Transportation Research Part F: Psychology and Behaviour 103 (2024) 340–352

Contents lists available at ScienceDirect

Transportation Research Part F: Psychology and Behaviour

journal homepage: www.elsevier.com/locate/trf

Interpreting pedestrians' head movements when encountering automated vehicles at a virtual crossroad

Yue Yang *, Yee Mun Lee, Ruth Madigan, Albert Solernou, Natasha Merat

Institute for Transport Studies, University of Leeds, LS2 9JT, United Kingdom

A R T I C L E I N F O

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

A B S T R A C T

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.

1. Introduction

More than half of the road casualties worldwide involve Vulnerable Road Users (VRUs) (World Health Organization, 2019), 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

* Corresponding author.
E-mail address: tsyy@leeds.ac.uk (Y. Yang).

https://doi.org/10.1016/j.trf.2024.04.022
Received 22 June 2023; Received in revised form 25 January 2024; Accepted 24 April 2024
Available online 30 April 2024
1369-8478/© 2024 The Author(s). Published by Elsevier Ltd. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).

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 (SAE Level 4, 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.

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.

2. Method

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).

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 (Fig. 1). The lab provides a 9 m long × 4 m wide walking space, and the virtual scene is

Fig. 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.

reproduced by eight 4 K 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 Fig. 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.

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 Fig. 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 Fig. 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 s 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.

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 Fig. 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.

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 Fig. 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 min to complete.

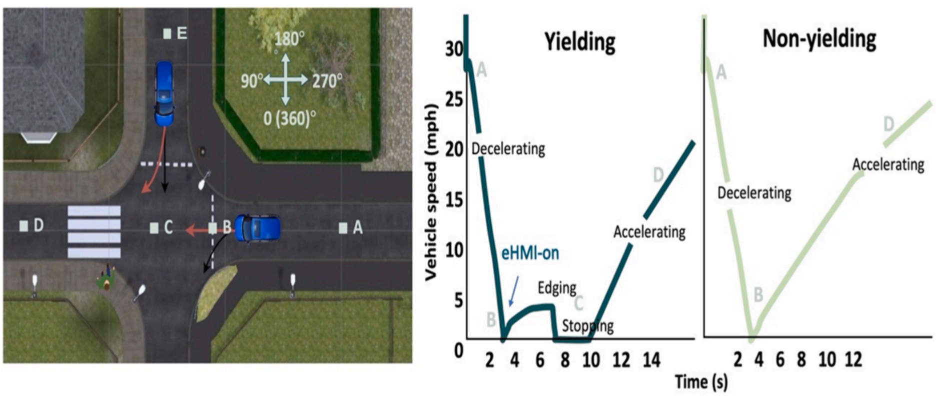

Fig. 2. A birds' eye view of the crossroad (left) and the speed profiles used for the yielding and non-yielding AVs (right). Note that the eHMI onset occurred at the same time as the "edging" behaviour started. The compass in the left figure indicates that the head-turning angle was 180° when pedestrians were facing the front and 270° when turning to the right.

3. Data analysis — measuring head-turning behaviour

Participants wore a pair of stereoscopic motion-tracking glasses (see Fig. 3) to track their head movements, which were captured by 10 VICON Vero v2.2 (2.2MP) cameras at 100 Hz. 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., in Review).

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 3 Hz 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).

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 Fig. 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 1 provides a detailed list of the trials in each condition, also showing the average crossing initiation time (CIT) and crossing duration time (CDT).

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 (Kleinke, 1986; Frischen & Tipper, 2006). 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., in Review), 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. (in Review) 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

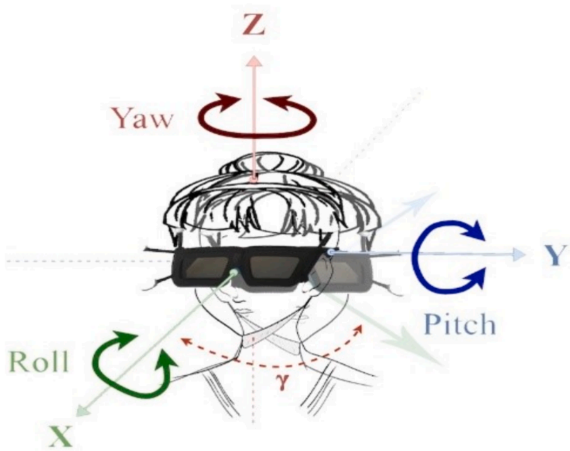

Fig. 3. A schematic of a pedestrian wearing the stereoscopic motion-tracking glasses, showing the three dimensions of the head movement in the HIKER.

Table 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**		

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 %.

3.2. *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 Fig. 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

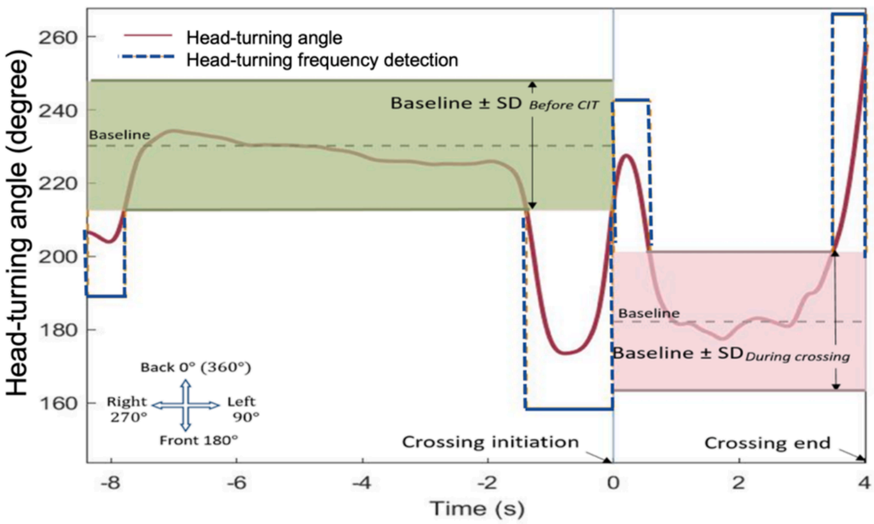

Fig. 4. Example plot of pedestrian's head-turning angle (Pedestrian #1, Block #NoZebra, Trial #26, right-approaching AV yielding without eHMI) plotted in a continuous red line from the start of the trial to the end of the crossing, where the crossing initiation time is the zero point on the x-axis. The 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).

chosen (baseline ± standard deviation – the shaded green area in Fig. 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 Fig. 4). A head turn during the crossing was counted if the head-turning angle was beyond the pink detection area.

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 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 %.

4. Results

4.1. The absolute head-turning rate

As shown in Table 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 Fig. 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.

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 Fig. 5A).

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 Fig. 5B).

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 χ2 (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 Fig. 5C).

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 Fig. 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).

Results from the GLMM model (see Table 3) showed a significant impact of zebra crossing on pedestrians' head-turning frequency

Table 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

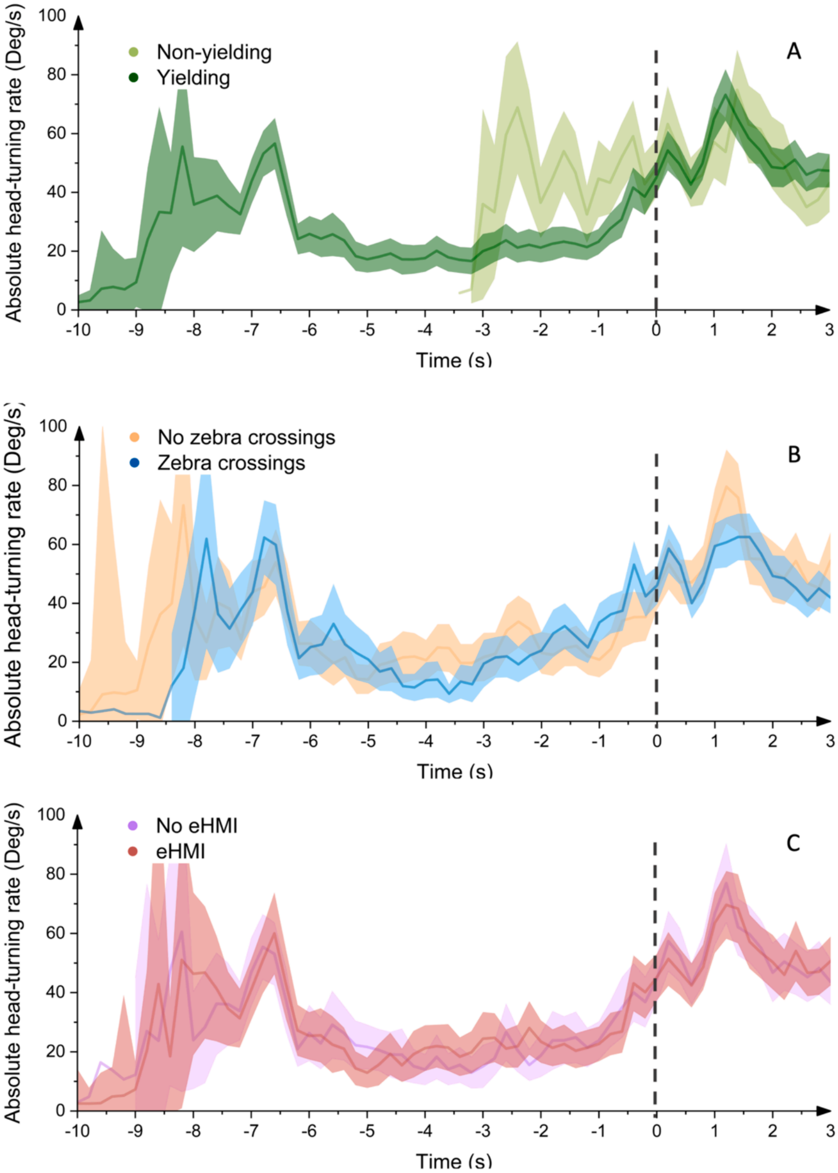

Fig. 5. Pedestrians' absolute head-turning rate with 95% CI in the shaded area across: (A) yielding behaviour, (B) zebra crossing presence/absence, and (C) eHMI presence/absence (yielding trials only). The dashed line at zero indicates crossing initiation times.

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 Fig. 7). The interaction between the number of encounters and eHMI was not significant ($F(1,352) = 3.157$, $p > 0.05$).

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

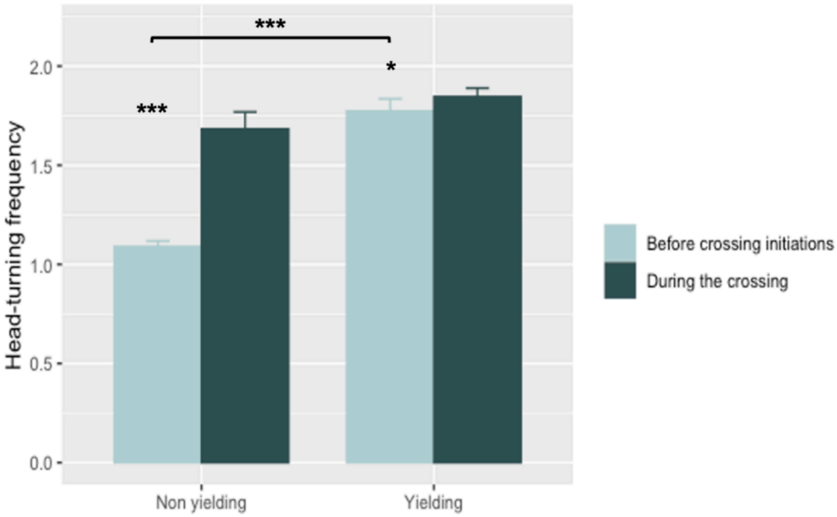

Fig. 6. Pedestrians' head-turning frequency across the yielding behaviour and crossing status. The error bar indicates standard error.

Table 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.

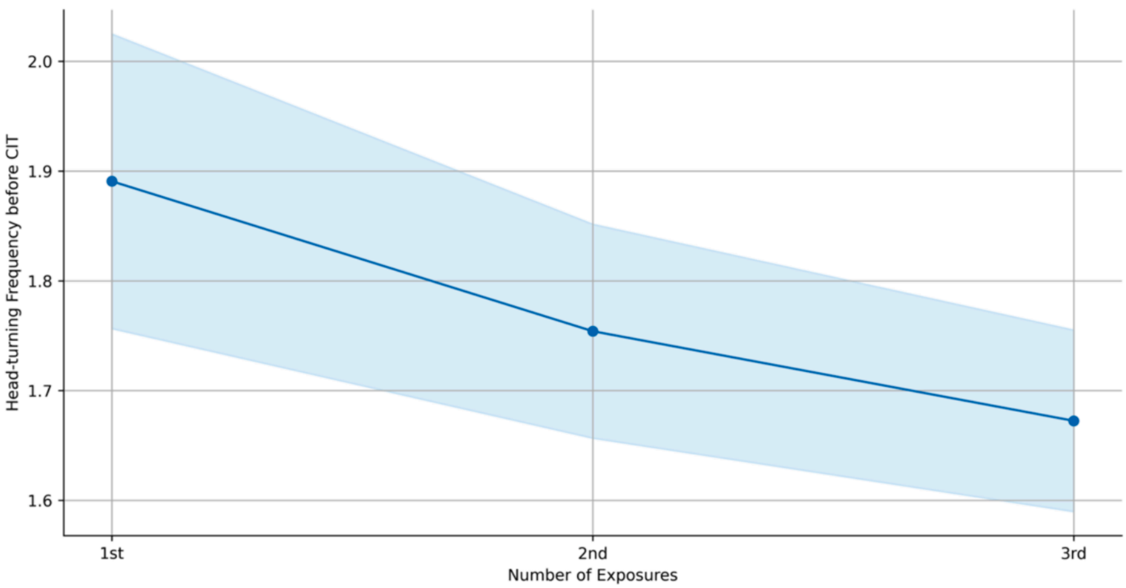

Fig. 7. Pedestrians' head-turning frequency in response to repeated encounters. The shaded area represents the standard error.

repeated exposures to the approaching AVs.

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 Fig. 5A-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., in Review). 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.

5.2. Factors influencing pedestrians' head-turning behaviour

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 (Fig. 5A), 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, Aubert, & Cummings, 2017; Havard & Willis, 2012; Sakamoto et al., 2019; Velasco, Farah, van Arem, & Hagenzieker, 2019), and further illustrate how head turns can serve as an indicator of confidence in decision-making during crossing events.

5.3. The impact of an eHMI and learning effects on head-turning behaviour

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 Fig. 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).

6. 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.

7. 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.

CRediT authorship contribution statement

Yue Yang: Conceptualization, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – original draft. **Yee Mun Lee:** Conceptualization, Investigation, Methodology, Supervision, Validation, Visualization, Writing – review & editing. **Ruth Madigan:** Conceptualization, Methodology, Validation, Visualization. **Albert Solernou:** Software, Visualization. **Natasha Merat:** Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing – review & editing.

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.

Acknowledgements

Funding: This work was supported by the interACT project, under the European Union's Horizon 2020 research and innovation programme (Grant agreement No. 723395). The lead author is supported by SHAPE-IT, funded by from the European Union's Marie Skłodowska-Curie project (Grant agreement No 860410).

References

Anderson, J., Kalra, N., Stanley, K., Sorensen, P., Samaras, C., & Oluwatola, O. (2016). Autonomous Vehicle Technology: A Guide for Policymakers. In *Autonomous Vehicle Technology: A Guide for Policymakers*. doi: 10.7249/rr443-2.

Avineri, E., Shinar, D., & Susilo, Y. O. (2012). Pedestrians' behaviour in cross walks: The effects of fear of falling and age. *Accident Analysis and Prevention, 44*(1), 30–34. https://doi.org/10.1016/j.aap.2010.11.028

Bazilinskyy, P., Dodou, D., & de Winter, J. (2019). Survey on eHMI concepts: The effect of text, color, and perspective. *Transportation Research Part F: Traffic Psychology and Behaviour, 67*, 175–194. https://doi.org/10.1016/j.trf.2019.10.013

Carsten, O., & Martens, M. H. (2019). How can humans understand their automated cars? HMI principles, problems and solutions. *Cognition, Technology and Work, 21*(1), 3–20. https://doi.org/10.1007/s10111-018-0484-0

Clamann, M., Aubert, M., & Cummings, M. (2017). Evaluation of Vehicle-to-Pedestrian Communication Displays for Autonomous Vehicles. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 57*(3), 407–434.

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

de Winter, J., Bazilinskyy, P., Wesdorp, D., de Vlam, V., Hopmans, B., Visscher, J., & Dodou, D. (2021). How do pedestrians distribute their visual attention when walking through a parking garage? *An eye-tracking study. Ergonomics, 64*(6), 793–805. https://doi.org/10.1080/00140139.2020.1862310

Department for Transport. (2020). *Reported road casualties in Great Britain : 2019 annual report. September*, 1–51.

Dey, D., Habibovic, A., Löcken, A., Wintersberger, P., Pfleging, B., Riener, A., Martens, M., & Terken, J. (2020). Taming the eHMI jungle: A classification taxonomy to guide, compare, and assess the design principles of automated vehicles' external human-machine interfaces. *Transportation Research Interdisciplinary Perspectives, 7*. https://doi.org/10.1016/j.trip.2020.100174

Dey, D., Martens, M., Eggen, B., & Terken, J. (2019). Pedestrian road-crossing willingness as a function of vehicle automation, external appearance, and driving behaviour. *Transportation Research Part F: Traffic Psychology and Behaviour, 65*, 191–205. https://doi.org/10.1016/j.trf.2019.07.027

Dey, D., Walker, F., Martens, M., & Terken, J. (2019). Gaze patterns in pedestrian interaction with vehicles: Towards effective design of external human-machine interfaces for automated vehicles. *Proceedings - 11th International ACM Conference on Automotive User Interfaces and Interactive Vehicular Applications, AutomotiveUI 2019*, 369–378. doi: 10.1145/3342197.3344523.

Dietrich, A. T. U. M., Bengler, K., Portouli, E., Nathanael, D., Ruenz, J., Wu, J., Merat, N., Madigan, R., Lee, Y. M., & Markkula, G. (2018). *interACT D. 2.1 Preliminary description of psychological models on human-human interaction in traffic*.

Eisma, Y. B., van Bergen, S., ter Brake, S. M., Hensen, M. T. T., Tempelaar, W. J., & de Winter, J. C. F. (2020). External human-machine interfaces: The effect of display location on crossing intentions and eye movements. *Information (Switzerland), 11*(1). https://doi.org/10.3390/info11010013

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

Frischen, A., & Tipper, S. P. (2006). Long-term gaze cueing effects: Evidence for retrieval of prior states of attention from memory. *Visual Cognition, 14*(3), 351–364. https://doi.org/10.1080/13506280544000192

Geruschat, D. R., Hassan, S. E., & Turano, K. A. (2003). Gaze behavior while crossing complex intersections. *Optometry and Vision Science, 80*(7), 515–528. https://doi.org/10.1097/00006324-200307000-00013

Grasso, R., Bianchi, L., & Lacquaniti, F. (1998). Motor patterns for human gait: Backward versus forward locomotion. *Journal of Neurophysiology, 80*(4), 1868–1885. https://doi.org/10.1152/jn.1998.80.4.1868

Grossman, G. E., Leigh, R. J., Abel, L. A., Lanska, D. J., & Thurston, S. E. (1988). Frequency and velocity of rotational head perturbations during locomotion. *Experimental Brain Research, 70*(3), 470–476. https://doi.org/10.1007/BF00247595

Gruenefeld, U., Virgilio, I., Weiß, S., Kun, A. L., Löcken, A., & Boll, S. (2019). Vroad: Gesture-based interaction between pedestrians and automated vehicles in virtual reality. *Adjunct Proceedings - 11th International ACM Conference on Automotive User Interfaces and Interactive Vehicular Applications, AutomotiveUI 2019*, 399–404. doi: 10.1145/3349263.3351511.

Guo, F., Lyu, W., Ren, Z., Li, M., & Liu, Z. (2022). A Video-Based, Eye-Tracking Study to Investigate the Effect of eHMI Modalities and Locations on Pedestrian-Automated Vehicle Interaction. *Sustainability (Switzerland), 14*(9). https://doi.org/10.3390/su14095633

Hamaoka, H., Hagiwara, T., Tada, M., & Munehiro, K. (2013). A study on the behavior of pedestrians when confirming approach of right/left-turning vehicle while crossing a crosswalk. *IEEE Intelligent Vehicles Symposium, Proceedings, 10*(2011), 106–110. https://doi.org/10.1109/IVS.2013.6629455

Hariyono, J., Shahbaz, A., Kurnianggoro, L., & Jo, H. (2016). Estimation of collision risk for improving driver's safety; Estimation of collision risk for improving driver's safety. In *IECON 2016 - 42nd Annual Conference of the IEEE Industrial Electronics Society*. doi: 10.1109/IECON.2016.7793743.

Hassan, S. E., Geruschat, D. R., & Turano, K. A. (2005). Head movements while crossing streets: Effect of vision impairment. *Optometry and Vision Science, 82*(1), 18–26.

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

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

Hochman, M., Parmet, Y., & Oron-Gilad, T. (2022). Pedestrians' Understanding of a Fully Autonomous Vehicle's Intent to Stop: Utilizing Video-based Crossing Scenarios. *Proceedings of the RSS*.

Holländer, K., Wintersberger, P., & Butz, A. (2019). Overtrust in external cues of automated vehicles: An experimental investigation. *Proceedings - 11th International ACM Conference on Automotive User Interfaces and Interactive Vehicular Applications, AutomotiveUI 2019, September*, 211–221. doi: 10.1145/3342197.3344528.

Hollands, M., Patla, A., & Vickers, J. (2002). 'Look where you're going!': Gaze behaviour associated with maintaining and changing the direction of locomotion. *Experimental Brain Research, 143*(2), 221–230. https://doi.org/10.1007/s00221-001-0983-7

Imai, T., Moore, S. T., Raphan, T., & Cohen, B. (2001). Interaction of the body, head, and eyes during walking and turning. *Experimental Brain Research, 136*(1), 1–18. https://doi.org/10.1007/s002210000533

Kalantarov, S., Riemer, R., & Oron-Gilad, T. (2018). Pedestrians' road crossing decisions and body parts' movements. *Transportation Research Part F: Traffic Psychology and Behaviour, 53*, 155–171. https://doi.org/10.1016/j.trf.2017.09.012

Kaleefathullah, A. A., Merat, N., Lee, Y. M., Eisma, Y. B., Madigan, R., Garcia, J., & de Winter, J. (2020). External Human-Machine Interfaces Can Be Misleading: An Examination of Trust Development and Misuse in a CAVE-Based Pedestrian Simulation Environment. *Human Factors*. https://doi.org/10.1177/0018720820970751

Kaß, C., Schoch, S., Naujoks, F., Hergeth, S., Keinath, A., & Neukum, A. (2020). Standardized test procedure for external human-machine interfaces of automated vehicles. *Information (Switzerland), 11*(3), 1–19. https://doi.org/10.3390/INFO11030173

Kooij, J. F. P., Schneider, N., Flohr, F., & Gavrila, D. M. (2014). Context-based pedestrian path prediction. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 8694 LNCS*(PART 6), 618–633. doi: 10.1007/978-3-319-10599-4_40.

Kwak, J. Y., Ko, B. C., & Nam, J. Y. (2017). Pedestrian intention prediction based on dynamic fuzzy automata for vehicle driving at nighttime. *Infrared Physics & Technology, 81*, 41–51. https://doi.org/10.1016/J.INFRARED.2016.12.014

Lee, Y. M., Madigan, R., Giles, O., Garach-Morcillo, L., & Markkula, G. (2020). Road users rarely use explicit communication when interacting in today ' s traffic : Implications for automated vehicles. *Cognition, Technology & Work, 0123456789*. 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. doi: 10.1016/j.jsr.2021.12.010.

Lee, Y. M., Uttley, J., Solernou, A., Giles, O., Romano, R., Markkula, G., & Merat, N. (2019). Investigating Pedestrians' Crossing Behaviour During Car Deceleration Using Wireless Head Mounted Display: An Application Towards the Evaluation of eHMI of Automated Vehicles. *Proceedings of the 10th International Driving Symposium on Human Factors in Driver Assessment, Training and Vehicle Design: Driving Assessment 2019*, 252–258. doi: 10.17077/drivingassessment.1703.

Liang, K. Y., & Zeger, S. L. (1986). Longitudinal data analysis using generalized linear models. *Biometrika, 73*(1), 13–22. https://doi.org/10.1093/biomet/73.1.13

Liu, H., Hirayama, T., Morales, L. Y., & Murase, H. (2020). *What Is the Gaze Behavior of Pedestrians in Interactions with an Automated Vehicle When They Do Not Understand Its Intentions?* http://arxiv.org/abs/2001.01340.

Löcken, A., Golling, C., & Riener, A. (2019). How should automated vehicles interact with pedestrians? A comparative analysis of interaction concepts in virtual reality. In *Proceedings - 11th International ACM Conference on Automotive User Interfaces and Interactive Vehicular Applications*. https://doi.org/10.1145/3342197.3344544

Lyu, W., Lee, Y. M., Uzondu, C., Madigan, R., Gonçalves, R. C., de Pedro, J. G., Romano, R., & Merat, N. (in Review). *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

Meir, A., & Oron-Gilad, T. (2020). Understanding complex traffic road scenes: The case of child-pedestrians' hazard perception. *Journal of Safety Research, 72*, 111–126. https://doi.org/10.1016/j.jsr.2019.12.014

Melvill Jones, G., Guitton, D., & Berthoz, A. (1988). Changing patterns of eye-head coordination during 6 h of optically reversed vision. *Experimental Brain Research, 69*(3), 531–544. https://doi.org/10.1007/BF00247307

Patla, A. E., Adkin, A., & Ballard, T. (1999). Online steering: Coordination and control of body center of mass, head and body reorientation. *Experimental Brain Research, 129*(4), 629–634. https://doi.org/10.1007/s002210050932

Rasouli, A., Kotseruba, I., & Tsotsos, J. K. (2018). Understanding Pedestrian Behavior in Complex Traffic Scenes. *IEEE Transactions on Intelligent Vehicles, 3*(1), 61–70. https://doi.org/10.1109/TIV.2017.2788193

SAE. (2021). *Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles*.

Sakamoto, D., Francisco Mascarenhas, S., Yannis, G., Raghuram Kadali, B., Robert, L. P., Jr, Kumaar Jayaraman, S., Creech, C., Tilbury, D. M., Jessie Yang, X., Pradhan, A. K., & Tsui, K. M. (2019). *Pede*strian Trust in Automated Vehicles: Role of Traffic Signal and AV Driving Behavior. Frontiers in Robotics and AI | Www. *Frontiersin. Org, 1*, 117. https://doi.org/10.3389/frobt.2019.00117

Schieben, A., Wilbrink, M., Kettwich, C., Madigan, R., Louw, T., & Merat, N. (2019). Designing the interaction of automated vehicles with other traffic participants: Design considerations based on human needs and expectations. *Cognition, Technology and Work, 21*(1), 69–85. https://doi.org/10.1007/s10111-018-0521-z

Stroup, W. W. (2012). *Generalized linear mixed models: Modern concepts, methods and applications*. CRC Press.

Tapiro, H., Borowsky, A., Oron-Gilad, T., & Parmet, Y. (2016). Where do older pedestrians glance before deciding to cross a simulated two-lane road? A pedestrian simulator paradigm. In *Proceedings of the Human Factors and Ergonomics Society* (pp. 11–15). https://doi.org/10.1177/1541931213601003

Tom, A., & Granié, M. A. (2011). Gender differences in pedestrian rule compliance and visual search at signalized and unsignalized crossroads. *Accident Analysis and Prevention, 43*(5), 1794–1801. https://doi.org/10.1016/j.aap.2011.04.012

Velasco, J. P. N., 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

World Health Organization. (2019). *Global status report on road 2018*. World Health Organization.

Young, M. S., & Stanton, N. A. (2004). *Mental workload. In Handbook of human factors and ergonomics methods* (pp. 416–426). CRC Press.