the capability to predict the future of the components within the surrounding (Endsley, 1995).

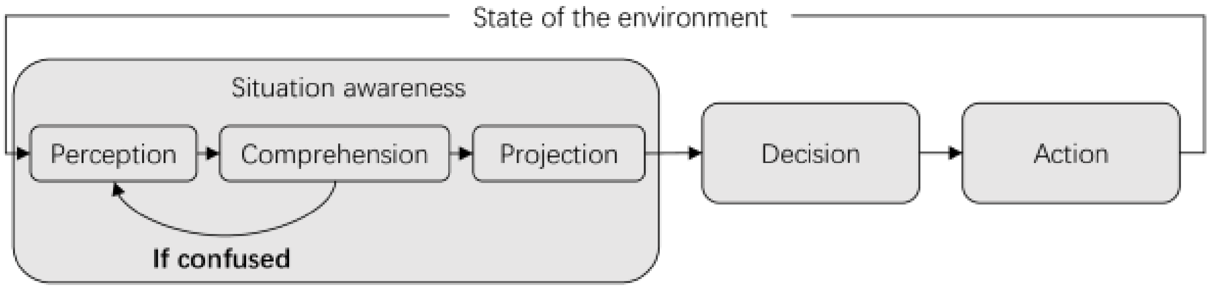


Figure 1: Information processing model (Endsley et al., 2017)

Few studies on pedestrians’ interaction with AVs have solely focused on pedestrians’ situation awareness on all three levels. Add to that, there are limited studies that have extensively examined the levels of situation awareness among pedestrians when e-HMIs and AVs are present. One of these studies is conducted by Liu et al. (2021) which reached the conclusion that educating pedestrians about the reasoning behind a particular e-HMI improved pedestrians’ comprehension of AVs’ driving intentions and the prediction of their behavior. For evaluation, they collected subjective measures of responses to situation awareness-related questions based on a five-point Likert scale. This study examines the impact of e-HMIs on pedestrians' situational awareness, focusing specifically on levels 2 (comprehension) and 3 (projection) as defined in Endsley's model of situational awareness (Endsley, 1995).

On another level, some studies explored pedestrians’ situation awareness with a secondary task, mainly phone usage (Lim et al., 2015; Lin & Huang, 2017; Nasar et al., 2007). For example, Lin and Huang (2017) inquired into how cognitive interference from using a smartphone affects pedestrians’ awareness of events on the roadside while walking. After simulating different events on the roadside and manipulating phone tasks, they collected several situation awareness-related dependent variables: objective measures and physiological measures like event detection time and event time delay, and subjective measures, namely the Situation Awareness Rating Technique (SART) (Taylor, 2011). Another study on the impact of pedestrians' usage of phones during a phone call on their situation awareness was published by Nasar et al. (2007). To measure situation awareness, researchers queried participants on things they recall seeing during the walk. Their analysis showed that there were more objects that pedestrians noticed when there was no phone call as compared to when there was a phone call. Lim et al. (2015) also uncovered significant effects of texting on pedestrians' situation awareness as well as their gait stability while walking. Findings revealed that participants missed 48.3% of the presented visual cues during walking and texting concurrently, compared to when they were only focused on the visual task. At the same time, the effect of texting on participants' walking gait was prevalent through participants' higher total medial-lateral excursion when walking and texting concurrently than when walking only.

Other studies indirectly evaluated pedestrians' situation awareness through monitoring their decision-making process, which precedes pedestrian situation awareness stage. According to Neider et al. (2013), older adults spent more time by the roadside before crossing in front of HDVs than younger adults. This delay was even worse during cell phone conversations, indicating that cognitive planning processes were impaired. Continuing with studies on the effect of mobiles on situation awareness, Byington and Schwebel (2013) investigated if Internet usage through mobile phones affects the safety of young adult pedestrians. While participants were distracted by their phones, they showed certain behaviors such as waiting for longer times before crossing, missing safe opportunities to cross, taking longer initiation times when a safe gap was available, checking the left and right directions less frequently, spending more time looking away from the road, and enduring higher chances of being hit or almost hit by a vehicle.

On another level, some work has been done to model pedestrians' situation awareness in real time. Tong et al. (2018) developed a real-time algorithm using Heart Rate Variability (HRV) and phone positions to monitor pedestrians' mental state and distractions. These were used as input to the Support Vector Machine (SVM) model that classified pedestrians' mental state into alert and fatigue.

In summary, some studies have focused on how e-HMIs affect pedestrians' situation awareness. Other studies have indirectly evaluated pedestrians' situation awareness by assessing performance in the presence of a secondary task and by analyzing decision-making processes. While these methods complement the direct evaluation of situation awareness and offer a comprehensive understanding of pedestrians' cognitive processing in real-world scenarios, the impact of e-HMIs on pedestrians’ situation awareness might differ again based on repeated interactions with AVs and e-HMIs, the context of interaction, and demographic factors. Therefore, it is important to examine pedestrians’ awareness in different studies tailored to specific contexts. Complimentarily, it is important to explore the impact of adding contextual cues to e-HMIs in enhancing pedestrians’ awareness across diverse settings.

2.4 Pedestrians’ trust in AVs

Pedestrians’ trust in AVs plays an important role in the use and acceptance of AVs among the public. To be able to improve pedestrians perceived and actual safety towards AVs, it is important to understand all factors that affect pedestrians’ trust in AVs. It is also indispensable to examine cases of pedestrians’ mistrust and overtrust in AVs to avoid dangerous and inefficient situations.

2.4.1 Factors that affect pedestrians’ trust in AVs

Several factors were found to affect pedestrians’ trust in AVs and were outlined in Zhou et al. (2021):

Individual attributes: In particular, age and gender have been cited in different studies as factors affecting pedestrians’ trust in AVs. In this regard, younger pedestrians are more enthusiastic about AVs than older pedestrians (Deb et al., 2017a, Deb et al. 2018), who exhibited a more cautious and hesitant behavior while interacting with AVs (Deb et al., 2017a). As for gender, male pedestrians demonstrate greater trust in AVs than female counterparts (Deb et al., 2017a).

Knowledge in AVs and other similar technologies: Pre-existing knowledge regarding AVs’ performance, AVs’ encircling processes, and AVs’ objectives influences pedestrians’ trust in AVs (Das 2021, Hengstler et al., 2016; Rahman et al., 2021; Reig et al., 2018). Similarly, familiarity with AV-related technology or other transportation modes impacts pedestrians’ trust in AVs through development of prior knowledge to AVs (Hoff & Bashir, 2015; Velasco et al., 2019).

External environment: Another factor that was found to affect pedestrians' trust in AVs is the existence of traffic signals (Jayaraman et al., 2019). In their virtual reality-based experiment, Jayaraman et al. (2019) found that pedestrians' trust in AVs was higher at signalized crosswalks than at unsignalized ones and that traffic signals assisted in moderating the unfavorable effects of aggressive driving behavior on pedestrians' trust.

Incompatibility: The contradictory cues between distracted or inattentive drivers/ passengers and AVs' maneuvers and yielding intention plays a major role in impacting pedestrians' trust in AVs. According to Hudson et al. (2018), the presence of an inattentive passenger resulted in pedestrians' confusion due to opposite implications from the AV intention communicated through the e-HMI, unlike the case of an AV without a passenger.

Driving style: AV's driving style, characterizing its kinematical features like speed and acceleration, is considered as an AV's implicit form of intent communication (Ackermann et al., 2019; Jayaraman et al., 2019). For instance, pedestrians were found to rely mostly on legacy behaviors of AVs (distance to vehicle, speed, traffic density) in making their crossing decisions in Clamann et al. (2017) and Dey & Terken (2017). When it comes to studies quantifying pedestrians' trust as a function of AVs' driving style, results in Jayaraman et al. (2019) concluded that AV's aggressive driving style reduced pedestrians' trust in AVs, unlike AV's defensive style.

External features of AVs: Several researchers demonstrated that the presence of e-HMIs has significantly increased pedestrians' trust in AVs, especially in ambiguous crossing scenarios (unsignalized crosswalks or intersections, mid-block crossings). According to Hollander et al. (2019), e-HMIs had the potential to increase pedestrians' perceived safety and thus trust and acceptance of AVs based on lower crossing decision times compared to the case of no displays. In Faas et al. (2020), it was found that any e-HMI contributes to a more positive feeling towards AVs compared to the baseline condition: participants felt significantly safer, reflected greater trust and user experience ratings, and perceived the AV as more intelligent and transparent.

2.4.2 Pedestrians' overtrust in AVs

Pedestrians might develop unrealistic expectations towards AVs, leading to overly trusting beliefs regarding their behavior. That is, pedestrians might falsely assume that AVs will always stop for pedestrians and thus cross the road with less attention (Habibovic et al., 2018; Palmeiro et al., 2018; Tabone et al., 2021). In their paper, Jayaraman et al. (2019) reported some risky behavior as a result of pedestrians' overtrust in AVs. These behaviors were demonstrated through pedestrians coming closer to the AV while crossing, jaywalking more, waiting longer to cross, and consuming more time to complete the crossing task (due to lesser speed). Jaywalking was further reported by Tabone et al. (2021) as a form of pedestrians' risky behavior due to overtrusting AVs.

Other behaviors of pedestrians' overtrust in AVs were reported in the presence of e-HMIs. E-HMIs have the potential to make pedestrians assume that all surrounding traffic will behave in a similar manner to the host AV they are interacting with, and thus falsely making pedestrians assume that it is always safe to cross. As a result, pedestrians may be less inclined to check for oncoming traffic, resulting in risky conflicts. In the presence of an e-HMI, pedestrians explored other traffic less carefully as compared to the absence of an e-HMI (Lee et al., 2021). In a similar manner, pedestrians were less likely to check for oncoming traffic in the presence of a dynamic e-HMI as compared to a static one (Kitazaki & Daimon, 2018). Another form of pedestrians' risky behavior was observed in Kaleefathullah et al. (2020) when pedestrians misused e-HMIs after repeated exposure resulting in blindly following its message while ignoring implicit communication from AV.

Moreover, some researchers have reported fears from pedestrians' overtrust in AVs in the presence of advice-based e-HMIs. Advice communicated through e-HMIs may cause false interpretations of the overall traffic situation: it leads to pedestrians falsely assuming that other vehicles will also stop since the host the AV is stopping (Metayer & Coeugnet, 2021; Andersson et al., 2017). Other researchers were also alerted by the presence of status e-HMIs. When e-HMIs exclusively display its automated driving mode, it may imply the impression that the AV will always come to a full stop, due to its defensive and rule-abiding driving behavior (Millard-Ball et al., 2018).

2.4.3 Pedestrians' distrust in AVs

Pedestrians may react over-cautiously in the presence of AVs and hesitate to cross the street due to lacking confidence in the capabilities of AVs. For example, Hudson et al. (2018) reported that an AV with a distracted human passenger made pedestrians uncomfortable and cautious about the vehicle's intended action. This suggests that participants may be confused when the passenger's behavior indicates lack of awareness to the pedestrian despite the AVs' communicated intention. Jayaraman et al. (2019) also presented a case of pedestrians' distrust in AVs in the case that the AV was driving aggressively. Similarly, Dey et al. (2021a) showed pedestrians' decreased willingness to cross when the AV shifted from "gentle" or "early" brake condition to "aggressive brake" and "constant speed" conditions, despite the presence of an e-HMI. Pedestrians' distrust in AVs might also occur as a result of pedestrians' poor knowledge in AVs prior to any actual interaction (Velasco et al., 2019, Rahman et al., 2021, Reig et al., 2018). In addition to that, the absence of communication cues from the AV was found to diminish pedestrians' trust and trusting behaviors. In Hollander et al. (2019), pedestrians expressed low levels of trust and increased decision-making times in the absence of an e-HMI as compared to its presence.

2.4.4 Measurements of trust

Several measurements of trust have been used to assess pedestrians' trust in AVs, primarily those developed to measure trust in automation.

Self-reported measures: these involve individuals' own assessment of behaviors, beliefs, attitudes, or intentions by responding to surveys or questionnaires. Several self-reported measures of trust in automation have been developed, such as the Checklist for Trust (Jian et al., 2000), Human-Computer Trust Questionnaire (Madsen & Gregor, 2000), Desai's (2012) dynamic reporting of trust, and Muir and Moray's (1996) integrated model of trust.

Behavioral trust measures: these measures reflect on individuals' actions and decisions in response to interaction with automation. Examples of behavioral trust measures include decision-time (Yuksel et al., 2017), response time (Korber et al., 2018). Such measures are a result of observing and analyzing individuals' behaviors in contexts involving their interaction with automated technology.

Physiological trust measures: these measures reflect on individuals' biological responses ranging from electrodermal activity (Akash et al., 2018) to eye gaze data (Hergeth et al., 2016). Other measures include heart rate change and variability (Waytz et al., 2014). These measures have the advantage of measuring trust dynamically, that is during real-time, providing more accuracy as compared to self-reported and behavioral measures.

Literature has highlighted several factors that influence pedestrians' trust in AVs, including the presence of e-HMIs. Trust is often linked to how well pedestrians understand and anticipate AVs' actions, which e-HMIs aim to improve by providing explicit communication cues. Research indicates that both overtrust and distrust can occur in interactions with AVs. However, there remain some gaps and inconsistencies that need to be addressed. First, the effectiveness of e-HMIs in building pedestrians' trust varies across different pedestrian demographics and contexts including crossing locations. Second, there is a need to distinguish between increased trust levels that lead to overtrust and calibrated trust levels that accurately reflect AVs' capabilities. Third, combining self-reported, behavioral, and physiological measures can provide a more comprehensive understanding of trust.

These gaps underscore the importance of conducting context-specific research to understand how different environments (e.g., signalized intersections, midblock) and pedestrian populations influence trust in AVs. Moreover, further effort should be put in designing e-HMIs that calibrate pedestrians' trust by reducing distrust and building realistic expectations. This cannot be achieved without integrating self-reported, behavioral, and physiological measures in a unified framework to provide a more nuanced understanding of trust dynamics and its interaction with pedestrians' workload and awareness.

2.5 Research contributions

This dissertation work consists of three phases (Figure 2): phase 1 constitutes of analyzing crash data to uncover the contributing factors to the increasing likelihood of pedestrians being seriously injured or killed using statistical models; phase 2 involves the collection of user needs and challenges for the design of an e-HMI through directing surveys to the general population and to experts in the field; and phase 3 encompasses the designing of e-HMI prototype solutions and testing their effect on pedestrians' trust and situation awareness during ambiguous and unambiguous ROWs.

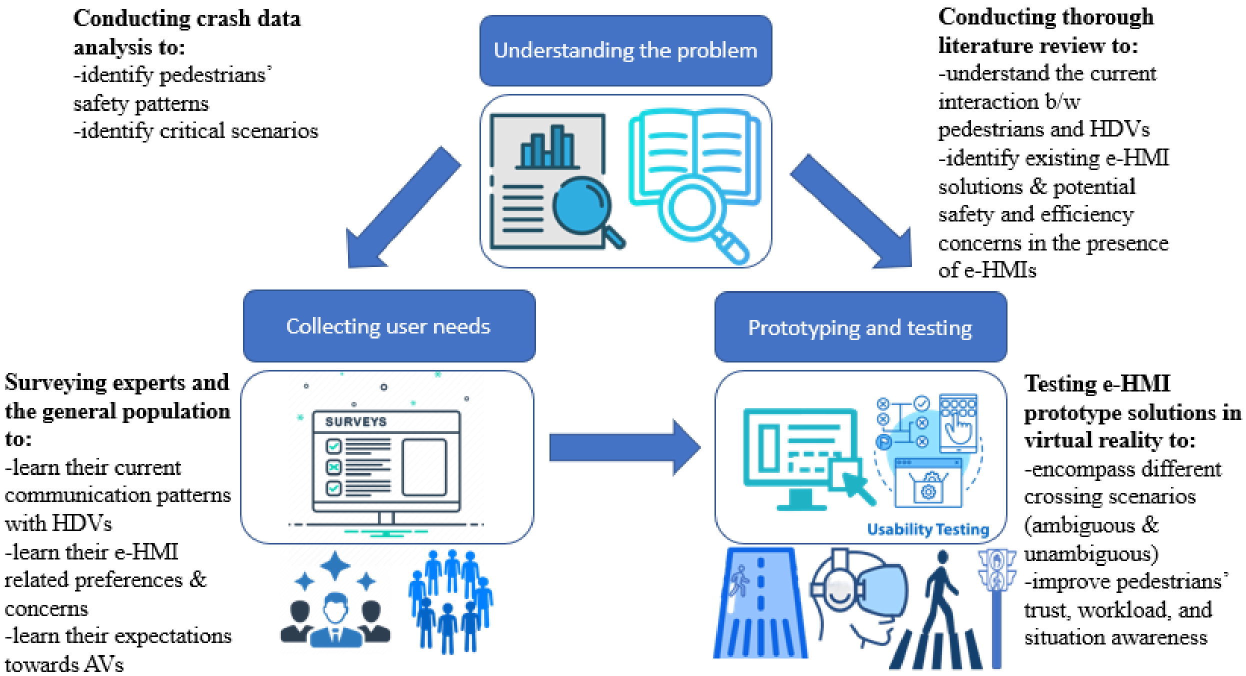


Figure 2: Dissertation framework

Following these phases, a theoretical framework (Figure 3) for the design of e-HMI was developed and applied. This framework addresses three key research questions:

1. What are typical and challenging vehicle-pedestrian interactions that can be generated to support the evaluation of AVs and the development and assessment of e-HMIs?
2. What are pedestrians' needs under those typical and challenging use cases in terms of safety and efficiency?
3. How to satisfy these needs while supporting pedestrians' information processing during the use cases?

To answer the first research question, we need to formulate AV-pedestrian typical and challenging scenarios whereby AVs can be introduced, and e-HMIs can accordingly contribute. To formulate these scenarios, there is a need to examine current HDV-pedestrian interactions based on available datasets such as HDVs-pedestrian crash databases, naturalistic driving study databases, and observational and traffic monitoring databases. Further insights can be obtained from questionnaires, focus groups, and simulator studies. As a result of employing these databases, we can provide a taxonomy for scenarios by identifying internal and external factors that impact vehicle-pedestrian interactions. Internal factors include pedestrian-specific variables such as age, gender, personality, behaviors and pre-motions while interacting with vehicles. Other key internal factors are the vehicle-specific variables such as pre-maneuver, body type, and travelling speed. External factors, on the other hand, include variables such as roadway configurations, infrastructural elements, and environmental conditions like weather and lighting. The formulation of these scenarios is an indispensable step since pedestrians' needs and AVs' behaviors might vary depending on the interaction scenario.

To answer the second research question, we need to elicit pedestrians' needs to derive design solutions that can address the identified issues and promote smooth interactions between AVs and pedestrians. In the first step, we need to conduct a thorough literature review to determine available solutions and to identify pedestrians' basic needs (requirements) characterizing e-HMIs. These requirements are clarity, understandability, intuitiveness, effectiveness, and trust-building (acceptance) (Carmona et al., 2021; Schmitt et al., 2021; Loew et al., 2022; Ammar et al., 2023). In the second step, we need to conduct user studies (e.g., surveys, interviews) while considering a representative sample of the population to cater for the varying needs, preferences, expectations, and capabilities of different road users, including children, the elderly, and those with disabilities. However, we should simultaneously account for different stakeholders including vehicle manufacturers, regulatory authorities, and road safety experts for determining potential challenges and legal and practical considerations.

To answer the third question, we need to validate e-HMI design solutions that cater pedestrians' needs derived in the previous phase. The goal of this validation stage is to evaluate the impact of e-HMIs on pedestrians' different psychological constructs (trust, situation awareness, workload, multiple resource theory) through the design of experiments and collection of different performance metrics. Thes metrics assess the different human information processing elements including the three different levels of SA, trust and perceived trust, and mental workload

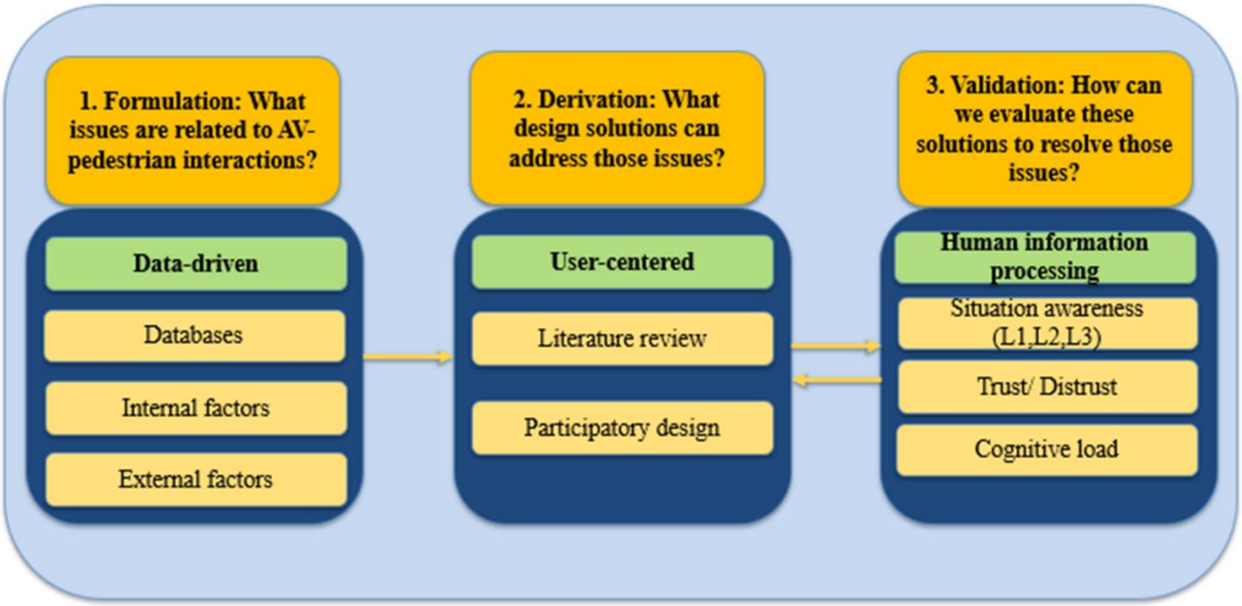


Figure 3: Proposed Theoretical Framework for the design of e-HMIs

Chapter 3 Examination of Recent Pedestrian Safety Patterns at Intersections through Crash Data Analysis

Pedestrian safety is an important consideration in the transportation system design as everyone can be a pedestrian in this current system. Pedestrians are also known as the most vulnerable road users when involved in traffic accidents (Ni et al., 2016). Their fatality rate has increased about 53 percent from 2009 to 2018, and pedestrian-involving crashes have become more deadly and more frequent. In 2019, there were 6,201 pedestrian fatalities that occurred on the roadways in the United States (U.S.), corresponding to 17 deaths every day across the country. On average, one pedestrian was killed every 1.4 hours in traffic crashes in 2019, while this number was one pedestrian fatality in every 2.2 hours in 2009 (National Center for Statistics and Analysis, 2020). Therefore, pedestrian safety has become an increasing societal concern.

More specifically, the number of pedestrian fatalities at intersections has generally increased between the two durations, 2013-2015 and 2016-2018, according to a research brief prepared by the American Automobile Association (AAA) (Tefft et al., 2021). When exploring pedestrian safety at intersections, while some studies conducted field or simulator-based observations to identify pedestrian crossing behavior at intersections, a lot of studies used crash data to analyze the frequency and injury severity of pedestrian crashes at such locations. However, few studies have examined the trend in pedestrian crash related injury patterns and relevant factors over the years, which is critical to the understanding of recent yearly increase of pedestrian fatalities and crashes. Therefore, the objective of this phase is to better understand the problem of pedestrians' safety by identifying and comparing the contributing factors to pedestrian injury levels from crashes at intersections over the recent six years. It is expected that different injury patterns and associated corresponding factors in recent crashes will be observed when compared to the ones in previous crashes. Moreover, identifying contributing factors at such locations will guide the generation of our scenarios in future phases.

3.1 Data Extraction & Pre-processing

To achieve the study objective, the National Highway Traffic Safety Administration (NHTSA) crash data was employed. Two NHTSA crash databases were used in this study, namely the National Automotive Sampling System General Estimates System (NASS GES) and the Crash Report Sample System (CRSS). These databases correspond to a US representative sample of police reported motor vehicle crashes involving motor vehicles, drivers, and other road users such as pedestrians and bicyclists. These samples are randomly selected from all police crash reports, and they include all types of crashes that resulted in consequences ranging from property-damage-only to fatalities. Each sampled crash is characterized by around 90 data elements in the GES and by around 120 data elements in the CRSS databases. Those data elements correspond to five main categories including temporal attributes such as time of crash, roadway attributes such as the number of lanes and roadway profile, environmental attributes such as weather and lighting conditions, vehicle attributes such as vehicle body type and travelling speed, and personal attributes such as age, gender, and alcohol/drug involvement. The NHTSA CRSS has replaced the GES since 2016; therefore, pedestrian crash data from both systems was extracted and analyzed independently in this study.

All the data related to pedestrian crashes at intersections were extracted from both databases. We selected a total of fourteen potential factors from both datasets in this analysis based on findings from the literature review. Personal characteristics (age, sex) of both involved drivers and pedestrians were firstly identified and followed by detailed crash occurrence time (month, day of week, and hour), and the lighting and weather conditions. The body type of the vehicle involved in the crash was also considered. In addition, pedestrian and vehicle pre-crash motion parameters which describe the movement of pedestrians (e.g., crossing, waiting to cross and movement along the roadway) and the direction of vehicles (e.g., left turn, right turn, and straight through) were also included in the analysis. Moreover, we collected the total number of road lanes and vehicle speeding behavior (i.e., speeding or not). Finally, we extracted data on pedestrians' injury outcomes. Datapoints of an unknown injury category were excluded from our analysis. As a result, a total of 2,522 and 2,722 pedestrian crashes were identified in the 2013-2015 GES database and the 2016-2018 CRSS database, respectively.

The resultant pedestrian injury severity level from a crash with a vehicle was processed. The initial pedestrian injury severity levels (no injury, possible injury, minor injury, severe injury, fatal injury) under this variable were combined into two categories:1 indicating a serious or a fatal crash and 0 indicating non-serious or non-fatal crash from the pedestrian's perspective. Among other extracted parameters, pedestrian age was separated into six categories: children (0-18 years old), younger1 (18-25 years old), younger 2 (25-55 years old), middle-aged 1 (55-65 years old), middle-aged 2 (65-75 years old), and older (over 75 years old). Driver age was separated into six different classes: children (0-18 years old), younger 1 (18-25 years old), younger 2 (25-55 years old), middle-aged 1 (55-65 years old), middle-aged 2 (65-75 years old), and older (over 75 years old). Hour was also divided into five periods including morning (6:00-9:59), noon (10:00-14:59), afternoon (15:00-17:59), night (18:00-20:59), and midnight (21:00-5:59). Days were partitioned into (1) weekdays and (2) weekend days, while months were decomposed into four three-month periods: (1) January-March, (2) April-June, (3) July-September, and (4) October-December. The lighting condition factor was separated into four categories including daylight (1), dark (2), dawn (3), and dusk (4). The weather was classified as normal (1), rain (2), and snow (3). Moreover, five different types of vehicles (passenger car (1), light truck (2), large truck (3), motorcycle (4), and bus (5)) were identified. Along with five different types of pedestrian pre-motion (crossing (1), working in trafficway/ present in the roadway (playing/ working) (2), movement along roadway or adjacent to it (3), jogging/ running, (4) and other (5) and five different types of vehicles' pre motion (turn right (1), straight (2), turn left (3), backing (4), and other (5)) were recorded in the database. The number of lanes parameter was divided into six groups: two lanes (1), one lane (2), three lanes (3), four or more lanes (4), non-trafficway or driveway access (5), and unreported/unknown (6).

3.2 Data Analysis

A logistic regression model with a binary dependent variable was used to identify the key factors associated with pedestrian-related crash injuries, and the corresponding odds ratios were computed to quantify the risk levels on pedestrian safety under different scenarios. The logistic regression model follows the equation below:

$$\Pr(Y = 1|X) = \frac{e^{X\beta'}}{1 + e^{X\beta'}} \qquad (1)$$

such that Pr is the probability of the pedestrian's crash injury to be serious or fatal, β is a vector that corresponds to the log-odds of the fixed effects (factors characterizing the crash), and X is a matrix of known constants associated with the fixed effects.

We used two separate logistic regression models, one for each dataset. In order to obtain the final logistic regression models for the GES and CRSS datasets in this study, backward elimination was applied to sequentially remove the non-significant factors from both initial models, each independently. This methodology involves the elimination of the non-significant factor with the highest p-value greater than the determined significance level and re-fitting the model on the remaining factors. The removal of a nonsignificant factor depends on the lowest p-value among its levels. Then the process is re-applied until at least one p-value corresponding to one level for each of the remaining factors is less than the target significance level; we considered a 5% significance level.

To compare the log-odds of the two crash data analysis models, we used the Wald log-linear Chi-square test. This test is a non-parametric variant of the Wald Chi-square test. The explicit formula of the Chi-square test statistic as used by Allison (1999) is:

$$w = \frac{(b_{GES} - b_{CRSS})^2}{[s.e.(b_{GES})]^2 + [s.e.(b_{CRSS})]^2} \qquad (2)$$

such that b_{GES} and b_{CRSS} are the log-odds of the GES and CRSS models and s.e. is the standard error for each estimated log-odd such that the chi-square test statistic for each pair of coefficients has one degree of freedom.

3.3 Results

Based on the two final models, four factors happened to be commonly significant for both the GES 2013-2015 dataset and the CRSS 2016-2018 dataset including pedestrian age, lighting condition, vehicle body type, and vehicle pre-movement (Figure 3). However, the 2013-2015 data analysis implied four additional significant factors being driver’s age, weather, pedestrian prior action, and speeding whereas the 2016-2018 data analysis implied two additional significant factors being the year quarter and the number of lanes. In both models, we select the first level/row of each variable as the base category. The index of Exp(B) was calculated to represent the Odds Ratio of the comparison between this current category and the selected base category of the target-independent variable.

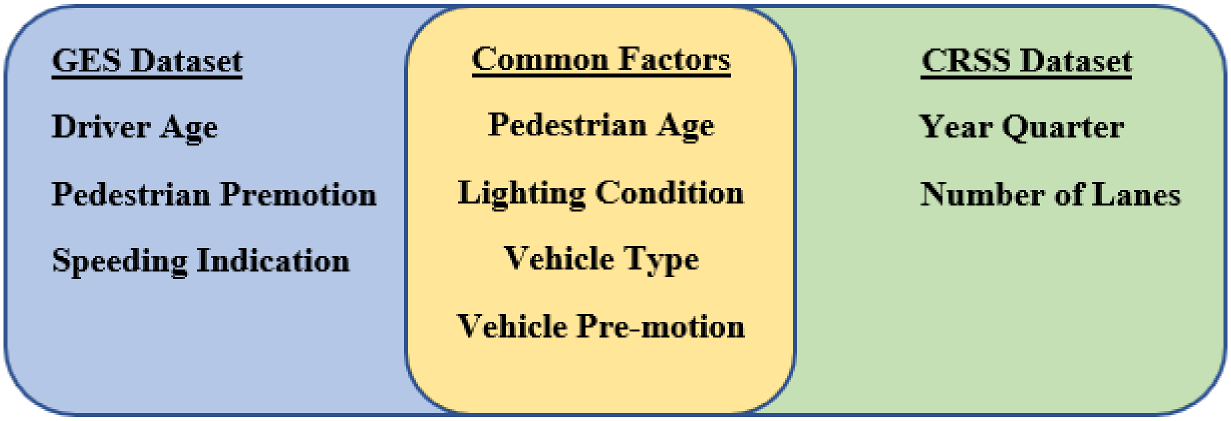


Figure 4: Significant variables in the two final models

The results of the two logistic regression models are shown in Table 1 and Table 2. For the parameter 'Pedestrian Age', children's age (0-18 years old) was selected as the base category. We found that the index Exp(B) (Odds Ratio) of the other five categories were all larger than one, representing adults' higher risks of developing severe injuries than children pedestrians from car crashes at intersections. In particular, it was found that the odds of a pedestrian whose age ranged between 26 and 55 in being fatally or seriously injured during a crash with a motor vehicle was 1.54 and 1.69 times more than those of 18 years or younger for the earlier (GES) and recent (CRSS) datasets respectively. This likelihood increased to reach 3.16 and 3.49 times more for pedestrians who were greater than 75 in age compared to the children for the GES and CRSS datasets respectively.

Results on the 'Lighting Condition' parameter showed that a pedestrian who was involved in a crash at dark time had a significantly higher likelihood of being seriously or fatally injured in both datasets compared to during daylight (OR=1.93 for GES data; OR=1.90 for CRSS data). Vehicle type was another significant parameter related to fatal crash property in both datasets. The category of passenger cars was used as the base category in the comparison. GES data analysis showed a statistically significant effect of light trucks that the odds of a pedestrian getting seriously or fatally injured from a crash with a light truck was 1.27 times higher than the one with a passenger car. Interestingly, the CRSS dataset analysis revealed the same odds ratio of light truck impact, but not at a statistical significance level of 0.05 (was marginally significant at 10% significance level). In the CRSS analysis, a pedestrian-vehicle crash had a significantly higher likelihood of resulting in a serious or fatal injury when the involved vehicle was a bus (OR=3.16) in reference to a passenger car. However, this significant effect was not observed in the GES data at 5% significance level.

As for the vehicle's pre-movement parameter, turning right was used as the comparison base category. Going straight movement of the vehicle prior to a crash with a pedestrian significantly elevated the latter's possibility to get seriously or fatally injured (OR=1.99 in GES data; OR=3.95 in CRSS data), when compared to turning right maneuver. In the CRSS dataset, other vehicle maneuvers (i.e., accelerating, passing or overtaking, leaving/entering parking position, negotiating a lane, or changing lanes) led to 3.80 times more likely to leaving the pedestrian seriously or fatally injured compared to turning right. When compared to the maneuver of going straight, two vehicle pre-crash movements including tuning right and turning left in the GES dataset and all pre-crash maneuvers excluding the "Other" maneuver category in the CRSS dataset showed a significantly lower likelihood of resulting a serious or a fatal injury for pedestrians.

Reflecting on the impact of pedestrian crash prior action in the GES 2013-2015 dataset, crossing was selected as the base category. Compared to a pedestrian crossing at an intersection, the odds ratio of a pedestrian working in the trafficway (in the form of an incident response) or being present in the roadway for other reasons (such as playing or working) showed a 72% decrease in its odds of being seriously or fatally injured. Interestingly, this significant effect was not observed in the CRSS data analysis.

Results from the GES dataset analysis also revealed a 32% decrease in the odds of a pedestrian developing a serious or fatal injury from a crash under raining condition than normal weather condition, suggesting potential more conservative behavior from pedestrians and drivers under adverse weather condition. In the GES data analysis, the odds of resulting in a serious or fatal injury to a pedestrian was 117% higher when the driver was reported to be speeding than when the driver was not speeding.

Moreover, younger drivers (i.e., between 19 and 25 years old) were found to have an 80% higher likelihood associating with a serious or fatal pedestrian injury outcome compared to the teen drivers as demonstrated in the GES dataset model results.

Using two lanes as the base category for the number of lanes factor, the CRSS dataset demonstrated a rise of 44% on average in the probability of a pedestrian facing a serious or a fatal injury when found at an intersection that was characterized by three or four-plus lanes. Besides, the pedestrian-motor vehicle crashes in the third year-quarter contributed to 50% more chance of generating a serious or a fatal pedestrian injury for the pedestrian in comparison with the first quarter of the year in the CRSS dataset.

Table 1: Logistic Regression Results for GES 2013-2015 dataset

	Log-odds	Std. Error	Z-score	dof	P-value	Odds ratio
Pedestrian Age<=18				5		
19-25	-.09	.18	-.50	1	.62	.91
26-55	**.43**	**.14**	**3.03**	**1**	**.00**	**1.54**
56-65	**.44**	**.18**	**2.44**	**1**	**.01**	**1.56**
66-75	**.89**	**.20**	**4.48**	**1**	**.00**	**2.44**
>75	**1.15**	**.23**	**5.03**	**1**	**.00**	**3.16**
Driver Age: 0-18				5		
19-25	**.59**	**.25**	**2.37**	**1**	**.02**	**1.81**
26-55	.31	.23	1.33	1	.18	1.36
56-65	.24	.26	.91	1	.37	1.27
66-75	.27	.28	.96	1	.34	1.31
>75	.30	.32	.95	1	.34	1.35
Light Condition: Daylight				3		
Dark	**.66**	**.10**	**6.33**	**1**	**.00**	**1.93**
Dawn	.08	.36	.23	1	.82	1.09
Dusk	.29	.31	.95	1	.34	1.34
Weather: Normal				2		
Rain	**-.38**	**.15**	**-2.56**	**1**	**.01**	**.68**
Snow	.20	.38	.513	1	.61	1.22
Vehicle Type: Passenger car				4		
Light truck	**.24**	**.12**	**2.02**	**1**	**.04**	**1.27**
Large truck	-.55	.56	-.99	1	.32	.58
Motorcycle	-.27	.76	-.35	1	.72	.76
Bus	.54	.33	1.63	1	.10	1.71
Vehicle Premotion: Turn right				5		
Straight	**.69**	**.14**	**4.89**	**1**	**.00**	**1.99**
Turn left	-.10	.14	-.71	1	.48	.90
Starting in road	.06	.34	.18	1	.86	1.06
Backing	-.31	.59	-.52	1	.60	.73
Other	.21	.39	.53	1	.60	1.23
Pedestrian Premotion: Crossing				4		
Working in trafficway/Present in roadway	**-1.28**	**.55**	**-2.32**	**1**	**.00**	**.28**
Moving along roadway	.30	.58	.51	1	.61	1.35
Jogging/Running	.23	.44	.53	1	.60	1.26
Other	-.03	.44	-.08	1	.94	.97
Speeding: Not speeding				2		
Speeding	**.77**	**.34**	**2.28**	**1**	**.02**	**2.17**
Not reported	-.38	.15	-2.61	1	.01	.68
Constant	-2.18	.28	-7.84	1	.00	.11

Table 2: Logistic Regression Results for CRSS 2016-2018 dataset

	Log-odds	Std. Error	Z-score	dof	P-value	Odds ratio

Pedestrian Age<=18				5		
19-25	.16	.22	.71	1	.48	1.17
26-55	**.53**	**.18**	**2.97**	**1**	**.00**	**1.69**
56-65	**1.07**	**.20**	**5.27**	**1**	**.00**	**2.90**
66-75	**.86**	**.25**	**3.47**	**1**	**.00**	**2.37**
>75	**1.25**	**.29**	**4.30**	**1**	**.00**	**3.49**
Year Quarter: Jan-March				3		
April-June	.25	.16	1.58	1	.11	1.28
July-September	**.41**	**.15**	**2.63**	**1**	**.01**	**1.50**
October-December	.14	.14	1.01	1	.31	1.16
Light Condition: Daylight				3		
Dark	**.64**	**.12**	**5.57**	**1**	**.00**	**1.90**
Dawn	.07	.37	.20	1	.84	1.08
Dusk	.10	.36	.29	1	.77	1.11
Vehicle Type: Passenger car				4		
Light truck	.24	.14	1.74	1	.08	1.27
Large truck	-.08	.51	-.16	1	.88	.92
Motorcycle	-1.21	1.07	-1.13	1	.26	.30
Bus	**1.15**	**.41**	**2.82**	**1**	**.00**	**3.16**
Vehicle Premotion: Turn right				5		
Straight	**1.37**	**.17**	**8.26**	**1**	**.00**	**3.95**
Turn left	.27	.17	1.56	1	.12	1.30
Starting in road	-.75	.75	-1.00	1	.32	.47
Backing	-.82	1.05	-.78	1	.43	.44
Other	**1.57**	**.33**	**4.76**	**1**	**.00**	**4.80**
Number of Lanes: Two				5		
One	-.90	.77	-1.18	1	.24	.40
Three	**.40**	**.19**	**2.08**	**1**	**.04**	**1.50**
Four+	**.33**	**.16**	**2.06**	**1**	**.04**	**1.39**
Non-trafficway or driveway access	-.72	1.05	-.69	1	.49	.49
Not reported/unknown	-.33	.14	-2.40	1	.02	.72
Constant	-3.27	.25	-12.98	1	.00	.04

To compare the coefficients of the above identified significant factors between the two models (GES and CRSS), pairwise comparisons of the log-odds of the common factors in both models using the Wald chi-square statistic test were conducted. The non-significant Chi-Square values suggested similar log-odds of that comparison between both models. For example, adult pedestrians who were 66 years or older were more likely to have serious or fatal injuries when crashed with vehicles at intersections compared to children pedestrians during 2013-2015, while the same trend with similar log-odds was also observed during 2016-2018. Results showed similar values of the log-odds of most categories for the four commonly significant factors in both models (Table 3). However, there were few exceptions that revealed significant differences observed in the influence of three coefficients: 56-65 age category in pedestrian, going straight in the vehicle’s pre-crash maneuver, and other activities in the vehicle’s maneuver. The log-odds of pedestrians belonging to the 56-65 age group compared to children on the likelihood of being seriously or fatally injured in the CRSS data analysis became about 2.4 times the one in the GES data analysis. Similarly, the impact of vehicles moving straight compared to turning right on the log-odds of pedestrians getting seriously or fatally injured was about 1.99 times in the CRSS dataset as it is in the GES dataset. These results suggest that pedestrians between 56 and 65 years old become more vulnerable, and vehicles going straight are more deadly for pedestrians than before.

Table 3: Comparison between the two models

	2013-2015 (GES)		2016-2018 (CRSS)		
	Log-odds	Std. Error	Log-odds	Std. Error	Chi-Square
Pedestrian Age<=18					
19-25	-.09	.18	.16	.22	.75
26-55	.43	.14	.53	.18	.17
56-65	.44	.18	1.07	.20	5.29*
66-75	.89	.20	.86	.25	.01
>75	1.15	.23	1.25	.29	.07
Light Condition: Daylight					
Dark	.66	.10	.64	.115	.01
Dawn	.08	.36	.07	.37	.00
Dusk	.29	.31	.10	.36	.16
Vehicle Type: Passenger car					
Light truck	.24	.12	.24	.14	.00
Large truck	-.55	.56	-.08	.51	.39
Motorcycle	-.27	.76	-1.21	1.07	.51
Bus	.54	.33	1.15	.41	1.36
Vehicle Premotion: Turn right					
Straight	.69	.14	1.37	.17	9.83*
Turn left	-.10	.14	.27	.17	2.73
Starting in road	.06	.34	-.75	.75	.97
Backing	-.31	.59	-.82	1.05	.18
Other	.21	.39	1.57	.33	7.08*

3.4 Discussion

Pedestrians' age: The results of the models indicated that the probability of having a seriously or fatally injured pedestrian increased with pedestrians' age. This finding is consistent with previous studies including Kim et al. (2008) whose study attributed it to older pedestrians' fragility, increased willingness to cross streets under critical circumstances, and delayed reaction and movement, when compared with younger age groups. Running a pairwise comparison for all pedestrian age categories relative to the children group between the two models produced significant differences in the log-odds of both models for pedestrians belonging to the 56–65 age group. This growing fatal risk suggests a great need for increasing the safe walking environment (e.g., building more traffic control infrastructures and crossing regulations) for pedestrians. It also suggests the need to establish clear vehicular signals that can support older pedestrians' reaction and decision times upon the introduction of AVs. Further implications emphasize the need to include older adults in the testing scenarios to ensure that AVs and designed e-HMIs can handle interactions with pedestrians of all ages effectively.

Driver's age: Drivers in the second age group (19–25) imposed a greater risk on pedestrians' safety at intersections than teen drivers. In a study conducted by AAA (Gross, 2017), young millennials aged 19–24 were classified as the worst-behaved U.S. drivers; it was reported that 88.4% of this age group involve in at least one risky driving behavior such as texting, speeding, or red light running compared with 69.3% of teens (ages 16–18). The results further suggest that younger drivers between 19 and 25 years old may need more assistance or interventions at intersections when interacting with pedestrians, compared with teen drivers. Moreover, results suggest the need to examine the interaction of pedestrians and AVs under different driver models resembling those of different human drivers.

Vehicle's body: For the vehicle characteristics' effects, passenger cars were less likely to be associated with serious or fatal crashes, while light trucks and buses have a much higher probability. As explained in studies by Lefler and Gabler (2004), light trucks demonstrated a higher risk of running over pedestrians thus inducing fatality after projecting them forward as a result of their raised bumpers hitting the pedestrians at points higher than the center of gravity. The high risk imposed by buses could be linked to buses' massive masses, buses operating very close to pedestrians, and buses' design features such as clothing pinch points. In this study, it is further found that light trucks and buses showed different effects in both models (i.e., only light trucks' impact was significant in GES data analysis while only buses' effect was significant in CRSS data analysis), suggesting that bus involving crashes are of higher safety concerns for pedestrians at intersections in recent years. These findings emphasize the importance of including AVs of different body types in the testing scenarios.

Vehicle's pre-motion: Straight moving vehicles had the highest probability of causing severe or fatal injuries to pedestrians compared with turning right. The potential reason can be different speed characteristics among different vehicle prior-crash maneuvers, as vehicles moving straight are more likely to be traveling at a relatively higher speed than those making turns. Results suggest that reducing the driving speed at intersections is expected to significantly improve pedestrian safety. The impact of going straight in comparison with turning right in the CRSS data analysis is two times that in the GES data analysis in relation to log-odds. This recent increased risk of going straight on pedestrians' fatal injuries of pedestrians suggests that drivers and pedestrians can benefit from some advanced assisting technologies in helping with their gap perception and decision-making at intersections. The results further suggest the need for intensifying the focus of testing the effectiveness of ADAS and highly AVs in mitigating the effect of straight pre-maneuvers particularly in the presence of e-HMIs.

Lighting conditions: The analysis also found that daylight had the lowest property of a serious or a fatal crash as communicated by Uddin and Ahmed (2018). Although it is expected that the current rapid development of automated vehicle technologies (e.g., LIDAR and camera sensors) will help to compensate human vision limitations at nighttime, the current study did not observe such potential benefit; instead, the results of this study suggest a homogenous risk of resultant serious injuries for pedestrians at intersections during nighttime driving across a recent 6-year period. In particular, a recent study conducted by Insurance Institute for Highway Safety (IIHS) (Cicchino, 2022) has revealed that the performance of pedestrian detection and pedestrian automatic emergency braking (PAEB) in several vehicles was found to be hindered by poor lighting conditions during nighttime. Therefore, future studies are needed to examine whether and how the integration of advanced sensors and adaptive lighting systems can be enhanced to further assist drivers' detection of pedestrians to yield early enough at nighttime. Furthermore, results underscore the urgency to evaluate AVs' reactions to pedestrians' behavior in low-light conditions and to account for high-visibility e-HMI signals and back-up auditory signals in low-light conditions.

Roadway configuration: It is also found in this study that intersections with three or more lanes were more dangerous to pedestrians than those that were made up of two lanes. As the number of lanes increases, vehicles' traveling speeds and pedestrians' crossing time both increase which increases higher risks on pedestrians (Mukherjee & Mitra, 2019). Therefore, at intersections with multiple lanes, special traffic control devices are needed to assist with pedestrians' crossing. Subsequently, the evaluation of e-HMI effectiveness at similar high-risk road configurations requires careful consideration, even in the presence of traffic lights.

3.5 Limitations

This study runs a unique analysis on the time-related changes in pedestrian injuries at intersections, but there are several limitations. One limitation is the lack of behavioral information of both drivers and pedestrians in the crash data, which prevents the findings from linking to their behavior directly. The other limitation is that some factors that were identified as important factors to pedestrian risk in other studies were not considered in this study (e.g., vehicles' traveling speed). The reason is that such factors have a considerable portion of missing values denoted as not reported/unknown in the GES and CRSS datasets. Other factors were also omitted from this analysis because they have all their data points almost falling in only one of their levels (e.g., drugs consumed by drivers or pedestrians) which might yield low precision results because of wide confidence intervals. These limitations can be addressed in future studies by expanding the data collection effort to examine data from other driving studies or new data collection effort.

3.6 Conclusion

This study provides a systematic examination of the recent patterns and changes in involving factors to pedestrian safety at intersections. Pedestrian crash data were compared between previous and recent years to explore the characteristics and potential changes in pedestrian safety at intersections. For this purpose, 2013–2015 GES and 2016–2018 pedestrian crash data collected by NHTSA were analyzed in this study. A total of 5,294 pedestrian-related crashes at intersections were identified and used. Two logistic regression models were applied to identify the key factors influencing pedestrian crash severity (serious/fatal or not). Altogether, 14 explanatory variables were included in the model. In the final models, four factors—pedestrian age, lighting condition, vehicle body type, and vehicle's pre-crash movement— showed significant impacts on pedestrian crash severity in both GES and CRSS datasets. Findings of this study help to improve the understanding of changing patterns of the context and contributing factors related to pedestrians' injury levels from crashes at intersections, and to provide potential countermeasure design suggestions through the introduction of AVs and the development and evaluation of tailored e-HMI prototype solutions. As observed, several factors persist in posing higher risk to pedestrians at intersections. While the introduction of AVs will help in addressing several issues related to pedestrian safety, particularly those related to human drivers and accompanying human errors, some issues related to pedestrians' behavioral aspects and to external factors will remain unresolved. For instance, issues linked to pedestrians' behavioral aspects will be more likely to persist due to the absence or the inattentiveness of drivers in AVs. Similarly, the interaction between pedestrians and different external factors such as roadway configurations and environmental conditions will continue to introduce challenges in AV-pedestrian interactions. Through the introduction of AVs and the development of customized e-HMI prototypes, this study offers practical insights aimed at mitigating pedestrian injuries and improving overall safety at intersections. By understanding the interaction between pedestrians and vehicles at intersections through the results of the crash data analysis at hand, we will be able to derive critical use case scenarios for future AV-pedestrian testing and to determine design needs required to resolve these problems.

Chapter 4 Identifying User Needs, Preferences and Current Challenges of External Interface Design for AV-VRU Communications

The evaluation of various e-HMI options has yielded disparate findings regarding the essential characteristics needed to develop an efficient and effective prototype (Brill et al., 2023; Bazilinskyy et al., 2019; De Clercq et al., 2019). Previous studies aimed at assessing different e-HMI alternatives have predominantly focused on a single stakeholder group, neglecting the perspectives of other crucial stakeholders. This limitation hinders the ability to gather comprehensive user-centered insights. Additionally, most studies have concentrated solely on assessing visual interfaces located on AVs, resulting in a limited exploration of all other relevant e-HMI attributes (Brill et al., 2023; Dey et al., 2020). Furthermore, there remains a notable lack of definitive investigation regarding whether the integration of AVs will require e-HMIs that replicate the attributes of cues commonly exchanged in HDV-to-pedestrian interactions. In other words, it remains uncertain whether the introduction of AVs will give rise to novel pedestrian needs beyond those currently fulfilled by cues exchanged with human drivers and other traffic components. This is not to forget that understanding potential differences in preferences for e-HMI features among pedestrians with various characteristics, such as gender and age, is also essential. Surprisingly, these differences have been rarely examined in existing research (Hensch et al., 2022).

Therefore, this study is designed to address such critical research gaps, aiming to achieve the following key objectives: (1) *Inclusivity*: By involving all stakeholders, encompassing the general public and experts from diverse sectors, the study seeks to enhance the e-HMI design process; (2) *User Needs*: Through comprehensive exploration, the research aims to uncover user preferences for different e-HMI attributes, while also identifying associated challenges and expectations; and (3) *Influence Analysis*: The study delves into the impact of current HDV-to-pedestrian interactions, as well as pedestrians' personal attributes, on e-HMI-related preferences. To fulfill these objectives, two survey instruments were designed and distributed to two populations: (1) experts in the AV, VRU, and AV-to-VRU interaction domains, and (2) the general public in the United States (U.S.), including participants from AV-deployed cities.

The primary objective of this study is to address the crucial need for well-founded requirements and valuable insights to design influential and dependable e-HMIs. By comprehensively capturing the diverse needs of various stakeholders, the research endeavors to boost pedestrians' confidence, mobility, and overall acceptance of AVs. Ultimately, these efforts will contribute to a safer and smoother integration of AV technologies into our transportation systems. This user-centered approach serves to identify the needs of all stakeholders and to define optimal e-HMI prototype solutions that achieve maximal consensus. The findings from this study will play a crucial role in informing forthcoming usability testing for optimized e-HMI designs.

4.1 Insights from an Expert Survey Data Analysis

4.1.1 Method

Participants: Participants for this study were selected from a pool of experts with a background in AVs and VRUs safety, drawn from academia, industry, and government. The survey was distributed to various stakeholders, including the Michigan Department of Transportation (MDOT), planning offices, academic researchers, Original Equipment Manufacturers (OEMs) such as Ford, Toyota, Honda, GM, Tesla and Google, the League of American Bicyclists, the Michigan Pedestrian & Bicycle Safety Team (PBSAT), the Transportation Research Board (TRB) pedestrian committee, and the TRB bicycle committee. In total, 47 complete responses were received. The respondents were found to come from a variety of backgrounds, with 23.4% working at governmental agencies, 19.2% at research/academic institutes, 17% at OEMs, 4.3% at planning organizations, and 36.2% belonging to other occupations, 70.6% of whom were members of bicycle or pedestrian advocacy groups. Regarding their education, 61.7% held a Master's degree, 23.4% held a Ph.D. degree, 8.5% held a bachelor's degree, and 6.4% held some other degree. In terms of their experience, the respondents had an average of 6 years (median = 5 years) of involvement in the field of automated vehicles. Additionally, 61.7% were members of a pedestrian or bicycle advocacy group, and 78.8% had been involved in the topic of AV-VRU interaction for an average of 5.2 years (median = 4 years). The distribution of their work organization and educational level is found in Table 4.

Table 4: Experts' Work organization and educational level

Work organization distribution	Governmental agencies	Research/ academic institutes	OEMs	Planning organizations	Other
	23.4%	21.3%	17.0%	4.3%	34.0%
Educational level distribution	Doctoral degree	Master's degree	Bachelor degree	Other	
	23.4%	61.7%	8.5%	6.4	

Survey Design: The survey consisted of four distinct sections. The first section aimed to gather demographic data regarding the respondents' occupation, education level, expertise in AVs and AV to VRU interaction, and association with pedestrian or bicyclist advocacy organizations. The second section explored their perceptions and attitudes towards the existing interaction between VRUs and HDVs, the future interaction between VRUs and AVs, as well as the associated challenges. The third section assessed the feasibility and safety of different AV to VRU communication technologies, including e-HMIs. The fourth section gathered information on experts' ratings, rankings, and selections for various e-HMI design attributes, such as the type and source of communicated information, and the communication modality. Open-ended questions in this section were utilized to reveal previously unanticipated challenges associated with specific e-HMI technologies and to elicit experts' opinions on design considerations for accommodating VRUs with special needs, such as individuals with disabilities.

Survey Apparatus: The survey was designed in Qualtrics (Provo, UT,www.qualtrics.com), being a popular web-based survey tool. We also used Qualtrics for survey distribution through anonymous links and for data collection.

Upon completing the survey, participants were eligible to enter into a luck draw for the chance to win one of two $90 gift cards. The study was reviewed and approved by the Institutional Review Board (IRB) at the University of Michigan.

4.1.2 Data Analysis

The quantitative data was analyzed using descriptive statistics and statistical tests. The multiple -choice questions were analyzed using descriptive statistics, while the rating and ranking questions were analyzed using the Friedman rank sum test followed by the Wilcoxon signed-rank test with Bonferroni adjustment. The Friedman rank sum test is the non-parametric equivalent to repeated measures ANOVA and was used to test for the presence of significant differences in the mean ratings or rankings between design options of a particular e-HMI design attribute (Marshall et al., 2016). The dependent variable in this analysis corresponded to the subjects' ratings or rankings of the design options, and the independent variable corresponded to the e-HMI design attribute with three or more options in a question. The significance level was set to 0.05. The Wilcoxon signed-rank test was used as a post-hoc test to determine which particular pair(s) of the design attribute options had significantly different ratings or rankings.

In the study, open-ended questions were utilized to elicit user needs and identify critical e-HMI issues that require thorough examination. Qualitative content analysis, incorporating both inductive and deductive reasoning, was applied to the responses to these questions (Zhang et al., 2005). Through this process, concepts were generated from the unique content of each question's responses and from existing theories. The unit of analysis was individual themes, allowing for text segments of varying sizes to be placed under a specific category. After an initial reading of all responses to a particular question, categories were established, and a coding scheme was devised. This involved identifying category names, defining rules for assigning responses, and providing examples. It was possible for a single response to belong to multiple categories or for a single data segment to belong to multiple categories under the assigned rules for response allocation. A sample of the data was then coded and validated through comparison with another coder. The remaining data was subsequently manually coded by multiple coders. The consistency of the coding was assessed through re-examination of responses within a category for uniformity and comparison of coding results among the different coders. Discrepancies were discussed among the coders until agreements were reached, with additional discussions involving a separate individual until a final agreement was achieved by all coders. If sufficient data was present, sub-categories were established within each main category. Finally, the number of responses in each category was counted as an indicator of the topic's significance or prominence.

4.1.3 Results

In the second section of the survey, the majority of respondents indicated that human-driven vehicle kinematics (e.g., distance, speed, etc.) were the most relied-upon cue for communication between human-driven vehicles and VRUs, accounting for 53.2% of responses. Eye contact with the driver was ranked second at 42.6%, and hand gestures were ranked third at

38.3%. These top three options were followed by head nods, flashing lights, and smiles (Table 5(a)). Friedman's rank sum test demonstrated a significant difference between the mean ranking of at least two cues ($\chi^2 = 105.12$, *p-value* < 0.001). The Wilcoxon signed-rank test then categorized the cues into three groups: Group A, consisting of vehicle kinematics, eye contact, and hand gestures, as the most utilized cues; Group B, consisting of head nods, as a moderately used cue; and Group C, consisting of flashing lights and smiles, as the least utilized cues.

When asked about the most pressing issues facing VRUs in their interactions with AVs, the absence of communication cues with human drivers was identified as the most frequently selected concern (33%), followed by the presence of AVs in mixed traffic with human-driven vehicles (26.6%) (Figure 5). Other potential issues, such as under-trust and discomfort, AVs' inability to recognize VRUs, and unintended consequences of AV lighting communication were also mentioned. This highlights the requirement for e-HMI design technologies that can compensate for the loss of cues exchanged between human drivers and VRUs.

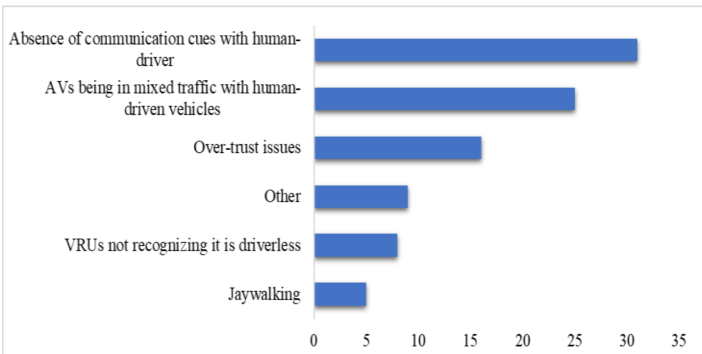


Figure 5: Potential intriguing issues in the interaction between AVs & VRUs

In regard to the respondents' perceptions of the integration of AVs into the current transportation system, while 48.9% believed that AVs will increase actual safety (e.g., reduce crash risk), only 34% believed that AVs will increase perceived safety (e.g., make individuals feel safe). Conversely, 74.5% disagreed with the notion that AVs will increase VRUs' risky crossing behavior (e.g., distracted walking behavior, illegal crossing behavior like jaywalking). Additionally, the majority of respondents (75%) believed that AVs should stop for pedestrians crossing illegally at mid-blocks or intersections with red pedestrian lights, regardless of the number of VRUs crossing. This highlights the importance of (1) designing and testing AVs to yield in such situations when the right-of-way is not for VRUs and (2) incorporating communication cues between AVs and

VRUs to ensure that VRUs feel safe and make the safest decision based on the existing circumstances.

In the third section of the survey, the respondents were asked to evaluate the efficiency, deployment practicality, and safety of three AV-VRU communication technologies, namely: (1) Segregation of AVs and VRUs, (2) Smart Infrastructure, and (3) e-HMIs. The results indicate that e-HMIs were rated as the most practical technology (mean = 3.4) but the least safe (mean = 3.15), while segregation of AVs and VRUs was rated as the safest technology (mean = 4.09) but the least practical (mean = 2.4) (Table 5(b, c)). Friedman's test showed significant differences in both deployment practicality ($\chi^2 = 20.88$, *p-value* < 0.001) and safety ($\chi^2 = 21.78$, *p-value* < 0.001). The post-hoc pairwise Wilcoxon's rank sum test revealed significant differences between e-HMI and segregation of AVs and VRUs in terms of both deployment practicality (*p-value* $= 0.003$) and safety (*p-value* < 0.001). The differences between smart infrastructure and segregation of AVs and VRUs were also significant in terms of practicality (*p-value* $= 0.005$) and safety (*p-value* $= 0.004$). However, there were no significant differences between e-HMI and smart infrastructure in terms of deployment practicality and safety. This indicates that experts rated e-HMIs and smart infrastructure similarly in terms of deployment practicality and safety, while both were considered more practical but less safe compared to the segregation design option.

In the fourth section of the survey, the respondents were asked to assess the level of importance of three crucial requirements in the design of e-HMIs for AV-VRU communication, which are recognizability, unambiguousness, and comprehensibility (Carmona et al., 2021). The results indicate that on average, 91.5% of the respondents rated these requirements as important or very important. Additionally, the respondents were presented with five categories of information to be conveyed through the e-HMI: (1) “Status”, referring to the autonomous driving mode (e.g., AV mode engaged), (2) “Awareness”, referring to the AV's detection of VRUs (e.g., I see you), (3) “Intent”, referring to the AV's communication of its state of motion to VRUs (e.g., stopping, starting), (4) “Advice”, referring to the AV's instructions to VRUs on crossing (e.g., cross, don't cross), and (5) “Kinematics”, referring to the AV's reporting of its dynamic motion elements (e.g., speed, distance to a crosswalk). The results, as indicated by Table 5(d), show that “Awareness” and “Intent” received the highest mean Likert-scale ratings (mean=4.45 and mean=4.40, respectively), followed by “Status”, “Advice”, and “Kinematics” (mean=3.36, mean=3.32, and mean=3.15, respectively). A Friedman’s test showed a statistically significant difference in the mean Likert scale between at least one pair of information types (χ^2 = *68.37, p-value < 0.001*). Subsequently, a Wilcoxon rank sum test was conducted, and significant mean differences were observed between all pairs of information types except between “Awareness” and intent, and among “Status”, “Advice”, and “Kinematics”. This suggests that “Awareness” and “Intent” were considered the most important, while “Status”, “Kinematics”, and “Advice” were ranked second in importance.

In the same section, the perceived communication effectiveness of three primary e-HMI modalities was evaluated by the respondents. The visual modality was rated highest with a mean score of 3.92, while the physical modality was rated lowest with a mean score of 2.89 (Table 5(e)). The comparison of the Likert-scale ratings of these modalities indicated a statistically significant difference between their mean ratings (χ^2 = *16.42, p-value < 0.001).* The subsequent pairwise Wilcoxon rank sum test revealed significant differences between the visual and auditory modalities (*p-value=0.002*) and between the visual and physical modalities (*p-value < 0.001*), indicating that the visual e-HMI modality was perceived as the most effective among the experts, while both auditory and physical modalities were deemed less effective in comparison.

The respondents were solicited to determine the modality or modalities that would be most effective for presenting each of the five distinct e-HMI information types. The results indicated that the visual modality was the preferred mode for conveying “Status” information by 62% of respondents, followed by “Awareness” information (49%), “Intent” information (51%), and “Kinematics” information (48%). Responses on the communication of “Advice” also conveyed the preference of a visual modality as selected by 40% of responses, but they also showed a relatively significant support for the auditory modality (35%) (Figure 6). These findings demonstrate a general consensus among respondents that visual e-HMIs are the most effective means of communicating all types of information, compared to auditory and haptic modalities.

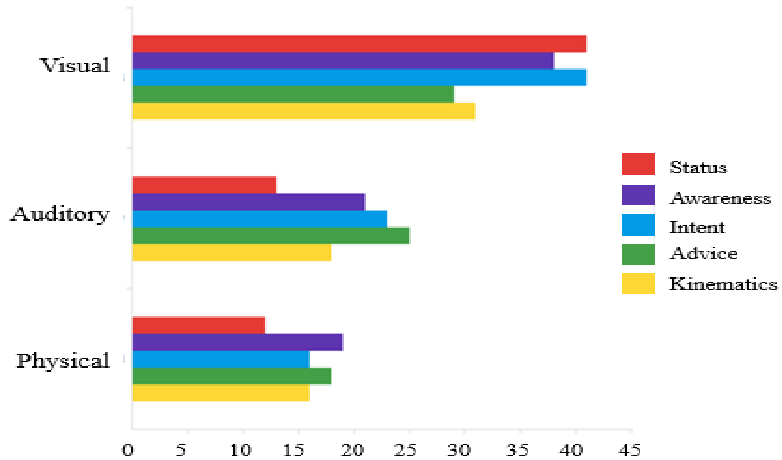


Figure 6: Respondents' assessment of each e-HMI modality at presenting different information types

At a subsequent stage of the survey, participants were asked to evaluate the communication effectiveness of three potential e-HMI locations: (1) on the AV, (2) on the road/roadside infrastructure, and (3) on a VRU wearable or handheld device. The highest average rating of perceived communication effectiveness was obtained for the AV install location, with a mean score of 3.62, followed by the roadside infrastructure with a mean score of 3.06 (Table 5(f)). Results from the Friedman test indicated a significant difference in the mean ratings between at least two locations (χ^2 = *25.05*, *p-value* < *0.001*), specifically between the AV and the road/roadside infrastructure compared to the VRU wearable/handheld device as determined through the Wilcoxon rank sum test (*p-value* < *0.001 and p-value* = *0.002, respectively*). Additionally, there was a significant difference found between the AV and the road/roadside infrastructure (*p-value* = *0.019*). These results indicate that the installation of an e-HMI on an AV was deemed the most effective, while installation on a wearable/handheld device was deemed the least effective.

The survey participants were further queried on the suitability of e-HMI locations for effective communication of auditory information. The results revealed that the AV location was rated the highest with a mean score of 3.32, followed by the roadside infrastructure with a mean score of 2.89 (Table 5(g)). Friedman's test confirmed a significant difference in the mean ratings of the e-HMI locations (χ^2= *29.25*, *p-value* < *0.001*). The Wilcoxon rank sum test indicated that there was a significant difference between the AV location and the other three options (*on road/roadside infrastructure, smartphone, and wearable devices; p-value* = *0.044*, *p-value* = *0.001*, *and p-value* < *0.001*, *respectively*) and between the road/roadside infrastructure location and wearable devices (p-value = 0.008). There was no significant difference detected between road/roadside infrastructure and smartphone or between smartphone and wearable devices. This suggests that the AV location was deemed the most effective location for communication of auditory information when compared to all other locations.

Table 5: Summary statistics of ranking and rating questions

	Min	Max	Mean	Median	SD
(a) Rankings of existent cues in communication between human-driven vehicles and VRUs					
Vehicle kinematics	1	6	2.28	1	1.68
Eye contact	1	6	2.32	2	1.14
Hand gesture	1	6	2.70	3	1.21
Head nod	1	6	3.81	4	1.39
Smile	3	6	5.04	5	0.93
Flashing light	1	6	4.85	5	1.22
(b) Ratings of AV-VRU communication technologies in terms of safety					
Segregation	1	5	4.09	4	1.05
Smart infrastructure	1	5	3.40	4	0.96
E-HMIs	1	5	3.15	3	1.15
(c) Ratings of AV-VRU communication technologies in terms deployment practicality					
Segregation	1	5	2.40	2	1.35
Smart infrastructure	1	5	3.17	3	1.10
E-HMIs	1	5	3.40	4	1.23
(d) Ratings of e-HMI information types in terms of importance					
Status	1	5	3.36	4	1.36
Awareness	2	5	4.45	5	0.99
Intent	1	5	4.40	5	0.84
Advice	1	5	3.23	3	1.42
Kinematics	1	5	3.15	3	1.24
(e) Ratings of three e-HMI modalities in terms of perceived effectiveness					
Visual	2	5	3.91	4	0.87
Auditory	2	5	3.36	3	0.84
Physical	1	5	2.89	3	1.22
(f) Ratings of three e-HMI locations in terms of perceived effectiveness					
On AV	1	5	3.62	4	1.14
On Road/Roadside infrastructure	1	5	3.06	3	1.21
On VRU’s Wearable/ Held devices	1	5	2.40	2	1.21

(g) Ratings of e-HMI locations in terms of effectiveness at communicating auditory information					
On Smartphone	1	5	2.40	2	1.36
On VRUs' Wearable devices	1	5	2.28	2	1.23
On AV	1	5	3.32	3	1.11
On Road/Roadside infrastructure	1	5	2.89	3	1.13

Another modality-location related question was to select the most effective locations on an AV if an AV is to be equipped with a visual e-HMI. Among the most selected choices were the windscreen and radiator grill positions (selected by 55.3% and 46.8% of respondents, respectively) followed by headlights and AV side positions (selected by 34% and 32% of respondents, respectively) (Figure 7).

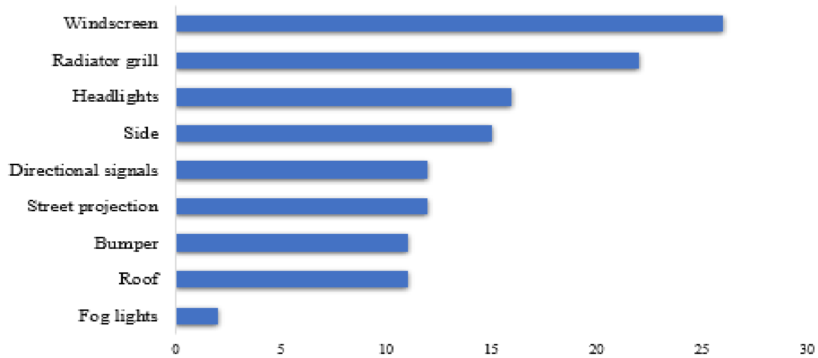
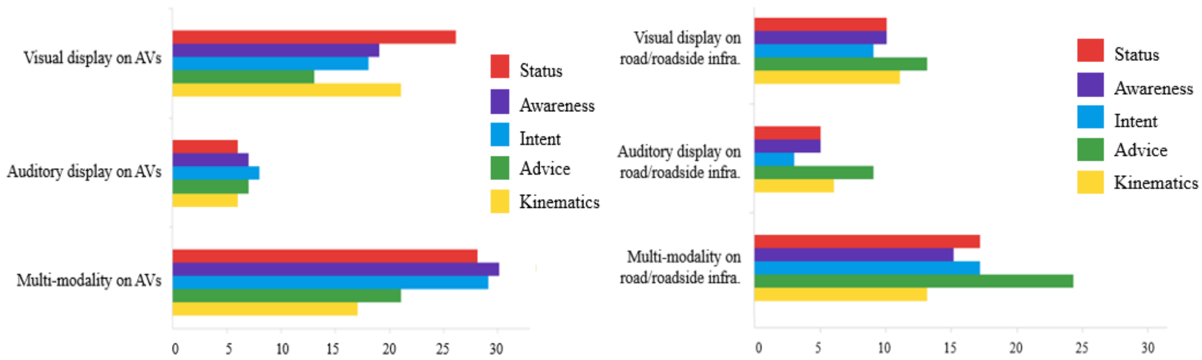


Figure 7: Respondent choices for most effective visual e-HMI locations on an AV

The final study task involved eliciting the respondents' preferred modality-location combinations for the effective presentation of each of the five e-HMI information types. The results indicated that for all information types except "Kinematics", the most commonly selected combination was a multi-modal display (visual and auditory) integrated into the AV. For the communication of "Kinematics" information, a visual display was most frequently preferred (Figure 8a). When the e-HMI was located on road/roadside infrastructure, all information types were favored to be conveyed through a multi-modal display (Figure 8b). Conversely, when the e-HMI was to be deployed as a wearable or handheld device for VRUs, a physical/vibrational e-HMI was perceived as the most effective option for the communication of all information types (Figure 8c).

(a) (b)



(c)

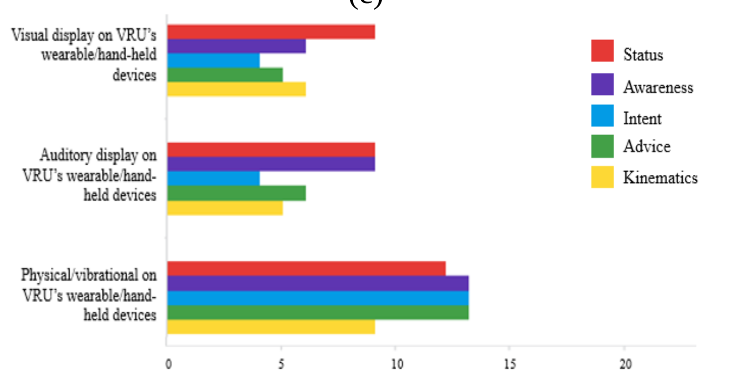


Figure 8: Respondents' assessment of each e-HMI modality-location combination at presenting different information types

In this study, 66% of respondents agreed that VRUs require training to understand e-HMI designs before deployment. However, 17% of the participants strongly disagreed with this notion, indicating the need for e-HMIs to be intuitive to VRUs without the need for training. This highlights the current lack of consensus among experts on whether e-HMIs should be designed to be highly intuitive or tolerate slight unfamiliarity. Additionally, 96% of the respondents agreed that special accommodations are necessary for the AV e-HMI design to cater to the needs of individuals with special requirements (such as elderly individuals with lower walking speed and worse reflexes, individuals with vision impairments, or individuals with cognitive impairment.

The results of six open-ended questions were analyzed using qualitative content analysis with 99% agreement between coders. The frequency of identified topics for each question is shown in Figure 9. The questions addressed the following topics: (1) issues related to the current interaction between VRUs and human-driven vehicles, (2) plans and practices for effective deployment of AVs, (3) concerns related to each e-HMI information type, (4) concerns related to each e-HMI modality, (5) concerns related to each e-HMI install location, and (6) design considerations for individuals with special needs. The coding schemes and the results of each question are detailed in Tables 6-11. The percentage associated with each identified topic represents the fraction of total responses identified under that topic (Figure 9).

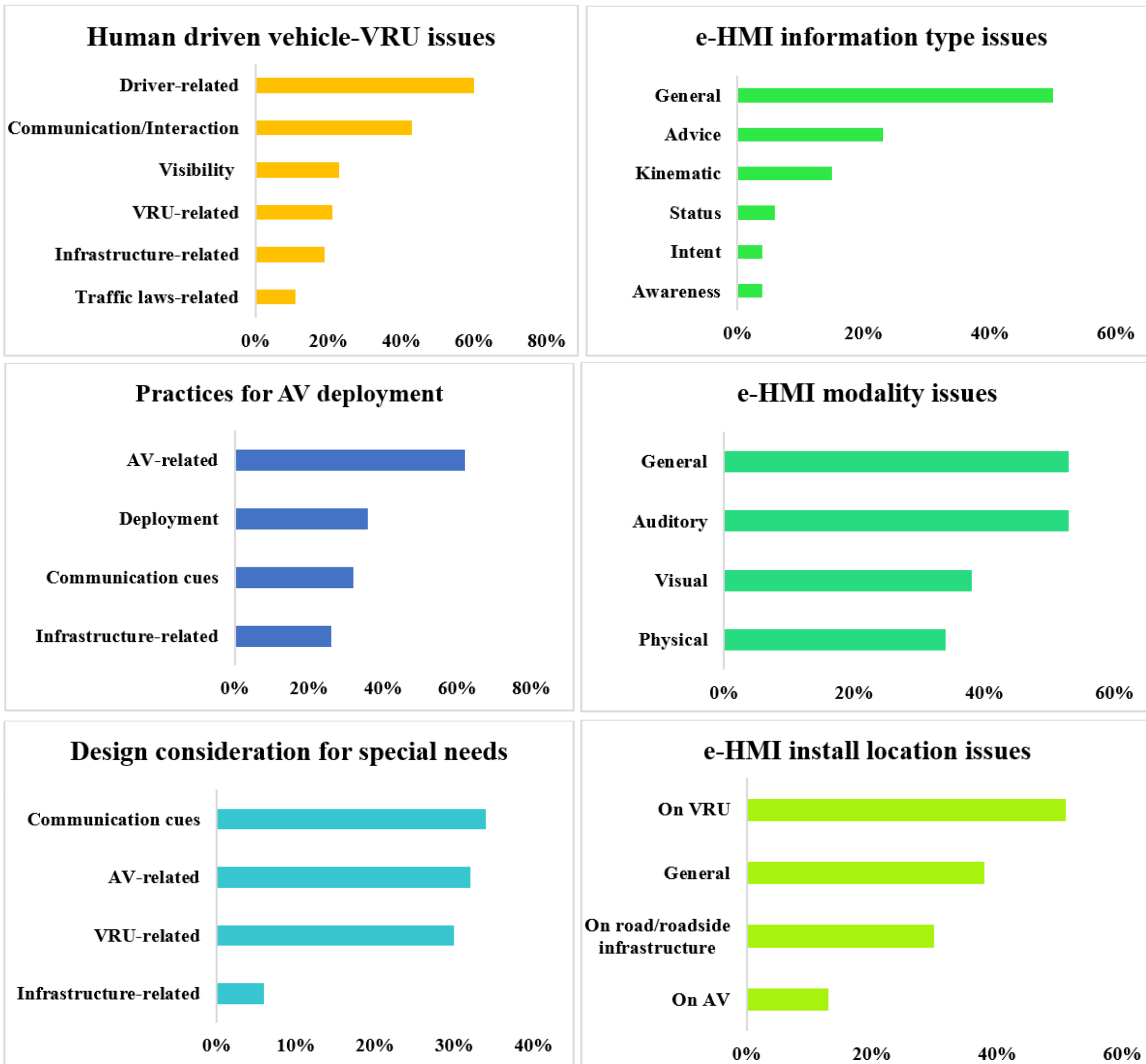


Figure 9: Frequency of identified topics for six open-ended questions

The analysis of the current interaction between human-driven vehicles and VRUs revealed that 60% of the responses were related to driver-related issues, such as driving behavior (e.g., aggressive and risky), behavior towards VRUs (e.g., biased and antagonistic), and inadequate knowledge of traffic rules. 43% of the responses highlighted interaction and communication issues, including non-diversity, uncertainty (e.g., misunderstandings and conflicts between courtesy and traffic laws), inaccessibility, and interaction circumstances (e.g., speed difference and asymmetric harm in crashes). Other issues included visibility (23%), VRUs (21%), infrastructure (19%), and traffic rules and laws (11%) (Table 6).

Table 6: Issues associated with the current interaction between VRUs and human-driven vehicles

Topic	Subtopics
Driver-related issues	**Driving behavior** (distracted, impatient, impaired, violating traffic laws), **Ability & knowledge** (diverse ability, inadequate knowledge of traffic rules & of VRUs' behavior), **Behavior towards VRUs** (aggressive & antagonistic, racially biased yielding, low expectancy)
VRU-related issues	**Behavior** (distracted, impatient, impaired, over-trusting, violating traffic rules), **Ability & knowledge** (diverse ability, inadequate knowledge of traffic rules, late recognition of vehicles)
Infrastructure-related issues	**Infrastructure status** (lacking maintenance), **Infrastructure for VRUs** (hostile & inadequate), **Road design** (high speed roads, complex intersection, prioritizing cars), **Accessibility** (inadequate infrastructure for individuals with disabilities)
Visibility issues	**Vehicle design** (blind spots associated with large vehicles, obstructed sight lines, reflection of windshield, tinted windows), **Environmental conditions** (low light, night, sun glare), **Size differences** (large vehicles & short VRUs)
Traffic rules-related issues	Unclear right of way, legal framework favoring drivers' and vehicles' convenience over VRUs' safety
Communication/ Interaction issues	**Diversity** (non-universal cues, cues relying on social-cultural context), **Certainty** (misunderstanding driver's awareness, intent & trajectory, inadequate cues, conflicts between courtesy & traffic laws, unpredictability), **Accessibility** (current interaction excluding aging adults & people with vision problems & disabilities), **Interaction** (speed difference, asymmetric harm in crash, multiple threat scenario & difficult decision making in presence of multiple road users)

With the aim of establishing seamless communication between AVs and VRUs, the experts provided a range of solutions, with the majority of their responses (62%) being centered on AV-related factors such as behavior, functionalities, algorithms, testing, and ease of access. Other solutions (36%) focused on deployment strategies for AVs and included raising awareness campaigns and training programs for VRUs, regulation of AV operations through restrictions to specific roads, and giving priority to VRUs over AVs. The desired characteristics of AV-VRU communication were also highlighted in 32% of the responses, which covered aspects such as universality, standardization, signal types, modality, visual cue type, information type, and installation location, as well as accessibility requirements. Finally, 26% of the responses dealt with infrastructure-related procedures (Table 7).

Table 7: Potential plans and practices for AVs' effective deployment

Topic	Subtopics
AV-related	**AVs' behavior** (clear, predictable, consistent, fair, similar to human-drivers, respectful, always yielding, following traffic rules), **AVs' capabilities** (accurate detection under different light & weather conditions, capable as skilled & careful human-drivers at least, prepared for unexpected VRUs' behavior), **AVs' technologies** (standardized, programmed predictable behaviors, AI, eye-tracking, high accuracy, ML, neural networks), **Testing** (smooth communication & ability to detect & avoid VRUs), **Accessibility** (disabled, children & aging adults)
Infrastructure-related	**VRUs Infrastructure** (designated crosswalks, bike lanes, sidewalks), **Separation of AVs and VRUs facilities** (under the condition that it doesn't go on the expense of VRUs' space & trip time), **Smart infrastructure combined with e-HMIs**, **Accessibility** (disabled, children & aging adults be granted more space)
E-HMI cues/ Communication cues	**Type** (light signals, audio & visual signals, warnings, human-like signals, showing driving mode or awareness), **Position** (on front of AV), **Requirements** (universal, standardized), **Accessibility** (signals inclusive to all ages & abilities including young, aging, & people with sensory or physical impairments)
Deployment	**Campaigns & trainings** (public campaigns, educating VRUs), **Regulations** (AVs on controlled routes only. i.e., freeways and designated arterials, reducing speed, consistency across jurisdictions), **Hierarchy** (prioritize VRUs over AVs)

For the attribute of the e-HMI information type, the information types that elicited the most concerns among experts were “Advice” (23%) and “Kinematics” (15%). Issues related to the “Advice” e-HMI included VRUs' resistance to being instructed, the surrounding environment potentially not aligning with the behavior of the target AV, and VRUs potentially becoming liable for their own safety by causing ambiguity around the distinction between advice and command. With regards to the “Kinematics” e-HMI, concerns centered around the potential for information overload due to its continuous nature, the potential for distraction, and ambiguity at low speeds. The information types of “Status”, “Awareness”, and “Intent” e-HMIs accounted for 6%, 4%, and 4% of experts' responses, respectively. Additionally, general concerns were noted in 50% of the responses (Table 8).

Table 8: Concerns associated with each e-HMI information type

Topic	Subtopics
Status	Not useful, information overload
Awareness	No added value in absence of intent, confusion with advice
Intent	Misinterpretation, not necessary since AVs should always stop to VRUs
Advice	Litigation about the line between advice & command (e.g., suing VRUs for disobeying advice), surrounding environment not necessarily following same behavior as AV, people refusing to be told what to do
Kinematics	Information overload (specially with its continuous stream), distraction, creating gamesmanship, interpretability (e.g., for children), unclear at low speed, informing bicyclists of speed & distance info through devices attached to bikes' handlebars are expensive, require charging, and not within the reach of all VRUs (children, seniors, disadvantaged populations)
General	Adaptation to new technology, information overload, distraction, confusion, misunderstanding, ambiguity, hard decision at high speeds, confusion due to lack of standardization/consistency, inaudibility, unrecognizable, over-reliance, VRUs' trust, language, units, clarity of pictograms, accessibility (pp with impairment/disabilities, young ppl, ppl with limited mobility), different social expectations, languages, and traffic laws across different countries, requiring attention from VRUs (VRUs' distraction/impairment), environmental conditions masking communication like bright sunlight, surrounding traffic responding in a different way than host vehicle

The attribute of e-HMI modality elicited a range of concerns among experts, with auditory cues being the most frequently cited source of concern, at 53%. Concerns with auditory cues included potential masking in loud environments, being masked by other surrounding traffic sounds, causing sound pollution, disrupting individuals with autism, and ineffectiveness when VRUs are wearing earbuds. The visual and physical options were subject to concerns in 38% and 34% of responses, respectively. Additionally, general concerns were expressed regarding all three modalities in 53% of the responses (Table 9).

Table 9: Concerns associated with each e-HMI modality

Topic	Subtopics
Visual	Ignored due to desensitization, requiring attention & alertness, distracting, difficulty processing when too many, problematic if non-intuitive & non-understandable (e.g., symbol not understood by all VRUs), visibility affected by location, weather & environment, ineffectiveness for VRUs with perception & visual disabilities

Auditory	Ignored due to desensitization, ambient noise issues, confusion, requiring attention, difficulty processing when too many vehicles & cues, conveyed as a negative sign, loud environment masking cues, cues masking existing sounds of surrounding traffic like buses, sound pollution, ineffectiveness for VRUs wearing earbuds & for VRUs with perception abilities & hearing disabilities, disturbing individuals with autism
Physical	Distracting, reaction time related concerns, negatively perceived (shock), hard implementation & requiring more infrastructure, need for education & learning due to rare existence in current transportation system, exclusionary (if limited to presence of a device with the VRU), unreliability, against asking VRUs to carry devices during walking, disconnection with target AV, ineffective for VRUs with disabilities preventing them from feeling haptic feedback
General	Malfunction, misuse, surrounding traffic not in line with AV, scalability issues, distraction of VRUs from other issues (walkability of surfaces, orientation), other stimuli competing with each modality, user acceptance, need to be as close as possible to human level, cost & standardization concerns, requiring education, inaccessibility to foreigners with other languages, accommodation concerns (VRUs with disabilities at risk if all three modalities not available at same time)

With regards to the attribute of e-HMI installation location, the most concerning design option identified by experts was the installation of e-HMI on VRUs' wearable or handheld devices, with a frequency of 51%. Conversely, the least concerning design option was the installation on AVs, which accounted for only 13% of concerns. The disadvantage of requiring VRUs to carry e-HMIs were cited in 51% of responses and included unrealistic deployment, communication lag, and the similarity to other notifications received on smartphones or smartwatches, as well as issues of discrimination and inequity, since not all VRUs have access to such devices. 30% of responses highlighted concerns related to road or roadside infrastructure installation locations, and general concerns for all three locations were identified in 38% of responses (Table 10).

Table 10: Concerns associated with each e-HMI install-location

Topic	Subtopics
On AV	Trust issues, fear from AV malfunction, non-standardization, messages ignored/overlooked when too many AVs, ineffectiveness during bad weather
On road/ roadside infrastructure	Different knowledge of traffic rules that infrastructure depends on, additional costs creating tax burdens, roadside infrastructure not universally present, difficulty in deployment (lead time, business aspects), unreliability in maintaining & modifying current & thus prospective infrastructure, impacts of bad weather, scalability

On VRU	Ignorance/non-perception of message, need to look at screen to match with AV, communication lag, distraction, interoperability between make/models of AV & wearables, non-realism, wearables not universally present/accessible (discrimination/non-equitability), refusal to require carrying a device while walking, cost and awareness burden on VRU while removing responsibility burden off the AV or manufacturer
General	Malfunctions, expensive cost, universal availability & application of technology, maintenance, need for more education about capabilities and limitations, compatibility challenges, user errors, distraction, being ubiquitous and understood by all, accessibility for people with disabilities, consideration for people with cognitive impairments & autism, & for children

In design considerations for individuals with special needs, experts provided suggestions at similar frequencies related to AVs (32%), VRUs (30%), and communication cues (34%). Infrastructure-related suggestions were depicted in 6% of the responses (Table 11).

Table 11: Design considerations for people with special needs

Topic	**Subtopics**
VRU-related	**Special devices** (wearing devices that send signals to AVs so these can learn their needs & can adapt accordingly, wearing devices for visual impairment), **Inclusion in design phase** (including individuals with disabilities)
AV-related	**Adaptive reaction** (providing more time for people with low walking speeds, setting parameters based on worst case user rather than average user), **AV behavior** (always yielding)
Communication/ signals	**Multi-modal communication, Signal characteristics** (providing near projections, visual symbols, and loud sounds, communicating intent, providing adjustable brightness depending on weather), **Signal requirements** (clear, standardized, consistent, prominent, legible, unambiguous)
Infrastructure	Reducing crossing distance & vehicle travelling speed, improving VRUs' traffic signals, increasing pedestrian-only space

4.2 Insights from a General Population Data Analysis

4.2.1 Method

Participants and Quota: We aimed to recruit 600 participants who are 18 years or older. Since each individual in the population is a candidate pedestrian, our target population was residents in the U.S. To improve our sample representativeness, we adopted stratified random sampling in which we stratified our target population with multiple variables, namely age group, gender, race, and city of residence. We targeted equal proportions of six age groups excluding children (18-24, 25-34, 35-44, 45-54, 55-64, 65+) and equal proportions of males and females. For the city of residence, we aimed at 50% responses from AV deployed cities/ Designated Market Areas (DMAs) in the U.S., in particular from San Francisco, Pittsburgh, Phoenix, Dallas-Fort Worth, Houston, Las Vegas, Palo Alto, Cupertino, and Ann Arbor, such that we collect 10% of total responses from each of the top AV deployed cities/DMAs namely San Francisco, Pittsburgh, and Phoenix. The remaining 50% were intended to be from all other U.S. cities. As for race, we embraced a proportionate sampling while targeting 66% from non-Hispanic White, 12% from non-Hispanic Black, 12% from Hispanic, and 10% others.

Survey Apparatus: The survey was built in Qualtrics (Provo, UT, www.qualtrics.com) which is a popular web-based survey tool. Qualtrics was also used to distribute the survey as well as to collect responses. Our research team collaborated with the Academic Research Services Team in Qualtrics for distributing the survey to collect responses.

The survey included questions of different types: multiple choice, raking, rating, and open-ended questions. We equipped the survey with images that correspond to different e-HMI options listed in several questions to make a good reference for respondents, especially those with zero to limited knowledge in AVs and e-HMIs. The images were created on Adobe Photoshop.

Upon completing the survey, participants were compensated per quality response. The study was reviewed and approved by the Institutional Review Board (IRB) at the University of Michigan.

Survey Design: The survey was composed of four sections:

(1) The first section collected participants' demographics, including age, gender, race, educational level, city of residence, membership in pedestrian/ bicyclist advocacy group, physical disability (assistive walking), previous crash with a vehicle as a pedestrian/ bicyclist, knowledge in Automated Driving Systems (ADS), and previous interaction with ADS.

(2) The second section aimed at evaluating participants' behaviors as pedestrians. For this purpose, we adopted the Pedestrian Behavior Questionnaire (PBQ) developed for the U.S. population by Deb et al. (2017b) while combining two items into one, thus reducing the number of items from 20 to 19. These items evaluated pedestrians' behavior using a 5-point Likert scale (1-Never, 2-Rarely, 3-Sometimes, 4-Very often, 5- Sometimes) based on five categories being violations (four items), errors (four items), lapses (four items), aggressive behaviors (three items), and positive behaviors (four items).

(3) The third section was designed to learn more about the existing interaction between the respondents as pedestrians and HDVs in the current transportation system.

-*Influence of contextual cues*: Two questions (ranking, and rating on a 5-point Likert scale: 1-Not at all influential, 2-Slightly influential, 3-Somewhat influential, 4-Very Influential, 5-Extremely influential) examined the types of contextual cues that influence pedestrians' crossing decisions. We classified these cues into three types. The first type is the cues they elicit from vehicles' maneuvers or kinematics like vehicle's speed, distance or time gap size, and acceleration or deceleration. The second type is the cues they receive from drivers acknowledging their detection such as eye contact. The third type is the cues pedestrians receive from drivers signaling whether to cross or not; these include driver's smile, hand gesture, head nod, flashing lights, and beeping horns.

-*Familiarity with cues modality*: Another two questions (ranking, and rating on a 5-point Likert scale: 1-Not at all familiar, 2-Slightly familiar, 3-Somewhat familiar, 4-Moderately familiar, 5- Extremely familiar) inspected the modes of cues that pedestrians are familiar with for road crossing purposes. We included two options, namely the visual and auditory cues, which are most prevalent in the current transportation system. We provided examples of visual cues like physical gestures from drivers, vehicle maneuvers, and traffic lights, and examples of auditory cues such as vehicle's engine sound (Wu et al., 2011), beeping horns (Nathanael et al., 2018), and spoken words (Wynne, 1983) or beeps from traffic signals (Uslan et al., 1988).

-*Trust in source of cues:* A third pair of questions (ranking, and rating on a 5-point Likert scale: 1-Very low trust, 2-Below average trust, 3-Average trust, 4-Above average trust, 5- Very high trust) looked into the source of cues that pedestrians trust during their crossing decisions. We listed two main sources of cues being traffic signals and vehicles or drivers.

-*Familiarity with visual cues*: A fourth pair of questions (ranking, and rating on a 5-point Likert scale: 1-Not at all familiar, 2-Slightly familiar, 3-Somewhat familiar, 4-Moderately familiar, 5- Extremely familiar) inquired about the types of visual cues that pedestrians are familiar with for road crossing purposes, mainly those observed on pedestrian traffic signals. We presented them with three main types: symbolic cues (e.g., standing pedestrian silhouette, walking pedestrian silhouette), textual cues (e.g., 'Cross', 'Don't Cross'), and human-like cues (e.g., smileys, animated eyes).

In addition to these, we were interested in determining the frequency of listening to music while walking and the level of pedestrians' safety when interacting with HDVs.

(4) The fourth section sought to elicit respondents' opinion on their perceived and actual safety during their future interaction with AVs, their opinion on the importance of communication means to communicate with AVs, including e-HMIs, and their receptivity to using these e-HMIs.

This section also sought to elicit respondents' preferences for several e-HMI related attributes including information type, modality, install location, type of visual cues, type of auditory cues, and composition of visual cues.

-*Information type*: Five options were presented: Status information indicating whether the vehicle is in automated driving mode, Awareness information indicating whether the AV is aware of the pedestrian, Intent information indicating the AV's maneuver intent such as stopping, moving, and turning, Advice information providing instructions to pedestrians on whether to cross or not, and Kinematics information reporting the AV's dynamic motion elements such as speed and distance to crosswalk.

-*Modality*: It involved three options: visual, auditory, and physical.

-*Install location*: We provided four options: on the AV, on-road projections, on the VRU in the form of wearable or handheld devices, and on the infrastructure. For the on AV install-location, several options were also presented in a separate question including the windshield, hood, bumper, sides, radiator grille, and roof.

In addition to that, we made participants choose between four different types of visual cues being textual cues, symbolic cues, light-based cues, and human-like cues. Similar to visual cues, participants had to select the desired type of auditory cues; they were presented with two types: spoken words and audio signals. Moreover, participants had to decide between static and dynamic visual cues.

Finally, this section presented some critical case scenarios identified through literature on AV-pedestrian interaction. We inquired about participants' potential behavior in these scenarios to understand their underlying expectations from AVs as pedestrians and to better identify their needs. The scenarios provided were as follows:

- When an AV is in self-driving mode, the driver might be inattentive (e.g., sleeping, busy on the phone) or there might not be any driver at all in the driver's seat.

As a pedestrian, rate the importance of the e-HMI informing you that the AV is in self-driving mode in such cases. (5-point Likert scale: 1-Not important, 2-Slightly important, 3-Fairly important, 4-Important, 5-Very important)

- As a pedestrian, you would still check on oncoming traffic even if the AV's e-HMI indicates that it is safe to cross. (5-point Likert scale: 1-Not at all likely, 2-Not too likely, 3-Somewhat likely, 4-Very likely, 5-Extremely likely)

- As a pedestrian, you would assume that all the incoming traffic (human-driven and/or automated vehicles) would also be stopping or yielding when an AV communicates its intent to yield or stop. (5-point Likert scale: 1-Not at all likely, 2-Not too likely, 3-Somewhat likely, 4-Very likely, 5-Extremely likely)

Data Cleansing: To ensure high-quality responses, we added two quality/ attention check questions and a speeding check that filtered out several responses. Upon using these two criteria, we collected a total of 698 responses. However, we also employed a screening plan to remove responses with further uncaptured quality issues. As a first step, we eliminated responses containing non-sensical data in open-ended questions (e.g., "*Great game to pass pass game*", "*Nothing to do it and I'm still trying not yet*") as these either correspond to bots or to not paying attention. As a second step, we penalized responses containing gibberish data, inconsistency and contradictory responses within related-questions, and straightlining in matrix tables. Consequently, we removed those responses that encompass a considerable occurrence of these issues. As a result, we were left with 580 responses (50.9% males, 49.1% females; 65.5% White, 12.2% Black, 11.7% Hispanic, and 10.5 % others). The age group and educational level distributions of our sample are presented in Table 12.

Table 12: General population’s age group and educational level

Age group distribution	18-20	21-24	25-34	35-44	45-54	55-64	65+
	8.1%	9.1%	16.9%	16.6%	16.2%	16.2%	6.9%
Educational level distribution	Doctoral degree	Master’s degree	Bachelor degree	Some college	High School degree	Some High School	Other
	2.1%	10.3%	24.1%	34.1%	23.6%	3.6%	2.1%

Moreover, 7.8% of our respondents reported being a member in a bicyclist or pedestrian advocacy group, 10.2% identified themselves as physically disabled and reported using assistive walking devices (e.g., cane, walker, crutch, wheelchair, rollator, cam brace, service dog, walking staff), 20.7% had previous crashes with vehicles as either pedestrians or bicyclists, 23.3% had previously interacted with ADS out of which 74.1% are from AV-deployed cities. Only 22% of those who declared interacting with ADS in AV-deployed cities were in the position of pedestrians or bicyclists. As for their knowledge in ADS, 68.6% of respondents outlined limited or moderate knowledge (40.5% and 28.1%, respectively), with 5.3% outlining advanced knowledge. The remaining 26% conveyed no knowledge of ADS.

4.2.2 Data Analysis

We employed a set of statistical methodologies to analyze the collected data, including K-means clustering, repeated measures ANOVA, Friedman rank sum test, Wilcoxon signed-rank test, factorial ANOVA, mixed ANOVA, binomial and multinomial logistic regression, and Chi-square goodness of fit test.

In all the following analysis, we transformed the six age groups into three: (1) 18-34 designating younger adult respondents, (2) 35-54 designating middle-aged adult respondents, and (3) 55+ designating older adult respondents.

Section 2:

The PBQ in Section 2 was firstly analyzed using K-means clustering (MacQueen, 1967). This unsupervised machine learning algorithm splits n observations into k clusters in order to minimize the within-cluster variance based on the objective function shown below:

$$\underset{\boldsymbol{c}}{\operatorname{argmin}} \sum_{i=1}^{k} \sum_{\boldsymbol{x} \in c_i} \|x - \mu_i\|^2 \quad (3)$$

such that μ_i is the mean point (centroid) of cluster c_i, x is the observation in cluster c_i,and $\|\cdot\|^2$ is the Euclidian distance.

To solve this optimization problem, the algorithm starts first by randomly assigning k observations as the initial centroids of the k clusters. Then, each other observation is assigned to the cluster corresponding to the closest centroid. After that, the centroid of each cluster, being the mean of the observations in that cluster, is calculated. The process then iterates itself by re-assigning each observation to the cluster whose centroid is the closest to that observation and by updating the centroid of each cluster. The iterations stop when the assignment process reaches convergence; that is, when observations become static in their clusters and incur no more cluster assignment changes. This algorithm is greedy such that at each iteration, it finds a local optimum with the hope of reaching the global optimum, which might not be reached.

K-means algorithm requires two primary inputs. First, we need to define the features or the input variables of the observations. Second, we need to pre-specify the number of clusters k for the algorithm to work. Several methods exist to determine the optimal value of its hyperparameter k, such as the Elbow method (Syakur et al., 2018). There also exists the majority rule approach which evaluates 30 different performance metrics including Davies-Bouldin index and the Silhouette Score. This approach yields the best value of k being the most frequently selected by the 30 indices (Charrad et al., 2014).

In our case, we used five features as input variables to our model: for each participant, we calculated five scores such that each score is the average of the PBQ items corresponding to a particular category (i.e., violations, errors, lapses, aggressiveness, positiveness). Using the majority rule approach, we determined the optimal number of clusters as two, as shown in Figure 10, and subsequently ran the K-means model.

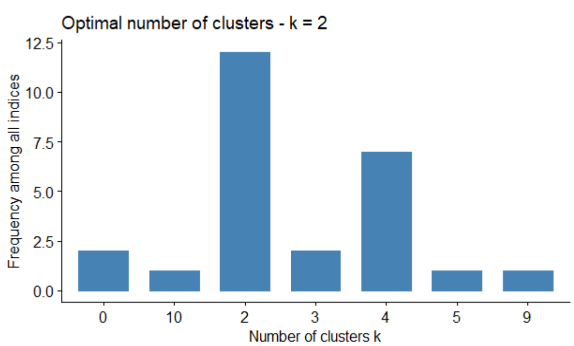


Figure 10: Majority rule approach to determine optimal number of clusters for K-means

After that, we used the resulting cluster labels from K-means as an input to a binomial logistic regression model. The labels served as the dependent variable to that model in order to determine the impact of age and gender on the odds of a participant belonging to Cluster 2 as compared to Cluster 1. To validate our results, we also run two-way ANOVA to determine the impact of these same attributes (i.e., age and gender) on the raw score of each PBQ category, independent from clustering results. In each of these two-way ANOVA tests, the dependent variable was the score of the PBQ category, and the independent variables were age group and gender. ANOVA models were run after MANOVA results indicated significant results on the several dependent variables.

Section 3:

For the rating-based questions on the different characteristics of communication cues between HDVs and pedestrians, we used repeated measures ANOVA, to determine if respondents' ratings of the existing cue options are significantly different. This was followed by pairwise comparisons with Bonferroni adjustment to determine the significantly different pair(s) of cues. In the case where we only have two cue options, the repeated measures ANOVA automatically reports the results of paired t-test. Only for the question on the type of influencing contextual cues, we used mixed ANOVA to determine the combined impact of cue type (within-subject variable) and pedestrian cluster (between-subject variable) on influence ratings.

For the question on perceived safety while interacting with HDVs, we utilized three-way ANOVA to determine the impact of age group, gender, and previous crash with a vehicle on respondents' ratings.

For the frequency of listening to music while walking, we also utilized a two-way ANOVA to determine the impact of age group and gender on frequency rating.

Section 4:

The questions seeking respondents' general opinion on their interaction with AVs (safety, importance of communication cues and receptivity to using e-HMIs) were analyzed using factorial ANOVA to model the ratings of each question as a function of age and gender. Knowledge in ADS and previous interaction with ADS was also considered as an independent variable in the questions on perceived and actual safety ratings.

Similar to the question on the type of influencing cues during the interaction between pedestrians and HDVs, the rating-based question on e-HMI information type was also analyzed using mixed ANOVA to report the combined effect of information type and pedestrian cluster on respondents' ratings. Repeated measures ANOVA was utilized to determine the effect of e-HMI install location on respondents' ratings. Friedman's rank sum test accompanied by Wilcoxon signed-rank test was applied for the ranking-based question on e-HMI's preferred modality to test for significant differences in the mean rankings between e-HMI's preferred modalities. In addition to analyzing ranking and rating questions, we analyzed multiple-choice questions on e-HMI attributes using Chi-square goodness of fit test to determine if there is unequal distribution between the options provided for each question. This was also followed by pairwise comparisons to determine significantly different votes between all pairs of options.

The questions on critical case scenarios were analyzed using three-way ANOVA to identify and quantify the impact of different factors including age group, gender, and respondents' cluster on respondents' ratings.

Section 3 & 4:

In order to investigate if pedestrians' current interaction patterns with HDVs influence their selections or ratings for e-HMI design attributes, we employed several statistical tests depending on the type of questions at hand (i.e., rating, ranking, multiple choice). More precisely, we used these tests to examine the impact of pedestrians' current interaction patterns, age group and gender on their preferences for e-HMI design options.

First, in order to study the impact of respondents' age group, gender, and the type of cues they're most influenced by during their interaction with HDVs on respondents' importance ratings for each e-HMI information type option, we ran three-way ANOVA for five times, once for each e-HMI information type rating, after MANOVA results yielded significant results.

Second, we employed a multinomial logistic regression model to examine the likelihood of respondents' selection to their most preferred e-HMI modality (visual, auditory, physical) as a function of respondents' age group, gender, and selection to the cue modality they are most familiar with during their interaction with HDVs. The model was run several times to account for all possible pairwise comparisons.

Third, to determine the effect of respondents' age group, gender, and the source of cues they trust most during their interaction with HDVs on respondents' effectiveness ratings for each e-HMI install location, we ran three-way ANOVA four times, once for each e-HMI install-location rating.

Fourth, we used multinomial logistic regression to model respondents' choice of the visual cue type (textual, symbolic, light-based, human-like) to be displayed on e-HMIs as a function of respondents' age group, gender, and selection to the visual cue they are most familiar with during their interaction with HDVs (textual, symbolic, human-like). We ran the model several times to account for all possible pairwise comparisons.

4.2.3 Results

Section 2:

Based on the recommended number of clusters as per the majority rule approach, we ran the K-means model on all data points with the input number of clusters being two. As a result, 81.4% of respondents were clustered into one group while the remaining 18.6% were clustered into another group. We defined these clusters based on the average values of the five pedestrian behavior scores and identified them as: (1) conservative pedestrians and (2) non-conservative pedestrians. Upon comparing the within-cluster mean frequency values of the five pedestrian behaviors, pedestrians in the conservative cluster were characterized by lower values for violations, errors, lapses, and aggressive behavior, and by a higher value of positive behavior than pedestrians in the non-conservative cluster. This trend is shown in Table 13 as reflected by Figure 11. Since we were dealing with five input features, we used Principal Component Analysis (PCA) to transform these five dimensions into two dimensions for plotting purposes. The resultant clusters are shown in Figure 12.

Table 13: Pedestrian behavior scores for resultant clusters

Cluster	Violations	Errors	Lapses	Aggressive Behavior	Positive Behavior
Conservative (472 points)	1.70	1.33	1.20	1.32	3.54
Non-conservative (108 points)	2.96	2.65	2.57	2.45	3.29

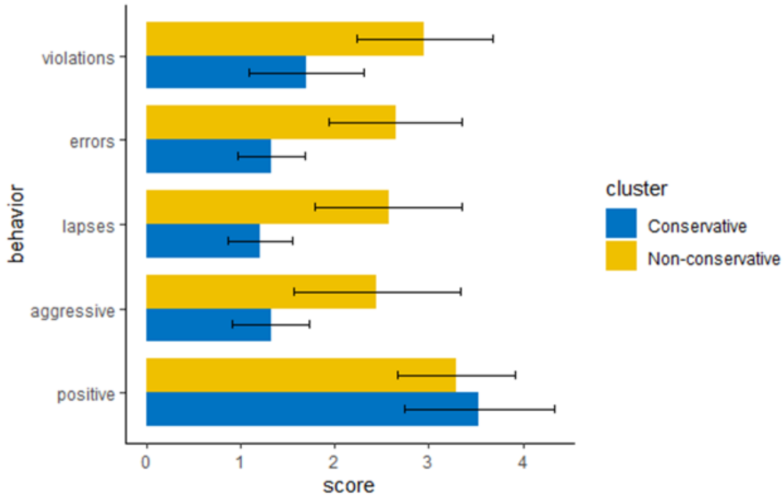


Figure 11: PBQ scores for each cluster

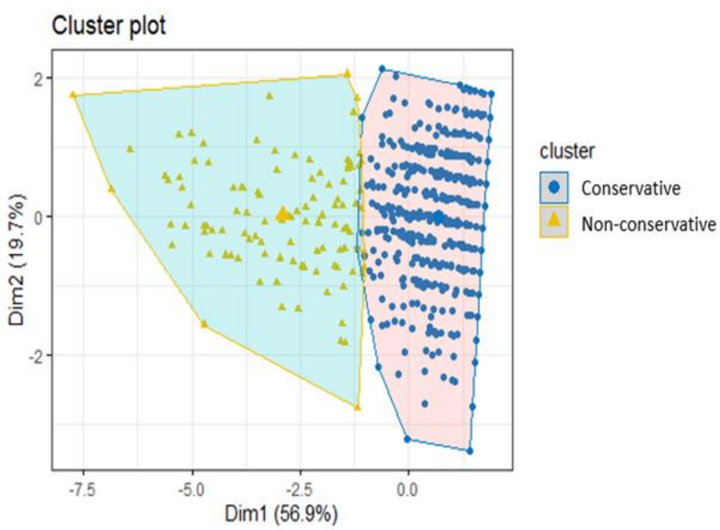


Figure 12: Cluster plot using Principal Component Analysis

As for the logistic regression model, results revealed significant main effects for both age group and gender. The interaction effect between age group and gender was non-significant, so the model was re-run while excluding the interaction effect. Table 14 summarizes the results with the younger adult respondents as the reference category for age and males as the reference category for gender. The significant main effect of age group revealed that the odds of younger respondents to be non-conservative are 2.2 and 7 times the odds of middle-aged and older adult respondents. As for the significant main effect of gender, the odds of males to act as non-conservative pedestrians is 2.1 times that of females.

Table 14: Logistic regression results for resulting respondents' clusters

Variable	Log-odds	Std. Error	Z-value	P-value	Odds Ratio
Gender: Males (reference category)					
Female	-0.72	0.23	-3.16	0.00**	0.49
Age Group: Younger (reference category)					
Middle-aged	-0.77	0.25	-3.10	0.00**	0.46
Older	-1.95	0.33	-5.87	0.00***	0.14
Intercept	-0.43	0.19	-2.25	0.02*	0.65

By looking more specifically at the features characterizing each cluster (score of each pedestrian behavior), ANOVA results followed by pairwise comparison with Bonferroni adjustment demonstrated significant age group and gender differences; no interaction effects were found significant, so interactions were removed. In particular, it showed that female respondents commit less violations (*F(1,576)=22.53, p-value<0.001*), errors (*F(1,576)=13.94, p-value<0.001*), lapses (*F(1,576)=6.88, p-value=0.009*), and aggressive behaviors (*F(1,576)=13.62, p-value<0.001*) as compared to male respondents. Age group significant differences were prevalent across all five pedestrian behavior scores (*violations: F(2,576)=10.11, p-value<0.001; errors: F(2,576)=21.86, p-value<0.001; lapses: F(2,576)=25.42, p-value<0.001; aggressive behavior: F(1,576)=18.33, p-value<0.001; positive behavior: F(2,576)=21.69, p-value<0.001*). Pairwise comparisons with Bonferroni adjustment further revealed several significant differences indicating that older adult respondents commit less errors, lapses, and aggressive behavior and behave more positively compared to younger and middle-aged adult respondents. Older adults also appeared to commit less violations compared to younger adults only. As for middle-aged adults, they were also found to commit less lapses and aggressive behavior while behaving more positively when compared to younger adults. The results of age group pairwise comparisons are shown in Table 15. Figure 13 shows the distribution of these pedestrian behavior scores across age groups and gender through boxplots.

Table 15: Descriptive statistics and pairwise comparisons of pedestrian behavior scores with respect to respondents' age groups

Pedestrian behavior	Mean score			Standard deviation			Pairwise comparisons (Age group)		
	Younger	Middle-aged	Older	Younger	Middle-aged	Older	Younger vs Middle-aged	Younger vs Older	Middle-aged vs Older
Violations	2.09	1.93	1.78	0.89	0.79	0.66	0.16	0.00	0.16
Errors	1.76	1.61	1.35	0.77	0.72	0.43	0.08	0.00	0.00
Lapses	1.69	1.46	1.22	0.81	0.73	0.40	0.00	0.00	0.00
Aggressive	1.71	1.54	1.34	0.83	0.68	0.42	0.04	0.00	0.01
Positive	3.27	3.45	3.76	0.74	0.80	0.71	0.04	0.00	0.00

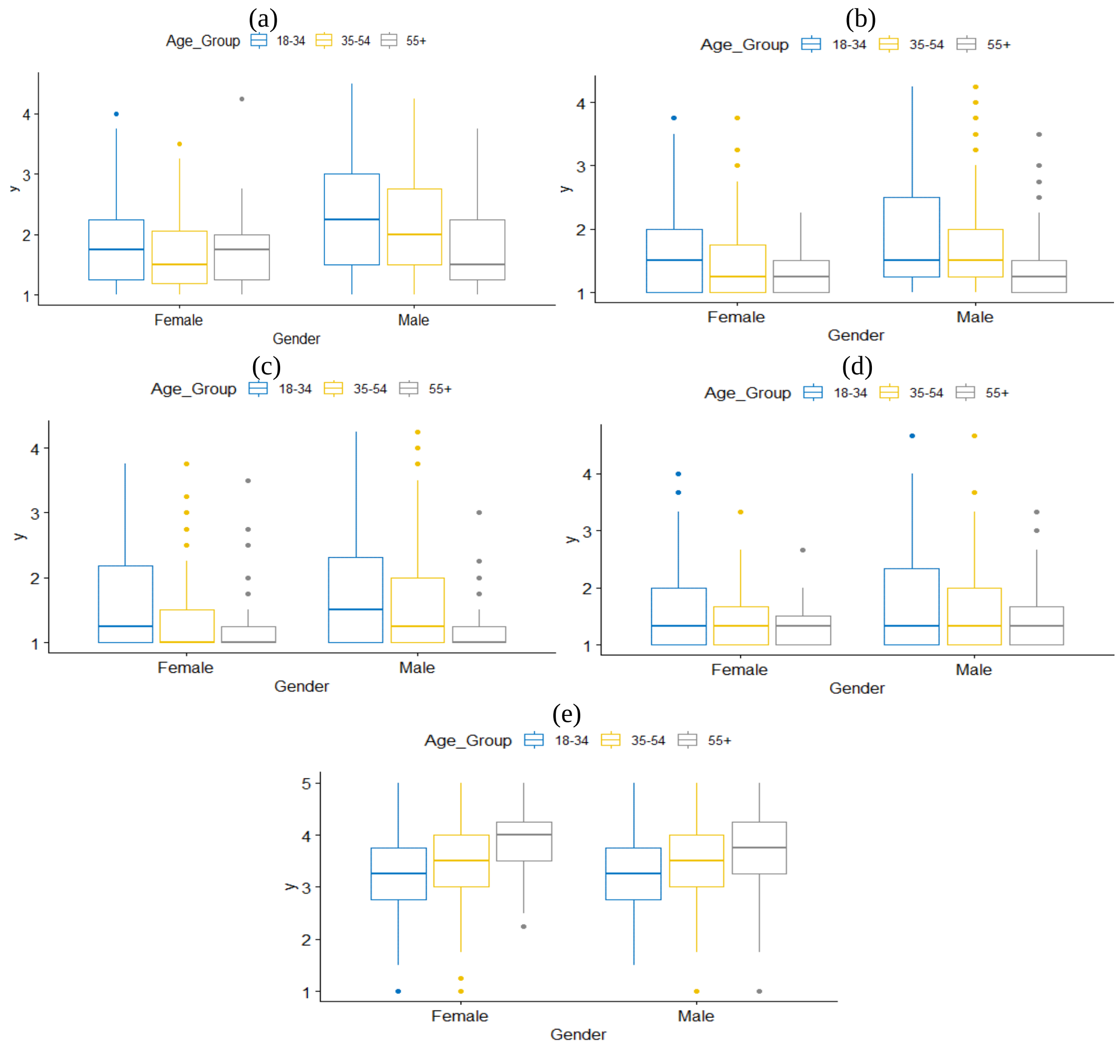


Figure 13: Pedestrian behavior scores as a function of age group and gender ((a) violations, (b) errors, (c) lapses, (d) aggressive behavior, (e) positive behavior)

HDV-to-Pedestrian Communication:

For perceived safety while interacting with HDVs, almost half the respondents (49.7%) reported average perceived safety, 32.2% reported above average perceived safety, and the remaining 18.1% reported below average perceived safety (Figure 14). Three-way ANOVA with interactions failed to show any significant effects for neither age group, gender, and previous crash with vehicles. We repeated the analysis by removing interaction effects which resulted in a significant main effect for gender only (*F(1,575)=5.24*, *p-value=0.022*). In this regard, females perceive themselves less safe while interacting with HDVs as compared to males. Age group and previous crashes with HDVs effects were non-significant.

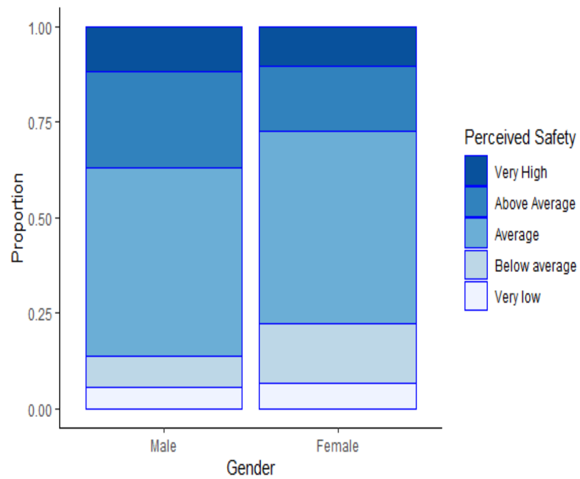


Figure 14: Perceived safety while interacting with HDVs as a function of gender

By investigating contextual cues' influence on crossing decisions, mixed ANOVA yielded a significant main effect for the type of contextual cues *(F(1.86, 1076.15)=33.41*, *p-value<0.001*). Further examination through pairwise comparisons revealed that all pairs of cues exhibited significant differences such that Type 3 cues (advising cues from the driver) exerted the most substantial influence on pedestrians' crossing decisions and Type 1 cues (vehicle's kinematics) exerted the least influence. Moreover, a significant interaction effect between pedestrians' cluster and the type of contextual cues (*F(1.86, 1076.15)=18.22, p-value<0.001*) highlighted an interesting pattern: the importance rating for Type 3 cues was different between conservative and non-conservative pedestrians with the latter reporting lower importance, while the ratings for Type 1 and Type 2 cues were quite similar between the two groups.

The results for the question on the communication cues' modalities identified a significant main effect for modality (*t-statistic=-7.14; p-value<0.001*) on pedestrians' familiarity ratings.

Compiled with descriptive statistics, results indicated that participants were more familiar with visual than with auditory cues. The familiarity ratings with visual cues, in particular, revealed significant differences between the presented three types (*F(2,1158)=927.69, p-value<0.001*). Pairwise comparisons elucidated significant differences between all pairs, such that respondents were most familiar with symbolic cues and least familiar with human-like cues.

As for the results on trusting the source of cues, the mean rating for traffic signals was higher than that for vehicles or drivers, with paired t-test results pointing out a significant difference between the two options (*t-statistic=3.76, p-value<0.001*). This implied that pedestrians generally trust cues coming from traffic signals more than those coming from vehicles or drivers. Further results comparing the presence of the two sources of cues separately to their presence concurrently revealed significant difference also (both sources vs. traffic signals: *t-statistic=12.6, p-value<0.001*; both sources vs. driver/ vehicle: *t-statistic=17.2. p-value<0.001*) translating into increased trust when the cues are coming from both sources at the same time.

Ratings corresponding to all questions are presented in Figure 15.

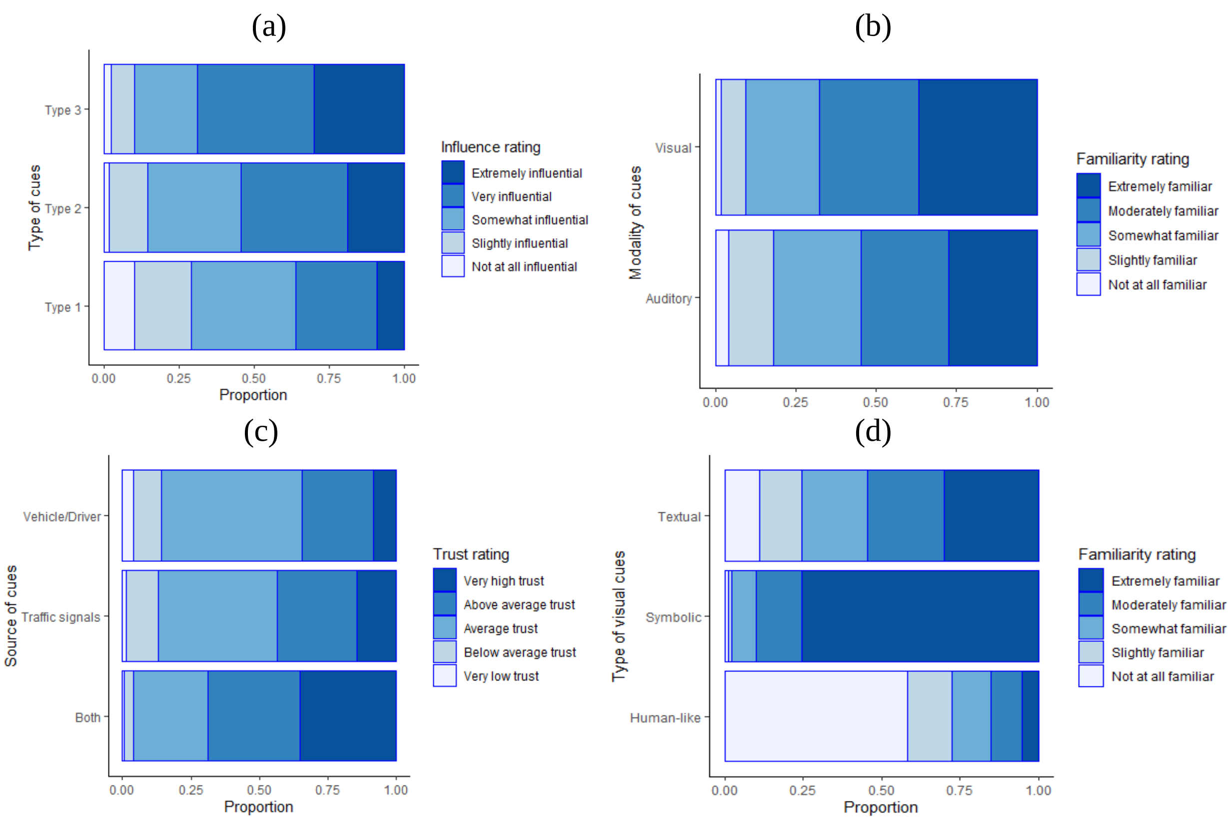


Figure 15: Respondents' ratings for cues with HDVs (a) influence ratings corresponding to contextual cues (b) familiarity ratings corresponding to mode of cues (c) trust ratings corresponding to source of cues (d) familiarity ratings corresponding to type of visual cues

When it comes to the frequency of listening to music while walking, the majority of respondents (51.9%) demonstrated a low likelihood of this behavior. Two-way ANOVA results showed significant main effect for age group only (*F(2,576)=99.60, p-value<0.001*) while gender and interaction effects were non-significant. By running pairwise comparisons, it appeared that all pairs of age groups were significantly different. As expected, younger adults reported the highest frequency while older adults reported the lowest frequency (Figure 16).

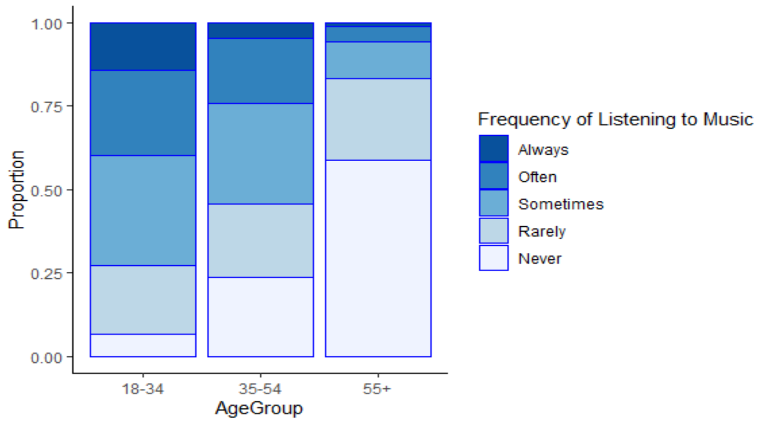


Figure 16: Frequency of listening to music as a function of age group

AV-to-Pedestrian Communication:

Factorial ANOVA results show three significant main effects on pedestrians' belief regarding AVs' enhancement to both actual and perceived safety as compared to HDVs. The first significant main effect is that of respondents' age group (*actual safety: F(2, 572)=5.96, p-value=0.003; perceived safety: F(2, 572)=5.60, p-value=0.004*). The second is that of respondents' previous knowledge in ADS (*actual safety: F(3, 572)=6.97, p-value<0.001; perceived safety: F(3, 572)=10.64, p-value<0.001*), while the third significant main effect is respondents' previous interaction with ADS (*actual safety: F(1, 572)=6.93, p-value=0.009; perceived safety: F(1, 572)=5.26, p-value=0.02*). For both actual and perceived safety, pairwise comparisons revealed significant differences between older adults from one end and younger adults (*actual safety: p-value<0.001; perceived safety: p-value<0.001*) and middle-aged adults (*actual safety: p-value<0.001; perceived safety: p-value<0.001*) from another end. Compared to the other two groups, older adults exhibited less agreement that AVs will enhance actual and perceived safety in contrast to HDVs. As for respondents' knowledge in ADS, all pairs of knowledge were found to be significantly different for both actual and perceived safety cases, except for zero and limited knowledge. Those participants who possessed advanced knowledge were found to have the highest level of agreement that AVs would improve safety when compared to HDVs, while those with zero or limited knowledge demonstrated the lowest level of agreement. Add to that, respondents with previous interaction with ADS reported higher levels of agreement than those with no previous interaction. Figure 17 and Figure 18 demonstrate respondent’ ratings.

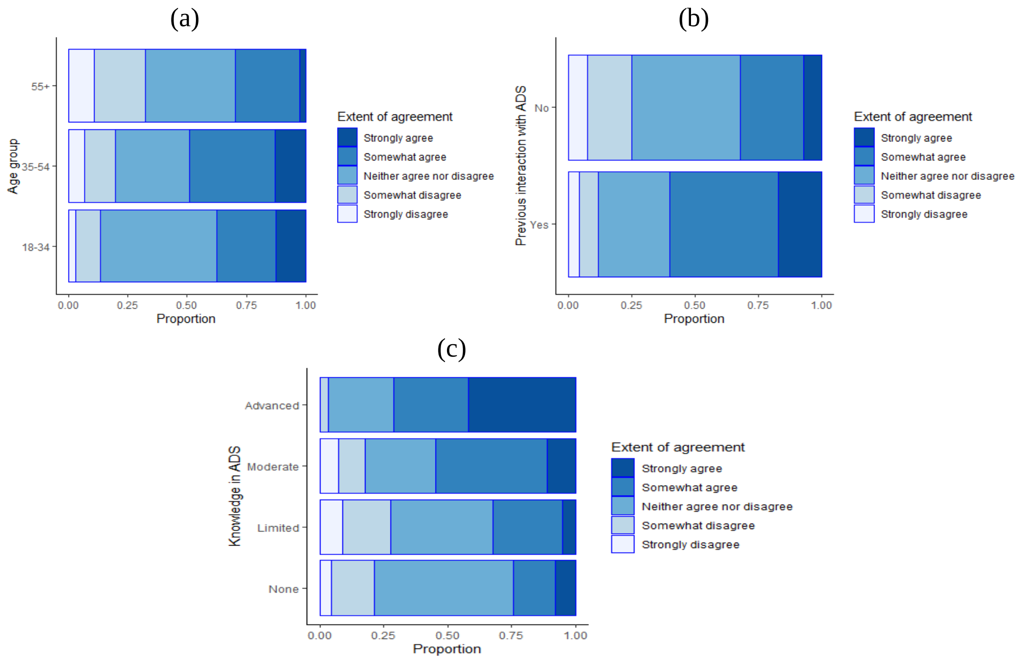


Figure 17: Respondents’ agreement on AVs enhancing actual safety as a function of (a) age group, (b) previous interaction with ADS, (c) knowledge in ADS

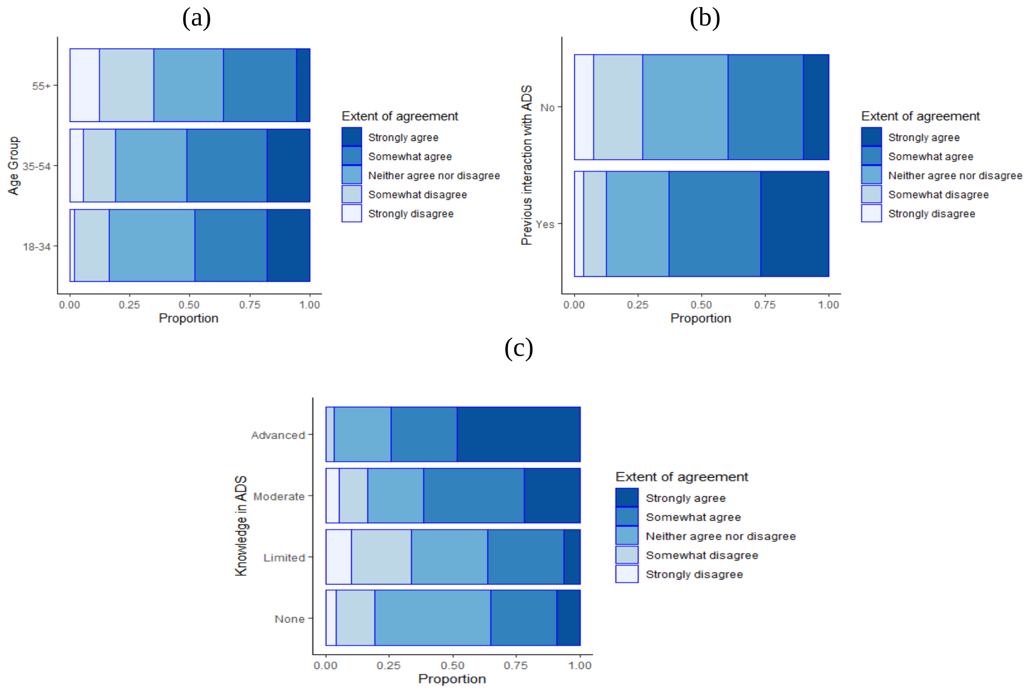


Figure 18: Respondents' agreement on AVs enhancing perceived safety as a function of (a) age group, (b) previous interaction with ADS, (c) knowledge in ADS

Moreover, significant age group (*F(2, 576)=3.48, p-value=0.031*) and gender (*F(1, 576)=4.27, p-value=0.039*) effects were observed when evaluating respondents' extent of agreement to the importance of communication cues between pedestrians and AVs. Age group pairwise comparisons gave a significant difference between younger and middle-aged adults (*p-value=0.008*), with younger adults indicating lower agreement towards the importance of communication cues (Figure 19(a)). Add to that, males were more in agreement than females (Figure 19(b)). The solution of providing e-HMIs did reveal a significant main effect for the age group (*F(2, 576)=8.36, p-value<0.001*) also, without further significant effects. This time, middle-aged and older adult respondents showed significant differences (*p-value<0.001*) with older adults expressing lower agreement on the perceived benefit of e-HMIs in increasing their perceived safety while interacting with AVs (Figure 20). This lower agreement was further confirmed by their lower ratings towards their receptivity to utilizing e-HMIs as compared to younger (*p-value<0.001*) and middle-aged (*p-value<0.001*) respondents (main effect: *F(2, 576)=16.35, p-value<0.001*) (Figure 21(a)). Gender effect was also found significant (*F(1, 576)=8.90, p-value=0.003*). Surprisingly, females demonstrated lower receptivity to using e-HMIs compared to males (Figure 21(b)).

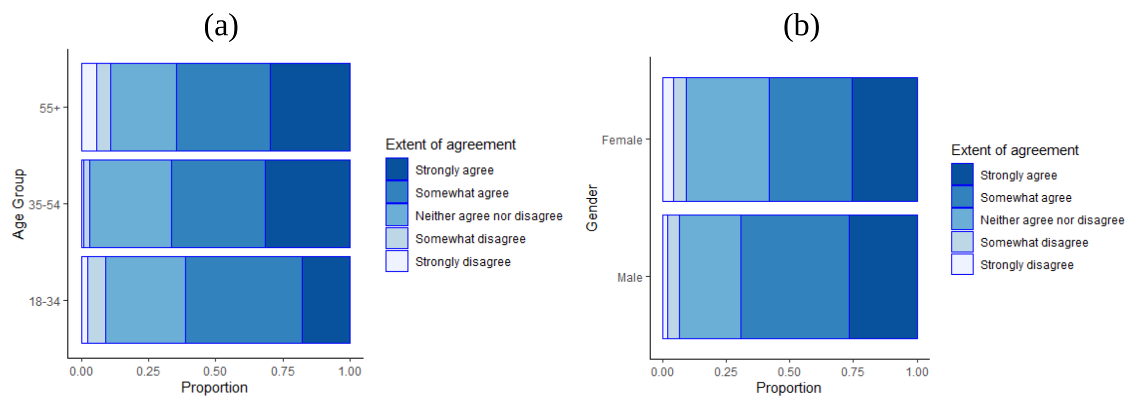


Figure 19: Respondents' agreement on importance of communication cues as a function of (a) age group, (b) gender

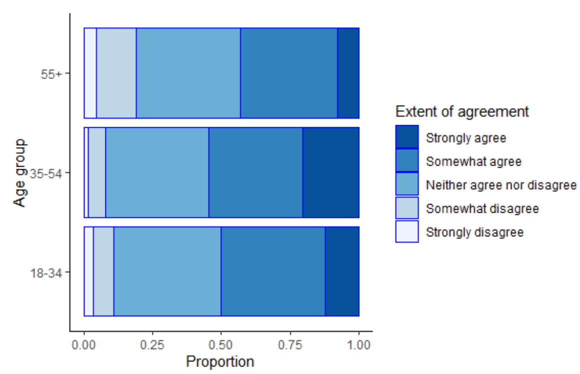


Figure 20: Respondents' agreement on e-HMIs enhancing safety as a function of age group

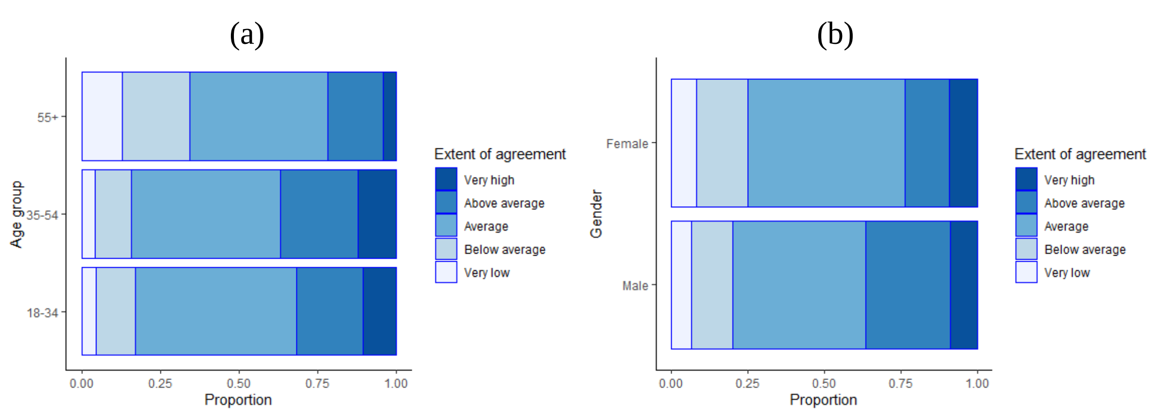


Figure 21: Respondents' receptivity towards using e-HMIs as a function of (a) age group and (b) gender

The analysis of the information type conveyed by e-HMIs revealed a significant main effect for the type of information on respondents' importance ratings (*$F(3.77, 2181.27)=34.29$, p-value<0.001*). Subsequent pairwise t-tests with Bonferroni adjustment indicated significant differences between Status and Kinematics on one hand and all other information types on the other hand (*p-values<0.001*). No further significant differences were observed. Combining these significant differences with descriptive statistics, the results indicated that respondents considered Awareness, Intent, and Advice as the most important e-HMI information types and Status and Kinematics as the least important (Figure 22).

The mean rankings for the three modality options revealed that visual e-HMIs received the highest mean rank and physical e-HMIs the lowest mean rank. The Friedman test results for e-HMI modality rankings demonstrated significant differences as well ($X^2(2)=142.39$, *p-value<0.001*). Particularly, there were significant differences between visual e-HMI and both auditory and physical e-HMIs (*p-values<0.001*), exhibiting a clear preference for visual e-HMI over other modalities (Figure 23). Notably, 54.1% of respondents considered one modality as sufficient, and this was found to be significantly different based on the Chi-squared results ($X^2(1)=3.97$, *p-value=0.046*).

Regarding auditory and visual e-HMI specific preferences, the distribution of respondents across speech-based and abstract-based cues and across static and dynamic cues was found to be significantly different (auditory: $X^2(1)=14.59$, *p-value<0.001;* visual: $X^2(1)=22.41$, *p-value<0.001*). For auditory e-HMIs, speech-based cues attracted the higher proportion of respondents (57.9%). Similarly for visual cues, dynamic cues attracted the highest proportion of respondents (59.8%).

The Chi-squared test also detected a significant difference in the distribution of respondents across the four types of visual cues ($X^2(3)=52.03$, *p-value<0.001*), with all pairs being significantly different except for symbolic and light-based cues. Specifically, textual cues were the most selected (36.4%) and human-like cues were the least selected (15.3%).

Repeated measures ANOVA conducted for e-HMI install-locations revealed a significant main effect on respondents' ratings ($F(2.87, 1661.28)=36.75$, *p-value<0.001*), with all pairs being significantly different. By considering the mean ratings alongside the significant differences, pedestrians perceived highest trust for placing e-HMIs on infrastructure and lowest trust for placing them on VRUs (Figure 24).

Regarding the placement of e-HMIs on AVs in particular, the Chi-squared test indicated significant differences in the allocation of responses ($X^2(5)=1029.6$, *p-value<0.001*) highlighting disparities between the windshield position and all other suggested positions. The windshield position was clearly the favorite garnering the consensus of 66.2% participants (Figure 25).

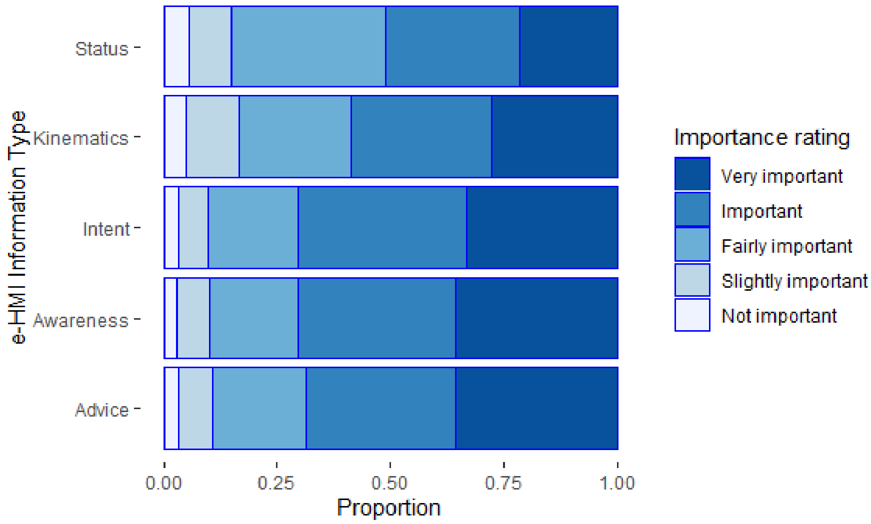


Figure 22: Respondents' importance ratings of e-HMI information types

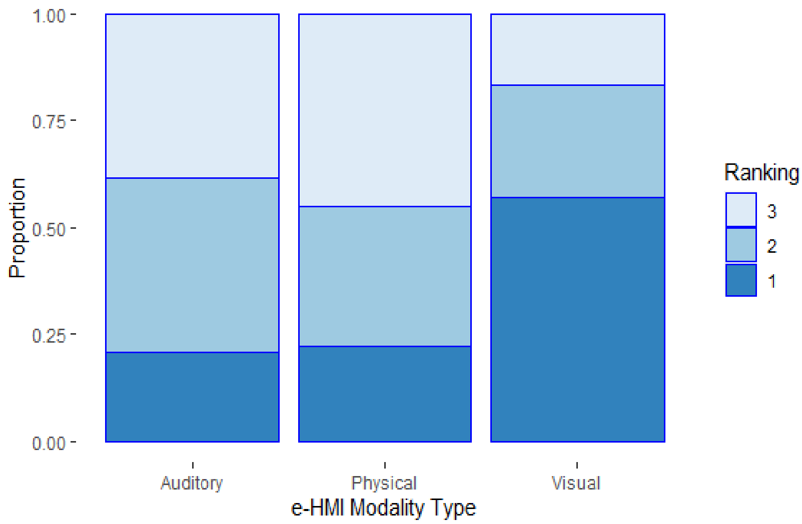


Figure 23: Respondents' rankings of e-HMI modality types

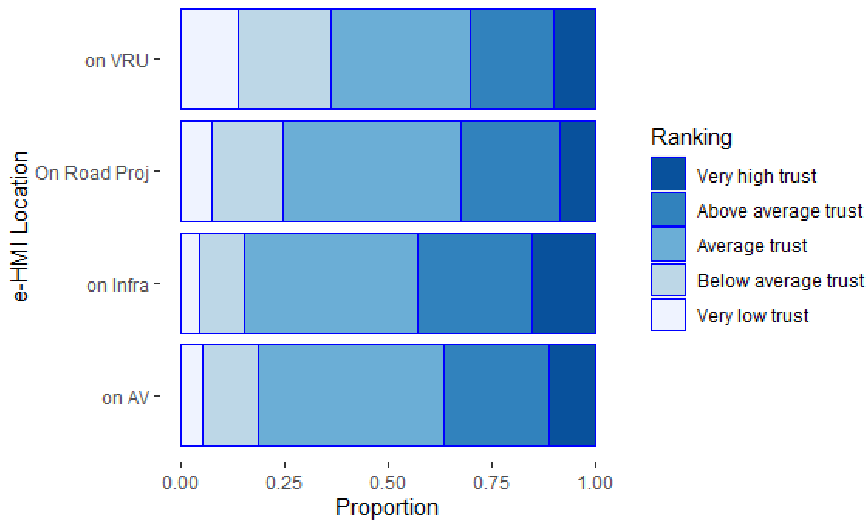


Figure 24: Respondents' ratings of e-HMI install-locations

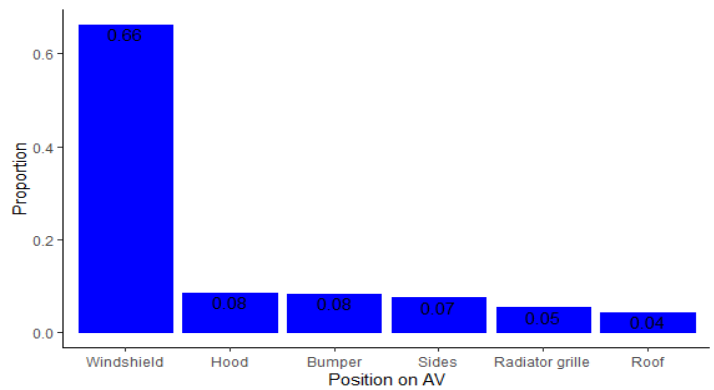


Figure 25: Respondents' selection of on-AV install points

For the behavioral questions related to their potential interaction with AVs, results yielded significant main effects for both age group (*F(2,575)=32.23, p-value<0.001*) and gender (*F(1,575)=4.81, p-value=0.015*) on the importance of the presence of a status e-HMI in the case that the driver is inattentive or is not present. All pairs of age groups were significantly different, with older adult respondents reflecting highest importance levels and younger adult respondents reflecting lowest importance levels (Figure 26(a)). Females also demonstrated higher importance ratings than males (Figure 26(b)). If we consider cluster: age group: *F(2,575)=32.23, p-value<0.001; gender: F(1,575)=4.81, p-value=0.029; cluster is non-significant*

Regarding the likelihood of checking for oncoming traffic even when the host AV indicates it is safe to cross, both age group and respondents' cluster resulted in significant main effects (age group: *F(2,575)=28.48, p-value<0.001;* cluster: *F(1,575)=22.43, p-value<0.001*). Younger adult respondents' ratings were significantly different from the other two age groups reflecting their lower likelihood to check on oncoming traffic as compared to middle-aged and older adults (Figure 27(a)). Furthermore, respondents characterized by their non-conservative behavior reported lower likelihood as compared to respondents characterized by their conservative behavior (Figure 27(b)).

Similarly, age group and cluster were found to have a significant impact on respondents' likelihood to assuming that all surrounding traffic will stop when the host AV stops (age group: *F(2,575)=8.50, p-value<0.001;* cluster: *F(1,575)=10.83, p-value=0.001*). Older adults were significantly different from the other two age groups, such that the likelihood of younger and middle-aged adults for such an assumption was higher (Figure 28(a)). Respondents reflecting non-conservative pedestrian behavior also reported higher likelihood for such an assumption (Figure 28(b)).

(a) (b)

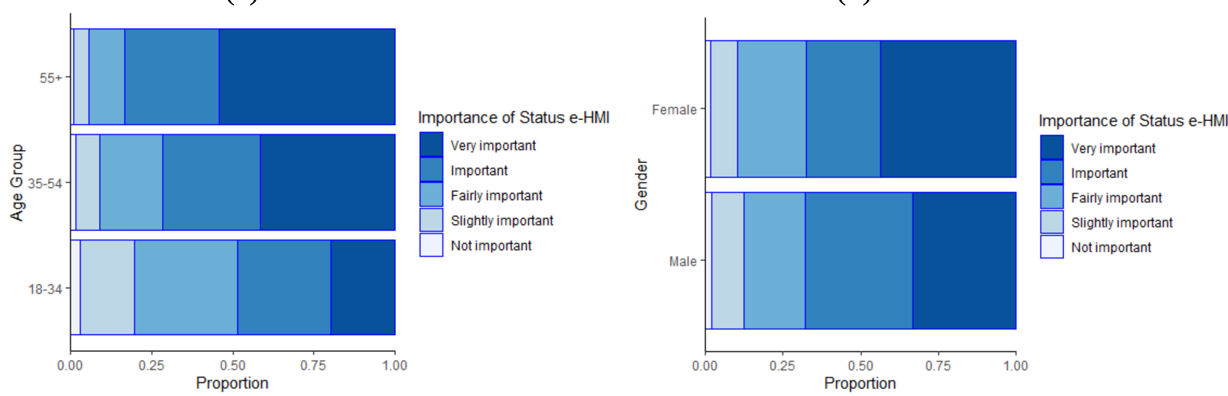


Figure 26: Importance of status e-HMI as a function of (a) age group and (b) gender

(a) (b)

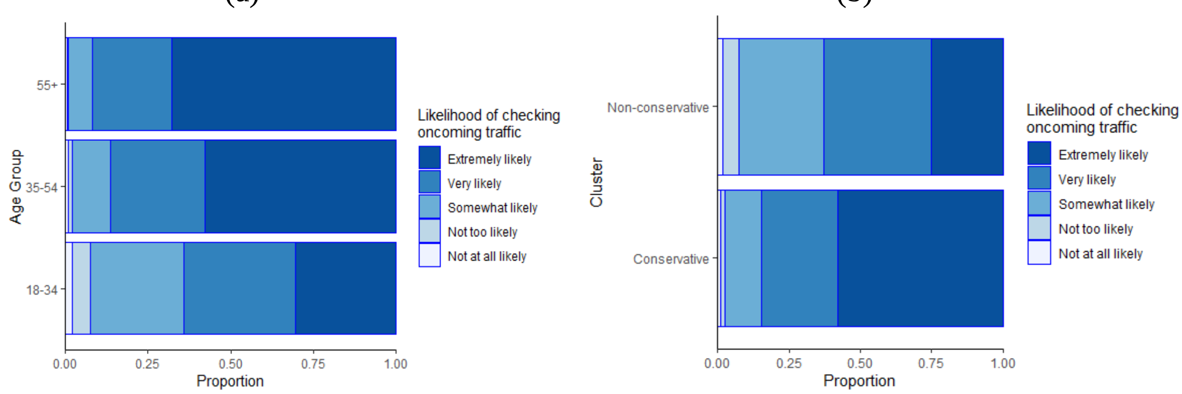


Figure 27: Likelihood of checking oncoming traffic as a function of (a) age group and (b) cluster

(a) (b)

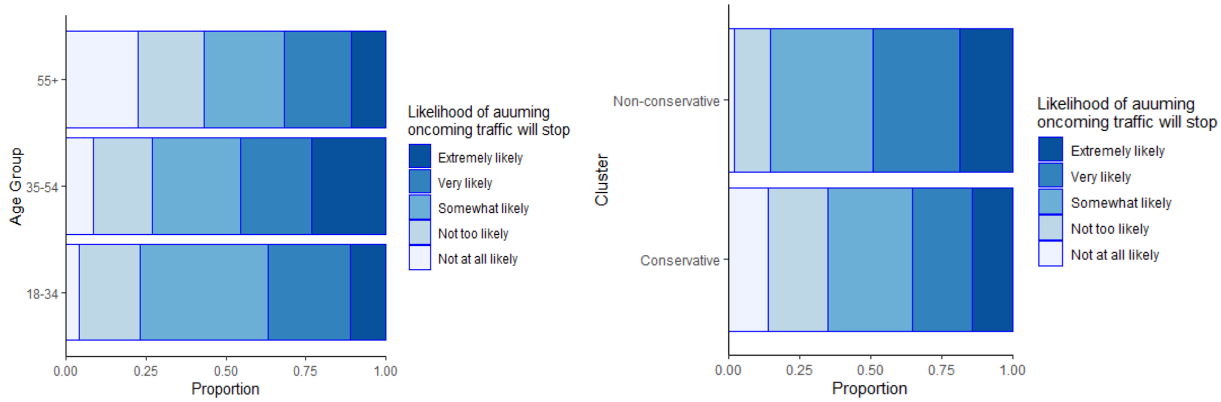


Figure 28:Likelihood of assuming oncoming traffic will stop as a function of (a) age group and (b) cluster

Relation between Individual Attributes, HDV-to-Pedestrian and AV-to-Pedestrian Interactions:

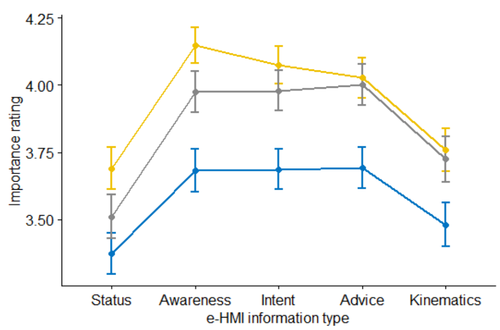
In attempt to employ the mixed ANOVA model to examine the effects of e-HMI information type, the influential cue in HDV-to-pedestrian interaction, respondents' age group, gender, and cluster on e-HMI importance ratings, the model was deemed complex and thence could not be fitted. Therefore, we ran two separate models instead: the first model included all effects except pedestrians' cluster, while the second model included e-HMI information type and pedestrians' cluster.

We observed significant age group differences ($F(2,562)=8.54$, $p\text{-}value<0.001$), with middle-aged and older adults reporting significantly higher ratings compared to younger adults. Simple main effect analysis showed that younger adults gave Awareness, Intent, and Advice information types lower ratings than other adults (Figure 29a). Based on a significant main effect of the most influential cue in HDV-to-pedestrian interaction ($F(3.79\ 2131.93)=23.57$, $p\text{-}value<0.001$) coupled with a significant two-way interaction with the e-HMI information type ($F(7.59,2131.93)=3.94$, $p\text{-}value<0.001$), the most influential cue exerted a significant effect on the importance ratings of Advice and Awareness e-HMI information types: those influenced by advising cues gave Advice-based e-HMI higher ratings than those influenced by intent or acknowledging cues. Similar results were found for Awareness-based e-HMI, with those most influenced by advising cues also rating it higher than those most influenced by acknowledging cues (Figure 29b). Moreover, the interaction between e-HMI information type and respondents' behavior cluster was significant ($F(3.78, 2184.09)=4.92$, $p\text{-value}<0.001$), with non-conservative respondents giving lower ratings for Advice-based e-HMI (Figure 29c).

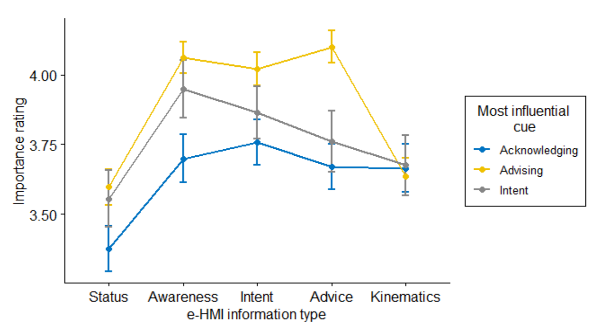
The mixed ANOVA modeling trust ratings of e-HMI install-locations showed significant main effects for age group ($F(2,568)=15.13$, $p\text{-value}<0.001$) and gender ($F(2,568)=6.27$, $p\text{-value}=0.002$), in addition to the previously detected significant main effect for the e-HMI install-location ($F(2.87, 1629.17)=35.10$, $p\text{-value}=0.03$).

We also observed significant interactions between several independent variables: the e-HMI install-location and the most trusted cue source in HDV-to-pedestrian interactions ($F(3,1704)=5.76$, $p\text{-value}=0.001$), the e-HMI install-location and pedestrians' age group ($F(6,1704)=4.11$, $p\text{-value}<0.001$), and pedestrians' age group and gender ($F(2,568)=6.27$, $p\text{-value}=0.002$). Participants with higher trust towards traffic signal cues while interacting with HDVs exhibited increased trust towards infrastructural e-HMIs as compared to those with higher trust towards drivers'/ vehicles' cues (Figure 30a). Older adults expressed lower trust ratings than other adults for all install-locations except for vehicular e-HMIs (Figure 30b). Males showed higher trust ratings than females, especially in younger and middle-aged groups (Figure 30c).

(a)



(b)



(c)

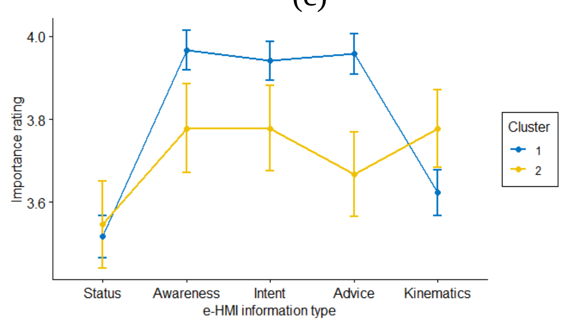


Figure 29: Interaction plots between e-HMI information types and (a) age group (b) most influential cue (c) pedestrians' cluster

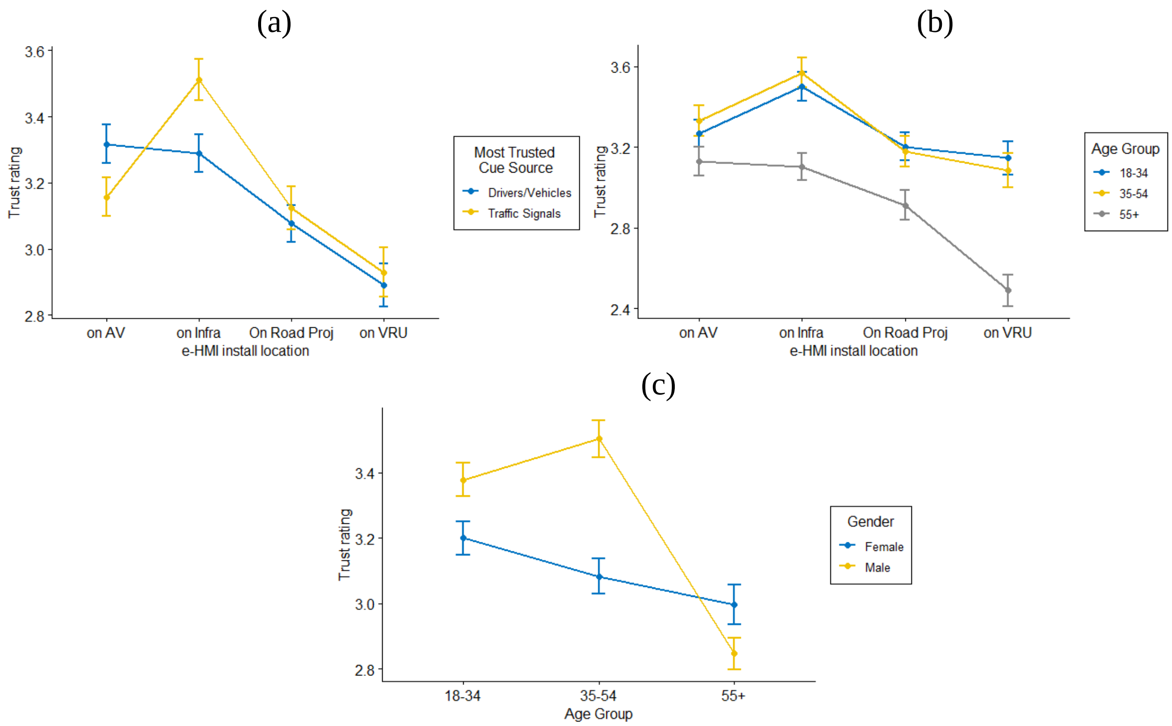


Figure 30: Interaction plots between e-HMI install-locations and (a) most trusted cue source (b) age group (c) age group and gender

The results of the MNL model pertaining to e-HMI modality did not show a significant effect of the cue modality that respondents were most familiar with during their interaction with HDVs on their preference for e-HMI modality. Nevertheless, the respondents' age group presented a significant impact. In particular, the odds of middle-aged adults preferring visual e-HMIs compared to auditory e-HMIs was 1.7 times more than younger adults. Also, the odds of older adults preferring visual e-HMIs compared to physical e-HMIs was 1.7 more than younger adults (Table 16). In fact, although the predicted probabilities to preferring visual e-HMIs was the highest amongst all e-HMI modalities for all three age groups, this likelihood was the lowest for younger adults compared to middle-aged and older adults (Figure 31a). At the same time, the predicted probabilities for preferring auditory and physical e-HMIs were higher for younger adults as compared to both middle-aged and older adults as can be seen from Figure 31b.

Table 16: Logistic regression model for preferred e-HMI modality

Visual e-HMI	Auditory e-HMI			Physical e-HMI		
	Log-odds	P-value	Odds ratio	Log-odds	P-value	Odds ratio
Most familiar modality: Auditory (reference category)						
Most familiar modality: Visual	-0.15	0.56	0.86	-0.21	0.42	0.81
Age: 18-34 (reference category)						
Age: 35-54	-0.54	0.04*	0.58	-0.35	0.16	0.71
Age: 55+	-0.46	0.07	0.63	-0.52	0.05*	0.60
Gender: male (reference category)						
Female	0.27	0.21	1.31	0.22	0.29	1.25
Intercept	-0.69	0.02	0.50	-0.60	0.04	0.55

The results of the second MNL model pertaining to visual e-HMIs (Table 17) showed that both the respondents' age group and the visual cue they were most familiar with during their interaction with HDVs had significant main effects on respondents' selection to their most preferred e-HMI visual cue. Respondents most familiar with textual cues in their interaction with HDVs were 2.1 times more than those most familiar with symbolic cues to prefer textual e-HMIs as compared to symbolic ones. At the same time, respondents most familiar with symbolic cues while interacting with HDVs had higher odds than those most familiar with textual cues for preferring symbolic and light-based e-HMIs as compared to textual e-HMIs (*OR=2.1 and OR=2.5*, respectively). As for age, the odds of older adults preferring human-like e-HMIs compared to textual e-HMIs was 2.2 and 2.3 times more than younger and middle-aged adults, respectively. They were also likely to prefer light-based e-HMIs relative to textual e-HMIs 1.8 and 2.6 times more than younger and middle-aged adults, respectively. Relative to symbolic e-HMIs, older adults were 2.5 times more in favor for human-like cues than the other two age groups, while they were 2.1 and 2.8 times more in favor for light-based cues than younger and middle-aged adults, respectively. The predicted probabilities plot (Figure 32) revealed some interesting results: for younger and middle-aged pedestrians, the likelihood of preferring textual e-HMIs was greater than that of preferring any other visual e-HMI type. This was followed by symbolic e-HMIs, emerging as the second highest probable preference for these age groups. On the other hand, older adults exhibited the highest likelihood for preferring light-based e-HMIs and not textual e-HMIs. Add to that, textual e-HMIs exhibited the highest predicted probability of preference for those who were most familiar with textual cues in their interaction with HDVs. Similarly, human-like e-HMIs scored the highest predicted probability of preference for those who were most familiar with human-like cues in their interaction with HDVs. Nevertheless, those who were most familiar with symbolic cues showed highest likelihood to prefer light-based cues.

Table 17: Logistic regression model for preferred visual e-HMI

Textual e-HMI	Human-like e-HMI			Light-based e-HMI			Symbolic e-HMI		
	Log-odds	P-value	Odds ratio	Log-odds	P-value	Odds ratio	Log-odds	P-value	Odds ratio
Most familiar visual cue: Symbolic (reference category)									
Most familiar visual cue: Textual	-0.59	0.12	0.55	-0.91	0.01*	0.40	-0.72	0.03*	0.49
Most familiar visual cue: Human-like	0.22	0.71	1.25	-1.24	0.12	0.29	-0.17	0.77	0.85
Age: 55+ (reference category)									
Age: 18-34	-0.80	0.01*	0.45	-0.61	0.02*	0.54	0.11	0.70	1.12
Age: 35-54	-0.84	0.01*	0.43	-0.96	0.00*	0.38	0.08	0.78	1.08
Gender: male (reference category)									
Female	-0.29	0.26	0.75	-0.08	0.74	0.93	-0.05	0.83	0.95
Intercept	-0.12	0.62	0.89	0.28	0.19	1.32	-0.34	0.16	0.71

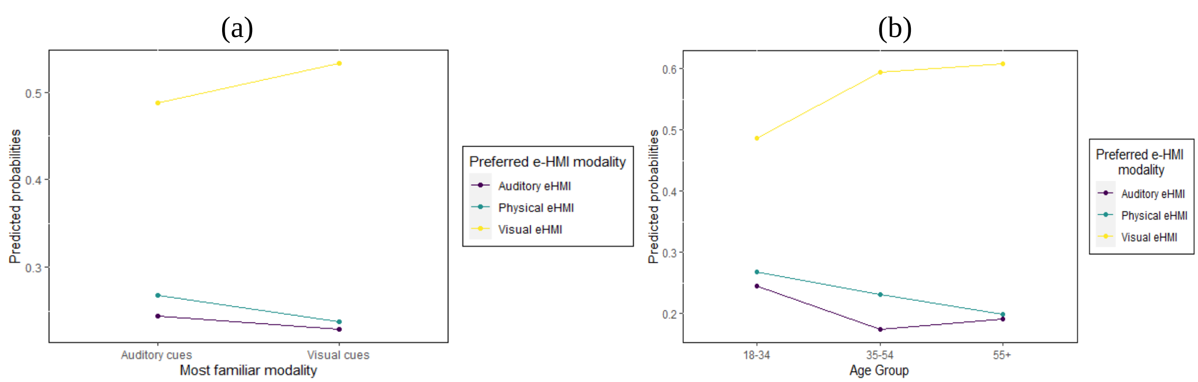


Figure 31: Predicted probabilities plot for e-HMI modality as a function of (a) most familiar cue modality (b) age group

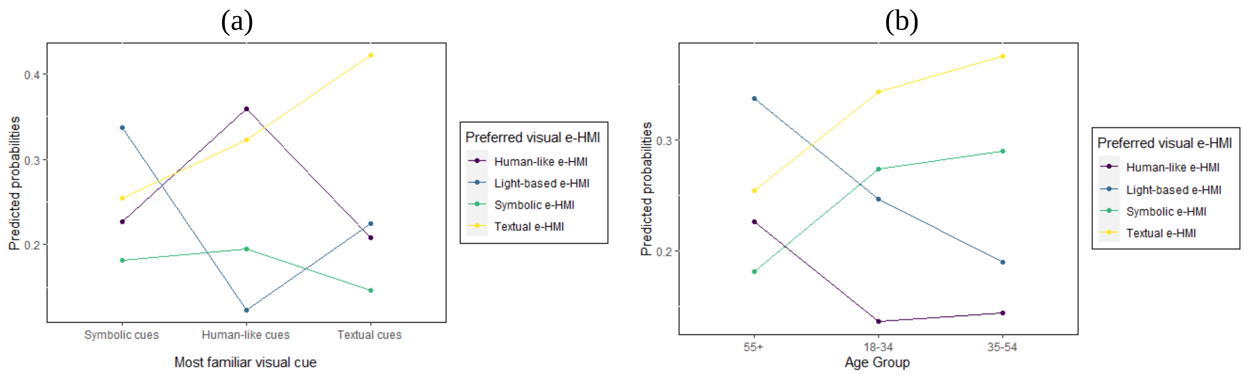


Figure 32: Predicted probabilities plot for e-HMI visual types as a function of (a) most familiar visual cue (b) age group

4.3 Discussion

Our findings revealed that advisory cues from drivers had the most significant influence on pedestrians' crossing decisions. Notably, non-conservative pedestrians showed lower reliance on these cues while exhibiting more violations and aggressive behavior. Moreover, pedestrians were most familiar with visual cues, especially those from traffic signals, trusting them more than cues from drivers or vehicles. Among standardized visual cues, they demonstrated highest familiarity with symbolic cues. In their interactions with AVs, pedestrians preferred dynamic visual interfaces installed on road infrastructure conveying Awareness, Intent, or Advice information. These preferences aligned with the findings from the experts' survey results, except for two notable differences. First, while the general population highly regarded Advice-based e-HMI, experts ranked it as one of the least important and associated it with the highest frequency of concerns. Second, while the general population exhibited higher trust in receiving cues from e-HMIs located on road infrastructure than on AVs, experts perceived e-HMIs placed on AVs to be more effective than those on road infrastructure.

Pedestrians' preferences for specific e-HMI attributes were found to be influenced by their interactions with HDVs. Pedestrians prioritizing advising cues assigned significantly higher importance to Advice-based e-HMI compared to those prioritizing other cues. Moreover, pedestrians’ familiarity with textual cues in their interaction with HDVs appeared to strongly influence their preference for textual e-HMIs over symbolic e-HMIs. Similarly, a stronger familiarity with symbolic than with textual cues seemed to impact pedestrians’ inclination towards preferring symbolic and light-based e-HMIs over textual e-HMIs. Additionally, individuals placing greater trust in cues from traffic signals expressed higher trust levels in infrastructural e-

HMI compared to those relying more on drivers' or vehicles' cues. This sheds light on the importance of examining HDV-to-pedestrian interactions in different socio-cultural contexts to develop compatible e-HMIs.

Individual differences were evident in pedestrians' e-HMI preferences. Younger adults expressed less favorability towards Awareness, Intent, and Advice e-HMI information types compared to other adults. Additionally, non-conservative pedestrians showed less inclination towards Advice-based e-HMI compared to conservative counterparts. This variation in preferences could be attributed to non-conservative pedestrians' reluctance to be directly instructed by AVs, as highlighted by experts. This finding, along with the experts' various concerns about Advice-based e-HMIs, indicates the importance of considering either Awareness-based or Intent-based e-HMIs, with a slight preference for the former based on descriptive statistics.

While the scarcity of auditory and haptic cues in the current transportation system (Berkowsky et al., 2017) could be a contributing factor to respondents' noticeably lower familiarity with auditory cues, younger adults' higher inclination towards auditory and physical e-HMIs relative to other adults could likely be due to their openness to new technologies. On the other hand, seniors may have reduced sensitivity to tactile sensations and vibrations (Gescheider et al., 1994; Campbell et al., 2007).

Additionally, our study highlights that older adults' stronger inclination towards preferring light-based and human-like visual e-HMIs over textual and symbolic visual e-HMIs, which aligns with Pak et al.'s (2012) work hypothesizing older adults' higher trust in anthropomorphic cues compared to younger adults. Furthermore, the relatively lower preference for textual cues among older adults could be related to higher cognitive load and lower visibility compared to other cue representations. This aligns with Verma et al.'s (2019) findings; their participants emphasized the importance of employing straightforward representations, like icons and pictographs, instead of text, to ensure comprehensibility and reduce cognitive burden for pedestrians. Additionally, visually impaired individuals find textual cues more challenging and less clear (Ouali et al., 2022), potentially causing older adults, who are more susceptible to visual impairments, to face additional difficulties in interpreting such cues.

Despite road infrastructure being the most preferred location for e-HMI, it is noteworthy that older adults exhibited lower trust in that particular e-HMI install-location compared to the two other age groups. These findings, combined with experts' preference for vehicular e-HMIs over infrastructural e-HMIs, underscore the importance of installing e-HMIs on road infrastructure and AVs simultaneously to cater to the needs of all pedestrians.

4.4 Limitations

First, survey studies make it difficult to eliminate biased responses and to achieve superior data quality. Despite the validation checks and the data scrubbing techniques we implemented, there was still a possibility for some randomized and inconsistent answers. Second, the general population survey did not include explanatory open-ended questions. Therefore, the ability to draw causal inferences and justifications to participants' selections was limited. Future survey-based studies should elicit respondents' qualitative data to support quantitative results through the inclusion of open-ended questions. Third, the number of respondents in the expert survey was also another limitation to our study, particularly the imbalance in the differing expert sectors (academia, OEM, government, etc.). This uneven representation might have caused some sector-specific insights to be over- or under-emphasized. Future research should aim for a larger and a further balanced sample to enhance the validity and reliability of the conclusions.

4.5 Conclusion

As a summary, this study has established the first step of understanding pedestrians' preferences and interactions with AVs and e-HMIs, as compared to those from experts. The findings emphasize the importance of considering diverse user demographics, distinct attitudes, and current interactions with HDVs to design effective and efficient e-HMIs. The road to fully integrating AV technologies into our transportation system requires careful consideration of pedestrians' perceptions, attitudes, and comfort levels with different e-HMI attributes. As we move forward, additional research in this field is needed to refine e-HMI designs, ensure better usability and acceptance of AV technologies across diverse user groups by involving users of different age groups and fields in this process.

Chapter 5 An Evaluation of Vehicular E-HMI Design on Pedestrians' Trust and Situation Awareness Under Dynamic Environment

In this phase of the study, we integrated the findings from the previous phases including literature review, crash data analysis, and the two surveys to develop and evaluate e-HMI prototype solutions. In particular, we are interested in examining the impact of these e-HMI prototypes on pedestrians' human information processing model through examining the impact of different e-HMI solutions on the different phases of the human information processing model. Situation awareness, being the first phase, can be measured through queries directly related to the components of pedestrians' crossing scenarios in front of AVs (Endsley, 1995). The decision-making phase can be assessed through risk evaluation translated into subjective trust measures. These subjective trust measures can be further validated through collecting trust behavioral measures in pedestrians' decision execution phase (Rasouli et al., 2017; Rothenbücher et al., 2016).

In their interaction with automated vehicles in the presence of e-HMIs, pedestrians might suffer from instances of distrust or over-trust. While pedestrians' distrust in AVs might lead to pedestrians' hesitant and overly cautious crossing behavior (Dey et al., 2019; Reig et al., 2018), pedestrians' over-trust in AVs might lead to hazardous crossing behavior and increased risk of crashes (Faas et al., 2021; Kaleefathullah et al., 2020). Therefore, the objective of this phase is to explore potential instances of pedestrians' distrust and over-trust in AVs, to examine its impacts on pedestrians' situation awareness and decision-making, and to provide scalable e-HMI solutions capable of improving pedestrians' situation awareness and calibrating pedestrians' trust to avoid unintended safety and efficiency consequences under real traffic conditions.

5.1 Experiment 1- Signalized intersection Scenario

Most of the developed solutions have focused on studying the effectiveness and usefulness of vehicular e-HMIs (i.e., e-HMIs located on AVs) and their impact on pedestrians' trust, perceived safety, comfort, and satisfaction. However, there has been very little research evaluating the impact of infrastructure-based e-HMIs (i.e., e-HMIs located on infrastructure) on pedestrians' various aspects. In this context, a study by Dey et al. (2020) reviewed 70 different e-HMI concepts, out of which 51 concepts were in the form of vehicular e-HMI whereas only one concept was in the form of an e-HMI physically placed on the road infrastructure. Moreover, most research has focused on examining vehicular e-HMIs at uncontrolled marked crosswalks or at unsignalized intersections (Clamann et al., 2017; Habibobic et al., 2018; Velasco et al, 2019; Rad et al., 2020). This leaves a gap in understanding how infrastructure-based e-HMIs might interact with vehicle-based e-HMIs. Moreover, results from our general population survey showed that pedestrians' perceived trust in receiving cues from vehicular e-HMIs and infrastructural e-HMIs (in the form of traffic signals) to be equally the same (non-significantly different). However, experts' survey results showed that vehicular e-HMIs are preferred over infrastructural e-HMIs. Therefore, it is important to examine whether the presence of vehicular e-HMIs optimizes pedestrians' levels of trust in the presence of traffic signals.

In this regard, the presence of traffic signals provides a clear and structured system for pedestrian movement. However, while traffic signals establish a predictable pattern of the right-of-way and enhances pedestrians' trust in the overall traffic environment including HDVs and AVs, several studies have shown that pedestrians often continue to monitor the oncoming traffic despite their clear right-of-way. For example, the majority of pedestrians were observed looking at oncoming traffic before and during the crossing task while crossing on the green-man phase at two different signalized intersections (Hamidun et al., 2016). In an outdoor experiment at a plus-shaped signalized intersection, participants were instructed to cross only after the pedestrian traffic light turns green under both distracting and undistracting conditions (Jiang et al., 2018). Upon analyzing fixation time and points before their crossing onset, pedestrians were found to equally monitor the traffic signals and oncoming traffic from both directions. Gruden et al. (2021) also confirmed that oncoming cars from the left and right directions were among the areas of interest that participants checked constantly before crossing at a signalized intersection. In a similar manner, 91% of observed adults accompanied by children checked the oncoming traffic to ensure it had stopped at signalized crosswalks after they pushed the green light button (Zeedyk & Kelly, 2003). Moreover, signalized crosswalks may be perceived by pedestrians as indicators of higher danger compared to unsignalized ones. Therefore, the presence of traffic signals can be seen as a cautionary cue, potentially influencing pedestrians' decision-making while crossing (Tom &

Granié, 2011). All these studies provide evidence that in the presence of traffic lights, pedestrians still need to ensure that vehicles will be yielding as expected either due to safe crossing habits or due to fears from drivers' non-compliance with traffic rules or malfunctions. Therefore, pedestrians' reliance on traffic signals can be limited, causing them to seek additional visual confirmation from traffic. Reflecting on these interaction patterns between pedestrians and HDVs at signalized intersections or crosswalks, the need to check for oncoming traffic underscores the significance of designing for vehicular e-HMIs that will account for pedestrians' natural tendency to ensure their safety in the presence of traffic signals.

However, more factors are also at the essence of pedestrians' lack of appropriate levels of trust in AVs, regardless of being at regulated crosswalks. Due to lack of confidence in the capabilities of AVs, pedestrians might exhibit excessive caution when AVs are present, leading to hesitancy in crossing the streets. Jayaraman et al. (2019) presented a case of pedestrians' distrust in AVs when the AV was driving aggressively. Similarly, Dey et al. (2021b) showed pedestrians' decreased willingness to cross when the AV shifted from "gentle" or "early" brake condition to "aggressive brake" and "constant speed" conditions, despite the presence of an e-HMI. Pedestrians' distrust in AVs might also occur as a result of pedestrians' poor knowledge in AVs prior to any actual interaction (Velasco et al., 2019, Rahman et al., 2021, Reig et al., 2018). In addition to that, the absence of communication cues from the AV was found to diminish pedestrians' trust and trusting behaviors. In Hollander et al. (2019), pedestrians expressed low levels of trust and increased decision-making times in the absence of an e-HMI as compared to its presence.

For this purpose, we designed a virtual reality (VR) based experiment to examine pedestrians' interaction with AVs and vehicular e-HMIs in the presence of pedestrian traffic signals at a four-way signalized intersection. This study aims at examining the effect of the presence of different sources of cues on pedestrians' trust, situation awareness (SA), and workload, especially under different driving styles. To the best of our knowledge, the interaction of pedestrians with AVs under dynamic traffic conditions and in the presence of both vehicular e-HMIs and traffic signals has not been examined before. In this experiment, we collected different subjective, objective, and physiological indicator measures for a group of participants. Upon the application of different statistical models, results will serve to determine whether vehicular e-HMIs are effective, efficient, and safe when traffic signals exist under dynamic conditions. This study allowed us to examine four main hypotheses:

H1: The addition of vehicular e-HMIs at signalized intersections increases pedestrians' trust even during AV's conservative driving behavior.

H2: The addition of vehicular e-HMIs at signalized intersections reduces pedestrians' distrust in AVs with the improvement being higher under aggressive driving conditions than under normal driving conditions.

H3: The presence of vehicular e-HMIs increases pedestrians' awareness of AV's intentions.

H4: Vehicular visual cues similar to those on traffic signals result in lower workload as opposed to dissimilar cue configuration.

5.1.1 Method

Participants: We initially planned to recruit a total of 36 individuals, while ensuring a balance in gender and age representation. The targeted age ranges were: (1) the younger adult group aged 18 to 34, the middle adult group aged 35 to 54, and the older adult group aged 55 or older. This indicated the recruitment of six participants for each gender-age group combination. However, females in the older adult age group exhibited very low participation interest rate, and consequently, only three participants were secured from that group. As a result, 33 participants were considered in this study (18 males and 15 females; younger adults age= 24.67 ± 2.77; middle adults age= 40.74 ± 3.25; older adults age= 63.11 ± 4.01). Participants were sampled from the pool of students and employees from the University of Michigan-Dearborn in addition to another recruitment pool of adults. The experiment obtained the necessary approval from the University of Michigan Institutional Review Board (HUM00232408).

Apparatus: This experiment was carried out in a laboratory setting at the University of Michigan- Dearborn within a VR environment. The VR setup consisted of an HTC Vive Pro Eye headset (Taoyuan City, Taiwan) which provides a 110 degrees field of view. The headset was accompanied by: (1) two base stations for accurate location tracking and (2) two hand controllers for wireless interaction with VR. In addition to that, the setup employed the eye tracking system integrated into the headset. The system, as powered by Tobii (Stockholm, Sweden), enabled the collection of different eye-tracking measurements at a sampling rate of 120 Hz. Furthermore, the scenarios projected into the VR were created using 3D Unity game engine (San Francisco, California, USA). As for the 3D models depicting the e-HMI visual cues, these were created using

Rhino (Seattle, Washington, USA). Moreover, Qualtrics (Provo, UT, www.qualtrics.com) was utilized as the platform to administer a survey designed to collect participants' self-reported measures.

Procedure: Six different scenarios were designed at a four-lane four-way signalized intersection (two lanes in each direction). The selection of this traffic-controlled location was based on elevated safety concerns at signalized intersections being a site for increased pedestrian-vehicle conflicts and injury risks (Bradbury et al., 2012; Stipancic et al., 2020). In each scenario, a participant, acting as a pedestrian, will have to wait at the edge of the crosswalk until the pedestrian traffic signal yields the right of way (ROW) for them. Just after the pedestrian traffic signal grants the ROW to pedestrians, the participant encounters an AV approaching from the nearest lane as depicted in Figure 33. The AV will eventually adhere to the traffic rules and give the ROW to pedestrians by coming to a full stop before the crosswalk. Dummy vehicles were included in the scenarios to simulate real-traffic flow during periods when vehicles had the ROW. Similarly, vehicles' engine sounds were considered as part of the scenario to simulate a real-traffic environment. Besides, the participant was instructed to perform two tasks: (1) designate the time at which they first realize that the AV started to slow down through a keyboard button press and (2) indicate their onset of crossing the street through another keyboard button press. A screenshot of the VR environment as developed in Unity is shown in Figure 34. In four scenarios, the AV was equipped with an external display located at the level of its windshield, and the displayed cues varied between textual intent-based e-HMIs and symbolic advice-based e-HMI. The cues were selected based on the similarities and differences obtained from the conducted expert and general population surveys. In the remaining two scenarios, the AV had no e-HMI. On top of that, the stopping behavior of the AV differed from one scenario to another: scenarios were split between conservative and aggressive stopping behaviors. The driving profiles were designed in consistency with previous works. A speed of 13.4 m/s was adopted for the conservative driving style whereas a speed of 15.6 m/s was adopted for the aggressive driving style (Jayaraman et al., 2019; Dey et al., 2021). As for the deceleration rates, 0-3 m/s^2 and 5-9 m/s^2 were considered for the conservative and aggressive driving styles respectively (Jayaraman et al., 2019; Abdulwahid et al., 2022). Accordingly, the AV would stop closer to the crosswalk under its aggressive slowing behavior as compared to its conservative behavior.

Moreover, the participant completed a Simulator Sickness Questionnaire (SSQ) (Kennedy et al., 1993) to monitor any potential risk for motion sickness; the SSQ was administered once after the completion of three scenarios.

At the end, the participant completed a post-experiment interview with questions related to the importance of vehicular e-HMIs relative to traffic signals, their preference for the source of cues (vehicular e-HMIs versus infrastructure-based e-HMIs), and their preference for the type of cues on the vehicular e-HMIs.

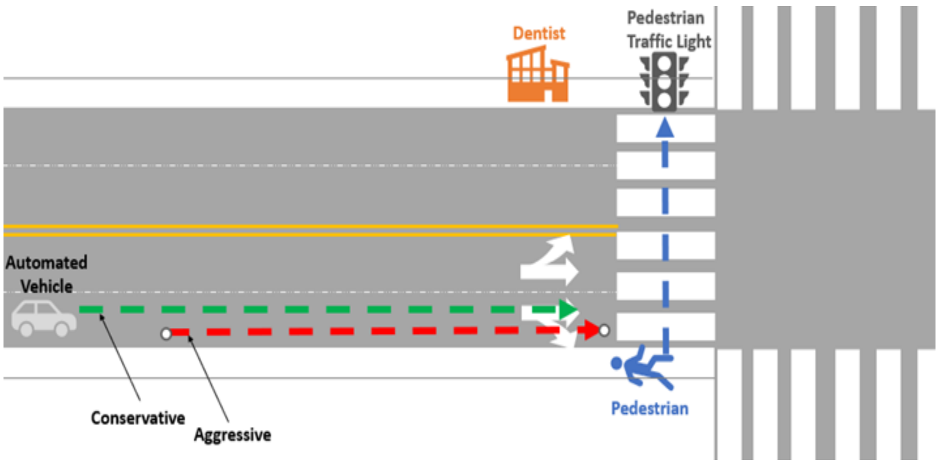


Figure 33: Scenario configuration for Experiment 1

Figure 34: VR traffic environment developed in Unity

Independent variables: The study implemented a within-subject design with two independent variables. The first factor was the vehicular e-HMI with three levels: absent, present with cues like those on pedestrian traffic signals (Figure 35), and present with cues different than those on pedestrian traffic signals (Figure 36). Cues similar to the traffic signal designated a red standing hand and a white walking silhouette. Cues different than those of the traffic signal were textual cues displaying the AV's intent. The second factor was the driving style of the AV, being of two levels: conservative and aggressive. As a result, each participant experienced a total of six different scenarios, however, with an order based on a Balanced Latin square design (Edwards, 1951).

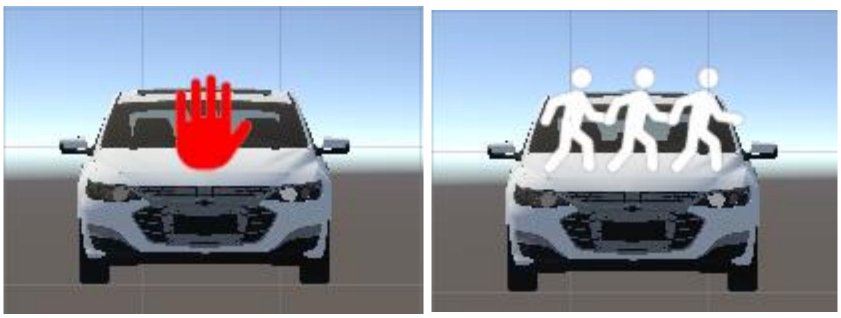


Figure 35: Vehicular e-HMI cues similar to pedestrian traffic signal

Figure 36: Vehicular e-HMI cues different from pedestrian traffic signal

Participants' involvement: Before the experiment started, participants read and signed the consent form. After that, they completed a pre-experiment questionnaire with questions related to demographics (age, gender, race, highest degree completed), level of knowledge in Automated Driving Systems, previous interaction with ADS, and their general perceived trust in AVs and in different cues they rely on during their interaction with HDVs. After that, they were given the instructions and scenario descriptions:

"As a pedestrian, you will be standing at the edge of a crosswalk at a four-way signalized intersection and will be waiting to cross the street to catch up with your dentist appointment. Please try to follow the traffic rules governing the signalized intersection through adhering to traffic lights. By the time the traffic lights give you the ROW, you will be approached by an AV in its driverless mode. During some trials, this AV will be equipped with an external display (e-HMI) which will communicate with you through different types of cues. The e-HMI is positioned at the level of the AV's windshield. When feasible, you are supposed to complete two tasks:

1.Press the target keyboard button the moment you realize that the AV has started to slow down.

2.Press the same button again when you feel it is convenient for you to start crossing.

After you conclude each trial by expressing your onset of crossing, you will be entitled to answer a set of questions pertaining to that scenario".

Dependent variables: We collected several response measures related to pedestrian's situation awareness, workload, and trust.

For situation awareness, we collected two measures being: (1) the yielding onset latency being the absolute difference between the AV's actual deceleration onset and the participant's recognition of the AV's deceleration onset; and (2) the clarity of the AV's stopping intent (on a 5-point Likert scale).

For workload, we collected two dependent measures: (1) a physiological measure being the change in pupil diameter in order to measure visual and cognitive workload; (2) a subjective measure being the Mental demand and the Frustration dimensions from the NASA TLX (Hart & Staveland, 1988), rated on a scale from 0 (very low) to 100 (very high).

As for trust, we collected both subjective and objective behavioral measures. For the subjective measure, we adopted Jian et al.'s Checklist for Trust (2000), one of the most cited self-reported measures for Trust in Automation (Kohn et al., 2021). The advantage of using this checklist is that it consists of unique items to assess trust and distrust at the same time. The original items were adjusted for clarification and scenario tailoring. The participants had to select the extent that best describes their impression towards the items on a 7-point Likert scale. As for the objective behavioral measure, we considered the onset of crossing with respect to the AV's full stop.

5.1.2 Data Analysis and Preprocessing

Data Preprocessing: The Distrust score was calculated as the average of its five items. Similarly, the Trust score was determined by averaging its five items.

As for the change in pupil diameter, the preprocessing involved several steps: In the first step, all invalid records were removed. In the second step, the average pupil diameter at each timestamp was calculated by considering the mean coordinates of the left and the right eye. In the third step, a moving average was applied to smooth the data and remove noisiness. This step was followed by removing outliers through excluding unlikely pupil diameter values upon visualizing the data distribution. By identifying the task-evoked period (post-stimulus; time between the onset of interaction with the AV as determined by the position of the AV in the scenario and the onset of crossing) and the baseline period (pre-stimulus; which preceded the onset of interaction), data was aggregated to determine the average pupil diameter in each period. To enable adequate comparisons between the subjects, the percentage change in pupil diameter was calculated as the difference between the pupil diameter in the two periods divided by the pupil diameter in the baseline period. This process was repeated across all treatment conditions and for all subjects.

Data Analysis: Given that the study utilized a within-subject design with two independent variables, we opted to employ two-way Repeated Measures Analyses of Variance (ANOVA) to test for main and interaction effects on all dependent measures. In the case of significant main or interaction effects, we derived pairwise comparisons of estimated marginal means to identify statistically significant different pairs of factor levels. While Repeated Measures ANOVA is known to be generally robust against the violation of the normality assumption (Blanca et al., 2023), we also employed the Aligned Rank Transform for non-parametric factorial ANOVA (ARTool) (Wobbrock et al., 2011) in case of residuals' non-normality. When the ANOVA and ARTool produced consistent results, we reported the ANOVA results. In instances of discrepancies (observed in the case of strong violation of the normality assumption), we performed data transformation so as to satisfy the normality assumption of residuals. In these cases, the ANOVA outcomes of the transformed data were aligned with the ARTool outcomes of the original data, and therefore, we reported the ARTool results for simplicity. Like ANOVA, we relied on contrasts of estimated marginal means to identify significantly different pairs. These pairwise comparisons were adjusted using Tukey method.

Due to the nature of eye tracking data, some values were omitted due to data invalidity. Therefore, the change in mean pupil diameter was analyzed using linear mixed effects model which can handle unbalanced and missing data. Analysis was conducted in R studio environment while employing cars, emmeans, ARTool, and lme4 packages.

5.1.3 Results

Situation Awareness (SA): ANOVA results captured a significant interaction effect between the e-HMI and the driving style (*$F(2,64)=8.58$; $p<0.001$; $\eta^2=0.035$*) on top of their significant main effects (*e-HMI: $F(1.6,51.34)=18.31$; $p<0.001$; $\eta^2=0.187$; driving style: $F(1,32)=39.96$; $p<0.001$; $\eta^2=0.140$*). Pairwise comparisons further revealed that, comparing to no vehicular e-HMI, the addition of any type of vehicular e-HMI significantly increased pedestrians' SA during both aggressive (*symbolic: $p_{adj}<0.001$; textual: $p_{adj}<0.001$*) and conservative (*symbolic: $p_{adj}=0.034$; textual: $p_{adj}=0.001$*) driving styles. However, the impact of adding a symbolic e-HMI was greater during the aggressive than during conservative as revealed by the differences of differences (Figure 37).

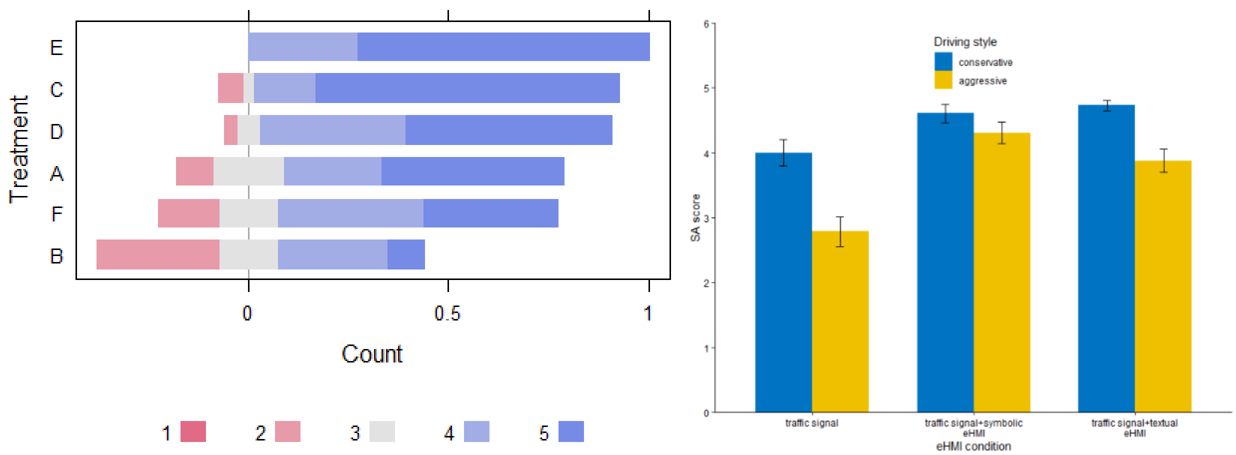


Figure 37: (a) Distribution of situation awareness of AV deceleration, color-coded by user rating ranging from "1: extremely unclear" to "5: extremely clear"; Treatment conditions, as a combination of e-HMI style and driving style, are "A: no e-HMI (conservative)", "B:no e-HMI (aggressive"), "C:symbolic e-HMI (conservative)", "D:symbolic e-HMI (aggressive)", "E:textual e-HMI (conservative)", "F:textual e-HMI (aggressive)". (b) Mean situation awareness across treatment conditions Bars correspond to standard errors

Trust score: According to ANOVA, both the e-HMI and the driving style had significant main effects (*e-HMI: $F(2,64)=12.95$; $p<0.001$; $\eta^2=0.078$; driving style: $F(1,32)=92.11$; $p<0.001$; $\eta^2=0.263$*). However, these effects were accompanied by a significant interaction effect (*$F(2,64)=5.78$; $p=0.005$; $\eta^2=0.020$*). Comparing to no vehicular e-HMI, both the symbolic and textual vehicular e-HMIs increased pedestrians' trust in AVs under the aggressive slowing behavior (*symbolic:* $p_{adj}<0.001$; *textual:* $p_{adj}=0.004$), while only the addition of the textual e-HMI was found to increase pedestrians' trust under the conservative behavior ($p_{adj}=0.013$) (Figure 38a).

Distrust score: Due to the data's prominent violation of the normality assumption, ARTool was run on the original data. Its results were consistent with ANOVA results on the transformed data. According to ARTool, the e-HMI and the driving style exhibited significant main effects (*e-HMI:* $F(2,160)=15.88$; $p<0.001$; *driving style:* $F(1,160)=131.14$; $p<0.001$) along with a significant interaction effect ($F(1,160)=11.62$; $p<0.001$). The pairwise comparison of the estimated marginal means further indicated that only the addition of the symbolic e-HMI in the presence of the traffic signal reduced pedestrians' distrust in AVs while stopping aggressively ($p_{adj}<0.001$) (Figure 38). However, pairwise comparisons showed that despite this reduction, the distrust in AVs during the control condition (no e-HMI; conservative driving style) was still significantly lower than distrust upon the addition of vehicular e-HMI under the aggressive slowing behavior.

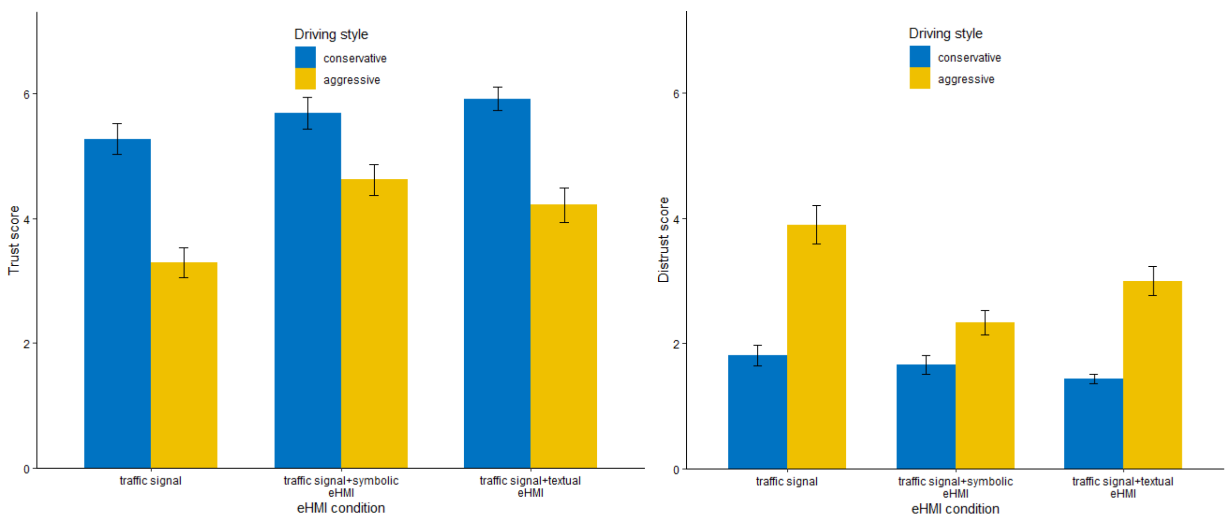


Figure 38: (a) Mean trust score (b) Mean Distrust score
Bars correspond to standard errors

Workload: For the NASA TLX mental workload, the interaction between the e-HMI and the driving style was also found to be significant ($F(2,64)=3.99$; $p=0.023$; $\eta^2=0.019$) besides their significant main effects (*e-HMI:* $F(2,64)=5.15$; $p=0.008$; $\eta^2=0.032$; *driving style:* $F(1,32)=47.01$; $p<0.001$; $\eta^2=0.129$). The subsequent pairwise comparisons indicated that only the addition of a symbolic e-HMI in the presence of the traffic light was capable of significantly reducing pedestrians' mental workload under the aggressive driving behavior ($p_{adj}=0.005$) (Figure 39a). The effect of adding the textual vehicular e-HMI, however, was only marginally significant ($p_{adj}=0.058$).

As for the NASA TLX frustration scale, both the main effects and interaction effect of the e-HMI and the driving style yielded significant outcomes using ARTool (*e-HMI:* $F(2,160)=8.33$; $p<0.001$; *driving style:* $F(1,160)=95.26$; $p<0.001$; *interaction:* $F(2,160)=6.26$; $p=0.002$). Accordingly, the pairwise comparison of marginal means also demonstrated that the addition of the symbolic e-HMI only reduced pedestrians' frustration particularly under the aggressive slowing behavior (Figure 39b).

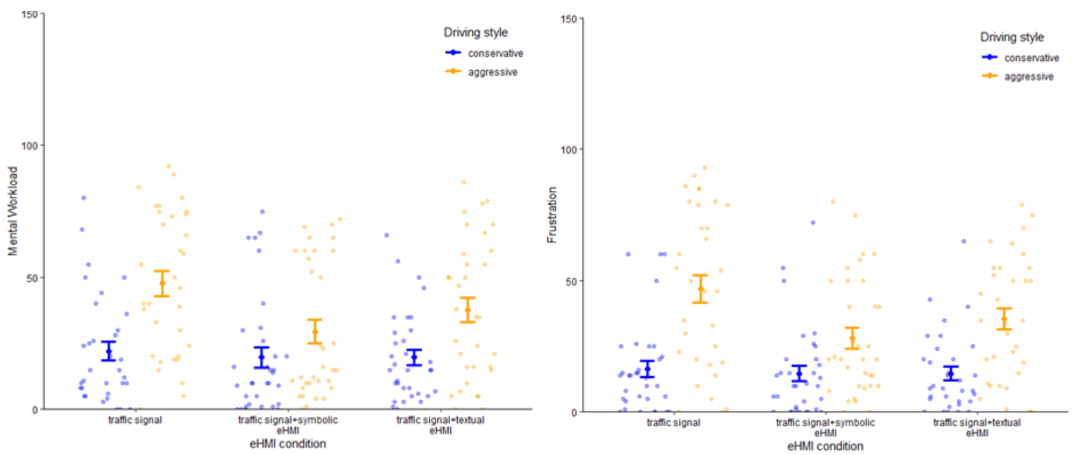


Figure 39: (a) Mean of Mental Workload (b) Mean of Frustration
Bars correspond to standard errors

Mean pupil diameter change: The mixed linear model results demonstrated a significant main effect of the e-HMI ($X^2=9.34$; $p=0.009$) on the change in mean pupil diameter. More specifically, the pairwise comparisons of the estimated marginal means uncovered a significant difference between the presence of the traffic signal on one end and the addition of either the symbolic vehicular e-HMI ($p_{adj}=0.036$) or the textual vehicular e-HMI ($p_{adj}=0.019$). Nevertheless, there was no significant difference between the addition of the symbolic and the textual e-HMI. The significant differences confirmed lower mean pupil diameter change upon the addition of any vehicular e-HMI (*symbolic:* $M=0.037$; $SD=0.058$; *textual:* $M=0.034$; $SD=0.046$) as compared to the presence of the traffic signal alone (M=0.058; SD=0.049) under any driving behavior (Figure 40).

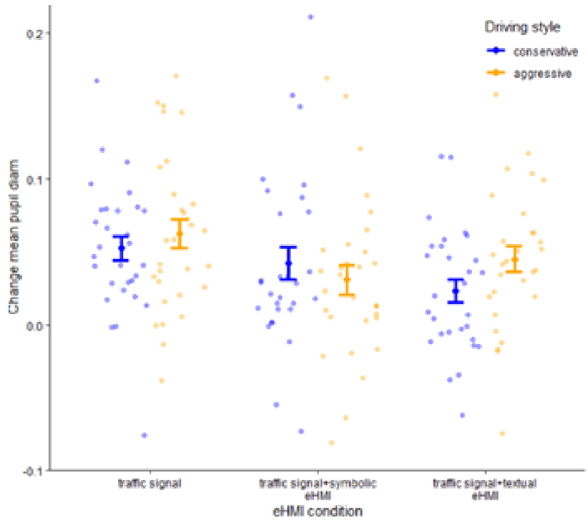


Figure 40: Mean of change in mean pupil diameter
Bars correspond to standard errors

Yielding onset latency: ANOVA did not detect a significant main effect for the e-HMI on yielding onset latency. It only detected a significant main effect for driving style (*F(1,32)=6.70; p=0.014;* η^2*=0.050*) with the latency being significantly lower for the aggressive driving style (*M= 1.03, SD=0.56*) than for the conservative (*M=1.39, SD=0.97*) (Figure 41a).

Onset of crossing (w.r.t. AV's full stop): ANOVA detected a significant main effect for both the e-HMI (*F(2,64)=5.42; p=0.007* η^2*=0.023*) and the driving style (*F(1,32)=12.58; p=0.001;* η^2*=0.064*) on pedestrians' waiting time. The pairwise comparison showed that the waiting time was significantly lower in the presence of the symbolic vehicular e-HMI (*M=-0.13, SD=1.16*) compared to its absence (*M=0.23, SD=1.02*). Similar to reaction time, the pedestrians' waiting time was significantly shorter under conservative driving conditions (*M=-0.18, SD=1.27*) than under aggressive (*M=0.41, SD=1.02*) (Figure 41b).

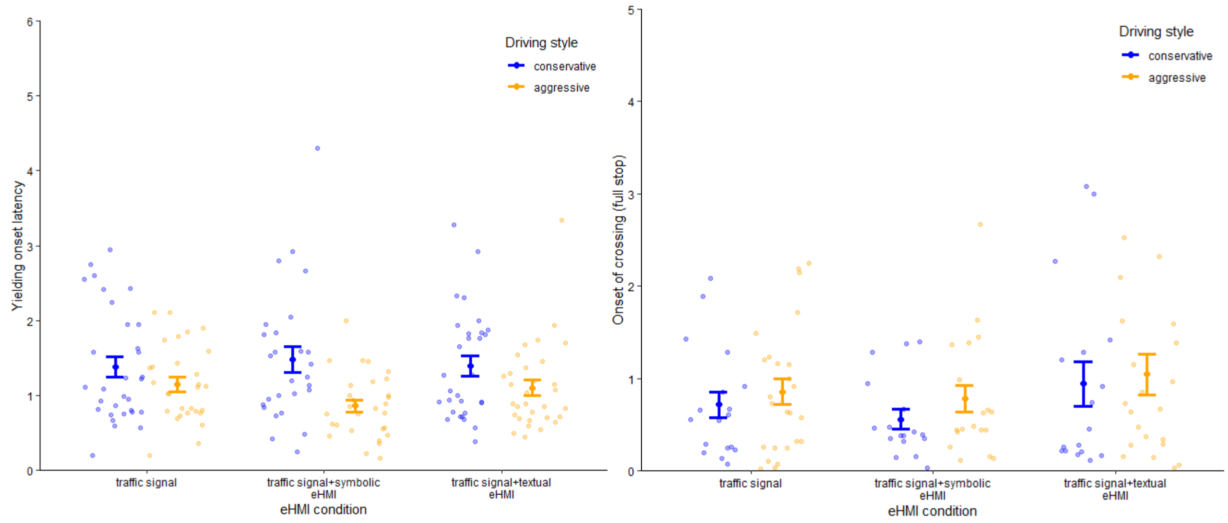


Figure 41: (a)Mean of yielding onset latency (b)Mean of onset of crossing
Bars correspond to standard errors

5.1.4 Discussion

SA: As expected, the perception of cues from vehicular e-HMIs on top of those coming from traffic signals enhanced pedestrians' comprehension of the AV's intent under the differing stopping behaviors. This indicates that even under a defensive stopping behavior, pedestrians still require a confirmatory cue from the AV to compensate for the absence of the driver. However, it is important to note that the enhancement was relatively higher upon adding these confirmatory cues during the AV's aggressive driving behavior.

While adding vehicular e-HMIs did not seem to enhance pedestrians' perception of the actual onset of the AV's deceleration, this setback could be related to participants' distraction by the appearance of the visual cues. Participants' distraction might have caused a delay in participants' task (reaction time) to report their recognition of the AV's onset of deceleration, impeding the e-HMI's improvement to the yielding onset latency. Additionally, the improvement in the yielding onset latency under AV's aggressive driving style, as compared to its conservative driving style, could be related to distance-related issues. Since conservative AVs started to yield at a farther distance as compared to aggressive AVs, it could have made it difficult for pedestrians to perceive their onset of yielding due to visibility issues.

Trust & Distrust scores: Results showed that the addition of a vehicular e-HMI generally improved pedestrians' trust in AVs, although the improvement was higher under the aggressive driving style. Nevertheless, the addition of a vehicular e-HMI was only capable of mitigating the effect of the aggressive slowing behavior on pedestrians' distrust in AVs. These distinct results highlight the importance of considering distrust as a separate construct from trust in evaluating the interaction between AVs and pedestrians (Sumpf, 2019). In this regard, Luhmann distinguished between trust and distrust by considering "no trust" as the lack in the expectation of a positive future course and distrust as the expectation of a negative future course. This distinction justifies why the addition of vehicular e-HMIs did not impact pedestrians' distrust under the conservative driving style, as such scenarios were not associated with negative outcomes or vulnerabilities. Therefore, there existed no room for e-HMIs to reduce distrust when AVs decelerated conservatively. On the other hand, vehicular e-HMIs demonstrated a potential for enhancing pedestrians' trust even under a conservative slowing behavior. This indicates that the addition of vehicular e-HMIs was perceived positively irrespective of any concern. In the structured interviews, several participants declared that vehicular e-HMIs reinforced the cues delivered by the traffic signal. Even though they knew the AV would stop because of the traffic light, they still appreciated the presence of these cues. Consequently, despite the presence of the traffic signal, there was still room to improve pedestrians' trust in AVs upon the addition of the e-HMI. This stems from pedestrians' constant search for additional reassurance from oncoming traffic before crossing to foster their feeling of security. These findings align with previous studies investigating pedestrians' behaviors at signalized intersections and crosswalks and demonstrating pedestrians' gaze at oncoming traffic before crossing even during the green-man signal (Hamidun et al., 2016; Jiang et al., 2018).

Interestingly, only the addition of a symbolic vehicular e-HMI reduced pedestrians' distrust while the addition of a textual e-HMI did not alter it. This finding could be linked to symbols' adverse effects on pedestrians' processing of the AV's driving style. More specifically, symbols distracted the participants from focusing on the AV's aggressive stopping behavior, thus offsetting its negative effect. This is analogous to Alon-Barkat's (2020) findings on symbols' reduction to citizens' distrust in weak and unpersuasive policy plans. The ineffectiveness of the textual e-HMI, on the other hand, could be linked to e-HMI's synchronization with the AV's movement making its aggressive behavior even more prominent.

Workload: The addition of the symbolic vehicular e-HMI was also at the essence of reducing pedestrians' both mental workload and frustration under the AV's aggressive driving behavior according to NASA TLX employed items. Again, the higher influence of the symbolic e-HMI as compared to the textual e-HMI could be attributed to the former's favorable features. Based on the social psychology theory, symbols can disrupt the process of elaborating on information through distracting participants and capturing their attention and thus their mental effort (Massaro et al., 1986). Moreover, symbols often induce a positive mood which in return impairs negative information processing while striving to maintain this positive mood. These phenomena could explain the symbolic e-HMI role in reducing self-reported mental workload, frustration, and distrust under the AV's aggressive conditions.

On the other side of the coin, pedestrians' self-reported mental workload and frustration levels were not altered upon the addition of the vehicular e-HMI during the AV's conservative driving condition. The inherently defensive driving style might have already made pedestrians feel safe, so the e-HMI did not significantly change their mental workload. Moreover, the presence of redundant cues from the traffic signal and the absence of contradictory behavioral cues from the AV's movement might have also resulted in maintaining the same level of mental workload.

Notably, while the self-reported mental workload highlighted the effectiveness of the symbolic vehicular e-HMI under the aggressive stopping behavior only, the change in mean pupil diameter highlighted the effectiveness of both types of vehicular e-HMIs under the differing stopping behaviors. Firstly, these results suggest that the absence of any vehicular e-HMI, as compared to its presence, caused a higher dilation in the pupil diameter relative to the baseline period even during the AV's conservative behavior. Regardless of the AV's driving style, participants continued to practice increased vigilance; without the vehicular e-HMI, pedestrians might have felt less certain about the vehicle's intentions, leading to heightened alertness and scrutiny and thus to increased eye pupil diameter.

Although symbolic cues are more intuitive and less mentally demanding than textual cues, the average change in mean pupil diameter was non-significant between them. In this regard, pupil diameter is not solely affected by mental workload; it is also affected by light conditions and emotional responses (Näätanën, 1992). In our study, the symbolic cues were presented in red (standing hand) and white (walking man) colors, while the textual cues were presented in blue. In a previous study investigating the workload of different colors on employee performance, blue color introduced the lowest stress levels as compared to red and white (Ruwana et al., 2020). Therefore, the balance between the lower cognitive demand and higher stress levels associated with symbolic cues and between the higher cognitive demand and lower stress levels associated with the textual cues might explain the non-significant difference in the change of mean pupil diameter when comparing the two types of cues.

5.2 Experiment 2- Midblock Scenario

As shown earlier, most of the research dedicated to examining the influence of e-HMIs on the communication between AVs and pedestrians has been done at ambiguous crossing situations, such as mid-block and parking lot crossing scenarios. The e-HMIs tested in most of these research works displayed either intent information or advice information. However, most of these works have been conducted in simple settings with one vehicle and one pedestrian only. This has led to several concerns related to oncoming traffic imposing critical conflicts. Therefore, more work needs to be done to explore the safety aspect of these e-HMIs under realistic traffic conditions involving more than one vehicle at a time. Some researchers have reported pedestrians' over-trust behaviors in the presence of e-HMIs in the form of less gaze checking the oncoming traffic (Kaleefathullah et al., 2020; Kitazaki & Daimon, 2018; Lee et al., 2021). In particular, Dey et al. (2021b) concluded that intent-based e-HMIs might be misleading especially that they do not provide information about where, when, or for whom the AV is stopping for in the case of multiple pedestrians in the scene. Comparably, advice e-HMIs were regarded as dangerous since other road users (e.g., conventional vehicles) will not necessarily behave in the same way as the host AV (Habibovic et al., 2018). Similarly, Andersson et al. (2017) and Metayer and Couegnet (2021) accused advice e-HMIs of leading to false interpretations of the overall traffic situation, that is, they lead to pedestrians falsely assuming that other vehicles will also stop since the host AV is stopping. Similar recommendations of refraining from communicating advice, instructions, or guidance in scenarios with multiple AVs and HDVs were cited (Hollander et al., 2019; Faas et al., 2020; Tabone et al., 2021; ISO, 2018). These concerns were similar to those reported in experts' responses to open-ended questions in our survey, while trying to explain their perception of advice-based cues as one of the least important information types. Contrary to experts, our general population survey results concluded to advice-based e-HMIs as one of the most important cues especially that respondents were found to be significantly influenced by cues from the driver signaling whether to cross or not (e.g., smile, hand gesture, head nod), in their interaction with HDVs, as compared to other types of cues. For this purpose, we are proposing to add some contextual cues to advice-based e-HMIs in an attempt to alert pedestrians to surrounding traffic while also comparing its effectiveness to intent-based e-HMIs as favored by experts and other studies in literature. To the best of our knowledge, adding contextual information in the form of warnings or cautionary messages at midblock AV-pedestrian interaction locations has not been examined before. Therefore, we conducted a preliminary study in a VR setup to investigate the impact of e-HMI's contextual information on pedestrian's trust levels and situation awareness at the midblock of a straight road. As a result of this study, we will be able to determine optimal e-HMI configurations associated with higher levels of pedestrians' safety and better interpretation of the traffic situation. In this part, we hypothesized that:

H1: The presence of visual vehicular e-HMIs (advice-based and intent-based) affects pedestrians' situation awareness and trust in AVs, impacting trust behavioral measures, as compared to the absence of a visual e-HMI.

H2: Advice-based e-HMI impacts pedestrians' decision-making differently as compared to intent-based e-HMI.

H3: The addition of the auditory contextual cue possesses a calibrating effect on pedestrians' trust and awareness.

5.2.1 Method

Participants: Same participants recruited in Part 1 were also recruited for this part. Therefore, a total of 33 participants were involved in this part.

Apparatus: We used the same VR setup as that used in Part 1.

Procedure: A total of six scenarios were designed at a midblock of a four-lane road (two lanes in each direction) with no crosswalk. The participant, playing the role of the pedestrian, waited at the edge of the sidewalk for their friend to come. It happens that their friend shows up from the other side of the road (Figure 42). When their friend shows up on the other side of the road, the participant had to decide when they would feel comfortable to cross the street to catch up with their friend. The pedestrian was approached by an AV with a normal driving style in the nearest lane just by the time their friend shows up. The AV eventually stopped for the pedestrian at all times. In four of these scenarios, the AV was equipped with a visual e-HMI at the level of its windshield (two scenarios with an advice-based e-HMI and two scenarios with an intent-based e-

HMI); in the remaining two scenarios, the AV had no visual e-HMI. The cues of the advice-based e-HMI were the same as those in Figure 35, while the cues of the intent-based e-HMI was the same as those in Figure 36. Another difference between the scenarios was the presence of a contextual cue in an auditory modality. The purpose of this cue was to remind participants to stay alert if they decided to cross the street, using a verbal message that said, "Please be aware of other oncoming traffic". The contextual cue was introduced once for each visual e-HMI condition. The selection of the auditory mode was based on Carmona's et al. (2021) guidelines on using voice to complement the delivery of a message. While explaining the procedure to participants, we emphasized that this is a two-way roadway and that the status of other traffic was unknown.

Figure 42: VR environment designed in Unity

Independent variables: This part also employed a within-subject design in which every participant encountered all available treatments. We employed two independent variables. The first was the visual vehicular e-HMI of three levels: (1) no e-HMI, (2) intent-based e-HMI, and (3) advice-based e-HMI. The second was the auditory contextual cue of two levels: (1) absent and (2) present. Order of scenarios was administered based on a Latin Square.

Participants' involvement: After completing the first part of the experiment (Part 1) at a signalized intersection, participants were given some break after which they were given the instructions and scenario descriptions of Part 2:

"As a pedestrian, you will be standing at the edge of a sidewalk at midblock on a two-way roadway, where traffic is expected from any direction. You will be waiting for your friend. It happens that your friend shows up on the other side of the road, and that's when you decide if you would cross the road and catch up with them. By the time your friend shows up, you will be approached by an AV. During some trials, this AV will be equipped with an external display (e-HMI) which will communicate with you through different types of cues. The e-HMI is positioned at the level of the AV's windshield. In some scenarios, the AV will give an auditory message. When feasible, you are supposed to complete one task:

1.Press the target keyboard button when you feel it is convenient for you to start crossing

After you conclude each trial by expressing your onset of crossing, you will be entitled to answer a set of questions pertaining to that scenario".

Dependent variables: In this part, we collected measures related to: (1) participants' situation awareness (SA) particularly pertaining to participants' projection of information to predict the future of other vehicles in the surrounding, and (2) participants' trust in AVs.

The situation awareness measure was collected by explicitly asking participants to rate the likelihood that any other oncoming AV will behave in a similar manner to the host AV and yield to them based on the information presented in the scenario (on a 5-point Likert scale).

Similar to Part 1, we used Jian et al's Checklist for Trust (2000) for self-reported trust measures. As for the objective behavioral measure, we considered the onset of crossing with respect to the AV's start of deceleration.

Similar to Part 1, the SSQ was administered once after the completion of three scenarios.

At the end, the participant completed a post-experiment interview with questions related to the importance of visual vehicular e-HMIs, and the auditory contextual cue.

5.2.2 Data Analysis

Similar to Part 1, we also employed two-way Repeated measures ANOVA and ARTool.

5.2.3 Results

SA: ANOVA results captured a significant main effect for the visual e-HMI only ($F(2,64) =9.24; p<0.001; \eta^2=0.066$). Pairwise comparisons further revealed that, compared to no visual e-HMI, the addition of any type of e-HMI significantly increased pedestrians' likelihood to believe that any other oncoming AV will behave in a similar manner to the host AV and yield to them (*advice-based:* $p_{adj}<0.001$; *intent-based:* $p_{adj}=0.007$). However, the impact of adding the contextual auditory cue was not significant ($F(1,32) =2.57; p=0.119$). Although the interaction effect was non-significant, the visual representation showed a decrease in that likelihood upon the addition of the contextual cue, and it was mostly salient in the presence of the advice-based e-HMI (Figure 43). Therefore, we decided to conduct pairwise comparisons of estimated marginal means which showed that that likelihood was significantly lower for an advice-based e-HMI with a contextual cue as compared to an advice-based e-HMI without a contextual cue (p_{adj}*=0.013*). Contrasts for all other pairs were non-significant.

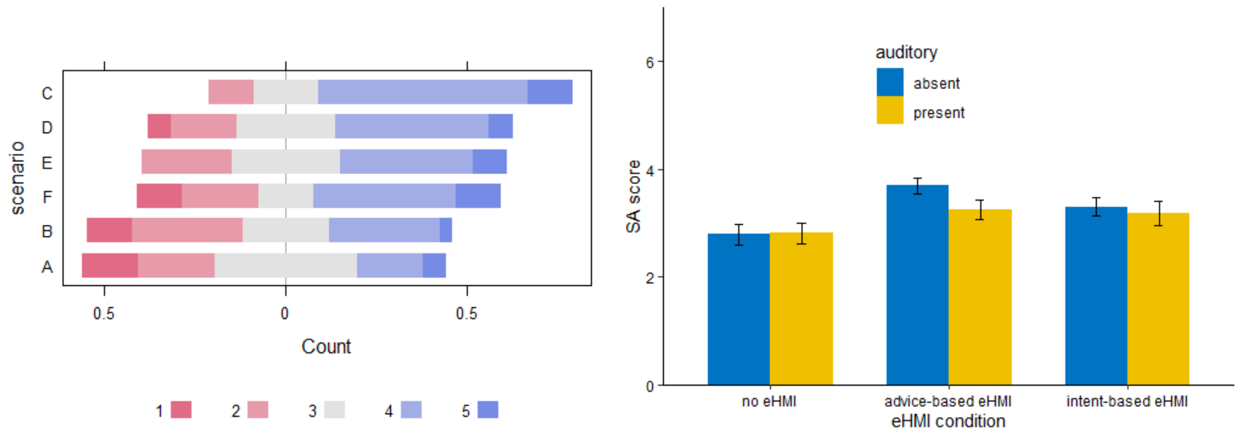


Figure 43: (a) Distribution of situation Awareness (b) Mean situation awareness across treatment conditions *1 stands for Extremely unlikely, *5 stands for Extremely likely, A:no visual e-HMI (auditory absent), B:no visual e-HMI (auditory present), C: advice-based e-HMI (auditory absent), D:advice-based e-HMI (auditory present), E:intent-based e-HMI (auditory absent), F:intent-based e-HMI (auditory present)

Trust score: According to ANOVA, both the visual e-HMI and the auditory contextual cue had significant main effects (*visual e-HMI:* $F(2,64)=21.99$; $p<0.001$; $\eta^2=0.140$; *auditory textual cue:* $F(1,32)=26.81$; $p<0.001$; $\eta^2=0.063$) on the trust score. These two main effects were accompanied by a significant interaction effect ($F(2,64)=5.17$; $p=0.008$; $\eta^2=0.15$). Comparing to no visual e-HMI, the addition of any visual e-HMI increased pedestrians' trust in AVs, while the addition of the auditory contextual cue was found to increase pedestrians' trust only when added to the no visual e-HMI case ($p_{adj}<0.001$) and to the advice-based e-HMI case ($p_{adj}<0.001$) (Figure 44a). However, on average, the difference in participants' trust in AVs between the intent-based and the advice-based e-HMI was non-significant. Nonetheless, when looking at the moderating effect of visual e-HMIs on the auditory contextual cue, we found that the addition of any visual e-HMI increased participants' trust in AVs during both the presence (*advice-based:* $p_{adj}<0.001$; *intent-based:* $p_{adj}<0.001$) and the absence of the contextual cue (*advice-based:* $p_{adj}<0.001$; *intent-based:* $p_{adj}=0.009$).

Distrust score: According to ANOVA, the visual e-HMI and the auditory contextual cue exhibited significant main effects (*visual e-HMI:* $F(1.47,47.10)=19.19$; $p<0.001$; $\eta^2=0.13$;

auditory contextual cue: $F(1,32) = 15.38$; $p<0.001$; $\eta^2=0.055$) along with a significant interaction effect (*$F(1.68,53.75) = 7.58$; $p=0.002$*). The pairwise comparison further indicated that again, the addition of the auditory contextual cue only impacted the case when no visual e-HMI was present. More specifically, the addition of the auditory contextual cue reduced pedestrians' distrust in the AVs in the absence of a visual e-HMI ($p_{adj}<0.001$). Similar to the trust score, participants' distrust was not significantly different between the two visual e-HMIs in the absence and in the presence of the contextual cue (Figure 44b). However, by looking at the moderating effect of the visual e-HMI on the auditory contextual e-HMI, results showed that in the absence of the contextual cue, the addition of any visual e-HMI reduced participants' distrust (advice-based: $p_{adj}=0.001$; intent-based: $p_{adj}<0.001$), while in the presence of the contextual cue, the addition of only the advice-based e-HMI reduced their distrust ($p_{adj}=0.004$).

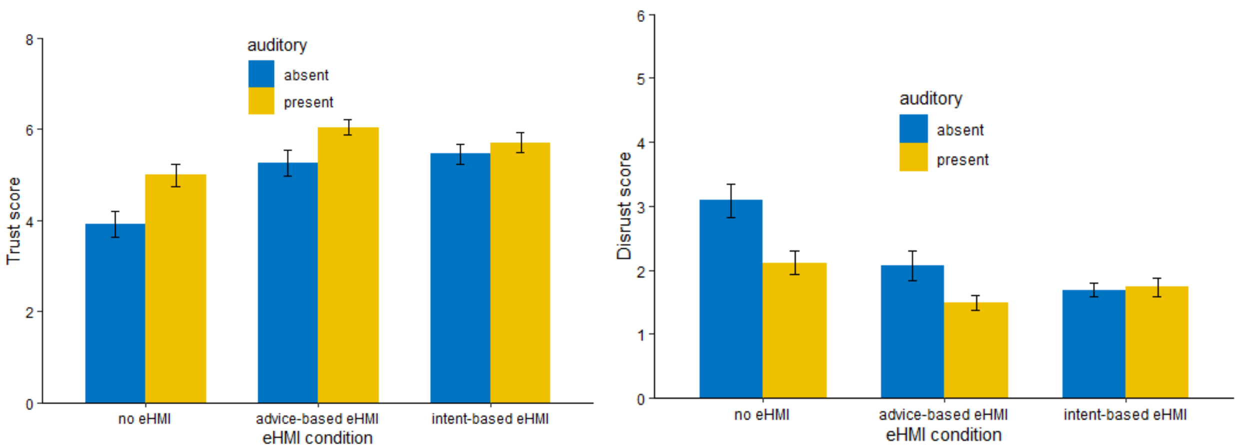


Figure 44: (a) Mean trust score (b) Mean Distrust score
Bars correspond to standard errors

Onset of crossing: In this respect, ANOVA revealed a significant main effect for the visual e-HMI only (*$F(1.41,42.24) = 9.27$; $p=0.002$; $\eta^2=0.074$*). According to pairwise comparisons, all accompanying pairs were significantly different. First, participants' onset of crossing was significantly delayed in the absence of any visual e-HMI as compared to the presence of advice-based e-HMI ($p_{adj}<0.001$) and as compared to the presence of intent-based e-HMI ($p_{adj}=0.035$). Moreover, the onset of crossing was significantly earlier in the presence of the advice-based e-HMI as compared to the presence of the intent-based e-HMI ($p_{adj}=0.022$) (Figure 45). However, since we were also interested in comparing the case of no visual e-HMI in the absence of any contextual cue to the cases of visual e-HMIs with contextual cues, we also ran pairwise comparisons to deduce the following: in the absence of an auditory contextual cue, only the onset of crossing was significantly earlier in the presence of an advice-based e-HMI as compared to no visual e-HMI (p_{adj}=*0.022*) while that of the intent-based e-HMI was not significantly different than no visual e-HMI.

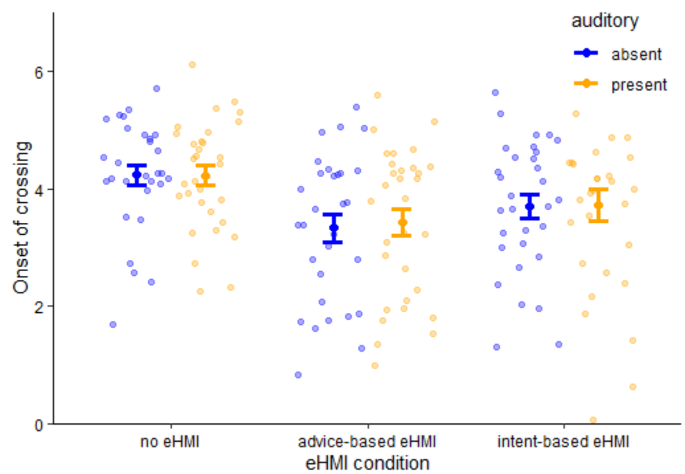


Figure 45: Mean of onset of crossing
Bars correspond to standard errors

5.2.4 Discussion

SA: Interestingly, the addition of both advice-based and intent-based e-HMIs to the AV led to the increase of participants' likelihood to believe that other approaching AVs in the traffic environment will also stop. These results indicated that the presence of any visual e-HMI increases the likelihood of pedestrians to project the host AV's intent to surrounding AVs and might therefore cause pedestrians to take risky decisions based on this false interpretation. Nevertheless, upon the addition of the contextual cue to the advice-based e-HMI, the difference in likelihood as compared to no visual e-HMI became non-significant. This indicated that the auditory contextual cue was capable of calibrating the adverse impact of advice-based e-HMI on the interpretation of the traffic environment. At the same time, the non-significant difference in SA between the no visual e-HMI and the intent-based e-HMI, in the absence of the auditory contextual cue, indicated that the intent-based e-HMI was not associated with an adverse effect unlike the case of advice-based e-HMI. As expected, the two different types of visual e-HMIs have differing impact on pedestrians' information processing.

Trust and distrust scores: The results indicated that the addition of the auditory contextual cue improved pedestrians' levels of trust and distrust in scenarios without any visual e-HMI and in scenarios with advice-based visual e-HMIs. The improvement with respect to no visual e-HMI suggested that despite the cautionary nature of the auditory cue, participants perceived it positively. Particularly, in the absence of any visual e-HMI, the auditory cue fostered pedestrians' trust and distrust levels similar to those achieved in the presence of any type of visual e-HMIs.

One possible reason for this outcome is that participants interpreted the cautiousness suggested by the auditory contextual cue as a sign of the AV's advanced capabilities and proactive safety measures. Similarly, warnings might have been seen as an additional layer of security, which increased participants' trust in AVs. These assumptions were further emphasized by participants' responses during the post-experiment interview.

Given this positive impact, we began to consider the visual e-HMI as a moderating factor on the effectiveness of the auditory contextual cue. When participants were advised to remain cautious while crossing, the addition of the advice-based e-HMI significantly reduced their distrust in AVs. This suggests that advisory cues or their symbolic nature lowered participants' expectations of potential harmful outcomes from the AV's stopping behavior, unlike intent-based cues, which maintained a certain level of participants' alertness. These findings provide evidence that advice-based e-HMIs might induce overtrust in AVs' capabilities by reducing the levels of perceived risk.

Onset of crossing: Similar to our expectations, the presence of any visual e-HMI resulted in a faster reaction time as compared to its absence, which reflects pedestrians' higher levels of trust upon receiving visual cues from the AVs. Add to that, the presence of advice-based e-HMI also resulted in faster crossing onsets as compared to the intent-based e-HMI. While this could be related to the intuitiveness of the symbolic nature of the advisory cues as compared to the textual nature of the intent cues, it could also be related to the lower perceived risk (i.e., lower distrust) observed in the presence of advice-based e-HMIs.

Unlike the case of SA, participants' decision-making process in the presence of advice-based e-HMI did not seem to be affected by the auditory contextual cue. Upon asking participants about their perception of this contextual cue during the post-experiment interview, the majority indicated that they found it important, especially that it reminded them to look around carefully. However, they also mentioned that while it made them more aware of the need to look around, it did not delay their action of crossing. They justified their behavior by the fact that in their everyday experiences, they typically begin crossing and take a few steps into the lane (knowing it is safe from that direction) before looking in the other direction. This reason could be why we did not observe a significant influence of this contextual e-HMI on their reaction time, although it did slightly increase the reaction time when added to advice-based e-HMIs.

The findings discussed above indicate that the slowing behavior of the AV coupled with presence of a cautionary contextual cue might be sufficient to calibrate pedestrians' trust in AVs especially at midblock locations. It is important to note that the auditory contextual cue did not provide any information related to the AV's stopping behavior; yet it was still as effective as an advice-based or intent-based visual e-HMI. Despite the contextual cue improving participants' SA in the presence of advice-based e-HMI, the findings further underscored the risks associated with symbolic visual cues and its advisory nature in altering participants' decision-making process and reducing perceived risk. Add to that, introducing contextual cues in the auditory modality can be limited, especially in high traffic density situations, opening the door for future research to determine an optimized configuration of a cautionary contextual cue at high risk crossing points.

5.3 Limitations

First, conducting the experiment in a VR environment, we acknowledge that the setting cannot fully capture the complexities of the real-world including unpredictable elements, thus generally affecting the realism of participants' behaviors as pedestrians. Due to the lower perceived risk in the simulated environment and the nature of tasks involved (pressing the button to walk instead of physically walking), participants might have exhibited different behaviors in the experiment as compared to real-life. Second, another significant limitation of our experiment is the consideration of one AV and one pedestrian at a time. Again, this fails to capture the complexity of real-world interactions which normally involve pedestrians interacting with multiple vehicles simultaneously. Therefore, future studies should incorporate further dynamic elements including a mixed traffic of AVs and HDVs to enhance the validity of results. Third, the experiment did not involve the collection of gaze points. Gaze behavior data might have given better insights onto pedestrians' attention allocation (distribution) between traffic signals and the oncoming AV. However, to account for this lack, we asked participants to indicate their extent of reliance on traffic signals versus oncoming traffic to cross. Pairwise t-test revealed no significant difference, indicating that participants depended equally on both sources of information simultaneously before they cross. Fourth, while we recruited participants from different age groups and genders, we still did not elicit significant main effects pertaining to these characteristics. Therefore, future work should account for a larger sample size for better generalizability of the results.

5.4 Conclusion

In conclusion, the first part of this study presented a unique examination of the interaction between pedestrians and AVs in the presence of both vehicular and infrastructure-based e-HMIs. The experiment was designed in a VR environment at a four-way signalized intersection. The results reporting on pedestrians’ trust, situation awareness, and workload translated e-HMIs’ role in promoting safe and smooth interactions. More specifically, results showed that relying solely on traffic lights is not enough to alleviate pedestrians' concerns and fears towards AVs, especially under aggressive driving conditions. Add to that, results also indicated that implicit driving cues from AVs were insufficient for pedestrians to efficiently and effectively recognize the yielding behavior of AVs, indicating the need for e-HMIs to improve pedestrians’ SA. Moreover, the results aided in identifying the most effective cue configuration for vehicular e-HMIs required to lessen pedestrians’ workload as they received cues from traffic signals, while also uncovering interesting insights associated with symbolic e-HMIs. The bottom line, this study contributes to the development of scalable e-HMIs fostering calibrated trust levels in AVs to promote safe and efficient AV-pedestrian interaction. It also adds to the standards that oversee the design of e-HMIs at regulated crossing points.

The second part of this study presented preliminary insights into the design of e-HMIs for mid-block AV-pedestrian interactions. While all previous studies focused on assessing the effectiveness of visual e-HMIs of particular information types (advice, intent, awareness, status) to resolve ambiguous right of way situations between pedestrians and AVs, the current study indicated that the introduction of a contextual cue was also capable of increasing pedestrians’ trust in AVs while maintaining favorable levels of awareness upon adding it to visual advice-based e-HMIs. Similar to conclusions drawn on assessing advisory cues of symbolic nature at a signalized intersection, its assessment at midblock interactions further emphasized the adverse effects of such cue configuration on mitigating perceived risk and alertness by lowering distrust levels and shortening reaction time.

Chapter 6 Conclusion

6.1 Research achievements

To collect a comprehensive list of pedestrians' needs for e-HMIs and to complement research efforts dedicated to calibrating pedestrians' trust in AVs, the objectives of this dissertation were outlined as follows:

1. Generate AV-pedestrian testing scenarios upon examining the contributing factors to pedestrians' severe injuries through employing a national crash database.

2. Gather a comprehensive list of user needs, preferences, and expectations towards AVs and e-HMI technology, through a participatory design involving experts and end users.

3. Determine differences in user needs among pedestrians, based on their attributes (age group, gender), knowledge of AVs, behavior, and existing interaction patterns with HDVs.

4. Derive and evaluate theoretically valid e-HMI prototypes to determine the impact on pedestrians' information processing and accompanying performance metrics.

5. Improve e-HMI design solutions through the identification of associated shortcomings and limitations, particularly on pedestrians' constructs of trust.

In completing the first objective, we identified factors associated with increased pedestrians' risk by analyzing vehicle-pedestrian crash data. We determined the differences between factors in two time periods. Results underscored some changes in the factors' risk levels over the years and provided contextual information characterizing these critical interactions. Insights depicted from such results can be used for determining corner case scenarios and generating relevant AV-pedestrian testing scenarios.

In approaching the second and third objectives, we designed and administered two surveys, one for experts and another for the general public. We inquired about pedestrians' current behavioral patterns while interacting with HDVs, their preferred e-HMI attributes, their expectations, and their foreseen challenges. Results revealed preferences being influenced by individual differences and current HDV-pedestrian interactions. Further differences were highlighted between experts and the general public. Insights underscored the importance of accounting for diverse user groups in different processes.

In fulfilling the fourth and fifth objectives, we designed a VR experiment to examine if e-HMIs are necessary and to understand their role in calibrating pedestrians' trust in the presence of several safety concerns (e.g., driving style, misinterpretation at midblock conflict points). We collected different subjective, behavioral, and physiological measures to quantify pedestrians' situation awareness, trust, and workload. Results yielded significant impact differences between the assessed e-HMI types on pedestrians' decision-making process. Resulting insights highlighted substantial practical implications related to the discretion exercised in developing symbolic and advisory e-HMIs and to the significance of considering contextual e-HMIs, in the event that e-HMIs are proved necessary. The insights also provided evidence about the interaction between vehicular e-HMIs and infrastructure-based e-HMIs while revealing the ongoing relevance of vehicular e-HMIs despite existing safe-crossing infrastructure elements.

6.2 Intellectual merit and broader impact

The proposed framework will contribute to the design of e-HMI solutions that account for typical and challenging scenarios, the accompanying pedestrian needs, and the impact on various psychological constructs. This comprehensible approach plays a role in enhancing AVs' acceptance among the general public by bolstering their perceived safety and mitigating potential vulnerabilities. Compared with previous studies attempting to derive user needs, our study revealed interesting insights on the impact of pedestrians' attributes and current interaction patterns with HDVs on their e-HMI preferences. It also highlighted differing needs as identified by the general public and experts, formulating an exhaustive list of considerations for e-HMI design attributes should their presence be deemed necessary. Upon evaluating the impact of specific e-HMI design solutions on pedestrians' trust, results emphasized the importance of segregating self-reported trust and distrust measures and their interrelatedness with mental workload and frustration levels. The unique findings of our VR study emphasized the importance of adopting the proposed framework to build appropriate trust levels and revealed new findings pertaining to the interaction of pedestrians and AVs in the presence of e-HMIs. Other research fields in human-machine interaction can also benefit from the proposed framework and associated safety- improvements in their design for new products.

Intellectual merit: Findings from this research will aid in determining the importance of e-HMIs in particular scenarios and will eventually contribute to the structured development of expandable e-HMIs that meet the safety and efficiency requirements of AV-pedestrian communications and foster sufficient levels of trust across different forms of interactions. This will add to the standards that oversee the design of communication interfaces for AVs at both regulated and unregulated crossing points, especially with the uncovered impact of symbolic e-HMIs on the perception and decision-making process.

Broader impact: Among the earliest of its kind, this research identifies the requirements of various stakeholder groups. Integrating the specific demands of those stakeholders into e-HMI design and establishing appropriate levels of trust and SA in AVs will undoubtedly enhance public receptivity to this technology. Specifically, it will elevate their confidence and mobility during interactions with AVs.

6.3 Future work

This dissertation proposed and adopted a framework for the design of viable e-HMIs that can induce optimal levels of situation awareness and trust in pedestrians. Although this work contributed to refining e-HMI designs and to improving its usability by pedestrians, several other aspects need to be explored in future work:

First, in this work, we employed GES and CRSS crash databases to infer typical vehicle-pedestrian scenarios. However, future work should be focused on a more comprehensible exploration of scenarios through employing other databases, particularly natural observations. This exploration allows for uncovering more interesting insights and for developing a more structured taxonomy of scenarios.

Second, although we attempted to account for pedestrians with disabilities in our general population survey, their representativeness was limited. Future studies should be dedicated to resolve an overlooked issue being e-HMI designs that cater the needs for disabled and impaired pedestrians.

Third, the validation phase accounted for one-to-one interactions only. However, the traffic environment is more complex in reality, imposing higher risk to pedestrians. Therefore, the proposed evaluation framework, including the substantial segregation of trust and distrust constructs, must be evaluated in further traffic complexities and realistic situations to develop scalable e-HMIs.

Finally, future work should be focused on building pedestrian trust prediction models. By being able to predict pedestrians' trust level in real-time, the AV might be able to proactively adjust its behavior and display personalized and timely signals if applicable.

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