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Explaining unsafe pedestrian road crossing behaviours using a Psychophysics-based gap acceptance model

Kai Tian [a,*], Gustav Markkula [a], Chongfeng Wei [b], Yee Mun Lee [a], Ruth Madigan [a], Natasha Merat [a], Richard Romano [a]

[a] Institute for Transport Studies, University of Leeds, Leeds LS1 9JT, UK
[b] School of Mechanical and Aerospace Engineering, Queen's University Belfast, Belfast BT7 1NN, UK

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ABSTRACT

Accidents involving pedestrians are particularly common at unsignalised intersections and mid-block crosswalks, where vehicles often do not yield to them. Analysing and understanding pedestrian crossing behaviour at such locations is vital for improving road safety. Previous studies have repeatedly shown that pedestrians tend to accept smaller time gaps in conditions with higher vehicle speeds and thus potentially less safe. This has prompted the hypothesis that pedestrians rely on spatial distance to make crossing decisions. However, few studies have investigated the mechanism underpinning this phenomenon. We propose a novel approach to characterise pedestrian crossing behaviour: a psychophysics-based gap acceptance (PGA) model based on visual looming cues and binary choice logit method. Road crossing data collected in a simulated experiment were used to analyse pedestrian behaviour and test the model. Our analysis indicates that, in line with previous studies, higher vehicle speed increased the tendency of gap acceptance, leading to a higher rate of unsafe crossings. Crucially, the PGA model could accurately account for these crossing decisions across experimental scenarios, more parsimoniously than a conventional model. These results explain the speed-induced unsafe behaviour by suggesting that pedestrians apply visual looming, which depends on vehicle speed and distance, to make crossing decisions. This study reinforces the notion that for two vehicles with the same time gap, the one with higher speed can elicit more risky crossing behaviour from pedestrians, potentially resulting in more severe accidents. The practical implications of the results for traffic safety management, modelling and development of automated vehicles are discussed.

1. Introduction

With the increase in the number of vehicles on the roads, there are more and more traffic conflicts between pedestrians and vehicles (Li et al., 2020). Every year, nearly 300,000 pedestrians are killed globally, accounting for 22% of all transport fatalities (World Health Organization, 2018). Pedestrians are generally the most vulnerable road user due to the lack of protective equipment and slow movement compared to vehicles (El Hamdani et al., 2020). Signalised pedestrian crosswalks can effectively address conflicts between pedestrians and vehicles. However, their quantity is strictly limited for traffic efficiency and cost considerations (Pawar and Patil, 2015). Thus, accidents involving pedestrians are especially common at unsignalised and mid-block crosswalks, where vehicles are less likely to yield to pedestrians. Ensuring the safety of pedestrians is a challenge for researchers, because in unsafe environments involving vehicles, especially on crosswalks with no signal, it is not clear how pedestrians make decisions.

Unlike at controlled crosswalks where signal lights organise the crossing behaviour, the crossing behaviour of pedestrians at unsignalised crosswalks is affected by many factors, such as traffic characteristics (Ackermann et al., 2019), road environments (Zhao et al., 2019), pedestrians' psychological factors and demographics (Kalatian and Farooq, 2021). Among those factors, vehicle speed is one of the most critical factors associated with pedestrian safety and has been shown to have a strong correlation with the severity of pedestrian injuries in collisions (Leaf and Preusser, 1999). Not only that, current studies demonstrated that vehicle speed can also affect pedestrians' safety by changing their crossing behaviour, i.e., when compared to a low vehicle speed, pedestrians tend to accept small time gaps in high vehicle speed conditions, called speed-induced unsafe crossing behaviour (Oxley et al.,

* Corresponding author.
E-mail address: tskt@leeds.ac.uk (K. Tian).

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2005; Nuñez Velasco et al., 2019). This issue has impacts in different areas. In traffic safety research, a study by Lobjois and Cavallo 2007 indicated that speed-induced unsafe behaviour has a strong negative effect on the safety of elderly pedestrians. Not only does it affect pedestrians, but also it affects drivers. Schmidt and Färber 2009 suggested that drivers driving at high speed will tend to receive more dangerous crossings from pedestrians, potentially resulting in more accidents. However, few studies have studied the potential decision-making mechanism of this unsafe crossing behaviour specifically. Likewise, very few studies have investigated the correlation between this behaviour and pedestrian crossing safety. Also, it is not clear from the existing literature whether pedestrians may compensate for these smaller accepted time gaps by crossing faster, such that the actual safety margins are not affected by vehicle speed. Furthermore, considering vehicle speed effects on pedestrians is important for traffic modelling; for example, pedestrian crossing decision models applied in traffic micro-simulation or automated driving systems. Better models of pedestrian behaviour can help facilitate the development of better traffic simulation systems or automated vehicles (AVs) (Rasouli and Tsotsos, 2019). Nevertheless, few models have paid attention to the speed-induced unsafe crossing behaviour. Therefore, exploring this unsafe crossing behaviour could have significance for traffic safety management, traffic micro-simulation, and AV development.

In this study, we investigate and model pedestrian crossing behaviour based on a psychophysical mechanism, specifically explaining the speed-induced unsafe crossing behaviour and analysing its safety impacts. Two vital research questions are answered in this study:

(i) How does speed-induced unsafe crossing behaviour affect pedestrian road crossing safety?
(ii) Can we use the proposed psychophysics-based gap acceptance model to describe and interpret speed-induced crossing behaviour?

This paper is organised as follows: Section 1 provides a brief literature review. In Section 2, the proposed model and conventional binary choice gap acceptance model are introduced. Section 3 introduces two empirical datasets of pedestrian road crossing that are used to test these models. Section 4 describes the basic pre-processing and statistical analysis results of the main data. In Section 5, we describe how the PGA model fits the two datasets. Section 6 discusses the research results and their implications for improving traffic safety. Finally, conclusions are recorded in Section 7.

1.1. Pedestrian road crossing gap acceptance

Previous literature has explored several methods of studying and modelling pedestrian crossing behaviour, including pedestrian road-crossing gap acceptance research (Pawar and Patil, 2016; Oxley et al., 2005), pedestrian intention and trajectory prediction research (Hashimoto et al., 2016), communication between pedestrians and vehicles (Lee et al., 2022) and pedestrian motion dynamics modelling (Helbing and Molnar, 1995; Zeng et al., 2014). Among those studies, gap acceptance research aims to investigate and understand pedestrian road-crossing decisions by analysing traffic gap acceptance and rejection, where the gap is defined as the time or spatial distance between two consecutive approaching vehicles. Identifying and quantifying accepted gaps can help understand how pedestrians weigh their safety and efficiency and use different strategies to cross the road. Existing literature found that the gap acceptance behaviour is affected by many factors. These can be roughly categorised as external and internal attributes. External attributes which may affect pedestrian gap acceptance behaviour include vehicle speed (Schmidt and Färber, 2009), time to arrival (TTA) (Avinash et al., 2019; Pawar and Patil, 2016), distance (Lobjois and Cavallo, 2007; Schmidt and Färber, 2009), number of lanes (Chandra et al., 2014), and vehicle size (Beggiato et al., 2017; Lee and Sheppard, 2017). Internal attributes which may have an impact include gender, age (Hulse et al., 2018; Kalatian and Farooq, 2021) and group size (Pawar and Patil, 2015; Avinash et al., 2019).

1.2. Speed-induced unsafe road crossing behaviour

Among the factors mentioned above, common sense might suggest that TTA, i.e., the time available to cross before the vehicle arrives, ought to be the basis for pedestrian gap acceptance (Petzoldt, 2014). However, literature has repeatedly shown that high vehicle speeds negatively impact pedestrians, causing them to make potentially unsafe decisions compared to low vehicle speed conditions, i.e., pedestrians tend to accept smaller time gaps for high vehicle speed conditions (Beggiato et al., 2017; Lobjois and Cavallo, 2007; Oxley et al., 2005; Schmidt and Färber, 2009). This unsafe behaviour is also manifested as more pedestrians crossing the road under the same time gap in high vehicle speed conditions (Schmidt and Färber, 2009). A study conducted in a simulated environment indicated that young and old participants showed speed-induced unsafe behaviour and that the elderly were more severely affected (Lobjois and Cavallo, 2007). In addition to the simulated study, this unsafe behaviour pattern was also found in research based on video recordings (Nuñez Velasco et al., 2019) and field tests (Schmidt and Färber, 2009). Due to this behaviour, pedestrians may make more inappropriate decisions and face a risk of serious injury when interacting with high-speed vehicles (Huang et al., 2018). Moreover, drivers who travel at high speeds tend to receive more dangerous crossings from pedestrians, potentially resulting in more accidents. For a given time gap, higher vehicle speed implies a longer perceived spatial distance. This insight has prompted the hypothesis that pedestrians tend to rely on spatial distance from the oncoming vehicle to make road-crossing decisions (so-called distance dependent decisions) (Lobjois and Cavallo, 2007; Oxley et al., 2005; Schmidt and Färber, 2009). A study from Petzoldt. (2014) suggested that this might occur because pedestrians incorrectly factor speed into their judgment of TTA, and then use this biased TTA as the basis for their crossing decision. Indeed, it is well established that the speed of an approaching object can affect the accuracy of TTA estimates. Observers generally underestimate TTA, and this underestimation becomes more serious when objects approach at lower speeds (Sidaway et al., 1996).

Although the above conclusions are plausible, they do not really provide any information on the psychological mechanisms that cause these decision patterns. It is clear that not only distance but also time gap has an essential effect on gap acceptance behaviour (Oxley et al., 2005; Schmidt and Färber, 2009), but it is not clear from the studies cited above how or why time gap and distance both influence crossing behaviour. This also applies to the TTA estimation error hypothesis; it suggests an intermediate step of TTA estimation but does not explain why both time gap and distance should affect this estimate. Furthermore, one recent study on gap acceptance and TTA estimates from Beggiato et al. (2017) found that speed had different effects on TTA estimation and gap acceptance, casting some doubt on the idea of TTA estimation as an intermediate step towards a gap acceptance decision.

1.3. Collision perception theory for traffic research

The well-established perception theory indicates that as an object moves close to the observer, its increasing image on the observer's retina can cause the observer to perceive it as an approaching object (Gibson, 2014). If its image continues to expand and reaches a certain perceptual threshold, it suggests to the observer that a collision event is imminent (Hoffmann and Mortimer, 1994; Markkula et al., 2016). This phenomenon, called visual looming, has been shown to be critical visual stimuli related to the sense of collision threat and human avoidance behaviour (Gibson, 2014). In traffic safety research, many studies on rear-end collisions have shown that visual looming is a potentially important factor for collision avoidance, and drivers' responses to collision events were in line with a strategy of responding to visual cues, like visual angle or visual looming (Hoffmann and Mortimer, 1994; DeLucia and Tharanathan, 2005; Maddox and Kiefer, 2012; Markkula et al., 2016). These insights suggest that visual cues might provide clues for pedestrians' risky gap acceptance decision patterns. When humans perceive an approaching object, several different visual cues can provide information about the object's distance and movement, e.g., visual angle, expansion rate of the object (also called visual looming) (DeLucia, 2015), and Tau (Lee, 1976). A conceptual framework from DeLucia (2008) suggested that when the tasks happened at a far distance, due to the limitations of the human visual system, the humans tended to use pictorial depth cues (e.g., visual angle) and low order information (e.g., visual looming) to judge the situation. Moreover, several studies indicated that participants (or pedestrians) might judge the movement of the approaching vehicle by using visual cues, like visual looming (Lee and Sheppard, 2017; Ackermann et al., 2019). In short, although the literature on collision perception and rear-end collision studies have shown that humans rely on visual cues to avoid collision events, the situation is less clear regarding the relationship between collision perception and pedestrian road crossing gap acceptance.

2. Methodology

2.1. Visual looming model

Generally, visual looming refers to the expansion in the size of the images on the observer's retina, or the changing rate of the visual angle subtended by the object (Gibson, 2014; Lee, 1976). Based on the definition of looming, its psychophysical model can be derived. Considering an upcoming collision event, as shown in Fig. 1a, there is a rectangular object with length l and width w approaching the observer with a constant speed v(t). The object deviates from the horizontal axis by distance R and subtends a visual angle $\theta(t)$ at point O. The derivative of the $\theta(t)$ with respect to time refers to looming $\dot{\theta}(t)$.

To calculate the looming (Fig. 1a) in the road-crossing scenario, a set of variables are established to constrain the geometrical relationship between the pedestrian and the car, as shown in Fig. 1b. The model only considers the situation with a one-way lane and one vehicle driving at constant speeds to reduce the complexity. The position of the pedestrian is set at the origin of the coordinate axis. The vehicle moves forward with speed $v(t)$, while the pedestrian stands at the curb and waits to cross. w and l refer to the width and length of the vehicle, where w refers to the maximum width of the vehicle front profile. s is the length of the diagonal of the vehicle. $Z(t)$ is the distance between the pedestrian and the vehicle. $\theta(t)$ is the visual angle subtended by the approaching vehicle. R is the lateral distance from the car to the pedestrian. The length of the oa line and oc line are $D(t)$ and $B(t)$. The ∠oac is denoted by $\delta(t)$, which is comprised of angle $\delta_1(t)$ and angle δ_2. As shown in Fig. 1b, the diagonal of the vehicle is:

$$s = \sqrt{w^2 + l^2} \tag{1}$$

Since the lateral distance between pedestrian and vehicle is R, the length of oa line and oc line in Fig. 1b can be formulated as:

$$D(t) = \sqrt{Z(t)^2 + (R + w)^2} \tag{2}$$

$$B(t) = \sqrt{(Z(t) + l)^2 + R^2} \tag{3}$$

To calculate the angle $\delta(t)$, we separate it into two angles $\delta_1(t)$ and δ_2, which can be calculated by the following equations:

$$\delta_1(t) = \arctan\left(\frac{Z(t)}{R + w}\right) \tag{4}$$

$$\delta_2 = \arctan\left(\frac{l}{w}\right) \tag{5}$$

$$\delta(t) = \delta_1(t) + \delta_2 \tag{6}$$

Then, according to the sines rule, the visual angle, $\theta(t)$, in the road-crossing scenario is defined by the following equation:

$$\theta(t) = \arcsin\left(\frac{s \cdot \sin(\delta)}{B}\right) \tag{7}$$

Finally, take the temporal derivative of $\theta(t)$ to get the looming in the road-crossing scenario:

$$\dot{\theta}(t) = -F_1 \cdot \left(F_2 \cdot \frac{1}{R + w} - F_3\right) \cdot v(t) \tag{8}$$

where: $F_1 = 1/\sqrt{1 - (s \cdot \sin(\delta)/B)^2}$, $F_2 = s \cdot \cos(\delta)/(B \cdot (1 + F_4{}^2))$, $F_3 = s \cdot \sin(\delta) \bullet (B^{-1} \bullet (Z + l))/B^2$, $F_4 = Z/(R + w)$. The visual looming is calculated and plotted in Fig. 1c, showing that the visual angle and the

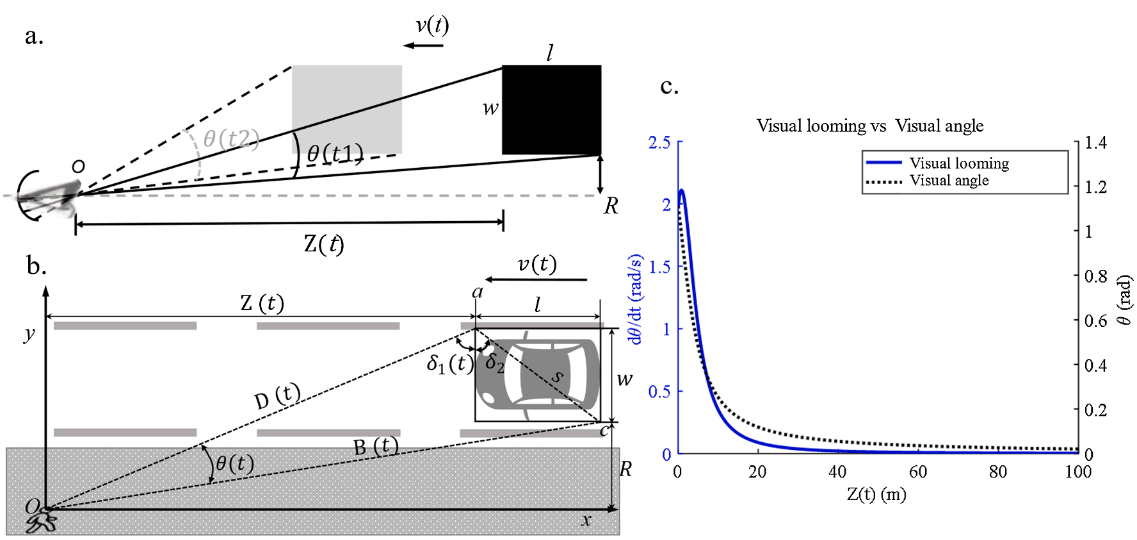


Fig. 1. (a) Looming model. The eye model comprises a semi-circular 'retina' and a pinhole O as 'pupil'. At timestep t_1, an object with speed v moves towards the observer from distance $Z(t)$. The visual angle on the retina at O equals to the angle $\theta(t_1)$ subtended by the object. At timestep t_2, when the object gets closer, the visual angle is $\theta(t_2)$ and the continuous change rate of θ is referred to as the looming$\dot{\theta}(t)$. (b) The looming model adapted to a road-crossing scenario. (c) Visual angle and looming calculated using the parameters, i.e., w = 1.95, l = 4.95, R = 2.45, v = 30 mph.

looming increase slowly as the 30 mph vehicle approaches from 100 m to 20 m distance. However, when the distance is<20 m, the visual angle increases sharply to 1.1 rad, and the looming value exceeds 2 rad/s. Further, the looming starts to decrease again at about 1 m. It can be found that looming has an approximately exponential relationship with the distance and TTA, which is similar to the pedestrian's perceived collision risk in previous studies (Gupta et al., 2009; Zhuang and Wu, 2013), in which a pedestrian's perceived risk to an approaching vehicle was defined as having an approximately exponential relationship with TTA, such as $f(1/\mathrm{TTA})$ (Gupta et al., 2009) and $\exp(-\beta\mathrm{TTA})$ (Zhuang and Wu, 2013). Hence, the looming has the potential ability to characterise pedestrian's feeling of risk in a road-crossing scenario.

2.2. Binary gap acceptance model with mixed effects

At uncontrolled crosswalks, pedestrians could either accept a traffic gap or not when approaching vehicles do not give way to them. Accordingly, pedestrian gap acceptance behaviour at such locations is typically modelled using a binary logit model, called binary gap acceptance model (BGA), as follows (Zhao et al., 2019):

$$\Pr(y|\mathrm{accept}) = \mathrm{logit}^{-1}(\boldsymbol{X\beta}+\boldsymbol{\varepsilon}) \tag{9}$$

where logit^{-1} is the inverse-logit transformation. $\Pr(y|\mathrm{accept})$ represents the probability that pedestrians accept the traffic gap. $\boldsymbol{X}$ is a matrix of the explanatory attributes. $\boldsymbol{\beta}$ is a vector of coefficients corresponding to explanatory attributes. $\boldsymbol{\varepsilon}$ are the error terms. However, for the analysis of the repeatedly measured data of subjects, the standard errors of the binary logit model are biased because the interdependencies among subjects violate the independence assumption (Hu et al., 1998). To avoid this problem, here we adopted a BGA model with mixed effects to establish pedestrian gap acceptance behaviour, which allowed heterogeneity of individuals to be retained (Gelman and Hill, 2006). A typical mixed-effects BGA model is given by:

$$\Pr(y|\mathrm{accept}) = \mathrm{logit}^{-1}(\boldsymbol{X\beta}+\boldsymbol{Zu}+\boldsymbol{\varepsilon}) \tag{10}$$

where $\boldsymbol{X}$ is a matrix of explanatory attributes and its corresponding coefficients are denoted by a vector $\boldsymbol{\beta}$, also known as the fixed effects. $\boldsymbol{Z}$ is the designed matrix for random effects and $\boldsymbol{u}$ is a vector of the random effects.

2.3. Psychophysics-based binary gap acceptance model with mixed effects

If the explanatory attribute set is a composite of conventional attributes, such as speed, age, and time gap, the gap acceptance model is called a conventional BGA model. In contrast to the conventional BGA model, the psychophysics-based gap acceptance (PGA) model with random effects of the visual looming can then be expressed as:

$$\mathrm{logit}\{\Pr(y_{ijk}|\mathrm{accept})\} = \beta_0+\beta_1 f(\dot{\theta}_{ijk})+u_{1,ijk}f(\dot{\theta}_{ijk})+u_{0,ijk} \tag{11}$$

where $\dot{\theta}_{ijk}$ is the kth replication ($k=1$ to 6) of the looming value of the ith traffic scenario ($i=1$ to 12) belonging to jth participant ($j=1$ to 60). β_1 and β_0 are coefficients and slope with fixed effects. $f(\hat{A}\cdot)$ is a transformation function, discussed in Section 5.2.1. $u_{0,ijk}$ and $u_{1,ijk}$ are random coefficient and slope of the ith traffic scenario for the jth participant, which are assumed to be normally distributed. In the study, the conventional BGA model included the fixed effects of the time gap and vehicle speed and participants' random effects of the time gap, which is given by:

$$\mathrm{logit}\{\Pr(y_{ijk}|\mathrm{accept})\} = \beta_0+\beta_1 v_{ijk}+\beta_2 t_{ijk}+u_{1,\,ijk}t_{ijk}+u_{0,\,ijk} \tag{12}$$

where v and t are the vehicle speed and time gap size. The BGA model was applied as a comparison to assess whether the PGA model could achieve equal or better performance with fewer coefficients than the BGA model. Therefore, we only considered the model with random effects of the time gap.

3. Empirical data

This study uses a dataset collected as part of a virtual reality experiment, previously reported on in Lee et al. (2022) with detailed information on the experimental setup; here a brief summary will be provided. The dataset was collected using the Highly Immersive Kinematic Experimental Research (HIKER) lab. As shown in Fig. 2 a, the HIKER is a virtual reality environment where the moving vehicles and road scenarios were generated in a cave-based pedestrian simulator with 9×4 m walking space (Sadraei et al., 2020). Eight 4 K projectors behind glass panels projected the virtual scene at 120 Hz, and ten cameras tracked the head position through tracking glasses on the participant's head so that the system could project images that fit the actual perspective of the participant.

In the experimental scenario, the simulated road and pavement widths were 3.5 m and 1.85 m. The cars were 1.95 m wide and 4.95 m long. A row of trees was included on one side of the road to indicate the starting position for the pedestrian. The lateral distance R between the pedestrian's starting position and the nearest side of the vehicles was 2.45 m.

In terms of the experimental procedure, participants stood on the side of the road and held a button to trigger the scenario, consisting of two approaching vehicles (Fig. 3). They were asked to cross or not between the two vehicles when they felt comfortable and safe to do so. The first car started 96 m away from the pedestrian, and the second car maintained one of four time gaps behind first car, 2 s, 3 s, 4 s or 5 s. When the rear of the first vehicle passed the participant, the time gap was available (Fig. 3). Both vehicles drove in the middle of the road at the same constant speed, one of the three speeds 25 mph, 30 mph or 35 mph. Therefore, $4\times3=12$ different traffic scenarios were included. All scenarios were replicated twice in three different blocks so that each participant experienced 72 trials in total. Sixty participants aged 19–34 participated in the experiment, and a total of 4,320 trials were thus recorded and included in the analyses here. It should be noted that the full experiment also included additional experimental scenarios, but the present scenario only used the above-mentioned scenarios, collected under constant vehicle speed without external human–machine interface conditions.

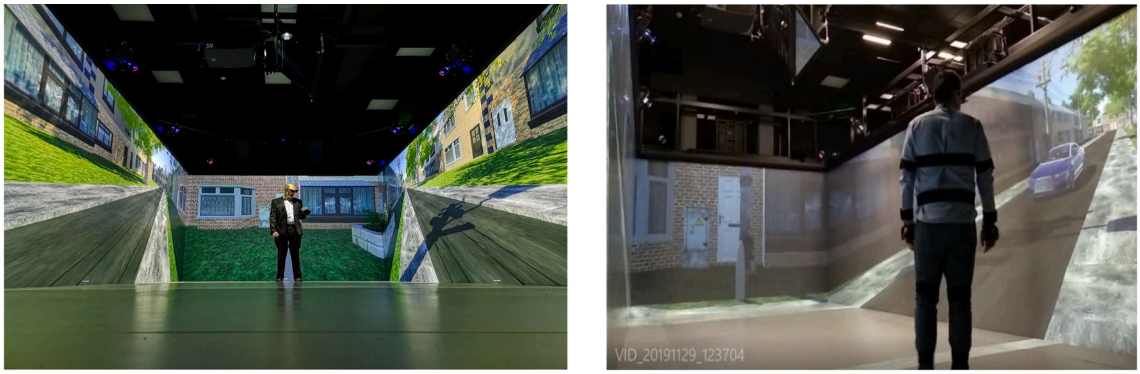
In addition to the Lee et al.'s (2022) dataset, the data from Lobjois and Cavallo (2007) was also used to evaluate the model in Section 5.2.1 and 5.2.2. In their experiment, a gap acceptance task was designed to investigate whether young and elderly participants selected the same gap for all vehicle speed conditions. The experiment setup was similar to Lee et al. (2022), except their traffic gaps ranged from 10 m to 135 m in 5 m increments, rather than temporal gaps. Since we did not have the detailed data for each participant in the second dataset, only the aggregated road-crossing percentages were used here. In addition, since age differences is not in focus in the present study, only the results for the 20–30 age group (Lobjois and Cavallo (2007), p. 937, Fig. 2, 20-30) were used, similar to the age range of participants in Lee et al. (2022). The main experimental parameters of two datasets are shown in Table 1.

4. Data analysis

As a first step, we analysed the data from Lee et al. (2022) to investigate whether this study replicated the potentially unsafe pedestrian behaviour patterns observed in previous studies (Beggiato et al., 2017; Lobjois and Cavallo, 2007; Oxley et al., 2005; Schmidt and Färber, 2009).

4.1. Data pre-processing

Before the data analysis, accurately capturing the pedestrian's street-crossing onset time is vital. Several previous studies used a button to indicate crossing decisions. However, it was shown that button pressing could make participants more aggressive than in actual crossing tasks



a. b.

Fig. 2. a. Highly Immersive Kinematic Experimental Research (HIKER) simulator. b. The experimental scenario in the HIKER.

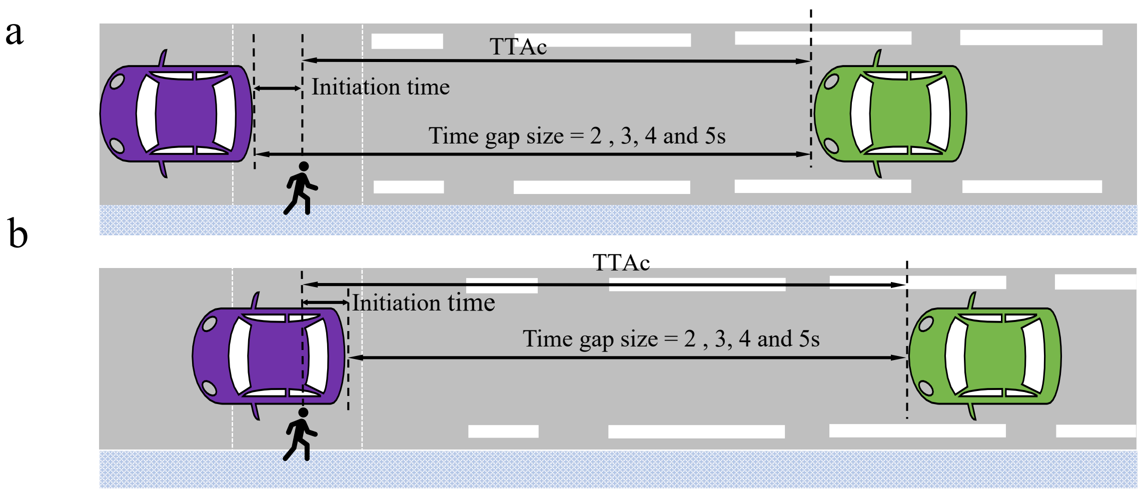


Fig. 3. Schematic diagrams of experiment scenario and crossing initiation. (a) Pedestrians started crossing after the previous car passed them, so the TTAc was smaller than the time gap. (b) Pedestrians started crossing before the previous car passed them, so the TTAc was bigger than the time gap.

Table 1
The experimental parameters of datasets.

Dataset	Parameters					
	l (m)	*w* (m)	*R* (m)	Z (m)	Time gap (s)	Speed
Lee et al. (2022)	4.95	1.95	2.45	–	2–5	25–35 mph
Lobjois and Cavallo (2007)	4.42	1.72	2.09	10–135	–	40, 60 km/h

(Lobjois and Cavallo, 2007). A recent study indicated that having the participant move forward naturally was a better way to measure the crossing onset time of the road-crossing (Faas et al., 2020). Therefore, in the analysis, the crossing onset time is the time when participants walked across the edge of the pavement and stepped out to the road. 4270 valid data trials were obtained. Four performance measures were discussed: road-crossing percentage (gap acceptance percentage), time gap at crossing initiation TTAc, crossing duration and safety margin. The results of these analyses are described in the following sections.

4.2. Unsafe road crossing decision

Time gap at crossing initiation. The TTAc was defined as the time gap between participants and the vehicles when participants started crossing the road (Fig. 3). When participants started crossing after the first car passed them, the TTAc was smaller than the time gap size (Fig. 3a). Note that a pedestrian could also begin their crossing slightly before the first car passed them, in which case the TTAc was slightly larger than the time gap size (Fig. 3b) (Schneider et al., 2021). Fig. 4b shows the box charts of TTAc of each condition. A two-way repeated ANOVA analysis was done on TTAc with speed and time gap size as independent variables. The results did not show significant interactive effects between speed and time gap size. The speed ($F(2, 22) = 7.272$, $p < 0.01$) and time gap size ($F(3, 33) = 967.56$, $p < 0.001$) had significant main effects on TTAc. For the same time gap size, more participants started crossing at smaller TTAc when vehicles drove at higher speeds. For instance, for the 2 s time gap group, the calculated mean TTAc was smaller when the vehicle approached 35 mph (M = 1.98 s, S.D. = 0.30 s) than 25mph (M = 2.16 s, S.D. = 0.31 s). As shown in Fig. 4b, this tendency was observed among all the groups.

Gap acceptance. Fig. 4a shows the percentage of gap acceptances for each condition. The gap acceptance percentage was the frequency of road-crossings divided by the quantity of all trials in each condition. The data showed that all three groups of participants were less likely to cross the road for the 2 s condition (road-crossing percentage is<6 %). With the increase in time gap size, the gap acceptance percentage grew steadily, and the largest percentage was observed for the 5 s time gap and 35 mph condition (82.91%). Logistic regression was performed with time gap and speed as independent variables and crossing decisions as the dependent variable to study the gap size and speed effects on the road crossing percentage. The results showed that time gap size (Coef. =

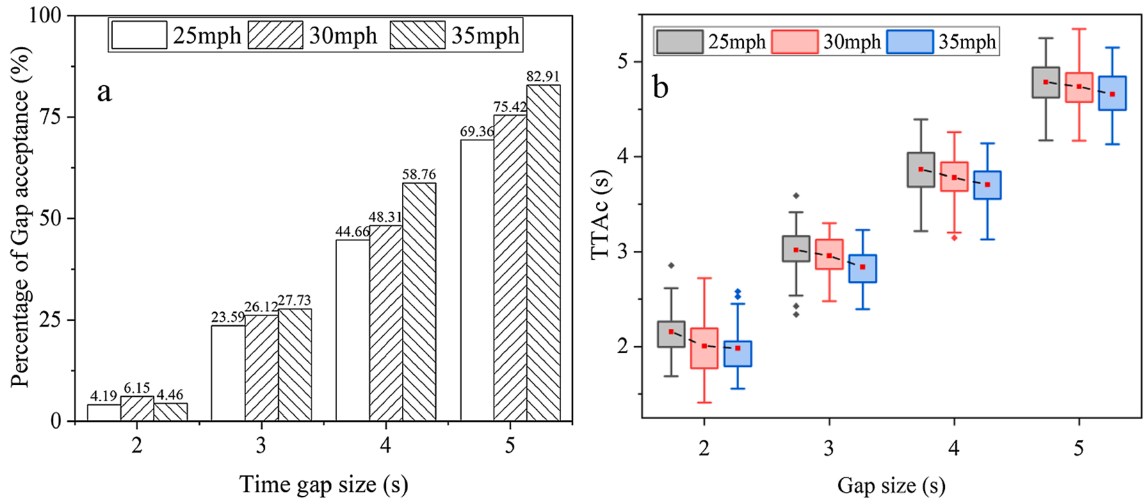


Fig. 4. (a) Percentage of gap acceptance. (b) Box chart of TTAc, and the small red squares represent the arithmetic mean.

1.263, $p < 0.001$) and speed (Coef. = 0.108, $p < 0.001$) were significantly positively correlated with crossing percentage, which indicated more pedestrians were willing to cross the street in higher speed conditions at the same time gap.

Crossing duration and safety margin. The crossing duration was defined as the time between when pedestrians initiated crossing and when they crossed over the edge of the opposite pavement. With speed and time gap size as independent variables, a two-way repeated ANOVA was conducted on crossing duration. There was a significant main effect of time gap on crossing duration ($F(3, 5) = 64.31$, $p < 0.001$), showing that participants' crossing duration increased with the time gap. No significant speed effect was found.

The gap acceptance and TTAc analysed above reflected that vehicle speed could negatively affect pedestrian crossing performance. However, their impacts did not directly reflect pedestrian safety level. According to the literature (Chu and Baltes, 2001; Oxley et al., 2005), pedestrian crossing safety is largely governed by TTAc and crossing duration. Therefore, in order to evaluate if vehicle speed affected pedestrian safety, we applied the safety margin as a safety indicator. The safety margin (also known as post-encroachment time) refers to the time between the moment when the pedestrian reached the edge of the opposite pavement and when the second vehicle reached the pedestrian crossing position. Note that this metric of pedestrian crossing risk depends on vehicle speed, distance, initiation time as well as crossing duration. In practice, the safety margin was calculated based on the time difference between TTA_c and the crossing duration of each trial. With

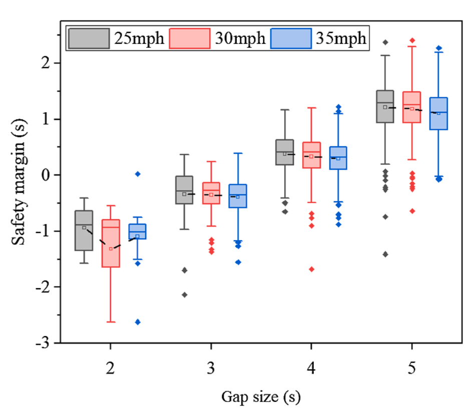


Fig. 5. Safety margin plotted as the function of time gap and vehicle speed. The arithmetic mean and median are represented by small squares and short horizontal lines in boxplots.

speed and time gap size as independent variables, a two-way repeated ANOVA was conducted on safety margin. As shown in Fig. 5, the analysis revealed a significant negative main effect of speed ($F(2, 5) = 6.25$, $p < 0.01$), showing that the increase in vehicle speed impaired pedestrian safety margin.

Furthermore, the other two types of safety indicators were identified to describe potential unsafe behaviour: 'unsafe decisions' and 'tight fits' (Lobjois and Cavallo, 2007). An 'unsafe decision' was counted when the safety margin was<0 s, indicating that participants' TTAc was insufficient to allow them to reach the opposite pavement, causing them to conflict with the approaching vehicle in the shared zone, leading to a potential collision. A 'tight fit' corresponded to the crossing with a safety margin between 0 s and 1.5 s, representing that although the TTAc was enough for participants to finish the crossing before the vehicle reached the conflict zone, it required them to have precise timing due to the small safety margin. Table 2 provides the full results, showing that almost no participants made safe decisions in the 2 s time gap condition, and this unsafe tendency to cross became worse with an increase in speed. In the 5 s condition, whereas few participants made unsafe decisions, the percentage of tight fits increased with speed, representing that their risk of crossing still increased with speed in long time gap conditions. In addition, we can see that participants attempted to walk faster at small time gap conditions. However, this was not enough to compensate for the speed's negative effect on their safety.

Finally, we also noticed that participants might not simply make the decision based on distance or time gap. As shown in Fig. 4a, for the 3 s and 35 mph conditions (distance was 46.9 m), the corresponding crossing percentage was 27.7 %. However, the crossing percentage was 44.7 % for the 4 s and 25 mph condition (the distance was 44.7 m). In both cases, the distances were quite similar, but with a notable difference in crossing response. Meanwhile, results from the TTAc also indicated a similar pattern; that is, participants' response times were clearly different between two conditions with similar initial distances. In short, the above analyses indicated that pedestrians tended to make riskier crossing decisions in higher speed conditions, and their crossing decisions seem affected by many different aspects of vehicle kinematics rather than any single factor.

5. Model calibration and comparison

5.1. Visual looming in the experimental scenarios

Fig. 6 shows the looming curves calculated using the experimental parameters of Lee et al.'s (2022) dataset (Table 1). The curves of the model are plotted as the functions of the TTA and the spatial distance

Table 2
Mean crossing duration (CD), gap acceptance (GA) and safety margin for speed and time gap conditions.

Performance variable	Time gap (s) and vehicle speed (mph)											
	2			3			4			5		
	25	30	35	25	30	35	25	30	35	25	30	35
CD	2.94	3.23	2.98	3.22	3.24	3.21	3.41	3.40	3.37	3.51	3.50	3.51
SM	−0.94	−1.32	−1.09	−0.34	−0.35	−0.39	0.38	0.33	0.29	1.21	1.18	1.10
GA	4.2	6.2	4.5	23.6	26.1	27.7	44.7	48.3	58.8	69.4	75.4	82.9
UD	100	100	100	79.5	88.0	90.6	15.8	16.0	17.5	2.4	2.7	1.4
TF	0	0	0	20.5	12.0	9.3	84.2	84.0	82.5	72.0	76.3	82.3

Note. CD: crossing duration (s); SM: safety margin (s); GA: gap acceptance (%); UD: unsafe decision (%); TF: tight fits (%).

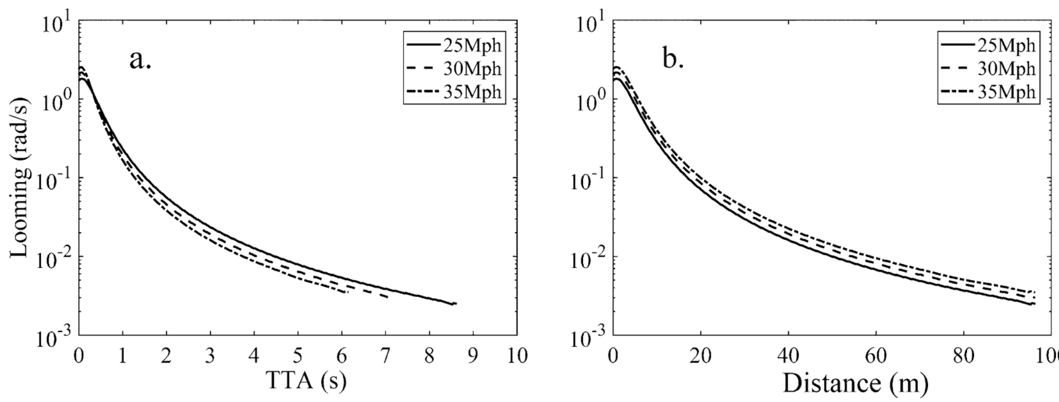


Fig. 6. The speed effect on looming in experiment scenarios. (a) The model is plotted as a function of TTA and speed. (b) The model is as a function of distance and speed. Note that the visual looming is shown on a logarithmic scale.

separately. Fig. 6a shows that, at least from 0.5 s to 6 s, the slower speed vehicle produces greater looming values than the faster car at the same TTA. As an indication of possible collision events with the approaching object, larger looming values could make pedestrians feel more threatened and uncomfortable. Therefore, because of the greater visual looming, pedestrians might not be willing to cross the road when they interact with a vehicle with a slower speed at the same TTA. In Fig. 6 b, when plotting looming curves as a function of distance, the effect of speed on looming reverses, i.e., the slower vehicle produces a smaller looming stimulus than the faster vehicle at the same distance. This might mean that pedestrians perceive greater risk when the vehicles approach them at a higher speed for a given distance. Based on the above analysis, variations of looming with speed and distance shown in Fig. 6 align qualitatively with the effects of speed and distance on pedestrian crossing as reported in the literature (Oxley et al., 2005; Schmidt and Färber, 2009) and in our statistical analysis in Section 4. This alignment provides a first indication that pedestrians' risky road crossing behaviour may stem from a reliance on visual looming cues.

5.2. Psychophysics-based gap acceptance model

To fully specify the PGA model, the first subsection below investigates if there is a linear relationship between road crossing probability, an important precondition for applying logit regression presented in Section 5.2.2. Afterwards, how the looming information might best be transformed into a utility for use in the logit formulation of the PGA model is also studied. After the above manipulations, in Section 5.2.2, the PGA model is then formally fit to two datasets. Finally, we compare the PGA model with the conventional BGA model in the third subsection. Therefore, the results presented in Table 3 and Table 4 are conducted for different purposes and cannot be directly compared.

5.2.1. Linear regression analysis

Since the PGA model is based on the binary choice logit model, an important assumption needs to be satisfied: the logit probability is a linear function of attributes. Therefore, a linear regression analysis was applied to both datasets to test if the assumption could hold. The linear function can be expressed by:

$$\text{logit}\{\Pr(y|\text{accept})\} = [f(\dot{\theta})]^T\beta_1 + \alpha_1 \tag{13}$$

Since a probability of one hundred and zero would result in infinite logit(Pr), the corresponding points were removed from the linear analysis. β_1 and α_1 are estimated coefficients. $\dot{\theta}$ represents the visual looming value measured at the time point when the rear of the first vehicle passed the participant. Before choosing an appropriate $f(\hat{A}\cdot)$, the $\dot{\theta}$ was input to the linear analysis without transformation. The results, as shown in Table 3, indicated that the $\dot{\theta}$ was significantly negatively related to logit(Pr), but the regression curves did not fit the data very well, as shown in Fig. 7a. Considering that the looming had an approximately exponential form, a logarithmic function was applied, i.e., $\ln(\bullet)$. The linear analysis yielded significant linear correlations

Table 3
Results of linear regression of the logit probability of road crossing onto looming, with and without a natural logarithm transformation.

$f(\,)$	Dataset	α_1	β_1	R^2	F	Sig.	Std. Error
~	Lee et al. 2022	1.161	−89.384	0.883	75.507	0.000	0.578
	Lobjois and Cavallo (2007)	2.281	−98.416	0.758	79.187	0.000	0.923
ln	Lee et al. 2022	−9.161	−2.036	0.978	447.046	0.000	0.250
	Lobjois and Cavallo (2007)	−8.911	−2.136	0.977	1037.631	0.000	0.288

Table 4
Estimated coefficients of the PGA model and BGA model in terms of Lee et al.'s (2022) data.

	PGA model			BGA model		
Fixed effects	Coef.	SE	tStat	Coef.	SE	tStat
Looming	−6.47***	0.40	−16.35	–	–	–
Vehicle speed		–	–	0.12***	0.01	8.06
Time gap		–	–	3.24***	0.16	20.36
Constant	−30.83***	2.13	−14.48	−16.41***	0.89	−18.49
Random effects	std(Coef.)	95% Conf. Interval		std(Coef.)	95% Conf. Interval	
Time gap	–	–	–	0.82***	0.57	1.20
Looming	2.39***	1.7	3.31			
Constant	13.55***	9.8	18.68	4.07***	2.88	5.74
Log-likelihood		−1055	–	−1067		
AIC		2119	–	2146		

Note. ***: $p < 0.001$; std: Standard deviation of coefficients.

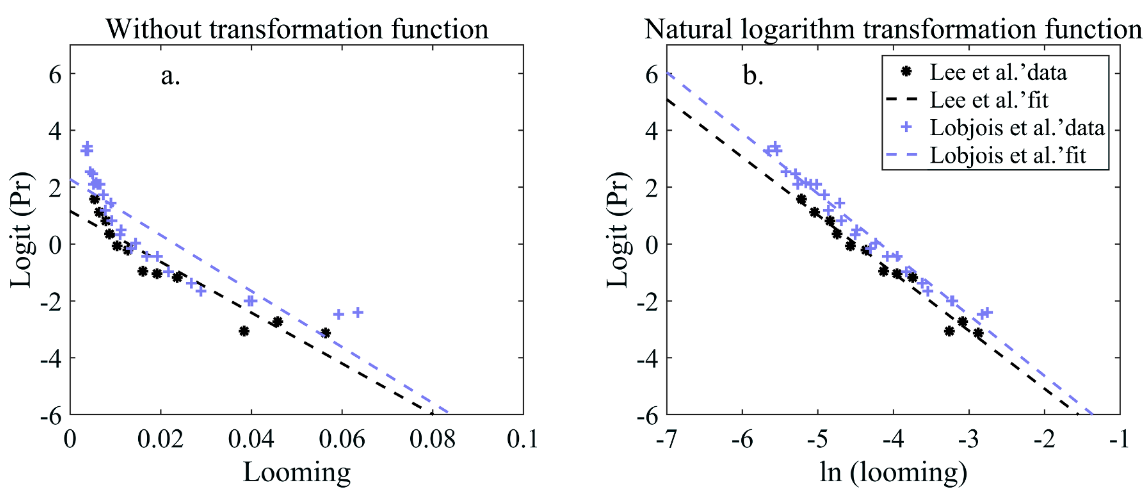


Fig. 7. Relationship between non-transformed (a) and ln-transformed (b) visual looming and the logit probability of road crossing. The black circles and blue crosses are the data points. The dashed lines show the fitted linear regression models in Table 3.

(Table 3, Fig. 7b), and the goodness of fit (R^2) with the logarithmic transformation was noticeably better than without transformation. Therefore, we adopted the natural logarithm as the transform $f(\ )$ in the PGA model.

5.2.2. *PGA model analysis*

The linear regression analyses in the previous subsection minimised error in the logit domain, but for our present purposes, it makes more sense to minimise error in the gap acceptance probability domain. Therefore, as a final step, we formally fitted the full PGA model to both datasets. Regarding Lee et al.'s (2022) data, as we have the detailed information of each trail, a PGA model with participants' random effects (Eq. (11)) was applied and estimated using the built-in function, 'fitglme', in MATLAB (MATLAB, 2021). Table 4 shows the estimated coefficients of the PGA model for Lee et al.'s (2022) dataset. For Lobjois and Cavallo's (2007) data, we only had the aggregated crossing percentage data rather than the detailed response of each trial. The PGA model was estimated instead using a Nonlinear Least Square Estimation method and did not consider individuals' random effects, where the estimated coefficients β_0 and β_1 equalled −9.740 and −2.295. As shown in Table 4, there was a significant random effect of looming, showing that responses to looming varied among participants. The PGA model retained the underlying heterogeneity of participants and indicated that the looming had a significant negative contribution to the gap acceptance (P < 0.001). Moreover, the fitting curves of the models and road crossing percentages of the two datasets are shown in Fig. 8. In panel a, the models and the data are plotted as functions of looming at the start of each scenario. Panels b through e show the same information, but instead plotted as functions of time gap and speed (panels b and d) or as functions of distance and speed (panels c and e). In Fig. 8 a, there is a clear negative correlation between the probability of crossing and the looming value. Meanwhile, these results were not only in line with the observed low safety margin decisions in Section 4.2, but also replicated the common time gap and distance effects on pedestrian behaviour, showing that looming in itself was enough to explain, in quite some detail, the various patterns of behaviour reported in previous studies (Fig. 8 b and c). Put differently, what looks like a rather complex set of dependencies, when seen from a perspective of time gaps, speeds, and distances in Fig. 8 b and c, collapses into just a single curve when seen from the perspective of looming in Fig. 8 a. Overall, the PGA model was able to capture both of these datasets well.

5.2.3. *Comparing the PGA model with the conventional BGA model*

As mentioned in Section 2, if the explanatory attribute set is a composite of conventional attributes (Eq. (12), then the model refers to the conventional BGA model, which is commonly used in pedestrian road-crossing behaviour research (Pawar and Patil, 2016). In this section, we fit the BGA model to data and compare it to the PGA model. Except fixed effects of speed and time gap (Pawar and Patil, 2015), the random effects of time gap among participants were also considered in the BGA model (Eq. (12). As shown in Table 4, the PGA model achieved a higher log-likelihood than the BGA model, indicating a better fit of the data. Notably, the PGA model achieved this better fit with one free parameter less than the BGA model. To formally compare the two models, we used Akaike Information Criterion (AIC).

$$\mathrm{AIC} = 2k - 2\ln(L) \tag{14}$$

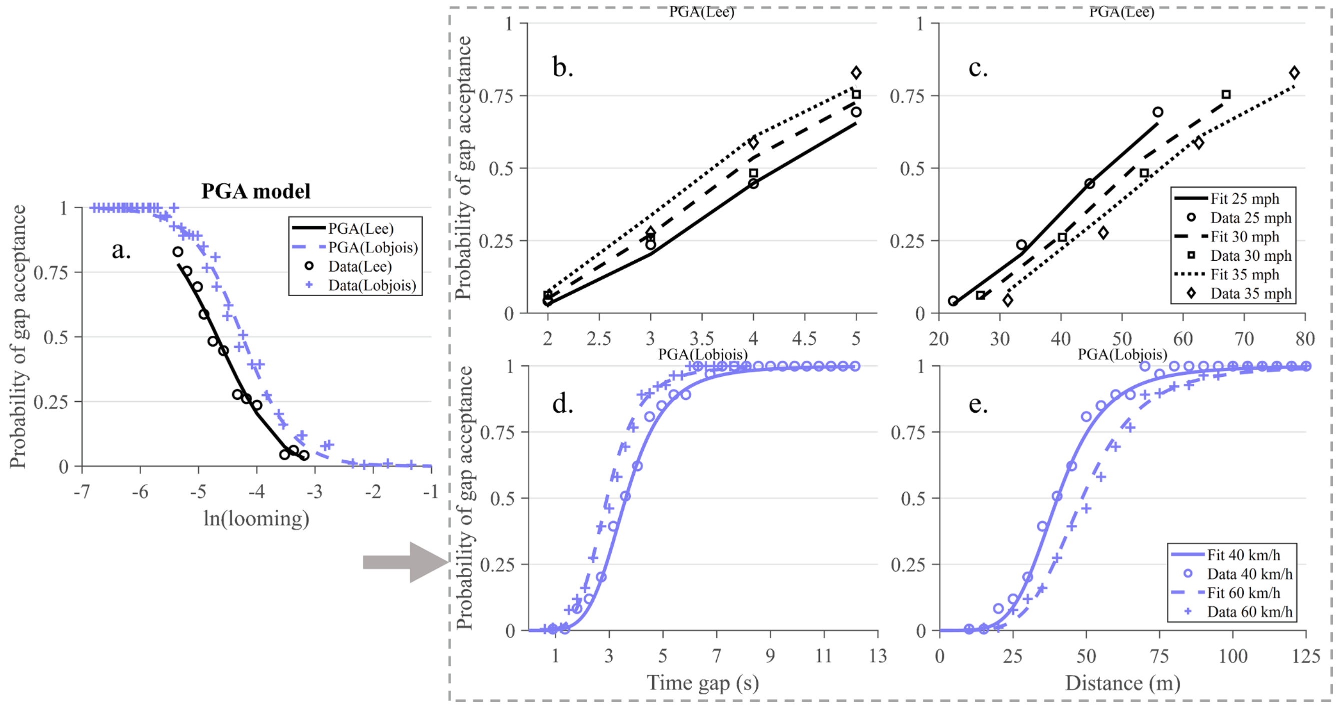


Fig. 8. Road-crossing probability in Lee et al.'s (2022) data (black symbols) and Lobjois and Cavallo's (2007) data (blue symbols), together with corresponding fits of the PGA model (line types related to speed conditions). (a) Observed and model-fitted crossing probabilities were shown as a function of ln(looming). (b)-(c) The same data and model predictions as in panel a, but plotted as a function of time gap and speed (panels b and d) or as a function of distance and speed (panels c and e).

AIC estimates the relative amount of information lost by a given model: the less information a model loses, the better. AIC considers both log-likelihood L and the number of free parameters k in the model to deal with the trade-off between goodness of fit and model complexity. The preferred model is the one with the minimum AIC value (Akaike, 1974). As shown in Table 4, the PGA model had a smaller AIC value than the BGA model by 27, suggesting that the PGA model was significantly better than the BGA model to be minimising the information loss (Akaike, 1974). In sum, both the PGA model and BGA model could describe the crossing probability data well, but the PGA model did so both better and more parsimoniously than the BGA model.

6. Discussion

6.1. Answering the research questions

Regarding the first main research question of the study, the data analyses indicated that the impact of vehicle speed on pedestrians differed across time and distance dimensions. Participants were less likely to cross the road in higher vehicle speed conditions for a given distance gap and did so with slower crossing initiation. Conversely, the participants were more prone to initiate quickly and cross for a given time gap in higher speed conditions, resulting in a vehicle speed influenced crossing behaviour. To investigate the safety impacts of this behaviour pattern, we conducted a safety margin analysis from two perspectives. First, an ANOVA analysis indicated that participants had a smaller average safety margin for higher speed conditions. Second, we categorised crossing decisions based on the safety margin and calculated the percentages of unsafe decisions. Results showed that both participants' unsafe crossings and tight fits were increased with vehicle speed. Although participants attempted to walk faster in smaller time gap conditions, such speed adaption strategy was not sufficient to compensate for the reduction in safety margins caused by the speed-induced unsafe behaviour. Researchers have suggested that this behaviour pattern was caused by pedestrians' over-reliance on the spatial distance from approaching vehicles (Schmidt and Färber, 2009). Pedestrians might not base their decisions on the time gap alone but also applied simplifying heuristics (i.e., distance-based heuristics), which were not always accurate but faster and easier to implement than time gap-based strategy (Lobjois and Cavallo, 2007). However, our results further showed that pedestrians had different gap acceptance and initiation times between conditions with similar spatial distances but different time gaps, suggesting that pedestrians relied on multiple sources of information from vehicle kinematics.

Concerning another main question of the study, we derived mathematical expressions for the visual looming of an approaching vehicle in pedestrian road-crossing situations. The results showed that the looming increases slowly at long distances and rapidly at short distances, which agrees qualitatively with the observation that pedestrians usually feel safe to cross for long-distance or big-time gap conditions but not when the vehicle is close. The proposed model demonstrated that the vehicle speed has a negative impact on the looming, that is, for a given TTA, looming decreases as the speed increases. This finding indicated that higher speed vehicles might produce smaller collision threats to pedestrians for a chosen TTA (Wann et al., 2011), which was qualitatively similar to the speed-induced unsafe crossing behaviour. Moreover, a linear regression analysis further supported the assumption that looming is significantly negatively related to the percentage of gap acceptance and the fit improved by applying a natural logarithm transformation. Consistent with the literature, DeLucia 2008 assumed that the possible heuristics for human collision perception are the optical size and its change rate (i.e., visual looming). Since a lower speed vehicle is associated with greater optical size and visual looming than a higher speed vehicle for a chosen time gap, a feeling of risk may cause participants to reject opportunities in lower speed conditions. In previous studies, researchers have established different models based on TTA to characterise the pedestrian perceived risk to approaching vehicles (Gupta et al., 2009; Zhuang and Wu, 2013). Although TTA is the key determinant associated with collision risk, our results have shown that TTA is not the only component. Pedestrians rely on multiple sources of information from vehicle kinematics, such as vehicle speed, which previous models have ignored. Therefore, the looming model combining the spatial–temporal information in light of the human perceptual model could better describe pedestrian perceived collision risk toward approaching vehicles.

Further, we proposed a PGA model based on our hypothesis, which predicts gap acceptance as a logit function of visual looming, could successfully characterise pedestrian gap acceptance behaviour and fit human data from VR studies well. The model replicated the speed-induced unsafe crossing and thus suggests that the mechanism behind this phenomenon is that higher speed situations provide weaker looming stimuli, leading to lower feelings of collision threat. The model comparison analysis indicated that the PGA model outperformed the conventional BGA model, that is, the PGA model could describe the gap acceptance behaviour better and with fewer model parameters than the conventional model. The above findings reinforce the notion that looming may cause a sense of collision threat that affects pedestrian crossing decisions and this would be an important mechanism behind unsafe crossing decisions.

6.2. Practical implications

We see several ways in which our results could be used to improve traffic safety:

- The speed-induced unsafe crossing behaviour identified in the present study provides empirical evidence for understanding the associations between pedestrian crossing behaviour and its influencing factors (e.g., vehicle speed). These findings suggest that necessary measures should be taken to increase the awareness of policymakers, road designers and pedestrians. For instance, to minimise the impact of speed on pedestrians, a possible policy direction is to control vehicle speed by placing speed limit signs, indicators, or cameras at appropriate locations.
- The study provides a clear and simple explanation of the cause of speed-induced unsafe crossing in terms of the human perception mechanism. Researchers and engineers may therefore develop an external human–machine interface to provide explicit information of vehicle behaviour for pedestrians and thus reduce the potential negative effects of implicit information, e.g., vehicle kinematics (Lee et al., 2022).
- The proposed PGA model could serve as a tool to investigate pedestrian crossing decisions and identify at-risk crossing locations, where pedestrians may often make speed-induced unsafe crossing decisions. For instance, the PGA model can be used to compare datasets collected from two crosswalks to determine which one has a greater impact on pedestrians' decisions.
- The proposed theory (i.e., speed-induced unsafe crossing behaviour) could increase precision in the pedestrian crossing decision modelling. One direct practical implication is to apply the proposed PGA model to the microscopic transport simulation model to promote a more naturalistic pedestrian crossing decision-making process.
- Finally, recent studies have been keen on AVs using pedestrian behaviour models to implement human-like pedestrian-AV interactive processes (Markkula et al., 2018). Our model could provide predictive information from a pedestrian perspective, helping design AVs that can better anticipate pedestrian crossing intentions.

6.3. Limitations and future work

Several limitations of the present study should also be borne in mind. Since the results and model considered only constant-speed scenarios, it cannot be concluded that looming is the only cue used by pedestrians, especially in scenarios with variable traffic speed and gaps. For example, in situations with vehicle deceleration, visual looming alone may not provide sufficient information to make crossing decisions (DeLucia, 2015). Moreover, based on the current research aims and dataset, the study is limited to single-gap crossings in the single-lane scenario. However, pedestrians often cross the road in complex traffic environments, such as multilane highways and traffic with different vehicle characteristics. In addition, the binary crossing decision assumption is strictly limited to the crossing scenarios at uncontrolled crosswalks, where drivers do not have to give way to pedestrians. In contrast, pedestrian crossing decisions may not be a binary choice in other cases. For example, if the vehicle is yielding to the pedestrian, in which case the pedestrian will always cross eventually, but possibly not until the vehicle has come to a near-full stop. Finally, compared with the crossing behaviour in real traffic scenarios where pedestrians and vehicles can flexibly adjust their behaviours, the data collected in the highly controlled VR experiment considers fewer influencing factors, and both this aspect as well as the virtual nature of the task may lead to more unsafe behaviour. The degree to which pedestrians are affected by distance and time gap differs between studies, depending on whether the pedestrian crossing is carried out in naturalistic settings, on a test track, or in a virtual environment (Feldstein and Dyszak, 2020; Schneider et al., 2021). However, it is not easy to draw general conclusions, partly because the research aims and tasks differ between studies. Based on the above limitations, to develop a comprehensive and practical pedestrian crossing behaviour model, one important future aim could be involving more factors of complex traffic environments, such as pedestrian strategies for identifying acceptable gaps across multiple lanes of traffic at once (Brewer et al., 2006; Kadali et al., 2015). In addition, it is also important to apply the model to reliable naturalistic datasets and investigate their differences from simulated datasets.

7. Conclusions

In summary, this study linked pedestrian gap acceptance behaviour to a potential perceptual mechanism and provided a new approach to characterise pedestrian road-crossing decisions. The proposed PGA model, modelling gap acceptance binary choice logit decision operating only on (log-transformed) visual looming, was found capable of explaining gap acceptance data from two datasets collected in simulated pedestrian-driver environments. More in-depth statistical analysis was performed on one of these datasets, showing patterns of speed-induced unsafe crossing. Furthermore, the correlation between the percentage of road-crossings and looming was identified by linear regression analysis. Finally, the PGA model was fitted to the data and compared with the conventional BGA model. Based on the results, the following conclusions can be made:

(i) For given time gaps with higher speed conditions, pedestrians tend to make more unsafe crossing behaviours.
(ii) The PGA model can characterise gap acceptance behaviour across a range of experimental scenarios, better and more parsimoniously than the BGA model, suggesting that looming is a critical visual cue that pedestrians may be using as an important part of their crossing judgment.
(iii) The PGA model captures speed-induced unsafe crossings and explains this behaviour pattern in terms of visual looming, which is affected by both vehicle speed and distance. Applied practical implications of he the results and proposed model for traffic safety management, modelling and development of AVs are discussed.

The authors declare that there is no conflict of interest.

CRediT authorship contribution statement

Kai Tian: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Gustav Markkula:** Writing – review & editing, Supervision, Conceptualization. **Chongfeng Wei:** Writing – review & editing, Supervision, Conceptualization. **Yee Mun Lee:** Writing – review & editing. **Ruth Madigan:** Writing – review & editing. **Natasha Merat:** Writing – review & editing, Funding acquisition. **Richard Romano:** Writing – review & editing, Supervision, Conceptualization.

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

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