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# Using distributed simulations to investigate driver-pedestrian interactions and kinematic cues: Implications for automated vehicle behaviour and communication

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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 were 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

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can assist pedestrian decisions, adding new knowledge in the development of human-like behaviour for future AVs.

## 1. Introduction

Technological advancements in driving systems are paving the way for the imminent arrival of highly automated vehicles (HAVs, Level 3 and 4, 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 can not 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. 2019). 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 and 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., 2020), 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 (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., 2021; Risto et al., 2017; Schneemann and 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

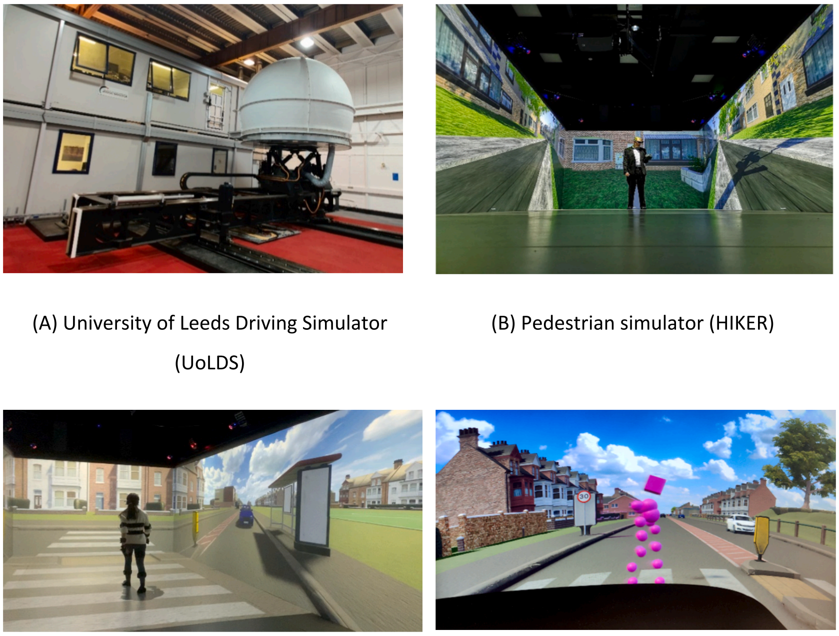
(Bazilinskyy et al., 2022; Kalantari et al., 2023; Kearney et al., 2020; Lyu et al., 2021; Mok et al., 2022; Sadraei et al., 2020). For example, using data from the same study, Kalantari et al. (2023) examined how the initial timing gap between pedestrians and drivers and the crossing locations influence 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; Nuñez 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, Krems, & Kiesel, 2022; de Clercq, Dietrich, Núñez Velasco, de Winter, & Happee, 2019; Hochman, Parmet, & Oron-Gilad, 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), fewer head turns (Yang et al., 2024), 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.

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?



(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)

**Fig. 1.** Set up of the distributed simulation, showing the pedestrian in the HIKER and the drivers' view of the pedestrian.

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. Method

### 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. Apparatus and the virtual environment

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; 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 (Fig. 1A). The CAVE-based pedestrian simulator (the Highly Immersive Kinematic Experimental Research or HIKER pedestrian laboratory), provides a 9 m long × 4 m wide walking area. Virtual scenes are projected on the floor and four glass walls (Fig. 1B).

For pedestrian detection, a body tracking suit, equipped with fourteen body markers, was worn along with a pair of stereoscopic motion-tracking glasses (Fig. 1C). 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) (Fig. 1D).

### 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 m, 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 Fig. 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 Fig. 1C and Fig. 1D).

Pedestrians were asked to cross the road either at a zebra crossing, or at an unsignalized section (see Fig. 2), in response to an auditory cue. 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

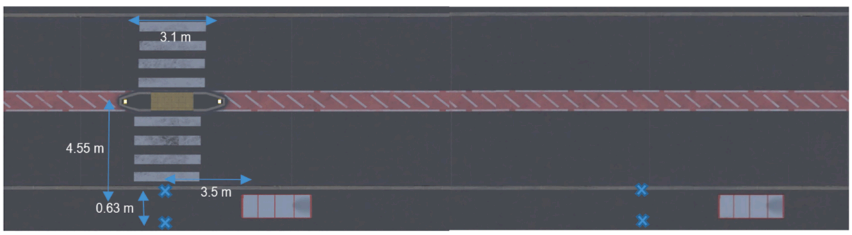



**Fig. 2.** A bird's eye view of the road, developed using Unity, illustrating the pedestrian crossing location: with zebra crossing (left two blue crosses) and without zebra crossing (right two blue crosses). The bottom cross was used to align the standing position for all pedestrians, who were hidden 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. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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.

### *2.4. 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 Fig. 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).

### *2.5. 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 s. Each of these scenarios was repeated four times, and the sequence of encounters (1st /2nd /3rd /4th) 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 Fig. 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 (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

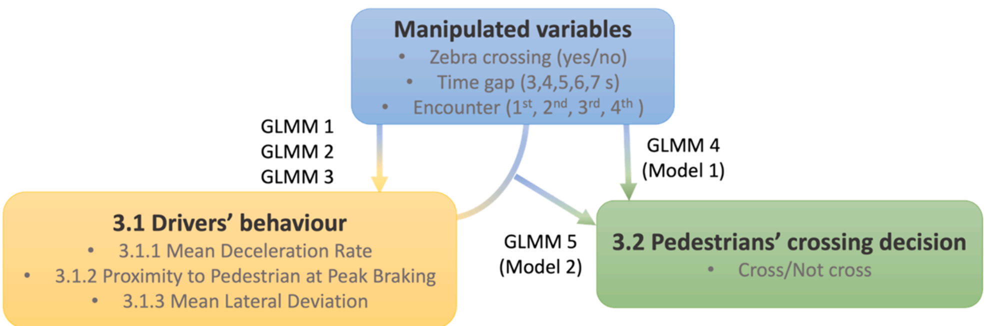



**Fig. 3.** Procedure used for the data analysis.Drivers' behaviour and pedestrians' crossing decisions are reported in section 3.1 and 3.2, respectively.

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. 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 (Fig. 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.

## 3. Results

### 3.1. Drivers' behaviour

#### 3.1.1. Mean deceleration rate

As shown in Table 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 ($p < 0.001$) (Fig. 4).

Drivers' average deceleration rates across different time gaps were visualized using a violin plot (Fig. 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 Fig. 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 $m/s^2$ at 6 s and 0.042 $m/s^2$ at the 7 s time gaps. Meanwhile, a bimodal distribution was identified when the time gap was smaller than 5 s. Drivers showed two

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

| | **Driver Behaviour** | | | | |
|---|---|---|---|---|---|
| *Predictors* | *EST* | *SE* | *t* | *CI (L-U)* | *p* |
| | **Deceleration** | | | | |
| 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) | 0.953 |
| | **Proximity to pedestrian at peak braking** | | | | |
| 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) | 0.341 |
| | **Lateral deviation** | | | | |
| 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** |

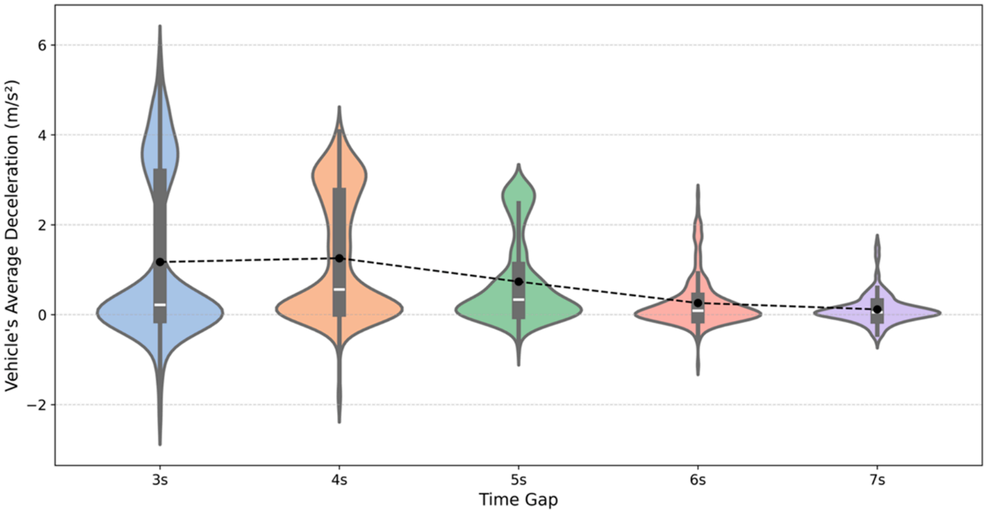



**Fig. 4.** The impact of time gaps on the drivers' average deceleration rate. A bandwidth (bw) setting of 0.2 is applied in the KDE, providing moderate smoothing that enhances the visibility of underlying data trends while smoothing over minor fluctuations. The boxplots show the quartiles, where the 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.

primary deceleration rates at shorter time gaps: these were close to 0.053 $m/s^2$ and 3.61 $m/s^2$ at 3 s, approximately 0.17 $m/s^2$ and 3.00 $m/s^2$ at 4 s, and around 0.16 $m/s^2$ and 2.59 $m/s^2$ at 5 s.

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

### *3.1.2. 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 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 ($p < 0.001$) (Fig. 5). Additionally, as shown in Fig. 5, as the time gap increased, the spread of the vehicles' proximity to pedestrian at peak braking became wider (generally indicating more variability).

### *3.1.3. Mean lateral deviation*

The GLMM analysis (Table 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,

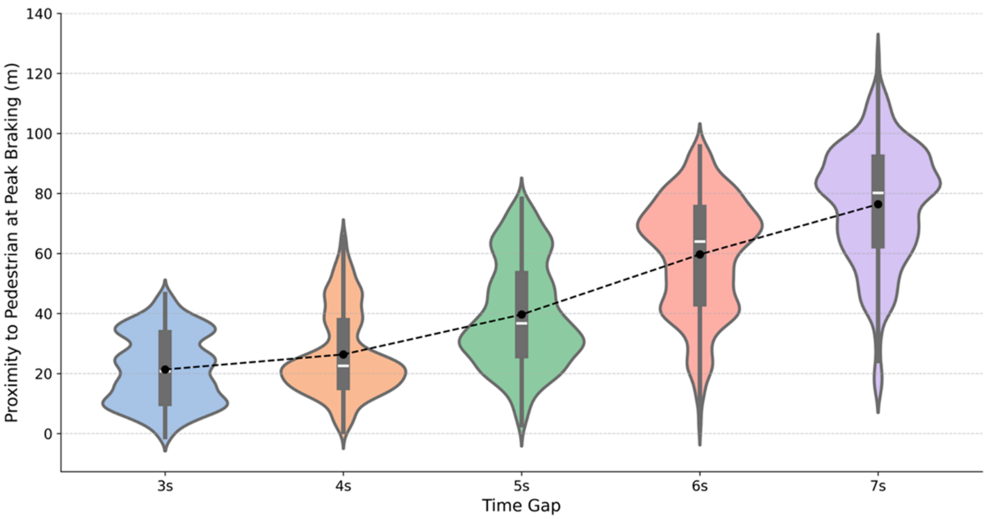



**Fig. 5.** The violins and box plots show the impact of time gaps on drivers' average proximity to pedestrian at peak braking.

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.

### 3.2. Pedestrians' crossing decisions

Data from Table 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 (Fig. 6A), whereby larger approaching time gaps continued to be associated with a significantly higher likelihood of crossings by pedestrians ($p < 0.001$), 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 (Fig. 6A). The likelihood of pedestrians crossing also increased with the number of encounters, especially for the 3 and 4 s time gaps (Fig. 6B).

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, $p < 0.001$). Fig. 7A 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 Fig. 7B, 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, $p < 0.001$). 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 Fig. 7C. 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 ($p < 0.001$), with a mean lateral deviation of 0.24 m (SE=0.01), compared to when pedestrians crossed (M=0.15 m, SE=0.02).

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

| | Pedestrian Crossing Decision | | | | | |
|---|---|---|---|---|---|---|
| *Predictors* | *EST* | *SE* | *z value* | *Odd Ratio* | *p* | *CI (L-U)* |
| | **Model 1** | | | | | |
| (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 | 720.098 | | | | | |
| | **Model 2** | | | | | |
| (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 | | | | | |

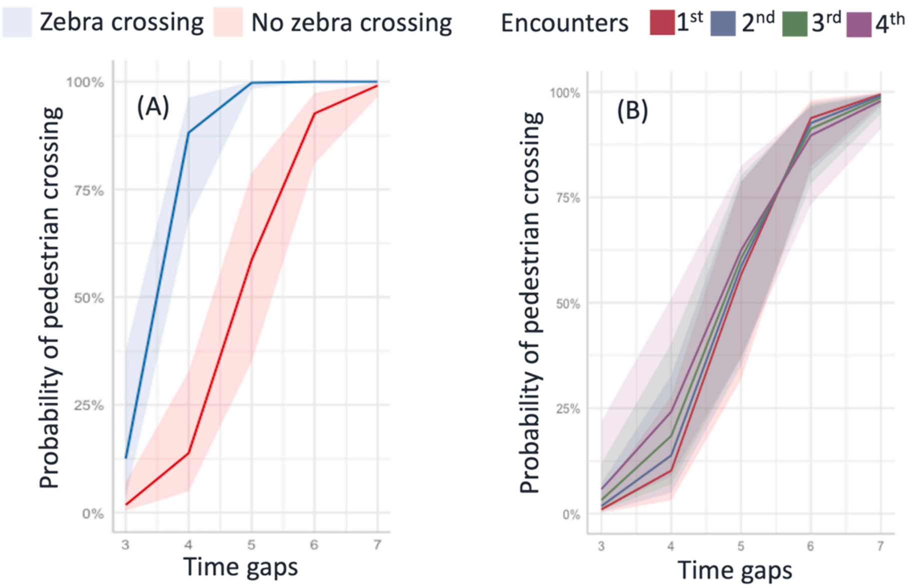



Fig. 6. Predicted probabilities of pedestrians crossing as a function of (A) zebra crossings and time gaps (B) time gaps and encounters. The shaded area represent 95% confidence intervals.

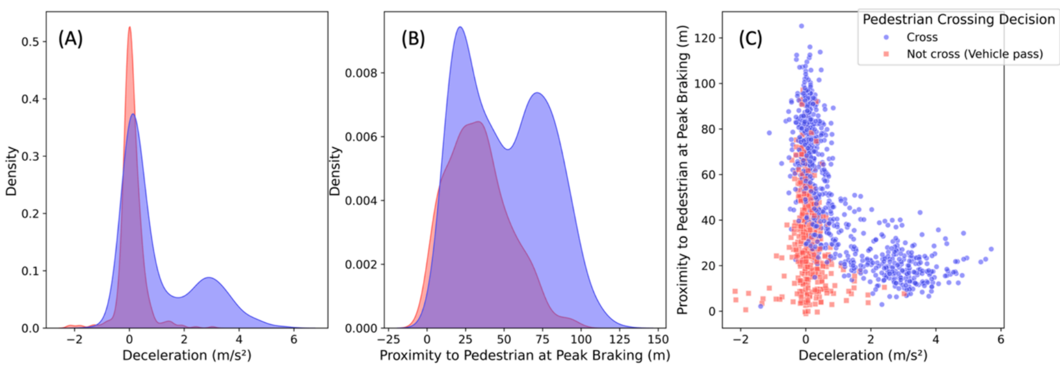



Fig. 7. Visualisations of vehicle's kinematics and pedestrian crossing decisions (A) The distribution of the vehicle's deceleration rate when pedestrians crossed (blue) and pedestrian did not cross (vehicle passed first, red). (B) The distribution of the vehicle's proximity to pedestrian at peak braking 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, categorized by pedestrian's crossing decision.

## 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 proritise 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 A), 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 A). This deceleration pattern was accompanied by a simultaneous lateral shift towards pedestrians (Appendix B). However, in the absence of zebra crossings, drivers showed softer deceleration and their peak braking occurred earlier (Appendix A), while shifting laterally away from pedestrians at the same time (Appendix 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 & 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 (Lee et al., 2022; Madigan et al., 2023; Nuñez Velasco et al. 2019; Tian et al., 2023), 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 s, 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), 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 s, 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.

## 5. Limitations

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. 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. Investigating driver response to more anthropomorphic and photorealistic avatars would be interesting in this context.

## 6. 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.

## CRediT authorship contribution statement

**Yue Yang:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yee Mun Lee:** Writing – review & editing, Supervision, Methodology, Investigation, Conceptualization. **Amir Hossein Kalantari:** Writing – review & editing, Methodology, Conceptualization. **Jorge Garcia de Pedro:** Visualization, Software, Methodology. **Anthony Horrobin:** Visualization, Software, Methodology. **Michael Daly:** Visualization, Software, Methodology. **Albert Solernou:** Visualization, Software, Methodology. **Christopher Holmes:** Methodology, Funding acquisition. **Gustav Markkula:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Natasha Merat:** Writing – review & editing, Supervision, Methodology, Funding acquisition.

## Declaration of Competing Interest

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

## Data availability

Data will be made available on request.

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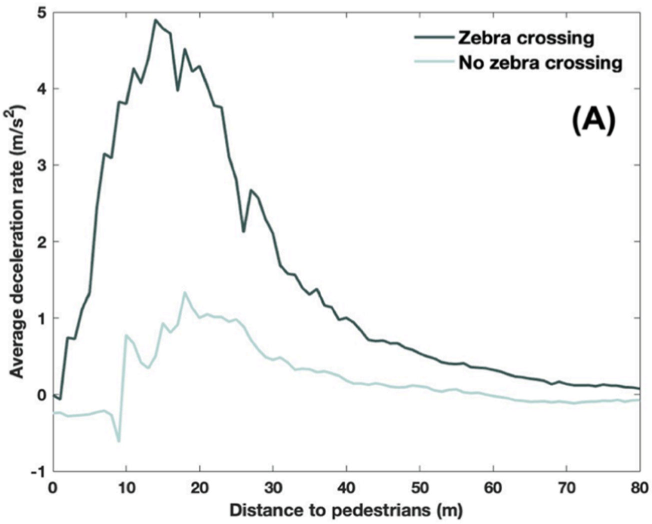
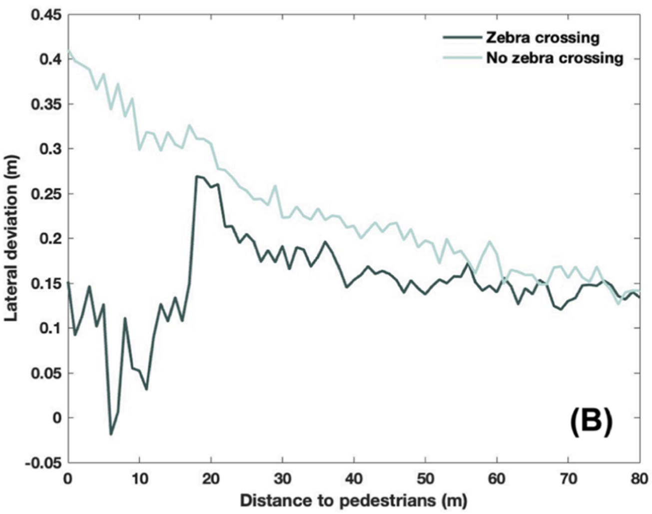
## Appendix

*Appendix A. Driver's average deceleration rates in relation to distances to a crossing pedestrian at different road infrastructures from the raw data*




*Appendix B. Driver's average lateral deviation in relation to distances to a crossing pedestrian at different road infrastructures from the raw data*




## References

Ackermann, C., Beggiato, M., Bluhm, L. F., Löw, A., & Krems, J. F. (2019). Deceleration parameters and their applicability as informal communication signal between pedestrians and automated vehicles. *Transportation Research Part F: Traffic Psychology and Behaviour, 62*, 757–768. https://doi.org/10.1016/j.trf.2019.03.006

Amini, A., Rosman, G., Karaman, S., & Rus, D. (2019). Variational end-to-end navigation and localization. *Proceedings - IEEE International Conference on Robotics and Automation, 2019-May*, 8958–8964. https://doi.org/10.1109/ICRA.2019.8793579.

Angioi, F., & Bassani, M. (2022). The implications of situation and route familiarity for driver-pedestrian interaction at uncontrolled mid-block crosswalks. *Transportation Research Part F: Traffic Psychology and Behaviour, 90*, 287–299. https://doi.org/10.1016/j.trf.2022.09.003

Bazilinskyy, P., Kooijman, L., Dodou, D., Mallant, K., Roosens, V., Middelweerd, M., Overbeek, L., & de Winter, J. (2022). Get Out of The Way! Examining eHMIs in Critical Driver-Pedestrian Encounters in a Coupled Simulator. *Proceedings of the 14th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, 360–371. https://doi.org/10.1145/3543174.3546849.

Beggiato, M., Witzlack, C., & Krems, J. F. (2017). Gap acceptance and time-to-arrival estimates as basis for informal communication between pedestrians and vehicles. *AutomotiveUI 2017 - 9th International ACM Conference on Automotive User Interfaces and Interactive Vehicular Applications, Proceedings*, 50–57. https://doi.org/10.1145/3122986.3122995.

Beggiato, M., Witzlack, C., Springer, S., & Krems, J. (2018). The right moment for braking as informal communication signal between automated vehicles and pedestrians in crossing situations. *Advances in Intelligent Systems and Computing, 597*, 1072–1081. https://doi.org/10.1007/978-3-319-60441-1_101

Bella, F., & Silvestri, M. (2015). Effects of safety measures on driver's speed behavior at pedestrian crossings. *Accident Analysis and Prevention, 83*, 111–124. https://doi.org/10.1016/j.aap.2015.07.016

Bindschädel, J., Krems, I., & Kiesel, A. (2022). Active vehicle pitch motion for communication in automated driving. *Transportation Research Part F: Traffic Psychology and Behaviour, 87*(April), 279–294. https://doi.org/10.1016/j.trf.2022.04.011

Brown, B., Broth, M., & Vinkhuyzen, E. (2023, April 19). The Halting problem: Video analysis of self-driving cars in traffic. *Conference on Human Factors in Computing Systems - Proceedings*. https://doi.org/10.1145/3544548.3581045.

Brown, B., Park, D., Sheehan, B., Shikoff, S., Solomon, J., Yang, J., & Kim, I. (2018). Assessment of human driver safety at Dilemma Zones with automated vehicles through a virtual reality environment. *Systems and Information Engineering Design Symposium (SIEDS), 2018*, 185–190.

Budzynski, M., Gobis, A., Guminska, L., Jelinski, L., Kiec, M., & Tomczuk, P. (2021). Assessment of the influence of road infrastructure parameters on the behaviour of drivers and pedestrians in pedestrian crossing areas. *Energies, 14*(12). https://doi.org/10.3390/en14123559

Clamann, M., Aubert, M., & Cummings, M. L. (2017). *Evaluation of vehicle-to-pedestrian communication displays for autonomous vehicles*.

de Clercq, K., Dietrich, A., Núñez Velasco, J. P., de Winter, J., & Happee, R. (2019). External Human-Machine Interfaces on Automated Vehicles: Effects on Pedestrian Crossing Decisions. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 61*(8), 1353–1370. https://doi.org/10.1177/0018720819836343

Dietrich, A., Maruhn, P., Schwarze, L., & Bengler, K. (2020). Implicit Communication of Automated Vehicles in Urban Scenarios: Effects of Pitch and Deceleration on Pedestrian Crossing Behavior. *Advances in Intelligent Systems and Computing, 1026*, 176–181. https://doi.org/10.1007/978-3-030-27928-8_27

Duffy, B. R. (2003). Anthropomorphism and the social robot. *Robotics and Autonomous Systems, 42*(3–4), 177–190. https://doi.org/10.1016/S0921-8890(02)00374-3

Faas, S. M., Kao, A. C., & Baumann, M. (2020). A Longitudinal Video Study on Communicating Status and Intent for Self-Driving Vehicle A- Pedestrian Interaction. *Conference on Human Factors in Computing Systems - Proceedings, 1–14*. https://doi.org/10.1145/3313831.3376484

Fu, R., Li, Z., Sun, Q., & Wang, C. (2019). Human-like car-following model for autonomous vehicles considering the cut-in behavior of other vehicles in mixed traffic. *Accident Analysis and Prevention, 132*(August), Article 105260. https://doi.org/10.1016/j.aap.2019.105260

Fuest, T., Michalowski, L., Traris, L., Bellem, H., & Bengler, K. (2018). Using the Driving Behavior of an Automated Vehicle to Communicate Intentions - A Wizard of Oz Study. *IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC, 2018-Novem*, 3596–3601. https://doi.org/10.1109/ITSC.2018.8569486.

Goodall, N. J. (2021). Comparison of automated vehicle struck-from-behind crash rates with national rates using naturalistic data. *Accident Analysis and Prevention, 154*. https://doi.org/10.1016/j.aap.2021.106056

Guéguen, N., Meineri, S., & Eyssartier, C. (2015). A pedestrian's stare and drivers' stopping behavior: A field experiment at the pedestrian crossing. *Safety Science, 75*, 87–89. https://doi.org/10.1016/j.ssci.2015.01.018

Harrell, F. E. (2001). *Regression modeling strategies: with applications to linear models, logistic regression, and survival analysis, 608*. Springer.

Havard, C., & Willis, A. (2012). Effects of installing a marked crosswalk on road crossing behaviour and perceptions of the environment. *Transportation Research Part F: Traffic Psychology and Behaviour, 15*(3), 249–260. https://doi.org/10.1016/j.trf.2011.12.007

Highway Traffic Safety Administration, N., & Department of Transportation, U. (2015). *TRAFFIC SAFETY FACTS Crash • Stats Critical Reasons for Crashes Investigated in the National Motor Vehicle Crash Causation Survey*.

Hochman, M., Parmet, Y., & Oron-Gilad, T. (2020). Pedestrians' Understanding of a Fully Autonomous Vehicle's Intent to Stop: A Learning Effect Over Time. *Frontiers in Psychology, 11*(December), 1–11. https://doi.org/10.3389/fpsyg.2020.585280

Huang, C.-M., & Mutlu, B. (2013). The Repertoire of Robot Behavior: Designing Social Behaviors to Support Human-Robot Joint Activity. *Journal of Human-Robot. Interaction, 2*(2). https://doi.org/10.5898/jhri.2.2.huang

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An introduction to statistical learning* (Vol. 112). Springer.

Kalantari, A. H., Yang, Y., Garcia de Pedro, J., Lee, Y. M., Horrobin, A., Solernou, A., Holmes, C., Merat, N., & Markkula, G. (2023). Who goes first? A distributed simulator study of vehicle–pedestrian interaction. *Accident Analysis & Prevention, 186*, Article 107050. https://doi.org/10.1016/j.aap.2023.107050

Kearney, J. K., Plumert, J. M., Schwarz, C., Baek, S., O'Neal, E., Wang, W., McGehee, D. V, & Beckwin, D. (2020). *Learning About Driver and Pedestrian Behaviors Through Connected Simulation Technology*. United States. Federal Highway Administration.

Kolekar, S., de Winter, J., & Abbink, D. (2020). Human-like driving behaviour emerges from a risk-based driver model. *Nature Communications, 11*(1). https://doi.org/10.1038/s41467-020-18353-4

Lee, Y. M., Madigan, R., Giles, O., Garach-Morcillo, L., Markkula, G., Fox, C., Camara, F., Rothmueller, M., Vendelbo-Larsen, S. A., Rasmussen, P. H., Dietrich, A., Nathanael, D., Portouli, V., Schieben, A., & Merat, N. (2021). Road users rarely use explicit communication when interacting in today's traffic: Implications for automated vehicles. *Cognition, Technology and Work, 23*(2), 367–380. https://doi.org/10.1007/s10111-020-00635-y

Lee, Y. M., Madigan, R., Uzondu, C., Garcia, J., Romano, R., Markkula, G., & Merat, N. (2022). Learning to interpret novel eHMI: The effect of vehicle kinematics and eHMI familiarity on pedestrian' crossing behavior. *Journal of Safety Research, 80*(January 2022), 270–280. https://doi.org/10.1016/j.jsr.2021.12.010

Lee, Y. M., Uttley, J., Solernou, A., Giles, O., Romano, R., Markkula, G., & Merat, N. (2020). *Investigating Pedestrians' Crossing Behaviour During Car Deceleration Using Wireless Head Mounted Display: An Application Towards the Evaluation of eHMI of Automated Vehicles*. 252–258. https://doi.org/10.17077/drivingassessment.1703.

Litman, T. (2021). *Autonomous Vehicle Implementation Predictions Implications for Transport Planning*.

Lyu, W., Lee, Y. M., Uzondu, C., Madigan, R., Gonçalves, R. C., de Pedro, J. G., Romano, R., & Merat, N. (2021). *A distributed simulation study to investigate pedestrians' head-turning behaviour when crossing in response to automated and human-driven vehicles displaying different braking patterns*.

Madigan, R., Mun Lee, Y., Lyu, W., Horn, S., Garcia de Pedro, J., & Merat, N. (2023). Pedestrian interactions with automated vehicles: Does the presence of a zebra crossing affect how eHMIs and movement patterns are interpreted? *Transportation Research Part F: Traffic Psychology and Behaviour, 98*, 170–185. https://doi.org/10.1016/j.trf.2023.09.003

Madigan, R., Nordhoff, S., Fox, C., Ezzati Amini, R., Louw, T., Wilbrink, M., Schieben, A., & Merat, N. (2019). Understanding interactions between Automated Road Transport Systems and other road users: A video analysis. *Transportation Research Part F: Traffic Psychology and Behaviour, 66*, 196–213. https://doi.org/10.1016/j.trf.2019.09.006

Mok, C. S., Bazilinskyy, P., & de Winter, J. (2022). Stopping by looking: A driver-pedestrian interaction study in a coupled simulator using head-mounted displays with eye-tracking. *Applied Ergonomics, 105*. https://doi.org/10.1016/j.apergo.2022.103825

Nuñez Velasco, J. P., Farah, H., van Arem, B., & Hagenzieker, M. P. (2019). Studying pedestrians' crossing behavior when interacting with automated vehicles using virtual reality. *Transportation Research Part F: Traffic Psychology and Behaviour, 66*, 1–14. https://doi.org/10.1016/j.trf.2019.08.015

Olivier, A. H., Marin, A., Crétual, A., Berthoz, A., & Pettré, J. (2013). Collision avoidance between two walkers: Role-dependent strategies. *Gait and Posture, 38*(4), 751–756. https://doi.org/10.1016/j.gaitpost.2013.03.017

Özkan, T., Lajunen, T., Chliaoutakis, J. E., Parker, D., & Summala, H. (2006). Cross-cultural differences in driving behaviours: A comparison of six countries. *Transportation Research Part F: Traffic Psychology and Behaviour, 9*(3), 227–242. https://doi.org/10.1016/j.trf.2006.01.002

Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2000). A model for types and levels of human interaction with automation - Systems, Man and Cybernetics, Part A, IEEE Transactions on. *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans, 30*(3), 1–12. papers3://publication/uuid/E9417351-236C-4C2B-821D-F874BB6215A8.

Petzoldt, T. (2014). On the relationship between pedestrian gap acceptance and time to arrival estimates. *Accident Analysis and Prevention, 72*, 127–133. https://doi.org/10.1016/j.aap.2014.06.019

Risto, M., Emmenegger, C., Vinkhuyzen, E., Cefkin, M., & Hollan, J. (2017). *Human-Vehicle Interfaces: The Power of Vehicle Movement Gestures in Human Road User Coordination. January*, 186–192. https://doi.org/10.17077/drivingassessment.1633.

Rothenbucher, D., Li, J., Sirkin, D., Mok, B., & Ju, W. (2016). Ghost driver: A field study investigating the interaction between pedestrians and driverless vehicles. *25th IEEE International Symposium on Robot and Human Interactive Communication. RO-MAN, 2016*, 795–802. https://doi.org/10.1109/ROMAN.2016.7745210

Sadraei, E., Romano, R., Merat, N., De Pedro, J. G., Lee, Y. M., Madigan, R., Uzondu, C., Lyu, W., & Tomlinson, A. (2020). Vehicle-pedestrian interaction: A distributed simulation study. *Actes (IFSTTAR), September*, 147–154.

Schmidt, H., Terwilliger, J., AlAdawy, D., & Fridman, L. (2020). *Hacking Nonverbal Communication between Pedestrians and Vehicles in Virtual Reality*. 78–84. https://doi.org/10.17077/drivingassessment.1678.

Schneemann, F., & Gohl, I. (2016). Analyzing driver-pedestrian interaction at crosswalks: A contribution to autonomous driving in urban environments. *IEEE Intelligent Vehicles Symposium, Proceedings*, *2016-Augus*(Iv), 38–43. https://doi.org/10.1109/IVS.2016.7535361.

Simpson, G., Johnston, L., & Richardson, M. (2003). An investigation of road crossing in a virtual environment. *Accident Analysis and Prevention, 35*(5), 787–796. https://doi.org/10.1016/S0001-4575(02)00081-7

Sripada, A., Bazilinskyy, P., & de Winter, J. (2021). Automated vehicles that communicate implicitly: Examining the use of lateral position within the lane. *Ergonomics*, 1–12. https://doi.org/10.1080/00140139.2021.1925353

Sucha. (2014). Road users' strategies and communication: Driver-pedestrian interaction. *Transport Research Arena (TRA), 12*.

Tian, K., Markkula, G., Wei, C., Sadraei, E., Hirose, T., Merat, N., & Romano, R. (2022). Impacts of visual and cognitive distractions and time pressure on pedestrian crossing behaviour: A simulator study. *Accident Analysis and Prevention, 174*. https://doi.org/10.1016/j.aap.2022.106770

Tian, K., Tzigieras, A., Wei, C., Lee, Y. M., Holmes, C., Leonetti, M., Merat, N., Romano, R., & Markkula, G. (2023). Deceleration parameters as implicit communication signals for pedestrians' crossing decisions and estimations of automated vehicle behaviour. *Accident Analysis and Prevention, 190*. https://doi.org/10.1016/j.aap.2023.107173

Várhelyi, A. (1998). Drivers' speed behaviour at a zebra crossing: A case study. *Accident Analysis and Prevention, 30*(6), 731–743. https://doi.org/10.1016/S0001-4575(98)00026-8

Waytz, A., Heafner, J., & Epley, N. (2014). The mind in the machine: Anthropomorphism increases trust in an autonomous vehicle. *Journal of Experimental Social Psychology, 52*, 113–117. https://doi.org/10.1016/j.jesp.2014.01.005

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).

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. https://doi.org/10.1016/j.trf.2024.04.022

Zhang, H., Guo, Y., Chen, Y., Sun, Q., & Wang, C. (2020). Analysis of pedestrian street-crossing decision-making based on vehicle deceleration-safety gap. *International Journal of Environmental Research and Public Health, 17*(24), 1–13. https://doi.org/10.3390/ijerph17249247