Automated Vehicle-Pedestrian Interaction

the Effects of Communication Strategies and Repeated Exposures

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Submitted in accordance with the requirements for the degree of

Doctor of Philosophy

Institute for Transport Studies

University of Leeds

December 2024

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The candidate confirms that the work submitted is her own, except where work which has formed part of jointly authored publications has been included.

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1. The work in **Chapter 2** of the thesis has appeared in publication as follows:

   Yang, Y., Lee, Y. M., Kalantari, A. H., de Pedro, J. G., Horrobin, A., Daly, M., Solernou, A., Holmes, C., Markkula, G., & Merat, N. (2024). Using distributed simulations to investigate driver-pedestrian interactions and kinematic cues: Implications for automated vehicle behaviour and communication. *Transportation Research Part F: Traffic Psychology and Behaviour, 107*, 84–97. https://doi.org/10.1016/j.trf.2024.08.027

   The candidate contributed to experiment conduction, data cleaning, data analysis, and drafting of the manuscript. The study design was developed by the candidate in collaboration with co-authors AHK, YML, GM, and NM, who also provided comments to improve the manuscript. It should be noted that some of the design choices reflect the collective direction of the broader project and were not part of the candidate's individual research focus. The last three also contributed through supervision. Data collection was conducted by the candidate and AHK. The creation of the virtual environment and distributed simulation was a collective effort of the simulator team, including co-authors JGP, AH, MD, and AS.

2. The work in **Chapter 3** of the thesis has appeared in publication as follows:

   Yang, Y., Lee, Y. M., Madigan, R., Solernou, A., & Merat, N. (2024). Interpreting pedestrians' head movements when encountering automated vehicles at a virtual crossroad. *Transportation Research Part F: Traffic Psychology and Behaviour*, *103*, 340-352.

   The candidate performed data analysis, interpreted the data, and drafted the manuscript. The data used in this study originated from an EU InterACT project designed and conducted by YML, RM, and NM. AS was responsible for the simulation. Comments from all co-authors helped improve the manuscript.

3. The work in **Chapter 4** of the thesis has been completed in a manuscript intended for submission for possible journal publication:

   Yang, Y., Lee, Y. M., Tabone, W., Sadraei, E., García de Pedro, J., Happee, R., de Winter, J., & Merat, N. (Ready for submission). The Effect of Augmented Reality on Pedestrians' Gaze Patterns and Crossing Probability while Interacting with Automated Vehicles.

   The candidate contributed to the experiment conduction, data cleaning, data analysis, interpretation of the data to address the research idea, and drafting of the manuscript. The study design was developed by the candidate in collaboration with all co-authors, including WT, YML, RH, JW, and NM, who also provided comments to improve the manuscript prior to submission. Additionally, the last four co-authors were responsible for supervision. It should be noted that some of the design choices reflect the collective direction of the broader project and were not part of the candidate's individual research focus. Data collection was carried out by the candidate and WT. The development of the virtual environment was led by JGP.

It is noteworthy to highlight the following journal publications and conference papers that have been partly or wholly generated from the current PhD project, where the candidate served as either the lead author or co-author:

Tabone, W., Happee, R., **Yang, Y.**, Sadraei, E., García, J., Lee, Y. M., … & De Winter, J. (2024). Immersive insights: Evaluating augmented reality interfaces for pedestrians in a CAVE-based experiment. *Frontiers in Virtual Reality, section Virtual Reality and Human Behaviour, 5*, 1353941.

Kalantari, A. H., **Yang, Y.**, de Pedro, J. G., Lee, Y. M., Horrobin, A., Solernou, A., … & Markkula, G. (2023). Who goes first? A distributed simulator study of vehicle–pedestrian interaction. Accident Analysis & Prevention, 186, 107050.

Yang, Y., Lee, Y. M., Kalantari, A. H., de Pedro, J. G., Horrobin, A., Daly, M., Solernou, A., Markkula, G., Merat, N. (2023). The effect of different infrastructures on driver response to a crossing pedestrian: a distributed simulation study. In Proceedings of the driving simulation conference. Antibes, France.

Yang, Y., Kalantari, A. H., Lee, Y. M., Solernou, A., Markkula, G., & Merat, N. (2023, September). A Distributed Simulation Study to Examine Vehicle–Pedestrian Interactions. In *Adjunct Proceedings of the 15th International Conference on Automotive User Interfaces and Interactive Vehicular Applications* (pp. 327-329).

Li, Y., Lee, Y. M., **Yang, Y.**, Tian, K., Daly, M., Horrobin, A., … & Merat, N. (2023, September). Do Drivers have Preconceived Ideas about an Automated Vehicle's Driving Behaviour?. In *Proceedings of the 15th International Conference on Automotive User Interfaces and Interactive Vehicular Applications* (pp. 291-299).

Markkula, G., Lin, Y. S., Srinivasan, A. R., Billington, J., Leonetti, M., Kalantari, A. H., **Yang, Y.**... & Merat, N. (2023). Explaining human interactions on the road by large-scale integration of computational psychological theory. *PNAS nexus*, *2*(6), pgad163.

Kalantari, A. H., **Yang, Y.**, Lee, Y. M., Merat, N., & Markkula, G. (2023). Driver-pedestrian interactions at unsignalized crossings are not in line with the Nash equilibrium. *IEEE Access*.

Zhang, C., Kalantari, A. H., **Yang, Y.**, Ni, Z., Markkula, G., Merat, N., & Berger, C. (2023, June). Cross or wait? Predicting pedestrian interaction outcomes at unsignalized crossings. In *2023 IEEE Intelligent Vehicles Symposium (IV)* (pp. 1-8). IEEE.

Acknowledgement

The journey of pursuing a PhD has been filled with unexpected challenges, accompanied by the joy and satisfaction of solving problems and contributing, in my own way, to the edges of a growing field. This would not have been possible without the unwavering encouragement and support of those around me. First and foremost, my deepest gratitude goes to my supervisors, Prof. Natasha Merat and Dr. Yee Mun Lee. Your boundless support, meticulous guidance, and patient mentoring have shaped my understanding and learning in what was an entirely new domain for me. The time and effort you have devoted, along with your constant encouragement, have been the backbone of my entire PhD journey. Your dedication, precision, and relentless pursuit of academic excellence have exemplified the strength and impact of outstanding female researchers, inspiring me and providing a powerful role model to follow in my own academic journey.

I am also grateful to my examiners, Prof. Samantha Jamson and Prof. Marieke Martens, for their insightful and enlightening discussions and guidance in refining this thesis.

I would like to express my heartful thanks to my friends and colleagues from the Human Factors and Safety research group. Your companionship, kindness, and constant support have been a vital part of my joyful moments in Leeds. Special thanks to Dr. Rafael Goncalves, Yang Li, Yee Thung Lee, Cheng Hao Qian (and his lovely partner Min), Stefanie Horn, Yue Yang Wang, Kai Tian, Wei Lyu, and many others.

I am also deeply grateful to the senior staff members, Prof. Gustav Markkula and Dr. Ruth Madigan, for their guidance and support in helping me navigate the challenges along the way.

My sincere appreciation extends to the technical team, including Jorge Garcia de Pedro, Albert Solernou, Anthony Horrobin, and Michael Daily, whose expertise and assistance were invaluable throughout this journey.

I would like to express my sincere gratitude to the European research project “SHAPE-IT - Supporting the Interaction of Humans and Automated Vehicles: Preparing for the Environment of Tomorrow” (Marie Skłodowska-Curie grant agreement 860410) for funding this research and providing me with the opportunity to embark on this journal. This experience has been more than just a research endeavour; it has fostered collaborations with both academia and introduced me to many outstanding peers and experienced professors who have greatly contributed to my academic growth and professional development.

Special thanks go to my fellow ESRs: Dr. Nikol Figalová, Naomi Mbelekani, Dr. Chi Zhang, Dr. Chen Peng, Dr. Wilbert Tabone, Dr. Yuan-Cheng Liu, Dr. Amna Pir Muhammed, Dr. Siri Hegna Berge, Dr. Xiaolin He, Sarang Jokhio, Dr. Amir Hossein Kalantari, Ali Mohammadi, and Xiaomi Yang. Each of our gatherings, whether online or in person, even across screens, oceans, and during the pandemic, was filled with joy. Your companionship and mutual encouragement have been the highlight of my PhD journey.

I am also deeply thankful to the project coordinator, Prof. Jonas Bärgman and Jacqueline Plette, for making this project a reality, for always taking care of us, and for their unwavering support. In addition, I deeply appreciate the members of the Supervisory Board: Prof Klaus Bengler, Prof. Joost de Winter, Prof. Marjan Hagenzieker, Prof. Riender Happee, Prof. Martin Baumann, Prof. Olga Pollatos, Prof. Marco Dozza, Prof. Christian Berger, Prof. Meng Wang, Dr. Chongfeng Wei, and Dr. Eric Knauss, thank you for your care and invaluable feedback on my work.

Additionally, a huge thanks to Dr. Julia Drük, Michael Wittkämper, and Dr. Wilkens Kathrin, from VW for kindly hosting my secondments and providing thoughtful guidance and support throughout the secondment.

同时，我要由衷感谢我的家人们。无论我做出怎样的选择，你们始终无条件地支持着我，成为我最坚实的后盾和最温暖的港湾。特别感谢我的父母张立香和杨仁清，以及我的妹妹杨蕊，你们的陪伴与支持，让我在每一个人生岔路口都能够坚定向前。感谢我的姥爷张喜财†和姥姥赵玉芝†，作为人生的指路明灯，从小给予我悉心的教导。现在的我渐渐明白了你们曾经说过的话和传递的道理，是你们的善良、智慧与包容，潜移默化地塑造了今天的我。同时，也感谢所有亲戚朋友对我的关心与关注，你们的温暖牵挂如同风筝的线，无论我离家多远，始终让我感受到惦念与归属。

最后，我想特别感谢我的男朋友屠哲涵。在英国四年的陪伴和 Covid 期间的互相（多数是你单方面）的照顾和情绪价值让我一直能自信和快乐的做自己，还有我们最可爱的 Cola 小猫陪伴着需要情绪鼓舞的论文时光。

Abstract

This research investigated pedestrians' crossing decisions and attention allocation, as indicated by head and gaze movements, in interactions with automated vehicles (AVs) over repeated exposures, aiming to provide insights for developing safe and effective AV communication strategies. The work addressed questions relating to (i) drivers' kinematic cues in different contexts and their impact on pedestrians' crossing decisions for proposing AV implicit communication strategies, (ii) pedestrians' attention allocation behaviour in front of AVs employing explicit communication strategies, and (iii) the impact of repeated exposures on pedestrians' adaptation in crossing decisions and attention allocation behaviour in response to implicit and explicit communication strategies.

To address these questions, a series of experiments were conducted in virtual environments using a CAVE-based pedestrian simulator to explore AV-pedestrian interactions across varying contextual factors. Additionally, a distributed simulation setup was developed, connecting the pedestrian simulator to a motion-based driving simulator, enabling real-time interactions between both actors in a controlled and repeatable environment. Results revealed that drivers' kinematic cues, such as braking and lateral movements, served as effective implicit communication strategies, significantly influencing pedestrians' crossing decisions and surpassing the impact of infrastructure cues like zebra crossings. Furthermore, pedestrians' attention allocation patterns in front of AVs were similar to those observed with conventional vehicles. However, the presence of explicit communication methods from AVs, such as external human-machine

interfaces (eHMIs) or augmented reality (AR), reduced pedestrians' head-turning and gaze behaviours, indicating lower attentional demands and effectively conveying AV intent. Repeated exposures to these implicit and explicit communication strategies revealed a learning effect, with pedestrians adapting their crossing decisions and attention allocation behaviours over time.

This thesis concludes by providing a comprehensive understanding of AV-pedestrian interactions through novel experimental approaches and measurements, offering insights for designing effective implicit and explicit communication strategies for AVs.

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List of Abbreviations

A number of abbreviations and acronyms are used throughout this thesis. They are listed here for reference in alphabetical order.

ACC	Adaptive Cruise Control
ADAS	Advanced Driver Assistance Systems
AIC	Akaike Information Criterion
AOI	Area of Interest
AR	Augmented Reality
AV	Automated Vehicle
BW	Bandwidth
CDT	Crossing Duration Time
CIT	Crossing Initiation Time
CI	Confidence Interval
ΔFD	Change in Fixation Duration
eHMI	Explicit Human-Machine Interface
EST	Estimate
FH	Flashing Headlights
FIR	Finite Impulse Response
GEE	Generalised Estimating Equation
GLMM	Generalised Linear Mixed-Effects Model
HAV	Highly Automated Vehicle
HIKER	Highly Immersive Kinematic Experimental Research
HMI	Human-Machine Interface
HUD	Heads-Up Display
IIR	Infinite Impulse Response
KDE	Kernel Density Estimation
LKS	Lane Keeping Systems
LoA	Levels of Automation
LoDA	Levels of Driving Automation
LSD	Least Significant Difference
M	Mean

Odd Ratio	Odds Ratio
PPPB	Vehicle Proximity to Pedestrian at Peak Braking
SE	Standard Error
SD	Standard Deviation
SPLB	Slow Pulsing Light Band
TTA	Time to Arrival
UoLDS	University of Leeds Driving Simulator
VR	Virtual Reality
VRUs	Vulnerable Road Users

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

Vulnerable Road Users (VRUs), including pedestrians, cyclists, and motorcyclists, account for more than half of all road casualties worldwide (WHO, 2018), with pedestrians being the most vulnerable group due to their lack of physical protection and slower movement compared to other traffic participants. In the UK, pedestrians account for 27% of all road fatalities (Department for Transport, 2020). This vulnerability has driven extensive research into pedestrian behaviours to enhance road safety and develop effective traffic policies. Recent technological advancements are paving the way for the imminent arrival of automated vehicles (AVs), particularly highly automated vehicles (HAVs, Level 4 and 5) (SAE, 2021), which promise improvements in traffic safety (Litman, 2021) and aim to protect road users by reducing human error, a factor thought to be responsible for over 90% of road crashes (Highway Traffic Safety Administration & Department of Transportation, 2015). The introduction of AVs is also expected to bring benefits such as lower emissions and improved traffic efficiency by reducing congestion (Anderson et al., 2016; Litman, 2021). However, it remains unclear how these autonomous systems will interact with vulnerable road users, particularly pedestrians, in future urban scenarios (Schieben et al., 2019). This uncertainty underscores the importance of understanding the role of AVs in the traffic ecosystem before their widespread deployment (Alvarez et al., 2019).

The shift towards AVs may introduce a new challenge by replacing human drivers with autonomous systems that do not yet conform to the social norms of current traffic systems (Rasouli & Tsotsos, 2020). Driving is a task that involves social interaction with other road users while establishing right-of-way and navigating in urban environments (Domeyer, Lee, & Toyoda, 2020; Sucha, 2014). These interactions involve interpreting rules, norms, expectations, and situational factors while providing clear cues to other road users to maintain orderly and safe movement, prevent collisions, and ensure efficient transport systems (Rezwana & Lownes, 2024; Wang et al., 2022) However, AVs currently lack such social intelligence (Kihlstrom & Cantor, 2000) to interpret these cues from pedestrians or communicate effectively with other road users (Loke, 2019), which could lead to traffic accidents or erratic behaviour towards pedestrians (Sparrow & Howard, 2017). Additionally, current research has suggested five capabilities required by an AV for a successful interaction process between AVs and VRUs. These include (1) object detection, (2) object classification, (3) trajectory prediction, (4) intent prediction, and (5) communication with vulnerable road users (Reyes - muñoz & Guerrero - ibáñez, 2022). To date, the former three stages have been achieved relatively well by advanced technology and sensors, whereas the latter two stages still remain as challenges for the current AV technologies (Huang et al., 2024; Reyes - muñoz & Guerrero - ibáñez, 2022).

Although substantial research has focused on facilitating smooth interactions between pedestrians and AVs through mutual understanding of intent to address these concerns, most studies only examine pedestrians' initial responses. There is a noticeable lack of research on how pedestrians adapt and learn from repeated exposures to AVs that utilise new communication forms. Addressing this gap is critical, as pedestrian behavioural adaptation is key to day-to-day interactions (Vissers et al., 2017) and can evolve with repeated encounters, leading to adjustments in their responses and corresponding changes in AV behaviour and interpretation. Understanding these adjustments is essential for developing intuitive and natural mechanisms for AVs to achieve social interactions and seamlessly integrate into urban environments.

The aim of this PhD programme is to understand pedestrians' adaptability and learning behaviours in response to AV communication mechanisms, providing insights to guide the development of effective communication strategies with other road users, and intuitive designs for AVs. To deepen the understanding of this research topic, the next section of this chapter outlines the context of automated driving and the associated human factors challenges. This is followed by a literature review from three perspectives: i) road user interactions in the current traffic, ii) pedestrians' interactions with automated vehicles, and iii) repeated exposures of AV-pedestrian interactions. The chapter concludes with a summary of identified research gaps and the specific research questions this thesis aims to address.

1.2 INTERACTIONS IN CURRENT TRAFFIC

Despite ongoing efforts to improve pedestrians' safety, they still account for 23% of global road traffic fatalities, with deaths increasing by 3% to 274,000 between 2010 and 2021 (World Health Organization, 2023), the highest proportion among all road user groups. In the UK, pedestrians represent 27% of all road fatalities (Department for Transport, 2020), while in the EU, they account for 18.1% of traffic deaths (European Commission, 2022). Although AVs are expected to reduce these figures through advanced sensors and technological improvements, the transition to fully automated traffic will involve a prolonged period of coexistence between conventional vehicles, partially automated vehicles, and fully automated vehicles (Dresner & Stone, 2007; Litman, 2021). Ensuring road safety during this transition remains a critical challenge for academia and industry alike, as some existing road user interactions may be altered, while others may persist (Habibovic et al., 2018; Rasouli & Tsotsos, 2020). This section examines current research on interactions within today's traffic systems, providing a foundation for exploring how these dynamics might evolve with the introduction of AVs.

1.2.1 Road user interactions and non-verbal communication

Markkula et al. (2020) define road user interactions as occurring during "space sharing conflicts," situations in which "two or more road users are intending to occupy the same region of space at the same time in the near future." During these interactions, it is critical for all participants to share a common interpretation of the situation to safely negotiate the priority of using the shared space. Achieving this requires effective communication to ensure mutual understanding, which is vital for resolving ambiguities and preventing misinterpretations (Klein et al., 2004). The lack of effective communication can significantly increase the risk of traffic conflicts (Endsley, 1995; Portouli et al., 2014), as evidenced by Risser (1985) observational study, which found that over a quarter of traffic conflicts were due to ineffective communication, with nearly half of these conflicts arising from no communication attempts.

Communication, as defined by Risser (1985), involves the exchange of information aimed at specific objectives. Within the context of road user interactions, these objectives often include sharing intentions and coordinating access to shared spaces (Portouli et al., 2014). This coordination is facilitated through various communicative acts (Domeyer, Lee, & Toyoda, 2020; Habibovic et al., 2018; Lundgren et al., 2017; Markkula et al., 2020). Linguistically, these acts are categorised into declarative utterances (verbal cues or locutionary acts) and directive requests for intentions (behavioural cues or illocutionary acts) (Austin, 1975). Given the physical separation between pedestrians and vehicles, there is a greater reliance on non-verbal cues (Färber, 2016), with over 90% of interactions involving non-verbal communication, such as changes in pedestrians' head orientations, as analysed by Rasouli et al. (2018) from 240 hours of observations of road user interactions recorded in Canada, the USA, Germany, and Ukraine.

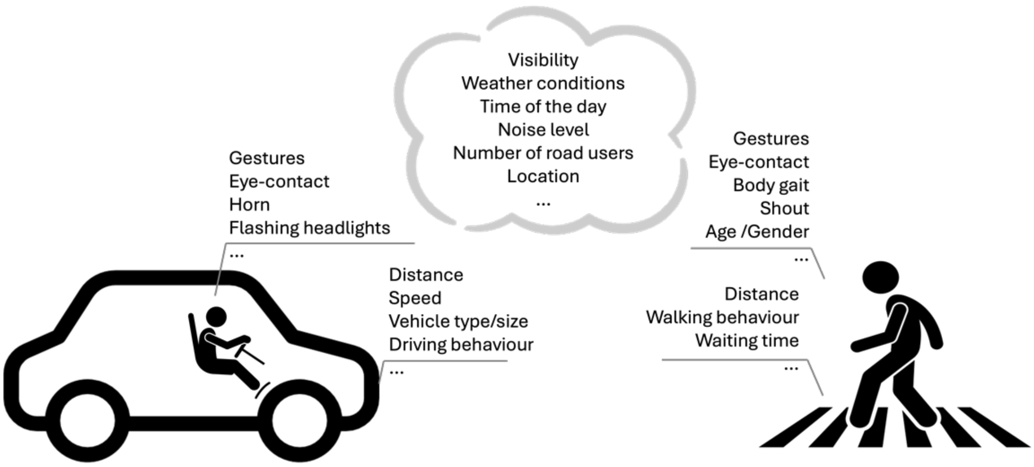

Figure 1.1 Model of pedestrian-vehicle interaction in current traffic with non-verbal cues from both actors and some factors influencing the interaction.

In the model of vehicle-pedestrian interaction (**Figure 1.1**), non-verbal cues from both actors are generalised and interpreted differently by each other depending on the context (e.g., location, weather). They can be categorised as explicit or implicit, although definitions vary (Fuest, Sorokin, et al., 2018; Markkula et al., 2020; Powelleit et al., 2018; Rasouli & Tsotsos, 2020). Implicit communication involves conveying messages through behavioural cues or illocutionary acts, such as vehicles communicating intentions through changes in speed, while pedestrians use anticipatory behaviours, like changing walking speed or stepping onto the curb, to indicate readiness or hesitation to cross (Beggiato et al., 2017; Dey & Terken, 2017; Schmidt & Färber, 2009). Conversely, explicit communication entails direct cues, or locutionary acts, such as drivers using turn indicators and brake lights or pedestrians employing eye contact and hand gestures to clearly convey their intentions (Rasouli et al., 2017; Sucha et al., 2017).

Among these explicit cues, eye contact is particularly critical as it makes pedestrians feel acknowledged and significantly affects drivers' decisions to yield (Guéguen et al., 2015; Mok et al., 2022; Rasouli et al., 2018). Using a field study at a pedestrian crossing in France, Guéguen et al. (2015) found that drivers were more likely to stop for pedestrians who made eye contact (68%) compared to those who did not (45%). Similarly, observations by Uttley et al. (2020) in a UK car park revealed that pedestrians' failure to look toward a driver increased uncertainty, leading drivers to slow down but not fully stop. However, a disparity exists regarding the relevance of eye contact. For example, Sucha et al. (2017) found that 84% of pedestrians seek it during crossings, but this was only seen for 34% of drivers. This discrepancy highlights pedestrians' greater need for reassurance due to their vulnerability and underscores the necessity for AVs to effectively signal recognition and intent (Lundgren et al., 2017; Onkhar et al., 2022; Velasco et al., 2019). As traditional forms of explicit communication from drivers will decrease with the advent of higher-level AVs, there is the potential likelihood of increasing ambiguities during traffic interactions with other road users, since AVs are not currently able to provide explicit communication cues. Addressing these challenges requires a focus on the communication needs and mechanisms between AVs and pedestrians, which will be developed in detail later in Section 1.3.

1.2.2 Pedestrians' situation awareness and attention allocation

The process by which pedestrians receive and interpret cues from vehicles and their environment can be effectively explained through the Situation Awareness (SA) model. Endsley (1995) provides a widely recognised definition of SA as "the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future." This definition further delineates SA into three hierarchical levels: Level 1 (Perception), Level 2 (Comprehension), and Level 3 (Prediction), as shown in Figure **1.2**. Essentially, SA enables pedestrians to observe cues in their environment (depicted in Figure **1.1**), identify and comprehend relevant features for assessing crossing tasks, and predict the potential actions of vehicles before deciding whether to cross (Figure **1.2**).

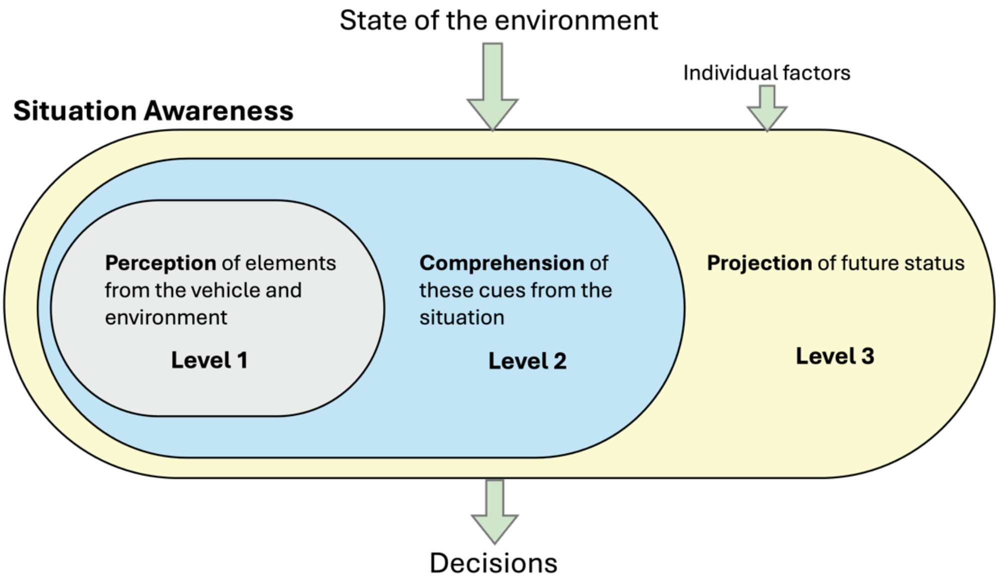

Figure 1.2. Model of situation awareness in dynamic decision making, adapted from Endsley (1995).

Attention plays a pivotal role in the SA, affecting nearly all aspects of perception, comprehension, and action (Endsley, 1995). In Level 1 (Perception), the allocation of pedestrians' attention determines which cues are gathered for processing during decision-making. Due to the brain's limited capacity to handle multiple information streams simultaneously, attention operates as a selective mechanism that filters relevant (signal) from irrelevant (noise) elements based on the specifics of the task (Carrasco, 2011). In the context of crossing tasks, pedestrians must selectively focus on necessary cues, a process that can be understood through a feature-based structure, distinguishing between bottom-up (salience and novelty-driven) and top-down (goal and experience-driven) processes (Connor et al., 2004; Corbetta & Shulman, 2002; Katsuki & Constantinidis, 2014). Bottom-up attention is an externally driven process where information is automatically processed based on salient sensory stimuli, such as interfaces that capture attention or distractions in the environment. Conversely, top-down attention is an internally driven process where information is actively sought based on an individual's expectations, experience, and the likelihood of encountering specific information in a given context, such as vehicle behaviour in a particular situation. This selection is influenced by mental models, memory, and past experiences and exposures, which help in guiding attention allocation in a planned, goal-directed manner in Level 1 (Perception) and interpreting environmental signals in Level 2 (Comprehension). These attentional mechanisms are not mutually exclusive and often coexist in visual search tasks.

Gaze allocation reliably reflects attention distribution and cognitive processing, as pedestrians focus on elements that capture their attention, a connection rooted in the brain's mechanisms for stimulus selection and processing, established by psychologists such as Posner et al. (1980). Research on pedestrian-vehicle interactions demonstrates that gaze patterns are highly context-dependent, shaped by pedestrians' efforts to gather information from vehicles, environmental cues such as infrastructure, and individual characteristics like age and gender (Lévêque et al., 2020). Field studies highlight these variations in gaze behaviour in front of conventional vehicles. Trefzger et al. (2018) found that pedestrians navigating predefined routes in Germany focused primarily on the path ahead. Conversely, Geruschat et al. (2003) observed distinct gaze patterns at signalised intersections in the U.S., where compliant pedestrians focused on traffic lights, while non-compliant ones directed their attention to vehicles. This study also found gaze patterns varying at different stages that pedestrians focused on crossing elements while walking to the curb but shifted their attention to approaching vehicles when standing at the curb. As vehicles approach, gaze behaviour shifts dynamically. In a field study on a straight campus road in the Netherlands, Dey et al. (2019) reported that pedestrians transitioned their focus from the road surface to the vehicle's bumper, hood, and windshield as the vehicle approached pedestrians. Similarly, de Winter et al. (2021) observed that in parking environments, pedestrians focused on vehicles' sides, wheels, fronts, and the surrounding ground.

In addition to gaze allocation, research on gaze fixations, defined as periods when the eyes remain relatively still while focusing on a specific element (Salvucci & Goldberg, 2000), provides deeper insights into the process of comprehension (Level 2) in pedestrians' SA in the crossing task. Longer fixation durations can indicate greater visual effort (He & McCarley, 2010; Herten et al., 2017; Jacob & Karn, 2003), difficulty in processing visual information (Kotval & Goldberg, 1998; Milton et al., 1950), or increased uncertainty of the vehicle's intent (Liu et al., 2023), while shorter fixations suggest quicker information absorption and easier decision-making. For example, field experiments conducted at two uncontrolled crosswalks in China by Liang et al. (2022) found that higher vehicle speeds and closer proximity between pedestrians and vehicles resulted in longer fixation durations on the approaching manual-driven vehicle. This finding highlights the potential of using fixation durations as a metric to evaluate communication strategies for conveying vehicle intent and supporting pedestrians' crossing decisions.

Eye-tracking studies can provide valuable insights into how pedestrians allocate their attention interacting with conventional vehicles, although such data can sometimes be ambiguous due to factors like distance, calibration errors, and varying lighting conditions (de Winter et al., 2022). Another useful metric is tracking pedestrians' head movements, which can reveal where they are directing their attention. Head movements typically occur simultaneously with gaze behaviour, helping to infer the direction of gaze (Melvill Jones et al., 1988). Head movements and eye-gaze are used to guide attention swiftly and automatically to specific areas, essential for gathering information about our surroundings (Frischen & Tipper, 2006; Kleinke, 1986). In hazardous environments like road crossings, humans often turn their heads to expand their scanning field, compensating for the limited range of eye movements (±55°) (Avineri et al., 2012). Recent studies, such as those by Lyu, Lee, et al. (2024) and de Winter et al. (2021), utilize head-turning rates to measure active visual search behaviours in simulations and real-world environments. These studies demonstrate that a higher rate of head turns indicates a more intense need for information, particularly in uncertain crossing situations. Moreover, the frequency of head movements during crossings, as shown in studies like that by Hamaoka et al. (2013), correlates with the need to establish the proximity of approaching vehicles.

Head movements constitute a large proportion of non-verbal communication, signalling pedestrians' situation awareness in real-world interactions with conventional vehicles (Grasso et al., 1998; Kooij et al., 2014; Patla et al., 1999). As they are readily observable, they can be utilised by drivers to infer and predict pedestrians' crossing intent (Hariyono et al., 2016; Hassan et al., 2005; Kooij et al., 2014; Kwak et al., 2017; Schmidt & Färber, 2009). Real-world observation studies with conventional vehicles have shown that pedestrians' crossing intent can be predicted from the direction of head movements, the frequency of head turns, and their body gait. For example, at the start of a crossing, pedestrians typically turn their heads towards an approaching vehicle (Grasso et al., 1998; Imai et al., 2001; Patla et al., 1999), a behaviour that signals their awareness of the vehicle's approach, thereby reducing the risk of an unsafe crossing (Kooij et al., 2014). Observations from roundabouts and intersections have shown that, for a vehicle approaching from the right, pedestrians tend to turn their heads to the left before stepping off the curb and then to the right before crossing (Geruschat et al., 2003). Head-turning frequency tends to increase about 4 seconds before a crossing, reaching a peak during the last second before the crossing begins (Hassan et al., 2005). Finally, pedestrians are found to turn their heads first just before a crossing initiation, followed by movement of the rest of the body (Kalantarov et al., 2018).

Overall, understanding pedestrians' gaze and head movements is crucial for analysing their interactions in current road-crossing scenarios. However, how these patterns change with the introduction of automated vehicles remains largely unexplored, a topic that will be further addressed in Section 1.3. Considering the context-based nature of pedestrians' behaviour and decision-making, the next section will explore the factors influencing these behaviours.

1.2.3 Factors influencing interactions

In terms of pedestrian interactions with manually controlled vehicles, extensive research has been conducted to understand what factors influence their crossing decisions and behaviours (Ezzati Amini et al., 2021; Rasouli & Tsotsos, 2020). It is widely recognised that pedestrian characteristics vary significantly, and there is no definitive "average" pedestrian (Ackermann, Beggiato, Bluhm, et al., 2019). Pedestrian behaviour diverges based on personal factors such as demographics, personality, expectations, past experiences, and abilities, as well as social factors such as norms, local customs, and culture, and environmental characteristics like street delineations, speed limits, and road configurations, as shown in Figure **1.3**. Despite the many factors influencing pedestrians' crossing decisions and behaviours in interactions with conventional vehicles, this section will focus on two factors relevant to this PhD programme.

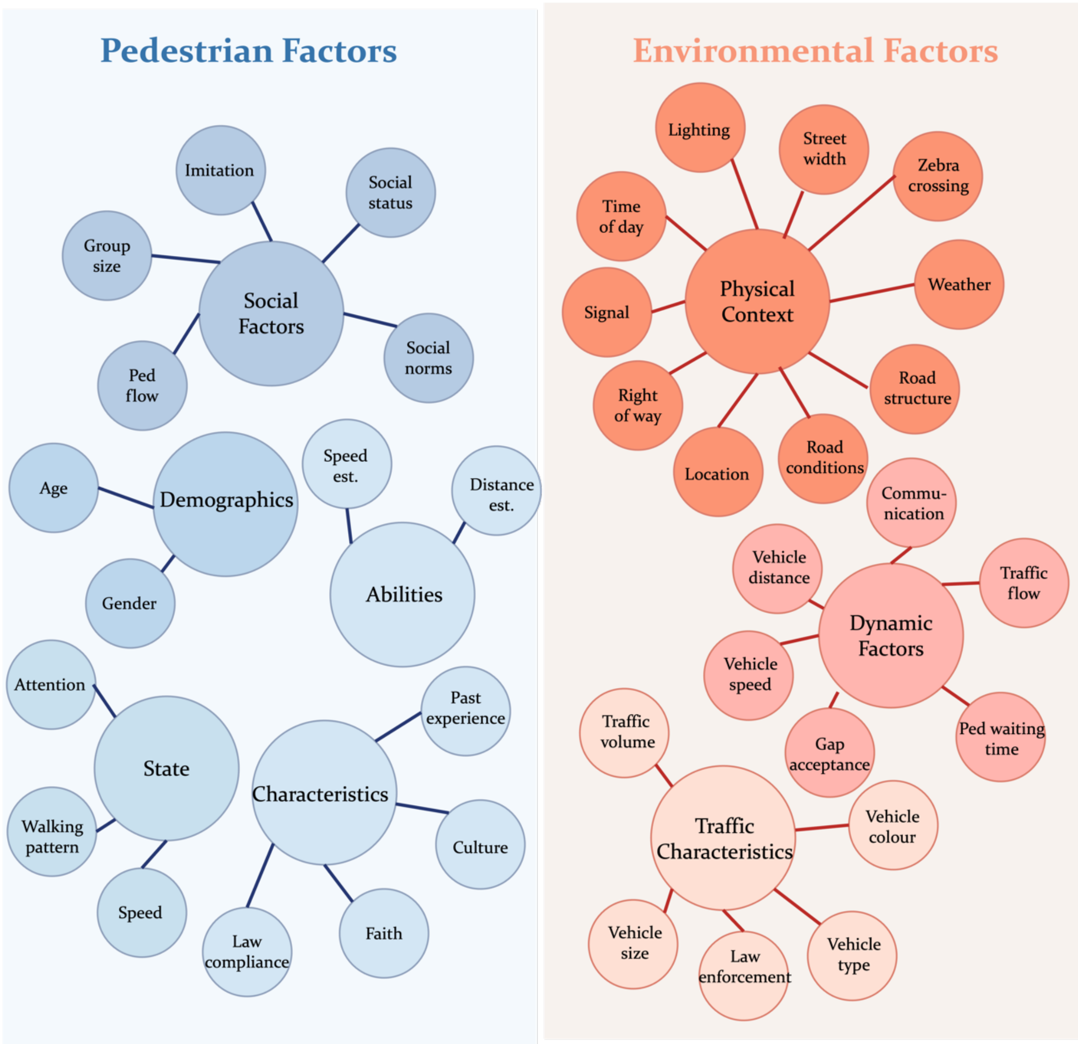

Figure 1.3. Factors involved in the pedestrian decision-making process at the time of crossing. Redrawn from Rasouli and Tsotsos (2020).

Vehicle kinematics

Vehicle kinematics, such as speed, acceleration, and time gap, play a critical role in shaping pedestrian crossing behaviour and driver-pedestrian interactions in the current traffic. Pedestrians rely on these dynamic cues to assess crossing safety and make timely decisions, while drivers adjust these kinematic behaviours to communicate their intent to yield or not. Subtle changes in vehicle movements, such as speed adjustments or braking patterns, are often used as non-verbal signals in these interactions (Ackermann et al., 2018; Bindschädel et al., 2022; Dey, Matviienko, et al., 2020; Domeyer, Lee, Toyoda, et al., 2020; Fuest, Michalowski, et al., 2018; Lee et al., 2022; Rettenmaier et al., 2021; Risto et al., 2017; Várhelyi, 1998; Zach Noonan et al., 2023). For example, Risto et al. (2017) observed that drivers intending to yield typically brake early and maintain a lower speed, signalling their willingness to give way. Conversely, rolling forward at low speed or maintaining a steady or accelerating pace communicates the intention to retain the right of way. Similarly, Schneemann and Gohl (2016) noted that deceleration is often interpreted by pedestrians as an intent to yield. These kinematic behaviours enable implicit communication between road users, allowing pedestrians to infer a driver's intentions. For safe crossings, pedestrians must accurately interpret these cues while factoring in the dynamic nature of traffic.

A particularly critical kinematic factor is the time gap, also referred to as Time to Arrival (TTA), which defines the time remaining before a vehicle reaches a pedestrian's location at its current speed (Tresilian, 1995). Gap acceptance, a related concept, refers to the point at which a pedestrian perceives a gap in traffic as sufficient to cross safely (Beggiato et al., 2017). Research suggests that pedestrians generally do not cross if the TTA is below 3 seconds (DiPietro & King, 1970) and are likely to cross when it exceeds 7 seconds (Schmidt & Färber, 2009). However, gap acceptance thresholds are highly context-dependent, influenced by factors such as age and gender (Harrell & Bereska, 1992; Oxley et al., 2005; Petzoldt, 2014; Wang et al., 2010), group size (DiPietro & King, 1970), cultural norms (Schmidt & Färber, 2009), the level of law compliance (Ishaque & Noland, 2008), street width (Sucha, 2014), waiting times (Sun et al., 2002), vehicle size (Beggiato et al., 2017) and speed (Beggiato et al., 2017; Oxley et al., 2005; Velasco et al., 2019). However, most existing research on time gap and gap acceptance has been primarily focused on pedestrian safety assessments, with limited attention to the corresponding driving responses that could influence crossing decisions. Understanding the dynamic interplay between time gaps and driver behaviours is critical for developing AV systems that replicate human-like interactions and ensure safety in pedestrian crossings.

Additionally, research has also shown humans' imperfect ability to accurately perceive speed, especially from a distance (Cavallo & Laurent, 1988; DeLucia, 2008). This could lead to risky crossing decisions, such as crossing in front of a vehicle approaching at higher speeds when it is further away, even though the TTA is insufficient (Beggiato et al., 2017; Oxley et al., 2005; Schmidt & Färber, 2009; Velasco et al., 2019). Such perceptual challenges are likely to intensify with the integration of AVs, which lack the intuitive, non-verbal cues used by human drivers. It highlights the need for effective communication mechanisms in AVs, to clarify ambiguities in communicating the intent and reducing potential hazards arising from pedestrians' inaccurate estimations of these kinematics in road user interactions, which will be developed in detail later in Section 1.3.

Infrastructure cues

Environmental factors significantly impact pedestrian behaviour and crossing decisions in current road user interactions, including aspects such as traffic volume, road width, crossing location, and weather and illumination conditions (Crompton, 1979; Harrell, 1991; Schmidt & Färber, 2009; Sucha, 2014). Among these, traffic signals play a pivotal role in shaping pedestrian behaviours and compliance with laws, with pedestrians displaying varied behaviours at different crossing types (Moore, 1953; Sisiopiku & Akin, 2003; Sucha et al., 2017; Tom & Granié, 2011; H. Wang et al., 2020). For example, at signalised intersections, they pay close attention to both traffic signals and vehicle movements, facilitating safer and more regulated crossings. In contrast, at unsignalised crossroads where traffic lights are absent, pedestrians rely heavily on assessing vehicle dynamics and movements to make safe crossing decisions (Tom & Granié, 2011). This reliance becomes particularly critical due to the ambiguity in legal rules and unclear pedestrian right-of-way, which may pose challenges, especially with the integration of AVs.

Zebra crossings, a specific type of infrastructure cue, are particularly influential in current traffic systems, affecting both pedestrian and driver behaviour. They offer pedestrians a sense of safety and clarity and serve as a visual prompt for drivers to yield. In the UK, drivers are legally required to give way at zebra crossings (Rule H2 in The Official Highway, 2023). Studies have shown that pedestrians are more likely to use zebra crossings, wait less time before crossing, and walk at a slower pace compared to unmarked crossings (Havard & Willis, 2012). These findings have been further corroborated through simulation studies (Clamann et al., 2017; Velasco et al., 2019). Additionally, pedestrians in the UK report feeling safer and having greater perceived control when crossing at marked crossings (Havard & Willis, 2012; O'Dell et al., 2022).

However, drivers do not always yield at zebra crossings even when they know they should (Dabrowska-Loranc et al., 2021; Várhelyi, 1998). For instance, field studies in Poland by Dabrowska-Loranc et al. (2021) revealed that only 45% of drivers approaching unsignalised zebra crossings yielded to pedestrians, often due to urgency or failure to notice pedestrians in time. It is important to note that this study was conducted prior to the June 2021 amendment to Polish traffic law, which extended pedestrian priority to include not only those already on a zebra crossing, but also those approaching it with the intention to cross. Research on driver behaviour at zebra crossings has not been conclusive. While research in China found that drivers braked more frequently at zebra crossings compared to unmarked locations (Zhang et al., 2020), naturalistic driving data used in this study is often difficult to draw causal relationships, making it difficult to isolate specific factors affecting driver behaviour (Dozza, 2013). Another research by Dozza et al. (2020) addressed these challenges by using a fixed-base simulator to examine driver responses to pre-programmed pedestrian movements and found that driver behaviour was influenced primarily by pedestrian time-to-arrival and visibility, while zebra-crossing presence had minimal effects. However, the lack of interactions between drivers and pedestrians in such simulations reduces their applicability to real-world scenarios, as real-world behaviour is shaped dynamically by both parties' actions.

To address these limitations, distributed simulation enables real-time, interactive environments where both driver and pedestrian simulators are connected. Kearney et al. (2020) demonstrated this approach in a study where pedestrians wearing head-mounted displays interacted with both simulated and human-driven cars at intersections and midblock crossings. The results showed that pedestrians crossed more frequently at intersections than midblock crossings, while drivers were less likely to yield at midblock locations. Despite these advancements, current research remains limited in exploring the dynamic interplay of kinematic cues (e.g., time gaps) and infrastructure cues (e.g., zebra crossings). Investigating this dynamic interaction is essential for understanding road user behaviour and designing AV systems that respond safely and effectively.

The next section, 1.3 explores how AV integration may alter road user interactions, focusing on focusing on how implicit and explicit communication affect pedestrians' behaviour.

1.3 INTERACTIONS WITH AUTOMATED VEHICLES (AVS)

1.3.1 Definition of automated vehicles

The concept of automation is defined as the partial or entire substitution of manual work in a function using machines to complete tasks (Parasuraman & Riley, 1997). With machines taking over "operating" tasks, humans are responsible for intellectual and cognitive tasks, such as problem-solving and planning (Wei et al., 1998) Automated systems are designed to leverage the respective strengths and weaknesses of humans and machines, involving varying levels of human interventions and machine operations. To precisely describe this collaboration, Levels of Automation (LoA) are utilised to specify the extent to which a task is automated, varying across a continuum of levels from completely done by humans to entirely operated by automation (Parasuraman et al., 2000; Sheridan et al., 1978).

In terms of vehicle automation, this generally refers to substituting some or all of the human labour of driving with electronic or mechanical devices (Shladover, 2018). Automated vehicles are defined as motor vehicles capable of partially or totally controlling the lateral and longitudinal aspects of driving, without active human interaction (NHTSA, 2013). Similar to definitions of LoA, the Level of Driving Automation (LoDA) is defined by the degree of human intervention required (SAE, 2021). The most widely accepted definition for levels of driving automation, used in this thesis, is outlined by the SAE J3016 standards (SAE, 2021). These include Level 0 (No Driving Automation), Level 1 (Driver Assistance), Level 2 (Partial Driving Automation), Level 3 (Conditional Driving Automation), Level 4 (High Driving Automation), and Level 5 (Full Driving automation), (SAE, 2021, **Figure 1.4**).

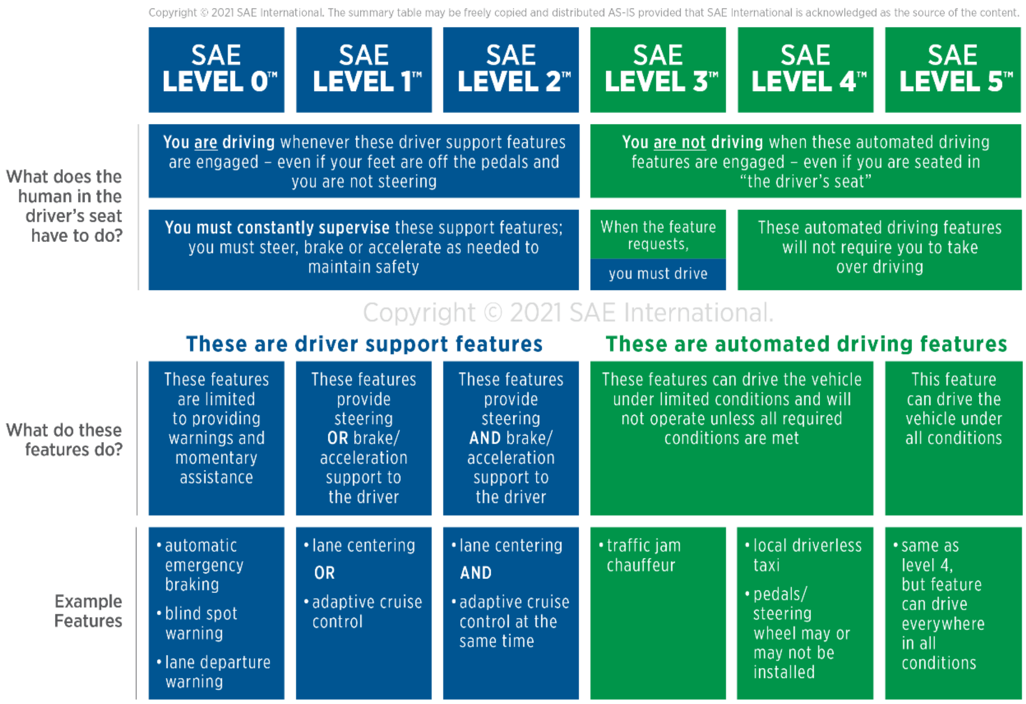

Figure 1.4. Descriptions for the five levels of driving automation defined by SAE J3016, derived from SAE (2021).

Here, Levels 1 to 2 are categorised as "driver support" features, where drivers are relieved of physical control of certain aspects of the driving task, but they must constantly supervise these support features, requiring near-continuous human despite occasional machine control. On the other hand, Levels 3 to 5 are considered as "automated driving" features, where the automated system executes driving entirely once active with occasional or no human intervention. At Level 3, the automated system can manage all driving tasks under specific conditions but still requires the driver to be seated and ready to take over when requested. In contrast, Level 4 and Level 5 AVs do not require any human intervention to resume control of the vehicle. In such vehicles, there may be no steering wheel or pedals installed. Two types of Level 4 AVs currently exist: pod-like shuttles (ITSInternational, 2016), which lack steering wheels and pedals entirely, and personal AVs (Zhang et al., 2024), where the driver may or may not occupy the driving seat.

While AVs at Levels below 3 resemble conventional vehicles and require a driver in the driving seat to perform driving tasks, Highly Automated Vehicles (HAVs) (level 4 and above) may look significantly different externally, e.g., Level 4 pod-like AVs or personal AVs without a driver present for supervision. This shift in appearance or driver's role is likely to influence pedestrians' crossing decision and behaviour around these vehicles. For instance, research suggests that pedestrians feel more stressed and hesitant to cross in front of a vehicle when the driver appears distracted (e.g., talking on the phone or reading a newspaper) or is absent, as observed in simulated environments (Velasco et al., 2019) and Wizard-of-Oz experiments (Lundgren et al., 2017). Furthermore, pedestrians tend to spend more time observing and gathering information about crossing safety in front an AV compared to a human-operated vehicle, as noted by Liu et al. (2023) in a Wizard-of-Oz experiment. Additionally, Madigan et al. (2019), in their analysis of 22 hours of video data recorded from Greece and France, observed that pedestrians kept a greater lateral distance from AV pods than from other vehicles on a 2 km route. Taken together, these studies highlight notable behavioural changes in pedestrian interactions with HAVs. Consequently, this thesis focuses on HAVs (Level 4 and above) to examine how repeated exposures to these HAVs would influence the interactions. It explores how AVs should negotiate the right-of-way with pedestrians to facilitate efficient and safe interactions between road users.

While some researchers (Millard-Ball, 2018), argue that pedestrians do not need to communicate with AVs because they expect AVs to always comply with the rules of the road and yield for pedestrians. However, others believe that ambiguities between pedestrians and AVs in conveying their intent to the other actor cannot always be resolved (Domeyer, Lee, & Toyoda, 2020; Habibovic et al., 2018; Löcken et al., 2019; Lundgren et al., 2017; Merat et al., 2018). For example, a field study by Merat et al. (2018) has shown that pedestrians expect AVs to communicate crucial information such as acknowledgment of pedestrian detection, the vehicle's automated status, its speed, stopping intentions, and its perception of the environment. However, current guidance on how and where this communication should be implemented and how pedestrians adapt to it remains unclear. In the following sections, we will examine research results from studies investigating the use of both implicit and explicit communication strategies and assess their effectiveness in facilitating effective communication during road user interactions.

1.3.2 Implicit communication from AVs

Implicit communication, which is directly related to a vehicle's kinematics, is the primary method for conveying a vehicle's intent during vehicle-pedestrian interactions, as discussed in Section 1.2.3. Research consistently highlights its prevalence over explicit communication methods. For example, video-based observations in the Netherlands by Dey and Terken (2017) revealed that nearly 97% of pedestrians do not use explicit methods (e.g., gestures) and that explicit communication from drivers is even rare. Similarly, a study by Lee et al. (2020), which analysed 701 road user interactions at Leeds, Athens and Munich, found that explicit communications like eye contact, hand gestures, and honking among drivers and pedestrians are rare. While researchers, such as Sucha et al. (2017), acknowledged occasional instances of explicit communication in road interactions, implicit communication remains the dominant and most intuitive approach, as it aligns with the natural way pedestrians interpret vehicle behaviour in everyday scenarios.

As AVs integrate into traffic systems, adopting these familiar implicit cues becomes essential for maintaining traffic efficiency and ensuring safe road user interactions. These cues allow pedestrians to interact with AVs in ways they already understand, minimising confusions and fostering intuitive information exchanges (Ackermann et al., 2018; Dietrich, Maruhn, et al., 2020; Rettenmaier et al., 2021; Zach Noonan et al., 2023). Research also shows that humans are more likely to trust and accept automated systems that exhibit human-like motions, as these behaviours are perceived as more natural and competent (Duffy, 2003; Waytz et al., 2014). For AVs, this means emulating the behaviour of a competent and experienced human driver (Pillai, 2020). To achieve this, researchers have proposed various algorithms designed to replicate human-like driving behaviours, such as human-like car following, driving trajectories, navigation reasoning, and motion planning (Fu et al., 2019; Gu et al., 2017; Kolekar et al., 2020; C. Wang et al., 2020). By developing human-like implicit communication strategies, AVs are expected to negotiate the road in a manner similar to (good) human drivers adhering to designated traffic rules (Dietrich, Maruhn, et al., 2020; Schneemann & Gohl, 2016). Furthermore, situations such as standoffs between AVs and human road users highlight the importance of AVs understanding and adopting the subtle (implicit) cues humans use when interacting on the road (Brown et al., 2023). Incorporating these cues can improve the flow of movement and coordination among all road users. To explore this potential, the following section will examine two specific human driving behaviours, i.e., braking and lateral movements, that could be applied to future AV implicit communication strategies in AV-pedestrian interactions.

Braking behaviour

There has been extensive research on how AVs should brake in response to pedestrians, focusing on designing braking rates and timing to effectively communicate intent through implicit cues (Ackermann, Beggiato, Bluhm, et al., 2019; Ackermann, Beggiato, Schubert, et al., 2019; Beggiato et al., 2018; Bella & Silvestri, 2016; Dietrich, Maruhn, et al., 2020; Lyu, Lee, et al., 2024; Schmidt et al., 2020; Tian et al., 2023; Zach Noonan et al., 2023). For example, Ackermann, Beggiato, Bluhm, et al. (2019) tested pedestrians' reaction times of noticing vehicle's adjustments in driving behaviour across braking strategies, presenting different deceleration rates (5, 3.4, 1.5 m/s^2) and two deceleration onsets (an early onset at 3.5 s- 4.5 s TTC, a late onset at 2-3 s TTC), in a video-based study. Their results indicated that pedestrians' reaction time to acknowledge deceleration onset was shorter when vehicles presented a higher deceleration rate (5 and 3.4 m/s^2), while the impact of braking onset timing was not significant. In contrast, with a lower deceleration rate at 1.5 m/s^2, pedestrians presented a shorter reaction time with an early braking onset compared to the late onset. This finding aligns with research that suggested an earlier braking onset for AVs (Pillai, 2020; Risto et al., 2017; Schneemann & Gohl, 2016; Tian et al., 2023), while highlighting the consideration of deceleration rates together (Dietrich, Tondera, et al., 2020).

However, pedestrians in a simulation study in VR done by Schmidt et al. (2020) can detect earlier the intent of the vehicle when the braking onset is late than early. This contradiction might be due to varying time gaps used in these two studies, where the Schmidt et al. (2020) adopts a large gap of 8 s. It has been noted by Tian et al. (2023) that if the traffic gap was sufficiently large, vehicle behaviour estimation might not directly affect crossing decisions as pedestrian crossing decisions are mainly based on the size of the traffic gap rather than on estimations of vehicle-yielding behaviour. It is therefore reasonable to propose different braking strategies for AVs under different time gaps and other context factors, such as zebra crossings (Zhang et al., 2020), however, this area is largely overlooked in the driver-pedestrian interaction.

Lateral movements

While pedestrians can distinguish a vehicle's intent through changes in speed and braking behaviour, research has shown the potential for incorporating other implicit cues, such as lateral movements (Fuest, Michalowski, et al., 2018; Sripada et al., 2021; Sucha, 2014) with accompanying braking of the vehicle to communicate its intentions. Lateral movements have also been widely used in vehicle-vehicle communication. For example, drivers often shift toward the centre lane at bottlenecks to assert their right of way (Rettenmaier et al., 2020; Rettenmaier et al., 2021), or signal a lane change on the highway well ahead of the manoeuvre (Färber, 2016; Kauffmann et al., 2018). This technique is also preferred by human drivers when interacting with AVs (Potzy et al., 2019). In a driving simulation study by Rettenmaier et al. (2021), drivers negotiated right-of-way with AVs employing lateral offsets at bottlenecks, resulting in shorter passing times and fewer accidents, suggesting these movements are an intuitive method for communicating intent.

In terms of vehicle communication towards pedestrians, Fuest, Michalowski, et al. (2018) investigated drivers' non-yielding behaviours in a survey, with some opting to deviate 50 cm laterally away from pedestrians. This behaviour was later simulated in a Wizard-of-Oz vehicle to assess its communicative effectiveness. Although pedestrians showed a preference for non-yielding vehicles with a lateral offset, no significant differences were observed in the time it took for pedestrians to recognise the vehicle's intentions between trials with and without lateral deviations. This might be attributed to insufficient trials for pedestrians to clearly associate lateral deviation with driver intent, leading them to rely on other cues like vehicle speed and deceleration instead. Additionally, this study was conducted in scenarios where interactions occurred within a 3-second time gap, creating a risky context that likely compelled pedestrians to prioritise braking behaviour over lateral movements. However, lateral deviations may still have potential in scenarios with larger time gaps, where pedestrians have more time to interpret these signals.

Sripada et al. (2021) investigated the manipulation of lateral deviations by AVs for signal yielding or non-yielding intentions. Their video-based research, which varied in timing, magnitude, and directional mapping of deviations, found that movements towards pedestrians to indicate yielding, and movements away pedestrians to signal non-yielding, were intuitively understood more than the reverse option. However, only 34% of participants accurately interpreted these signals, with the remainder uncertain or misinterpreting the intent, likely due to the limitations of visibility in video studies and limited trial numbers to facilitate learning effects.

Investigating the potential for adopting this communication strategy may be warranted, for example by using of lateral offset as a communicative tool when a speed estimation by pedestrians is compromised by factors such as higher speeds or greater distances of an approaching vehicle (Clay, 1995; Sucha, 2014; Sun et al., 2015). However, a gap exists in confirming the real value of such strategies in more realistic settings, as this behaviour is only found by studies using self-reported surveys or focus groups (Fuest, Michalowski, et al., 2018; Sucha, 2014). Moreover, how this behaviour correlates with pedestrian crossing decisions remains unexplored, particularly in scenarios involving repeated encounters that allow for the development of understanding towards this implicit cue.

Overall, this section highlights the importance and potential of implicit communication strategies for AVs to convey intent to pedestrians through human-like motions. While these cues are familiar and intuitive, pedestrians often require more information from AVs, such as the vehicle's automated status, its speed, whether it will stop, whether it has detected the pedestrian, and its perception of the environment (Böckle et al., 2017; Dziennus et al., 2016; Habibovic et al., 2018; Lagström & Lundgren, 2015; Merat et al., 2018). These details cannot be adequately conveyed through motion alone. Additionally, substantial evidence supports the role of eye contact in pedestrian–vehicle interactions (Markkula et al., 2020; Rasouli et al., 2017; Rasouli & Tsotsos, 2020; Sucha et al., 2017), the absence of which in AVs may lead to increased hesitancy in pedestrians' crossing decisions and less perceived safety (Onkhar et al., 2022). Furthermore, research has shown humans' imperfect ability to accurately perceive implicit cues, especially from a distance (Cavallo & Laurent, 1988; DeLucia, 2008). These create opportunities for explicit communication strategies, including eHMI and AR displays, to complement implicit communication in situations where kinematics cues may be ambiguous and insufficient. The following section will explore these explicit strategies in detail.

1.3.3 Explicit communication from AVs

External human machine interface (eHMI)

External Human-Machine Interfaces (eHMIs) have been proposed as a solution to compensate for the lack of direct human communication and to mitigate uncertainty in pedestrian behaviours (Bengler et al., 2020; Carsten & Martens, 2019), in order to address these concerns and enhance the social capabilities of AVs alongside implicit cues. They provide visual information either on the vehicle or projected on the road (Bazilinskyy et al., 2019; Carmona et al., 2021; Dey, Habibovic, et al., 2020), featuring modalities such as light signals (Hensch et al., 2019; Lee et al., 2022), textual messages (Nissan Motor Corporation, 2015), and anthropomorphic symbols (Semcon, 2016). Researchers and OEMs have been actively exploring developing various prototypes and concepts for explicit AV communication, such as the Mercedes-Benz F015 Concept (Daimler, 2015), Jaguar/Land Rover Virtual Eyes Concept (Jaguar Land Rover, 2018), and Smiling Car Concept (Semcon, 2016).

However, research on the suitability and effectiveness of eHMIs for conveying AV intentions in facilitating AV-pedestrian interactions is not conclusive. On one hand, the use of eHMIs has been shown to increase pedestrian trust, acceptance, and perceived safety of AVs (de Clercq et al., 2019; Faas et al., 2020; Holländer et al., 2019), leading to a greater willingness to cross and faster crossing decisions

(Lee et al., 2022; Löcken et al., 2019; Madigan et al., 2023). On the other hand, much research has pointed out that although eHMIs provide important information, they are considered supplementary to the physical movement cues from the vehicle (Clamann et al., 2017; Hochman et al., 2020; Li et al., 2018). Studies have also explored if eHMI complicated the efficacy of AV's communication of intent and pointed out that eHMIs are context-dependent. For example, these are found to be most effective in the absence of formal road markings, such as zebra crossings (Madigan et al., 2023), or during certain kinematic conditions, such as during gentle and early braking (Dey, Matviienko, et al., 2020), lower speed and time gaps (Lee et al., 2022) (Lee et al., 2022), or at greater AV distances (Horn et al., 2023).

Studies have examined how infrastructure cues, such as zebra crossings, influence the effectiveness of eHMIs in AV-pedestrian communication and crossing behaviour. Clamann et al. (2017) developed a prototype forward-facing display on a Dodge Sprinter van, simulating an autonomous vehicle, to provide pedestrians with safety crossing information at either marked crosswalks or unmarked midblock locations in a naturalistic setting. Their findings indicated that while the display type did not significantly affect pedestrian response times, pedestrians at crosswalks responded faster than those at midblock locations. This suggests that pedestrians tend to rely more on familiar behaviours and environmental cues rather than novel information provided by technology. However, the study's realism was limited as it used a human-driven vehicle posing as an autonomous one, potentially making the eHMI more of a distraction since the driver was visibly present. In contrast, Velasco et al. (2019) employed a virtual reality setup that removed the visibility of a driver and tested various road crossing scenarios. The findings highlighted that the presence of a zebra crossing, a shorter time gap, and the presence of an eHMI significantly increased the likelihood of pedestrians' crossing decision Unlike findings from Clamann et al. (2017), the impact of eHMIs was observed regardless of the presence of zebra crossings.

However, both studies overlooked interaction of zebra crossings and eHMIs and focused on simple road contexts, like straight, one-directional streets, where driving behaviour is easier to predict. Addressing these limitations, Madigan et al. (2023) examined pedestrian crossing decisions at a virtual crossroad with varying AV behaviours, eHMI presence, and road infrastructure. The study found that eHMIs significantly reduced crossing initiation times, but only when zebra crossings were present. This highlights the importance of considering the specific context, such as road infrastructure and traffic complexity, when adopting eHMI strategies.

Although research suggest that pedestrians may disregard eHMI messages in favour of the vehicle's kinematics when there is conflicting information (Dey, Matviienko, et al., 2020), repeated exposure to eHMIs can gradually alter this pattern, leading to over-reliance on explicit communication. For example, Kaleefathullah et al. (2020) found that about 35% of pedestrians in a simulation crossed the road when an eHMI was present, despite the vehicle not decelerating, indicating increasing reliance on the eHMI over time. This suggests that as pedestrians gain familiarity with eHMIs through repeated exposures, their understanding, trust, and acceptance of these systems improve (Holländer et al., 2019). While this can enhance communication and facilitate crossing decisions in road user interactions (Lee et al., 2024), it also raises potential safety concerns, as over-trust during the learning phase could lead to risky crossing decisions. Furthermore, increasing exposure to eHMIs may influence pedestrians' attention allocation during crossing tasks, potentially shifting their focus to the eHMI at the expense of other critical cues, such as vehicle speed or braking behaviour. Understanding these changes in attention and behaviour is vital to identify potential safety risks associated with over-reliance on eHMIs. Unfortunately, this aspect has been largely overlooked in existing research, highlighting the need for further investigation.

Furthermore, eHMIs can face challenges in their scalability and ability to manage multiple interactions in dynamic traffic scenarios (Dey et al., 2021; Holländer et al., 2022; Lyu, Zhang, et al., 2024; Wilbrink et al., 2021). Typically, these interfaces are used in one-to-one interactions between a pedestrian and an AV (Colley et al., 2020). In contrast, real-world traffic often involves simultaneous interactions with multiple road users, which necessitates the creation of eHMIs that can effectively communicate across various distances and directions. This complexity introduces challenges in identifying which pedestrian an AV is signalling to and which AV a pedestrian should pay attention to the message, issues that are sometimes exacerbated by eHMI visibility problems, such as those caused by their placement and size (Dey, Habibovic, et al., 2020). To address these challenges, personalised communication strategies such as Augmented Reality (AR) are being explored. These approaches aim to provide tailored safety information to pedestrians, thereby enhancing the efficiency and reliability of pedestrian-AV interactions (Calvi et al., 2020; Matviienko et al., 2022; Peereboom et al., 2024; Tabone et al., 2023; Tabone et al., 2021; Tran et al., 2023; Tran et al., 2022).

Augmented reality (AR)

Advancements in wearable AR technology (e.g., Microsoft HoloLens, Google Glass, Apple Vision pro) have sparked significant interest and diverse applications within the automotive industry, particularly for in-car users. Features like heads-up displays and windshield projections enhance navigation, highlight potential hazards, and facilitate a clearer understanding between drivers and automated systems, ultimately boosting both safety and comfort (Riegler et al., 2021; Wiegand et al., 2019). Building on these in-car benefits, recent research has expanded to explore AR's potential for enhancing interactions between AVs and road users. Wearable AR allows for simultaneous interactions between the AV and an unlimited number of road users, providing precise, customised visual information that can adapt to individual user preferences and needs (Dey, Habibovic, et al., 2020; Tabone et al., 2020; Tran et al., 2023). Furthermore, by overlaying digital content onto the physical world, wearable AR helps users maintain situational awareness and can swiftly respond to safety notifications, making it a critical tool in managing complex traffic interactions and improving overall road safety (Tong et al., 2021). However, it may also risk overwhelming pedestrians with information presented from multiple sources or directions, a challenge that will be discussed in the following sections.

Various AR concepts have been proposed to convey road-crossing information (Hesenius et al., 2018; Matviienko et al., 2022; Prattico et al., 2021; Tabone et al., 2023; Tong et al., 2021; Tran et al., 2023; Tran et al., 2022). Different from eHMIs, which are typically attached to the AV, ARs can be more versatile. Three main design locations have been proposed for current ARs. These are designs that: follow the crossing path (e.g., projections of zebra crossings, arrows, and safe paths) (Prattico et al., 2021; Tran et al., 2022), following pedestrians' head movements, (e.g., head-up displays, HUDs) (Peereboom et al., 2024), and following the vehicle's movements, (e.g., car overlays) (Matviienko et al., 2022; Tran et al., 2022). However, research to suggest the best placement for AR has been largely overlooked.

As mentioned, one potential challenge of adopting AR is the increased cognitive effort required from pedestrians, as they need to process additional visual information. Research in the fields of learning and skill acquisition has shown that while mobile AR applications can reduce cognitive load by providing direct, relevant information, it can also overwhelm users when too much information is presented simultaneously (see reviews from Buchner et al. (2022);Suzuki et al. (2024)). In the context of road user interactions, pedestrians may face cognitive and information overload when confronted with an excess of visual cues, which could compromise their safety (Mahadevan et al., 2018; Moore et al., 2019). However, it remains unclear whether the use of AR increases the cognitive and visual demands on pedestrians, as this has not yet been thoroughly explored. Additionally, investigating how AR can be designed to mitigate this overload is important. Factors such as the placement of AR elements and other design considerations (e.g., the intuitiveness of the design and consideration of its learnability) should be examined to understand how they could help alleviate the cognitive and visual burden on pedestrians.

A useful approach to addressing these concerns is to investigate pedestrians' visual attention in these scenarios. As introduced in Section 1.2.2, pedestrians' gaze and head movements can indicate how they allocate their attention and their need for gathering additional information during crossing tasks. Therefore, the next section will provide a detailed analysis of pedestrian behaviour and attention during interactions with automated vehicles, to examine the visual load introduced by exposure to these novel explicit interfaces.

1.3.4 Pedestrians' head and gaze behaviour

Research on pedestrians' gaze behaviour provides insights into how they seek information during crossing tasks when interacting with conventional vehicles (de Winter et al., 2021; Dey et al., 2019; Gruden et al., 2021; Lévêque et al., 2020; Zhao et al., 2023). Dey, Holländer, et al. (2020) showed that pedestrians' gaze patterns in front of an AV exhibit similarities to those observed with manually driven vehicles, with an increasing focus on the vehicle and windscreen as it approaches. In their Wizard-of-Oz experiment, pedestrians stood at the curb and used slider input devices to indicate their willingness to cross as the AV approached, which either featured an eHMI, a turquoise light bar on the grille indicating yielding intent, or no eHMI. The results revealed that the presence of the eHMI did not significantly influence gaze behaviour, except that pedestrian displayed less gaze density on the windscreen compared to manual driven vehicles, likely because eye contact was unnecessary in the absence of a human driver. However, this study involved stationary pedestrians who pressed a button to indicate their crossing intention rather than making actual crossing decisions and the vehicles in this experiment always yielded to pedestrians, which may have affected their perception of the situation (Te Velde et al., 2005). Additionally, while gaze on the vehicle was analysed, attention to other environmental cues and their role in information gathering were not considered.

Other research on pedestrians' gaze behaviour in AV-pedestrian interactions has predominantly focused on assessing the placement and design of various eHMIs, rather than investigating their impact on visual load (Eisma et al., 2020; Guo et al., 2022; Hochman et al., 2020; Lyu, Zhang, et al., 2024). For example, in a video-based eye-tracking study, Guo et al. (2022) evaluated different eHMI modalities and found that text, icons, and arrows centralised visual attention, scored highest for clarity, and led to the shortest decision times. In contrast, light strip-based eHMIs, while noticeable, did not significantly reduce decision times and led to longer fixation durations. Regarding the placement of eHMIs, Eisma et al. (2020) projected the same textual eHMIs in different locations and found that projecting them on the windscreen effectively concentrated pedestrian gaze, whereas projections on the road dispersed gaze patterns between the vehicle and the road, increasing visual effort. Hochman et al. (2020) examined pedestrians' gaze fixations across multiple trials to assess the learnability of various eHMI designs. Their findings revealed that learning occurred regardless of the specific design, as gaze fixation durations decreased with increasing exposure to each eHMI. A common limitation of these studies is their reliance on desktop-based video setups, which may not accurately reflect how pedestrians' gaze is dispersed in the real-world, or within 3D environments where multiple environmental cues are present simultaneously.

As for pedestrians' head movements in AV-pedestrian interactions, only one recent study has investigated this aspect. Lyu, Lee, et al. (2024) conducted a distributed simulation study integrating a CAVE-based pedestrian simulator with a desktop driving simulator to explore pedestrian road-crossing decisions and head movement responses to various vehicle kinematics at un-signalized, single-lane, roads. Pedestrians either encountered predefined automated braking behaviours, including soft braking at a deceleration of 2.5 m/s^2 when the vehicle was 40 metres away from the pedestrian, that stopped when it was 4 meters away, or hard braking at a deceleration of 3.2 m/s^2 stopping 12 meters away from the pedestrian. A series of non-braking trials, with the vehicle maintaining a speed of 30 mph were also introduced. In another set of trials, pedestrians interacted with human-driven vehicles, when a human driver (hidden from them) was asked to take control of the driving, when the vehicle was 60 meters away from the pedestrian. The driver had to decide whether or not to brake. Pedestrians' head-turning rate and frequency before and during the crossing was measured. Results indicated that head-turning behaviour could reliably signal crossing intent, highlighted by a significant increase in head-turning rate during the last two seconds before beginning the crossing as a final safety check, in line with observations in interactions with conventional vehicles (Hassan et al., 2005). Moreover, there was a more frequent and greater head-turning rate when pedestrians intended to cross, compared to when they did not, suggesting that head-turning behaviour could serve as an indicator for predicting pedestrians' crossing intent (Hassan et al., 2005). The study also revealed differences in head-turning behaviour based on vehicle kinematics: pedestrians increased their head-turning frequency when facing automated vehicles which exhibited hard braking compared to soft braking, a lower frequency of head turns during the automated soft braking conditions, compared to conditions controlled by the human. However, this study was limited to a single-lane scenario with a single vehicle always approaching either from the right. Future research could explore more dynamic situations, such as crossroads (Hamaoka et al., 2013), where vehicles approach from various directions. Moreover, there is currently no research investigating pedestrians' head-turning behaviour when exposed to AVs employing explicit communication methods.

Overall, pedestrians' gaze and head-turning behaviour during interactions with AVs exhibit similarities to those observed with conventional vehicles, though significant gaps remain in understanding these patterns across different contexts. Additionally, repeated exposure to AV interactions may further influence these behavioural changes (de Clercq et al., 2019; Hochman et al., 2020; Lee et al., 2022), a topic that will be explored in detail in the following section.

1.4 REPEATED AV-PEDESTRIAN INTERACTIONS

1.4.1 The effect of learning

Exposures to novel or unfamiliar information can initiate a learning process, a topic extensively explored in human-computer interaction research (Grossman et al., 2009). These studies demonstrate that learning occurs when users engage with new interfaces and novel interaction approaches. It is suggested that such exposure facilitates the formation and adjustment of mental models (Kahneman, 2011; Zhang & Xu, 2011), which are conceptual frameworks representing users' understandings of external objects, systems, and the broader environment, including the dynamics between actions and environmental events (Carroll & Olson, 1987; Durso & Gronlund, 1999). These models are continuously updated with novel information, thus enhancing the efficiency of user interactions (Grossman et al., 2009). Mental models are also important for making predictions in a task, acting as hierarchical generative models that become more accurate with repeated exposures (Clark, 2013; Engström et al., 2018). Regular interaction with new information not only strengthens these models but also enhances knowledge accumulation, which may be declarative, acquired through formal education, or procedural, developed through practical experience (Endsley, 2000; Nersessian, 2009; Shiffrin & Schneider, 1977). Both modes of knowledge acquisition contribute to the refinement of mental models and memory formation, leading to behavioural adjustments. However, learning through practical experience can sometimes occur unintentionally and implicitly, yielding knowledge that is difficult to express (Berry & Dienes, 1993; Ivanchei, 2014). Nevertheless, the outcomes of this implicit learning can be observed through the level of automaticity in behaviour, occurring without a person's conscious decision-making.

Previous research has indicated that when an individual consistently reacts in the same manner to a social stimulus, their response becomes automatic over time. This automaticity arises because the mental representations associated with the stimulus are frequently and consistently activated, eventually becoming preconsciously triggered by the stimulus, thereby bypassing conscious decision-making processes (Bargh et al., 1996; Shiffrin & Schneider, 1977). Consequently, if a person regularly exhibits the same behavioural response to specific situational features, this behaviour becomes automatically associated with those features, indicating the application of acquired knowledge (Mischel et al., 1995; Shoda et al., 1994). This association, although not intentionally learned, becomes integrated into an individual's response patterns. Therefore, by observing and measuring changes in behaviour across repeated exposures, researchers can capture such implicit learning processes, even if the individual is not actively and consciously trying to learn.

To quantify the learning process in relation to time and exposures across various activities such as decision-making and problem-solving, the concept of the "power law of practice," also known as the "power law of learning," has been introduced. This psychological theory establishes a relationship between the amount of practice and task performance (Newell & Rosenbloom, 1981), where there is a sharp initial improvement in performance, followed by a stabilization as the number of trials and practice sessions increases. This pattern aligns with empirical observations in diverse learning contexts like skills training, memory, perception, and problem-solving, where significant, rapid improvements are initially evident, but the rate of improvement decelerates as one gains proficiency. However, there is a debate concerning the method of applying this power function when averaging scores across participants rather than analysing individual differences (Brown & Heathcote, 2003). To tackle this, it's important to account for individual differences in studies.

In the driving domain, the power law has been applied, for example, to understanding how drivers learn to use regenerative braking in electric vehicles (Cocron et al., 2013) and how they acquire skills in operating in-vehicle information systems (Jahn et al., 2009). It has also been applied to study how drivers develop mental models and become accustomed to autonomous functions, such as Adaptive Cruise Control (ACC) (Beggiato & Krems, 2013; Beggiato et al., 2015; Forster et al., 2019, 2020). In the following session, we will review the research about learning in autonomous driving with long-term studies, and how it can be developed for road user interactions.

1.4.2 Repeated exposures for learning

Research on pedestrians' learning in AV interactions is limited, whereas substantial work has focused on how drivers adapt to advanced driver assistance systems (ADAS) such as Adaptive Cruise Control (ACC) and Lane Keeping Systems (LKS), as well as to AVs. Although longitudinal studies in this context vary in duration, ranging from one week (Miller & Boyle, 2019) to two months (Beggiato & Krems, 2013), with intermediate durations of two weeks (Simon, 2005) and four weeks (Weinberger et al., 2001), findings consistently show that significant learning and behavioural changes can stabilise within just a few repeated exposures (Forster et al., 2020; Martens & Fox, 2007). For instance, using a moving-base driving simulator, Forster et al. (2020) observed that drivers' mental models towards several driving use cases in automated vehicles (Level 2 and 3) stabilised after five repeated interactions, with the most significant learning occurring during the first block of trials. Similarly, in a low-cost simulation driving setup, Martens and Fox (2007) noted that drivers' gaze durations on designated traffic signs decreased sharply on the first day, suggesting rapid adaptation to repeated visual stimuli.

Similar findings were obtained in longitudinal research from pedestrians' research. In a Wizard-of-Oz experiment, Joisten et al. (2022) assessed pedestrians' perceived safety across different crossing scenarios during three sessions across five days. The results indicated that perceived safety was higher when crossing in front of an AV compared to a conventional vehicle on the first day and increased with subsequent sessions, although the difference between Day 2 and Day 3 was not statistically significant. Despite limitations such as sequence effects, this study demonstrated that pedestrians' learning could stabilize after the initial day of exposure, suggesting that experiments involving repeated measures may require only a single day visit per participant.

Since pedestrians are not the primary intended users of AVs and typically do not receive manuals or instructions about AV features, their understanding and interpretation of these vehicles' behaviours or external interfaces (eHMIs and ARs) are likely to improve only through repeated exposures. This scenario is an example of implicit learning, a process where learning occurs unintentionally and without explicit instruction, leading to gradual adaptations in behaviour. Moreover, road users' interactions typically require rapid reactions from pedestrians (0.5 – 6.5 s) to accurately understand AV's driving intention from Liu et al. (2020). Given that learning tends to stabilise quickly after initial exposures (Forster et al., 2020; Joisten et al., 2022; Martens & Fox, 2007), this study focuses on capturing learning effects within a single visit, within a few repeated exposures. By measuring such behavioural changes and the learning process when pedestrians are exposed to various communicative strategies employed by AVs, we aim to provide knowledge on the creation of more efficient, safe, and less distracting mechanisms for developing communication cues by future AVs.

1.4.3 The effect of learning on pedestrians' behaviour over repeated exposures

Research on the impact of learning in AV-pedestrian interactions has primarily focused on evaluating various eHMI designs to inform design guidelines (de Clercq et al., 2019; Faas et al., 2020; Hochman et al., 2020; Lee et al., 2022). In a head-mounted display study, de Clercq et al. (2019) assessed the percentage of "feeling safe" responses from pedestrians, who pressed handheld buttons to indicate their feeling of safety across multiple eHMI designs, each repeated nine times: (1) baseline without eHMI, (2) front brake lights, (3) Knight Rider animation, (4) smiley, and (5) text ("WALK"). The results indicated that pedestrians felt significantly safer when interacting with AVs equipped with eHMIs compared to those without any eHMI. Additionally, learning effects were observed in all eHMI types except for the text-based eHMI, with safety perceptions increasing initially and then stabilising after several exposures. However, text-based interfaces, while intuitive, have other disadvantages such as a shorter visual range and significant cross-cultural barriers due to language dependencies when compared to graphical eHMIs (Zheng et al., 2023). This underscores a critical limitation of the study: evaluations that depend solely on learning effects and self-reported safety perceptions, rather than direct behavioural measurements, which may not yield a comprehensive understanding of eHMI effectiveness (Te Velde et al., 2005). In contrast, Hochman et al. (2020) observed learning effects with text-based eHMIs using desktop-based video simulations. These simulations, which measured pedestrians' gaze fixations across 100 trials, featured eHMIs with varying background colours (red/green), message types (status/advice), and presentation modalities (text/symbol). The authors suggest that the complexity of these elements could potentially lead to information overload, with participants needing some time to learn and interpret the designs, including those with text-based eHMI.

Lee et al. (2022) corroborated the importance of intuitive designs in a CAVE-based simulator study. They compared a novel eHMI design (SPLB: slow pulsing light band) with a more familiar one (FH: flashing headlights) within three repeated blocks. Results showed that participants quickly grasped the meaning conveyed by the FH within the first block of trials, whereas understanding the message from the SPLB required exposure to 12 eHMI trials (one block). On average, crossings with the FH occurred approximately 800 ms earlier than with the SPLB. However, the between-subjects design, where different groups of pedestrians were exposed to different eHMIs, may have introduced individual differences that influenced the results. Despite this, novel eHMI concepts may require time for road users to fully comprehend their meaning, posing a challenge for AV manufacturers who need to communicate clear messages to pedestrians. This underscores the importance of considering long-term exposure and familiarity when introducing new eHMI messages.

Using a longitudinal video study spanning three sessions with intervals of seven to nine days between each session, Faas et al. (2020) assessed the effectiveness of eHMIs, including (i) no eHMI (baseline), (ii) status eHMI, and (iii) status + intent eHMI. Measurements included pedestrian crossing onset time, perceived safety, trust, acceptance, and user experience, which encompassed learnability. As exposure to the eHMIs increased, pedestrians demonstrated higher trust, greater reliance, and faster crossing times. Both eHMI types (status and status + intent) improved understanding of the surrounding environment, thus facilitating quicker crossing. Notably, the status + intent design proved more influential than the status-only design. However, there is potential that providing more information to pedestrians may raise workload, which remains a research gap in this context.

Overall, most research investigating pedestrians' learning processes when interacting with AVs focuses on the use of eHMIs, leaving a significant gap in understanding other communication mechanisms, such as the learning value of implicit driving cues or AR as a communication tool for AVs. Furthermore, evaluations predominantly rely on self-reports or crossing decision times (de Winter & Dodou, 2022; Rasouli & Tsotsos, 2020), while studies examining pedestrians' attention allocation over repeated exposures remain largely overlooked.

1.5 RESEARCH GAPS AND QUESTIONS

Understanding AV-pedestrian interactions is vital for ensuring safer and more effective road-sharing environments. The growing body of literature has investigated various implicit (e.g., vehicle kinematics) and explicit (e.g., eHMIs and AR displays) communication strategies to bridge the gap left by the absence of a human driver. However, several critical aspects of these interactions remain underexplored, limiting the current understanding of how pedestrians interpret and adapt to AV communication methods over repeated encounters. To address these gaps, this thesis focuses on three key research areas that require further investigation to enhance AV design and pedestrian safety.

Firstly, while extensive studies, as discussed in Section 1.3, have explored the influence of zebra crossing (Clamann et al., 2017; Havard & Willis, 2012; O'Dell et al., 2022; Velasco et al., 2019) and vehicle kinematics (Ackermann et al., 2018; Bindschädel et al., 2022; Dey, Matviienko, et al., 2020; Domeyer, Lee, Toyoda, et al., 2020; Fuest, Michalowski, et al., 2018; Lee et al., 2022; Rettenmaier et al., 2021; Risto et al., 2017; Várhelyi, 1998; Zach Noonan et al., 2023) on pedestrians' crossing decisions and behaviours in current traffic, few has examined their interactive effects. For instance, drivers may exhibit different kinematic patterns depending on the presence or absence of a zebra crossing (Dabrowska-Loranc et al., 2021; Várhelyi, 1998; Zhang et al., 2020), which could, in turn, prompt corresponding adjustments in pedestrians' decisions and behaviours. However, it remains unclear which factor, zebra crossings or vehicle kinematics, is more influential in shaping pedestrians' crossing decisions, and little is known about their effects on attention allocation, such as head-turning behaviours.

Most existing research typically involves a single actor (a pedestrian) and examines their reactions to preprogrammed driving behaviours rather than investigating dynamic, interactive scenarios involving both pedestrians and drivers (Ezzati Amini et al., 2021; Rasouli & Tsotsos, 2020). Although naturalistic observations have been employed to study these interactions, they are limited in their ability to establish causal relationships or support repeated measurements under controlled conditions (Dozza, 2013). This highlights a critical gap in understanding how natural driving responses serve as implicit communication with pedestrians and how pedestrians' crossing decisions are shaped by the interplay between zebra crossings and vehicle kinematics (e.g., time gaps and drivers' responses). Addressing this gap requires a controlled and repeatable experimental environment where both parties can dynamically interact in real time, such as a distributed simulation (Kearney et al., 2020; Lyu, Lee, et al., 2024; Sadraei et al., 2020). These considerations lead to the following research question:

- ***RQ 1:*** *How do zebra crossings and vehicle kinematics (e.g., time gap, yielding decision and behaviours, and lateral deviation), influence pedestrians' crossing decisions and attention allocation, such as head-turning behaviours?*

Another notable research gap exists in understanding how pedestrians allocate their attention during crossing tasks when AVs are in their vicinity, particularly with explicit communication strategies, such as eHMIs or AR displays. While most existing studies focus on real-world observations of conventional vehicles, little is known about whether pedestrian head-turning (Avineri et al., 2012; Hamaoka et al., 2013; Hassan et al., 2005; Kalantarov et al., 2018) and gaze behaviours (de Winter et al., 2021; Dey et al., 2019; Lévêque et al., 2020) observed in driver-pedestrian interactions persist or change in AV contexts. Explicit cues from eHMIs or AR displays may further influence attention allocation (Dey, Matviienko, et al., 2020; Eisma et al., 2020; Guo et al., 2022), raising concerns about potential visual overload if such visual stimuli would distract pedestrians from critical vehicular or environmental signals.

Currently, the evaluation of explicit communication strategies relies primarily on measuring pedestrians' crossing initiation times and self-reported trust or acceptance (Ezzati Amini et al., 2021; Rasouli & Tsotsos, 2020). However, head-turning and gaze behaviours, which are closely linked to situational awareness and uncertainty/need to gather more information (Endsley, 1995; Grasso et al., 1998; Kooij et al., 2014; Patla et al., 1999), offer a valuable yet underexplored means of assessing the effectiveness of these cues in communicating AV's intent. These considerations motivate the following research question:

- ***RQ 2****: How do explicit communication strategies (eHMI and AR displays) from AVs influence pedestrians' crossing decisions and attention allocation, such as head-turning and gaze behaviours?*

A third research gap exists in understanding how repeated exposures influence pedestrians' learning and adaptation to communication strategies used by AVs. Most studies focus on single encounters (Ezzati Amini et al., 2021; Rasouli & Tsotsos, 2020), neglecting the learning processes that occur as pedestrians repeatedly interact with implicit cues (e.g., vehicle kinematics) and explicit strategies (eHMI and AR displays). While pedestrians may become more adept at interpreting these cues over time (de Clercq et al., 2019; Faas et al., 2020; Hochman et al., 2020; Lee et al., 2022), poorly designed strategies can increase task complexity, frustrate users, and undermine their effectiveness, potentially requiring pedestrians to rely more on head-turning or gaze to search for relevant information (Mahadevan et al., 2018; Moore et al., 2019). Understanding how pedestrians' decision and attention allocation adapt to these communication methods is crucial for designing AV systems that dynamically adjust their strategies to evolving pedestrian behaviours. Such insights are essential for fostering safer and more efficient interactions between AVs and pedestrians. These rationales give rise to the following research question:

- ***RQ 3****: How do repeated exposures to vehicle kinematics (e.g., yielding decision and behaviours, time gap, and lateral deviation) and explicit communication strategies (eHMI and AR displays) influence pedestrians' crossing decisions and attention allocation, such as head-turning and gaze behaviours?*

Understanding the pedestrians' crossing behavioural patterns in these situations over repeated exposures is valuable for traffic safety, planning and management. At the same time, these investigations can facilitate the development of more realistic computational models of pedestrian crossing decisions as well as the design of the corresponding AV communication strategies.

1.6 THESIS OBJECTIVES AND OUTLINE

This thesis investigates AV-pedestrian interactions, focusing on how pedestrians learn and adapt their behaviours to implicit and explicit communication strategies through repeated exposures. In this context, learning and behavioural adaptation refer to pedestrians' short-term changes in crossing decisions (e.g. crossing probabilities) and attention allocation (e.g. gaze and head-turning behaviour) observed across three repeated exposures to AVs within a single experimental session in this study. Although intuitive communication strategies are desirable, as they impose minimal cognitive demand and can be readily interpreted based on prior experience, novel cues introduced by AVs may not be immediately intuitive. This research therefore considers the learnability of such cues by evaluating how easily pedestrians adapt to them over repeated exposures.

While this thesis involves the investigation of explicit interfaces (e.g. eHMI and AR), it does not focus on the specifics of interface design. Rather, it contributes methodologically by proposing and applying an evaluation approach that uses gaze and head-turn metrics across repeated exposures to assess how different communication strategies affect pedestrian behaviour.

The research addresses three key gaps and answers the associated research questions across three empirical studies, each constituting a chapter either published or under review in peer-reviewed journals.

Chapter 2 presents a published paper that develops a distributed simulation environment that connects a driver's lab and a pedestrian's lab to capture dynamic, real-time interactions in a virtual and controlled setting. This study addresses **RQ1**

by exploring how zebra crossings and vehicle kinematics (e.g., time gaps, drivers' yielding behaviours and lateral deviation) influence pedestrians' crossing decisions. Additionally, it addresses **RQ3** by examining how pedestrians adapt their crossing decisions through repeated exposures to these implicit cues. The findings contribute to designing human-like AV driving behaviours for effective implicit communication.

Chapter 3 comprises a published study examining pedestrians' head-turning behaviour at a virtual UK crossroad in front of an AV across different crossing scenarios in a CAVE-based simulator. It addresses **RQ1** by analysing how infrastructure cues such as zebra crossings and vehicle yielding decisions affect head-turning behaviours, **RQ2** by examining pedestrians' head-turning behaviours in response to eHMI cues, and **RQ3** by exploring changes in head-turning behaviours over repeated exposures.

Chapter 4 consists of a paper currently under review that investigates pedestrians' gaze behaviours and decision-making when encountering AVs with various AR displays signalling their intent. Using a CAVE-based simulator, it addresses **RQ2** by analysing how AR displays influence pedestrians' gaze behaviours and crossing decisions, and **RQ3** by exploring how repeated exposures shape gaze fixation patterns.

While the study presented in Chapter 2 introduces a distributed simulation setup to investigate pedestrians' crossing decisions in response to varying implicit driving behaviours, it does not directly involve automated vehicles. Although not an AV–pedestrian interaction per se, the findings provide valuable insights to inform AV design by revealing how pedestrians react to diverse non-verbal cues. In contrast, the studies in Chapters 3 and 4 involve the evaluation of explicit communication strategies of AVs. Since the vehicle behaviour was pre-programmed and consistent in these two studies, a distributed setup was no longer required, and the studies relied solely on the pedestrian simulator. While the methodological approaches vary across chapters, the studies are connected by a shared objective of examining how pedestrians interpret and adapt to different vehicle communication strategies across repeated exposures.

Chapter 5 includes the discussion and conclusion section of the thesis. It summarises the main findings, highlights both theoretical and practical contributions, discusses the research limitations, and provides recommendations for future research.

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CHAPTER 2

USING DISTRIBUTED SIMULATIONS TO INVESTIGATE DRIVER-PEDESTRIAN INTERACTIONS AND KINEMATIC CUES FOR AVS

ABSTRACT

As we move towards a future with Automated Vehicles (AVs) incorporated in the current traffic system, it is crucial to understand driver-pedestrian interaction, in order to enhance AV design and optimization. Previous research in this area, which has primarily used naturalistic observations or single-actor virtual reality simulations, has been limited by its inability to draw causal conclusions, also due to a lack of real human-human interactions. Our study addresses these limitations by employing a high-fidelity distributed simulation setup that links drivers in a motion-based simulator with pedestrians in a CAVE-based environment. This method allows for the examination of real-time and reciprocal interactions across a range of road-crossing scenarios. Using thirty-two pairs of drivers and pedestrians, we investigated how different factors, such as the presence of zebra crossings and varying time gaps of the approaching vehicle, influence driver behaviour and pedestrian crossing decisions. The effect of drivers' control of the vehicle during such crossings (e.g., braking behaviour and lateral deviation) on pedestrians' crossing decisions were also analysed.

We found that the distribution of drivers' average deceleration values was bimodal, where drivers either markedly yielded to pedestrians, or continued in their path, with very few instances of intermediate behaviour. We also found that pedestrian decisions were seemingly influenced by the different braking strategies adopted by the driver, with pedestrians crossing before the vehicles in response to soft and early, or late and hard braking, while late and soft braking often resulted in the vehicle passing first. We also observed a slight lateral movement of the vehicle away from pedestrians when drivers were not yielding, but more of a lateral deviation towards them when yielding. This may be because drivers subconsciously transfer their walking interaction habits to their driving behaviour, to avoid a collision with pedestrians. Finally, our results showed a stronger influence of these kinematic cues on pedestrian crossing decisions, when compared to zebra crossings. As well as highlighting the value of a novel approach for investigating vehicle-pedestrian interactions, this study illustrates how vehicle cues can assist pedestrian decisions, adding new knowledge in the development of human-like behaviour for future AVs.

Keywords: AV, Distributed simulation, Implicit communication, Lateral deviation, Behavioural adaptation, Gap acceptance, Zebra crossing

2.1 INTRODUCTION

Technological advancements in driving systems are paving the way for the imminent arrival of highly automated vehicles (HAVs, Level 4 and 5) (SAE, 2021), with promised improvements in traffic safety and efficiency (Litman, 2021). When compared to human-operated vehicles, AVs are expected to increase road safety by removing human error, which is thought to contribute to over 90% of road crashes (Highway Traffic Safety Administration & Department of Transportation, 2015). However, as AVs begin to share road space with other humans, including other drivers, and vulnerable road users (VRUs), such as pedestrians and cyclists, we see the emergence of a "substitution myth" (Parasuraman et al., 2000), with new types of human error, leading to new and previously unknown safety concerns. This may be because these new forms of transport do not yet conform to the social norms of our current traffic system, leading to confusion for other road users sharing the same space. For example, higher level AVs that are not controlled by a human cannot currently use any explicit or implicit cues from other road users to predict their intentions (Brown et al., 2023). These vehicles are also able to provide any explicit messages to communicate their intention to surrounding traffic, which can result in frustrating stand-offs between the AV and other road users, for example at unsignalised junctions (Madigan et al., 2023). This is because the right of way is not clear at such crossings, and the absence of a human in the AV, or formal traffic infrastructure such as traffic lights, precludes any other form of communication and right of way.

Recent studies suggest that the robotic behaviour of AVs, which conforms to the rules of the road, but is perhaps unexpected by humans, can lead to crashes. Recent real-world examples include an increase in the number of human-driven vehicles rear-ending AVs (Brown et al., 2018; Goodall, 2021). Although the ethical and moral debate about how AVs should behave in traffic is not the focus of the current study, it has been argued that they should at least negotiate the road in the same way as (good) human drivers, who obey the designated rules of the road (Dietrich et al., 2020; Schneemann & Gohl, 2016). On the other hand, standoffs between AVs and humans are one example of a situation where AVs can benefit from understanding and adopting some of the more subtle (implicit) cues used by humans when interacting with each other on the road. This will likely lead to a good flow of movement between all actors on the road.

Therefore, as AVs are introduced on our roads, it may be beneficial for them to use these existing implicit cues for communicating intention, since they are already well-known to, and regularly used by, humans. Research has also shown that humans are more likely to accept, trust, and understand the behaviour of robots or automated systems that exhibit more human-like motions (Duffy, 2003; Waytz et al., 2014). This is because these anthropomorphic behaviours are perceived as more natural, and the robot considered more competent, leading to a higher level of acceptance and perceived safety (Huang & Mutlu, 2013). To date, a range of control algorithms have been proposed for creating human-like driving by AVs, including human-like car following (Fu et al., 2019), human-like driving trajectories (Kolekar et al., 2020), and human-like reasoning for navigation (Amini et al., 2019).

One approach for creating AVs that provide more intuitive, human-like, behaviour is to study the interaction and communication patterns portrayed between humans in current traffic, which can then be used to train the algorithms used to guide future AVs. Pedestrians are seen to mostly use implicit kinematic cues from the vehicle in these interactions, such as its yielding behaviour (Rothenbucher et al., 2016). Other examples of implicit cues include vehicle speed (Ackermann et al., 2019; Lee et al., 2019), distance (Simpson et al., 2003), time to arrival (TTA) (Beggiato et al., 2017; Petzoldt, 2014; Schmidt et al., 2020), time gaps (Tian et al., 2022), deceleration rate (Ackermann et al., 2019; Dietrich et al., 2020; Risto et al., 2017), brake timing (Beggiato et al., 2018), and vehicle pitch angle (Bindschädel et al., 2022; Dietrich et al., 2020). Lateral movements are also thought to serve as a potential implicit cue in driver-pedestrian interactions. In a focus group study, Sucha (2014), found that drivers reported moving toward the centre of the road, in order to prevent pedestrians from crossing. Similarly, 58% of the drivers surveyed by Fuest et al. (2018) reported that they indicate their non-yielding intentions by adopting a lateral deviation towards the road centre. Using a Wizard of Oz study, Fuest et al. (2018) found that pedestrians recognised the AV's yielding intent more quickly when it was accompanied by a lateral deviation. Finally, a video-based simulation study by Sripada et al. (2021) revealed that pedestrians found the behaviour of non-yielding AVs more intuitive when they moved laterally away rather than towards them. Therefore, lateral movements of the vehicle do seem to provide pedestrians with some form of message about the vehicle's intentions. Pedestrians themselves are also known to use implicit cues, such as changes in walking speed or stepping on the kerb to indicate their crossing intent (Beggiato et al., 2017). However, to date, most research on vehicle-pedestrian interactions has focused on observing the behaviour of one of these actors, rather than investigating how the behaviour of one actor affects the other in a truly interactive way.

Naturalistic observations, where datasets are complex and uncontrolled, have shed some light in this context (Lee et al., 2020; Risto et al., 2017; Schneemann & Gohl, 2016), but it is challenging to disentangle single factors that influence each actor, and understand how they influence the final outcome. Moreover, naturalistic studies do not allow repeated measurements. Alternatively, human-in-the-loop simulation provides a controlled and repeatable setup, with recent developments in distributed simulation enabling us to observe the simultaneous interaction of two actors in Virtual Reality, assessing how the response of one actor affects the other (Bazilinskyy et al., 2022; Kalantari et al., 2023; Kearney et al., 2020; Lyu et al., 2024; Mok et al., 2022; Sadraei et al., 2020). For example, using data from the same study, Kalantari et al. (2023) examined how the initial timing gap between pedestrians and drivers and the crossing locations influence who crosses first in a vehicle-pedestrian crossing study. The current study builds on their results, and extends the state-of-the-art, by examining the mutual interactive behaviour between drivers and pedestrians, investigating if the behaviour of one actor is likely to influence the response of the other, and whether this changes over repeated interactions.

Observational (Budzynski et al., 2021) and simulation (Kearney et al., 2020) studies have shown that as well as influencing each other's behaviour in a crossing scenario, drivers' and pedestrians' road-crossing behaviour can be influenced by different road infrastructures. For example, results from a distributed simulation study conducted by Kearney et al. (2020) showed that pedestrians were more likely to cross (and drivers yielded more) at intersections, than midblock crossings. In terms of the influence of infrastructure on pedestrian behaviour, studies suggest that pedestrians are more willing to cross, make quicker crossing decisions, and feel safer, at zebra crossings, when interacting with both conventional (Clamann et al., 2017; Havard & Willis, 2012; Velasco et al., 2019), and automated vehicles (Madigan et al., 2023). However, it is not currently known how different kinematic cues from the vehicle, such as how variable time gaps for its approach to the pedestrian affect subsequent pedestrian behaviour. An understanding of how different road infrastructures, such as unsignalised sections and zebra crossing affect the behaviour of each actor in this interaction is also lacking.

Finally, as AVs are introduced on our roads, in addition to understanding how pedestrians interpret their behaviour during a crossing scenario, it is important to establish whether this interpretation is improved over time, and what contributes to this learning behaviour. There is currently some evidence that, following repeated encounters with AVs, pedestrians learn to interpret the meaning of novel explicit cues provided by approaching AVs (in the form of explicit Human Machine Interfaces, or eHMIs) (Bindschädel et al., 2022; de Clercq et al., 2019; Faas et al., 2020; Hochman et al., 2020; Lee et al., 2022; Madigan et al., 2023). This is reflected by a faster decision-making time (Lee et al., 2022; Madigan et al., 2023), an adjustment of crossing behaviour (Hochman et al., 2020), and an increased feeling of safety, trust or acceptance (Bindschädel et al., 2022; Faas et al., 2020). However, understanding how pedestrians use implicit cues from vehicles to aid their crossing behaviour and how these change over time, is not yet well-understood. Yet, this information is valuable for improving the implicit cues provided by AVs. As with any multi-actor interaction, understanding how and if any changes in pedestrian behaviour affects drivers' response over time can help to develop more effective communication strategies between drivers and pedestrians interacting with automated vehicles in the same road space.

2.1.1 Research questions

In light of the above discussions, the following research questions were addressed in this study:

1. How do infrastructural elements (such as zebra crossings), and kinematic cues (i.e., time gaps), influence drivers' deceleration and lateral vehicle control?
2. Does this behaviour change over repeated interactions?
3. How does driver behaviour (i.e., deceleration and lateral vehicle control) affect pedestrians' crossing decisions, and does this change over repeated interactions?

To address these questions, the current road crossing study examined the behaviour of pairs of pedestrians and drivers who interacted with each other in real time, by means of a distributed simulation environment. Each actor was encouraged to cross in front of the other across a different set of scenarios, also differentiated by a range of infrastructural settings, as outlined below. In addition to enhancing our understanding of how road infrastructure and vehicle kinematics affect pedestrian and driver interactions, we investigated the reciprocal and interactive effect of driving patterns on pedestrian response, and vice versa. This research aims to identify driving patterns that contribute to human-like behaviours and responses, enabling future AVs to achieve safer and more efficient interactions in urban environments.

2.2 METHOD

2.2.1 Participants

Following approval from the University of Leeds Ethics Committee (Reference No AREA 21-022), we recruited thirty-two pairs of pedestrians (aged 19 – 34, M = 25.09, SD = 0.87) and drivers (aged 19 – 50, M =31.53, SD = 1.72), using the University of Leeds Driving Simulator Database. Gender was balanced by including 8 pairs of male-male, male-female, female-female, and female-male, pedestrian-driver participants. Eligibility criteria stipulated that pedestrians should have resided in the UK for over a year, while drivers were required to possess a minimum of three years of regular driving experience in the UK/EU. Participants were compensated £20 for taking part in the study.

2.2.2 Distributed simulation setup

The experiment was carried out by connecting a CAVE-based pedestrian simulator to a high-fidelity driving simulator, enabling concurrent interaction of driver and pedestrian participants within the virtual environment (for a more detailed methodology see: Kalantari et al. 2023 and Yang et al. 2023).

The University of Leeds Driving Simulator (UoLDS) consists of a Jaguar S-type cabin situated within a 4-meter diameter sphere. This sphere incorporates a 300° field-of-view projection system and operates on an 8-degree of freedom motion platform (**Figure 2.1**A). The CAVE-based pedestrian simulator (the Highly

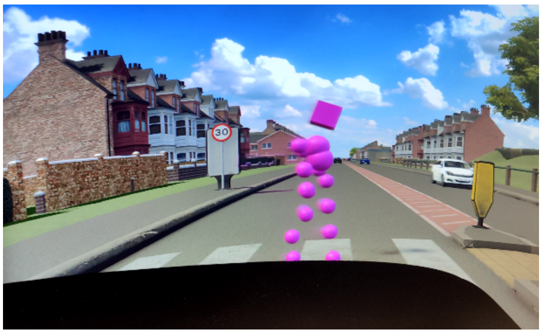
Immersive Kinematic Experimental Research or HIKER pedestrian laboratory) provides a 9 meters long × 4 meters wide walking area. Virtual scenes are projected on the floor and four glass walls (**Figure 2.1**B).

For pedestrian detection, a body tracking suit, equipped with fourteen body markers, was worn along with a pair of stereoscopic motion-tracking glasses (**Figure 2.1**C). Pedestrian movement in the HIKER setup was monitored with ten VICON infrared cameras. This provides the driver with graphical representations, depicting the pedestrian's body motions (Sadraei et al., 2020) (**Figure 2.1**D). Pedestrians could see the traffic but not the driver, although they were informed they were interacting with a real human driver.

(A) University of Leeds Driving Simulator (UoLDS)

(B) Pedestrian simulator (HIKER)

(C) Pedestrian's view of the approaching vehicle (in the HIKER)



(D) Driver's view of the pedestrian (in the UoLDS)

Figure 2.1. Set up of the distributed simulation, showing the pedestrian in the HIKER and the drivers' view of the pedestrian.

2.2.3 Experimental design

Participants assuming the driver's role were asked to navigate a two-lane contraflow road, each with a width of 4.5 meters, while adhering to the posted speed limit of 30 mph (48 km/h). This road included pedestrian refuges, positioned in the centre of the two lanes (the yellow block in **Figure 2.2**), which is a raised island in the centre of the road, providing a safe waiting area for pedestrians to cross one direction of traffic at a time (see in **Figure 2.1**C and **Figure 2.1**D).

The road design was illustrated in **Figure 2.2**, showing the pedestrian crossing location: with zebra crossing (left two blue crosses) and without zebra crossing (right two blue crosses). The bottom cross was used to align the standing position for all pedestrians, who were hidden behind an obstacle (e.g., bus stop), which is depicted as the grey block on the right hand of each crossing location. These were used to ensure pedestrians and drivers were concealed from each other prior to an interaction (not all bus stops had a concealed pedestrian). Pedestrians stepped out to the top cross when they heard a beep, signifying the start of a crossing trial, and stopped at the pedestrian refuge (the yellow block in the middle of the street), before returning to the blue crossed as the end of the trial.

Figure 2.2. A bird's eye view of the road, developed using Unity

The auditory cue's activation was determined by the temporal distance of the approaching vehicle to the centre of the pedestrian refuge, and the vehicle's speed.

This synchronization enabled pedestrians to step onto the crossing area and initiate interaction with the driver when the approaching vehicle's time gap was 3 s, 4 s, 5 s, 6 s, and 7 s. Drivers did not hear the auditory tone, but they needed to react to the pedestrians after they stepped out on the road. This setup allowed us to investigate how each time gap influenced drivers' responses and pedestrians' crossing decisions.

2.2.4 Procedure

Before attending the study, drivers and pedestrians were provided with their respective information sheets, which included details of the study, and their role in the experiment. Upon arrival, they were directed to their respective briefing area within the driver or pedestrian simulator. Here, they reviewed and signed the consent form, with another opportunity to read the information sheet. Both parties were informed about the presence of the other participant, but never met them in person.

At the start of the study, both participants were told they would interact with each other in a series of road crossing scenarios, in a virtual reality distributed simulation experiment. They were instructed to imagine being late for an important meeting, and asked to avoid unnecessary delays during this interaction, while ensuring their safety. Additionally, drivers were reminded that pedestrians hold priority in scenarios involving zebra crossings.

To facilitate familiarity with the tasks and the virtual environment, two practice sessions were conducted. The initial session focused on drivers, allowing them to familiarise themselves with vehicle control and speed management. Once drivers expressed comfort with the virtual environment, the second practice session commenced. This involved interaction between the driver and pedestrian, exposing each to the task and the virtual environment through ten randomized trials. Subsequently, the actual experiment began, featuring two identical blocks, each comprising of 20 randomized trials.

Drivers received instructions to navigate a two-lane road, with two-way traffic, which included other virtual vehicles. Drivers were asked to respond to crossing to pedestrians who were concealed behind the bus stop. Pedestrians were equipped with motion tracking markers on their body and a pair of glasses. They were asked to stand on the first blue cross marked on the CAVE's floor, which obstructed their view of approaching vehicles. Upon hearing a short auditory beep, pedestrians were instructed to move to the second blue cross, enhancing their visibility of the approaching vehicle (see **Figure 2.2**). From this position, pedestrians were asked to assess the situation and make a crossing decision if they felt it was safe to do so. Drivers did not hear this auditory beep and only reacted to the pedestrian.

After concluding the experiment, participants were requested to complete a post-session questionnaire regarding their encounters within the virtual reality environment. Additionally, they were tasked with providing their demographic details and offering insights into their interactions with their fellow participant, particularly regarding factors that influenced their decisions to either proceed first, or not, during the interaction. These results are reported in Kalantari et al. 2023.

2.2.5 Data analysis

Each pair of participants experienced ten unique interactions, consisting of two types of crossing (with or without a zebra crossing) across five different time-gaps ranging from 3 to 7 seconds. Each of these scenarios was repeated four times, and the sequence of encounters (1^{st} /2^{nd} /3^{rd} /4^{th}) was treated as an independent variable for evaluating the influence of exposures on learning patterns for pedestrians. Overall, the data was collected from 32 participant pairs, each having

40 interactions. Out of these 1280 trials, 1279 were analysed, as one trial was omitted due to technical issues. A generalised linear mixed-effects model (GLMM) was used to analyse the data collected in the repeated measures design.

To answer the first and second research question, we examined the influence of factors such as zebra crossings, approaching vehicle time gaps, and the sequence of encounters on drivers' behaviour (see **Figure 2.3**, GLMM 1-3). Drivers' behavioural data was collected from the start of the auditory tone. If pedestrians crossed before the vehicle passed, the driving behaviour data used for the analysis ended when pedestrians' crossing initiation began. If the pedestrian had not crossed by the time the vehicle had reached the central refuge, vehicle data was collected until after the car passed this refuge.

A decrease in speed can represent driver's intent to give pedestrians the right of way (Ackermann et al., 2019; Dietrich et al., 2020; Risto et al., 2017). Consequently, we recorded average deceleration rates to capture this aspect of driver response. Meanwhile, braking behaviour is also typically considered to be indicative of a driver's intention to yield and pedestrians' crossing decisions can be influenced by brake timing (Beggiato et al., 2018). To study the relationship between drivers' braking behaviour at different pedestrian positions, we created the "Vehicle Proximity to Pedestrian at Peak Braking" (PPPB) metric. This identified the distance of the vehicle to pedestrians, when maximum brake force was applied. Previous studies have used braking distance to evaluate an early or late brake time (Bella & Silvestri, 2015) with drivers simply reacting to a crossing pedestrian. In our study, this relationship was more interactive, causing variable driving patterns, such as intermittent and repeated braking (Bella & Silvestri, 2016). Additionally, traditional measures such as Time-to-Collision (TTC) were not suitable in this context, as slow vehicle speeds in this study (e.g. creeping forward) often led to highly extreme TTC values, making interpretation difficult. The PPPB was used to signify the timing of drivers' first decision to yield, or not. A lower PPPB signified a later brake response. Additionally, we examined the vehicle's average lateral deviation during the interaction, as this has been used in previous studies to represent drivers' yielding intent (Fuest et al., 2018).

To address the third research question, the GLMM was applied to examine the impact of drivers' responses on pedestrians' crossing decisions (**Figure 2.3**). A binary response variable indicating interaction outcomes (1 = pedestrian crossed, 0 = pedestrian did not cross, and vehicle passed), was used. A forward selection regression modelling approach, commonly referred to as a stepwise regression, was employed, to allow for a structured and hierarchical understanding of the data and avoid overfitting (James et al., 2013). This stepwise approach was utilised to disentangle direct and indirect effects (Harrell, 2001), since drivers' behaviour was likely to be influenced by presence of the zebra or the approaching time gap, which was then likely to have influenced pedestrians' crossing decisions. In the Step 1, Model 1 (GLMM 4) integrated factors such as the presence of zebra crossings, time gaps, and the number of encounters to establish the baseline understanding of how these factors directly influenced pedestrians' crossing decisions. Building upon the foundation of Model 1, Model 2 (GLMM 5) in step 2 extended this by incorporating drivers' behaviour and the interactive effects of zebra crossings, time gaps, and encounters, to identify the key factors influencing pedestrian crossing decisions. Apart from these fixed effects, participants were considered as a random effect. This stepwise approach was utilised to disentangle these direct and indirect effects (Harrell, 2001) and account for individual differences in all models. The analysis was carried out using the lme4 function of the R package.

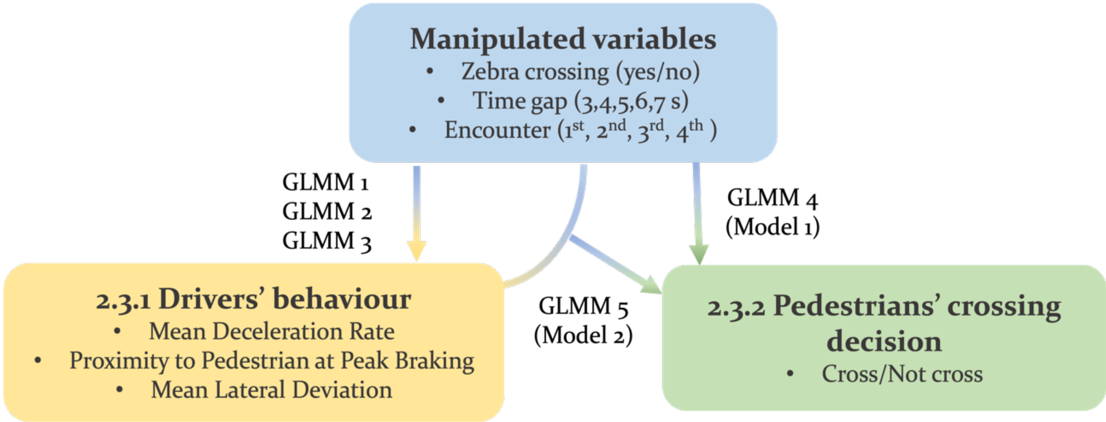


Figure 2.3. Procedure used for the data analysis. Drivers' behaviour and pedestrians' crossing decisions are reported in section 2.3.1 and 2.3.1, respectively.

2.3 RESULTS

2.3.1 Drivers' behaviour

Mean deceleration rate

As shown in **Table 2-1**, the GLMM revealed a significant effect of zebra crossing on drivers' average deceleration ($p < 0.001$), compared to scenarios without zebra crossings (M = 0.68, SE = 0.04 vs M = 0.18, SE = 0.03). Additionally, the drivers' mean deceleration decreased with the increasing time gaps ($p < 0.001$) (**Figure 2.4**).

Table 2-1. Results of three GLMM estimates analysing the impact of zebra crossing, time gap and encounter on driver behaviour

	Deceleration				
Predictors	*EST*	*SE*	*t*	*CI (L-U)*	*p*
Intercept	0.90	0.07	12.14	(0.75, 1.04)	**<0.001**
Zebra crossing [Presence]	0.50	0.03	17.13	(0.44, 0.55)	**<0.001**

Gap	-0.14	0.01	-12.86	(-0.16, -0.12)	**<0.001**
Encounter	0.00	0.01	-0.06	(-0.02, 0.02)	.953
	Proximity to pedestrian at peak braking				
Predictors	*EST*	*SE*	*t*	*CI (L-U)*	*p*
Intercept	-23.85	2.18	-0.93	(-28.13, -19.57)	**<0.001**
Zebra crossing [Presence]	-8.21	0.86	-9.51	(-9.90, -6.52)	**<0.001**
Gap	14.35	0.31	46.99	(13.75, 14.94)	**<0.001**
Encounter	0.37	0.39	0.95	(-0.39, 1.12)	.341
	Lateral deviation				
Predictors	*EST*	*SE*	*t*	*CI (L-U)*	*p*
Intercept	0.25	0.05	4.91	(0.15, 0.34)	**<0.001**
Zebra crossing [Presence]	-0.09	0.01	-8.00	(-0.12, -0.07)	**<0.001**
Gap	-0.01	0.00	-3.35	(-0.02, -0.01)	**<0.001**
Encounter	0.02	0.01	3.39	(0.01, 0.03)	**<0.001**

Drivers' average deceleration rates across different time gaps were visualized using a violin plot (**Figure 2.4**). This combines elements of a box plot and a density plot, using Kernel Density Estimation (KDE) to create empirical probability density curves that show the data's central tendency, density, distribution, and spread. The width of the violin at any point represents data density, with wider sections indicating higher concentrations of data points. The shape of the violin shows the overall distribution. For instance, a bimodal distribution appears as two bulges. The vertical boundaries indicate the data range and variability, with longer violins suggesting greater variability and shorter ones indicating consistency

As shown in **Figure 2.4**, the spread of the violin decreased with the increasing time gaps. This indicates that drivers tended to decelerate at a more consistent rate when they had more time, where the most common deceleration rates were 0.033 m/s^2at 6 s and 0.042 m/s^2at the 7 s time gaps. Meanwhile, a bimodal distribution was identified when the time gap was smaller than 5 s. Drivers showed two primary deceleration rates at shorter time gaps: these were close to 0.053 m/s^2 and 3.61 m/s^2 at 3 seconds, approximately 0.17 m/s^2 and 3.00 m/s^2 at 4 seconds, and around 0.16 m/s^2 and 2.59 m/s^2 at 5 seconds.

The number of encounters did not present a statistically significant effect on deceleration rates (p = 0.953).

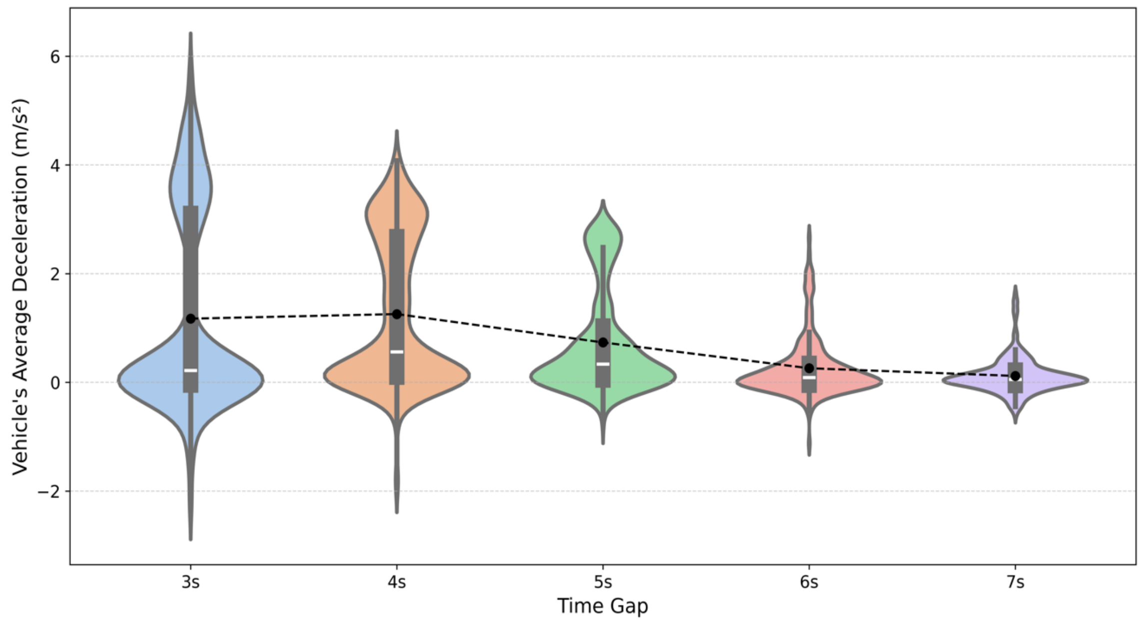


Figure 2.4. The impact of time gaps on the drivers' average deceleration rate. A bandwidth (bw) setting of 0.2 is applied in the KDE, providing moderate smoothing that enhances the visibility of underlying data trends while smoothing over minor fluctuations. The boxplots show the quartiles, where the bottom and top of each box represents the first (Q1) and third (Q3) quartile. The white lines inside the box denote the median and means (in black dots), connected by the dashed lines.

Proximity to pedestrian at peak braking

The outcomes obtained from the GLMM analysis revealed that peak braking occurred at much closer distances to pedestrians during the zebra crossing trials

(M = 40.6, SE = 1.05), than the no zebra crossing trials (M = 48.8, SE = 1.02) ($p < 0.001$) (**Table 2-1**). This pattern remained the same across the four encounters ($p = 0.341$). Conversely, as the time gap increased, peak braking occurred at further distances from pedestrians ($p < 0.001$) (**Figure 2.5**). Additionally, as shown in Figure 2.5, as the time gap increased, the spread of the vehicles' proximity to pedestrian at peak braking became wider (generally indicating more variability).

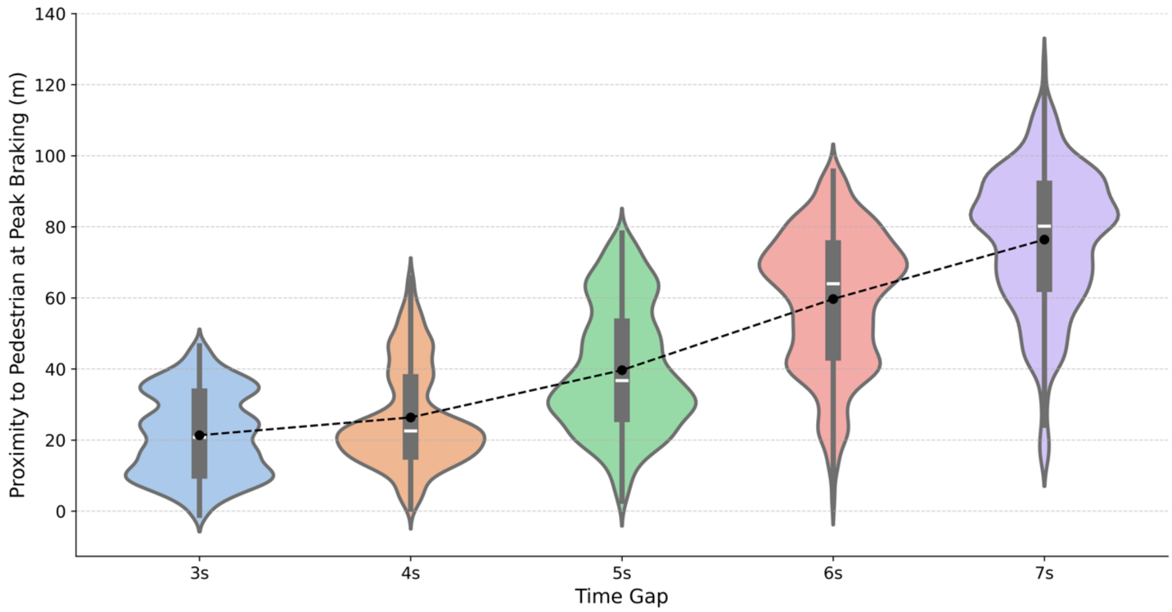


Figure 2.5. The violins and box plots show the impact of time gaps on drivers' average proximity to pedestrian at peak braking.

Mean lateral deviation

The GLMM analysis (**Table 2-1**) exhibited a significant impact of the presence of zebra crossings ($p < 0.001$) on the vehicle's lateral deviation. Drivers tended to exhibit greater lateral deviation away from pedestrians (M = 0.22, SE = 0.04) in the no zebra crossing trials, compared to those with zebra crossings (M = 0.13, SE = 0.04). There was also an effect of time gap ($p < 0.001$), with more lateral deviation away from the pedestrian, at closer distances. There was also a significant effect of encounter ($p < 0.001$), with a minor increase in lateral deviation away from pedestrians, over time.

In the next section, we report on how this behaviour from the vehicle affected pedestrian behaviour.

2.3.1 Pedestrians' crossing decisions

Data from **Table 2-2** shows that the presence of zebra crossings ($p < 0.001$) and larger time gaps ($p < 0.001$) led to a higher likelihood of pedestrians crossing in Step 1 (Model 1), where the number of encounters showed no effect ($p = 0.768$).

However, for Step 2 of the model, where drivers' behaviours were included, there seems to be no effect of zebra crossing ($p = 0.117$). This shows that pedestrians' crossing decisions were influenced by drivers' behaviour. There was also an interaction between time gaps and zebra crossing (**Figure 2.6**A), whereby larger approaching time gaps continued to be associated with a significantly higher likelihood of crossings by pedestrians ($p < .001$), especially in the absence of zebra crossings. Although zebra crossings increased the likelihood of pedestrian crossings, this was only the case for the lower time gaps of 3- and 4-seconds (**Figure 2.6**A). The likelihood of pedestrians crossing also increased with the number of encounters, especially for the 3 and 4 s time gaps (**Figure 2.6**B).

Table 2-2. Results of the GLMM estimates for pedestrians' crossing decision.

Pedestrian crossing decision						
			Model 1			
Predictors	*EST*	*SE*	*z*	*OR*	*p*	*CI (L-U)*
(Intercept)	-10.08	0.00	-12.62	0.00	<0.001	0.00 – 0.00
Zebra Crossing [Presence]	5.53	92.17	15.21	253.25	<0.001	124.09 – 516.82
Gaps	1.86	0.82	14.46	6.41	<0.001	4.98 – 8.24

Encounters	-0.03	0.09	-0.30	0.97	0.768	0.82 – 1.16
Observations				1279		
Marginal R2 / Conditional R2				0.696 / 0.843		
AIC				720.09		
				Model 2		
Predictors	*EST*	*SE*	*z*	*OR*	*p*	*CI (L-U)*
(Intercept)	-17.61	0.00	-7.87	0.00	**<0.001**	0.00 – 0.00
Zebra Crossing [Presence]	-3.53	0.06	-1.62	0.03	0.105	0.00 – 2.08
Gaps	2.50	4.88	6.21	12.3	**<0.001**	5.52 – 26.67
Encounters	1.35	2.25	2.32	3.86	**0.021**	1.23 – 12.0
Vehicle Average Deceleration	3.5	7.63	9.62	23.31	**<0.001**	12.27 – 44.28
Proximity to Ped at Peak Braking	0.07	0.01	5.91	1.07	**<0.001**	1.05– 1.10
Lateral Deviation	-1.29	0.18	-1.99	0.28	**0.046**	0.08 – 0.98
Gaps × Encounters	-0.24	0.09	-2.20	0.78	**0.028**	0.63 – 0.97
Zebra Crossing [Presence] × Gaps	1.95	3.92	3.48	7.01	**<0.001**	2.34 – 2.00
Observations				1279		
Marginal R2 / Conditional R2				0.832/0.94		
AIC				425.953		

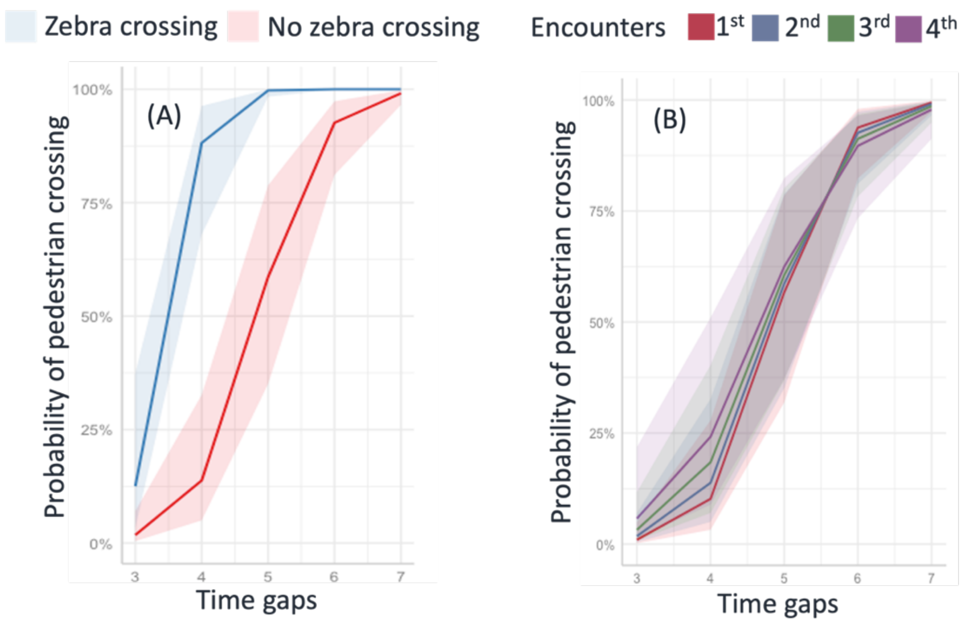


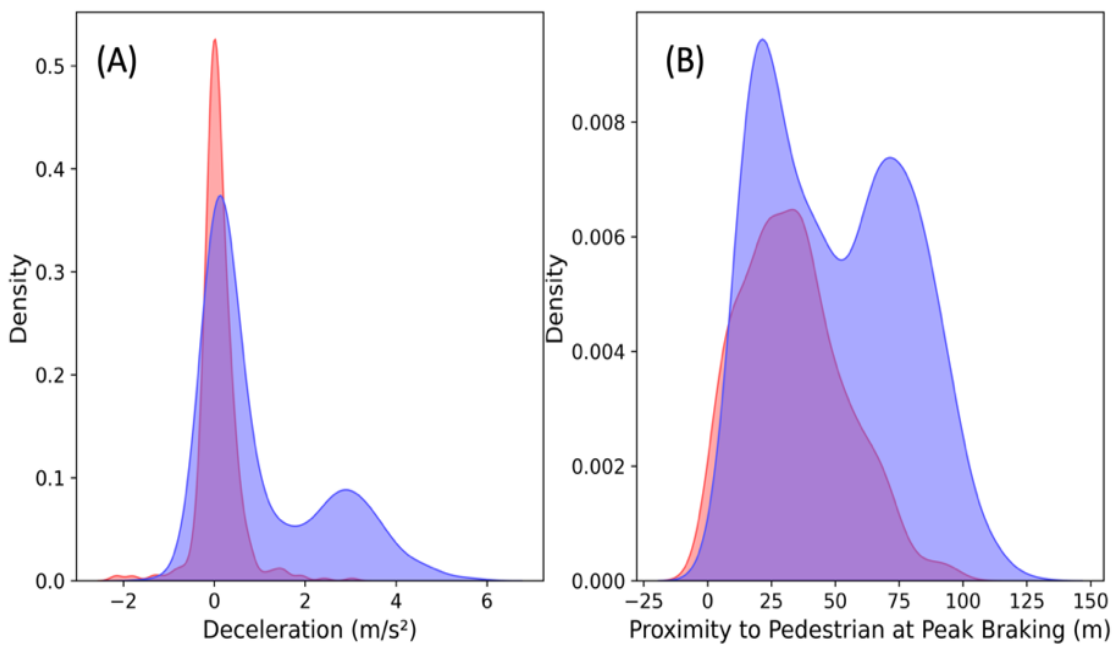
Figure 2.6. Predicted probabilities of pedestrians crossing as a function of (A) zebra crossings and time gaps (B) time gaps and encounters. The shaded area represents 95% confidence intervals.

In addition, pedestrians demonstrated a higher probability of crossing in front of the vehicle when it exhibited greater deceleration rates (Cross: M = 1.03 m/s^2, SE = 0.05; Not cross: M = .09 m/s^2, SE = 0.02, $p < .001$). **Figure 2.7**A presents the density spread of vehicle average deceleration rate when pedestrians crossed and did not cross. When pedestrians crossed (blue shaded area), vehicle average deceleration rate shows a bigger spread, ranging from -1.38 m/s^2 to 5.70 m/s^2, with a bimodal distribution, peaking at 0.18 m/s^2 and 2.88 m/s^2. However, when pedestrians did not cross (red shaded area), vehicle average deceleration rate shows a smaller spread, ranging from -2.17 m/s^2 to 3.03 m/s^2, peaking at 0.02 m/s^2.

Similarly, the proximity to pedestrian at peak braking also predicted pedestrians' crossing decision. As shown in **Figure 2.7**B, when pedestrians crossed, the average vehicle proximity to pedestrian at peak braking was at a significantly further distance (M = 50.54 m, SE = 0.95), compared to when they did not cross (M = 33.60 m, SE = 0.95, $p < .001$). The figure also shows a bimodal distribution for the peak braking values at 22.15 m and 72.15 m, from pedestrians, when they crossed. However, when they did not cross, the proximity to pedestrian at peak braking was at 31.89 m.

We further examined the bimodal relationship between the vehicle's average deceleration and the proximity to pedestrian at peak braking when pedestrians crossed in **Figure 2.7**C. When pedestrians crossed, they were more likely to cross either when the driver presented a deceleration rate of around 0.18 m/s^2, initiating a peak braking behaviour around 72.15 m away from them, or when there was a deceleration rate around 2.88 m/s^2, with peak braking at around 22.15 m away from them. When pedestrians did not cross, drivers drove at near-zero deceleration rates (max: 0.02 m/s^2) throughout the interaction.

Finally, we also found that the vehicle exhibited greater lateral deviation away from the pedestrian path when pedestrians did not cross ($p < .001$), with a mean lateral deviation of 0.24 m (SE = 0.01), compared to when pedestrians crossed (M = 0.15 m, SE = 0.02).



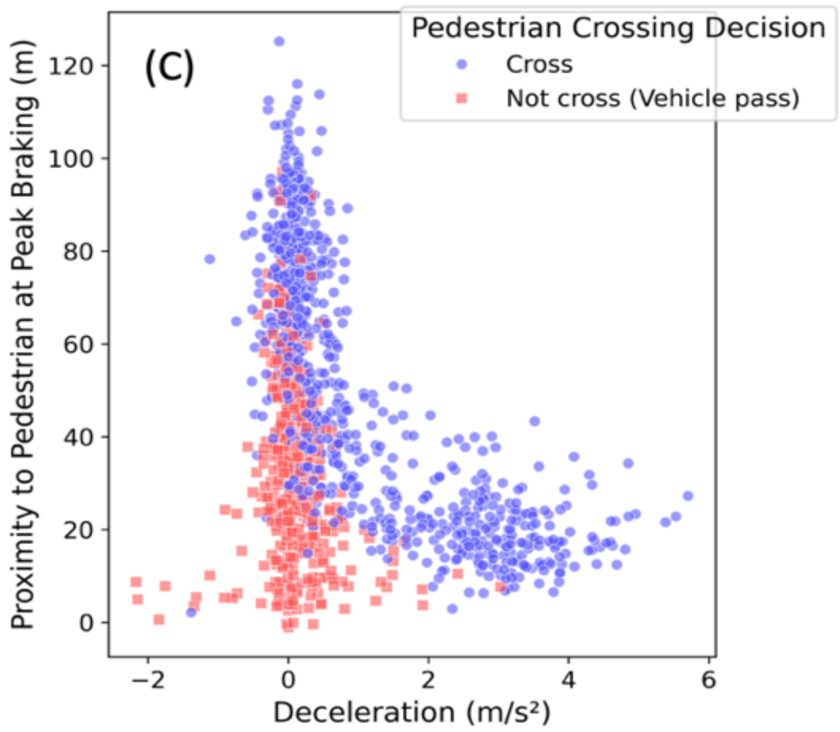


Figure 2.7. Visualisations of vehicle's kinematics and pedestrian crossing decisions (A) The distribution of the vehicle's deceleration rate when pedestrians crossed (blue) and pedestrian did not cross (vehicle passed first, red). (B) The distribution of the vehicle's proximity to pedestrian at peak braking when pedestrians crossed (blue) and pedestrian did not cross (vehicle passed first, red). (C) The scatterplot matrix illustrates the relationship between vehicles' deceleration and proximity to pedestrian at peak braking, categorised by pedestrian's crossing decision.

2.4 DISCUSSION

The aim of this distributed simulation study was to explore the complex dynamics of vehicle-pedestrian interactions in a scenario which encouraged both to beat the other in a road crossing scenario. We investigated the effect of infrastructural differences and the time gap between the vehicle and the pedestrian on drivers' behaviour and whether these changed over time. We then examined how these responses from the driver, in turn, affected pedestrians' crossing decisions.

Results showed that drivers applied harder deceleration in approach to zebra crossings, when compared to sections without this infrastructure. This finding aligns with road safety norms associated with zebra crossings in the UK, where drivers are expected to be more cautious and considerate of crossing pedestrians who have the right of way (Zhang et al., 2020). Previous studies have found that non-yielding intent by drivers is often characterised by maintaining a constant speed, or even accelerating, on approach to pedestrians at zebra crossings (Várhelyi, 1998). However, in this study, where the driver and pedestrian were encouraged to prioritise their own progress in the crossing task, because they were both late for a meeting, some interesting observations were made. For example, a subtle brake was seen around 20 m from pedestrians (Appendix to Chapter 2), for the no zebra crossing trials. Based on regulations in the real world, drivers do not need to yield in these conditions. However, since the pedestrians' task was also to cross if they felt safe to do so, drivers are seen to apply a gentle brake, in order to avoid colliding with the pedestrian. This driving pattern was also clearly understood by pedestrians, who used the vehicle's overall dynamics and refrained from crossing.

Our data also indicates an interesting relationship between braking patterns and lateral deviation. For example, at zebra crossings, when drivers illustrated harder deceleration rates, they were also seen to apply peak braking at closer distances to pedestrians (Appendix to Chapter 2, **Figure 6.2**a). This deceleration pattern was accompanied by a simultaneous lateral shift towards pedestrians (Appendix to Chapter 2, **Figure 6.2**b). However, in the absence of zebra crossings, drivers showed softer deceleration and their peak braking occurred earlier (Appendix to Chapter 2, **Figure 6.2**a), while shifting laterally away from pedestrians at the same time (Appendix to Chapter 2, **Figure 6.2**b). Similar patterns have been seen in real-world studies (Fuest et al., 2018), where drivers chose to drive laterally away from pedestrians, which the authors suggest was an attempt to indicate their non-yielding intent. However, the Fuest et al. (2018) study is based on a survey, whereas we believe that our study is the first to empirically document the existence of lateral movements in driver-pedestrian interactions, also demonstrating the correlation of lateral movements and braking behaviours. The lateral movements seen in this study showing a clear difference between proactive and reactive driving, with later and harsher braking likely associated with a desire to avoid colliding with pedestrians when approaching at a higher speed in the zebra conditions.

These lateral movements have also been observed in pedestrian-pedestrian interactions. When pedestrians encounter each other on intersecting paths, they must quickly decide who will pass first and who will yield, in order to avoid a collision. As detailed by the study of Olivier et al. (2013), the pedestrian who is to pass first will adjust their trajectory forward relative to the other (A veers in front of B), while the yielding pedestrian shifts their path to move behind (B veers to the back of A). Results of our study demonstrate that drivers, transfer their navigational habits into their driving, particularly in interactions involving right-of-way decisions with pedestrians.

In line with Angioi and Bassani (2022), drivers' mean deceleration decreased with the increasing time gaps. When they had more time, drivers tended to drive at near-zero deceleration rates. In contrast, when the time gap was smaller, there was a bimodal distribution of deceleration, where drivers either tended to drive at near-zero deceleration rates or at 2.59 to 3.61 m/s^2, depending on the time gap. This bimodal pattern reflected drivers' intentions, where near-zero rates suggest a non-yielding behaviour and the other cluster of average deceleration rates indicate a yielding intent. In addition, as the time gap increased, drivers' peak braking occurred at further distances from pedestrians, and there was less lateral deviation away from pedestrians. These results highlight the diverse patterns in drivers' behaviour in response to different time gaps and different yielding intents, providing valuable insights for the design of AVs that mimic human driving behaviours. Additionally, understanding these patterns can assist pedestrians in accurately estimating vehicle movements, thereby enhancing safety for crossing pedestrians.

In terms of pedestrians' responses, in line with previous research (Clamann et al., 2017; Havard & Willis, 2012; Lee et al., 2022; Madigan et al., 2023; Tian et al., 2023; Velasco et al., 2019), our results from the Model 1 analysis showed a higher likelihood of crossings by pedestrians in the presence of zebra crossings, and/or when there was a higher time gap for the approaching vehicle. In addition, there was a significant interactive effect between zebra crossing and time gaps from the Model 2 analysis, which showed that, at zebra crossings, pedestrians appeared more willing to cross during shorter time gaps, compared to locations without such markings. However, this distinction between zebra and non-zebra locations became negligible when the time gaps exceed 5 seconds, or more. This suggests that, for smaller time gaps, pedestrians relied on the zebra for their crossing decisions, but were more willing to engage in jay walking behaviour when the vehicle was further away, reducing the relative value of the zebra crossings as a safety aid for these conditions. However, the main effect of zebra crossings became non-significant in Model 2, when the effect of driver behaviour and its interactive effects between time gaps and road infrastructure were introduced. We found that the effect of zebra crossing on pedestrians' crossing behaviour was also influenced by the driver's actions, which then subsequently shaped pedestrians' crossing decisions. This suggests that drivers' responses, particularly their braking behaviour, was a crucial intermediary factor which supersedes any infrastructure-based cues.

Using Model 2 we also found that pedestrians were able to use the different types of braking patterns to inform their crossing decisions. For example, aggressive and late, or soft and early braking patterns led to more crossings, when compared to soft and late braking patterns. Results also showed that a higher rate of deceleration, applying peak braking earlier, and less lateral deviation away from pedestrians were all easily perceived, increasing the likelihood of crossings. This supports findings from previous studies where early and assertive braking can foster a greater propensity to cross in both virtual (Ackermann et al., 2019; Dietrich et al., 2020; Tian et al., 2023) (Ackermann et al., 2019; Dietrich et al., 2020; Risto et al., 2017; Tian et al., 2023), and real-world observations (Risto et al., 2017).

We also found some behavioural adaptation by pedestrians and drivers across trials. As the experiment progressed, while drivers' mean deceleration and proximity to pedestrians at peak braking remained the same, there was an increase in lateral deviation away from pedestrians, indicating that drivers were less willing to yield (Fuest et al., 2018; Sripada et al., 2021). At the same time, pedestrians demonstrated a trend of increasing their intention to cross as the experiment progressed. This trend was particularly pronounced at shorter time gaps of 3 and 4 seconds, implying that pedestrians adopted riskier crossing behaviour, over the trials. This adaptive behaviour likely reflects pedestrians' evolving comprehension of how drivers reacted to their presence, and may illustrate an increased sense of trust or safety, that they would not be hit by the vehicle. Meanwhile, the results indicate how both road users managed to "win" the crossing, by adapting their interactive behaviours.

2.4.1 Limitations and future work

In terms of limitations, this study only investigated pedestrian interaction with one type of vehicle, with regards to its size and direction of approach. Future studies with more realistic interactions of pedestrians with vehicles of different size (Beggiato et al., 2017), approaching from different directions (Madigan et al.,

2023) would provide a better understanding of how crossing decisions are affected by such ecologically valid scenarios. To understand how AVs should behave in different regions, studying the interaction of drivers (Özkan et al., 2006) and pedestrians (Lee et al., 2021) from different cultural backgrounds may also be of value. Additionally, this study primarily focused on the impact of driver behaviour on pedestrian crossing decisions, assuming that drivers have greater control over these interactions. However, in certain cases, actions by pedestrians, such as stepping into the roadway, could have triggered the observed driver deceleration (Guéguen et al., 2015), indicating that causality might also originate from pedestrian to driver. This bidirectional influence was not extensively explored and requires further investigation to fully comprehend the dynamics of driver-pedestrian interactions. Furthermore, this study offers insights into implicit driving behaviours observed for interactions between pedestrians and drivers. Therefore, further work is warranted to study the reciprocal interaction between pedestrians and real AVs, to study how humans adapt to the driving behaviour of these vehicles over time. Additionally, the driver was not visually rendered to pedestrians, which may have reduced face validity and led some to perceive the vehicle as automated, despite being told it was human-driven. This could have influenced responses to vehicle behaviour, and future studies could examine whether framing the vehicle as an AV would affect pedestrian behaviour. Finally, due to technical limitations, the VR representation of pedestrians to drivers in our labs is currently achieved via a set of spherical and cuboidal markers. While functional for movement tracking, this results in a non-human-like 'pink bubble' appearance, which may limit face validity as the pedestrian does not resemble a typical human form. Investigating driver response to more anthropomorphic and photorealistic avatars would be interesting in this context.

2.4.2 Conclusions

This research contributes to a deeper understanding of the complex interaction between road infrastructure and vehicle kinematics when pedestrians and drivers are interacting in a distributed simulation VR study, also illustrating how behaviour changes over time in this type of short duration study. The insights gained from the examination of kinematic cues from the vehicle, and their influence on pedestrian behaviour underscores the potential of incorporating these cues into the design of automated vehicles' behaviour to aid decisions of a crossing pedestrian, which could work in harmony with other means of communication, such as externally presented HMI. By incorporating human-like behaviours and responses into an automated vehicle's kinematic cues, we can enhance its communication with pedestrians, thereby fostering safer and more harmonious interactions in dynamic urban environments, improving traffic flow.

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CHAPTER 3

INTERPRETING PEDESTRIANS' HEAD MOVEMENTS WHEN ENCOUNTERING AUTOMATED VEHICLES AT A VIRTUAL CROSSROAD

ABSTRACT

In the future, Automated Vehicles (AVs) may be able to use pedestrians' head movement patterns to understand their crossing intentions. This ability of the AV to predict pedestrian crossing intention will improve road safety in mixed traffic situations and may also enhance traffic flow, allowing the vehicle to gradually reduce its speed in advance of a yield, eliminating the need for a complete and erratic halt. To date, most of the work conducted on studying pedestrian head movements has been based on observation studies. To further our understanding in this area, this study examined pedestrians' head movements when interacting with AVs during a range of road crossing scenarios, developed in a VR environment. Thirty-eight participants took part in this CAVE-based pedestrian simulator study. Head movements were recorded using stereoscopic motion-tracking glasses, as pedestrians crossed the road in response to an AV which approached from the right (UK-based road). A zebra crossing was included in half of the trials to understand how it affected crossing behaviour. The effect of different approaching speeds of the AV, and the presence of an external Human-Machine Interface (eHMI), on head movements and crossing behaviour was also studied. Results showed that the absolute head-turning rate (change in pedestrians' head-turning angle, per frame) increased significantly at around 1 s before a crossing initiation, reaching a peak at the crossing initiation, where pedestrians presented a "last-second check" before the crossing decision. Another increase in absolute head-turning rate to the right was seen at the end of the crossing (~ 1.5 s after crossing initiation), to check the proximity of the approaching vehicle. A higher rate of head-turning was also seen for AV-non-yielding scenarios. Finally, the least number of head turns was seen for the yielding conditions which included an eHMI, in the presence of the zebra crossing. These results show the value of infrastructural and vehicle-based cues in assisting pedestrians' crossing decisions and provide an insight into how head-turning behaviour can be used by AVs to better predict pedestrians' crossing intentions in urban settings.

KEYWORDS: Automated Vehicle; Head-turning behaviour; Zebra Crossing; eHMI; Vulnerable Road Users; Virtual Reality, CAVE-based pedestrian simulator

3.1 INTRODUCTION

More than half of the road casualties worldwide involve Vulnerable Road Users (VRUs) (WHO, 2018), among which pedestrians are one of the most vulnerable groups, accounting for 27% of total road fatalities in the UK (Department for Transport, 2020). Automated Vehicles (AVs) are expected to protect VRUs from traffic accidents (Anderson et al., 2016), as they can promptly respond to obstacles and critical situations, without some of the delayed judgements caused by humans. However, while the AV's radars and sensors may be better than humans for such obstacle detection, they are not currently able to *predict* the crossing intention of pedestrians, especially in the absence of clear external cues, such as head and hand movements. At the same time, there is currently no standard or globally adopted form of externally presented form of communication by higher level AVs. For these AVs, the human inside the vehicle is no longer in charge of the driving task and may not even be seated in the traditional driver's seat (Level 4 and 5) (SAE, 2021). This creates new challenges for human factors experts, including how AVs should safely interact with, and communicate their intent to, vulnerable road users that share the same road space (Schieben et al., 2019).

Externally presented Human-Machine Interfaces (eHMI) have been proposed as one solution for facilitating the mutual understanding and safe interaction between AVs and VRUs. It is argued that these new forms of communication might assist VRUs by replacing the explicit communication cues traditionally used by drivers. eHMIs can be sound-based or visual, with a wide range of locations and designs used for presenting visual information, either on the vehicle, or on the road, including lights, texts, and symbols (Bazilinskyy et al., 2019; Carsten & Martens, 2019; Dey et al., 2020). Research has shown that the adoption of an eHMI can increase pedestrians' trust, acceptance, and perceived safety of AVs (Faas et al., 2020; Holländer et al., 2019). These interfaces also lead to a greater willingness to cross and faster crossing decisions from pedestrians (Lee et al., 2022; Löcken et al., 2019). However, research in this area is not conclusive, with some also suggesting that eHMIs merely provide supplementary information, because implicit cues, such as the vehicle's yielding and stopping behaviour are more informative (Dey, Martens, et al., 2019; Lee et al., 2020).

Additionally, some argue that eHMIs can cause visual and mental overload for pedestrians, as the meaning of these, mostly novel, messages may not be intuitive and needs to be correctly interpreted and learnt over time (Lee et al., 2022). In the context of pedestrian-AV interactions, workload pertains to the cognitive resources required by pedestrians to perform the crossing task (Young & Stanton, 2004). Kaß et al. (2020)have proposed that incorporating eHMIs could improve communication and significantly reduce pedestrian mental workload. However, contrary evidence has been reported by Gruenefeld et al. (2019), suggesting a negative effect of eHMIs on mental workload.

One method used to investigate pedestrian attention and workload during crossings is an overview of their gaze behaviour (Dey, Walker, et al., 2019; Eisma et al., 2020; Guo et al., 2022; Hochman et al., 2020). For example, pupil size is shown to increase with increased workload, and fixation duration is known to correlate with the level of processing required, while the location of a fixation is a strong indicator of the location of visual attention. Research into pedestrians' attention allocation shows that both the frequency and duration of fixations increase when the AV's intention, and the meaning of its eHMIs, are ambiguous (Guo et al., 2022; Liu et al., 2020). Studies also suggest that gaze patterns and pedestrian behaviour adapt and change with increased exposure to AVs or eHMIs. For example, using a desk-based simulation study Hochman et al. (2020) showed that pedestrians' gaze fixations and crossing response time (based on button presses) changed after repeated exposure to approaching AVs with different eHMIs, regardless of eHMI design.

Although eye-tracking studies provide useful information about pedestrians' information-seeking behaviour and are useful for guiding optimal eHMI placement (de Winter et al., 2021; Dey, Walker, et al., 2019), the value of this methodology may be limited if vehicles are positioned too far from pedestrians, leading to inaccurate calibrations, or challenges with missing data, due to changing light conditions. One solution may be a better understanding of how pedestrians' head movements can be used to understand the decision-making process, and ultimately the attention and workload of a crossing pedestrian. Head orientation patterns are thought to be as equally informative as gaze behaviour to interpret pedestrians' information-seeking and attention-allocation, since pedestrians' gaze behaviour and realignment are constantly initiated with head orientation (Hollands et al., 2002; Melvill Jones et al., 1988).

Previous studies have shown that, with repeated exposure, pedestrians gradually learn the meaning of messages portrayed by AV eHMIs, based on faster decision times for crossing and learnability scores, and decreased gaze fixations (Faas et al., 2020; Hochman et al., 2020; Lee et al., 2022). There is also a general increase in trust, feelings of safety, and acceptance with repeated exposure (Faas et al., 2020). Based on these results, it is reasonable to assume that, with repeated exposure, pedestrians' head-turning behaviour may also change over time and correlate with a better understanding of AV behaviour and eHMI messages.

Finally, while an understanding of the AV's behaviour by pedestrians is important, it is also valuable for the AV to correctly interpret pedestrians' intent and situation awareness. Non-verbal cues such as head movements are typically used by drivers as a key indicator of pedestrians' intention to initiate a crossing (Hariyono et al., 2016; Kooij et al., 2014; Kwak et al., 2017), and their situation awareness (Hassan et al., 2005; Hollands et al., 2002; Rasouli et al., 2018). According to these real-world observation studies, pedestrians' crossing intent can be predicted from: i) the direction of head movements, ii) the frequency of head turns, and iii) body gait. For example, studies have shown that at the start of a crossing initiation, pedestrians tend to turn their heads first in the direction of an approaching vehicle (Grasso et al., 1998; Imai et al., 2001; Patla et al., 1999), which indicates an awareness of its approach, reducing the likelihood of an unsafe crossing (Kooij et al., 2014). Observations from roundabouts and intersections have shown that, for a vehicle approaching from the right, pedestrians tend to turn their heads to the left before stepping off the curb and then to the right before crossing (Geruschat et al., 2003). In terms of head-turning frequency, these tend to increase around 4 s before a crossing, reaching a peak during the last second before the crossing begins (Hassan et al., 2005). Observations also show that the highest number of head turns occur at the start and middle of the crossroad, to confirm the vehicle's proximity and ensure a safe crossing (Hamaoka et al., 2013). Finally, pedestrians are found to turn their heads first just before a crossing initiation, followed by movement of the rest of the body (Kalantarov et al., 2018).

As indicated above, most of the research in this area has focused on investigating the interactions between pedestrians and manually driven vehicles, and findings are mainly based on observation studies. However, little is known about how pedestrians might interact with future AVs, especially those without a driver (Level 4; SAE, 2021). In addition, a large proportion of studies investigating pedestrian interaction with AVs have used a single-lane road environment, with little known about more complex settings, such as a 4-way crossroad. In terms of the effect of traffic infrastructure on crossing behaviour, previous studies have shown that pedestrians are more willing to cross, make quicker crossing decisions, and feel safer at zebra crossings (Clamann et al., 2017; Havard & Willis, 2012; Velasco et al., 2019). Regarding interactions with AVs, both a VR study by Velasco et al. (2019), and a naturalistic study by Clamann et al. (2017), have found that pedestrians had a higher willingness to cross, and spent less time on crossing decisions, at zebra crossings.

3.1.1 The current study

Based on the current state of the art, the main aim of the present study was to close the research gap in this area, by investigating the head-turning behaviour of a group of pedestrians, who crossed the road in front of AVs, which approached a four-way crossing from the right. To understand how crossing behaviour and head turns were affected by different infrastructures, a zebra crossing was included in half of the trials. We also investigated the effect of different yielding patterns from the AV, the presence of an eHMI, and repeated exposures to the AV, on head-turning behaviours. In addition to furthering our understanding of how these different conditions affect pedestrians' head-turning behaviour, we hoped that the use of a head-tracking device in a more controlled virtual environment would allow us to provide more knowledge to developers and designers wishing to enhance their intent-recognition algorithms for future AVs.

3.2 METHOD

3.2.1 Participants

Thirty-eight participants (20 female, 18 male) were recruited for the study (Age range 22-58 years, M=33.82, SD=10.30), using the University of Leeds database, and reimbursed £30 for their participation. All participants were required to be residing in the UK for at least one year and provided written consent to take part in the study. Participants reported normal or corrected-to-normal vision and were free from any head or upper/lower ailments that could impair their walking ability. The study was approved by the University of Leeds Ethics Committee (Ref: LTTRAN-107) and complied with all guidelines set out in the declaration of Helsinki.

This study used the head-tracking data collected as part of a virtual reality experiment developed for the EC project interACT (Grant Agreement No. 723395) to investigate the impact of road infrastructure and eHMIs on pedestrian crossing decisions at a residential crossing (see (Madigan et al., 2023)).

3.2.2 Apparatus and the virtual environment

The experiment was conducted in a CAVE-based pedestrian simulator: the Highly Immersive Kinematic Experimental Research (HIKER) lab, at the University of Leeds (**Figure 3.1**). The lab provides a 9 m long × 4 m wide walking space, and the virtual scene is reproduced by eight 4K projectors behind glass panel walls and adjusted constantly in line with the pedestrian's head position (using trackers on a pair of glasses), to ensure the projection fits the pedestrian's visual perspective. As shown in Figure 3.1, the scenario was created using the Unity game engine. It consisted of a residential 4-way crossing with a single lane (3.6 m wide) in each direction.

Figure 3.1. Interaction between the pedestrian at the zebra crossing and the AV approaching from the right, with the eHMI on, in the HIKER lab. The yellow cross indicates the pedestrian's starting position.

3.2.3 Study Design

A fully within-participant experimental design was implemented for this study, with participants experiencing 52 trials involving four variables. The independent variables were: (i) the presence/absence of a zebra crossing, (ii) the vehicle's approaching direction (oncoming/right), (iii) vehicle yielding behaviour (yielding/non-yielding/no encounter), and (iv) the presence/absence of an eHMI, when it was yielding. The 52 trials were divided into two counterbalanced blocks. To minimise participant confusion, the zebra/no zebra crossing trials were blocked. Each block included 26 trials, with AVs approaching from the oncoming direction (13 trials) or the right (13 trials). Also, within each block, pedestrians came across six yielding, six non-yielding and one no-encounter AV from each direction. The "no encounter" AV trial was used as a ghost trial, such that the AV did not pass the pedestrian's path (depicted by the black arrows in Figure 3.2). If the AV approached from the right, the "no encounter" AV would turn to the left. If the AV approached from the oncoming road, the "no encounter" AV would continue to drive straight through the intersection. Finally, half of the yielding AVs displayed an eHMI indicating its intent. There was no sound associated with the approaching AV and order of trials in each block was randomised.

The vehicle's trajectory, speed profile and timings for each driving behaviour are shown in **Figure 3.2**. For each right-approaching trial, the AV drove from point A (27.4 m from the pedestrian) at a speed of 25 mph, and decelerated to stop after 3 s at the junction (point B, 9.4 m from the pedestrian). If it was a non-yielding AV, it would accelerate instantly (to point D) at a rate of 0.89 m/s^2. For yielding trials, the AV took 4 seconds to edge forward between point B and C, and stopped before the zebra crossing (point C, 3.42 m from the pedestrian) for 3 s, before accelerating away. The "edging" behaviour was used to mimic real-world yielding behaviour at junctions (Dietrich et al., 2018), providing an implicit form of communication by the AV.

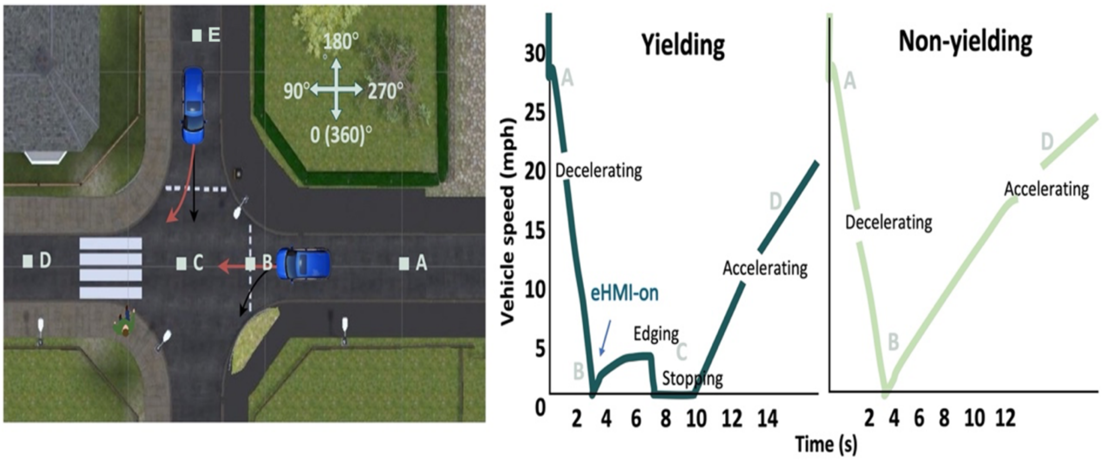


Figure 3.2. A birds' eye view of the crossroad (left) and the speed profiles used for the yielding and non-yielding AVs (right). Note that the eHMI onset occurred at the same time as the "edging" behaviour started. The compass in the left figure indicates that the head-turning angle was 180° when pedestrians were facing the front and 270° when turning to the right.

In half of yielding trials, an eHMI was displayed in addition to the "edging" behaviour to indicate the intent. The eHMI, which was designed as part of the interACT project, was a Slow Pulsing Light Band (SPLB) – a cyan-coloured light placed on the front side of the vehicle's windscreen (see **Figure 3.1**), which when turned on, pulsed at a rate of 0.4 Hz, to indicate the vehicle's intent 'I am giving way' (Lee et al., 2019). However, the meaning of the eHMI was not mentioned to pedestrians, as one aim of the study was to establish if pedestrians learnt its meaning over time and if the presence of this eHMI sped up their crossing decisions.

3.2.4 Procedure

Before attendance, and due to the Covid-19 pandemic, pedestrians were sent a copy of an online consent form, an information sheet describing the study, and a questionnaire collecting their demographic information. If selected for the study, participants were invited to the lab, and provided with brief instructions about the study by the experimenter. After wearing the head-tracking glasses, they started with a practice block of eight crossings, to become familiar with the overall set-up.

All participants were aware that the approaching vehicles were driven automatically in the virtual environment. For both the practice and experimental trials, pedestrians stood at the edge of the crossroad, on a yellow cross (see X marked in **Figure 3.1**) and were asked to cross when they felt safe. A short beep was used to notify the start of each trial, after which participants were free to look around and could cross either before or after the AV. After crossing the road, participants had to walk back to the yellow cross to start the next trial. Participants were offered a short break after the first block of trials. The experiment took approximately 30 minutes to complete.

3.3 DATA ANALYSIS - MEASURING HEAD-TURNING BEHAVIOUR

Participants wore a pair of stereoscopic motion-tracking glasses (see **Figure 3.3**) to track their head movements, which were captured by 10 VICON Vero v2.2 (2.2MP) cameras at 100Hz. The head's yaw (turning γ degrees around the Z-axis, left/right head-turning behaviour), pitch (rotating β degrees around the Y-axis, looking up/down) and roll (turning α degrees around the X-axis, tilting left/right) movement around the torso were collected in quaternion format and converted into Euler angle for analysis. This study focused on horizontal head movements (yaw), reflecting how pedestrians turned their heads from left to right (and back) to collect information from the environment and the approaching vehicle (Lyu et al., 2024).

The infinite impulse response (IIR) filter was employed to smooth the discrete data and filter any noise from the tracked head-turning angle, using the MATLAB Signal Processing Toolbox 8.6. A low pass filter with a cut-off frequency of 3Hz was designed to filter the higher frequency signals, based on a study showing that the head-turning rotation is normally lower than 2.6 Hz during locomotion (Grossman et al., 1988).

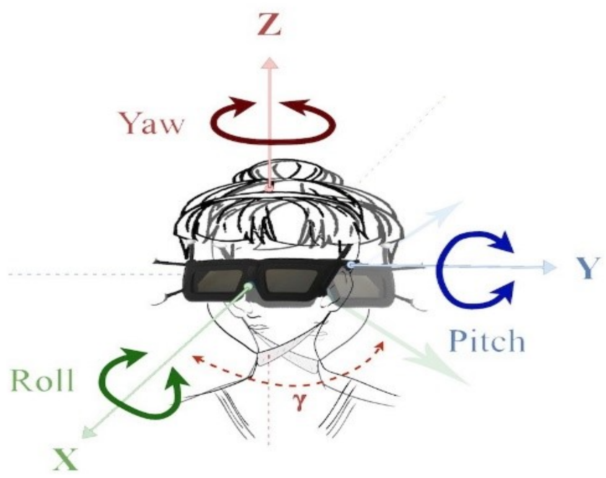


Figure 3.3. A schematic of a pedestrian wearing the stereoscopic motion-tracking glasses, showing the three dimensions of the head movement in the HIKER.

This paper only reports the head-turning behaviour for trials which included an AV approaching from the right, since pedestrians did not need to move their head to see the AVs which approached the junction from the oncoming direction (point E in **Figure 3.2**) to gather information for the crossing task. Data were excluded if (1) AVs had no interaction with pedestrians (76 no encounter trials), (2) pedestrians crossed after the AV had passed (431 trials), and (3) missing due to technical issues (1 trial). A total of 480 (357 yielding trials and 123 non-yielding trials) were included in the final analysis. **Table 3-1** provides a detailed list of the trials in each condition, also showing the average crossing initiation time (CIT) and crossing duration time (CDT).

Table 3-1. Overview of the dataset, for each condition which involved an AV approaching from the right

Vehicle behaviour	Zebra crossing	eHMI	No. of trials (per ped)	Total trials (missing data)	Trials ped cross after AV	Trials ped cross before AV	Mean CIT (s)	Mean CDT (s)
Yielding	Present	Present	3	114	14	100	6.11	4.64
		Absent	3	113(1)	16	97	6.17	4.44
	Absent	Present	3	114	29	85	8.28	4.69
		Absent	3	114	39	75	9.35	4.59
	Total		**12**	**456**	**98**	**357**		
Non-yielding	Present		6	228	135	93	5.35	4.63
	Absent		6	228	198	30	6.97	4.73
	Total		**12**	**456**	**333**	**123**		
No encounter			2	76	/	/	/	/
Total			**26**	**988**	**431**	**480**		

3.3.1 The absolute head-turning rate

Research from cognitive psychology suggests that we use both head movements and eye-gaze to automatically and swiftly guide attention to specific areas, for gathering information about our surroundings (Frischen & Tipper, 2006; Kleinke, 1986). Real-world observation studies have also shown that, in complex and hazardous environments such as road crossings, humans turn their heads to widen their scanning field, compensating for the limited range of eye movements (±55°) (Avineri et al., 2012). Therefore, the speed at which head-turning shifts occur potentially reflects the intensity of active scanning, and information seeking during a crossing. This metric has been used in a CAVE-based simulation study (Lyu et al., 2024), and also an eye-tracking study which investigated pedestrians' crossing behaviour in a parking garage (de Winter et al., 2021). Results from de Winter et al. (2021) showed a higher rate of head-turns to the left and right, looking at other cars and humans during a crossing. Results from Lyu et al. (2024) found pedestrians presented a higher rate of head-turning around crossing initiations in response to a human driven braking vehicle compared to a soft-braking AV.

Therefore, the absolute head-turning rate was calculated in this study, to investigate how actively pedestrians were turning their heads to the left and right during the crossing, to understand how the different conditions affected their attention seeking behaviour. Head-turning rate was measured as the absolute change in head-turning angle between the current and subsequent frame and divided by the sampling frequency (0.01 s). The change in head-turning angle per frame (0.01 s) fluctuated around 0 degrees, where the positive and negative angle change represented the right and left turn from the previous frame to the adjacent frame, respectively. This measure used the absolute value, to avoid the positive and negative values cancelling each other out.

In the subsequent statistical analyses, an average value of the absolute head-turning rate was tallied every 0.2 s, calculating the average absolute head-turning rate of the previous and next ten frames, to reduce the overall volume of data. This metric provided a sensitive and accurate approach to identify any minor head-turning behaviour and how pedestrians turned their heads over time. The Generalised Estimating Equation (GEE) was used to analyse changes in the absolute head-turning rate, over time. This method is suitable for analysing non-normally distributed, repeated measurements (Liang & Zeger, 1986). The impact of vehicle yielding behaviour, zebra crossing presence, time, and their interactive effects on the absolute head-turning rate was analysed (N=480). The model examined the absolute head-turning rate by employing a Gamma distribution coupled with a log link function. Crossing behaviour was analysed for the period starting 10 s before and 3 s after the crossing initiation, to enable the inclusion of sufficient data. This period was used because as 99.4% of pedestrians had initiated the crossing at 10 s and 95% of pedestrians were still crossing 3 s after the initiation.

A second GEE model was established to investigate the impact of eHMI, and its interactive effects with time, on the absolute head-turning rate in the yielding trials (N=123). The level of statistical significance was set to be lower than 5%.

3.3.2 Head-turning frequency

Head-turning frequency was used to understand head-turning behaviour in the crossing task, by tallying the number of major head turns before the crossing initiation time (CIT, which is the time from the start of the trial, until the pedestrian started crossing) and during the crossing (from the moment the crossing started to the end of the crossing), respectively. In a test track study by Hamaoka et al. (2013), more frequent head movements by pedestrians during crossings were associated with a higher need to establish the proximity of approaching vehicles. Therefore, we assumed in this study that a higher head-turning frequency implies a greater demand for information acquisition about the approaching vehicle.

An example plot of a pedestrian's head-turning angle in one trial is shown in **Figure 3.4**, where two major head turns were detected in blue lines before the CIT, and two during the crossing. To calculate head-turning frequency before the CIT, firstly, a baseline was selected as the head-turning angle, which was where the pedestrian's head was mostly oriented, before the CIT. A detection area was chosen (baseline ± standard deviation - the shaded green area in **Figure 3.4**) before the CIT. One head turn was counted if the head-turning angle was beyond the detection area before the CIT.

Similarly, head-turning frequency during the crossing was collected by selecting the baseline of the head-turning angle during the crossing and defining a detection area (baseline ± standard deviation - the shaded pink area in **Figure 3.4**). A head turn during the crossing was counted if the head-turning angle was beyond the pink detection area.

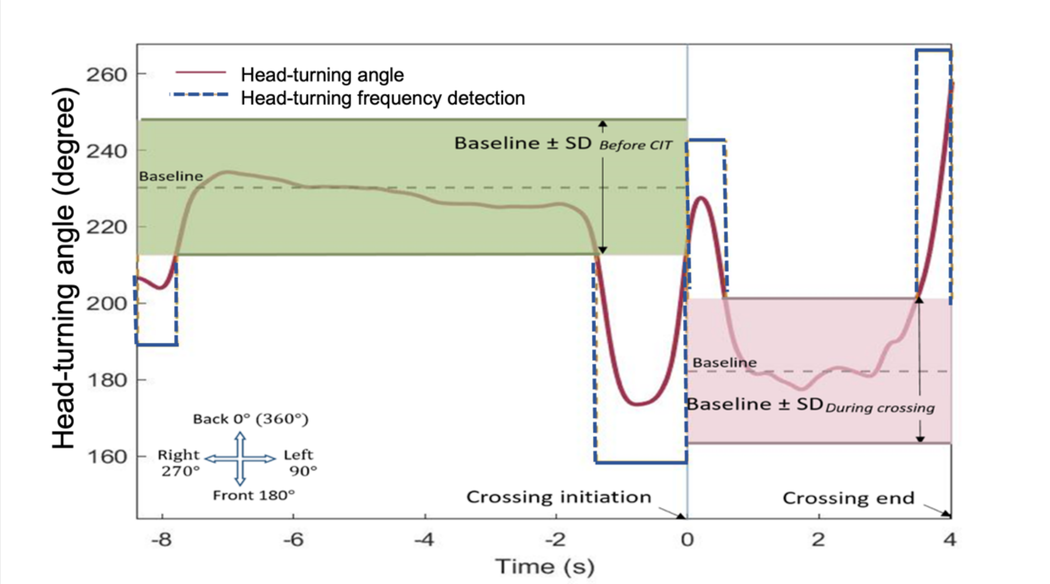


Figure 3.4. Example plot of pedestrian's head-turning angle (Pedestrian #1, Block #NoZebra, Trial #26, right-approaching AV yielding without eHMI) plotted in a continuous red line from the start of the trial to the end of the crossing, where the crossing initiation time is the zero point on the x-axis. The highlighted green and pink areas represent the detection area (Baseline ± SD) before CIT, and during the crossing, respectively. For this trial, two major head turns were detected before the crossing initiation, and two during the crossing (blue dashed lines).

The non-parametric Wilcoxon-signed-rank test was used to compare the head-turning frequency before and during the crossings, for the two yielding behaviours (N = 123 for non-yielding behaviour and N = 357 for yielding behaviour, see **Table 3-1**). A Generalised Linear Mixed Model (GLMM) was applied to estimate the effects of the zebra crossing, eHMI, and the number of encounters on pedestrians' head-turning frequency, in yielding trials (N = 357), before the crossing initiation. As discussed in the Introduction, pedestrians will need to learn to interpret the meaning of eHMIs through repeated exposures. Therefore, an interactive effect of the eHMI and the number of encounters (1st / 2nd / 3rd) was also included in the model. The GLMM is recommended for repeated measures analysis of data that is not normally distributed (Stroup, 2012). The analysis applied a Poisson distribution to assess the head-turning frequency using a log link function. The level of statistical significance was set to be lower than 5%.

3.4 RESULTS

3.4.1 The absolute head-turning rate

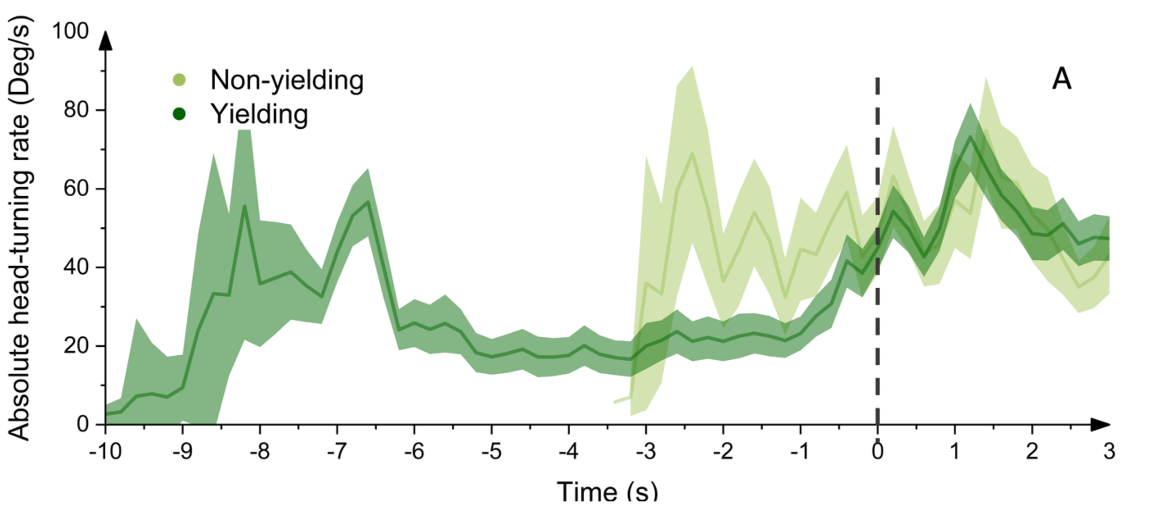
As shown in **Table 3-2**, there was a main effect of time on the absolute head-turning rate (Wald χ^2 (38) = 1.248E+ 14, p < .001). As shown in **Figure 3.5**(A-C), pedestrians showed a significant increase in absolute head-turning rate around 1 s before the crossing initiation, which reached a peak at 1.5 s after they started crossing. This peak in the head-turning rate between -10 s and -6 s was caused by the rapid right-turning behaviour at the start of each trial.

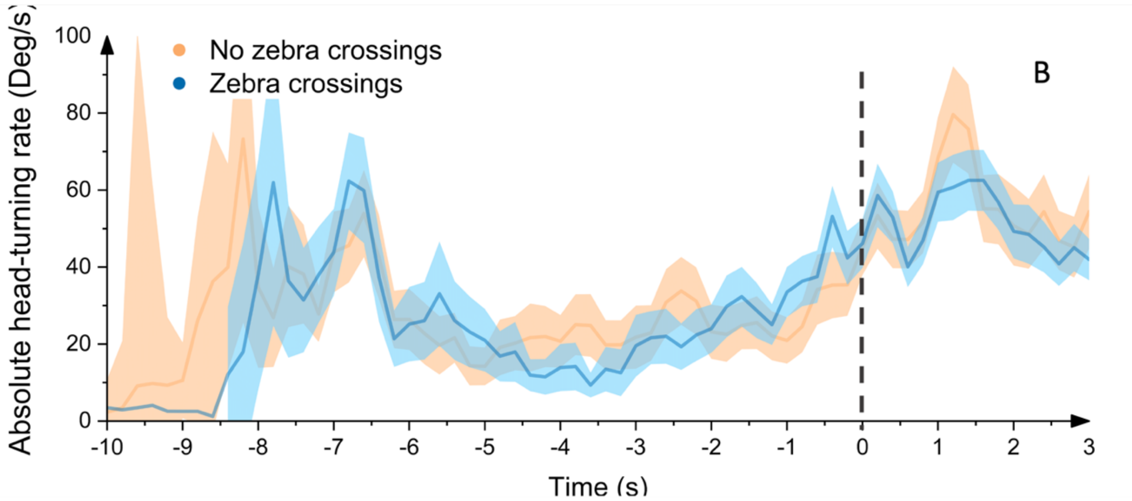
Table 3-2. Results of the GEE model analysing the impact of a zebra crossing, vehicle yielding behaviour, and time on the absolute head-turning rate for trials where pedestrians crossed before the AV had passed.

	Wald Chi-Square	df	Sig.
(Intercept)	450.363	1	.000
Time	1.248E+ 14	38	.000
Zebra	10.550	1	.001
Yielding behaviour	8.042	1	.005
Zebra * Time	4.361E+ 12	38	.000
Yielding behaviour * Time	2724.289	32	.000

The vehicle's yielding behaviour had a significant impact on pedestrians' absolute head-turning rate (Wald χ^2 (1) = 10.550, p < .001). Pedestrians showed a significantly higher average absolute head-turning rate for the non-yielding conditions (M = 0.436, SE = 0.032), compared to the yielding conditions (M = 0.247, SE = 0.017). A significant interaction was also seen between yielding behaviour and time (Wald

χ^2 (32) = 2724.289, p < .001). Post-hoc analysis, with Least Significant Difference (LSD) corrections, indicated that the absolute head-turning rate was significantly later for the non-yielding conditions, highest around ~3.4 s before the crossing initiation until ~0.4 s after the crossing initiation (see **Figure 3.5**A).





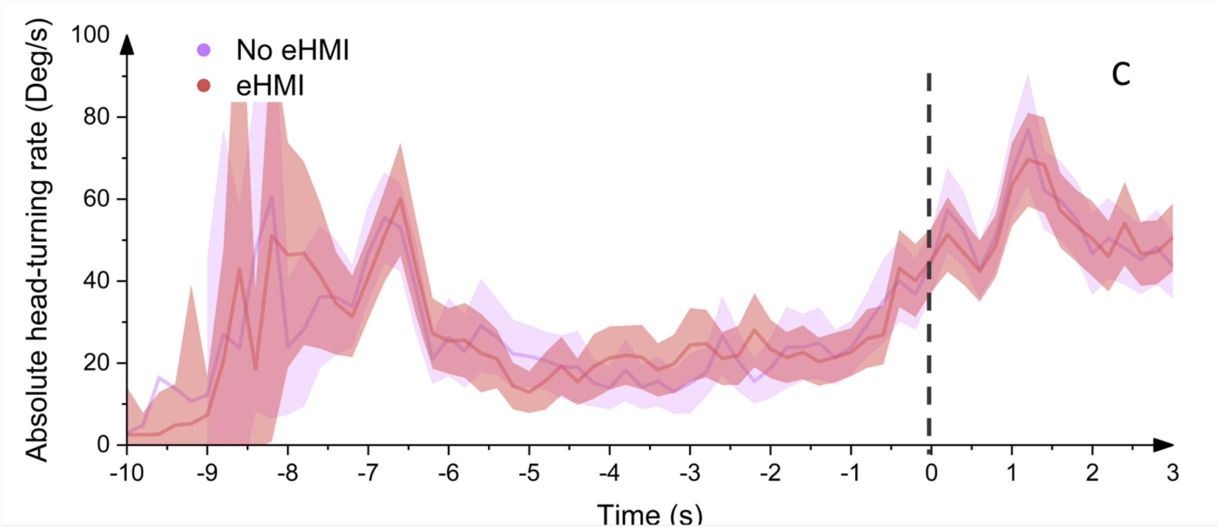


Figure 3.5. Pedestrians' absolute head-turning rate with 95% CI in the shaded area across: (A) yielding behaviour, (B) zebra crossing presence/absence, and (C) eHMI presence/absence (yielding trials only). The dashed line at zero indicates crossing initiation times.

Results also showed a significant influence of the zebra crossing on the average absolute head-turning rate (Wald χ^2 (1) = 10.550, p < .001), with a lower absolute head-turning rate in the presence of the zebra crossing (M = 0.275, SE =0.016), compared to the no zebra crossing trials (M = 0.324, SE =0.023). The GEE analysis showed a significant interaction between the presence of zebra crossings and time (Wald χ^2 (38) = 4.361E+ 12, p < .001). Post-hoc analysis (LSD) showed that pedestrians exhibited a significantly higher absolute head-turning rate from -10 s to -8 s, at 3.6 s and 2.4 s before crossing, and at 1.4 s after the CIT, for the trials without a zebra crossing (see **Figure 3.5**B).

Results from the second GEE analysis investigating the impact of eHMI on the absolute head-turning rate in yielding trials showed that the presence of eHMIs had a significant impact on the absolute head-turning rate (Wald χ^2 (1) = 4.609, p < .05). Pedestrians' head-turning rate was significantly higher for AVs approaching without an eHMI (M = 0.318, SE =0.025) than those with an eHMI (M = 0.277, SE

=0.023). There was also a significant interaction between eHMI and time (Wald χ^2 (37) = 7.228E+14, $p < .001$). Post-hoc analysis (with LSD corrections) showed that pedestrians showed a significantly higher head-turning rate around 2.2 s before CIT when the eHMI was present, compared to the no-eHMI conditions (see **Figure 3.5**C).

3.4.2 Head-turning frequency

Results from the Wilcoxon signed-rank test showed that pedestrians presented significantly more head turns during the crossings, than before crossing initiations, for both yielding ($z = -2.001$, $p < 0.05$, $N = 357$, $r = 0.11$) and non-yielding conditions ($z = -6.284$, $p < .001$, $N= 123$, $r = 0.57$), as seen in **Figure 3.6**. In addition, there were significantly more head turns for the yielding trials than the non-yielding trials before a crossing initiation was made ($z = -5.199$, $p < .001$, $N = 123$, $r = 0.47$), while the difference in head turns during the crossing was not significant for the yielding and non-yielding trials ($z = -1.620$, $p > 0.05$ $N = 123$, $r = 0.15$).

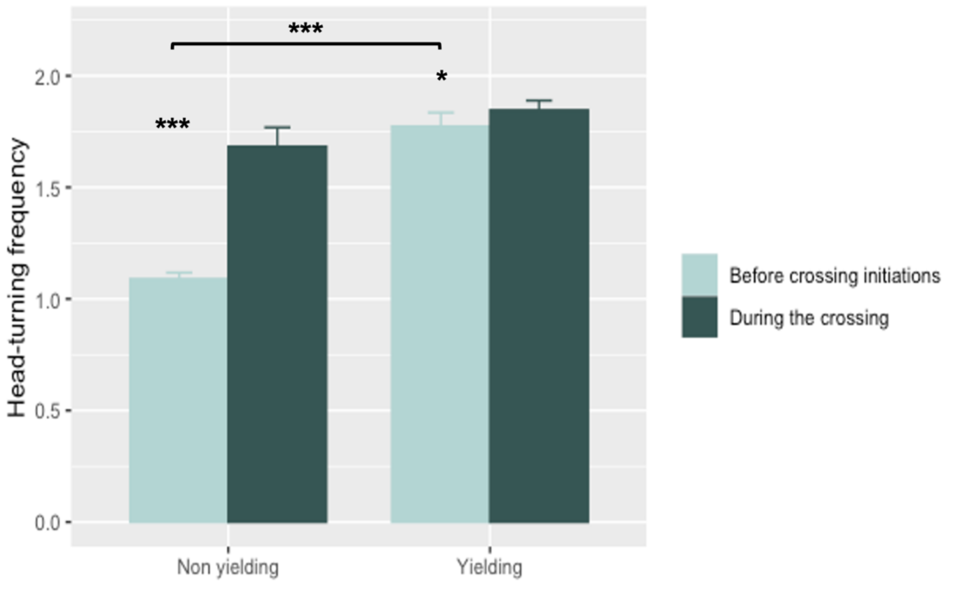


Figure 3.6. Pedestrians' head-turning frequency across the yielding behaviour and crossing status. The error bar indicates standard error.

Results from the GLMM model (see **Table 3-3**) showed a significant impact of zebra crossing on pedestrians' head-turning frequency before crossing initiations in front of a yielding AV ($F(1,352) = 9.463$, $p < 0.01$), with pedestrians presenting significantly fewer head turns in the presence of a zebra crossing ($M = 1.601$, $SE = 0.099$, vs $M = 1.861$, $SE = 0.119$). The eHMI presence also influenced pedestrians' head-turning frequency, before crossing initiations ($F(1,352) = 6.493$, $p < 0.05$), with a lower head-turning frequency in the eHMI trials ($M=1.601$, $SE = 0.098$) than without an eHMI ($M = 1.861$, $SE = 0.121$).

Finally, in terms of learning the pattern of behaviour of the AV, a significant negative relationship was found between the number of exposures and pedestrians' head-turning behaviour ($F(1,352) = 4.110$, $p < 0.05$), where pedestrians' head-turning frequency decreased with increased exposures to AVs (see **Figure 3.7**). The interaction between the number of encounters and eHMI was not significant ($F(1,352) = 3.157$, $p > 0.05$).

Table 3-3. Results of GLMM estimations for pedestrians' head-turning frequency before crossing initiations towards a yielding AV.

Predictors	*Coefficient*	*SE*	*t-statistics*	*p-value*	*Exp (Coefficient)*	*95% CI Lower*	*95% CI Upper*
Intercept	.411	.1032	3.982	.000	1.508	1.231	1.847
Zebra Crossing [Absence]	.150	.0489	3.076	**.002**	1.162	1.056	1.279
eHMI [Absence]	.363	.1424	2.548	**.011**	1.437	1.086	1.902
Exposure	-.008	.0391	-.197	**.043**	.992	.919	1.072
Exposure * [eHMI Absence]	-.107	.0600	-1.777	.076	.899	.799	1.011

Probability distribution: Poisson   Link Function: Log

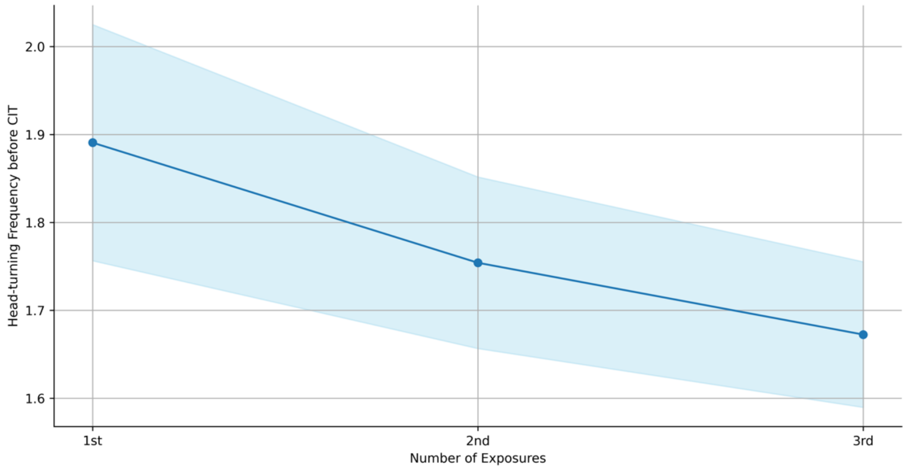


Figure 3.7. Pedestrians' head-turning frequency in response to repeated encounters. The shaded area represents the standard error.

3.5 DISCUSSION

This study utilised a CAVE-based pedestrian simulation environment to examine pedestrians' head movements, when interacting with AVs at a virtual road crossing scenario. The effects of a vehicle's yielding behaviour, zebra crossing, and eHMIs on head-turning behaviour were investigated to understand how each condition affected pedestrians' attention allocation and information acquisition during the crossings. Pedestrians' ability to learn the behaviour of the AV was also examined, by comparing head-turning patterns with repeated exposures to the approaching AVs.

In this study, pedestrians' mean crossing speed was calculated to be 1.16 m/s, which is consistent with average values reported in real-world observations, approximately 1.2 m/s (Montufar et al., 2007). Although slightly lower, this value falls within a realistic range and may reflect the cautious behaviour induced by the vehicle approach in the simulation. This finding supports the ecological validity of pedestrian behaviour observed in the virtual environment.

3.5.1 Pedestrians' head-turning behaviour and crossing intent

Results identified an increase in the absolute head-turning rate from approximately 1 s prior to crossing initiations, which reached a peak value at 1.5 s after the crossing (see **Figure 3.5**A-C). This behaviour pattern has been termed the "last-second check" in previous real-world observation studies (Hassan et al., 2005; Tom & Granié, 2011), where pedestrians presented a more active head-turning behaviour in the last 4 s before commencing a crossing, with the number of head turns being highest during the last second. A "last-second check" was also found in a CAVE-based pedestrians simulation study, where there was a significant increase in head-turning rate in the last 2 s before a crossing initiation (Lyu et al., 2024). The reason these head turns were not observed as early as 4 s or 2 s before the CIT in this study may be due to the experimental design used, with a relatively short time between the start of the approaching vehicle and pedestrians' crossing initiation. While the time at which this increase in head-turning rate before a crossing is seen is scenario dependent, our results demonstrate that such a surge in head-turning rate could be a good indicator of pedestrians' intention to cross, which, if identifiable by an AV's sensor, could be a good cue for speed reduction by the approaching AV, before it comes to a complete stop in front of a pedestrian.

We also saw a surge in absolute head-turning rate 1.5 s after the crossing initiation. Both head-turning frequency and head-turning rate were higher during the crossing than before crossing initiations. This finding is in line with results from a test-track study by Hamaoka et al. (2013) which showed that the head-turning frequency was the highest at the start and middle of the crossing, a behaviour which is used to confirm the proximity of an approaching vehicle. This finding shows the natural tendency of pedestrians to be safe when crossing in front of a vehicle, continuing to observe their surroundings, even in an artificial and safe virtual reality environment.

3.5.2 The impact of kinematic and infrastructure cues

Our results showed that the behaviour and dynamics of the vehicle, as well as the zebra crossing played a significant role in influencing pedestrians' head-turning behaviour, during interactions with AVs. Previous studies have shown that pedestrians increase their head-turning behaviour to compensate for their oculomotor limitation, when scanning the environment during high-risk tasks such as road crossings (Avineri et al., 2012). In our study, such behaviours were predominantly seen during the non-yielding trials (**Figure 3.5**A), where heightened risk and time constraints resulted in more frequent and rapid head movements. Conversely, in the yielding trials, where AV intentions were clearer, thanks to both kinematic and eHMI messages, there was a notable decrease in the rate of head-turnings before crossings.

We also found a significantly higher frequency of head turns and a greater head-turning rate before crossing initiations, for trials without a zebra crossing. This is likely due to the increased risk associated with these situations (Avineri et al., 2012). The fewer head turns observed in the zebra crossing trials might be associated with greater confidence, and less uncertainty, about the decision to cross, as pedestrians are aware of their right of way for this type of setting. These findings align with other research emphasizing the role of road infrastructure, such as zebra crossings, in shaping pedestrian behaviour (Clamann et al., 2017; Havard & Willis, 2012; Sakamoto et al., 2019; Velasco et al., 2019), and further illustrate how head turns can serve as an indicator of confidence in decision-making during crossing events.

3.5.3 The impact of an eHMI and learning effects

Since higher head movements imply a greater demand for information acquisition (Hamaoka et al., 2013), the reduced frequency of head movements in the presence of eHMI suggests that pedestrians used the message to establish the AV's intention, reducing the need for information gathering. This reduction in visual search during the eHMI trials, denoting a better understanding of the AV's intent, is also noted by Liu et al. (2020). However, Kaleefathullah et al. (2020) found that over a series of trials, pedestrians began to over-trust the eHMI, which lead to unsafe crossings and collisions in a CAVE-based study, if the eHMI's message was misleading - i.e. the AV did not yield when the eHMI (incorrectly) indicated it would. This suggests that pedestrians may over-trust such messages, leading to unsafe crossings.

This study identified a learning effect, evident by the decreased frequency of head movements over repeated trials, regardless of the presence of eHMIs (as illustrated in **Figure 3.7**). Previous research has indicated that pedestrians gradually comprehend the messages displayed by AV eHMIs (Faas et al., 2020; Hochman et al., 2020; Lee et al., 2022). Sometimes trusting these more than the implicit message provided (Kaleefathullah et al., 2020). In this study, we observed learning of the AV's implicit driving behaviours when intentions were ambiguous through edging forward. This observation highlights the necessity to ensure that messages from AV eHMI are not in contrast to the AV's driving behaviour, to reduce ambiguity in the AV's intentions, as suggested by Hochman et al. (2022).

3.5.4 Limitations and future work

This study investigated head-turning behaviour in response to one vehicle approaching from the right. It is acknowledged that head-turning patterns might differ in more elaborate scenarios, as noted by Hamaoka et al. (2013). Therefore, more complex and dynamic scenarios should be designed in the future to explore more realistic head-turning behaviour during crossings. For example, including more vehicles, approaching from different directions, with varying time gaps may help us understand interactions relevant to real-world traffic scenes (Meir & Oron-Gilad, 2020). This will also help us understand how/if user response to automated vehicles may be different to that of human-driven vehicles. Additionally, considering the study's UK location, future research should account for variations in traffic directionality, present in other countries.

A further limitation lies in the diversity of the participants, specifically concerning those with different walking abilities, such children and older adults. This understanding is crucial if head-turning metrics are to be used for intention recognition by AVs. For example, results from Tapiro et al. (2016) showed that older adults tend to engage in fewer head turns towards the extremities of the road, focusing more centrally on their crossing path. This suggests that head movement assessment techniques for intent recognition should be tested on a wider range of users in the lab, including children, younger adults and those with mobility impairments.

3.5.5 Conclusions

This VR-based study provides novel insights into pedestrian head movements in response to AVs approaching a junction with and without a zebra crossing, and how these are affected by implicit behaviour and eHMIs. Although it remains to be seen if these results are relevant to a more complex traffic environment and a wider range of users, this study confirms the similarity of head-turning behaviours between real-world and virtual environments before and during a crossing for a simple scenario. The value of CAVE-based pedestrian simulators for testing these behaviours in a safe and repeatable VR-set up is highlighting, allowing studies on human response to fully driverless AVs, not yet available in the real world. The study demonstrates that, as an alternative but complementary measure to eye movements, head motion can serve as a reliable indicator of crossing intentions, and a measure of pedestrians' information-seeking and risk-taking behaviour.

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CHAPTER 4

THE EFFECT OF AUGMENTED REALITY ON PEDESTRIANS' GAZE PATTERNS AND CROSSING PROBABILITY WHILE INTERACTING WITH AUTOMATED VEHICLES

ABSTRACT

The investigation of Augmented Reality (AR) implementation in transportation has been growing rapidly, with potential applications such as communicating the intentions of approaching automated vehicles (AVs) to other road users. However, it remains unclear whether AR increases pedestrians' visual load during crossing decisions by presenting additional information. This study addressed this research gap by examining pedestrians' gaze behaviour and crossing decisions when interacting with AVs featuring AR interfaces placed in various locations (on the AV's travel path, on the pedestrian's crossing path, or as a heads-up display [HUD]). Thirty participants took part in the study, conducted in a CAVE-based virtual reality (VR) pedestrian simulator. We measured pedestrians' total gaze fixation duration on AR interfaces and the vehicle before crossing decisions to assess attentional demands. Results showed that the presence of an AR reduced total gaze fixation duration compared to trials without an AR before crossings were initiated, indicating lower attentional demands for crossing decisions. Intuitive AR designs and repeated encounters to the AR further reduced fixation duration. Among the AR locations, HUD ARs yielded the greatest reduction in total gaze fixation duration compared to no AR, followed by ARs on the crossing path, and then those on the AV's travel path. However, HUD ARs appeared to distract pedestrians when the AV was more than 10 metres away, as participants frequently looked away to avoid them. Additionally, analysis of pedestrians' gaze heat maps revealed that, regardless of AR presence or location, their attention focused more on the vehicle as it approached, correlating with an increased likelihood of crossing. When AR was present, pedestrians initiated crossings at greater distances compared to scenarios without an AR, suggesting an AR effectively conveys AV intent, particularly when the vehicle is farther away. These findings highlight AR's potential to reduce attentional demands and promote earlier crossing decisions, offering valuable insights for designing effective, distance-based AR interfaces to enhance AV-pedestrian interactions.

Keywords: augmented reality, automated vehicle, AV- pedestrian interaction, intuitiveness, learning effects, CAVE pedestrian's simulator, gaze fixation, gaze heat map

4.1 INTRODUCTION

The introduction of automated vehicles (AVs) leads to a significant transition in transportation, promising many benefits, including a major reduction in accidents involving vulnerable road users by eliminating human errors (Anderson et al., 2016). However, higher-level AVs, which operate without human drivers, are currently unable to effectively communicate their own intentions to surrounding traffic. This limitation can lead to frustrating standoffs, particularly in ambiguous situations where both the AV and other road users are trying to occupy the same space but are uncertain about who has the right of way, such as at unsignalised crossings (Brown et al., 2023; Loke, 2019; Maurer et al., 2016; Schwarting et al., 2019; Vinkhuyzen & Cefkin, 2016). The absence of a human driver or traffic signals at these crossings prevents clear communication, further complicating the determination of priority and increasing the likelihood of hesitation or hazardous interactions.

External Human-Machine Interfaces (eHMIs) have been proposed as a solution for bridging this communication gap by externally displaying information about AV intentions to pedestrians (Faas et al., 2020; Guo et al., 2022; Hochman et al., 2020; Holländer et al., 2019; Lee et al., 2022; Lyu et al., 2024; Wilbrink et al., 2021). Although eHMIs can help pedestrians make quicker decisions and increase their perceived safety (Faas et al., 2020; Holländer et al., 2019), they face challenges in scalability, particularly for managing multiple interactions simultaneously and effectively communicating across various distances and directions (Colley et al., 2020; Dey et al., 2021; Holländer et al., 2022; Lyu et al., 2024; Wilbrink et al., 2021). These challenges raise concerns about how an AV communicates with specific pedestrians among many road users and the visibility of eHMIs in complex, real-world traffic scenarios (Dey, Habibovic, et al., 2020).

Given these challenges, personalized interaction strategies like Augmented Reality (AR) are being explored as a complementary approach in assisting with communication for AV-pedestrian interactions (Calvi et al., 2020; Matviienko et al., 2022; Tabone et al., 2020; Tabone et al., 2023; Tabone et al., 2024; Tabone et al., 2021; Tran et al., 2023). AR allows for simultaneous communication with multiple road users, providing precise, customized visual information to pedestrians (Dey, Habibovic, et al., 2020). By overlaying digital content onto the physical world, this approach offers several benefits, such as resolving language barriers through person-specific feedback (Tabone et al., 2020), and maintaining users' situational awareness (Tong et al., 2021). Although the use of AR for road user communication may seem futuristic and raise concerns about reliance on costly headsets (Tabone et al., 2020), advancements in wearable AR technology (e.g., Microsoft HoloLens, Google Glass, Apple Vision Pro) are making its adoption in AV-pedestrian communication increasingly feasible.

Despite these potential benefits, there are concerns that AR might overly burden pedestrians with additional visual elements (Tabone et al., 2020). Research in learning and skill acquisition domains has shown that while mobile AR can decrease cognitive load by providing direct information, it can also overwhelm users when presenting excessive information simultaneously (see reviews from Buchner et al. (2022); Suzuki et al. (2024)) . In road user interactions, pedestrians may experience cognitive and information overload with too many visual cues, posing safety risks (Mahadevan et al., 2018; Moore et al., 2019). Eye-tracking offers a method to measure pedestrians' visual attention, helping to assess whether they are visually overloaded by these cues. Additionally, research examining gaze fixations, defined as periods when the eyes remain relatively still and focus on a specific element, helps to gain deeper insights into how pedestrians engage with visual information (Salvucci & Goldberg, 2000). Longer fixation durations may indicate increased visual efforts (He & McCarley, 2010; Herten et al., 2017; Jacob & Karn, 2003) or difficulty in processing the visual information (Kotval & Goldberg, 1998; Milton et al., 1950), while shorter fixations suggest quicker information absorption. However, investigations assessing pedestrians' gaze behaviour when exposed to AR interface signalling the intentions of AVs are overlooked.

Research into pedestrians' gaze behaviour can guide the placement and design of AR interfaces (de Winter et al., 2021; Dey et al., 2019), although most current eye-tracking research in AV-pedestrian interactions has been focused on eHMIs (Eisma et al., 2020; Guo et al., 2022; Hochman et al., 2020; Lyu et al., 2024). For instance, Eisma et al. (2020) found that windscreen-mounted eHMIs effectively focused pedestrian gaze, while road projections dispersed gaze patterns and increased visual effort, making them less ideal. Also, this study used a desktop-based 2D simulation setup, which may not have accurately reflected gaze behaviour in a 3D environment. Using a Wizard-of-Oz study, Dey et al. (2019) observed that pedestrians' gaze shifted from the surrounding environment to the car's bumper and gradually to the windshield as the vehicle approached. They recommended distance-based eHMIs considering these visual attention patterns from pedestrians. However, Dey et al. (2019) study involved the use of stationary pedestrians pressing a button to indicate their crossing intention, rather than making real crossing decisions, possibly limiting insights into natural behaviour in dynamic environments (Te Velde et al., 2005). Additionally, this work mainly examined gaze directed towards the vehicle's approach while overlooking pedestrians' attention to surrounding environmental cues and the crossing path. While the above studies suggest that vehicle distance and eHMI's display placement affect pedestrian gaze, it remains unclear whether AR displays are likely to influence gaze patterns in a similar manner, and whether the pattern is likely to be the same. Addressing these gaps could significantly inform AR location strategies and potential use cases, as AR can be more versatile in its location compared to eHMIs, which are typically fixed to the vehicle.

In AV-pedestrian interactions, longer gaze durations on AVs are linked to uncertainty about the AV's intentions and increased feelings of danger (Liu et al., 2023). Similarly, longer gaze duration on eHMIs designs indicates lower perceived clarity in communicating AV intent to pedestrians (Guo et al., 2022). Research suggests that intuitive eHMI designs can reduce confusion and ease pedestrians' information load (Moore et al., 2019), with repeated exposures fostering greater trust, faster crossing decisions, fewer gaze fixations, and reduced attentional behaviours like head-turning (Faas et al., 2020; Hochman et al., 2020; Yang et al., 2024). Intuitive AR designs may offer similar benefits, potentially streamlining decision-making by enabling pedestrians to assess crossing safety more quickly (Tabone et al., 2024), especially with repeated exposures. This increased efficiency in comprehension could lead to shorter gaze fixation durations on both AV and AR elements in AR-present versus no-AR trials, indicating reduced visual demands. However, the correlation between intuitive design and gaze fixation patterns, particularly with repeated exposures, remains underexplored. Investigating this relationship could significantly inform AR design for safer and more efficient AV-pedestrian interactions.

Additionally, if pedestrians' gaze patterns could be influenced by different AR locations at different AV's distances, one can assume that their crossing decisions could also change correspondingly, as gaze behaviour often correlates with decision-making in value-based choice experiments (Anderson, 2013; Gluth et al., 2020; Gluth et al., 2018; Krajbich et al., 2010; Krajbich & Rangel, 2011; Shimojo et al., 2003; Thomas et al., 2019). Research has shown that pedestrians presented higher crossing probabilities with the presence of eHMI communicating AV's intentions at greater AV distances before fully stopping (Dey, Matviienko, et al., 2020; Lee et al., 2022; Pekkanen et al., 2022; Schneemann & Gohl, 2016). AR could have a similar effect, potentially leading pedestrians to decide to cross earlier, while the AV is still at a greater distance. However, the effect of AR location on both gaze and the timing of crossing decisions remains unexplored. Investigating this relationship could provide critical insights into where AR should be positioned to optimise AV-pedestrian communication at various distances.

4.1.1 Research questions

In response to these considerations, our study posed the following research questions:

1. How do the locations of AR interfaces affect pedestrians' gaze patterns at various distances as AV approach?
2. How do the location, intuitiveness and repeated encounters of AR affect pedestrians' change in fixation duration compared to no AR condition before crossing decisions?
3. How do the locations of AR affect pedestrians' crossing probabilities at various distances as AVs approach?

To address these questions, our road crossing study examined pedestrians' gaze behaviour while exposed to a variety of AR concepts, which was proposed in Tabone et al. (2023) and Tabone et al. (2024), in a CAVE-based pedestrians simulator environment.

4.2 METHOD

4.2.1 Participants

Thirty participants were recruited for this study through the University of Leeds Driving Simulator Database, social media and university mailing lists. Among the participants, 20 were males, nine were females, and one was unspecified (age range 22-53 years, M = 31.50, SD = 7.98). All participants were required to be aged 18 and above, possess proficient English language skills, and be free from significant mobility limitations, epilepsy, claustrophobia, or proneness to disorientation. To compensate for their time in taking part in the study (60-90 minutes), each participant received a £15 Amazon gift voucher. The study received ethical approval from the University of Leeds Research Ethics Committee (Ref: LLTRAN-150).

4.2.2 Apparatus and the virtual environment

The study was conducted in the Highly Immersive Kinematic Experimental Research (HIKER) simulator, a 9 × 4 m CAVE environment at the University of

Leeds (as shown in **Figure 4.1**). It comprised eight 4K projectors and 10 Vicon Vero 2.2 IR cameras, managed via Vicon Tracker 3.9. The experimental virtual environment, designed in Unity, replicated a residential one-way street featuring a single lane 3.6 meters wide, which was the same as Lee et al. (2022). Eye-tracking data were captured at a frequency of 50 Hz using the Tobii Pro Glasses 2, operated and calibrated with Tobii Controller Software.

Figure 4.1. A participant in the HIKER lab waits for the start of a trial. In the coordinate system, the 'Y' axis aligns with the participant's height, the 'Z' axis aligns with the pedestrian's intended path, and the 'X' axis aligns with the AV approaching trajectory. The cyan circle in front is an attention attractor used to control the direction of pedestrians' initial focus. It appears randomly, counterbalanced to the left, front, or right of the pedestrian. Pedestrians were required to look at this area, to trigger the start of each trial.

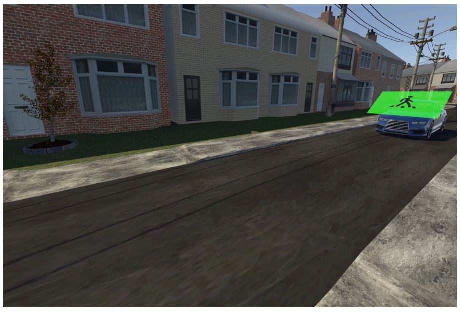
4.2.3 Study design

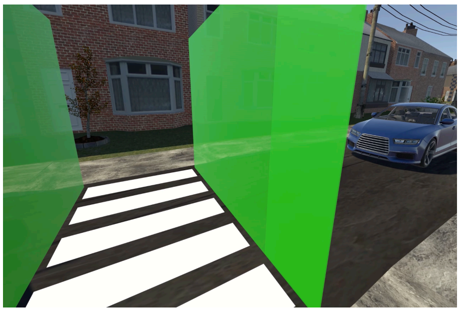
This study built on the experiment conducted in Tabone et al. (2024), a within-participant experimental design, where each participant experienced 10 blocks of 12 trials each. There were three independent variables. (1) Each block featured a single AR condition, covering nine AR designs and one baseline without AR. (2) To simulate real-life situations where pedestrians may be looking in different directions before crossing, they were asked to focus on an attention-attractor circle at the start of the trial (the cyan circle shown in **Figure 4.1**), located on either the left, centre, or right. They were only allowed to look freely after the circle disappeared. (3) There were three trials of yielding AVs and one trial of non-yielding AV, all approaching from the right. The blocks and trials within each block were counterbalanced and presented in a randomised order.

The AR designs included in this study are illustrated in **Table 4-1** and further categorised based on its location. Four ARs following Car Path directed pedestrians' attention to the area that constantly following the AV's travel path and adjusted based on its movements. Two ARs on the pedestrian's Crossing Path directed pedestrians' attention to the area in front of them overlapping with the intended crossing path. Two HUD ARs directed pedestrians' attention to a fixed area following their heads movements and always in their visual field regardless of AV's movements. A ninth design in the original study design (Tabone et al., 2023; Tabone et al., 2024) was excluded from the analysis because it featured Fixed Pedestrian Traffic Lights positioned still in front of the crossing path, which was not directing pedestrians' attention to the vehicle's travel path, crossing path or following their heads, making it distinct in location from the other AR designs.

Table 4-1. Description of AR concepts with categorizations based on its locations

Category	Design	AR concept

Car Path		**Planes on Vehicle** A plane displayed on the vehicle's windshield area
		**Conspicuous Looming Planes** A scalable plane that changed size, growing in the non-yielding state or shrinking in the yielding state as the vehicle approached the pedestrian
		**Field of Safe Travel** A projection on the road in front of the vehicle indicating a safe travel area
		**Phantom Car** Showed the vehicle’s predicted future motion
Crossing Path		**Augmented Zebra Crossing** A conventional zebra crossing displayed on the ground

		**Virtual Fence** Semi-translucent walls around the zebra crossing with a gate that opened during the yielding state
HUD		**Nudge HUD** Text and icons displayed in the user's field of view
		**Pedestrian Lights HUD** A head-locked version of pedestrian traffic lights

At the beginning of each trial, participants, positioned at Point E (**Figure 4.2**), were instructed to focus on the attention-attractor circle. After maintaining their gaze on the circle for one second, the AV began its journey from a concealed starting point (Point A, **Figure 4.2**), travelling at a constant speed of 48 km/h (30 mph). Seven seconds after leaving point A, the AV reached a location 43 meters from the participant (Point B, **Figure 4.2**), marking the activation of the AR interfaces in non-baseline trials.

In yielding trials, the AV began to decelerate 0.8 seconds after leaving Point B, starting at Point C, 33 meters away from the participant. Its yielding behaviour was the same from the research by Kaleefathullah et al. (2020), with a deceleration rate of 2.99 m/s^2. The AV reached a full stop four seconds later, at Point D (Figure 4.2.

), and 3 meters from the participant. Precisely 0.2 seconds after the deceleration began (1 seconds after AV leaving Point B), the stationary attention-attractor circle disappeared, allowing pedestrians to freely observe their surroundings and make a crossing decision as the AV was 30 meters away.

In non-yielding trials, the stationary attention-attractor also disappeared 1 seconds after AV leaving Point B and the AV maintained its initial speed throughout the trial.

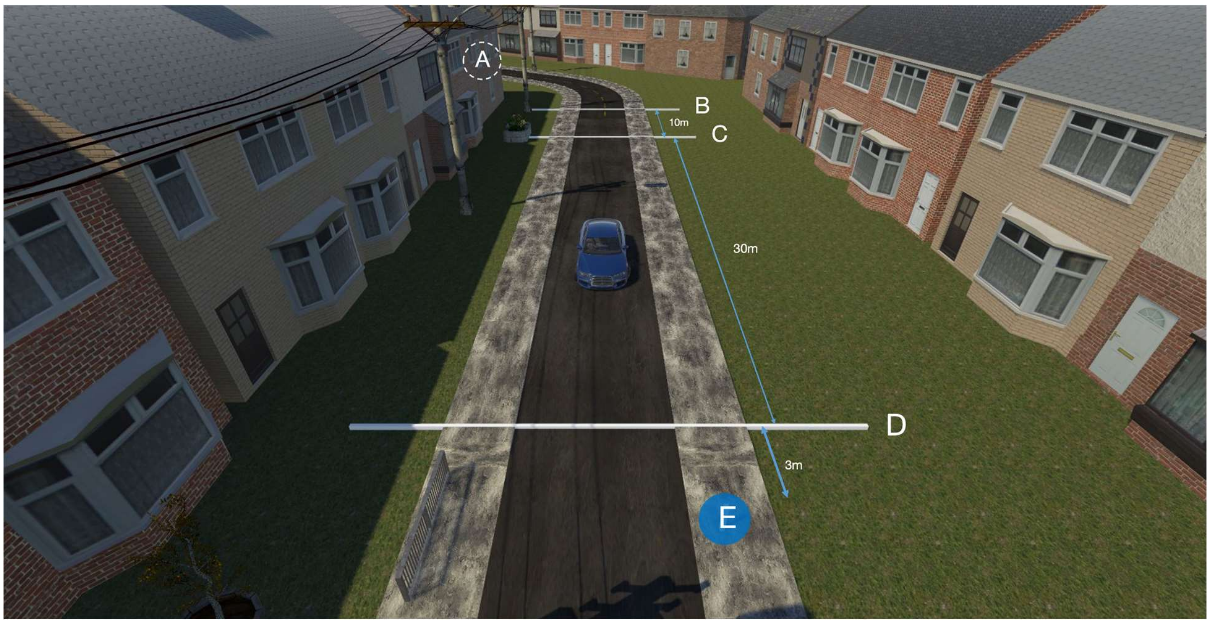


Figure 4.2. A bird's-eye view of the virtual road layout. Point A marks the starting position of the AV. Point B denotes the activation of the AR interfaces in non-baseline trials. Points C and D represent the onset of deceleration and the stopping point of the AV, respectively, during yielding trials. Point E shows the initial standing position of pedestrians at the beginning of each trial.

After completing a crossing or allowing the AV to pass if they chose not to cross, participants answered a question displayed on the front screen. In yielding trials with AR presence, they rated their agreement on a scale from 1 (Strongly disagree) to 7 (Strongly agree) to the statement: "The interface was intuitive for signalling:

'Please cross the road'". This collects the perceived self-report intuitiveness of the AR for each trial.

4.2.4 Procedure

Upon arrival at the lab, participants were provided with an information sheet detailing the study and were given a consent form to sign after their queries were addressed. They then completed questionnaires to provide information such as demographics, nationality, and experience with AR/VR etc, with details reported in Tabone et al. (2024).

Before starting the trials, the eye tracker was calibrated. Pedestrians were instructed to stand on a blue marker at the beginning of each trial. Once positioned, they initiated the trial by focusing on a stationary, cyan-coloured circle. A continuous one-second gaze on this attention-attracting circle was required to start the trial. If participants' attention deviated, an automatic beeping sound reminded them to refocus on the circle. Successful adherence to this instruction triggered the start of the trial, with the AV entering the simulation from a concealed position. Participants' primary task was to safely cross the virtual road from one curb to another when they felt safe. After providing their answer to the perceived intuitiveness verbally, participants returned to the starting point to begin the next trial.

Two practice trials were conducted before the main experiment: one with a non-yielding vehicle and another with a yielding vehicle. The study began after participants confirmed their understanding of the environment and the task and provided consent to take part. Upon completion, participants were thanked for their involvement and received compensation for their time.

4.2.5 Data analysis

In the current study, non-yielding trials, where the AV maintained its speed were excluded in the further analysis, because pedestrians did not initiate crossings in these scenarios, and no learning could be assessed with only a single repetition of non-yielding AVs. As a result, this study analysed 81 trials per participant, covering nine AR conditions (three location-based groups covering eight AR designs plus one baseline), with each condition further subdivided by three initial attention directions and three yielding AVs, totalling 2430 trials. The order of each yielding AV within the initial attention directions and within each AR conditions was also labelled as the $1^{st}/2^{nd}/3^{rd}$ encounter to analyse behaviour changes with repeated exposures.

In this study, the positions of vehicles and pedestrians were consistently logged at a frequency of 120 Hz and pedestrians' gaze data were recorded at 50 Hz. Raw gaze data were selected for analysis from the moment the attention-attractor circle disappeared until either the pedestrian initiated a crossing, or the AV passed, for trials where pedestrians chose not to cross. This period captured the interaction phase between the pedestrian and AV.

Gaze data were collected using a Tobii Glasses 2 (firmware 1.25.6-citronkola-0; head unit 0.062) mobile eye-tracker, which was operated and calibrated using the Tobii Controller Software v.1.114.20033, with thorough calibration procedures conducted before data collection to ensure accuracy and precision. However, factors such as frequent blinking or missing data could reduce the gaze sample rate. To ensure the quality of gaze data analysis, we identified gaps in the recorded eye-movement data, considering any gap longer than 400 milliseconds as missing data rather than a short interruption like blinking, which typically lasts between 100 and 400 milliseconds, with an average duration of 260 milliseconds (Bartoshuk & Schiffman, 1977; Caffier et al., 2003; Fatt & Weissman, 2013). Trials with more than 30% missing data were excluded, as well as data from Participants 6, 17, and

18, where over 30% of their trials contained more than 30% missing data, resulting in the exclusion of 396 trials (Bindschädel et al., 2022). After further exclusion of 51 trials, where pedestrians did not cross, the final analysis included data from 1983 trials, comprising 1768 AR-present trials and 215 no-AR (Baseline) trials.

Pedestrian gaze patterns

To analyse pedestrians' gaze behaviour during interactions with AVs in a 3D HIKER environment, we visualized heat maps of their gaze points on the Y-Z plane (see coordinate system in **Figure 4.1**) as the AV approached at different *Distance Intervals* along the X-axis. Grouping gaze data into intervals, rather than using raw continuous distance, ensures sufficient data points per interval for meaningful visualisation, reducing noise and creating smoother and more interpretable gaze heat maps. This method also highlighted distance-specific shifts in gaze behaviour, making it easier to track attention changes as the AV approached.

Once the attention attractor disappeared, allowing pedestrians to observe the situation and begin their interaction with the AV at a distance of 30 meters, gaze data were grouped into 10-meter *Distance Intervals* for the remaining approach time, with intervals defined as (-30, -20), (-20, -10), and (-10, 0) meters away from the pedestrians. These intervals were chosen based on findings from Dey et al. (2019), which suggest significant changes in pedestrians' gaze patterns every 10 meters as a vehicle approaches. Starting the interaction at 30 meters, with a time gap of less than 3 seconds between the pedestrian and the AV, has been shown in previous research to be a situation of higher uncertainty (Tian et al., 2023), necessitating explicit communication mechanisms for right-of-way decisions to ensure safe and smooth interactions.

For each *Distance Interval*, the coordinates of pedestrians' gaze points were visualized on the Y-Z plane, and heat maps were created using Kernel Density Estimation (KDE), a statistical method that smooths data points to produce a continuous density surface. The resulting heat map uses a colour gradient from blue (lower density) to red (higher density) to illustrate how heavily pedestrians scanned the environment, elements of the AV or AR, at different distances as the AV approached. All data processing and visualization were conducted using Python 3.

Change in Fixation Duration (ΔFD)

Longer gaze fixations are associated with higher visual effort and greater difficulty in processing the visual information (He & McCarley, 2010; Herten et al., 2017; Jacob & Karn, 2003; Kotval & Goldberg, 1998; Milton et al., 1950). To investigate how AR would influence pedestrians' visual load, we analysed their gaze fixations on specific area-of-interest (AOI) by tracking the gaze location frame by frame, starting from when the attention-attractor circle disappeared until the pedestrian initiated crossing. The AOIs investigated in this study were: (1) Car body: The AOI for the car body was defined by its moving 3D spatial boundaries, with the car's centre position (XYZ coordinates) and its dimensions (length, width, and height) being updated for each frame. (2) AR interface: The AOI for the AR interface was represented by a moving plane in the 3D environment, with its centre position and size defined in the virtual space each frame. Gaze points that did not fall within either of these two AOIs were classified as falling into the "other" AOI. A fixation was considered valid if the gaze remained within any AOI for more than 100 milliseconds (12 frames) (Salvucci & Goldberg, 2000), although typical fixation durations can range from 50 to 500 milliseconds depending on the task (Negi & Mitra, 2020; Rayner, 2009). The total fixation duration for both the car and AR AOIs was calculated during AR-present trials, and solely on the car during no-AR baseline trials for further analysis.

To assess the impact of AR on pedestrian visual load, we introduced the "Change in Fixation Duration (ΔFD)" metric. We first established a baseline by averaging each participant's total gaze fixation duration on the vehicle during no-AR trials, representing their average visual load. In each AR-present trial, the ΔFD was calculated by subtracting each corresponding participant's baseline fixation time from the total fixation duration on both the AR interface and the vehicle. This metric quantified the additional attention required by the AR, accounting for individual differences in visual load, and addressed the challenge of distinguishing gaze focus between AR interfaces and the vehicle when AR elements were integrated into the vehicle. A positive ΔFD indicated an increased visual load and attentional demand, while a negative ΔFD suggested a reduced visual load, compared to baseline, during crossing decisions.

To answer the second research questions, we conducted a Generalized Linear Mixed Model (GLMM) considering repeated measures analysis (Stroup, 2012) on ΔFD. The model applied a linear distribution with an identity link function and included the following variables to answer the second research question: (1) *AR Location* (Car Path, Crossing Path, or HUD), (2) *Intuitiveness Rating* (post-trial scores verbally provided by pedestrians), and (3) *Encounter* (number of interactions within each condition: $1^{st}/2^{nd}/3^{rd}$).

Crossing probabilities

A GLMM was conducted to analyse the likelihood of pedestrians deciding to cross when the AV was at different *Distance Interval* ((-30, -20), (-20, -10), and (-10, 0) meters), due to the time sequential nature of these distance intervals (Stroup, 2012). The analysis involved a binary logistic regression with a logit link function, including the main effect of *Distance Interval* and its interaction with *AR Location* (Baseline/ Car Path/ HUD/ Crossing Path) to investigate how are pedestrians' crossing probabilities at various AV approach distances influenced by different AR locations in answering the third research question.

In this paper, all GLMM analyses included participant as a random effect to account for individual differences, with Least Significant Difference (LSD) test used for post-hoc analyses. The analysis was conducted using SPSS 28, with a significance level set at $p < .05$.

4.3 RESULTS

4.3.1 Gaze heat map

In the Baseline condition without AR, **Figure 4.3** from the left to right shows pedestrians' gaze heat map as the AV approached. When the AV was 30 to 20 meters away, pedestrians' gaze was more on the environment in front of them or on the ground. When the vehicle was closer to 20 to 10 meters, pedestrians increasingly focused on the car itself. Finally, when the AV was within 10 meters, their gaze concentrated predominantly on the AV, particularly on the windscreen. This gaze pattern, where pedestrians' attention shifted from the environment to the car and driver's seat as the AV approached, was also observed with different AR locations (**Figure 4.4**, **Figure 4.5**, **Figure 4.6**), with slight variations depending on the design.

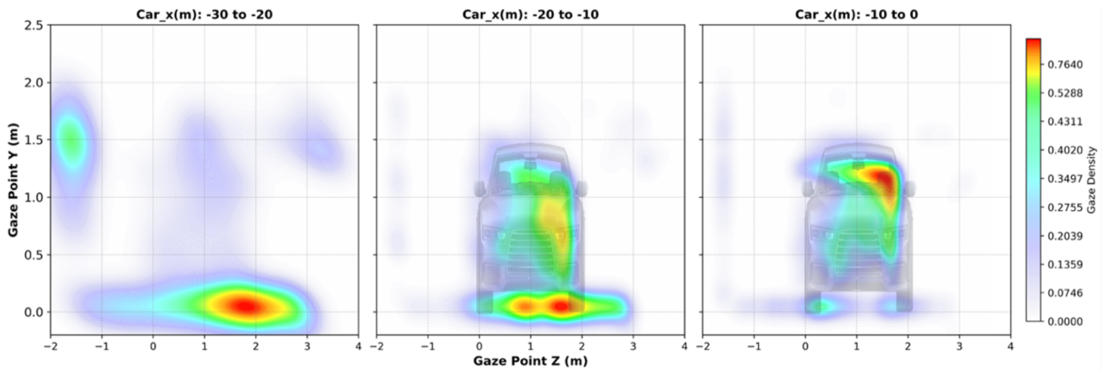


Figure 4.3. In Baseline trials with no AR concepts, from left to right are pedestrians' gaze heat map on Y-Z plane when the AV's distance to pedestrians (Car_x) was -30 to -20, -20 to -10, and -10 to 0, metres.

With AR on the Car Path (**Figure 4.4**a-d), pedestrians' gaze patterns generally resembled the Baseline (**Figure 4.3**) when the AV was 30 to 20 meters, focusing mainly on the environment. However, when a Phantom Car appeared (**Figure 4.4**d), their gaze shifted more towards the vehicle's position in the Y-Z plane (likely focusing on the approaching Phantom Car) between 30 and 20 meters, before concentrating on the windscreen as the AV approached within 20 meters.

In contrast, the other ARs on the Car Path (**Figure 4.4**a-c) notably altered gaze behaviour as the AV moved closer, especially between 20 and 10 meters. Compared to the Baseline (**Figure 4.3**, pedestrians focused more on the car and windscreen when the AR was projected onto the windscreen, such as Planes on Vehicle (Figure 4.4a) and Conspicuous Looming Planes (**Figure 4.4**b), with less attention paid to the grill area as the AV was nearly 10 meters away. When AR was projected onto the road, as with the Field of Safe Travel (**Figure 4.4**c), pedestrians' attention shifted towards the road between 20 and 10 meters but became more dispersed across the vehicle and the ground as the AV closed within 10 meters.

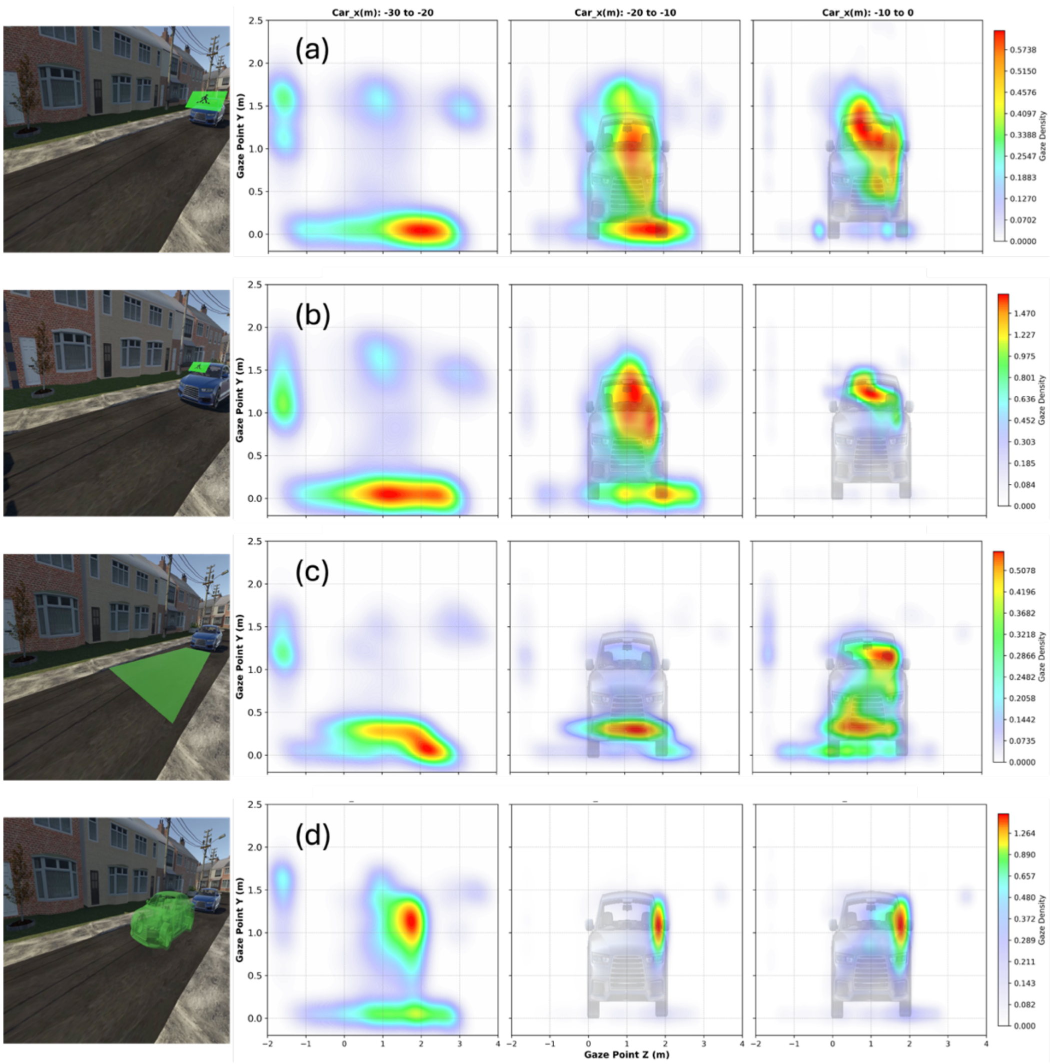


Figure 4.4. In AR on Car Path, pedestrians' gaze heat maps for designs: (a) Planes on Vehicle, (b) Conspicuous Looming Planes, (c) Field of Safe Travel, and (d) Phantom Car.

In HUD conditions (**Figure 4.5**a and b), when the AV was 30 to 10 meters away, pedestrians focused less on the environment than in Baseline trials, concentrating instead on two areas: the HUD AR and another area likely on the car. As the AV came within 10 meters, their gaze on the windscreen became more dispersed, but there was less focus on the grill compared to the Baseline (**Figure 4.3**).

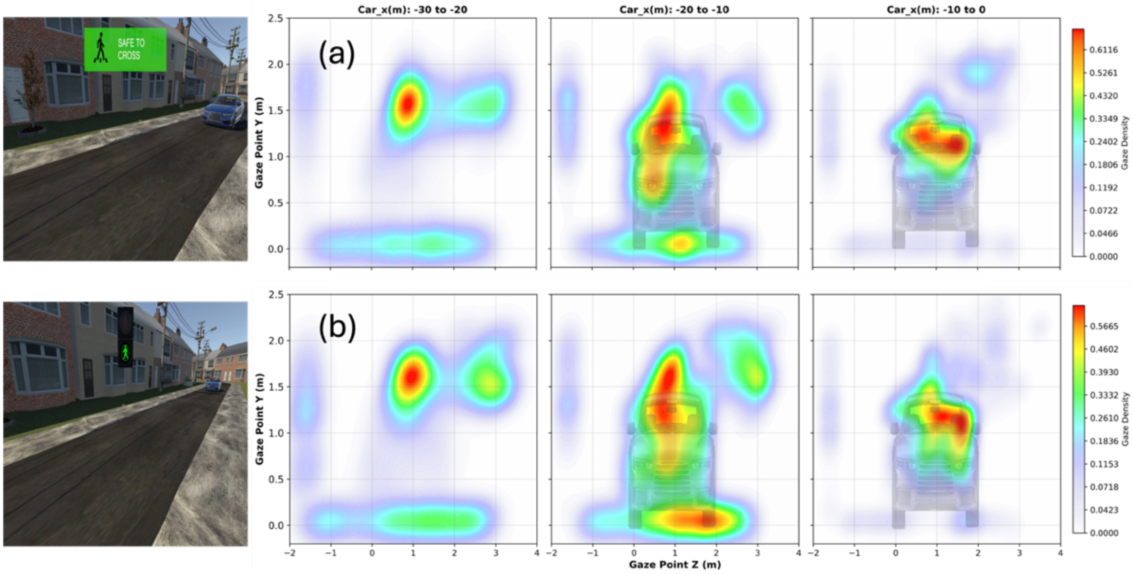


Figure 4.5. In AR HUD trials, pedestrians' gaze heat maps for designs: (a) Nudge HUD, and (b) Pedestrian Lights HUD.

As to AR on Crossing Path (**Figure 4.6**a and b), with an Augmented Zebra Crossing (**Figure 4.6**a), pedestrians focused more on the ground and less on the car when the AV was beyond 10 meters, but their gaze became more dispersed across the vehicle and towards the ground as the AV approached within 10 meters, compared to Baseline (**Figure 4.3**). With a Virtual Fence added (**Figure 4.6**b), pedestrians' gaze remained concentrated on the fence's edge, regardless of the AV's distance.

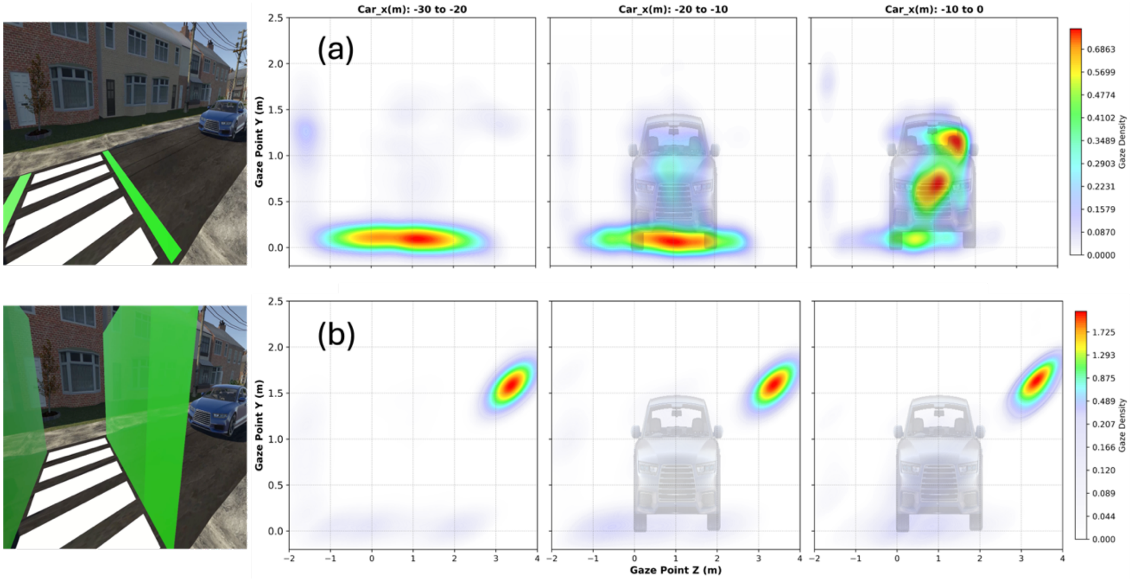


Figure 4.6. In AR Crossing Path trials, pedestrians' gaze heat maps for designs: (a) Augmented Zebra Crossing, and (b) Virtual Fence.

4.3.2 Change in Fixation Duration (ΔFD)

A GLMM analysis was conducted to investigate the effects of *AR Location* (Car Path, Crossing Path, or HUD), *Intuitiveness Rating* and *Encounter* on pedestrians' Change in Fixation Duration and results were shown in **Table 4-2**.

Results revealed significant main effects of AR's *Intuitiveness Rating* ($F(6, 1717) = 33.549$, $p < .001$), as shown in **Figure 4.7**. In trials with the highest *Intuitiveness Rating* (rated 7), ΔFD was significantly more negative, indicating a greater reduction in visual load compared to the baseline, than in trials with lower ratings, including those rated 6 ($p < .001$), 5 ($p < .001$), 4 ($p < .001$), 3 ($p < .001$), 2 ($p < .001$), and 1 ($p < .001$).

Trials with the lowest *Intuitiveness Rating* (rated 1), ΔFD became positive, indicating an increase in visual load compared to the baseline. Post hoc analysis indicated that compared to these trials, ΔFD was significantly more negative in trials with higher ratings, including those rated 2 ($t = 3.90$, $p < .001$), 3 ($t = 4.75$, $p < .001$), 4 ($t = 5.18$, $p < .001$), 5 ($t = 5.49$, $p < .001$) and 6 ($t = 6.16$, $p < .001$), suggesting a greater reduction in visual load compared to the baseline.

Additionally, post hoc analysis also showed that, compared to trials rated 6, ΔFD was significantly less negative in trials rated 5 ($t = 6.31$, $p < .001$), 4 ($t = 5.50$, $p < .001$), 3 ($t = 5.51$, $p < .001$) and 2 ($t = 4.67$, $p < .001$). Furthermore, trials rated 5 resulted in a significant more negative ΔFD compared to those rated 3 ($t = 2.10$, $p < .05$).

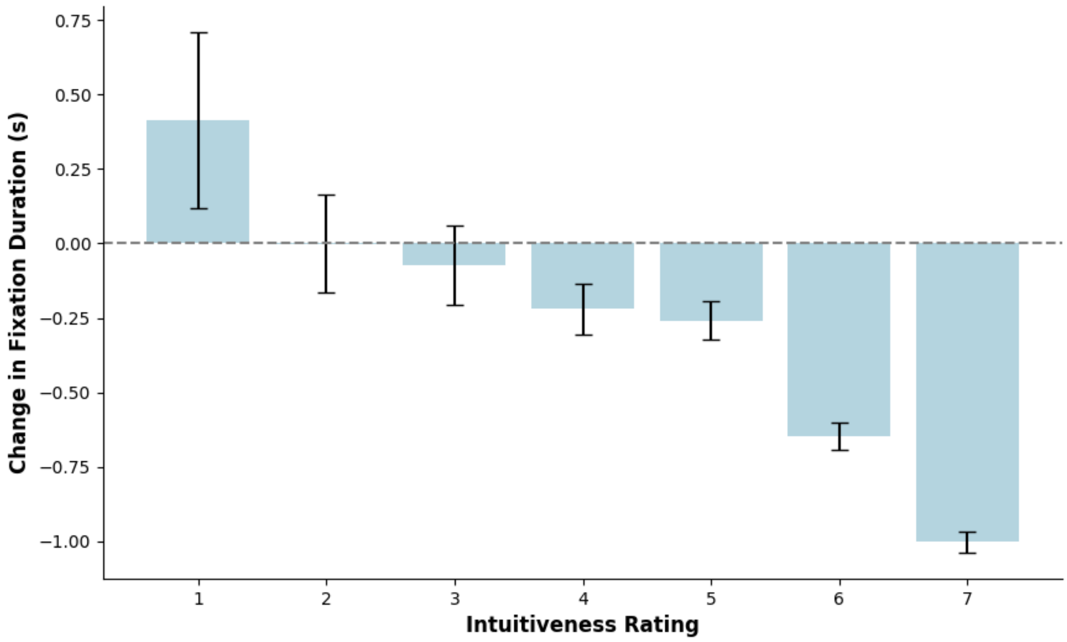


Figure 4.7. The bar plots and error bars (SE) for the impact of Intuitiveness Rating of AR on the Change in Fixation Duration.

The GLMM analysis also showed significant main effects of *AR Location* ($F(2, 1717) = 31.060$, $p < .001$) on pedestrians' Change in Fixation Duration, as shown in **Figure 4.8**. Among the *AR Location*, HUD resulted in the most negative ΔFD, signifying a greater decrease in fixation duration time compared to the baseline, consequently, a more substantial reduction in visual load compared to other *AR*

Location: Crossing Path (p < .001) and Car Path (p < .001). Post hoc pairwise comparisons indicated that the ΔFD was significantly less negative with *AR Location* Crossing Path compared to Car Path (t = 1.189, p < .05).

Table 4-2. Results of GLMM estimations for Change in Fixation Duration.

Predictors	***Coef.***	***Std. Error***	***t***	***Sig.***	***CI (L–U)***	***M***	***SE***
(Intercept)	-1.338	.1231	-10.873	.000	-1.580 – -1.097		
Intuitiveness Rating							
1	1.422	.1824	7.798	**<.001**	1.064 – 1.780	0.395	0.210
2	.876	.1253	6.988	**<.001**	0.630 – 1.122	-0.152	0.163
3	.964	.1233	7.823	**<.001**	0.723 – 1.206	-0.063	0.161
4	.798	.0929	8.586	**.000**	0.615 – 0.980	-0.230	0.139
5	.707	.0666	10.614	**.000**	0.576 – 0.837	-0.321	0.124
6	.292	.0523	5.578	**<.001**	0.189 – 0.394	-0.736	0.118
7 [ref]	0	.	.	.	.	-1.028	0.116
AR Location							
Crossing Path	.326	.0563	5.789	**<.001**	0.215 – 0.436	-0.216	0.125
Car Path	.385	.0501	7.688	**<.001**	0.287 – 0.483	-0.157	0.119
HUD [ref]	0	.	.	.	.	-0.542	0.125
Encounter							
1	.204	.0498	4.105	**<.001**	0.107 – 0.302	-0.175	0.123
2	.017	.0467	.370	.712	-0.074 – 0.109	-0.362	0.122
3 [ref]	0	.	.	.	.	-0.379	0.122

Probability distribution: Normal   Link function: Identity

There was also a significant main effect of the number of *Encounters* (F (2, 1717) = 9.814, p < .001) on pedestrians' Change in Fixation Duration. Compared to the 1st *Encounter*, ΔFD was significantly more negative during the 3rd *Encounter* (p < .001), suggesting a smaller reduction in visual load. There was no significant difference between the 2nd *Encounter* (p > .05) and 3rd *Encounter*. Post hoc pairwise indicated that the ΔFD was significant more negative during 2nd *Encounter* compared to 1st *Encounter* (t = 3.698, p <.001), reflecting a greater reduction in visual load with repeated exposure to the AR.

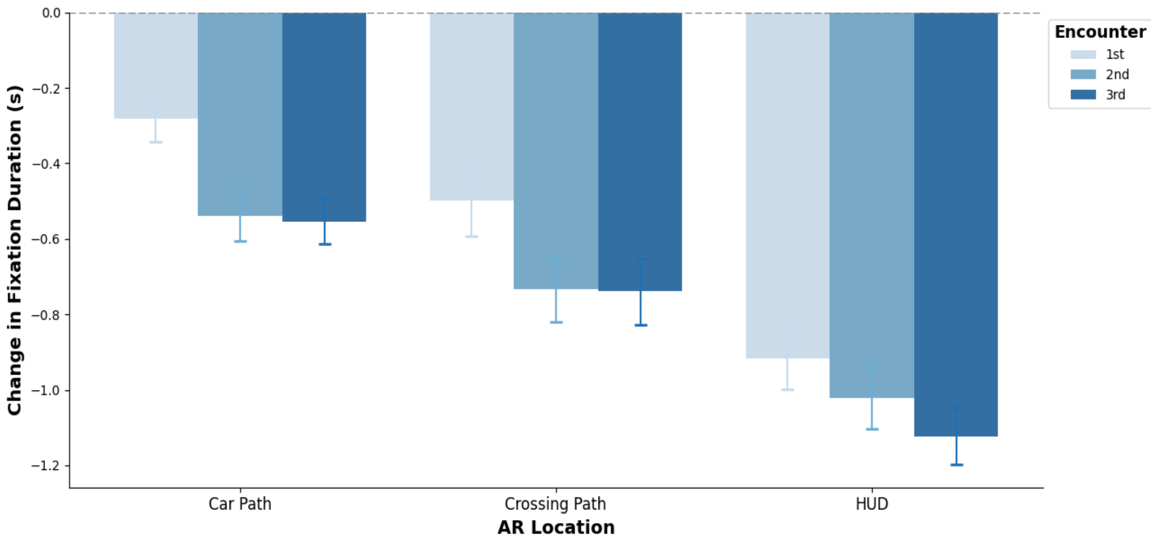


Figure 4.8. The bar plots and error bars (SE) for the impact of AR Location, and the number of Encounter, on the Change in Fixation Duration.

4.3.3 Crossing probability at different AV approach distances

A GLMM was conducted to analyse the likelihood of pedestrians deciding to cross when the AV was at different *Distance Interval* and its interaction with *AR Location*.

The analysis revealed significant effects of *Distance Interval* of AV (F (2,5937) = 237.630, p<.001) and interaction with *AR Location* (F (9, 5937) = 51.553, p < .001) on the probability of crossing, as shown in **Table 4-3**.

As shown in **Figure 4.9**a, compared when AV was (-30, -20) meters away (, the likelihood of pedestrians crossing significantly increased as the vehicle approached closer to (-20, -10) meters (p < .001) and (-10, 0) meters (p < .001). Post hoc analysis using LSD showed that crossing probabilities significantly increased as the AV approached closer, from (-20, -10) meters to (-10, 0) meters ($t = -18.981$, $p < .001$). However, further post hoc analysis of the interaction effect revealed that this increasing tendency was significant only in the Baseline and AR Car Path conditions. In contrast, crossing probabilities did not differ significantly between the *Distance Interval* of (-20, -10) meters and (-10, 0) meters in both the AR Crossing Path ($t = -0.824$, $p > .05$) and HUD conditions ($t = -0.620$, $p > .05$).

When the AV was at both (-30, -20) and (-20, -10) meters, the Baseline condition showed significantly lower crossing probabilities compared to the AR Car Path condition ($p < .001$; $p < .001$). Additionally, the crossing probabilities in both the Baseline and AR Car Path conditions were significantly lower than those in the AR Crossing Path condition ($p < .001$; $p < .001$) and the AR HUD condition ($p < .001$; $p < .001$). The differences between AR Crossing Path and AR HUD were not significant in these two intervals ($t = -1.597$, $p > .05$; $t = -1.399$, $p > .05$).

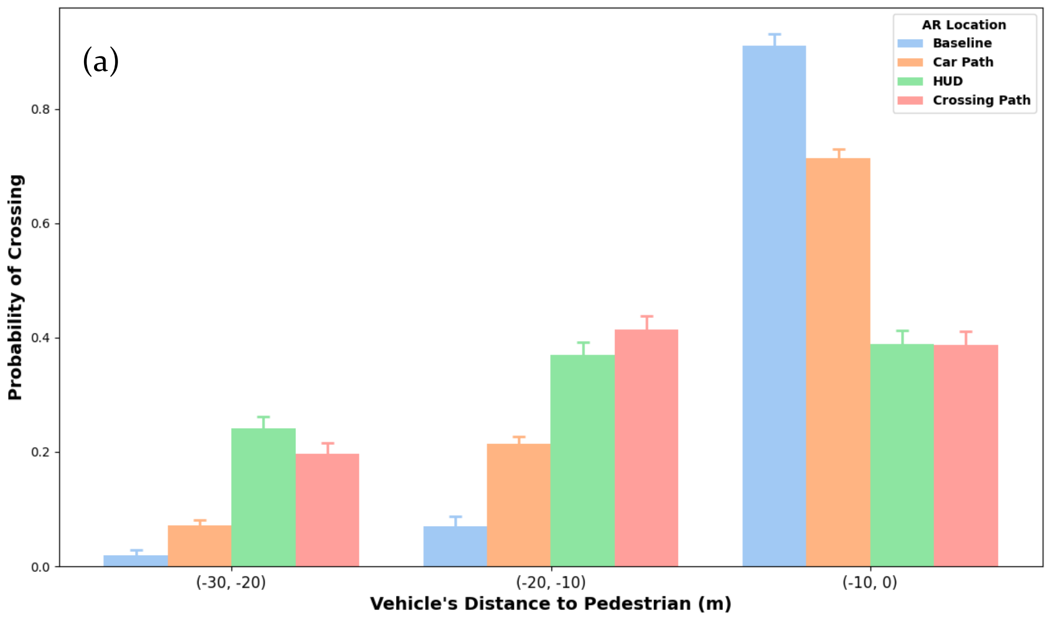
When the AV was (-10, 0) meters away, the Baseline condition showed significantly higher crossing probabilities compared to the AR Car Path condition ($p < .001$). Both conditions had significantly higher crossing probabilities than the AR Crossing Path condition ($p < .001$ and $p < .001$ respectively), and the AR HUD condition ($p < .001$ and $p < .001$ respectively), with no significant difference between AR Crossing Path and AR HUD ($t = -0.046$, $p > .05$).

Table 4-3. Results of GLMM estimations for crossing probability at different AV approach distances.

Predictors	*Coef.*	*Std. Error*	*t*	*Sig.*	*CI (L–U)*	*Odds Ratio*	*M*	*SE*
Intercept	-1.144	.1106	-10.342	.000	-1.361 – -0.927	.319		
Distance								
(−10, 0)	.693	.1472	4.711	**<.001**	.405 – .982	2.001	0.643	0.016
(−20, −10)	.608	.1479	4.112	**<.001**	.318 – .898	1.837	0.233	0.014
(−30, −20) [ref]	0	.	.	.	.	.	0.094	0.012
Location × Distance								

Baseline (−10, 0)	2.784	.2594	10.734	**.000**	2.276 – 3.293	16.185	0.912	0.019
Crossing Path (−10, 0)	-.006	.1378	-.046	.963	-.277 – .264	.994	0.388	0.023
Car Path (−10, 0)	1.369	.1225	11.173	**.000**	1.129 – 1.609	3.932	0.715	0.015
HUD (−10, 0) [ref]	0	.	.	.	.	.	0.389	0.023
Baseline (−20, −10)	-2.054	.2854	-7.199	**<.001**	-2.614 – -1.495	.128	0.070	0.017
Crossing Path (−20, −10)	.192	.1378	1.397	.162	-.078 – .463	1.212	0.197	0.019
Car Path (−20, −10)	-.767	.1281	-5.990	**<.001**	-1.018 – -0.516	.464	0.214	0.014
HUD (−20, −10) [ref]	0	.	.	.	.	.	0.369	0.023
Baseline (−30, −20)	-2.822	.5172	-5.456	**<.001**	-3.836 – -1.808	.060	0.019	0.009
Crossing Path (−30, −20)	-.260	.1630	-1.592	.111	-.579 – .060	.771	0.197	0.019
Car Path (−30, −20)	-1.419	.1714	-8.279	**<.001**	-1.755 – -1.083	.242	0.072	0.009
HUD (−30, −20) [ref]	0	.	.	.	.	.	0.242	0.020

Probability distribution: Binomial   Link function: Logit



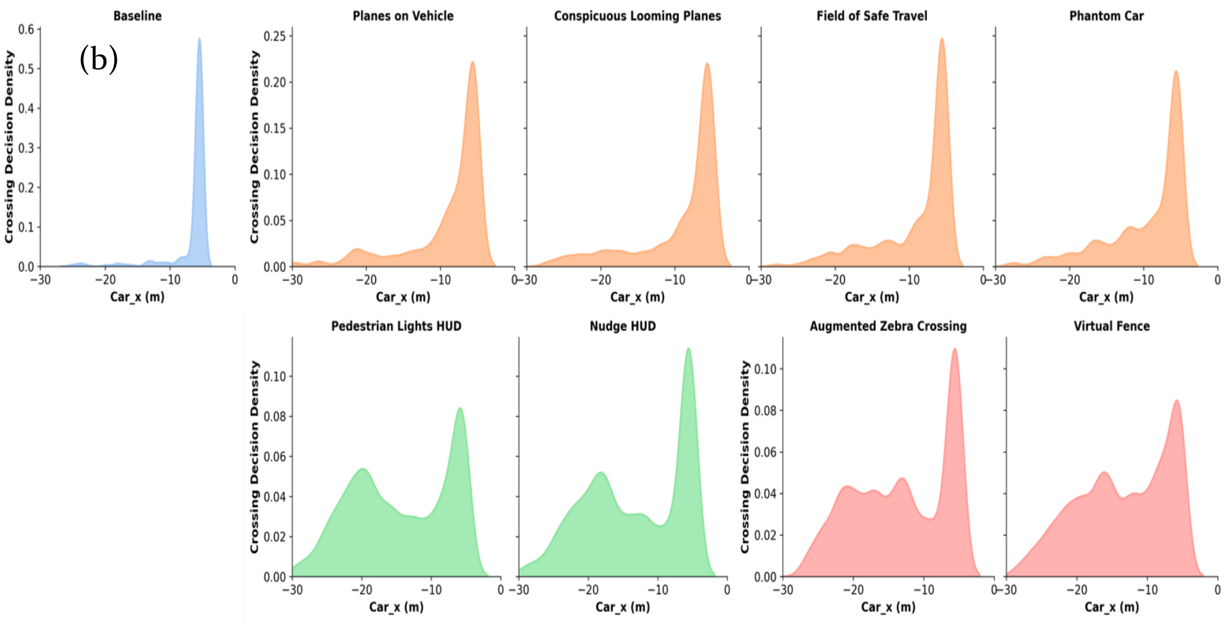


Figure 4.9. (a) Results from GLMM showing bar plot of pedestrians' crossing decision probabilities across different Distance Interval of AV, clustered by the AR Location. Error bar stands for the standard error. (b) Density plots of crossing probabilities using KDE, depicting their relationship to AV distance in each AR design. The colour scheme matches that of panel (a): blue for Baseline, orange for AR Car Path, green for AR HUD, and red for AR Crossing Path, regarding the AR Location.

4.4 DISCUSSIONS

This study used a CAVE-based virtual reality pedestrian simulator to investigate the pedestrians' gaze patterns and crossing probabilities at various distances as an AV approached, under different AR locations. It also examined the effects of AR location, intuitiveness and repeated encounters on pedestrians' change in fixation duration compared to no AR condition before crossing decisions.

Results showed that AR facilitated pedestrians' understanding of the vehicle's intent, as indicated by increased crossing probabilities before the vehicle fully stopped, regardless of AR locations (**Figure 4.9**a and b). Prior studies (Dey, Matviienko, et al., 2020; Lee et al., 2022; Pekkanen et al., 2022; Schneemann & Gohl, 2016) identified a bimodal distribution of crossing decisions, where pedestrians typically crossed either when the vehicle came to a complete stop or when it was still at distances. In scenarios where the initial time gaps between AVs and pedestrians were less than three seconds, crossing decisions were predominantly made when the AV had stopped (Lee et al., 2022; Tian et al., 2023). This trend was confirmed in our baseline condition without AR. However, the introduction of AR led to a notable increase in crossing decisions even when the AV was farther away. This effect aligns with findings on the effectiveness of eHMI (Dey, Matviienko, et al., 2020; Lee et al., 2022; Madigan et al., 2023), underscoring AR's ability to facilitate earlier crossing decisions by clarifying right-of-way ambiguities before the vehicle fully stops.

Gaze heat maps (**Figure 4.3**, **Figure 4.4**, **Figure 4.5**, **Figure 4.6**) revealed a distinct pattern as the vehicle approached, consistent with eye-tracking studies involving manually driven vehicles (de Winter et al., 2021; Dey et al., 2019). When the vehicle was distant, pedestrians primarily scanned the environment or focused on the crossing path or road surface ahead of the vehicle. This natural visual search behaviour likely occurred because a distant car posed no immediate threat. However, when an immediate threat appeared, such as a phantom car approaching to pedestrians ahead of the AV, pedestrians' attention was captured immediately (**Figure 4.4**d). While prior studies mainly examined gaze directed towards the vehicle's approach (Dey et al., 2019), this work proposed a novel method of mapping gaze density on a Y-Z plane across various distance intervals along the X-axis. This approach captured not only pedestrians' focus on the vehicle but also their attention to environmental cues and the crossing path, providing a more comprehensive understanding of their information-seeking processes.

The presence of AR displays significantly influenced pedestrians' gaze patterns and crossing probabilities, depending on its location and the AV's distance. In AR Crossing Path (**Figure 4.6**) and HUD (**Figure 4.5**) trials, pedestrians' gaze patterns changed notably compared to the Baseline condition (**Figure 4.3**) when the AV was 30 to 20 meters away. Pedestrians directed more gaze towards the AR displays during this interval, which corresponded to increased crossing probabilities compared to Baseline. In contrast, significant gaze shifts in AR Car Path (**Figure 4.4**) trials were observed when the AV was within 20 meters, where crossing probabilities also increased relative to Baseline. These findings highlight AR's potential to enhance AV-pedestrian communication through distance-based strategies. Specifically, AR on Crossing Path and HUD proved particularly effective when the AV was farther away, helping pedestrians interpret the vehicle's intent earlier. Meanwhile, AR on Car Path was most suitable at close distances, where it facilitated immediate crossing decisions.

Among the AR designs, HUD facilitated earlier crossing decisions (**Figure 4.9**) and led to the greatest decrease in fixation duration compared to baseline (**Figure 4.8**). This aligns with findings from Tabone et al. (2023), where a HUD was preferred over cues projected on the road or the approaching vehicle. However, the HUD seemed to distract pedestrians when the AV was more than 10 meters away, as they looked aside to avoid it (**Figure 4.5**). Peereboom et al. (2024) found similar results, where HUD received lower ratings and was less preferred compared to baseline, potentially causing discomfort, especially at close distances. While this study highlights the potential of HUD for scenarios involving distant AVs, future designs must account for potential visual distractions and their impact on pedestrians' attention and safety. Achieving a balance between effective communication and minimising unintended distractions is essential to ensure HUD's practicality in real-world applications.

Additionally, previous research suggested that embedding AR in the environment could divide pedestrians' attention from oncoming vehicle to the road instead (Peereboom et al., 2024; Tabone et al., 2023). However, this study showed that this was not the case when the AV was farther away. Even with an Augmented Zebra Crossing on the Crossing Path (**Figure 4.6**a), pedestrians' attention pattern did not change much compared to Baseline (**Figure 4.3**) when the AV was 30 to 10 meters away, as they were not focused on the vehicle during this phase. On the other hand, Virtual Fence led to a more concentrated gaze patterns from pedestrians (**Figure 4.6**b). This suggests that AR on the Crossing Path may be best used when the AV is farther away to avoid distracted attention as it approaches.

Some research has highlighted that visually demanding tasks and distractions pose significant risks to pedestrians (Tapiro et al., 2020). This raises concerns that the addition of external interfaces, such as AR and eHMIs could exacerbate these issues, particularly when pedestrians rely primarily on kinematic cues from vehicles to make crossing decisions (de Winter & Dodou, 2022; Li et al., 2018). However, our findings reveal that the presence of AR concepts did not increase pedestrians' fixation duration on the AR and the vehicle in AV-pedestrian communication, provided these are intuitively designed (**Figure 4.7**). As illustrated in **Figure 4.7**, the ΔFD was negative when the AR concept was perceived as intuitive, indicating a reduction in visual load compared to the baseline scenario with no external messages. This aligns with prior eHMI research, which recommends designing messages that are both intuitive and familiar to pedestrians (de Clercq et al., 2019; Hensch et al., 2019; Lee et al., 2022).

Moreover, repeated exposure to AR interfaces significantly enhanced their effectiveness in communicating AV's intent to pedestrians as demonstrated by greater reduction in ΔFD across all three locations (**Figure 4.8**). Notably, ΔFD decreased even after the first encounter, suggesting a rapid learning process through which pedestrians become familiar with these interfaces. This observation is consistent with studies indicating that pedestrians can quickly adapt to novel types of eHMIs after several encounters (de Clercq et al., 2019; Eisele & Petzoldt, 2022; Hensch et al., 2019; Lee et al., 2022; Yang et al., 2024). However, the increasing reliance on AR might lead to potential hazards, such as over-trust (Holländer et al., 2019; Kaleefathullah et al., 2020). This highlights the need for further investigation to ensure the safe and effective integration of AR technologies into pedestrian environments

4.4.1 Limitations and future works

While this study offers insights for designing AR interfaces in AV-pedestrian communication, it also has limitations that suggest areas for future research. First of all, while ARs have the advantage of communicating with multiple road users over eHMIs, this research involves simple one-to-one interactions, leaving uncertainty about how the presence of multiple vehicles might impact visual load for some designs, particularly those associated with the AV (Car Path). For instance, with multiple AVs, each vehicle could project different information, potentially overwhelming pedestrians with competing signals. In contrast, HUD and Crossing Path designs are intended to provide consistent, situationally aware guidance that doesn't change with each individual vehicle. This discrepancy in AR concepts could have a significant effect on visual load, especially as pedestrians attempt to process information from multiple sources simultaneously.

Additionally, the experimental context was simplified, focusing on an open, straight road and future research can be built on a complex traffic scenario such as intersections or roundabouts, as well as different road infrastructure such as zebra crossings (Madigan et al., 2023; Yang et al., 2024). Additionally, further research can extend this study under different kinematic situations with different driving behaviours and time gaps, which may identify a different role of explicit communication in varying implicit conditions (Dey, Matviienko, et al., 2020; Lee et al., 2022; Madigan et al., 2023). Furthermore, the homogeneity of participant demographics, such as age and gender, which are known to influence attention allocation (Tapiro et al., 2016), can be further explored to proposed more personalised AR. Future research should aim to test these AR interfaces in more varied and dynamic outdoor scenarios to validate their effectiveness across different pedestrian populations and urban settings.

4.4.1 Conclusions

This study showcases the promising role of AR in enhancing pedestrian safety and decision-making in AV contexts, emphasizing the importance of intuitive, familiar, and repeatedly exposed AR interfaces in reducing visual load. HUD and Crossing Path AR designs were effective at greater distances, while Car Path AR worked best at closer ranges, highlighting the importance of distance-based strategies. A novel gaze density mapping method provided comprehensive insights into pedestrians' attention allocation, capturing their focus on both the vehicle and surrounding environmental cues. However, it is still crucial to continue refining these technologies through real-world testing and broader user engagement to ensure that they meet the varied needs of all pedestrians in increasingly automated urban environments

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CHAPTER 5

DISCUSSIONS AND CONCLUSIONS

This PhD programme examined pedestrians' crossing decisions and attention allocation during repeated exposures to a set of AV communication strategies, employing various implicit (vehicle behaviours) and explicit (eHMI and AR displays). By investigating repeated interactions across diverse contexts in virtual simulated environments, this thesis provides a comprehensive understanding of AV-pedestrian interactions and offers design guidelines for AV communication strategies in a mixed traffic setting with other road users. This chapter discusses how the main research questions have been addressed, outlines contributions, and discusses research limitations and recommendations for future research.

5.1 PRINCIPAL FINDINGS

This section revisits the three research questions introduced in Chapter 1, summarising the main findings from the studies conducted in this PhD programme.

- ***RQ 1:*** *How do zebra crossings and vehicle kinematics (e.g., time gap, yielding decision and behaviours, and lateral deviation), influence pedestrians' crossing decisions and attention allocation, such as head-turning behaviours?*

The study reported in Chapter 2 revealed that pedestrian crossing decisions were more strongly influenced by kinematic cues (time gap and vehicle behaviour) than by the presence of zebra crossings. Similarly, the study in Chapter 3 showed that the pattern of pedestrians' head-turning rate was significantly lower in yielding versus non-yielding scenarios, but was minimally affected by zebra crossings. This finding aligns with Madigan et al. (2023), who identified vehicle kinematics as the primary source of information used by crossing pedestrians, followed by the traffic infrastructure, although these authors' conclusion was based on interviews rather than behavioural analyses. The current work extends this finding using empirical results. The work in Chapter 2 integrated dynamic interactions between time gaps, zebra crossings, and drivers' responses under these varied conditions to explore how they influenced pedestrians' crossing decisions. Using a stepwise analysis, this work highlighted that the impact of zebra crossings existed, which is similar to results from other studies (Clamann et al., 2017; Crompton, 1979; Havard & Willis, 2012; Velasco et al., 2019), but this was limited to crossing with shorter time gaps between the pedestrian and the approaching vehicle. This may be due to the higher uncertainty of the vehicle's intent in such situations, as shorter time gaps reduce the reaction time available for pedestrians to observe and interpret the vehicle's speed or behaviour, making it harder to predict whether it will yield. In these scenarios, zebra crossings provide a clearer visual cue and a legal indicator that supports pedestrians to make crossing decisions.

Given pedestrians' primary reliance on kinematic cues for crossing decisions, future AVs should prioritise the use of clear kinematic signals to communicate their intent to other road users. The work in Chapter 2 also shows that clear and easily observable yielding patterns (i.e. 'soft and early' or 'late and hard' braking), and non-yielding (soft and late braking) patterns, can be useful for providing information to other road users and may be a useful consideration by AV designers. While previous studies have debated whether early braking (Pillai, 2020; Risto et al., 2017; Schneemann & Gohl, 2016; Tian et al., 2023) or late braking (Schmidt et al., 2020) is more effective for conveying yielding intent, these studies often rely on pedestrian responses to pre-programmed vehicle behaviours, limiting insights into real-time interactions. Moreover, they have overlooked the need for braking strategies tailored to different time gaps between the pedestrian and the approaching AV (Tian et al., 2023) or contextual factors like zebra crossings (Zhang et al., 2020). In contrast, our work in Chapter 2 used real braking patterns during real-time interactions with a human driver and a pedestrian, in a distributed simulation setup. However, as drivers exhibited intermittent and repeated braking behaviour, it was challenging to pinpoint the exact timing of braking intent. To address this challenge, the research proposed a novel metric using the "proximity to pedestrians at peak braking", which was found to show greater variability at smaller time gaps between the pedestrian and the approaching vehicle but remained consistent at larger time gaps. This metric was to identify the timing of the most obvious brake onset to depict yielding intent in such dual-actor interactions.

In addition to braking patterns, this work highlighted the use of lateral deviation as an implicit cue to communicate AV intent. Results showed that pedestrians were more likely to cross when vehicles yielded with a lateral deviation towards them, whereas deviation away from pedestrians was associated with non-yielding, reducing crossing likelihood. While previous studies have recognised lateral deviation away from pedestrians as a non-yielding indicator based on surveys and focus groups (Fuest et al., 2018; Sucha, 2014), this work is the first to document real-time yielding and non-yielding behaviours linked to specific lateral deviations. A video simulation study by Sripada et al. (2021) further supports these findings, showing that pedestrians preferred yielding with lateral deviation towards them and non-yielding with deviation away, likely because this aligns with natural driving expectations observed in the current study. These findings reinforce the importance of designing AV behaviours that mimic familiar patterns to enhance effective decision-making.

Despite the importance of implicit cues for communication between road users, there remains room for explicit cues to complement implicit signals, resolving ambiguity in some situations. Similar to how zebra crossings provide clear visual guidance and support pedestrians' crossing decisions when there is a small time gap between the pedestrian and the approaching vehicle, explicit communication tools such as eHMIs can clarify vehicle intent by providing a cue, although deciphering their meaning is not always easy (Dey et al., 2020; Lee et al., 2022; Madigan et al., 2023). Findings from the work in Chapter 4 reinforced this proposal by demonstrating that, at small time gaps, AR displays communicating the intent of an AV facilitated pedestrians' crossing decisions before it came to a full stop. This suggests that AR displays can complement a vehicle's implicit communication by reducing uncertainty in challenging scenarios. However, while explicit communication tools like AR displays and eHMIs have proven effective in some studies, concerns remain about whether additional elements associated with the AV might visually overload pedestrians during a crossing (de Winter & Dodou, 2022; Gruenefeld et al., 2019; Li et al., 2018). To address this issue, we examined pedestrians' attention allocation, by recording eye and head movements. This prompted the next research question, addressed by studies reported in Chapters 3 and 4.

- ***RQ 2:*** *How do explicit communication strategies (eHMI and AR displays) from AVs influence pedestrians' crossing decisions and attention allocation, such as head-turning and gaze behaviours?*

Results from studies reported in Chapter 3 and 4 showed that, overall, pedestrians' head-turning patterns and gaze behaviour in response to an AV which presented explicit communication cues was similar to that seen in real world studies involving conventional vehicles. A notable observation was the "last-second check," characterised by a surge in head-turning rate approximately 1 s before crossing initiation, which is seen in both real-world (Hassan et al., 2005; Tom & Granié, 2011) and a CAVE-based simulation studies (Lyu et al., 2024). These results demonstrate the high fidelity of pedestrian simulators for replicating natural behaviours, in a controlled and artificial environment.

If detected by AV sensors, this head turning behaviour behaviour could serve as a reliable indicator of crossing intent, and enable early speed reductions by the AV, enhancing crossing safety and preventing a full stop by the vehicle, improving traffic flow. However, our results also showed that the onset of this surge in head-turning rate varied between scenarios, highlighting its context-dependent nature and the need for further investigation before using this information for the creation of algorithms for recognition of pedestrian intent. Compared to previous studies relying on manual counting of head turns (Hassan et al., 2005; Tom & Granié, 2011), the current research introduced a novel approach for calculating absolute head-turning rates, quantifying head-turning behaviour in a continuous time series analysis.

The study reported in Chapter 4 revealed a set of distinct gaze patterns towards approaching AVs approached, consistent with findings from studies on manually driven vehicles (de Winter et al., 2021; Dey et al., 2019). Specifically, pedestrians initially focused on the environment and road surface when the AV was far away, gradually shifting their attention to the AV, particularly towards its windscreen, as it drew closer. Unlike prior research, which primarily examined gaze directed towards the approaching vehicles (Dey et al., 2019), the current study introduced a novel method to visualise pedestrians' gaze behaviour. By mapping gaze density on a Y-Z plane at different distance intervals along the X-axis, the method captured how pedestrians distributed their attention between the vehicle, environmental cues, and the crossing path, providing a more comprehensive view of their information-seeking process.

Additionally, when pedestrians gradually focused more on the AV as it approached, their crossing probabilities increased correspondingly. By examining the relationship between pedestrians' gaze patterns and crossing probabilities across different AV distances with AR displays, this study highlights the potential for distance-based AR design strategies to communicate AV intent effectively. For example, AR displays following pedestrians' head movements (HUD) or projected onto the crossing path drew pedestrians' attention at greater AV distances, resulting in higher crossing probabilities at those distances compared to trials without AR displays. This indicates that these AR locations are effective conveying AV intent from a distance. Conversely, AR displays following the vehicle path primarily influenced gaze patterns at shorter AV distances, likely due to their greater visibility at close range, making them more suitable for intent communication during closer interactions.

Results from the work reported in Chapter 3 revealed that before initiating crossing decisions, pedestrians exhibited significantly lower head-turning frequencies when eHMIs were present. Similarly, the study in Chapter 4 showed that with AR displays, pedestrians demonstrated shorter total gaze fixation durations on both the AR and the AV compared to their fixation durations on the vehicle in baseline conditions without AR. These behaviours suggest that explicit communication through eHMIs or AR reduces the need for extensive visual search, allowing pedestrians to rely less on head-turning or prolonged gaze to gather information from the vehicle or environment. These findings indicate that explicit communication channels do not increase visual demand on pedestrians but instead effectively support their crossing decisions. While previous studies primarily evaluated the effectiveness of explicit communication through crossing initiation times and self-reported measures (Dey et al., 2020; Lee et al., 2022; Madigan et al., 2023), this research introduced two novel metrics using head-turning frequency and changes in fixation duration. These metrics provide a quantitative approach to evaluate how explicit communication influences pedestrians' attention allocation and reduces their need on visual search for information gathering.

While explicit cues can reduce visual demand in crossing tasks, their effectiveness also depends on whether pedestrians can interpret the meaning of these cues through repeated exposures. Communication strategies that are difficult to understand may frustrate pedestrians and increase the complexity of the crossing task, undermining their intended purpose as an aid (Mahadevan et al., 2018; Moore et al., 2019). Thus, evaluating how implicit (vehicle behaviours) and explicit (eHMI and AR displays) communication strategies are learned and adapted to over time remains critical. These considerations motivated the subsequent research question addressed by studies reported in Chapters 2, 3, and 4.

- ***RQ 3:*** *How do repeated exposures to vehicle kinematics (e.g., yielding decision and behaviours, time gap, and lateral deviation) and explicit communication strategies (eHMI and AR displays) influence pedestrians' crossing decisions and attention allocation, such as head-turning and gaze behaviours?*

The work reported in Chapter 2, 3, and 4 collectively demonstrates pedestrians' behavioural adaptation to both implicit and explicit cues through repeated exposures in a virtual environment. Prior research has shown that pedestrian's interpretation of eHMIs signalling the AV's intent improves over repeated exposures, with reduced duration of gaze fixations, higher self-report scores for learning, and quicker crossing decisions (Faas et al., 2020; Hochman et al., 2020; Lee et al., 2022). However, these studies focused on interactions along straight roads, where AVs only employed uniform deceleration behaviours. The study reported in Chapter 3 extended the state-of-the-art by examining pedestrians' head-turning behaviour over repeated exposures to AVs at a virtual crossroad. The AVs also exhibited a two-step yielding behaviour, involving deceleration upon approaching the junction and edging forward before fully stopping. The findings revealed a decrease in head-turning frequency as pedestrians gained more exposure to these AVs equipped with eHMIs, with the learning effect becoming evident after the first exposure. A similar adaptation was observed with AVs lacking eHMIs, where pedestrians gradually interpreted the ambiguous edging-forward behaviour, resulting in reduced head-turning frequency before crossing.

The work reported in Chapter 4 revealed that pedestrians exposed to AR displays signalling AV intent exhibited reduced gaze fixation durations with repeated exposures, with the most significant decrease occurring after the first exposure. These findings highlight the effectiveness of familiar and intuitive communication approaches, such as the Slow Pulsing Light Bands (SPLB) used in Chapter 3, in facilitating rapid learning, often beginning with the first exposure. However, truly long-term evaluations will be needed in a range of real-world scenarios to fully understand the phases of learning and adaptation to such newly developed externally presented cues by AVs.

As outlined in Chapter 2, while interacting with AVs that showed a consistent driving style, i.e., unchanged deceleration rates and proximity to pedestrians at peak braking, pedestrians demonstrated adaptation over four trials by showing an increased willingness to cross, particularly at shorter time gaps of 3 and 4 seconds. However, these results also suggest that after learning the behaviour of the AV, pedestrians may develop riskier behaviours in close distance interactions, such as at junctions or during smaller time gap between the pedestrians and the approaching vehicle scenarios. Over time, pedestrians demonstrated fewer head-turning checks and made crossed more frequently, potentially increasing the risk of unsafe interactions. These findings underscore the importance of researching pedestrians' behavioural adaptation as AVs are introduced on public roads, to mitigate the risks associated with initial learning phases and the potential for misinterpretation of AV behaviours. They also illustrate that any sensor malfunctions which may lead to a sudden change in the typical behaviour of the AV may lead to unexpected conflicts and collisions.

5.2 CONTRIBUTIONS

This research contributes to a deeper understanding of AV-pedestrian interactions by examining pedestrians' crossing behaviours, attention allocation, and learning processes during repeated exposures to implicit and explicit communication strategies. By leveraging controlled experiments in virtual environments, this research contributes to theoretical, methodological and practical insights, with implications for AV design and road safety. Each of these is outlined in further detail below.

5.2.1 Theoretical contributions

This research contributes to the deeper understanding of pedestrians-vehicle interactions where vehicle kinematics have a more significant influence than static infrastructure like zebra crossings on pedestrians' crossing decisions. It also enriches the theoretical framework of attention allocation by providing detailed insights into how pedestrians manage their visual resources during interactions with AVs, particularly through head-turning and gaze patterns. Additionally, the research highlights the role of learning in shaping pedestrian behaviours and decision-making when repeatedly exposed to both implicit and explicit communication cues. These insights add to the growing body of knowledge on pedestrian decision-making and attention in AV-pedestrian interactions.

5.2.2 Methodological contributions

This thesis introduces innovative methodologies to study AV-pedestrian interactions including newly developed metrics, use of distributed simulations for studying driver-pedestrian interactions, and data analysis techniques for examining learning through repeated exposures. New metrics such as head-turning rate are used to capture continuous head-turning behaviour and head-turning frequency to evaluate uncertainty in crossing tasks, as outlined in Chapter

3. The study reported in Chapter 4 introduces a novel approach to visualising gaze density in a 3D immersive environment across varying AV distances while considering the environmental cues, and quantifies changes in visual load through fixation duration analysis while accounting for individual differences. Additionally, a vehicle kinematics metric based on proximity to pedestrians at peak braking is proposed in Chapter 2 to depict dynamic braking behaviour, offering applications for analysing diverse interactions in naturalistic driving data and serving as an indicator of braking intent.

This research also develops a distributed simulation setup integrating a high-fidelity driving simulator and a CAVE-based pedestrian simulator to enable real-time, reciprocal interactions between the two agents. This approach addresses limitations of traditional methods, such as the lack of experimental control in naturalistic studies and the shortcomings from single-agent simulation studies to capture bidirectional interactions. The distributed simulation study balances ecological validity and experimental precision, providing a controlled yet realistic environment for studying dynamic, mutual influences between drivers and pedestrians.

In terms of data analysis, this thesis utilises Generalised Estimating Equations (GEE) to handle correlations in repeated measures and longitudinal data, providing population-averaged behavioural trends, such as changes in head-turning patterns over time. Complementing this, the use of Generalised Linear Mixed Models (GLMM) accounts for fixed and random effects, offering deeper insights for considering individual variability. Together, these methods ensure a comprehensive analysis, balancing population-level and individual-level findings. Finally, the study reported in Chapter 2 introduces a forward selection regression modelling approach to disentangle the direct and indirect effects of variables such as time gaps, zebra crossings, and driver behaviours on pedestrian crossing decisions. This framework enables clearer understanding of complex variable relationships and supports analysis of large datasets, including naturalistic driving studies.

5.2.3 Practical contributions and design implications

Findings from this thesis contribute to the enhancement of traffic management and road safety for both current and future traffic systems involving AVs in several ways. Firstly, the study identifies how drivers negotiate right-of-way through their braking and steering movements under different contextual conditions. These driving patterns, which are already familiar to pedestrians, play a critical role in facilitating mutual understanding during interactions. By leveraging these established behaviours, future AVs can emulate human-like driving styles to boost traffic efficiency in mixed traffic environments. Secondly, the study emphasises the value of head-turning behaviour as a reliable indicator of pedestrian intent to cross. Incorporating this anticipatory behaviour into AV systems could significantly enhance their ability to predict pedestrian actions more accurately, improving decision-making and safety.

This research also contributes to designing effective communication mechanisms between AVs and pedestrians. The work reported in Chapter 2 identifies several human-like driving behaviours, such as braking patterns and lateral deviations, that can be integrated into AV systems to enhance their implicit communication strategies across various contexts. Research reported in Chapters 3 and 4, although not intended for design development, highlight the importance of intuitive and familiar designs, as well as context-specific and distance-dependent strategies, for effective explicit communication. By evaluating explicit communication strategies, such as eHMIs and AR displays, through pedestrians' head-turning and gaze behaviours, these studies identified how such cues can facilitate pedestrians' crossing decisions without increasing their visual resource demands. These contributions pave the way for the successful deployment of AV systems, ensuring safe and efficient communication with pedestrians in human-centric urban environments.

5.3 REFLECTIONS ON RESEARCH LIMITATIONS

This thesis contributes to the current knowledge on AV-pedestrian interactions, with a particular focus on pedestrians' attention allocation and learning over repeated exposures. Nonetheless, certain limitations should be recognised, offering opportunities for future research to build upon these findings.

Firstly, the generalisability of the findings might be constrained by the controlled scenarios employed for the empirical studies. All interactions occurred in a one-to-one setting, where pedestrians responded to a single vehicle approaching from the right. While this setup ensured experimental control, it does not fully capture the complexity of real-world traffic scenarios involving multiple vehicles, varying directions of approach, or interactions at more complex locations such as roundabouts and busy intersections. Exploring more dynamic and multi-agent environments in future studies will enhance understanding of pedestrians' attention and behaviours in more complex settings (Meir & Oron-Gilad, 2020). Moreover, all participants were based in the UK, which may have influenced how they interpreted vehicle behaviour, road infrastructure, and pedestrian priority norms. Cultural factors and local driving practices can shape pedestrian decision-making, and future studies should replicate this research in other cultural contexts to evaluate the generalisability of AV–pedestrian interactions across different countries and traffic environments. Such research would also help evaluate the generalisability of these findings across various real-world scenarios.

Secondly, a limitation lies in the reliance on a simulated environment in all studies. Although the CAV-based pedestrian simulator offered an immersive environment, allowing controlled and repeatable studies, the absence of real-world risks and consequences may have influenced participants' behaviours (Dietrich et al., 2018). For instance, repeated crossing tasks in a risk-free setting may not fully replicate the cautious decision-making exhibited in natural environments. Validating these findings through naturalistic studies or real-world experiments will be crucial to ensure their applicability beyond the lab.

Thirdly, while the experiments achieved gender balance, they lacked representation from broader demographic groups, such as older adults, children, or individuals with mobility challenges. These populations may exhibit unique interaction patterns or face additional barriers that require tailored communication strategies (Tapiro et al., 2016). Incorporating greater demographic diversity in future research will ensure that AV systems are inclusive and meet the needs of all road users, particularly vulnerable populations.

Finally, this research focuses on highly or fully automated vehicles, although some interaction patterns observed may also be relevant to partially automated or manually driven vehicles. For example, pedestrians' head-turning and gaze behaviours in front of HAVs in this study were similar to those reported in real-world interactions with manually driven vehicles. However, pedestrian behaviour in relation to other levels of automation, such as SAE Level 3, remains underexplored. Additionally, the presence of a human driver may influence pedestrian gaze behaviour, potentially leading to more focused attention compared to interactions with driverless HAVs. Future research could investigate these differences to support the development of more accurate AV algorithms for pedestrian intent recognition.

5.4 FUTURE OUTLOOK

This PhD project has explored AV-pedestrian interactions, investigating behavioural changes in pedestrian response during repeated encounters with AVs. The research focused on studying the effect of repeated exposures to approaching

AVs in the short-term, in a laboratory setting, mainly due to the absence of fully developed HAVs on public roads. These findings provide a valuable basis for future longitudinal studies to examine pedestrian adaptation to AVs over extended periods in real-world settings. Such studies will be crucial in determining whether the behavioural patterns identified in this thesis generalise to everyday traffic scenarios and persist as HAVs become widely integrated into traffic systems.

When HAVs become commonplace, further exploration will be needed to understand the pedestrians' interactions with AVs over time. Arising questions will be the length of the initial learning phase required for pedestrians to adapt their attention allocation and crossing behaviours to different AV behaviours in different contexts. Additionally, it will be essential to investigate whether these adaptive behaviours are consistent across different population groups. More vulnerable road users, such as older adults or those with mobility challenges, may have unique needs that demand tailored approaches. Addressing these questions will support the development of inclusive and safer environments, designed to accommodate diverse user needs while reducing risks for vulnerable populations.

Furthermore, while this study demonstrates the value of using a distributed simulation to examine reciprocal, real-time interactions between drivers and pedestrians, the current analysis primarily focused on pedestrians' decisions using traditional statistical approaches, without modelling mutual behavioural responses. Future research should explore analytical frameworks that move beyond stimulus–response paradigms and account for mutual adaptation and interdependence, such as joint decision modelling, game-theoretic models, or probabilistic frameworks such as dynamic Bayesian network (Kalantari, 2023; Zhang, 2023). Applying such frameworks would support a more detailed analysis of mutual behaviours in AV–pedestrian interaction.

Additionally, while this thesis explored how AVs can adopt human-like driving behaviours, real-world traffic is far more dynamic, with a much wider range of scenarios than those studied here. Future research needs to examine how AVs navigate interactions involving multiple agents, such as overtaking vehicles, stationary objects, clusters of pedestrians, or animals, in contexts like roundabouts, crosswalks, or bottlenecks. Environmental factors such as lighting, weather, and road conditions further complicate these interactions. To address these complexities, future research should leverage extensive naturalistic datasets that capture the full range of real-world traffic scenarios. The methodologies and insights from this thesis pave the way for analysing these datasets and creating human-like driving strategies for AVs.

Overall, this thesis not only deepens academic understanding of AV-pedestrian interactions during repeated exposures but also addresses critical communication needs as AV technology becomes increasingly prevalent. Building on this work, future research can further enhance road safety by conducting long-term studies to inform the development of intuitive, predictable, and reliable AV designs that accommodate the diverse needs of all road users, particularly vulnerable populations.

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CHAPTER 6

APPENDIX

6.1 APPENDIX TO CHAPTER 2

Appendix A Supplementary results: vehicle kinematics

This section provides supplementary visualizations derived from raw vehicle kinematics data to complement the analysis presented in Chapter 2. While the work presents average scores obtained through GLMM, the visualizations below depict real-time dynamics of vehicle-pedestrian interactions using raw data processed in MATLAB.

The data were segmented from the start of the interaction (triggered by a beep sound and the pedestrian stepping out to initiate interaction) to the trial's end, defined as either the pedestrian initiating crossing or the driver passing the pedestrian's intended path. Frame-by-frame visualizations were created to show the vehicle's position relative to the pedestrian. At each frame, the average driver deceleration and lateral deviation were calculated for the same distance to the pedestrian. These metrics were plotted to provide a continuous representation of vehicle dynamics throughout the interaction. This real-time depiction enriches the understanding of how drivers adapt their behaviour during pedestrian encounters beyond the average trends discussed in the main analysis.

Figure 6.1 illustrates the mean deceleration and lateral deviation of a vehicle as it approaches pedestrians under two interaction outcomes regarding who crossed first: pedestrian crossing first (PedCross), represented by solid lines, and pedestrian not crossing but vehicle passing first (VehiclePass), represented by dashed lines. The x-axis shows the vehicle's distance to pedestrians in meters, while the left y-axis (blue lines) represents mean deceleration, and the right y-axis (red lines) represents mean lateral deviation.

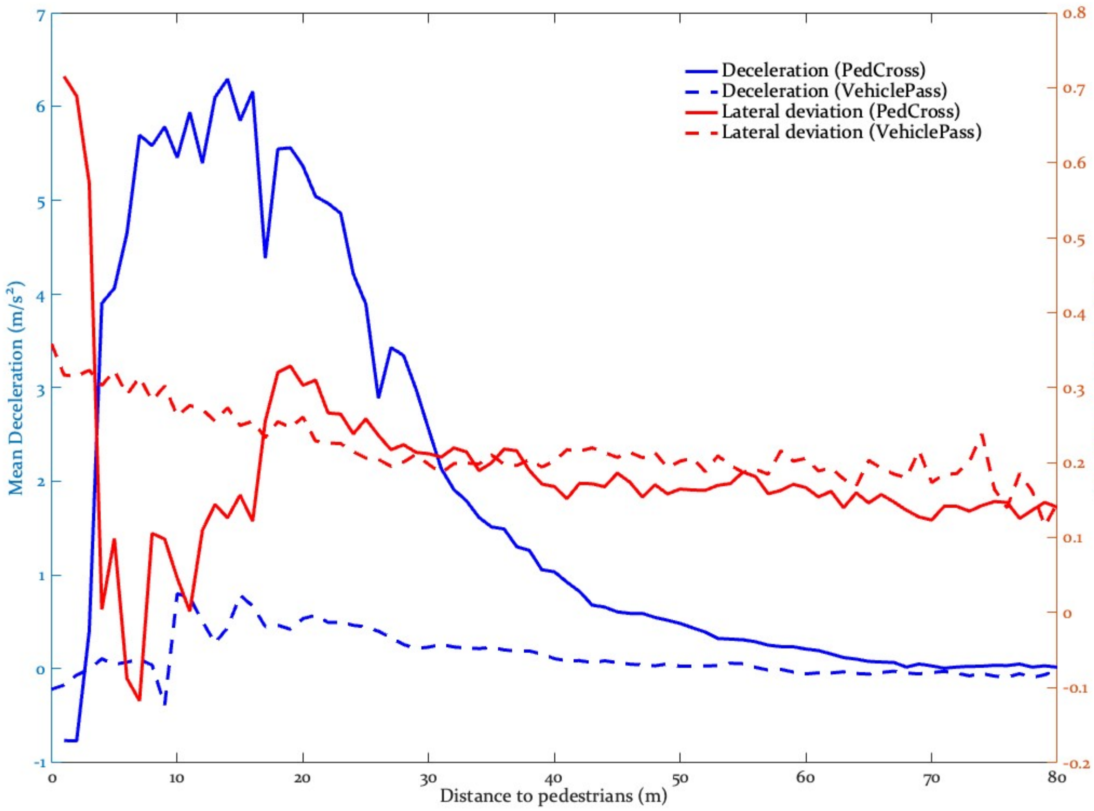


Figure 6.1. Drivers' mean deceleration and lateral deviation relative to the distance to pedestrians across two interaction outcomes: pedestrian crossing first (PedCross, solid lines) and vehicle passing first (VehiclePass, dashed lines).

In trials where the pedestrian crossed first (PedCross, solid lines), the mean deceleration (solid blue line) shows a sharp increase as the vehicle approaches the pedestrian, peaking between 10 and 20 meters from the pedestrian. Meanwhile, the driver's lateral offset (solid red line) initially shows a slight deviation away from the pedestrian but exhibits a significant lateral deviation towards the pedestrian starting at 20 meters, accompanying the increasing deceleration observed in the solid blue line.

Conversely, in trials where the vehicle passed first and pedestrians did not cross, the driver's braking behaviour (dashed blue line) shows minimal and relatively stable deceleration, with only a slight braking response observed during the approach. In terms of lateral deviation, there is an increasing deviation away from the pedestrians as the vehicle approaches.

These raw data visualizations highlight distinct yielding and non-yielding driving behaviours through longitudinal and lateral vehicle control. This supplements the averaged results presented in the main analysis, offering a frame-by-frame depiction of driver responses in pedestrian interactions.

However, drivers' behaviour is also influenced by the road infrastructures. They are more likely to yield at zebra crossings and less likely to yield at locations without zebra crossings, as shown in **Figure 6.2** derived from the raw data. When a zebra crossing is present, drivers exhibit significantly higher deceleration rates, peaking sharply at approximately 10–20 meters from the pedestrian, as indicated by the darker green line in **Figure 6.2**a. In contrast, deceleration rates for locations without zebra crossings remain lower and more gradual, represented by the lighter green line.

In terms of lateral deviation, with a zebra crossing, drivers display significant lateral deviation towards pedestrians starting from around 20 meters, as shown in **Figure 6.2**b. Conversely, without a zebra crossing, lateral deviation increases steadily away from pedestrians, reflecting reduced yielding behaviour. These patterns underscore the impact of road infrastructure on driver behaviours and can be further utilised to inform the development of human-like driving behaviour models at different road segments.

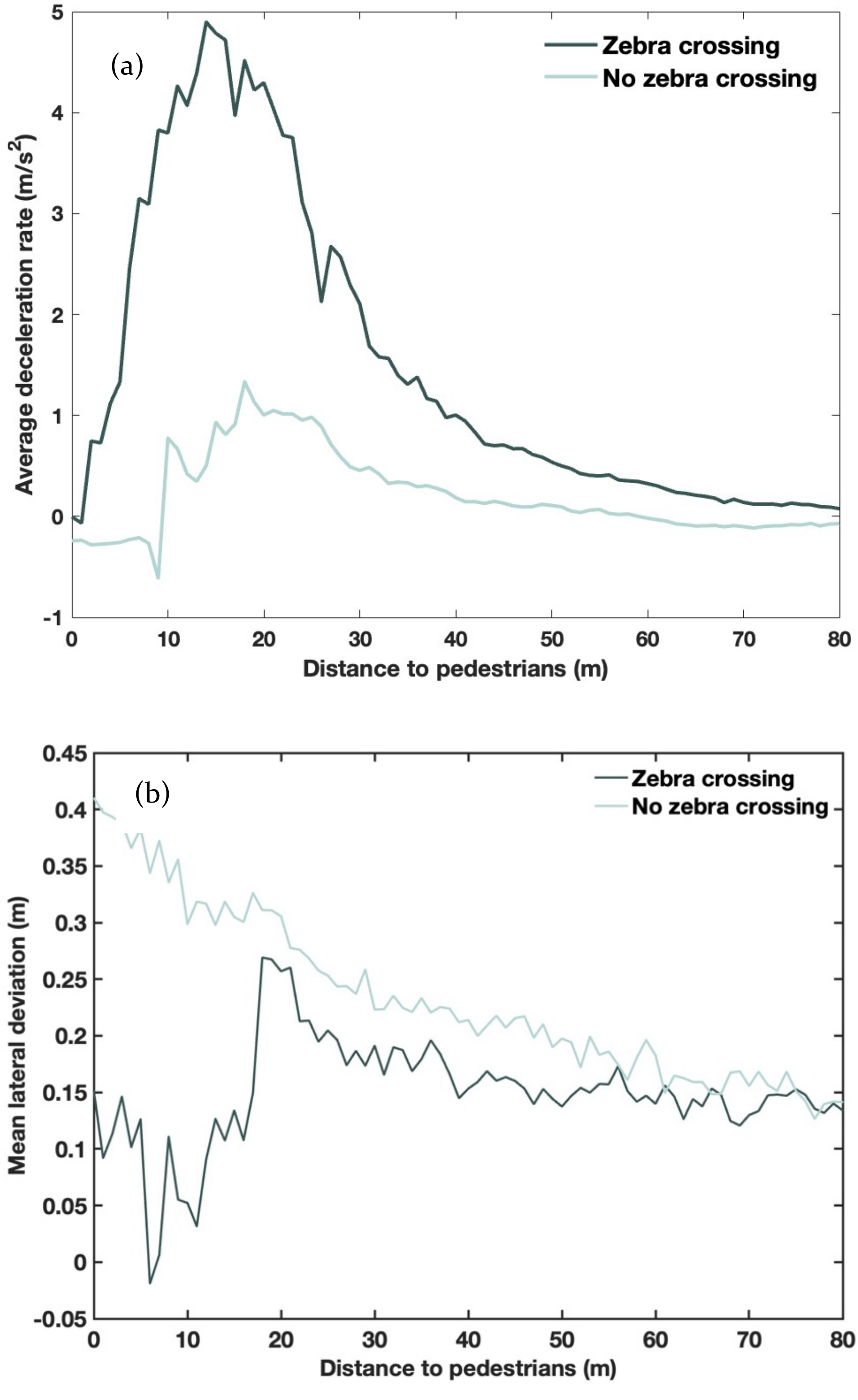


Figure 6.2. Driver's (a) average deceleration rates and (b) lateral deviation, in relation to distances to a crossing pedestrian at different road infrastructures, derived from the raw data.

6.2 APPENDIX TO CHAPTER 3

Appendix B Demographics information

The demographics information provided below was collected to ensure participant diversity and to offer additional context for the study. However, this data was not directly analysed in the main body of the research.

Q1. Age
Participants' ages ranged from 22 to 58 years: 22–30 years: 55.26% (n = 21), 31–40 years: 23.68% (n = 9), 41 years and above: 21.05% (n = 8).

Q2. Gender
Male: 47.37% (n = 18), Female: 52.63% (n = 20).

Q3. Nationality
British: 65.79% (n = 25), Chinese: 15.79% (n = 6), Other (e.g., Irish, Iranian, South African, Algerian, USA, French, Italian/Brazilian): 18.42% (n = 7)

Q4. How long have you been living in the UK?
Less than 1 year: 10.53% (n = 4), 1–5 years: 21.05% (n = 8), 6–10 years: 7.89% (n = 3), More than 10 years: 60.53% (n = 23).

Q5. Do you have a driving license?
Yes: 71.05% (n = 27), No: 28.95% (n = 11).

Q6. Which country issued your driving license?
UK: 66.67% (n = 18), China: 11.11% (n = 3), Other countries (e.g., USA, Iran, France, Germany): 22.22% (n = 6).

Q7. How many years of active driving experience do you have?
Less than 1 year: 20% (n = 6), 1–10 years: 40% (n = 12), More than 10 years: 40% (n = 12).

Q8. What is your annual mileage?
0–3000 miles: 52% (n = 13), 3000–6000 miles: 12% (n = 3), 6000–9000 miles: 24% (n = 6), More than 9000 miles: 12% (n = 3).

Q9. Do you use glasses or other instruments to improve your vision in daily life?
Yes: 50% (n = 19), No: 50% (n = 19).

Appendix C Methodology: head-turning data filter

The raw head-turning data obtained in the HIKER pedestrian lab was recorded in quaternion format, $q = (q0, q1, q2, q3)$, for its efficiency, robustness against gimbal lock, compact representation, and suitability for accurate 3D orientation tracking and smooth interpolation. To analyse the head-turning data in Euler angles, specifically pedestrians' head's yawing (turning γ degrees around Z-axis), pitching (rotating β degrees around Y-axis) and rolling (turning α degrees around X-axis) movement around the torso, we used the following equation for conversion:

$$\begin{bmatrix}\alpha\\ \beta\\ \gamma\end{bmatrix} = \begin{bmatrix} atan2(\frac{2(q_0q_1+q_2q_3)}{1-2(q_1^2+q_2^2)}) \\ \arcsin\big(2(q_0q_2-q_1q_3)\big) \\ atan2(\frac{2(q_0q_3+q_1q_2)}{1-2(q_2^2+q_3^2)}) \end{bmatrix}$$

As introduced in the Section 3.2, this study only focused on the horizontal head yaw angle (γ degrees around the Z-axis), representing pedestrians' left/right head-turning behaviour. To smooth the discrete data and filter noise in the tracked head yaw angle, we employed an Infinite Impulse Response (IIR) filter using MATLAB Signal Processing Toolbox 8.6, with the filter structure created in MATLAB Simulink (**Figure 6.3**). The IIR filter uses a recursive structure, where the output samples depend on both past input and previous filtered output samples as feedback (Regalia, 2018). A low-pass filter was designed to address the high-frequency noise and abrupt artefacts in head movements, considering evidence that spontaneous head movements, as well as those passively influenced by body dynamics during walking and running, typically occur around 2 Hz, as shown in reviews by Gresty and Halmagyi (1979). Based on this, a cutoff frequency of 3 Hz was selected to filter out signals above this threshold. The sampling frequency was set to 100 Hz, and the filter order was set at 4, optimising performance in preliminary tests.

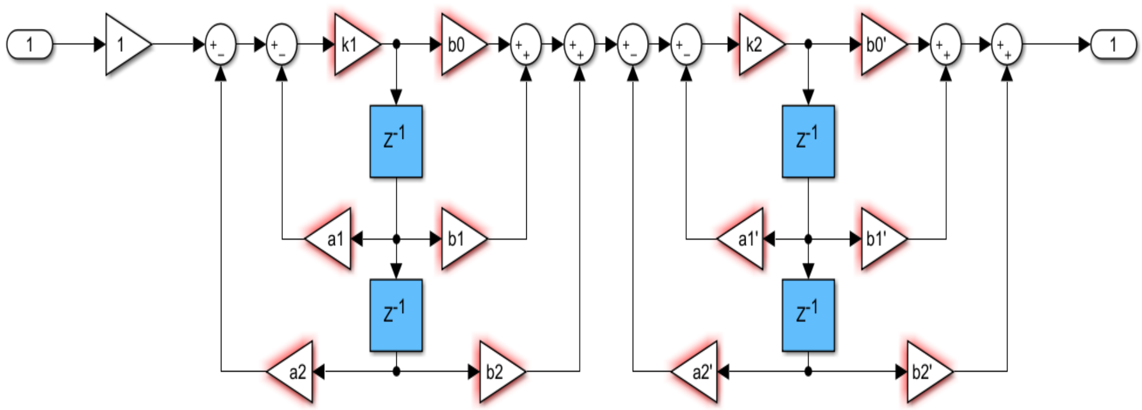


Figure 6.3. A 4th-order IIR filter, in a Direct-Form II, Second-Order Sections structure, with the z^{-1} operator indicating a unit time delay.

Figure 6.3 illustrates the 4th-order IIR filter implemented in a Direct-Form II structure, divided into two second-order sections. This configuration includes feedforward and feedback paths, governed by the following recursive equation:

$$y(n) = \sum_{k=0}^{N} b_k x(n-k) - \sum_{j=1}^{M} a_j y(n-j)$$

Here:

- b_k: Feedforward coefficients, weighting the current and past input samples $x(n-k)$, forming the numerator of the transfer function.
- a_j: Feedback coefficients, weighting past output samples $y(n-j)$, forming the denominator of the transfer function.
- $y(n)$: Current output
- $x(n)$: Current input.

The corresponding z-domain transfer function is expressed as:

$$H(z) = \frac{Y(z)}{X(z)} = \frac{\sum_{k=0}^{N} b_k z^{-k}}{1 - \sum_{j=1}^{M} a_j z^{-k}}$$

In **Figure 6.3**, the z^{-1} operators represent unit time delays, enabling the filter to process discrete-time input and output samples. By using these delays, the filter computes the current output $y(n)$ from weighted contributions of past inputs and outputs. To enhance numerical stability, the 4th-order filter is divided into two cascaded second-order sections, with the overall transfer function represented as:

$$H(z) = \frac{Y(z)}{X(z)} = k_1 \times \frac{b_0 + b_1 z^{-1} + b_2 z^{-2}}{1 - a_1 z^{-1} - a_2 z^{-2}} + \frac{b_{0'} + b_{1'} z^{-1} + b_{2'} z^{-2}}{1 - a_{1'} z^{-1} - a_{2'} z^{-2}} \times k_2$$

Here, k_1 and k_2 are gains introduced to normalise the filter output across sections, ensuring consistent amplitude. Each second-order section includes:

- A numerator with feedforward coefficients (b_0, b_1, b_2 for the first section and $b_{0'},\ b_{1'},\ b_{2'}$ for the second),
- A denominator with feedback coefficients (a_0, a_1 for the first section and $a_{0'},\ a_{1'}$ for the second).

The specific parameterisation used in this study is:

$$H(z) = \frac{0.00826(1 + 2z^{-1} + z^{-2})}{1 - 1.833z^{-1} + 0.866z^{-2}} + \frac{0.00755(1 + 2z^{-1} + z^{-2})}{1 - 1.675z^{-1} + 0.705z^{-2}}$$

This transfer function directly corresponds to the filter structure in **Figure 6.3**, where the connections between coefficients b_k and a_j, gains k_1 and k_2, and delays z^{-1} are visually represented. By adopting this design, the filter ensures precise low-pass characteristics, smoothing the signal and removing high-frequency noise for accurate analysis of pedestrian head-turning behaviour.

When processing head yaw angle data, one significant challenge is the phase distortion introduced by IIR filters when using feedback from past outputs in addition to current and past inputs. It results in a non-constant delay in the time domain, which can misalign important signal features. For this reason, zero-phase filtering was applied to ensure the filtered signal retained its temporal alignment with the original data.

This sequence of operations zero-phase filtering, as shown in **Figure 6.4**a, effectively cancels out the phase shift from the forward and backward filtering steps. First, the raw input signal $x(n)$ was passed through the IIR filter in the forward direction, producing an intermediate output $u(n)$, which has a non-constant delay. Secondly, this filtered signal was reversed in time, effectively flipping it to $u(-n)$, and passed through the same IIR filter again. This backward filtering step corrected the phase distortion introduced during the initial forward filtering. Finally, the backward-filtered signal was reversed again in time, restoring the correct temporal order and yielding the final zero-phase filtered signal $y(n)$. **Figure 6.4**b shows an example of filtered data input in the black line, $u(n)$ in the blue line, and $y(n)$ in the red line as the final output after zero-phase filtering removing the delay.

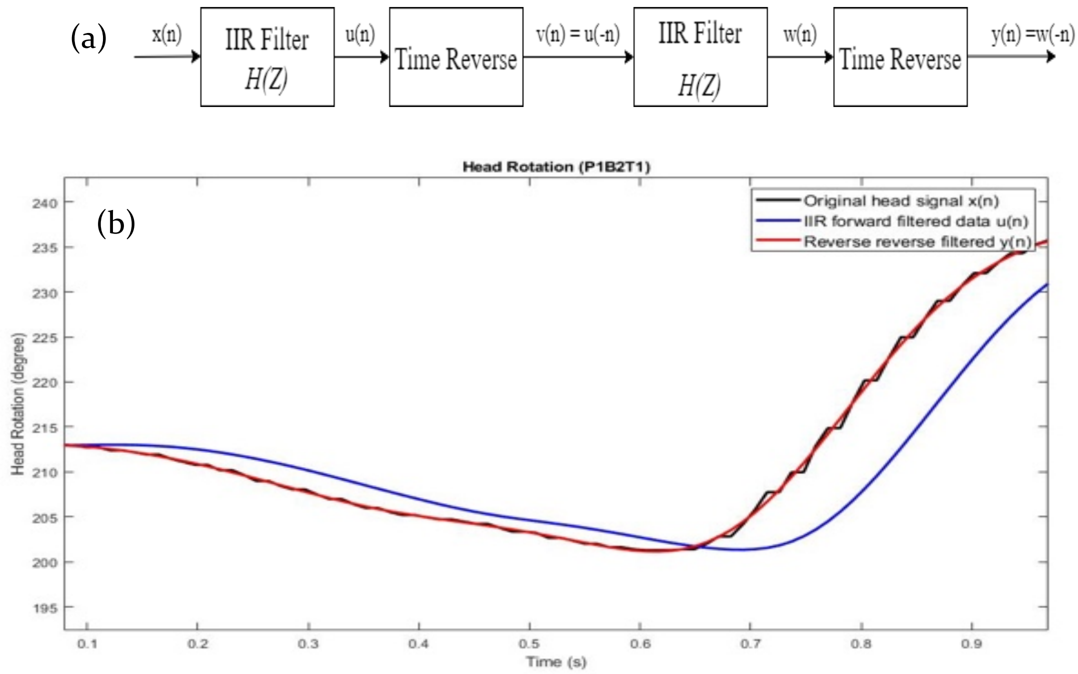


Figure 6.4. (a) The process of zero-phase filtering. (b) An example of the filtered head yaw angle of Participant #1 in Trial #1 at the 1st second of the trial, with the original signal x(n) shown in black, the IIR forward-filtered signal in blue, and the reversed-filtered signal in red, illustrating the final zero-phase filtered data.

Appendix D Methodology: head-turning behaviour relative to vehicle movements

This appendix presents an analysis of pedestrians' head-turning behaviour in relation to AVs and their movements over time. The purpose of this analysis is to demonstrate that pedestrians' head-turning behaviour is not merely the following of vehicle motion but rather an active, context-sensitive response to the AV's actions. The calculated yaw angle change rates are compared to observed head-turning rates in different scenarios to support this argument.

Vehicle Trajectory

The vehicle's motion is divided into four phases in yielding trials: decelerating, edging, stopping, and accelerating. During each phase, the vehicle's speed v_t and distance to the pedestrian x_t were modelled as a function of time (t), as shown below:

Decelerating phase:

For 0 =< t =<3 s, $\begin{cases} v_t = v_0 - a_1 t = 11.176 - 3.725t \\ x_t = x_0 - v_0\, t + 0.5 * a_1 t^2 = 27.4 - 11.176t + 1.8625t^2 \end{cases}$

v_0 : Initial vehicle speed, 11.176 m/s, x_0: Initial distance between the vehicle and the pedestrian, 27.4 m, a_1: Deceleration rate, 3.725 m/s^2

Edging phase:

For 3 < t =< 6.5 s, $\begin{cases} v_t = a_2\,(t-3) = 0.3832(t-3) \\ x_t = x_1 - 0.5 * a_2 t^2 = 6.1024 - 0.1916(t-3)^2 \end{cases}$

For 6.5 < t =< 7 s,

$$\begin{cases} v_t = v_1 - a_3\,(t-6.5) = 1.3411 - 2.6822\,(t-6.5) \\ x_t = x_2 - v_2\,(t-6.5) + 0.5 * a_3 (t-6.5)^2 = 3.7552 - 1.3411(t-6.5) + 1.3411(t-6.5)^2 \end{cases}$$

a_2 : Acceleration rate, 0.3832 m/s^2, a_3 : Deceleration rate, 2.6822 m/s^2,

x_1 : 6.1024 m, x_2 : 3.7552 m

Stopping phase:

For 7 < t =< 10 s, $v_t = 0, x_t = 3.42$ m

Accelerating phase:

For t > 10 s, $\begin{cases} v_t = a_4\,(t-10) = 0.89\,(t-10) \\ x_t = x_3 - 0.5 * a_4 (t-10)^2 = 3.42 - 0.445 (t-10)^2 \end{cases}$

a_4 : Acceleration rate, 0.89 m/s^2, x_3 : 3.42 m

Head-turning rate relative to vehicle trajectory/time (theoretical)

When pedestrians are visually tracking an AV and continuously adjusting their head yaw angle continuously, their movements can be analysed in terms of their position, p(m), speed, v(m/s), and yawing rate, $\dot{\theta}(°/s)$.

According to Ward et al. (2015), the angular velocity $\dot{\theta}(°/s)$ is influenced by the motion of the AV relative to the pedestrian's fixed point of reference. Specifically, when the AV is rotating around the pedestrian, the yawing rate $\dot{\theta}(°/s)$ is calculated as:

$$\dot{\theta} = \frac{(p_v - p_p) \times \overrightarrow{v_p} - (p_v - p_p) \times \overrightarrow{v_v}}{||p_p - p_v||^2}$$

In this equation:

- $p_p(0,0,0)$: The pedestrian's position, fixed at the origin.
- $p_v\left(x_t, width_{half\_lane}, 0\right)$: The AV's position, where x_t is the longitudinal distance to the pedestrian and $width_{half\_lane}$ is the lateral distance (1.8 m in this study).

- $\overrightarrow{v_p}\,(0,0,0)$: The pedestrian's velocity before the crossing initiation time (CIT), assumed to be stationary.

- $\overrightarrow{v_v}\,(v_t, 0,0)$: The AV's velocity, determined by its speed v_t.

Simplifying this using the cross-product formulation, the yawing rate can be expressed as:

$$\dot{\theta} = -\frac{\left(x_t, width_{half\_lane}, 0\right) \times (v_t, 0,0)}{\sqrt{x_t{}^2 + width_{half\_lane}{}^2}^{\,2}}$$

$$\dot{\theta} = -\frac{\begin{vmatrix} \hat{\imath} & \hat{\jmath} & \hat{k} \\ x_t & width_{half\_lane} & 0 \\ v_t & 0 & 0 \end{vmatrix}}{x_t{}^2 + width_{half\_lane}{}^2}$$

$$\dot{\theta} = \frac{v_t * width_{half\_lane}}{x_t{}^2 + width_{half\_lane}{}^2}$$

This equation provides a clear relationship between the AV's velocity v_t, its distance from the pedestrian x_t, and the pedestrian's yawing rate. Using the vehicle's dynamic phases described earlier, the yawing rate $\dot{\theta}$is calculated for the following time intervals: Take $width_{half\_lane} = 1.8m$,

$$\dot{\theta} = \begin{cases} Deceleration\text{:} \ \dfrac{1.8(11.176 - 3.725t)}{3.24 + (27.4 - 11.176t + 1.8625t^2)^2} & t\epsilon[0,3] \\ Edging\text{:} \ \dfrac{1.8 * 0.3832(t-3)}{3.24 + (6.1024 - 0.1916(t-3)^2)^2} & t\epsilon(3,6.5] \\ \dfrac{1.8\left(1.3411 - 2.6822\,(t-6.5)\right)}{3.24 + (3.7552 - 1.3411(t-6.5) + 1.3411(t-6.5)^2)^2} & t\epsilon(6.5,7] \\ Stopping\text{:} \ 0 & t\epsilon(7,10] \\ Acceleration\text{:} \ \dfrac{1.8 * 0.89\,(t-10)}{3.24 + (3.42 - 0.445(t-10)^2)^2} & t\epsilon(10,\infty) \end{cases}$$

These equations describe how the pedestrian's yawing rate changes as the vehicle transitions through its motion phases in yielding trials. The head yaw angle rate

$\dot{\theta}$ when the pedestrians' head is simply following the vehicle's trajectory, is plotted as below:

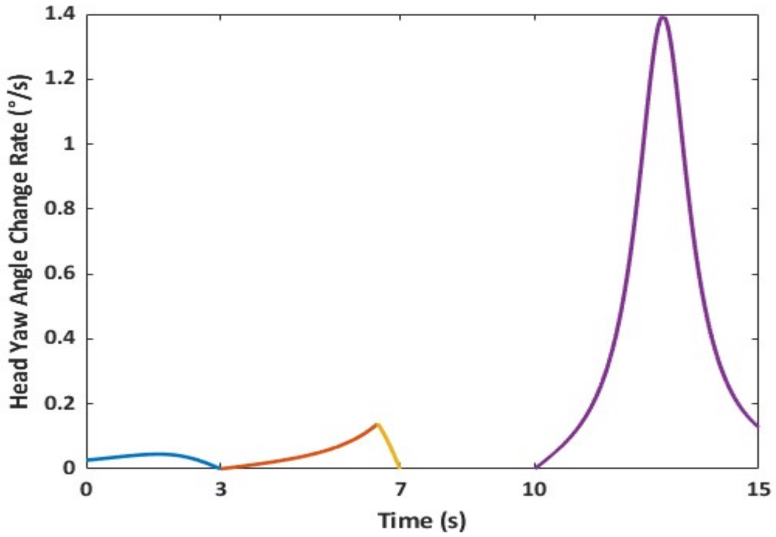


Figure 6.5. Pedestrians' head yaw angle change rate in response to time when simply following AV's motions.

Head-turning rate relative to vehicle trajectory/time (observed)

While the previous section presents pedestrians' theoretical head-turning rate when following the motion of an AV, this section examines the observed head-turning rate over time. **Figure 6.6** illustrates pedestrians' average head yaw rate from the start of each trial to the end of the crossing when interacting with both yielding (top, darker green line) and non-yielding (bottom, darker blue line) AVs. The distributions of crossing initiation time are also shown for yielding (top, lighter green line) and non-yielding (bottom, lighter blue line) trials. The orange lines indicate the time at which the AV passed the pedestrian for both yielding behaviours.

A significant peak in head-turning rate is observed at the beginning of the trial and approximately 1 second before the peak of the crossing initiation distribution.

This pattern highlights the effectiveness of head-turning behaviour as an indicator of pedestrians' crossing intent in both yielding and non-yielding trials.

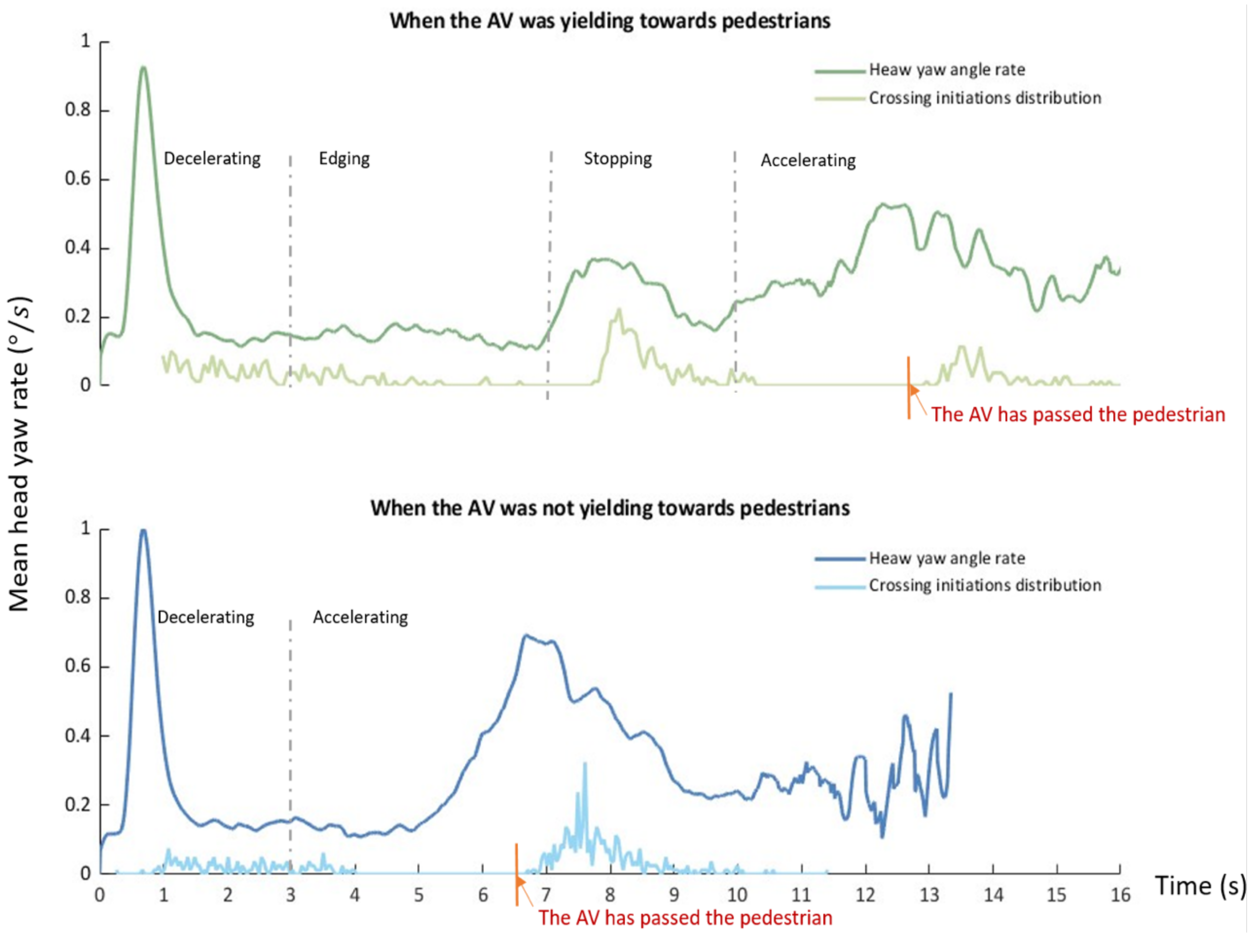


Figure 6.6. Observed head-turning rate in relation to time in (a) yielding and (b) non-yielding AV trials.

Comparing the observed and theoretical head-turning rates in **Figure 6.5** and **Figure 6.6**a, it is evident that pedestrians' head-turning patterns differ significantly from theoretical predictions across all yielding stages of the vehicle's movements. This discrepancy highlights the context-dependent nature of head-turning behaviour, suggesting the need for further exploration to better understand its underlying mechanisms and contributing factors.

6.3 APPENDIX TO CHAPTER 4

Appendix E Demographics information

The demographics information provided below was collected to ensure participant diversity and to offer additional context for the study. However, this data was not directly analysed in the main body of the research.

Q1. Gender
Participants identified as 60% (n = 18) female and 40% (n = 12) male.

Q2. Age
Participants' ages ranged from 18 to 58 years: 18–30 years: 50% (n = 15), 31–40 years: 30% (n = 9), 41 years and above: 20% (n = 6).

Q3. Nationality
Participants included 70% (n = 21) British, 20% (n = 6) from other European countries, and 10% (n = 3) from non-European countries.

Q4. Length of Residence in the UK
Participants reported living in the UK for less than 1 year: 30% (n = 9), 1–5 years: 27% (n = 8), 5–10 years: 3% (n = 1), and more than 10 years: 40% (n = 12).

Q5. Familiarity with Traffic Systems
Familiarity was reported as 43% (n = 13) with left-hand traffic (LHT), 23% (n = 7) with right-hand traffic (RHT), and 33% (n = 10) familiar with both systems.

Q6. Affinity for Technology Interaction (ATI) Scale
The mean Affinity for Technology Interaction (ATI) scale score was 4.25, indicating moderate interaction affinity.

Q7. Use of VR Headsets
A total of 73% (n = 22) of participants had used VR headsets before, while 27% (n = 8) had not.

Q8. Use of AR Apps or Games
Participants reported using AR apps or games at 57% (n = 17), with 43% (n = 13) having never used them.

Q9. Participation in CAVE-Based Simulator Experiments
A total of 43% (n = 13) had previously participated in CAVE-based simulator experiments, while 57% (n = 17) had not.

Q10. Daily Walking Time as a Pedestrian
Participants reported daily walking times were 15–30 minutes: 50% (n = 15), 30–45 minutes: 10% (n = 3), 45–60 minutes: 23% (n = 7), and more than 60 minutes: 17% (n = 5).

Q11. Primary Mode of Transportation
The primary mode of transportation was walking for 46.7% (n = 14), private vehicles for 23% (n = 7), public transportation for 17% (n = 5), and cycling for 13% (n = 4).

Q12. Possession of a Driving License
A total of 87% (n = 26) of participants reported having a driving license, while 13% (n = 4) did not.

Q13. Year of License Acquisition
Among licensed participants, 77% (n = 20) obtained their license in the last 10 years, while 23% (n = 6) obtained it more than 10 years ago, with the earliest year being 1993 and the most recent being 2020.

Q14. Driving Frequency
Driving frequency for licensed participants was every day: 34% (n = 9), weekdays only: 4% (n = 1), weekends only: 8% (n = 2), once per week: 8% (n = 2), once per month: 12% (n = 3), never: 27% (n = 7), and preferred not to respond: 8% (n = 2).

Q15. Annual Mileage
Participants with licenses reported annual mileage as 0 miles: 12% (n = 3), 1–5,000 miles: 38% (n = 10), 5,001–10,000 miles: 23% (n = 6), 10,001–15,000 miles: 12% (n = 3), 15,001–20,000 miles: 8% (n = 2), and preferred not to respond: 8% (n = 2).

Q16. Colour Blindness Test
A total of 3% (n = 1) of participants were identified as colourblind, based on three or more incorrect responses to the six-item Ishihara test, while 97% (n = 29) were not colourblind.

Appendix F Results: intuitiveness ranking distribution

This section summarises the data distribution for intuitiveness rankings of the AR designs evaluated in Chapter 4, providing supplementary descriptive data for the analysis presented in Section 4.3.2. Furthermore, the correlation between these intuitiveness rankings and changes in fixation gaze for each AR design is explored to enrich the interpretation of the results.

Figure 6.7 presents bar plots illustrating participant ratings on a 7-point scale, where 1 represents 'strongly not intuitive' and 7 indicates 'strongly intuitive' for each AR design. The mean and standard error (SE) for each design is annotated above each plot. The plots are organised in descending order of mean intuitiveness scores, allowing for easy comparisons across the designs.

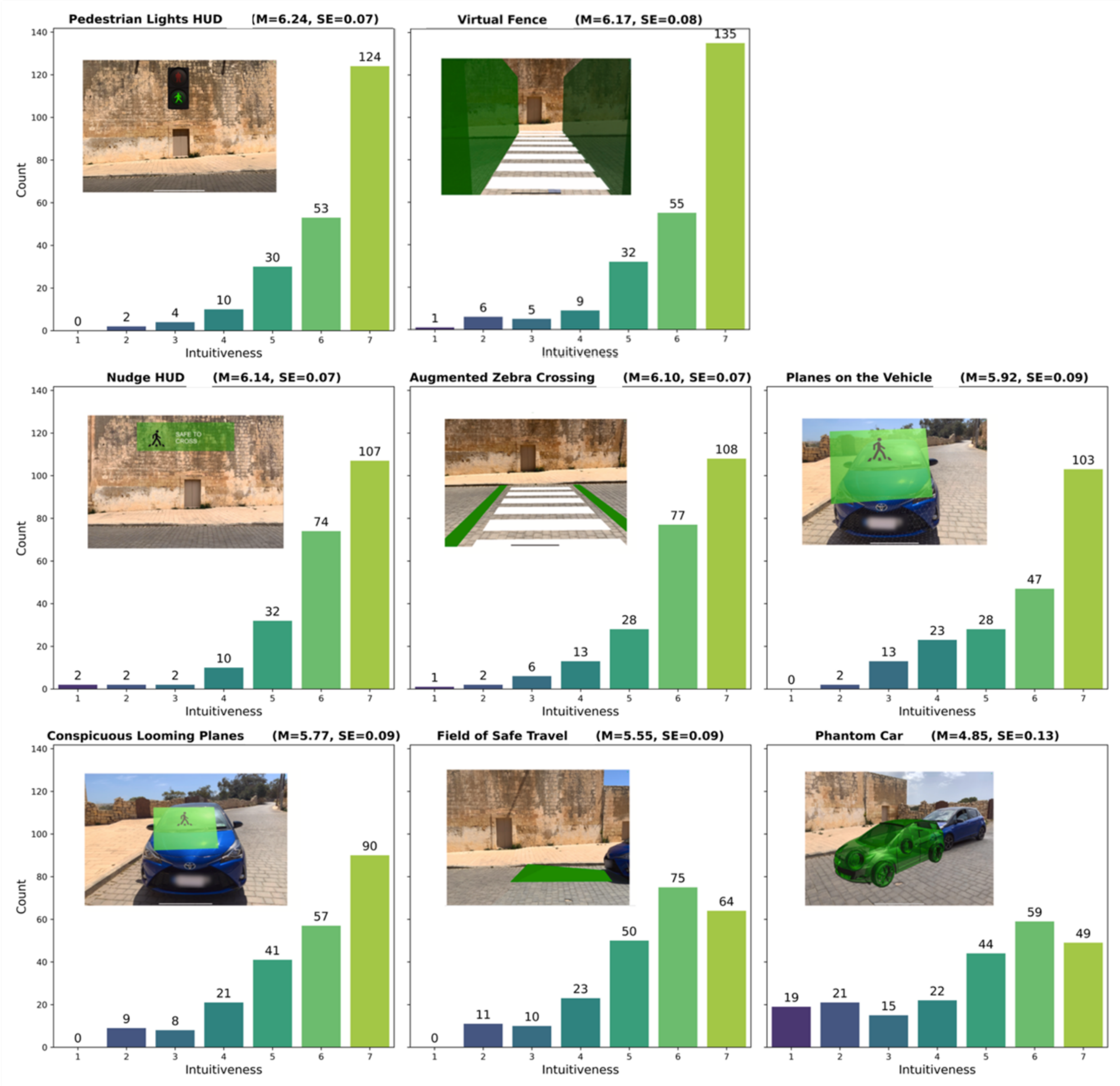


Figure 6.7. The distribution of intuitiveness ranking for each AR concept, in descending order based on their mean intuitiveness scores.

Participant ratings reveal mean intuitiveness scores ranging from 4.85 to 6.24. Higher-scoring AR designs exhibit concentrated ratings within the higher range (scores of 5 to 7) whereas designs with lower scores display broader distributions, with notable ratings in the lower range (scores of 1 to 3). The 'Pedestrian Lights HUD' AR design achieved the highest average intuitiveness score of 6.24, followed closely by 'Virtual Fence' at 6.17 and ‘Nudge HUD’ at 6.14. Conversely, the 'Phantom Car' design received the lowest mean score of 4.85 and demonstrated a higher SE (0.13), suggesting variability in participant responses, potentially indicating confusion or divided opinions regarding its effectiveness.

Results in Section 4.3.2 have shown how pedestrians’ change in fixation duration relate to intuitiveness rankings and AR locations. To provide a detailed examination, **Figure 6.8** illustrates the relationship between mean intuitiveness ranking and changes in fixation duration for each AR design. The designs are classified into three location categories: Car Path (orange boundary), Crossing Path (green boundary), and HUD (pink boundary). The results show a clear trend where higher intuitiveness rankings are linked with greater reductions in fixation duration, suggesting that more intuitive AR designs can enhance pedestrian-AV communication by reducing visual demands and facilitating efficient interaction.

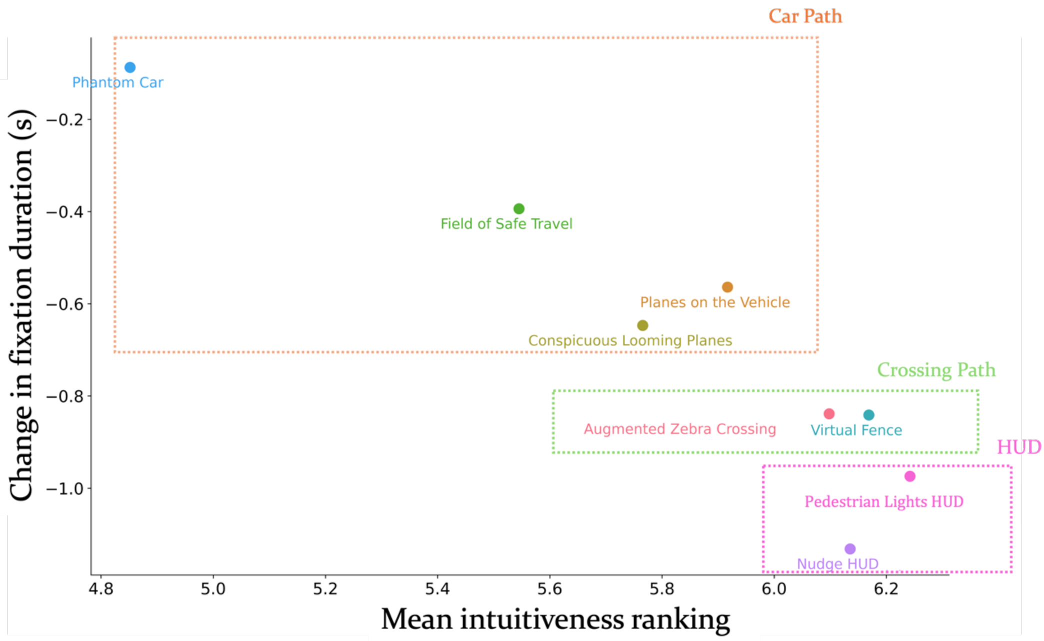


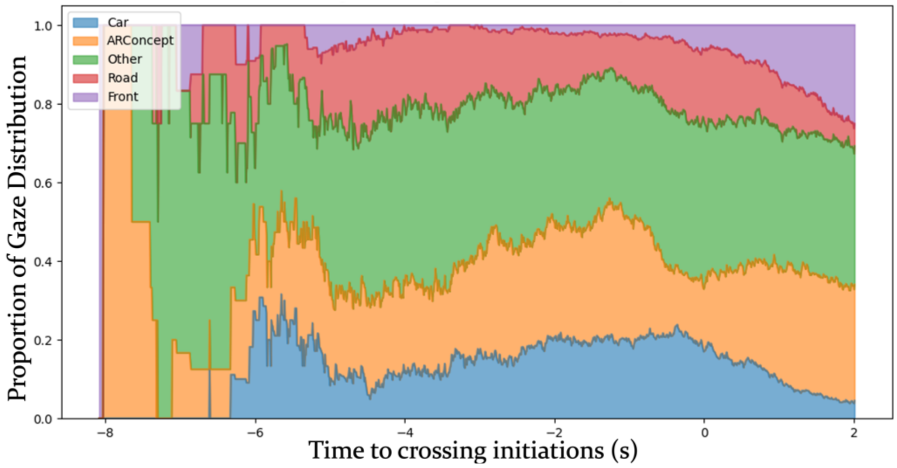
Figure 6.8. Relationship between mean intuitiveness ranking and change in fixation duration (s) for each AR design.

Appendix G Gaze distribution

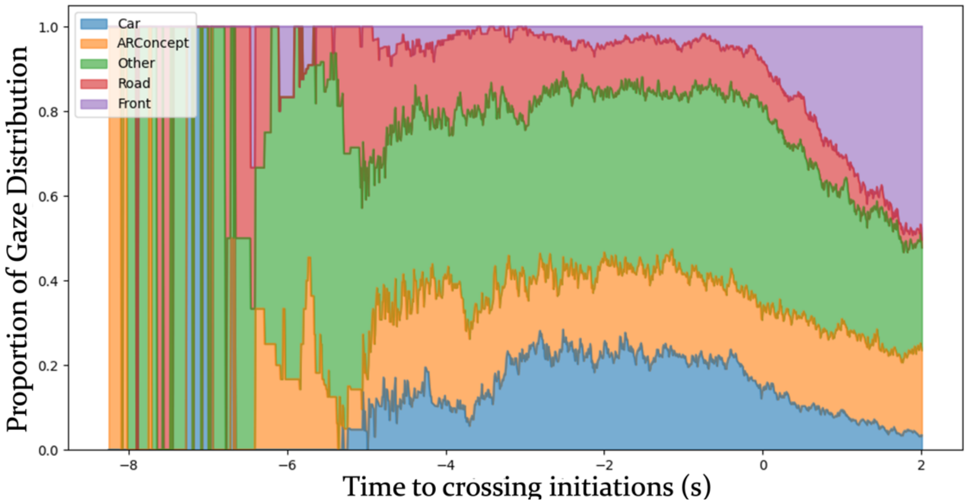
One of the key metrics for analysing gaze behaviour is the distribution percentage, representing how much gaze is allocated to different Areas of Interest (AOIs). In this research, the relevant AOIs have been identified in Section 4.2.1, including AR concepts and the car body. Additionally, this section provides supplementary data on gaze percentage, including gaze on the road (the surface on the ground, regardless of its distance from pedestrians), the front of pedestrians (the screen directly in their line of sight as they intended to cross), and "Other" for all remaining areas. **Figure 6.9** illustrates gaze distribution across these AOIs for the four AR locations, in relation to the time before crossing initiation, to examine how visual resources are allocated for crossing decisions.

As information from the AR and vehicle is crucial for crossing decisions, the combined gaze allocation on these two AOIs increases steadily, peaking around -6 and -2 seconds before crossing initiation in the AR HUD and Crossing Path conditions. In contrast, the combined gaze distribution on these AOIs in the Car Path and Baseline conditions peaks later, between -2 and 0 seconds before crossing initiation. These patterns align with the distance-based design strategy outlined in the main body of this work.

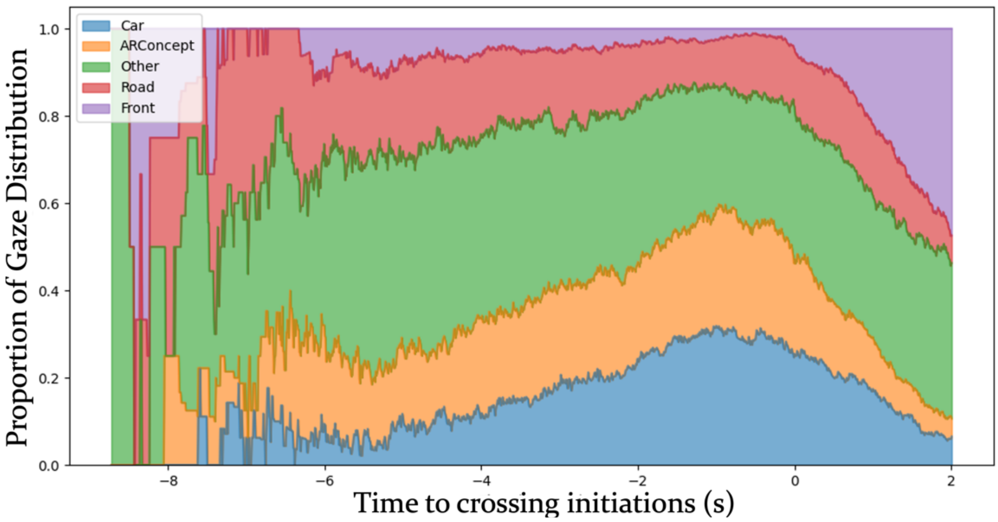
AR Location: Crossing Path



AR Location: HUD



AR Location: Car Path



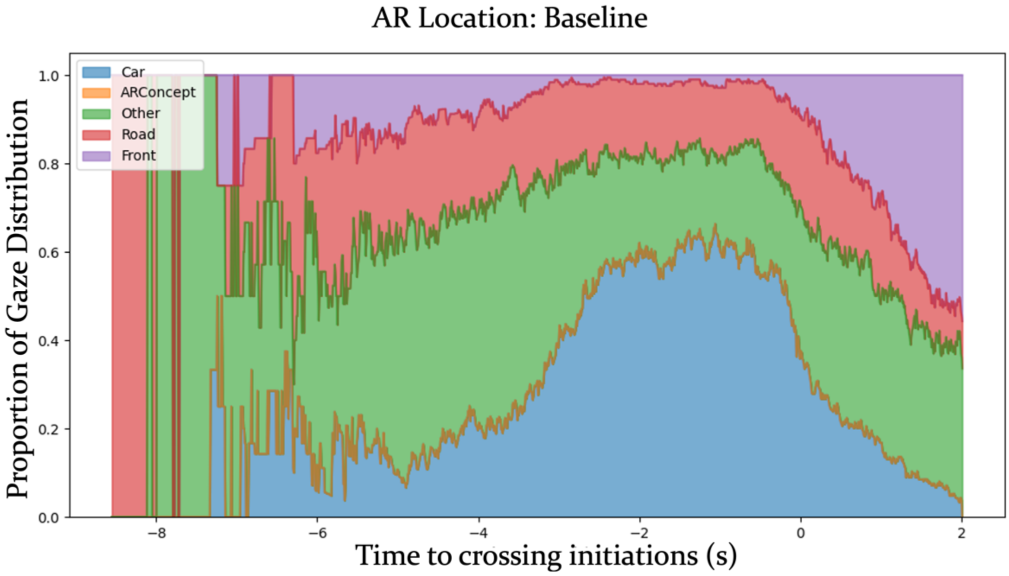


Figure 6.9. Gaze distribution across AOIs over time before crossing initiation for four AR locations, from top to bottom: Crossing Path, HUD, Car Path, and Baseline.

6.4 REFERENCES

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