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Psychological Mechanisms in Pedestrian Road Crossing Behaviour: Observations and Models

Kai Tian

University of Leeds

Institute for Transport Studies

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Intellectual Property Statement

The candidate confirms that the work submitted is his own, except where work which has formed part of jointly authored publications has been included. The contribution of the candidate and the other authors to this work has been explicitly indicated below. The candidate confirms that appropriate credit has been given within the thesis where reference has been made to the work of others.

Five publications or manuscripts have been produced from research that was undertaken as part of this thesis. Each publication or manuscript is listed below with a full reference and details of its location within this thesis. The work in chapters 2 to 6 of the thesis has appeared in publications or manuscripts as follows:

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

Tian, K., Markkula, G., Wei, C., Lee, Y. M., Madigan, R., Merat, N., & Romano, R. (2022). *Explaining unsafe pedestrian road crossing behaviours using a Psychophysics based gap acceptance model*. Safety Science, 154, 105837.

The candidate developed the main idea for this work, under the guidance of Richard Romano, Gustav Markkula, and Chongfeng Wei. The empirical data used to validate the assumption and model were provided by Natasha Merat, Yee Mun Lee, Ruth Madigan. The candidate performed the modelling work, data analysis, and wrote the manuscript. The model and results were reviewed by Richard Romano, Gustav Markkula, and Chongfeng Wei. The manuscript was improved by comments from all the co-authors.

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

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Under the guidance of Richard Romano, Gustav Markkula, and Chongfeng Wei, the candidate and Athanasios Tzigieras developed the main idea for this work and designed the experiment. The candidate performed the data analysis and wrote the manuscript. The results were reviewed by Richard Romano, Gustav Markkula, and Chongfeng Wei. The manuscript was improved by comments from all the co-authors.

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The candidate developed the main idea for this work, under the guidance of Richard Romano, Gustav Markkula, and Chongfeng Wei. The empirical data used to validate the assumption and model were provided by Natasha Merat, Yee Mun Lee, Ruth Madigan, Toshiya Hirose, and Richard Romano. The candidate performed the modelling work and wrote the manuscript. The model and results were reviewed by Richard Romano, Gustav Markkula, and Chongfeng Wei. The manuscript was improved by comments from all the co-authors.

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Abstract

As automated vehicles (AVs) become advanced, there is a growing concern over how AVs should interact with pedestrians. Increasing attention has, therefore, been drawn to pedestrian crossing behaviour research. Given the complexity of human behaviour and the traffic environment, existing studies have identified many influential factors related to pedestrian crossing behaviour. An important problem, however, is the need for more effort to uncover the human psychological mechanisms underpinning these observed behavioural patterns. Hence, the key aim of this project is: to narrow the gap between psychology and pedestrian crossing behaviour by bringing ideas from psychology into the analysis of pedestrian crossing behaviour and modelling this behaviour from a psychological perspective. This doctoral project conducted a range of research, including experimental study and empirical data analyses, to investigate pedestrian crossing behaviour in different traffic scenarios, i.e., uncontrolled intersections with a constant-speed vehicle, constant-speed continuous traffic flow, or a yielding vehicle. It was found that visual looming $\dot{\theta}$ (the rate of change of the optical size of the vehicle on the pedestrian's retina) is significantly negatively related to the percentage of crossing gap acceptance in constant-speed scenarios, supporting that looming may cause a sense of collision threat that affects pedestrian crossing decisions. In vehicle-yielding scenarios, the empirical data indicated that another looming-related visual cue $\dot{\tau}$ (the rate of change of τ, $\tau = \theta/\dot{\theta}$) is a potential visual cue for detecting vehicle-yielding behaviour. A hybrid perception framework was then developed to account for pedestrian crossing behaviour by combining both $\dot{\theta}$ and $\dot{\tau}$. In continuous constant-speed traffic flow scenarios, it was found that pedestrians might dynamically adjust their crossing decisions by comparing $\dot{\theta}$ of the previously rejected gap, the currently faced gap, and the following gap. Based on these findings, this project developed models to characterise both pedestrian crossing decision and its time-dynamic nature. Crucially, validations across different datasets demonstrated that these models reproduce pedestrian crossing decisions qualitatively and quantitatively. Predictions from these models highlight the notion that looming-related visual cues are directly available to the pedestrian visual system. Finally, in addition to these psychological mechanisms and models, this project also provided novel observations in pedestrian crossing behaviour. It suggested that the behaviour of pedestrians tending to accept smaller gaps at higher vehicle

speed conditions might lead to potential safety issues for pedestrians. Distracted pedestrians might self-regulate their engagement between the crossing task and distraction based on the traffic situation in the continuous traffic flow, such as time gap size. Moreover, in a vehicle behaviour estimation study, it was found that in the early stage of road-crossing scenarios, pedestrians tended to interpret low driving speeds as a signal to give way, regardless of whether the vehicle was slowing down. Overall, understanding pedestrian road-crossing behaviour and its underlying mechanisms is a difficult challenge. Beyond purely experimental research and data analysis, this project demonstrates that applying theories and models developed in psychology will bring considerable benefits to pedestrian road-crossing behaviour research.

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CHAPTER 1

Introduction

1.1 Background

The flexibility, low carbon footprint, and beneficial impact of walking make it one of the most popular sustainable trip modes for city residents. At the same time, with the increase in motor vehicle ownership, the potential for conflict is greatly increased when pedestrians and vehicles share the same road space (Zhao et al., 2019). Since pedestrians usually are regarded as the most vulnerable road users, lacking protective equipment and moving more slowly than other road users (El Hamdani et al., 2020), investigating pedestrian road-crossing behaviour has applied relevance through the link to road safety. Under this purpose, pedestrian road-crossing behaviour has been the subject of extensive research for many years. One of the earliest works can be dated back to 1953, when Moore (1953) investigated the potential factors associated with pedestrian road-crossing behaviour, like gender and age. In recent years, in the context of the rapid development of automated vehicles (AVs), more research questions have arisen, such as the impacts of external human-machine interface (eHMI) on pedestrians. Given the complexity of human behaviour and the traffic environment, it is not surprising that the number of influential factors identified to date in relation to pedestrian crossing behaviour is large (Ishaque and Noland, 2008; Rasouli and Tsotsos, 2019). However, what is perhaps more surprising is the lack of research trying to understand road-crossing behaviour in terms of the underlying human psychological mechanisms. Most existing research has focused on observing patterns of pedestrian crossing behaviour, whereas very limited studies attempted to investigate the psychological mechanisms underpinning how and why pedestrians make road-crossing decisions. In the following sections, to provide a basic understanding of the existing studies on pedestrian crossing behaviour, we review the studies in relation to pedestrian crossing behaviour from three aspects: previous observations and models, collision perception theory, and cognitive theory and models.

1.1.1 Observations on pedestrian crossing behaviour

One key concept in past empirical studies of pedestrian road-crossing is gap acceptance (Lobjois and Cavallo, 2007). The time for a vehicle to reach the pedestrian's position when the pedestrian starts to cross is often measured to quantify the size of the accepted crossing gap. According to the literature, pedestrians accept traffic gaps within a wide range. For instance, Brewer et al. (2006) showed that the observed accepted gap was between 5 s and 9.4 s, while the values observed by Pawar and Patil (2016) ranged from 5.3 s to 5.8 s. Prior studies found that vehicle speed (Petzoldt, 2014), vehicle yielding behaviour (Ackermann et al., 2019), traffic density (Lobjois et al., 2013), and vehicle size (Yannis et al., 2013) have significant impacts on pedestrian crossing gap acceptance. Not limited to that, the effects of several road environment factors were also found to be significant, such as the number of lanes (Chandra et al., 2014), weather condition (Borzendowski et al., 2013), road width (Ishaque and Noland, 2008), and crossing location (Zhao et al., 2019). In addition, some studies indicated that pedestrian characteristics, like gender (Hulse et al., 2018), age (Kalantarov et al., 2018), and group size (Pawar and Patil, 2015), also had an influence on pedestrian crossing gap acceptance.

Typically, before pedestrians start the action of crossing the road, there is usually a period of time, called crossing initiation time or response time (Lobjois and Cavallo, 2007). When there are consecutive vehicles driving on the road, the crossing initiation time refers to the duration between when the rear end of the preceding vehicle passes the pedestrian position and when the pedestrian starts crossing (Tian et al., 2022). While, if there is only one car approaching the pedestrian, crossing initiation time is the duration between when the vehicle appears in the lane and when the pedestrian initiates (Pekkanen et al., 2021). Although the specific definition of crossing initiation time depends on the study, it reflects the efficiency of pedestrian cognitive and locomotor systems. Previous studies indicated that pedestrian crossing initiation time was affected by vehicle distance, speed (Lobjois and Cavallo, 2009; Lee et al., 2022), and age (Oxley et al., 2005).

Furthermore, except for the factors mentioned above, when pedestrians cross the road under time pressure or engaging in distraction tasks, there are significant pattern changes in their crossing behaviour (Kalantarov et al., 2018; Larue and Watling, 2021). Specifically, pedestrians who use a cell phone while crossing the road may have a reduced walking speed and initiate crossings late (Campisi et al., 2022; Jiang et al., 2018). Time pressure may increase their propensity to take risks and reduce the quality of pedestrians' crossing decisions (Coeugnet et al., 2019).

1.1.2 Modelling pedestrian crossing decisions

According to the above literature, it can be found that researchers have conducted extensive studies regarding pedestrian crossing behaviour at intersections and identified numerous factors that might affect pedestrian crossing behaviour. Naturally, it is of interest to researchers to consider how to use computational models to reproduce realistic pedestrian crossing behaviour by involving those factors, which do have real social implications in terms of traffic safety, transportation management, infrastructure development, and more. In recent years, more research has been drawn to this research field due to the development of AVs and the great anticipation of highly automated vehicles (Camara et al., 2020; Rasouli and Tsotsos, 2019). The reason for this is that expanding the deployment of AVs from a few confined areas to a range of operational design areas may inevitably increase conflicts with pedestrians. AVs that fail to comprehend pedestrian behaviour and interact appropriately may not improve traffic efficiency and safety as expected, but rather add traffic dilemmas and additional issues (Jennings and Figliozzi, 2019; Markkula et al., 2020; Millard-Ball, 2018). Consequently, the lack of computational models of pedestrian behaviour could limit the deployment of AVs. To date, many models have been developed to account for different aspects of pedestrian road-crossing behaviour, such as decision-making (Sun et al., 2003), walking speed (Iryo-Asano and Alhajyaseen, 2017), and walking trajectory (Zhang et al., 2020a; Farina et al., 2017). However, as the works in this thesis mainly focused on pedestrian crossing decisions, the literature on computational models of pedestrian crossing decisions is briefly presented below.

As described in the previous section, since empirical observations suggest that pedestrian crossing decisions at uncontrolled intersections are made by evaluating the size of the traffic gap, a branch of models has been proposed based on this assumption. The earliest approach, i.e., Raff's method (Raff and Hart, 1950), estimated the minimum gap accepted by half of the pedestrians, called the critical gap, as a threshold for crossing decision-making. Subsequent models based on this assumption are collectively referred to as fixed critical gap models, which model the fixed critical gap as a function of various predictors, such as vehicle speed or distance. For example, HCM (2010) provided a fixed critical gap model considering the length of the crosswalk and pedestrian walking speed. Furthermore, several recent models estimated the critical gap by involving vehicle speed and distance (Fu et al., 2018; Zhang et al., 2020a). Rasouli and Kotseruba (2022)'s model further posited that the critical gap decreased with the increase in the wait time.

Although fixed critical gap approaches were simple to develop, these approaches neglected the uncertainty of pedestrian crossing behaviour and posited that the critical gap is a fixed value for given predictors. Therefore, to solve this problem, maximum likelihood approaches were proposed, which calculated the probability of the critical gap between the largest rejected gaps and accepted gaps by using the Maximum Likelihood Estimation. These approaches assumed the largest rejected gaps and accepted gaps as a random variable obeying a certain distribution, such as Lognormal, Erlang, Weibull and Gamma distributions (Sun et al., 2003). Brilon et al.

(1999) and Pawar and Patil (2016) showed maximum likelihood approaches performed better than fixed critical gap approaches.

However, the maximum likelihood methods did not provide a solution to the issue, i.e., heterogeneity of pedestrians and environments. These approaches assumed pedestrians and environments were homogeneous. In other words, many characteristics of pedestrians and environments were neglected, such as pedestrian group size, age, and number of road lanes, potentially engendering poor generalisation performance. Accordingly, researchers found another way to characterise pedestrian crossing decisions. Instead of using the critical gap assumption, researchers assumed that pedestrian crossing decisions were binary responses, i.e., either cross or not, obeying a Bernoulli distribution (Himanen and Kulmala, 1988). Accordingly, machine learning methods, i.e., Artificial Neural Networks (Raghuram Kadali et al., 2014) and Support Vector Machine (Pawar et al., 2016), were applied to predict pedestrian crossing decisions. For instance, Raghuram Kadali et al. (2014) established an artificial neural network for modelling pedestrian crossing gap acceptance and found that pedestrian rolling gap had a major effect. However, despite their efficiency, advanced machine learning models may struggle to explain the key aspects of the decisions due to their poor interpretability. For instance, it is not easy to identify relationships between independent and dependent variables (Markkula and Dogar, 2022). Another class of models, i.e., logit binary crossing gap acceptance models, built on the same assumption, but employed the binary logit model and was more explanatory (Sun et al., 2003; Himanen and Kulmala, 1988; Zhao et al., 2019). These models could involve many factors, such as gap size, vehicle speed, vehicle size, pedestrian age, and clearly demonstrate their relationship to pedestrian crossing decisions. Specifically, Himanen and Kulmala (1988) established a logit model and found that pedestrian group size, vehicle speed, and vehicle size had the most important effects on pedestrian crossing decisions. Zhao et al. (2019) used a logit model and showed that gap size and crossing distance were critical factors that affected pedestrian crossing decisions. Not limited to that, extensive studies on logit models have been conducted. Numerous factors influencing pedestrian decisions were identified, such as age (Lobjois et al., 2013), waiting time (Zhao et al., 2019), illegal parking car (Yannis et al., 2013), number of lanes (Kadali and Vedagiri, 2013), and more.

The above paragraphs shows that existing pedestrian crossing decision models have become mature tools for pedestrian crossing behaviour study. However, with the development of transport and vehicle technologies, e.g., the emergence of AVs, these models may not meet the needs of emerging technologies. In particular, existing models are rarely based on specific behavioural or psychological theories but rather focus on application purposes (Markkula et al., 2022). Establishing computational models of pedestrian crossing behaviour based on psychological theories facilitates the understanding of how and why pedestrians interact with vehicles in their way. Psychological theories can, on the one hand, increase the interpretability of the model and, on the other hand, extend it to relatively complex interactive scenarios. For example, most existing models posit that the vehicle approaches pedestrian crossing locations at constant speeds and do not explain pedestrian behaviour in vehicle-yielding scenarios (Zhang et al., 2020b). Meanwhile, extensive studies in psychology explore human decision-making mechanisms in their own fields (Ratcliff and McKoon, 2008; DeLucia, 2015). However, these theories have not been generalised to pedestrian-vehicle interactions. Hence, it is valuable to investigate how well the computational models explain pedestrian behaviour based on psychological theories. Furthermore, pedestrian decisions in existing models are established at a relatively coarse-grained level and ignore the details of decisions. For example, most models only determine pedestrian crossing decisions and do not account for the time-dynamic nature of crossing decisions, i.e., crossing initiation time (Fu et al., 2018; Zhao et al., 2019). In the following sections, the psychological theories related to pedestrian road-crossing decisions are provided.

1.1.3 Human collision perception theory for pedestrian crossing behaviour

In human perception theory, as an object moves closer to the observer, its increasing image on the retina causes the observer to perceive it as an approaching object (Gibson, 2014), which forms the basis of human collision perception. In more detail, if the image of the object, such as a vehicle, continues to expand and reaches a certain perceptual threshold, it indicates that pedestrians can perceive that the vehicle is approaching (Hoffmann and Mortimer, 1994). The human ability to recognise such continuously growing images, i.e., visual looming stimulus, has a close relationship with the human sense of collision threat and human avoidance behaviour (Ball and Tronick, 1971; Gibson, 2014). To specify the visual looming stimulus, a psychophysical model can be established, as shown in Fig. 1.1. The expansion rate of the image on the human retina is simplified as the change rate of the visual angle subtended by the approaching object at the observer's pupil (Lee, 1976), given by:

$$\theta = 2\tan^{-1}(\frac{w}{2Z}) \Rightarrow \dot{\theta} = \frac{wv}{(Z)^2 + w^2/4} \tag{1.1}$$

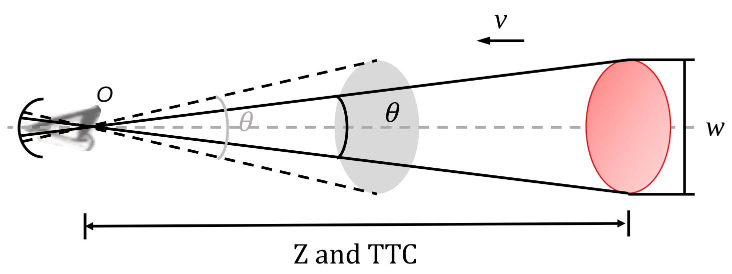

Figure 1.1: Psychophysical model for visual looming stimulus. The eye model comprises a semi-circular 'retina' and a pinhole O as 'pupil'. An object with speed v moves towards the observer from distance Z or TTC. The visual angle on the retina at O equals the angle θ subtended by the object. When the object gets closer, the visual angle θ increases and the continuous change rate of θ is referred to as the visual looming $\dot{\theta}$.

where $\dot{\theta}$ refers to the first temporal derivative of visual angle. Z and w denote vehicle distance from the pedestrian and its width. Previous studies on vehicle rear-end collisions indicated 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 looming (Hoffmann and Mortimer, 1994; DeLucia and Tharanathan, 2005; Maddox and Kiefer, 2012; Markkula et al., 2016).

In some situations, e.g., vehicle-yielding scenarios, humans require both the spatial and temporal properties of objects to avoid potential collision events. However, $\dot{\theta}$ does not provide information on time to collision (TTC) of an approaching car (DeLucia, 2008). Therefore, another visual cue has been studied, i.e., τ, which is the ratio of visual angle, θ, to the change rate of visual angle, $\dot{\theta}$. Lee (1976) has mathematically demonstrated that τ specifying the collision time between the observer and object for small visual angles. Moreover, the first temporal derivative of τ, i.e., $\dot{\tau}$, is relevant for detecting whether a collision will occur and $\dot{\tau} \geq -0.5$ represents that the current deceleration rate is adequate, and the collision events can be avoided (Bardy and Warren Jr, 1997). The equations are as follows:

$$\dot{\tau} = \frac{ZD}{v^2} - 1; \frac{v^2}{2D} \leq Z \Rightarrow \dot{\tau} \geq -0.5 \tag{1.2}$$

where D is the deceleration rate of the vehicle. D is adequate to stop a vehicle safely in front of the pedestrian only if the distance the vehicle will take to stop, $\frac{v^2}{2D}$, is less than or equal to its current distance, Z, from the pedestrian.

In addition to the perceptual cues that humans may use, the processes underlying space perception may be affected by certain perceptual strategies, e.g., the presence of information or the ability of humans to extract information from the environment. A conceptual framework proposed by DeLucia (2008) suggests that when the tasks happen at a far distance, due to the limitations of the human visual system, the humans tend to use 'heuristic' visual cues, such as visual angle and its change rate, to judge the situation. However, when collision events happen at a near distance, collision perception is predominated by optical invariants, like τ. Invariants refer to higher-order properties of the optic array that specify properties of a three-dimensional environment, which provide veridical and reliable information of the time. In contrast, information provided by heuristics is not necessarily veridical and reliable (DeLucia, 2004). Inspired by the above conceptual framework, in road-crossing scenarios, when an approaching vehicle is travelling at a near-constant speed, its deceleration rate may be too small to be noticed. Or, the vehicle is too far away from pedestrians, and the information provided by visual cues about the vehicle behaviour is too impoverished and inadequate for pedestrians to get a good understanding of the vehicle's position and movement. In these situations, pedestrians may tend to rely on 'heuristic' visual cues that are easy to acquire and process. Once visual invariants become abundant, like τ and its change rate, pedestrians may rely on these visual cues. Hence, this assumption implies that Humans or pedestrians may be selective in their use of visual cues, potentially contingent on the availability of those cues.

1.1.4 Emerging cognitive models for pedestrian crossing behaviour

With the development of psychological and cognitive theories, a new class of models has emerged in recent years, namely the evidence accumulation model (Giles et al., 2019; Markkula et al., 2018; Pekkanen et al., 2021), which has been proven to have the ability to address the shortcomings of traditional models (mentioned in Section 1.1.2). Building on the well-established decision-making theory, i.e., drift-diffusion process, in psychology and cognitive neuroscience (Ratcliff et al., 2016), these evidence accumulation models posit that the pedestrian crossing decisions result from an accumulation process of visual cues and noisy evidence, and decisions are finalised after the accumulated evidence reaches a certain threshold. The resulting response time distribution details the crossing decisions and their timing. These models, therefore, provide a powerful explanatory tool for pedestrian crossing decisions guided by visual cues from a human cognitive perspective.

In spite of the fact that evidence accumulation models are promising, these models need further refinement in some aspects. Firstly, the paradigm of standard evidence accumulation theory upon which these models are based was developed for relatively simple experimental tasks with single-stimulus, such as judging the direction of moving dots which are interspersed

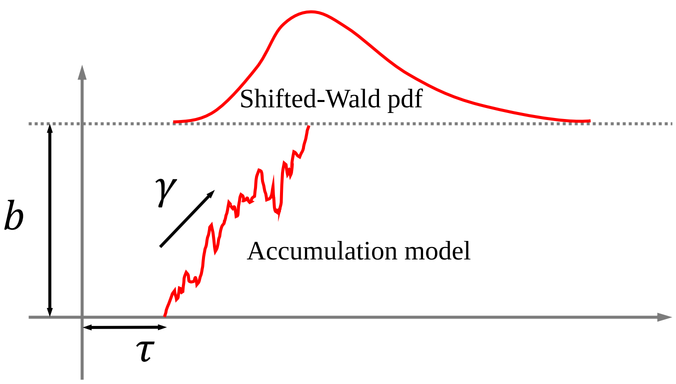

Figure 1.2: Schematic diagram of Shifted-Wald distribution and a single boundary evidence accumulation model. The Shifted-Wald distribution equals a single boundary evidence accumulation model with threshold b, drift rate γ, time shift τ, and standard Gaussian noise $\epsilon \sim N(0, 1)$.

with other randomly moving dots (Ball and Sekuler, 1982), comparing randomly presented numbers to a given number (Schwarz, 2001). Due to this nature, evidence accumulation models may not currently be able to describe the decision processes perfectly without elaborate design. Moreover, due to the great complexity of those models, they are computationally demanding (Schwarz, 2001; Anders et al., 2016). Regarding the second concern, psychologists have developed efficient response time distribution measurement tools instead of using the process models, such as the evidence accumulation model. These tools, known as quantitative response time models, are typically closed-form probability density functions with positive skew, such as Ex-Gaussian (Burbeck and Luce, 1982), Weibull distribution (Logan, 1992) , Shifted Wald distribution (Wagenmakers, 2009), in which the parameters describe the properties of the response time data. Considering the similarities of those methods, we only introduce the Shifted Wald distribution, not all of them. The Shifted Wald distribution is a simple and concise response time distribution modelling tool, which can fully quantify the response time with three parameters: b (deviation around the mode), γ (tail magnitude) and τ (onset of the distribution). Its equation is defined as:

$$\begin{gathered} x \sim \mathrm{SW}(b, \gamma, \tau) \\ \Rightarrow \frac{b}{\sqrt{2\pi(x-\tau)^3}} \cdot \exp\left(\frac{-[b-\gamma(x-\tau)]^2}{2(x-\tau)}\right) \end{gathered} \tag{1.3}$$

it can be shown that the Shifted Wald distribution is the response time distribution for a single boundary evidence accumulation model with threshold b, drift rate γ, time shift τ, and standard Gaussian noise $\epsilon \sim N(0, 1)$ (Figure. 1.2) (Anders et al., 2016). Accordingly, the Shifted Wald distribution shares the similar cognitive basis with the evidence accumulation model. However, it is more concise and simple to use. Therefore, it may be a useful tool for modelling the time-dynamic of pedestrian crossing decisions qualitatively and quantitatively.

1.2 Research gaps

As discussed in the previous sections, although there are many studies in pedestrian crossing decision modelling, several critical unanswered questions remain. The work in this thesis attempts to answer some of these questions by investigating pedestrian road-crossing behaviour and bringing those observations into computational models. The following critical gaps are identified:

Gap one: Critical visual cues for pedestrian crossing decisions in the pedestrian-vehicle interaction.

Since visual perception is the basis for pedestrians to establish situation awareness (Palmeiro et al., 2018; Coeugnet et al., 2019), the first key gap is a lack of studies investigating the psychological mechanisms underlying pedestrian road-crossing decision-making, especially from the visual perception perspective. As a result, traditional pedestrian crossing models have not considered pedestrian perceptual processes. Concerning this gap, one important issue is that the visual cues pedestrians use in the road-crossing task remain unexplored: what visual cues do pedestrians apply to perceive the motion of an approaching vehicle? However, as mentioned in Section 1.1.3, since pedestrians may rely on different visual cues based on the availability of these cues, another question is: what are the roles of these visual cues in crossing decision-making?

Gap two: Pedestrian crossing behaviour in diverse scenarios

The second gap is the lack of research investigating pedestrian crossing behaviour in diverse traffic scenarios. Specifically, many existing studies focused on the scenario with one vehicle or vehicle driving at a constant speed (Zhao et al., 2019; Dey et al., 2021). However, in real traffic, pedestrians often interact with continuous traffic flow or vehicles with different types of acceleration patterns (Ackermann et al., 2019; Lobjois et al., 2013). Moreover, less is known about how pedestrians adjust their crossing behaviour in different TTC conditions while affected by secondary tasks, such as time pressure and distractions. Therefore, the results of existing studies may not be easy to generalise to more complex traffic situations.

Gap three: Modelling pedestrian road-crossing decisions in less simplistic traffic scenarios based on perceptual information

According to the gaps discussed above, a third research gap naturally emerges: there is a lack of computational models to characterise pedestrian crossing behaviour in less simplistic traffic scenarios and to provide explanations of the underlying perceptual mechanisms. Moreover, as discussed in Section 1.1.2, existing pedestrian decision models has been established at a relatively coarse-grained level and ignored initiation time information of crossing decisions. Notable exceptions regarding this limitation are provided by Markkula et al. (2020); Giles et al. (2019); Pekkanen et al. (2021), who capture time information of crossing decisions by using evidence accumulation models. However, as discussed in Section 1.1.4, those models may be currently not competent in some aspects. Unlike those cognitive models, this study attempt to explore a different way to model pedestrian crossing decisions.

1.3 Research objectives

To bridge the identified research gaps above, this work has several distinct objectives, aiming to investigate pedestrian crossing decisions, the underlying perceptual mechanisms underpinning their behaviour, and to develop computational models of road-crossing decisions in less simplistic traffic scenarios. These objectives can be classified in terms of observation (using two existing datasets and one dataset collected as part of this thesis project) and modelling methods. In particular, objectives belonging to each of these themes are described below.

Observations

- **O1**: The first objective is to identify the visual cues related to pedestrian crossing behaviour in a simple road-crossing scenario using an empirical dataset. In this study, pedestrians face the approaching vehicle driving at constant speeds, where vehicle speeds and traffic gaps are controlled to investigate their impacts on pedestrian crossing decisions.
- **O2**: Afterwards, we plan to extend the road-crossing scenario to a more complex one, where the approaching vehicle either drives at constant speeds or yields to pedestrians at constant deceleration rates. Pedestrian crossing decisions and judgments about vehicle behaviour are investigated.
- **O3**: Moreover, in real traffic, pedestrians usually interact with multiple vehicles on a

lane, i.e., continuous traffic flow. Additionally, pedestrians are heterogeneous. For example, some pedestrians engage in secondary tasks, such as using their mobile phones while crossing the road. Therefore, our third objective of the observation research is to investigate pedestrian crossing behaviour when facing continuous traffic flow scenarios and compare their crossing behaviour under the influence of different secondary tasks.

Models

- **M1**: According to **O1**, the first modelling objective is to establish a visual cues-based crossing decision model in simple constant speed scenarios, hoping to reasonably reproduce pedestrian crossing decisions and explain the impacts of vehicle speed and traffic gap.
- **M2**: Based on the identified visual cues and theory from **O1** and **O2**, we aim to extend the model from a simple constant-speed scenario to a scenario involving both yielding and no-yielding vehicles. The model aims to predict pedestrian crossing decisions quantitatively and provide improved understanding of pedestrian crossing behaviour based on the perception theory.
- **M3**: According to the findings from **O3**, the third modelling objective is to adapt the crossing decision model to the continuous traffic flow scenario.
- **M4**: As discussed in the third research gap (Section 1.2), existing models characterise pedestrian crossing decisions at a relatively coarse-grained level and ignore the time-dynamic nature of crossing decisions. Therefore, the fourth modelling objective is to consider pedestrian crossing initiation time in the model.

1.4 Thesis outline

In order to demonstrate how this work have addressed the above objectives and closed the identified research gaps, this section briefly introduces each chapter (all of which have been published, submitted or prepared for publication as journal papers; see Intellectual Property Statement) and introduces how each study led to the later ones.

Chapter 2 presents a paper entitled ’Explaining unsafe pedestrian road-crossing behaviours using a psychophysics-based gap acceptance model’. By using an empirical dataset, the main purpose of this study was to investigate pedestrian crossing behaviour when interacting with constant speed vehicles at uncontrolled intersections and explore the correlation between crossing behaviour patterns and visual cues. Notably, in this study, an unsafe pedestrian crossing behaviour pattern, i.e., pedestrians tend to accept smaller time gaps in conditions with higher vehicle speeds, is explained using the visual cue-based crossing decision model. Therefore, this work addressed **O1** and **M1** (Section 1.3) and highlighted the notion that visual cues may cause a sense of collision threat that affects pedestrian crossing decisions, which would be an important mechanism behind pedestrian crossing decisions. The results of this work are the critical theoretical and modelling basis for the studies in **Chapter** 5 and 6.

In addition to the simple case of constant speed traffic, another typical scenario is where approaching vehicles may or may not give way to pedestrians. Accordingly, **Chapter 3** presents a paper entitled 'Driving manoeuvres of automated vehicles as implicit communication signals for pedestrian road-crossing behaviour and judgement'. The aim of this work was to investigate the patterns of pedestrian judgments of vehicle behaviour (either yielding or not) and their crossing behaviour. In this study, two different experimental tasks were designed at uncontrolled intersections: vehicle behaviour judgement and road-crossing tasks. We showed that pedestrians might base their crossing decisions on different strategies during the vehicle yielding process. Their decision pattern aligned with a visual cue related to yielding behaviour detection. Interestingly, pedestrians tended to interpret vehicle's low speeds as yielding signals, regardless of whether the vehicle slowed down or not. Therefore, this study addressed **O2** (Section 1.3) and provided evidence for modelling pedestrian crossing decisions in vehicle-yielding scenarios in **Chapter** 6.

Beyond the scenario where pedestrians interact with a single vehicle, it is often the case that pedestrians are faced with a queue of vehicles when crossing the road. Moreover, it is also interesting to investigate pedestrians engaged in different secondary tasks besides road-crossing. Hence, **Chapter 4** presents a paper entitled 'Impact of visual and cognitive distractions and time pressure on pedestrian crossing behaviour: a simulator study'. In an empirical simulated experiment, pedestrians were required to complete crossing tasks in a road-crossing scenario with a one-lane road with and continuous traffic and performed one of three tasks: time pressure, visual-manual, and auditory-cognitive tasks. Our analysis results highlighted that two types of distraction and time pressure impaired pedestrian safety, but in different ways. Interestingly, a significant effect of the traffic characteristic was found, motivating the assumption that participants compared the traffic gaps in the traffic flow to optimise their crossing decisions. Accordingly, this study solved **O3** (Section 1.3) and provided further theoretical and modelling basis for the study in **Chapter** 5.

Beyond the observation studies in previous chapters, simulating pedestrian crossing decisions in less simplistic traffic environments is another focus of this thesis. Based on our previous findings in **Chapter** 2, 3, and 4, two crossing decision models accounting for pedestrian crossing behaviour in different crossing scenarios are proposed in **Chapter 5** and **Chapter 6** .

Chapter 5 presents a paper entitled 'Deconstructing pedestrian crossing decisions in interaction with continuous traffic: an anthropomorphic model'. In this paper, based on the deconstructed cognitive process hypothesised to underlie the crossing decision, a visual cue-based crossing decision model is proposed to characterise pedestrian crossing behaviour in continuous traffic flow. The proposed crossing decision model successfully integrates the previous research findings: visual cue-based decision model (**Chapter** 2) and traffic flow impacts (**Chapter** 4). Notably, this study assumes that pedestrian crossing initiation time obeys a specific distribution and relates the visual cue to the parameters of the distribution model. Thus, simulated pedestrian agents can adapt their crossing initiation times to different traffic scenarios. Consequently, the proposed model not only addressed **M3** (Section 1.3) by modelling pedestrian crossing decisions in continuous traffic flow, but also solved **M4** (Section 1.3) by characterising the time-dynamic nature of pedestrian crossing decisions.

Chapter 5 did not provide solution to **M2**. Thus, **Chapter 6** presents a paper 'Pedestrians interact with yielding vehicles using a hybrid perception strategy: a modelling study'. According to the findings in **Chapter** 2 and 3, a hybrid perception assumption is proposed to explain how pedestrians may apply different visual cues to make crossing decisions in different stages of a vehicle's approach or yielding. Simple discrete choice models based on the hybrid perception strategy combined with the crossing initiation model (**Chapter** 5) simulate the details of pedestrian crossing decisions in front of a approaching or yielding vehicle. The results indicates that our model qualitatively and quantitatively predicts pedestrian road-crossing decisions across a range of vehicle-yielding scenarios. Therefore, **M2** was addressed in this study.

Finally, in **Chapter 7**, a general discussion is provided, drawing conclusions from the full range of studies. Potential implications of this thesis are discussed from theoretical and practical perspectives. Furthermore, important future steps regarding the identified gaps are also included.

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CHAPTER 2

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

Explaining Unsafe Pedestrian Road Crossing Behaviours Using a Psychophysics-based Gap Acceptance Model

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.

Keywords: Pedestrians; Unsafe crossing decision; Psychophysical model; Gap acceptance modelling; Safety margin

2.1 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, 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., 2005; Nunez 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 Farber (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:

- How does speed-induced unsafe crossing behaviour affect pedestrian road crossing safety?

- 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.

2.1.1 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 Farber, 2009), time to arrival (TTA) (Avinash et al., 2019; Pawar and Patil, 2016), distance (Lobjois and Cavallo, 2007; Schmidt and Farber, 2009), number of lanes (Chandra et al., 2014), and vehicle size (Beggiato et al., 2017; Lee et al., 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).

2.1.2 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 Farber, 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 Farber, 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 (Velasco et al., 2019) and field tests (Schmidt and Farber, 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 Farber, 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 Farber, 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.

2.1.3 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 indicates that pedestrians can perceive that the vehicle is approaching (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, 2004; 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 et al., 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.

2.2 Methodology

2.2.1 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 2.1a, there is a rectangular object with length l and width w approaching the observer with a constant speed $v(t)$. The object deviates from

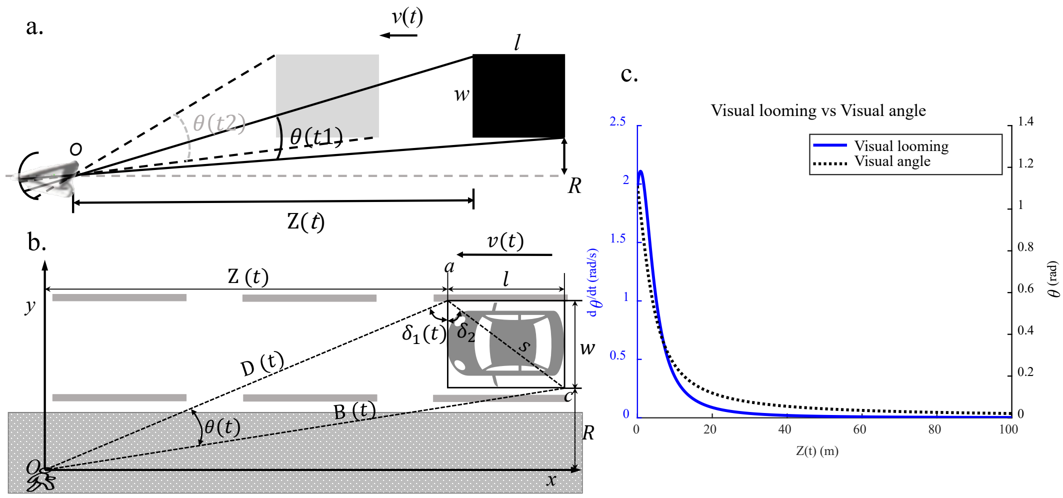

Figure 2.1: (a) Looming model. The eye model comprises a semi-circular 'retina' and a pinhole O as 'pupil'. At timestep $t1$, an object with speed v moves towards the observer from distance $Z(t)$. The visual angle on the retina at O equals to the angle $\theta(t1)$ subtended by the object. At timestep $t2$, when the object gets closer, the visual angle is $\theta(t2)$ 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., $\mathrm{w} = 1.95$, $\mathrm{l} = 4.95$, $\mathrm{R} = 2.45$, $v = 30$ mph

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 2.1a 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 2.1b. 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 $\angle oac$ is denoted by $\delta(t)$, which is comprised of angle $\delta_1(t)$ and δ_2 . As shown in Fig 2.1b, the diagonal of the vehicle is:

$$\mathrm{s} = \sqrt{\mathrm{w}^2 + \mathrm{l}^2} \tag{2.1}$$

Since the lateral distance between pedestrian and vehicle is R, the length of oa line and oc line in Fig 2.1b can be formulated as:

$$D(t) = \sqrt{Z(t)^2 + (\mathrm{R} + \mathrm{w})^2} \tag{2.2}$$

$$B(t) = \sqrt{(Z(t) + 1)^2 + \mathrm{R}^2} \tag{2.3}$$

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:

$$\delta_1(t) = \arctan\left(\frac{Z(t)}{\mathrm{R} + \mathrm{w}}\right) \tag{2.4}$$

$$\delta_2 = \arctan\left(\frac{1}{\mathrm{w}}\right) \tag{2.5}$$

$$\delta(t) = \delta_1(t) + \delta_2 \tag{2.6}$$

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

$$\theta(t) = \arcsin\left(\frac{s \cdot \sin(\delta)}{B}\right) \tag{2.7}$$

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

$$\dot{\theta}(t) = -F_1 \cdot \left(F_2 \cdot \frac{1}{\mathrm{R} + \mathrm{w}} - F_3\right) \cdot v(t) \tag{2.8}$$

where: $F_1 = 1/\sqrt{1 - (\mathrm{s} \cdot \sin(\delta)/B)^2}$, $\cdot F_2 = \mathrm{s} \cdot \cos(\delta)/\left(B \cdot (1 + F_4^2)\right)$, $F_3 = \mathrm{s} \cdot \sin(\delta) \cdot \left(B^{-1} \cdot (Z + 1)\right)/B^2$, $F_4 = Z/(\mathrm{R} + \mathrm{w})$. The visual looming is calculated and plotted in Fig 2.1c, showing that the visual angle and the looming increase slowly as the 30 mph vehicle approaches from 100 m to 20 m distance. However, when the distance is less than 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 $f(1/TTA)$ (Gupta et al., 2009) and $exp(-\beta TTA)$

(Zhuang and Wu, 2013). Hence, the looming has the potential ability to characterise pedestrian's feeling of risk in a road-crossing scenario.

2.2.2 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):

$$\operatorname{logit}(\boldsymbol{y} \mid \text{ accept }) = \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \tag{2.9}$$

where $\operatorname{logit}(\boldsymbol{y}) = \ln(\boldsymbol{y}/(1-\boldsymbol{y}))$. $\boldsymbol{y}$ represents the outcome variable. $\boldsymbol{X}$ 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:

$$\operatorname{logit}(\boldsymbol{y} \mid \text{accept}) = \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{Z}\boldsymbol{u} + \boldsymbol{\varepsilon} \tag{2.10}$$

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.

2.2.3 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:

$$\operatorname{logit}\left(y_i \mid \text{ accept }\right) = \beta_0 + \beta_1 f\left(\dot{\theta}_i\right) + u_{1,ij} f\left(\dot{\theta}_{ij}\right) + u_{0,ij} \tag{2.11}$$

where $\dot{\theta}_i$ is the looming value for ith trial, while $\dot{\theta}_{ij}$ is ith looming value belonging to jth participant. β_0 and β_1 are coefficients and slope with fixed effects. $f(\cdot)$ is a transformation function, discussed in Section 2.5.2 $u_{0,ij}$ and $u_{1,ij}$ are random coefficient and slope for 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:

$$\text{logit}\,(y_i \mid \text{ accept }) = \beta_0 + \beta_1 v_i + \beta_2 t_i + u_{1,ij} t_{ij} + u_{0,ij} \tag{2.12}$$

where v_i and t_i are the vehicle speed and time gap size for ith trial and t_{ij} is the time gap size for ith trial belonging to jth participant.

2.3 Empirical data

(a) (b)

Figure 2.2: a. Highly Immersive Kinematic Experimental Research (HIKER) simulator. b. The experimental scenario in the HIKER

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 2.2 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 4K 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.

a

b

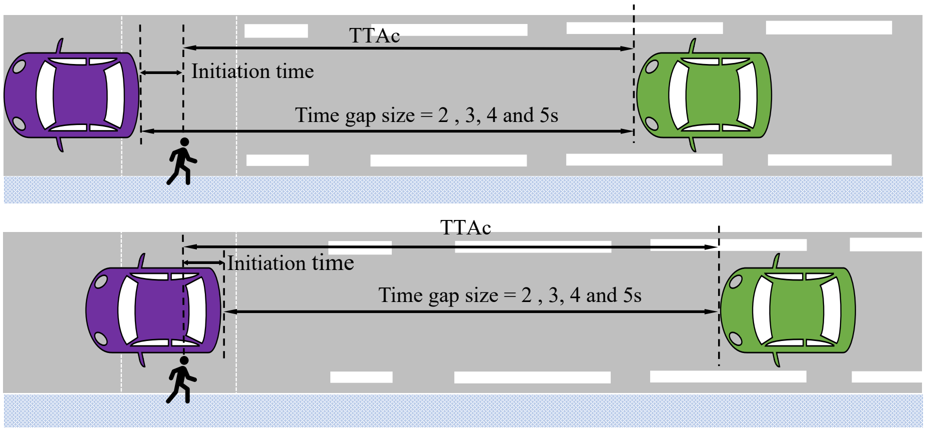

Figure 2.3: (a) Schematic diagrams of experiment scenario and crossing initiation. (a) Pedestrians started crossing after the previous car passed them, so the TTAc was smaller than the time gap. (b) Pedestrians started crossing before the previous car passed them, so the TTAc was bigger than the time gap.

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 2.3a). 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 2.3a). 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, $4x3 = 12$ 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 dataset from Lee et al. (2022), the data from Lobjois and Cavallo (2007) was also used to evaluate the model in Section 2.5.2 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 2.1.

Table 2.1: 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

2.4 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 Farber, 2009).

2.4.1 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 (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.

2.4.2 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 2.3). When participants started crossing after the first car passed them, the TTAc was smaller than the time gap size (Fig 2.3a). 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 (Schneider et al., 2021). Fig 2.4b 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 2.4b, this tendency was observed among all the groups.

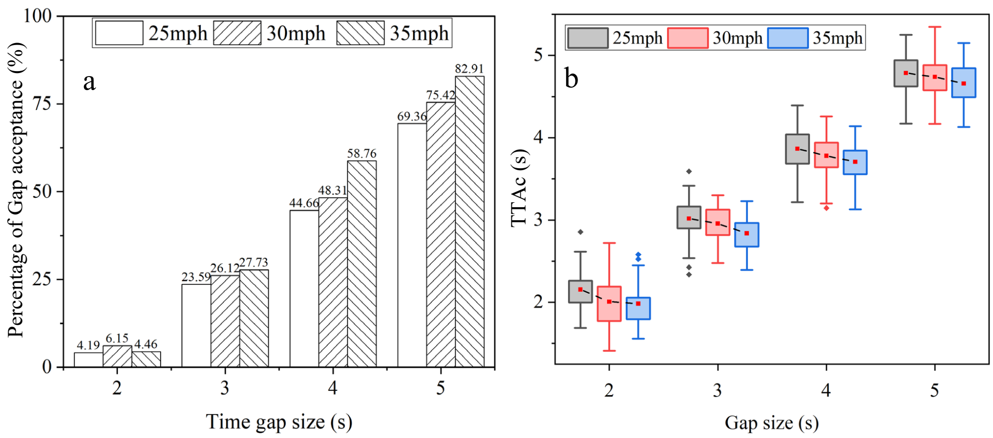

Figure 2.4: (a) Percentage of gap acceptance. (b) Box chart of TTAc, and the small red squares represent the arithmetic mean

Gap acceptance. Fig 2.4a 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 less than 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 ($Coef. = 1.263, p < 0.001$) 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.

Table 2.2: 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 (%)

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 TTAc and

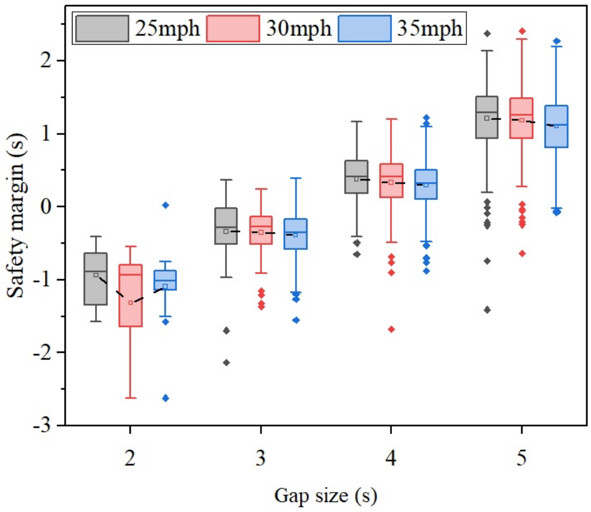

Figure 2.5: Safety margin plotted as the function of time gap and vehicle speed. The arithmetic mean and median are represented by small squares and short horizontal lines in boxplots

the crossing duration of each trial. With speed and time gap size as independent variables, a two-way repeated ANOVA was conducted on safety margin. As shown in Fig 2.5, 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 less than 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 2.2 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 2.4a, 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.

2.5 Model calibration and comparison

2.5.1 Visual looming in the experimental scenarios

Fig 2.6 shows the looming curves calculated using the experimental parameters from (Lee et al., 2022) (Table 2.1). The curves of the model are plotted as the functions of the TTA and the spatial distance separately. Fig 2.6a 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 2.6b, 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 2.6 align qualitatively with the effects of speed and distance on pedestrian crossing as reported in the literature (Oxley et al., 2005; Schmidt and Farber, 2009) and in our statistical analysis in Section 2.4. This alignment provides a first indication that pedestrians' risky road crossing behaviour may stem from a reliance on visual looming cues.

2.5.2 Psychophysics-based gap acceptance model

To fully specify the PGA model, the first subsection below investigates how the looming information might best be transformed into a utility for use in the logit formulation of the

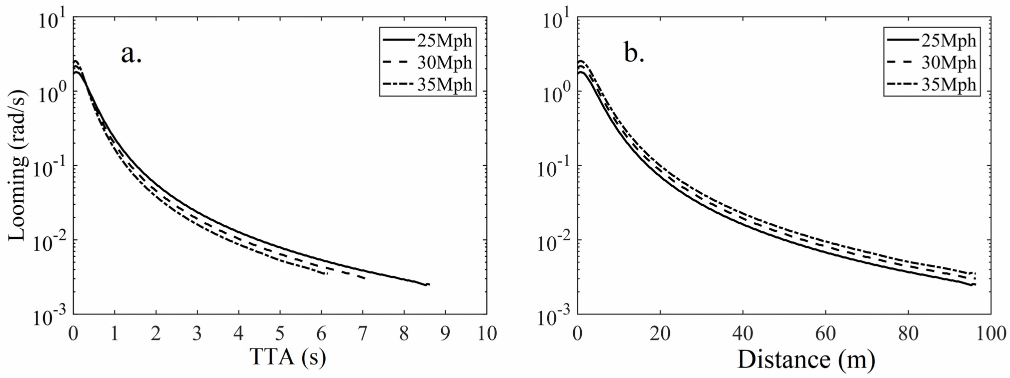

Figure 2.6: The speed effect on looming in experiment scenarios. (a) The model is plotted as a function of TTA and speed. (b) The model is as a function of distance and speed. Note that the visual looming is shown on a logarithmic scale.

PGA model. Then, the second subsection describes our fits of the PGA model to two datasets. Finally, we compare the PGA model with the conventional BGA model in the third subsection.

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:

$$\mathrm{logit}(\mathrm{Pr}) = [f(\dot{\theta})]^T \beta_1 + \boldsymbol{\alpha_1} \tag{2.13}$$

where Pr refers to the road-crossing percentage. Since a probability of one hundred and zero would result in infinite $\mathrm{logit}(\mathrm{Pr})$, 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 $f(\cdot)$, the $\dot{\theta}$ was input to the linear analysis without transformation. The results, as shown in Table 2.3, indicated that the $\dot{\theta}$ was significantly negatively related to $\mathrm{logit}(\mathrm{Pr})$, but the regression curves did not fit the data very well, as shown in Fig 2.7a. Considering that the looming had an approximately exponential form, a logarithmic function was applied, i.e., $\ln(\cdot)$. The linear analysis yielded significant linear correlations (Table 2.3, Fig 2.7b), 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.

Table 2.3: Results of linear regression of the logit probability of road crossing onto looming, with and without a natural logarithm transformation.

$f(\cdot)$	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

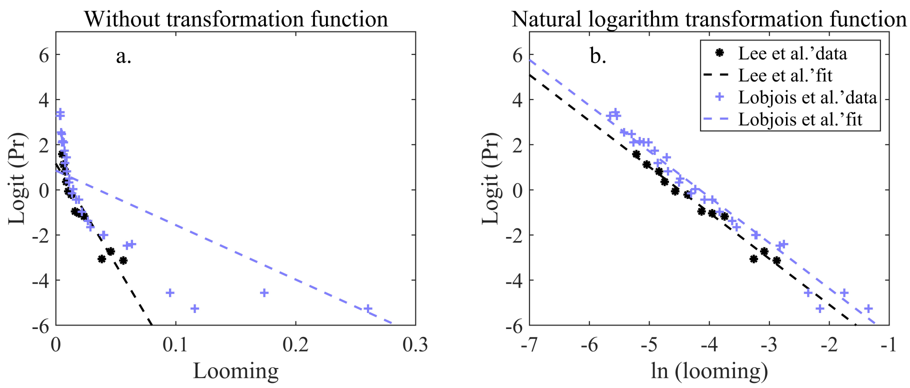

Figure 2.7: Relationship between non-transformed (a) and ln-transformed (b) visual looming and the logit probability of road crossing. The black circles and blue crosses are the data points. The dashed lines show the fitted linear regression models in Table 2.3

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. (2022)' data, as we have the detailed information of each trail, a PGA model with participants' random effects (Eq 2.11) was applied and estimated using the built-in function, 'fitglme', in MATLAB (2021). Table 2.4 shows the estimated coefficients of the PGA model for Lee et al. (2022)'s dataset. For Lobjois and Cavallo (2007)'s 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 2.4, there was a significant random effect of looming,

Table 2.4: Estimated coefficients of the PGA model and BGA model in terms of Lee et al. (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	Coef.	95% Conf. Interval		Coef.	95% Conf. Interval	
Time gap	-	-	-	0.46***	0.23	0.93
Looming	2.39***	1.7	3.31			
Constant	13.55***	9.8	18.68	10.51***	5.83	18.96
Log-likelihood		-1055	-	-1067		
AIC		2119	-	2146		

Note. ***: $p < 0.001$

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 2.8. 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 2.8a, 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 2.8 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 2.8 b and c, collapses into just a single curve when seen from the perspective of looming in Fig 2.8a. Overall, the PGA model was able to capture both of these datasets well.

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 2.12), then the model refers to the conventional BGA model, which is commonly used in pedestrian road-crossing behaviour research (Pawar et al., 2016). In this section, we fit the BGA model to data and compare it to the PGA model. Except fixed effects of speed and

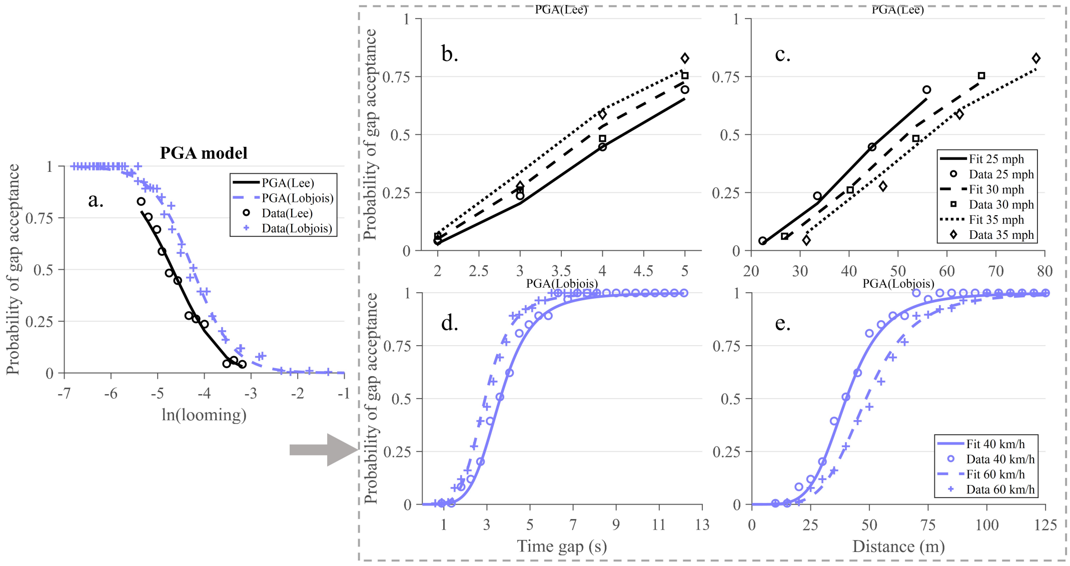

Figure 2.8: Road-crossing probability in Lee et al. (2022)' data (black symbols) and Lobjois and Cavallo (2007)'s data (blue symbols), together with corresponding fits of the PGA model (line types related to speed conditions). (a) Observed and model-fitted crossing probabilities were shown as a function 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).

time gap (Pawar and Patil, 2015), the random effects of time gap among participants were also considered in the BGA model (Eq 2.12). As shown in Table 2.4, 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).

$$\mathrm{AIC} = 2k - 2\ln(L) \tag{2.14}$$

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 2.4, 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.

2.6 Discussion

2.6.1 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 Farber, 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.

2.6.2 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.

2.6.3 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 (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.

2.7 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:

- For given time gaps with higher speed conditions, pedestrians tend to make more unsafe crossing behaviours.

- 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.

- 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.

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CHAPTER 3

Kinematics of automated vehicles as implicit communication signals for pedestrians to estimate vehicle behaviour and decide to cross the road

Kinematics of automated vehicles as implicit communication signals for pedestrians to estimate vehicle behaviour and decide to cross the road

ABSTRACT. Nowadays, society has high expectations for the large-scale deployment of automated vehicles (AVs). However, due to the absence of the driver role, the communication issues between pedestrians and AVs have not yet been solved. Prior findings have demonstrated the critical role of implicit signals. However, it is still not clear on the pattern of pedestrian crossing decisions when facing a vehicle with different driving manoeuvres. This study focused on vehicle kinematics as an implicit communication signal and explored its impacts on pedestrian road crossing behaviour and vehicle behaviour estimation. Two different simulator tasks, i.e., a natural road crossing task and a vehicle behaviour estimation task, were designed to investigate the influence of time to collision, vehicle speed, and driving manoeuvres on pedestrians when interacting with an approaching automated vehicle. For the first time, this study detailed the effect of implicit signals across a wide range of experimental traffic scenarios through a comprehensive analysis of pedestrian crossing behaviour and subjective estimates. Results showed that pedestrians could stably recognise different driving behaviours of the vehicle and correlate their estimates with their crossing decisions. However, pedestrians crossed the street earlier and estimated yielding behaviour more accurately in early-onset braking scenarios than in late-onset braking scenarios. Interestingly, vehicle speed critically impacted the pedestrian estimation, who tended to perceive the low-speed driving behaviour as yielding behaviour. We showed that visual cue $\dot{\tau}$ was associated with the detection of vehicle yielding behaviour, but may not be its simple immediate value. Finally, a multiple-decision strategy for pedestrian crossing decisions in the course of vehicle yielding was proposed. Our findings reveal in detail the impacts of vehicle kinematics on pedestrian crossing decisions and may have implications for road crossing safety and the development of AVs.

Keywords: Pedestrian-automated vehicle interaction; Road crossing; Vehicle behaviour estimation; Implicit communication signals.

3.1 Introduction

Automated vehicles (AVs), equipped with sensors, cameras and radars, use intelligent detection and motion planning algorithms to mitigate human operational errors and have become one of the most promising solutions to many current traffic issues (El Hamdani et al., 2020). However, AVs may bring about dramatic changes in the traditional communication mode between vehicles and other vulnerable road users (VRUs) due to the absence of a driver or driver not focused on the task of driving. For instance, the communication methods, like eye contact or hand gesture, may no longer exist, and pedestrians may have to purely rely on vehicles' movements to judge the situation (de Clercq et al., 2019). Recent studies have shown that failures in communication between AVs and VRUs (e.g., pedestrians) could lead to traffic dilemmas and additional safety issues (El Hamdani et al., 2020; Millard-Ball, 2018). Consequently, this concern has engendered a wide range of research in multiple fields, such as road user behaviour research (Lobjois and Cavallo, 2007), computational modelling (Pekkanen et al., 2021), external human-machine interface research (eHMI) (de Clercq et al., 2019) and more.

3.1.1 Explicit and implicit communication signals

In the communication between pedestrians and vehicles, the communication signals from approaching vehicles used by pedestrians can be divided into two categories, i.e., explicit and implicit signals. Explicit signals usually refer to a road user behaviour which can be interpreted as signalling information to other road users without affecting one's own movement or perception, while implicit signals are road user behaviour which affects own movement but can be interpreted as cues of its intention or movement by another road user (Markkula et al., 2020). In conventional traffic scenarios, the most observed explicit signals are eye contact, hand gesture, and light signal. There is convincing evidence to support the role of eye contact in pedestrian-vehicle interactions (Markkula et al., 2020; Nathanael et al., 2018; Rasouli and Tsotsos, 2019). Pedestrians seek eye contact to ensure that they have been seen by drivers or request the right of way. Not only that, the importance of eye contact is embodied by its safety impacts. That is, eye contact may increase the perceived safety of pedestrians (Onkhar et al., 2022). Compared to eye contact, the hand gesture and light signal are relatively less likely to be observed (Lee et al., 2021; Nathanael et al., 2018). For future traffic scenarios that include AVs, the conventional explicit signals may be compromised; eHMIs, therefore, act as a remedy to make up for missing communications and help reduce uncertainty in pedestrian behaviour. Evidence has showed that eHMIs could improve pedestrian performance at intersections (de Clercq et al., 2019; Lee et al., 2022). Meanwhile, road traffic can be seen as a social system in which continuous reciprocal communication between road users is necessary (Ackermann et al., 2019). Hence, the smooth integration of AVs in society requires them to clearly signal their intentions and movements to all other road users, and eHMIs thus may have critical significance in improving social acceptance of AVs (Carmona et al., 2021). To date, various types of eHMI prototypes have been proposed, such as textual messages (Nissan, 2015), light signals (Lee et al., 2022), anthropomorphic symbols (Semcon, 2016) and more.

However, there are some different opinions about explicit communication and eHMIs. Firstly, the reliability of eHMIs has been questioned as it may be affected by the weather (Kooijman et al., 2019), light condition (Rasouli and Tsotsos, 2019), as well as traffic situation (Dey et al., 2021b). Moreover, some studies have shown that pedestrians rarely use explicit signals in their daily life compared to implicit signals (Dey and Terken, 2017; Lee et al., 2021). The existence of explicit signals may not significantly affect the quality of pedestrian crossing behaviour, and reasonable implicit signals are enough for pedestrians to interact with AVs safely (Moore et al., 2019; Palmeiro et al., 2018; Sripada et al., 2021; de Clercq et al., 2019; Dey et al., 2021a). Furthermore, several recent studies have shown that the effect of eHMIs on pedestrians is itself influenced by implicit signals, such as vehicle deceleration and distance (de Clercq et al., 2019; Dey et al., 2021a).

Intuitively, implicit signals are more reliable than explicit signals, since they are directly related to the intention or movement of the vehicle. Existing studies have demonstrated that pedestrian road-crossing behaviour was affected by different implicit signals, contingent on traffic scenarios. In Chapter 2, at uncontrolled intersections, where drivers were not required to give way to pedestrians, distance and time to collision (TTC) were positively correlated to pedestrian crossing acceptance. Meanwhile, given a same TTC, pedestrians had increase tendency to cross the road as vehicle speed increased.

In vehicle-yielding scenarios, there is evidence that the speed adaption behaviour of drivers, e.g., deceleration, is a critical implicit signal affecting pedestrian behaviour (Ackermann et al., 2019; de Clercq et al., 2019; Lee et al., 2022). In a naturalistic observation, most pedestrians crossed the road when the approaching vehicle fully stopped or slowed down (Sucha et al., 2017). A field test done by Dey et al. (2021a) showed that pedestrian crossing willingness dramatically increased as vehicles significantly slowed down. They also found that pedestrian crossing willingness was not affected by eHMIs but depended on the vehicle kinematics in aggressive braking scenarios. Moreover, different deceleration patterns also have distinct impacts on pedestrians. Zimmermann and Wettach (2017) indicated that vehicle movement was correlated to pedestrian emotion and influenced pedestrian decisions. When approaching vehicles slowed down early and braked lightly, pedestrians felt comfortable and initiated crossing quickly. However, the late and harsh braking led to pedestrian avoidance behaviour (Dey et al., 2021a; Risto et al., 2017).

3.1.2 Pedestrian visual cues for vehicle behaviour

Up to this point, all findings mentioned above support the role of implicit signals. However, from a more general and psychological perspective, it has been shown that humans do not base their crossing decisions on direct estimation of absolute speed, TTC, distance or deceleration rates (Lee et al., 2019; Petzoldt, 2014; Sun et al., 2015), instead the movement of the vehicle is estimated from visual cues, such as visual angle, its change rate, and more (DeLucia, 2015; Lee, 1976). These visual cues have been proposed based on optical flow field theory and are thought to provide a more realistic description of pedestrian perceived collision risk (DeLucia, 2015; Lee, 1976). Visual angle represents the image size of objects on the observer's retina. Its change rate describes the image's expansion rate, which usually links to human perception of approaching objects. In Chapter 2, it has been found that pedestrian crossing behaviour is strongly correlated to the change rate of visual angle in scenarios where vehicles do not yield to pedestrians. Moreover, τ, i.e., the ratio of visual angle to the change rate of visual angle, specifies the TTC to approaching vehicles (Lee, 1976). If the change rate of τ is greater than -0.5, it means the deceleration rate of the approaching object is enough to stop in front of the observer, and then the collision events can be avoided (Lee, 1976). A detailed demonstration of visual cues in crossing scenarios is in Appendix A. According to above discussion, it would be valuable to investigate the correlation between visual cues and pedestrian crossing decisions.

3.1.3 Research gaps and questions

According to the above literature review, there is strong evidence to support the role of implicit signals in pedestrian-AV communications. However, several research gaps need to be addressed. First, although several studies investigated pedestrian behaviour in vehicle-yielding scenarios (Ackermann et al., 2019; de Clercq et al., 2019; Dey et al., 2021a; Dietrich et al., 2019), to the best of the authors' knowledge, almost no study specifically investigated pedestrians' ability to estimate implicit signals, such as whether pedestrians are able to estimate the behaviour of an approaching vehicle. Ackermann et al. (2019) studied reaction time of pedestrians when they detected the yielding behaviour of an approaching vehicle. Dey et al. (2021a) and de Clercq et al. (2019) measured pedestrian crossing willingness. However, the reaction time can only carry limited information of pedestrians' estimations. For instance, it cannot show the changes in estimations during the approach of the vehicle. Moreover, reaction time and crossing willingness does not provide a quantitative indication of the pedestrian's estimate of the vehicle's behaviour. Given the previous research gap, it is nature that no studies analysed correlation between pedestrian crossing decisions and their estimations of vehicle behaviour. Therefore, two research questions were addressed in this study:

- How do implicit signals of approaching vehicles affect the pedestrian estimation of vehicle behaviour and road crossing decisions?
- What is the relationship between pedestrian estimation of vehicle behaviour and road crossing decision?

3.2 Experiment

3.2.1 Participants

A simulated experiment was designed and performed to investigate our research questions, with approval from the University of Leeds Ethics Committee (No. LTTRAN-145). Thirty healthy adults, including 17 males and 13 females, aged from 20 to 67 (M = 30.73, SD = 8.63), were recruited from the University of Leeds Virtuocity participant recruitment list. All participants declared that they had no serious mobility problems or medical conditions such as epilepsy. In addition, participants were required to have normal or corrected-to-normal vision to ensure that they could accurately perceive traffic scenarios. Another criterion for participants to meet was that they had lived in the UK in the last 12 months because their experience of road traffic could influence their road crossing behaviour. Before participation, we provided them with written informed consent to the procedure. After participating, they received £15 as a reward.

3.2.2 Apparatus

The experiment was conducted in the Highly Immersive Kinematic Experimental Research (HIKER) lab at the University of Leeds. The pedestrian simulator provides a CAVE-based simulated environment with three glass wall projections and a floor projection, as shown in Fig 3.1. A $9\mathrm{m} \times 4\mathrm{m}$ walking space was provided for participants to move in the simulated environment. Eight 4K projectors behind the glass walls (or above the floor) project the scenario at 120 Hz. The tracking system tracks the position of the participant's head through tracking glasses on the participant's head so that the system can correct the image to match the participant's actual perspective. The virtual environment is established using Unity3D software. Internal code automatically records the kinematics of vehicles and participants at each time step, such as vehicle speed, position, and more.

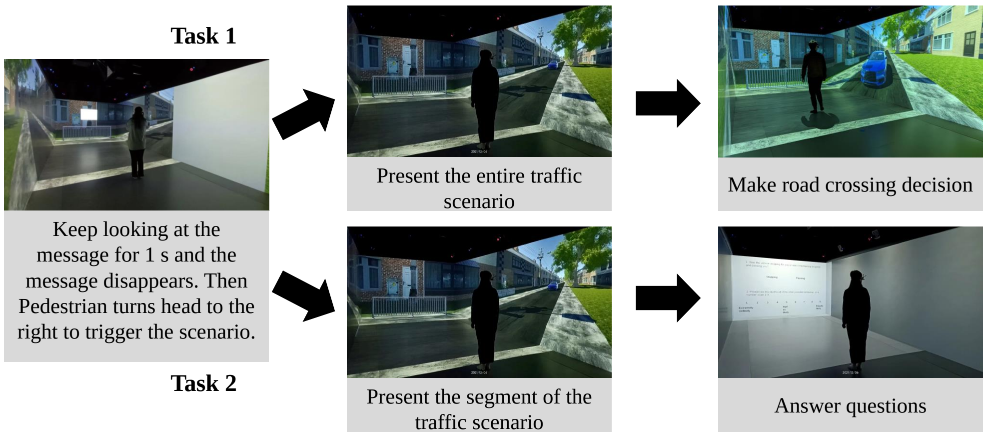

Figure 3.1: Experimental environment and the task procedures.

3.2.3 Environment and traffic

The virtual road environment was a residential block in daylight, with a 4.2 m wide one-lane road and an uncontrolled intersection, as shown in Fig 3.1. A blue sedan automated vehicle was driven in the middle of the lane with no driver inside. With respect to the traffic scenario, several kinematic variables of the approaching vehicle were manipulated, namely driving manoeuvres, initial TTC, and initial speed. The vehicle approached the pedestrian with three different initial speeds, i.e., 25, 40, and 55 km/h and two different initial TTCs, i.e., 3 and 6 s. Three driving manoeuvres were designed, including deceleration, mixed manoeuvre, and constant speed, as follows:

Deceleration: The car decelerated with a constant deceleration rate from the start of the scenario until it stopped 2.5 m from the participant, as shown in Table 3.1.
Mixed manoeuvre: In contrast to the deceleration scenario, we introduced a scenario with constant speed and deceleration manoeuvres to investigate whether the two kinds of manoeuvres had distinct effects on pedestrian crossing behaviour and estimation of vehicle behaviour. In the mixed scenario, the vehicle maintained constant speed for a certain period and then slowed down until it came to a stop at 2.5 m from the participant. To make sure the deceleration rate for each condition is greater than the deceleration rate of the corresponding condition of the

deceleration scenario, we determined a constant speed travel time of 1.5 s for 3 s initial TTC condition and 3.4 s for 6 s initial TTC condition, as shown in Table 3.1.

Constant speed: Finally, the constant speed scenario was applied as a baseline, where the vehicle maintained constant speed for the entire scenario duration, as shown in Table 3.1

Table 3.1: Parameters of traffic scenarios

Manoeuvres	Initial TTC (s)	Initial speed (km/h)	Initial distance to pedestrian (m)	Deceleration rate (m/s^2)	Constant speed duration (s)	Style
		25	20.75	-1.32		
	3	40	33.21	-2.00		
Deceleration		55	45.67	-2.69	-	Early-onset braking
		25	41.61	-0.62		
	6	40	66.58	-0.96		
		55	91.55	-1.31		
		25	20.75	-3.05		
	3	40	33.21	-4.36	1.5	
Mixed		55	45.67	-5.72		Late-onset braking
		25	41.61	-1.55		
	6	40	66.58	-2.34	3.4	
		55	91.55	-3.14		
		25	20.75		3	
	3	40	33.21		3	
Constant speed		55	45.67	-	3	Non-yielding
		25	41.61		6	
	6	40	66.58		6	
		55	91.55		6	

3.2.4 Tasks and procedures

In this study, participants were required to complete two different tasks, including a natural road crossing task and a vehicle behaviour estimation task.

Task one was a road crossing task. Participants were informed: " *If you decide to cross, please walk naturally as you would do everyday life and stop before that wall. If you decide not to cross, just wait for the vehicle to pass*". Regarding the procedure of the first task, as shown in Fig 3.1, participants initially stood at a marked starting point, 57 cm from the edge of the pavement. The road environment on the participants' right hand was obscured by a white rectangle to prevent participants from getting traffic information before the trial started. A message was presented on the screen opposite participants, saying: "*Please Look Here. Keep Looking*". The message would disappear after participants had looked at it for 1 second. After the disappearance of the message, participants were required to turn their heads to the right, which made the white rectangle disappear and triggered the traffic scenario simultaneously. During the scenario, participants would decide whether to cross the road or not. If participants crossed the opposite pavement, the trial ended when they reached the opposite side of the road. If participants rejected the crossing opportunity, the trial ended when the vehicle passed them. The current trial would end after the vehicle passed by them. Task one consisted of a practice session and a formal session. The practice session provided participants with 10 trials to familiarise with the task. In the formal session, 18 experimental conditions were presented randomly and repeated once. Accordingly, we collected $18\,(\text{Condition}) \times 2\,(\text{Repetition}) \times 30\,(\text{Participate}) = 1080$ trials of data. After the first task, participants had a 10-minute break before the second experimental task.

Task two was a vehicle behaviour estimation task. Participants were required to estimate if the vehicle was giving way to them or keeping a constant speed and passing by them after watching a segment of the traffic scenario (Fig 3.1). We collected their subjective feelings about vehicle behaviour using a questionnaire. The questionnaire consisted of two questions. The first one was "*Was the vehicle stopping for you, or was it maintaining its speed and passing you*". Participants could answer either "stopping" or "passing". The second one was "*How confident are you in your previous answer*". Participants could select their confident level from a scale of 1 to 9, where 1 and 9 mean not confident at all and totally confident respectively. In this study, we only analysed the data from the first question.

Regarding the procedure of the second task, the participants did not perform any actions

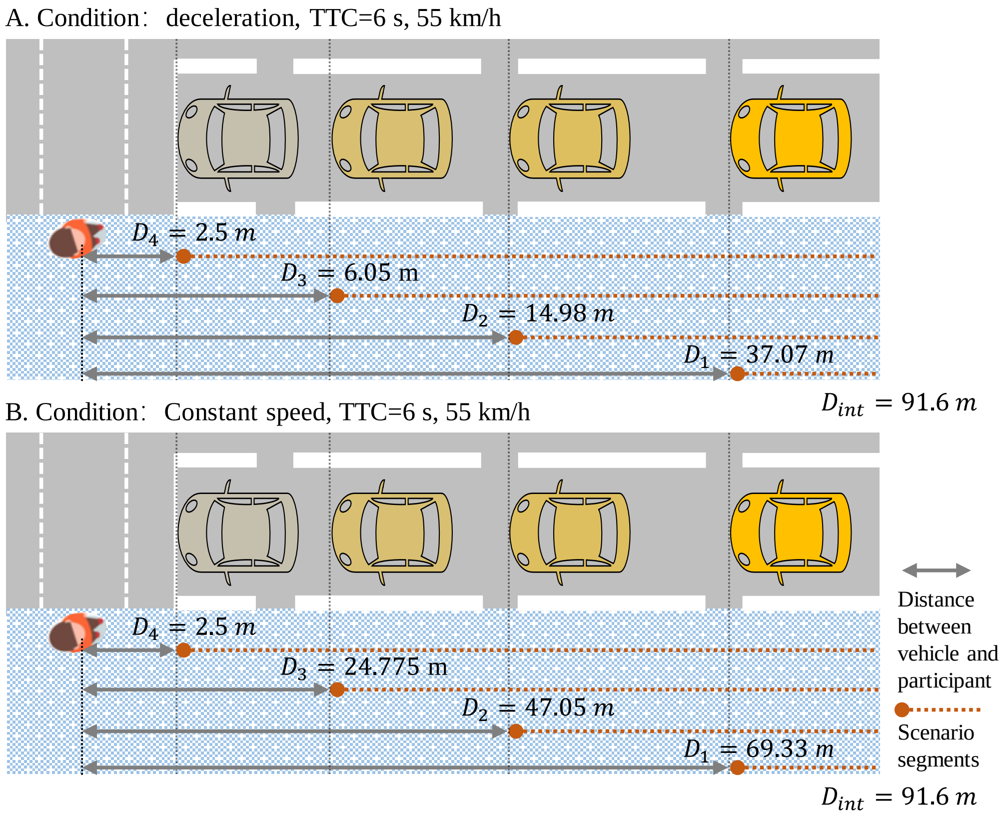

Figure 3.2: Demonstration of the scenario division method. Two example scenarios (A: deceleration, TTC=6 s, 55 km/h and B: Constant speed, TTC=6 s, 55 km/h) are divided into four segments.

but rather observed the traffic scenario segments and answered questions. At the beginning of each trial, participants stood at the marked starting point as in the first task. The scenario was triggered in the same way as in the first task. Afterwards, a scenario segment was presented. After the segment was played, the entire environment was obscured, and the question appeared on the screen for the participants to answer (Fig 3.1).

The scenarios (i.e., deceleration and mixed manoeuvre) were divided into segments, to acquire participants' estimations under different deceleration evidence intensities of the approaching vehicle. Each of the 12 traffic scenarios was clipped at specific timestamps corresponding to when the vehicle was at four different distances to participants. The aim of this manipulation was for the the first scenario segment to included no or subtle vehicle deceleration cues (i.e., $-1 \leq \dot{\tau} \leq -0.36$), with increasingly clear yielding evidence in the second and third scenario segments (The ranges of $\dot{\tau}$ were [-0.36, -0.16] and [-0.16, 0.99]), and very clear yielding behaviour in the fourth segments (i.e., $\dot{\tau} \geq 10e4$). To achieve this aim, since the visual cues, $\dot{\tau}$, increase exponentially (Fig A.1), a logarithmic distance division method was then developed, given by:

$$D_i = a^{5-i}; a = \sqrt[5]{D_{int}}, i = 1, \ldots, 3; D_4 = 2.5 \tag{3.1}$$

where D_i refers to the distance between the approaching vehicle and the pedestrian at the ith measuring point (Fig 3.2). a is a logarithmic base based on the initial distance of the approaching vehicle, D_{int}. D_4 is always equal to 2.5 m, i.e., the final stopping distance from pedestrians (Fig 3.2). The constant speed scenarios were also clipped to get four segments as comparisons with two yielding scenarios. The four measuring distances from participants were given as follows:

$$D_i = D_{int} - ai; a = (D_{int} - D_a)/4, i = 1, \ldots, 3; D_4 = 2.5 \tag{3.2}$$

As the duration of the 1st segment of the video for 3 s and constant speed conditions were too short, their duration was fixed at 1 s. The final parameters are shown in Table A.1, showing that the resulting $\dot{\tau}$ ranges at the end of the first three segments were [-1, -0.36], [-0.36, -0.16], and [-0.16, 0.99], (and large $\dot{\tau}$ after the fourth segment) thus achieving almost complete separation of $\dot{\tau}$ between divisions. The traffic scenarios of eighteen experimental conditions were divided into seventy-two segments for the participants to experience. We collected $18\,(\text{Condition}) \times 2\,(\text{Repetition}) \times 30\,(\text{Participate}) = 1080$ trials of data for the second task. The task also consisted of a practice session and a formal session. The practice session provided participants with ten trials. In the formal session, segments of all traffic scenarios were presented in random order.

3.3 Results

3.3.1 Data reduction

Regarding the first task, as each of the 30 participants completed 18 traffic scenarios and repeated them once, we collected 1080 trials of raw data. To recognise participants' decisions to cross the road, the following criteria were defined: (a) The longitudinal position of the participant should exceed the edge of the pavement; (b) The change in longitudinal position in one simulation time step, i.e., 120 Hz, should be bigger than 0.003 m; (c) 2 s after the first two conditions were met, the participant must be further than 1.1 m from the edge of the pavement.

After capturing participants' crossing decisions, a dependent variable was then applied, i.e., the distance between the participant and vehicle when the pedestrian started crossing, Z_c. For the second task, each participant experienced 72 trials, so 2130 trials of data were obtained. These answers were binary data, i.e., one indicated the judgment that the vehicle was stopping for the participant, and zero indicated that the vehicle was maintaining its speed.

3.3.2 Task one: Road crossing decisions across a range of traffic scenarios

A mixed-effects linear regression analysis was applied to Z_c with initial speed, initial TTC, and driving manoeuvre as independent variables. Individual differences were included as a random intercept in the model. As shown in Fig 3.3, pedestrian crossing decisions in deceleration and mixed scenarios significantly differed from their decisions in constant speed scenarios ($Coef. = -11.00, z = -6.25, p < 0.001; Coef. = -12.80, z = -7.29, p < 0.001$). Specifically, all pedestrians crossed the road in deceleration and mixed scenarios. In contrast, almost no pedestrians crossed in the constant speed conditions with 3 s initial TTC. At constant speed conditions with 6 s initial TTC, approximately half of the pedestrians accepted the opportunity. Hence, both types of yielding manoeuvres facilitated pedestrian crossing decisions. Significant main effects of initial speed and initial TTC were found ($Coef. = 0.62, z = 14.47, p < 0.001; Coef. = 9.88, z = 26.66, p < 0.001$). With the increase in the initial speed and TTC, pedestrians crossed the road further away from the car (Lee et al., 2022).

Moreover, as shown in subfigures in the third and fourth rows of Fig 3.3, pedestrian crossing decisions had a bimodal distribution. Some pedestrians chose to cross shortly after the traffic scenario was triggered, while the others crossed after the vehicle had stopped or before it was about to stop, consistent with previous studies (Giles et al., 2019; Lee et al., 2022). Meanwhile, for the three different driving manoeuvres, the patterns of early-onset crossings were similar. For example, under deceleration and mixed conditions with 3 s initial TTC, nearly no pedestrian crossed the road in the early stages of the scenarios. The same was true for the constant speed conditions with 3 s initial TTC. Moreover, for mixed manoeuvre conditions with 6 s initial TTC, the proportion of crossing decisions in the early stage was $29, 33,$ and 45% at 25, 40, and 55 km/h. The proportions in the deceleration and constant speed scenarios were $35, 41, 42\%$ and $32, 35, 38\%$, respectively. These results showed no significant difference. In addition, it was found that pedestrians appeared to adjust their decisions to the initial speed, with more and more pedestrians waiting for the car to stop as the initial speed decreased. Accordingly, the above results suggest that pedestrians might adopt different strategies to de-

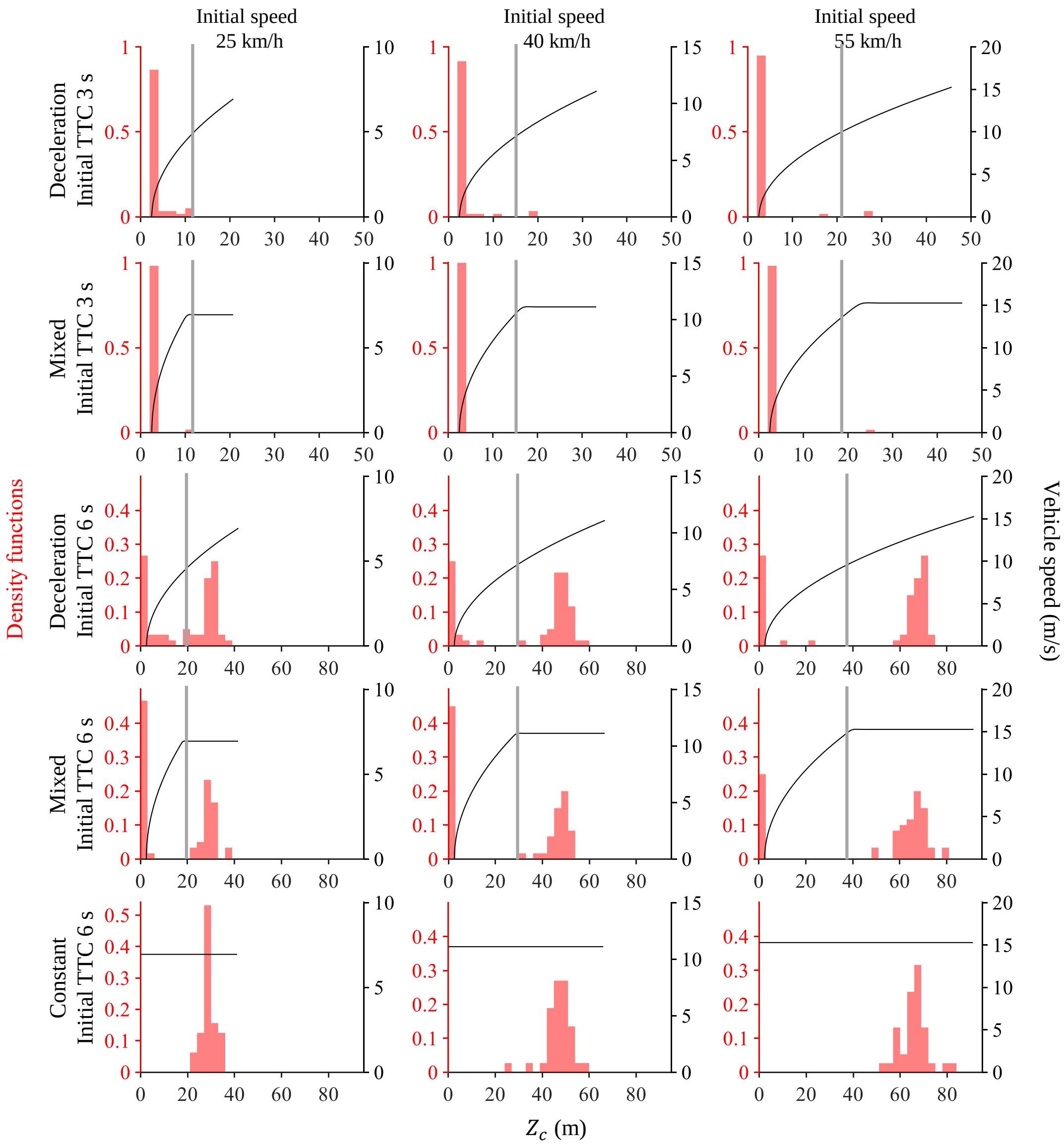

Figure 3.3: Density functions of Z_c in the first task. The rows have identical initial TTC and the columns have identical initial speed. Corresponding vehicle trajectory is denoted using a black solid curve. As there were no pedestrians crossing the road in 3 s TTC and constant speed conditions, no data are available for these conditions. The data of the deceleration and mixed scenarios are separated into early-onset and late-onset crossings using thresholds (grey solid lines).

termine their crossing decisions in vehicle-yielding scenarios as follows:

- In the early stage of a traffic scenario, pedestrians make crossing decisions based on a safe traffic gap (e.g., distance and TTC of the approaching vehicle) and are not concerned with yielding behaviour. This strategy is also valid in constant speed scenarios.

- After the early stage of a traffic scenario, pedestrians make crossing decisions based on the kinematics of a yielding vehicle (e.g., speed and deceleration behaviour of the approaching vehicle).

This assumption is consistent with previous study on braking behaviour (DeLucia, 2015), which indicated that drivers may used different visual cues to guide their braking behaviour as the distance between vehicle and object changes. To further investigate the above strategies, We categorised the crossing decisions of deceleration and mixed scenarios into early-onset and late-onset crossings. The separation thresholds were the end distances of the first scenario segments in the second task (Table A.1 and Figure 3.3). This is because there were no or subtle deceleration cues in scenarios before these thresholds, so pedestrians were less likely to make crossing decisions based on vehicle deceleration behaviour. If pedestrians crossed the road before the time threshold, these decisions were identified as early-onset crossings, while others were identified as late-onset crossings. For instance, in the mixed manoeuvre condition with 6 s initial TTC and 55 km/h initial speed, crossing decisions with Z_c longer than 37.06 m were identified as early-onset crossings (Table A.1 and Figure 3.3). The processed data were analysed using a mixed-effects linear regression model with initial speed, initial TTC, and driving manoeuvre as independent variables. Individuals' differences were included as a random intercept in the model.

Firstly, the early-onset crossings were compared to the crossings in constant speed scenarios. The results found no difference in pedestrian crossing decisions for constant speed, deceleration, and mixed scenarios (Fig 3.4), which indicated that the early-onset crossing decisions in vehicle-yielding scenarios had a similar pattern with the decisions in constant speed scenarios, supporting our assumption. Moreover, initial speed had an similar impact on pedestrian crossing decisions across three driving manoeuvres. Once again confirmed our assumption. That is, the initial speed had a significant main effect ($Coef. = 1.22, z = 68.75, p < 0.001$), showing that pedestrians crossed further away from the vehicles with the increase in the vehicle speed (Fig 3.4).

To further investigate the impacts of deceleration and mixed driving manoeuvres on pedestrian crossing decisions, the late-onset crossings in these two scenarios were compared.

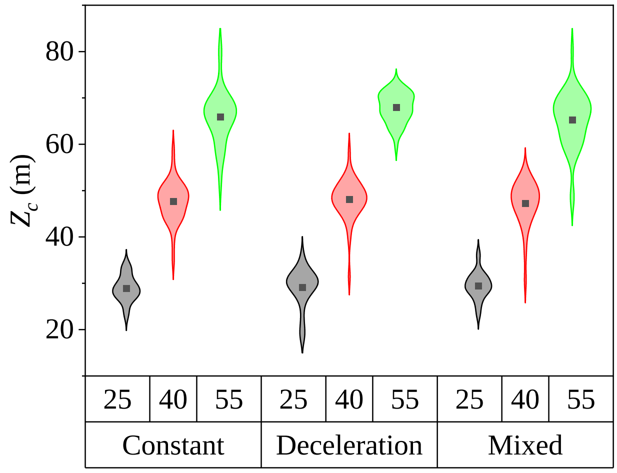

Figure 3.4: Comparison of crossing decisions in constant speed scenarios and early-onset crossing decisions. Z_c is plotted as a function of driving manoeuvre and initial speed. Black squares represent average values.

The results showed that initial speed, initial TTC, and driving manoeuvre had significant main effects. Specifically, with the increase in initial TTC, pedestrians crossed the road further away from the vehicle ($Coef. = 0.28, z = 4.34, p < 0.001$). However, the effect of speed was the opposite ($Coef. = -0.02, z = -2.40, p < 0.05$) (Fig 3.5). Pedestrian decisions were significantly different between deceleration and mixed manoeuvre scenarios ($Coef. = 0.78, z = 4.57, p < 0.001$). In mixed manoeuvre scenarios, pedestrians tended to wait for the vehicle to come to a complete stop. However, more pedestrians crossed the road before the vehicle stopped in deceleration scenarios compared to mixed manoeuvre scenarios (Fig 3.5).

3.3.3 Task two: Estimation of the vehicle behaviour

In the second task, we investigated in detail the pedestrian estimations of approaching vehicle behaviour. A mixed-effects logit regression model was applied to the pedestrian 'stopping' judgment with initial speed, initial TTC, and driving scenario as independent variables. Participants' individual differences were considered as a random intercept in the model. Significant main effects of initial speed, initial TTC, and driving scenario were found. Specifically, the initial TTC had a positive effect on the 'stopping' judgment ($Coef. = 0.94, z = 7.84, p < 0.001$), showing that pedestrians tended to believe that the vehicle was yielding to them at long initial TTC conditions (Fig 3.6). However, the initial speed negatively affected the 'stopping' judgment ($Coef. = -0.06, z = -11.80, p < 0.001$), indicating that the lower the initial speed,

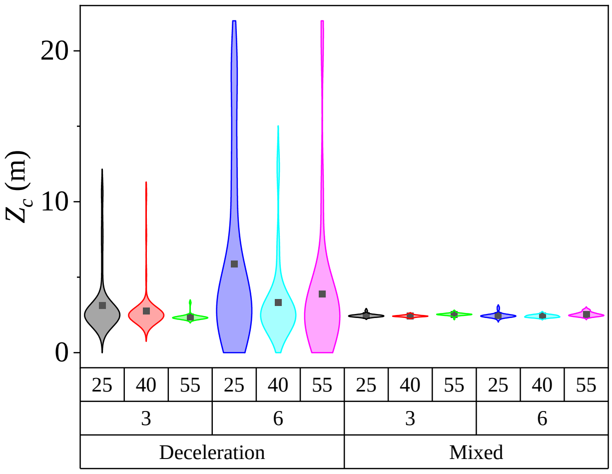

Figure 3.5: Impact of deceleration and mixed driving manoeuvres on late-onset crossing decisions. Black squares represent average values.

the higher the proportion of 'stopping' judgments (Fig 3.6). Moreover, pedestrians' estimations in different driving scenarios were also different. Obviously, pedestrians in deceleration and mixed scenarios were more likely to make a 'stopping' judgment, as the vehicle was indeed yielding to them (Fig 3.6). Furthermore, there was a significant difference between pedestrians' estimations in deceleration and mixed scenarios, indicating that pedestrians better estimated yielding vehicle behaviour in deceleration scenarios ($Coef. = 3.39, z = 8.38, p < 0.001$). Since there was a difference between different driving scenarios, we analysed pedestrians' estimations separately under the respective driving scenarios with initial speed, initial TTC, and scenario segment as independent variables, as described below.

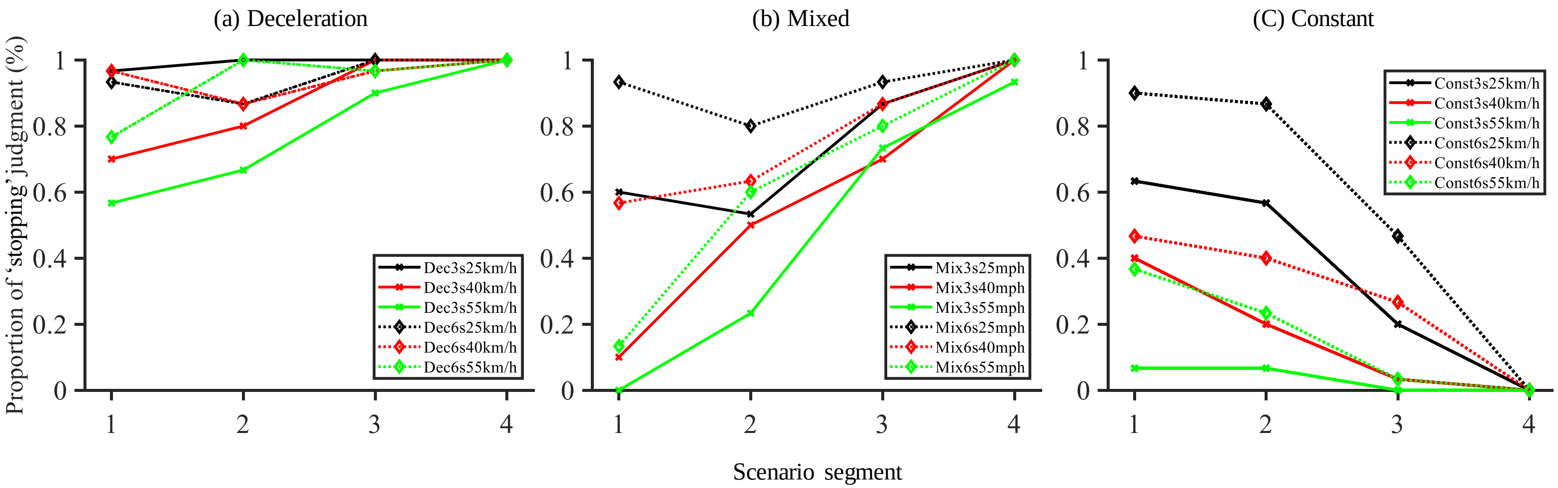

Figure 3.6: Proportion of participants' 'stopping' judgments for scenario segments in different driving scenarios. The numbers 1 to 4 on x-axis represent the four scenario segments defined in Section 3.2.4.

For the constant speed scenario, pedestrians tended to make more 'stopping' judgments at bigger initial TTC and lower initial speed conditions ($Coef. = 2.99, z = 9.90, p < 0.001; Coef. = -0.10, z = -9.02, p < 0.001$). With the increase in the scenario segment length, pedestrians could better anticipate vehicle behaviour ($Coef. = -1.18, z = -10.00, p < 0.001$) (Fig 3.6c). Regarding deceleration scenarios, the effects of initial TTC and initial speed had the same tendency with the results in constant speed scenarios ($Coef. = 1.40, z = 4.33, p < 0.001; Coef. = -0.05, z = -3.38, p < 0.001$). Furthermore, $\dot{\tau}$ was also added in the regression model as an independent variable. Larger $\dot{\tau}$ were associated with an increased tendency to judge that the vehicle was stopping ($Coef. = 4.70, z = 4.33, p < 0.001$), suggesting that with the increase in visual cues, the yielding behaviour of the approaching vehicle was more obvious to pedestrians (Fig 3.6).

Finally, the situation becomes somewhat more complicated in mixed scenarios, as shown in Fig 3.6b. A significant interaction effect was found between the initial TTC and scenario segment ($Coef. = -0.21, z = -9.29, p < 0.001$). For instance, in the scenario with the 3 s initial TTC and 25 mph initial speed, the proportion of 'stopping' judgements increased from about 60% to 100 % as the scenario segment length increased. However, for the 6 s initial TTC and 25 mph initial speed condition, the rate of 'stopping' judgments was high at the beginning (i.e., about 94%) and remained at this high level. It indicated that pedestrians' initial 'stopping' judgments in the 3 s initial TTC condition were higher than the values in the 6 s initial TTC condition. We further compared their estimations on the first scenario segments of the mixed and constant speed scenarios. No significant difference was found ($Coef. = -0.08, z = -1.64, p = 0.10$), indicating that pedestrians applied the same strategy to estimate vehicle behaviour in the first scenario segment of the mixed and constant scenarios. Moreover, the results of the other three scenario segments in the mixed and deceleration scenarios were also compared. A significant interaction effect was found between $\dot{\tau}$ and driving scenario ($Coef. = -4.49, z = -4.36, p < 0.001$), showing that proportion of pedestrians' 'stopping' judgments in the mixed scenario increased more than that in the deceleration scenario as $\dot{\tau}$ increased. Although pedestrians' could better estimate the yielding behaviour with the increase in $\dot{\tau}$ in both scenarios ($Coef. = 0.27, z = 6.70, p < 0.001$), the increasing level was different between the mixed and deceleration scenarios, showing that a similar level of $\dot{\tau}$, pedestrians could better anticipate the yielding behaviour in the deceleration scenario than in the mixed manoeuvre scenario ($Coef. = 0.13, z = 1.98, p = 0.047$).

3.4 Discussion

This study designed two tasks to investigate pedestrian crossing behaviour and estimation of vehicle behaviour when interacting with a AV. The primary aim was to identify the impacts of implicit signals on pedestrian crossing behaviour and estimation across a wide range of traffic scenarios.

In this first task, we studied the influence of initial vehicle speed, initial TTC, and driving manoeuvre on pedestrian road crossing behaviour. Firstly, the effects of initial vehicle speed and initial TTC had the same tendency across all scenarios, indicating that pedestrians crossed the road farther from the vehicle as speed and TTC increased. Consistent with previous studies (Giles et al., 2019; Lee et al., 2022), in yielding and non-yielding scenarios, pedestrians preferred to cross the road in larger spatial or temporal traffic gaps. This behaviour pattern usually refers to a distance-dependent crossing decision, indicating that pedestrians intend to rely more on the distance to the approaching vehicle to finalise crossing decisions when the traffic gap is available (Chapter 2) (Tian et al., 2022). We further divided pedestrian crossing decisions into early-onset and late-onset crossings. The early-onset crossing decisions did not differ significantly between yielding and non-yielding scenarios, thus supporting a hypothesis that pedestrians apply the same decision strategy at the early stage of the traffic scenario: pedestrians make crossing decisions based on a safe traffic gap (e.g., distance and TTC of the approaching vehicle) and are not concerned with yielding behaviour (DeLucia, 2015; Pekkanen et al., 2021).

We also showed that driving manoeuvres had an impact on pedestrian crossing behaviour. Intuitively, compared to constant speed scenarios, more pedestrians crossed the road as vehicles gave way to them in deceleration and mixed scenarios. More than that, a significant difference was found between the late-onset crossings of the deceleration and mixed scenarios; namely, more pedestrians crossed the road before the vehicle had fully stopped in the deceleration scenario compared to the mixed scenario, indicating that pedestrians were more cautious in the mixed scenario. Aligned with a prior study (Dey et al., 2021a), the driving manoeuvre in the deceleration scenario referred to a relatively early-braking style, which could encourage pedestrians to cross the road earlier. Conversely, the relatively late-braking style in the mixed scenario had the opposite effect. Furthermore, it is interesting to note that the impact of initial speed on timings of late-onset crossings was opposite to that in early-onset crossings, showing that as the initial speed decreased, more pedestrians crossed the road before the vehicle had fully stopped. This pattern enhances a hypothesis that pedestrians use different strategies or cues when crossing the road early versus late in vehicle-yielding scenarios (DeLucia, 2015; Pekkanen et al., 2021). That is, (i) when the vehicle is far from pedestrians, their crossing decisions are mainly based on the size of the traffic gap. However, (ii) when pedestrians notice a yielding vehicle, their crossings are mainly based on the evidence associated with deceleration rate and speed. This multiple-decision strategy may explain why the distribution of pedestrian crossing initiations in front of a yielding vehicle is bimodal.

The second task aimed to complement the findings in the first task and investigate pedestrian crossing estimation of vehicle behaviour in-depth. Firstly, although the deceleration rates in the mixed scenario were more intense than in the deceleration scenario, and we also controlled the level of visual cue, i.e., $\dot{\tau}$, for each scenario segment, we showed that pedestrians could better anticipate the yielding behaviour in the deceleration scenario than in the mixed scenario, which was consistent with the results in the first task that more pedestrians crossed the road before the vehicle had fully stopped in the deceleration scenario compared to the mixed scenario. Hence, both findings in the first and second tasks strengthen the conclusion that the early-braking style facilitates pedestrians to notice the yielding behaviour of vehicles and benefits their road crossing decisions (Dey et al., 2021a; Ackermann et al., 2019).

Another important finding of this study is that the initial speed has a negative effect on the proportion of 'stopping' judgments. Notably, pedestrians have a tendency to interpret low travelling speed as a yielding behaviour. For instance, even under constant speed conditions with 6 s initial TTC and 25 km/h initial speed, nearly 90% of pedestrians felt that the vehicle gave way to them at the beginning. The value was still very high (i.e., 65%) for the condition with 3 s initial TTC and 25 km/h initial speed. Therefore, We show that pedestrians may heavily rely on vehicle speed to estimate vehicle-yielding behaviour. This result is in accordance with the pedestrian late-onset crossing decision in the first task: as the initial speed decreased, more pedestrians crossed the road before the vehicle came to a complete stop. However, this is in contradiction to the early-onset crossings, where more pedestrians cross the road in higher initial speed conditions. This discrepancy between pedestrian crossing behaviour and their estimation of vehicle behaviour further supports the proposed multiple-decision strategy, whereby when the vehicle is far from pedestrians, their crossing decisions are mainly based on the size of the traffic gap rather than on judgments about vehicle-yielding behaviour.

In addition, the collision cue $\dot{\tau}$ was found to correlate significantly with the detection of yielding behaviour. With the increase in the $\dot{\tau}$, the yielding behaviour becomes more evident to pedestrians. Our findings align with previous proposals on the role of $\dot{\tau}$ as a visual cue used by pedestrians to estimate vehicle yielding behaviour (Giles et al., 2019; Pekkanen et al., 2021), and provide support for this hypothesis. However, one thing should notice that in the second task, we found pedestrians could better anticipate vehicle-yielding behaviour in the deceleration scenario than in the mixed scenario, whilst the levels of $\dot{\tau}$ in both scenarios were very close. The evidence accumulation theory may give a possible explanation for this phenomenon (Markkula et al., 2018): the pedestrian crossing decision is not simply associated with the immediate value of $\dot{\tau}$, but rather its integration over time. In the deceleration scenario, the period of time for deceleration evidence accumulation is longer than the time in the mixed scenario.

In a word, pedestrians' performance in the second task was quite stable. In the case of the mixed scenario, the pattern of behaviour estimations for the first scenario segment was similar to that in the constant speed condition. However, when the vehicle started to decelerate, pedestrians quickly shifted to a mode of deceleration judgment. Even in such complicated traffic scenarios, pedestrians could recognise changes in driving manoeuvres and quickly adjust their judgments. This finding again strengthens the critical role of implicit signals in pedestrian-AV interactions. To promote the acceptance of AVs, designing for human-friendly driving manoeuvres is essential.

In the end, several conclusions can be made from our study. (i) Pedestrians' detection of cars' yielding behaviour is stable, and their crossing behaviour is consistent with their estimations, demonstrating that the role of implicit signals of vehicle kinematics is critical in pedestrian-AV interaction. (ii) The visual cue $\dot{\tau}$ is associated with pedestrians' detection of cars' yielding behaviour, but may not its simple immediate value. (iii) Vehicle speed has a critical impact on the pedestrian estimation of vehicle-yielding behaviour, and pedestrians have a tendency to suppose that vehicles are giving way to them when vehicles are travelling at low speeds. (iv) Pedestrians may apply a multiple-decision strategy for their crossing decisions in the course of vehicle yielding.

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CHAPTER 4

Impact of visual and cognitive distractions and time pressure on pedestrian crossing behaviour: a simulator study

Impact of Visual and Cognitive Distractions and Time Pressure on Pedestrian Crossing Behaviour: A Simulator Study

ABSTRACT. Distractions have been recognised as one important factor associated with pedestrian injuries, as the increasing use of cell phones and personal devices. However, the situation is less clear regarding the differences in the effects of visual-manual and auditory-cognitive distractions. Here, we investigated distracted pedestrians in a one-lane road with continuous traffic using an immersive CAVE-based simulator. Sixty participants were recruited to complete a crossing task and perform one of two distractions, a visual-manual task and an auditory-cognitive task. Moreover, normal and time pressure crossing conditions were included as a baseline and comparison. For the first time, this study directly compared the impacts of visual-manual, auditory-cognitive distractions, and time pressure on pedestrian crossing behaviour and safety in a controlled environment. The results indicated that although pedestrian safety was compromised under both types of distraction, the effects of the applied distractions were different. When engaged in the visual-manual distraction, participants crossed the road slowly, but there was no significant difference in gap acceptance or initiation time compared to baseline. In contrast, participants walked slowly, crossed earlier, and accepted smaller gaps when performing the auditory-cognitive distraction. This has interesting parallels to existing findings on how these two types of distractions affect driver performance. Moreover, the effects of the visual-manual distraction were found to be dynamic, as these effects were affected by the gap size. Finally, compared to baseline, time pressure resulted in participants accepting smaller time gaps with shorter initiation times and crossing durations, leading to an increase in unsafe decisions and a decrease in near-collisions. These results provide new evidence that two types of distraction and time pressure impair pedestrian safety, but in different ways. Our findings may provide insights for further studies involving pedestrians with different distraction components.

Keywords: Pedestrian; Road crossing; Visual-manual distraction; Auditory-cognitive distraction; Time pressure; Crossing safety

4.1 Introduction

Pedestrians are generally regarded as the most vulnerable road users due to a lack of protective equipment and a slower pace of movement than other road users. Their safety issues have prompted extensive research and concern from academics and policy makers (El Hamdani et al., 2020). Every year, more than 300,000 pedestrians are killed worldwide, which accounts for 22% of all traffic fatalities (World Health Organization, 2018). In particular, pedestrian accidents are common at uncontrolled crossroads, such as unsignalised junctions. Contrary to controlled crossroads, where traffic signals can adequately coordinate all road users' behaviours, uncontrolled crossroads do not force vehicles to yield to pedestrians. Crossing at such locations is extremely complex and affected by multiple factors, such as traffic characteristics (Ackermann et al., 2019), road environments (Zhao et al., 2019), and the presence of various distractions (Ropaka et al., 2020). Among those factors, distractions have been recognised as one of the main contributing factors to pedestrian injury, particularly in the context of the increasing use of cell and personal devices (Jiang et al., 2018). A recent online survey reported that more than a third of U.S. respondents talked on the phone or listened to music quite frequently while walking (of Orthopaedic Surgeons, 2015). Nasar et al. (2008) analysed the data of the U.S. Consumer Product Safety Commission regarding injuries at hospital emergency rooms for 2009 and 2010 which showed that 69.5% of pedestrian injuries were associated with cell phone use.

Distraction refers to engagement in activities not critical for a safe main task (e.g., crossing), specifically activities such as scanning digital devices, texting, talking on a cell phone or listening to music (Walker et al., 2012). Distractions are typically categorised into visual, manual, and cognitive based on their components (Engstrom et al., 2017). The two former distractions involve perceptual or motor processes (e.g., pedestrians scanning the screen or typing), while cognitive distraction generally refers to the nonvisual and nonmanual tasks that take attentional resources away from the crossing task (e.g., pedestrians listen to music using a headset, where their vision and movement are not impeded) (Engstrom et al., 2017; Walker et al., 2012). Current research results share a general consensus that visual and manual distractions impair most aspects of road crossings. For instance, a field test by Jiang et al. (2018) compared the effects of texting, cell phone conversation, and music listening distractions on pedestrian crossing behaviour and found that texting on a cell phone had the greatest impact because it occupied most pedestrians' visual attention. Researchers indicated that the cognitive processes of texting affected pedestrians' ability to allocate attentional resources to road observation (Jiang et al., 2018). However, Pesic et al. (2016) investigated texting, cell phone conversation, and music listening distractions, and indicated that talking on cell phones stopped pedestrians from looking at the traffic and had the greatest impact on pedestrian safe crossing behaviour. The former study was conducted at a signalised intersection where pedestrian crossing behaviour was significantly affected by traffic lights instead of vehicle kinematics. In contrast, the latter study was performed in an uncontrolled environment and did not investigate the specific metric related to pedestrian crossing behaviour, such as initiation time or walking speed. Thus, different observation approaches and methodologies led to different results. Furthermore, in the case of distraction tasks which required pure listening, existing studies offer different opinions. Several studies indicate that these tasks could slow down pedestrian crossing initiation time (Schwebel et al., 2012). On the other hand, evidence from many studies indicates that a listening distraction task does not significantly affect pedestrian crossing behaviour (Neider et al., 2011; Simmons et al., 2020) and sometimes even makes them more cautious (Nasar et al., 2008; Walker et al., 2012). Therefore, from the above discussion, there is currently little understanding of the difference between auditory-cognitive distractions (from here on, we will refer to such distractions, including listening to music, as auditory-cognitive distraction (Siegmann et al., 2017)) and other types of distractions, such as those involving visual and manual resources, on pedestrians' crossing behaviour and safety. Further research is needed on the effects of auditory-cognitive distraction on pedestrian crossing

It is important to note that the observation approaches may also affect the results of distraction studies, as described in the previous section. Another case in point is that naturalistic observations generally indicated that pedestrians distracted by personal music devices could initiate crossing later and look less at traffic than non-distracted pedestrians (Liu et al., 2021; Pesic et al., 2016; Thompson et al., 2013), resulting in unsafe crossing behaviour. However, several controlled field and simulated tests showed that the use of personal music devices might not have a significant influence on pedestrian crossing behaviour (Neider et al., 2010; Walker et al., 2012). Although naturalistic observations typically reflect the real behaviour of pedestrians, the lack of effective control of variables can make it difficult to draw precise conclusions (e.g., pedestrians selecting music in the device includes visual-manual distractive components, and in a naturalistic setting it may be difficult to separate such distractions from purely auditory-cognitive music distractions). Accordingly, recent studies have focused on formulating hypotheses about distracted behaviour that occurs in the real world and experimentally testing these ideas in more controlled environments. Simulated experiments are one of the most applied approaches, although it has several possible limitations that need to be further improved. First, some studies applied semi-immersive simulated environments to evaluate pedestrians crossing behaviour, such as screens with fixed visual angles and walking on a treadmill (Lin and Huang, 2017; Neider et al., 2011). Those overly abstract simulated environments may not be able to reproduce the pedestrian crossing behaviour in real traffic. In addition, the head-mounted display (HMD) can obstruct the pedestrians' view making it difficult to interact with real distracting tasks (e.g., using a cell phone). Researchers attempted to add virtual distractions in the simulated environment to solve this problem (Schneider et al., 2019; Sobhani and Farooq, 2018). However, given the essential differences between virtual and real distraction tasks, such manipulations may introduce new and unknown variables to the experiment.

In addition to the differences between distractions, recent studies have explored the potential pedestrian crossing performance metrics or characteristics that may be associated with distractions, such as accepted gap (Ropaka et al., 2020), walking speed (Ropaka et al., 2020), crossing initiation time (Sobhani et al., 2017; Tapiro et al., 2018), age, and gender (Sobhani and Farooq, 2018; Tapiro et al., 2018). However, apart from the aforementioned factors, existing studies rarely shed light on some critical performance metrics related to pedestrian safety (e.g., crossing gap acceptance, time to arrival (TTA) and post encroachment time (PET). As pedestrians make crossing decisions by judging the gaps between two consecutive vehicles, gap acceptance is a critical performance metric identifying and quantifying pedestrian crossing behaviour (Oxley et al., 2005; Petzoldt, 2014). Without studying gap acceptance performance and how it is affected by distraction, it is hard to clearly understand how pedestrians weigh their safety and efficiency and whether they adopt certain decision strategies to deal with distractions. Moreover, to the best of our knowledge, no studies have explored the relationship between distractions and TTA and therefore less is known about how pedestrians adjust their crossing behaviour in different TTA conditions while distracted by secondary tasks. Furthermore, the PET have been applied as a strong indicator of pedestrian crossing safety (Avinash et al., 2019). However, few studies have investigated how distractions affects the pedestrian PET.

Finally, similar to distractions, time pressure has been regarded as one of the important factors associated with safe road crossings, which can reduce the quality of decisions (Coeugnet et al., 2019) and increase the propensity to take risks (Madan et al., 2015). It has also been shown that participants with time pressures have high crossing speeds (Kalantarov et al., 2018). The literature therefore suggests that in the context of street crossing under time pressure, participants usually prioritise walking progress over safety, which leads to more dangerous behaviour (Coeugnet et al., 2019). Concerning the safety impacts of the time pressure mentioned above, it is interesting to know how its effects on pedestrians differ from distractions. A controlled study that includes both factors is needed. However, this kind of research has not been previously done.

To address the research gaps mentioned above, this study systematically investigated pedestrian road crossings with and without secondary tasks using a CAVE-based pedestrian simulator.

- The CAVE-based simulator did not have the field of view or movement limitations of past controlled studies and allowed pedestrians to interact directly with a real handheld device.

- Three secondary tasks, namely, a time pressure task, a visual-manual task, an auditory-cognitive task, and a baseline task were applied to compare the effects between the different distractions and the effects between them and time pressure in this study.

- A range of metrics describing pedestrian crossing performance were investigated, including time gap, gap acceptance, initiation time, walking speed, and PET.

4.2 Methodology

4.2.1 Experiment

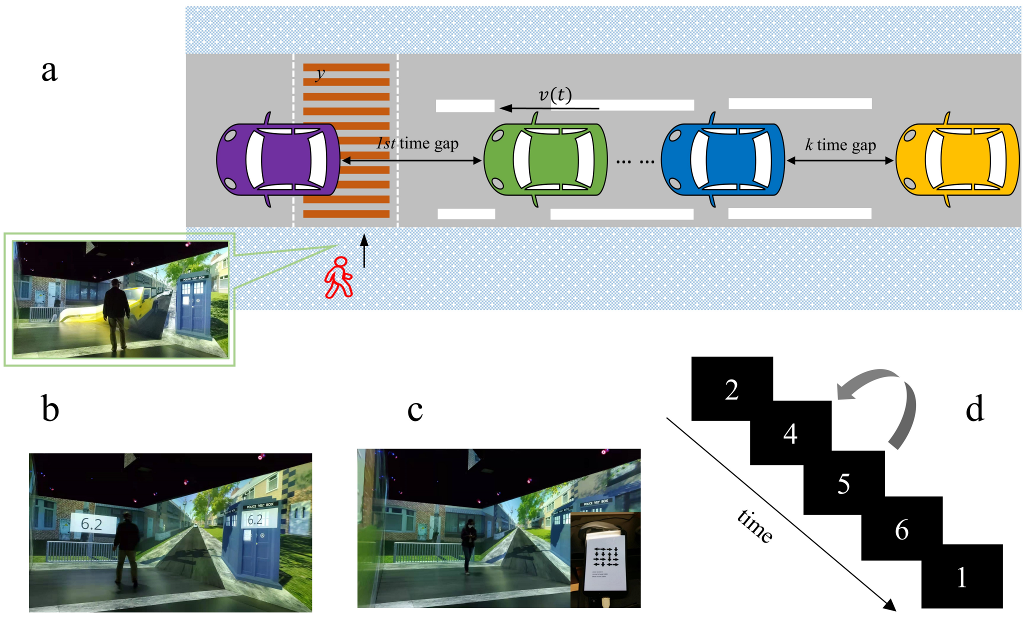

Figure 4.1: Experimental scenario and apparatus. (a) Crossing scenario in the Highly Immersive Kinematic Experimental Research lab. A police box to the right of pedestrians was included in the simulated environment to ensure that the road would not be visible from the participant's starting position. (b) Timer task. (c) Arrows task. (d) N-back task.

Using a CAVE-based pedestrian simulator, an experiment was designed to investigate pedestrian road crossings with and without secondary tasks. The simulator did not have the field of view or movement limitations of past controlled studies and allowed pedestrians to interact directly with a real handheld device. Three secondary tasks, namely, a time pressure task, a visual-manual task, an auditory-cognitive task, and a baseline task, were applied to compare the effects between the different distractions and the effects between them and time pressure in this study. A range of pedestrian crossing performance metrics were investigated, including time gap, gap acceptance, initiation time, walking speed, and PET. The experiment was approved by the University of Leeds ethics committee (reference number: LTTRAN-117).

Experimental design. Three secondary tasks, i.e., time pressure, visual-manual, and auditory-cognitive tasks, were named as Timer, Arrows, and N-back. In the Timer task, the participants were informed: ”During these scenarios, please cross the road as quickly as possible, but maintain a safe behaviour and do not run”. To produce a time pressure effect, two timers were shown prominently on the VR screen to inform participants of the time already spent. Participants could thus adjust their behaviour based on informed timing information (Fig 4.1b). The Arrows task has been commonly used as a visual-manual secondary task in driving studies (Jamson and Merat, 2005), and was adapted here to the pedestrian context. As shown in Fig 4.1c, a 4×4 grid of arrows was shown on the cell phone screen, and participants were required to find and select the single upward pointing arrow, as quickly as possible, by pressing on the screen, while also maintaining a safe crossing behaviour. Each response prompted a new 4 x 4 grid of arrows. To motivate participants to focus on the task, the phone vibrated after 4 seconds if they did not respond to the task, and a new set of arrows was displayed. The Arrows task started at the beginning of the trial and ended when participants returned to the starting point. The third task was the auditory version of the N-back task, used in multiple research areas to test working memory capacity (Reimer and Mehler, 2011) (Fig 4.1d). Specifically, an audio headset worn by participants played a series of numbers, and participants were required to say the number played just before the most recently played number. The N-back task started at the beginning of the trial and ended when participants returned to the starting point. Finally, a baseline condition with just the road crossing task, without any of the secondary tasks, was also included.

Regarding the design of the traffic environment, the simulated road and pavement widths were 3.5 m and 1.85 m. Four traffic flow scenarios with different time gap sequences were implemented (Fig 4.2), providing various opportunities for participants to cross. For example, in the first scenario, the time gap order was: 1, 1, 1, 3, 3, 3, 6, 1, 1, 6 s. According to our design, most participants would reject the first three one-second gaps. Then, some of them accepted one of the following three three-second gaps. Finally, all reminding participants crossed the road during the six-second gap. Thus, the one-second and two-second time gaps between vehicles were considered dangerous crossing opportunities, that few pedestrians would accept. For the three-second and four-second gaps, decisions were expected to differ significantly between participants, due to their heterogeneity (e.g., age and gender). The time gaps longer than four seconds were included as safe gaps, where most participants would be expected to cross. Therefore, we expected pedestrians to accept different time gaps in terms of their preferences and observed pedestrian crossing performance as a function of time gap size. Moreover, different traffic flow scenarios could avoid the influence of learning effects, as pedestrians had to continually adjust their crossing decisions in terms of traffic. In addition, the use of traffic flow made the crossing task more realistic and immersive. In each scenario, the traffic flow consisted of a range of compact, midsize, van and SUV types of vehicles, ranging in width from 1.67 m to 1.86 m, all driven at 48.3 km/h (30 mph), for an average traffic volume of 22 vehicles per minute. The time duration of the scenarios was between 43 to 62 s.

Procedure. Four tasks (i.e., the Timer, Arrows, N-back, and baseline) made up the four experimental blocks separately. Before each block, there was an approximate five-minute practice session to familiarise participants with the task. In order to counterbalance the order of experimental blocks, participants were spread as evenly as possible across all twenty-four possible orderings of the four experimental blocks. For each block, four traffic scenarios were presented in random order and repeated twice so that $4 \times 4 \times 2 = 32$ trials of data were collected for each participant, resulting in a total of $32 \times 60 = 1920$ trials. The whole experiment for each participant took approximately 60 minutes.

At the beginning of each trial, participants stood on the pavement and behind a police box, positioned there to occlude the participants' view of the road before the start of each trial (Fig 4.1b). Once participants felt prepared to start a new trial, they stepped up to the kerb, and (unbeknownst to them) this body movement triggered the start of the traffic scenario. From this position, participants could see the traffic as they stood at the edge of the pavement and prepared to cross the road. After crossing to the other side of the road and thereafter back to the starting point, the trial was completed. In the Arrows and N-back blocks, the participants were required to start the secondary task before they stepped out from behind the police box in the experiment, to ensure they crossed the road while engaging in distracting behaviour.

Apparatus. As shown in Fig 4.1, a single-lane road scenario with vehicles approaching from the right, was generated in a highly immersive CAVE-based pedestrian simulator with 9 $\times$ 4 m walking space. Eight 4K projectors behind glass panels were used to project the scene at

120 Hz. The simulated environment was controlled by eight computers and ten cameras, which tracked the head position through tracking glasses on the participant's head and corrected the projected image to the participant's perspective. The Unity3D platform was used to establish the virtual environment and control the simulation loop. Internal code automatically recorded the positions and velocities of vehicles and participants at 120 Hz (Sadraei et al., 2020).

Participants. Sixty participants, 30 males and 30 females aged 18-68 (M = 37.67, S.D. = 12.72) were recruited via the University of Leeds Driving Simulator recruitment pool. They all declared that they did not have serious mobility problems or medical conditions such as epilepsy. Also, we required them to have either normal or corrected-to-normal vision to make sure they could accurately perceive the traffic scenario. Before participation, each participant provided written informed consent to take part in the study. After the study, £10 was paid to them as compensation for their time.

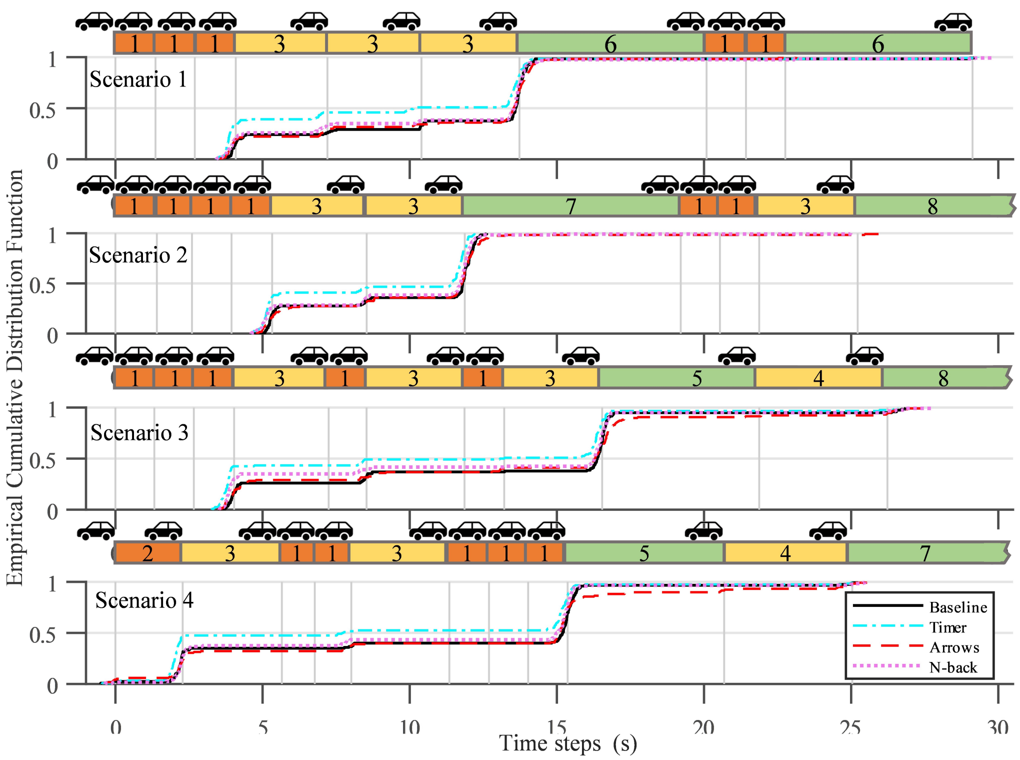

Figure 4.2: Empirical cumulative distribution functions of participants' crossings with different secondary tasks in four traffic scenarios. The several boxes above the curve plot denote the time gap sequence for the corresponding traffic scenario. The numbers in the boxes refer to the gap size in seconds. The vertical grey lines indicate the times when the rear end of a vehicle passed the participant's position.

4.2.2 Data reduction

Dependent variables. Four dependent variables were defined as pedestrian crossing behaviour indicators: crossing gap acceptance, crossing initiation time, crossing duration, and PET:

- Participants' gap acceptance data have a binary structure, representing whether participants crossed the street or not in each time gap in the sequence of vehicles.

- Crossing initiation time refers to the period between when the rear end of the previous vehicle passed the participant's position and when the participant began crossing the road. To calculate the initiation time, the crossing onset time point is defined as the time when the participant walked across the edge of the pavement and stepped into the traffic lane. The detailed criteria include (a) the longitudinal position of the participant should exceed the edge of the pavement; (b) change in longitudinal position in one 120 Hz simulation time step should be bigger than 0.003 m; (c) one second after the first two conditions are met, the participant must have walked one meter from the edge of the pavement. Note that small negative crossing initiation times are possible, if the participants entered the road slightly before the nearest vehicle had completely passed them.

- Crossing duration represents the time between when the participants started crossing and when they arrived at the opposite pavement.

- PET was applied as the safety performance indicator, representing the time difference between the accepted time gap (i.e., remaining time gap at time of crossing initiation) and crossing duration. It has been widely applied to quantitatively describe the risks of pedestrian crossing decisions (Avinash et al., 2019; Lobjois and Cavallo, 2007). In addition, three performance levels were identified to categorise crossing decisions in terms of the PET: 'near-collision' when the PET was less than 0; 'unsafe' decisions when the PET was between 0 and 1.5 s; 'safe' decisions when the PET was bigger than 1.5 s (Lobjois and Cavallo, 2007). The term, 'near-collision', represents that the accepted time gap is not enough for pedestrian to arrive at the opposite pavement, suggesting a potential collision risk. While the 'unsafe' indicates that the time margin for pedestrian crossings is too small to allow any hesitation.

Independent variables. In this study, several factors in the traffic flow that may influence pedestrian crossing decisions were considered and directly controlled and extracted by researchers, including time gap size, secondary tasks, and traffic flow characteristics: (i) Time gap size (numerical variable): This is the temporal distance between two consecutive vehicles. As shown in Fig 4.2, a variety of time gaps ranging from 1 second to 8 seconds were used in this study. (ii) Tasks (categorical variable). Categorical variables were used to represent these tasks (i.e., Timer, Arrows, N-back, and normal crossing), and the normal crossing task was set as the baseline. (iii) Traffic flow characteristics (categorical variables). We also tested for longer-range traffic flow effects on the gap acceptance decision, using the two indicator variables: T_{pre} and T_{follow}. T_{pre} denotes that the time gap currently faced by the participant was less than or equalled the maximum time gap previously rejected. T_{follow} represents that the next time gap was greater than the current one.

4.2.3 Statistical analysis

For the analysis of the repeatedly measured data from subjects, population-averaged (PA) regression models violate the independence assumption (Hu et al., 1998). Therefore, mixed-effects regression models (ME), also called hierarchical models, allowing heterogeneity of individuals or groups to be retained, were applied here.

Eq 4.1 shows a generalised linear mixed effects model (GLMM) for predicting the effects of independent variables on a binary response (i.e. crossing gap acceptance) (Gelman and Hill, 2006).

$$\begin{aligned} \text{logit}\left(y_{i[j]}\right) &= \beta_0 + \beta_1 x_{1,i} + \beta_2 x_{2,i} + \beta_3 x_{3,i} + u_{1,i[j]} z_i \\ &+ u_{0,i[j]}, \text{ for } i = 1, \dots, n, \\ u_{1,[j]} &= a_1 + b_1 u_{i[j]} + \tau_{1,j}, \text{ for } j = 1, \dots, J \\ u_{0,[j]} &= a_2 + \tau_{2,j}, \text{ for } j = 1, \dots, J \end{aligned} \tag{4.1}$$

where $y_{i[j]}$ is the jth participant's gap acceptance. $x_{1,i}$, $x_{2,i}$ and $x_{3,i}$ are independent variables (e.g., time gap, secondary task and traffic flow characteristics) of the ith trial and their corresponding coefficients are β_0, β_1 and β_2. These coefficients are known as fixed effects and do not vary across participants. z_i is the independent variables for random effects (i.e., time gap), and $u_{1,i[j]}$ and $u_{0,i[j]}$ are coefficients with random effects of ith trial data, belonging to the jth participant. Each participant's $u_{1,[j]}$ and $u_{0,[j]}$ are assumed to be independently normally distributed with error terms $\tau_{1,j}$ and $\tau_{2,j}$. In other words, the coefficients with fixed effects are modelled based on the average population and do not vary across pedestrians. By contrast, the random coefficients are modelled using the subject-specific data to retain unobserved heterogeneity between participants.

For the non-binary, numerical dependent variables (i.e., crossing initiation time, crossing duration, and PET), a linear mixed effects model (LMM) was applied to estimate the effects of independent variables on a continuous response. The model is given by:

$$y_{i[j]} = \beta_0 + \beta_1 x_{1,i} + \beta_2 x_{2,i} + \beta_3 x_{3,i} + u_{1,i[j]} z_i + u_{0,i[j]} \tag{4.2}$$

Similar to the GLMM model, the LMMs in the study also considered the fixed effects and participants' random effects on time gap and intercept. The MATLAB function 'fitglme' was used to estimate coefficients of all ME models through the maximum pseudo-likelihood method (MATLAB, 2021).

As described in Section 2.2, this study proposes two novel traffic flow characteristics (i.e., T_{pre} and T_{follow}) to analyse pedestrian crossing behaviour in traffic. To validate if these factors significantly improve the model, the refined models (Eq 4.1 and Eq 4.2) are compared to the basic models (similar to Eq 4.1 and Eq 4.2 , but without traffic flow characteristics) through a likelihood ratio (LR) test. In brief, the equation of the LR test can be defined as:

$$LR = -2\left(LL^R - LL^U\right) \tag{4.3}$$

where LL^R denotes the log-likelihood of the constrained model (basic model), and LL^U refers to log-likelihood of the unconstrained model (refined model). If the test rejects the null hypothesis (i.e., the performance of the two models is equal), then the refined model performs better than the basic model at a selected significance level. Therefore, the refined model will be applied. Otherwise, if both models have the same performance, the basic model will be performed to analyse the data.

4.3 Results

In Section 3.1, we first present the results of the GLMM on pedestrian gap acceptance data. In Section 3.2, the impacts of secondary tasks on crossing initiation time are analysed using LMM. Finally, the impact of each task on crossing duration and PET is presented in Sections

Table 4.1: Results of the Likelihood ratio test for the proposed GLMMs

Model	df	AIC	LL	LRStat	p	Null hypothesis
Basic model	9	2247	-1114	-	-	Rejected
Refined model	10	2241	-1110	7.38	0.01	

3.3 and 3.4.

4.3.1 Crossing gap acceptance

The cumulative distributions of participants' crossings are shown in Fig 4.2. For detailed gap acceptances and rejections for each secondary task and traffic scenario, please see Table A1.Since the four-second gap always occurred after a larger five-second time gap in the experiment (Fig 4.2), almost no participants accepted the four-second time gap (Table A1). We thus omitted the four-second time gap from all analysis of results.

First, the results of the likelihood ratio (LR) test on refined and basic GLMMs are presented in Table 4.1. The null hypothesis is rejected at a 0.01 significance level, indicating that the refined model's performance was significantly better than the basic model. Therefore, the GLMM with traffic flow characteristics was applied to the gap acceptance data.

The probability of gap acceptance is plotted as a function of the time gap and secondary task in Fig 4.3. Specifically, the GLMM indicated that the gap acceptance increased with the time gap ($Coef. = 5.01, z = 16.53, p < .001$). A significant main effect of the Timer task was found, whereby participants accepted smaller gaps under time pressure ($Coef. = 1.51, z = 8.70, p < .001$). The N-back task also significantly affected participants, who chose smaller traffic gaps ($Coef. = 0.41, z = 2.55, p < .05$). No significant main effect of the Arrows task was found. The pairwise comparison showed that the participants' gap acceptance behaviour was significantly different in Arrows task than in the N-back task ($Contrast = -0.55, p < .01$). Moreover, there was a significant interaction between the time gap and Arrows ($Coef. = -1.07, z = -4.59, p < .001$). In other words, the effect of time gap on gap acceptance was different between Arrows and baseline. A weak interaction was also found between the time gap and N-back task ($Coef. = -0.56, z = -1.88, p = .06$). Interestingly, only participants in the Arrows task accepted the four-second gap (Table A1). As shown in Fig 4.2, the four-second gap always occurred after a larger five-second time gap. The phenomenon, therefore, showed that some participants under the visual-manual distraction rejected a bigger gap, but accepted a smaller gap upstream in the traffic flow. Finally, a significant main effect of

Table 4.2: Crossing gap acceptance for T_{pre} and time gaps. The term ' Yes ' indicates that participant has previously rejected a bigger or equal gap in the same scenario; otherwise, it is indicated by ' No'

T_{pre}	Probability of gap acceptance (%) for time gaps (s)	
	3	6
Yes	9.27	33.33
No	32.03	96.82

T_{pre} was found ($Coef. = -0.32, p < .05$). As shown in Table 4.2, participants had a reduced tendency to accept 3 s and 6 s time gaps if they had previously rejected an equal or larger gap. However, T_{follow} did not have a significant influence.

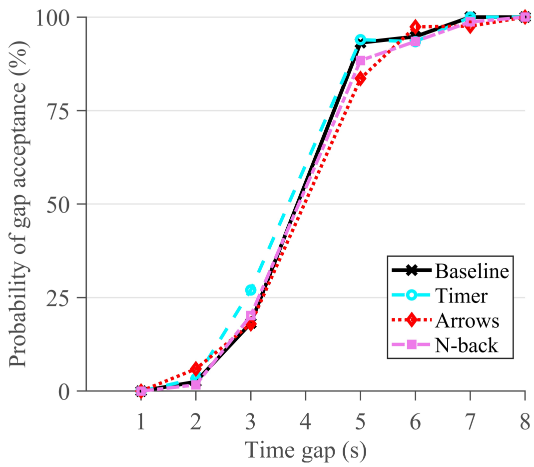

Figure 4.3: Crossing gap acceptance for each time gap and secondary task.

4.3.2 Crossing initiation time

Fig 4.4 shows the mean and 95 percentiles of initiation time for each secondary task and time gap. For detailed descriptive statistics of initiation time, please refer to Table A2. The LR test was applied to the LMM, indicating that the two models performed equally. Thus, the basic LMM model was used for the initiation time data. The effects of time gap, Timer, and N-back tasks were significant. In particular, initiation time increased with time gap ($Coef. = 0.04, z = 6.26, p < .001$) for all tasks. Compared to the baseline, participants started crossing quicker in the Timer ($Coef. = -0.18, z = -12.38, p < .001$) and N-back tasks ($Coef. = -0.07, z = -4.79, p < .001$). There was a weak positive effect for the Arrows task, suggesting that participants initiated their crossing later than in the baseline ($Coef. = 0.02, z = 1.70, p < .1$).

The pairwise comparison indicated that the influence of the Arrows on initiation time was significantly different from the N-back ($Contrast = 0.08, p < .001$).

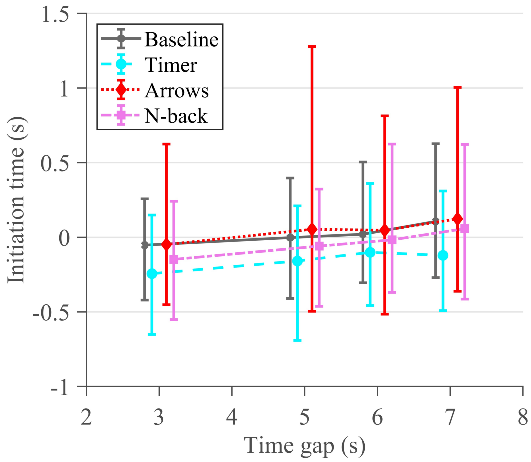

Figure 4.4: Means and 95 percentiles (error bars) of initiation time for each task and time gap.

4.3.3 Crossing duration

Since the effects of traffic flow characteristics on crossing duration were not significant, a basic LMM was applied, which revealed significant main effects of the time gap, Arrows, N-back and Timer, as shown in Fig 4.5. In particular, crossing duration under all tasks increased with time gap ($Coef. = 0.14, z = 17.24, p < .001$), showing a tendency for participants to cross more slowly as traffic gaps increased. In the Timer task, participants had smaller crossing duration than in the baseline ($Coef. = -0.10, z = -6.82, p < .001$). A main effect of the Arrows task indicated that participants under the visual-manual distraction had a longer crossing duration than in the baselines ($Coef. = 0.06, z = 4.06, p < .001$). The interaction between the Arrows task and time gap showed that the bigger the time gap, the more the crossing duration increased compared to baseline ($Coef. = 0.03, z = 3.23p < .001$). A similar main effect ($Coef. = 0.07, z = 4.93, p < .001$) and weak interaction ($Coef. = 0.02, z = 1.84, p < .1$) was found in the N-back task. The pairwise comparison revealed no significant difference between the N-back and Arrows task. For detailed descriptive statistics of crossing duration, please refer to Table A2.

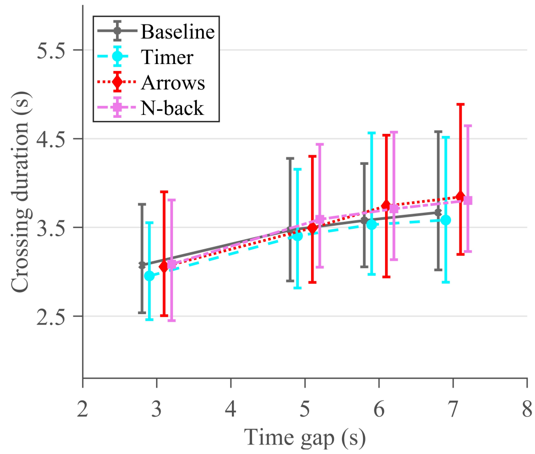

Figure 4.5: Means and 95 percentiles (error bars) of crossing duration for each task and time gap.

4.3.4 Post encroachment time

Due to the insignificant traffic flow effects, a basic LMM was applied on PETs. As shown in Fig 4.6, significant main effects of the time gap, Timer, Arrows, and N-back were found. In particular, participants' PETs significantly increased with time gap ($Coef. = 0.82, z = 81.56, p < .001$). In the Timer task, participants had bigger PETs than in the baseline ($Coef. = 0.28, z = 14.78, p < .001$). The Arrows task had significantly negative effects on pedestrians' safety ($Coef. = -0.09, z = -4.51, p < .001$). By contrast, no significant effect of the N-back task was found. The pairwise comparison on the Arrows and N-back tasks showed that PETs were significantly lower for the Arrows task than for the N-back task ($Coef. = -0.08, p < .001$). Further, there was an interaction, indicating that the PETs of the participants in the Arrows ($Coef. = -0.04, z = -3.45, p < .001$) and N-back ($Coef. = -0.04, z = -2.92, p < .01$) tasks did not increase as strongly with increasing time gaps as they did in the baseline condition. For detailed descriptive statistics of PETs, please refer to Table A2.

The above PET analysis shows the average level of safety of participants at each time gap, in the cases when participants accepted gaps. However, since the secondary tasks also affected participant gap acceptance, the PET analysis alone does not provide a full picture of the safety implications. Accordingly, a decision category analysis was conducted based both on participant crossing decisions and on PETs. First, each participant's crossing decision was grouped into three levels (i.e., near-collision, unsafe, and safe) in terms of the definition in Section 2.2. In order to determine the proportion of each decision category, the frequency of

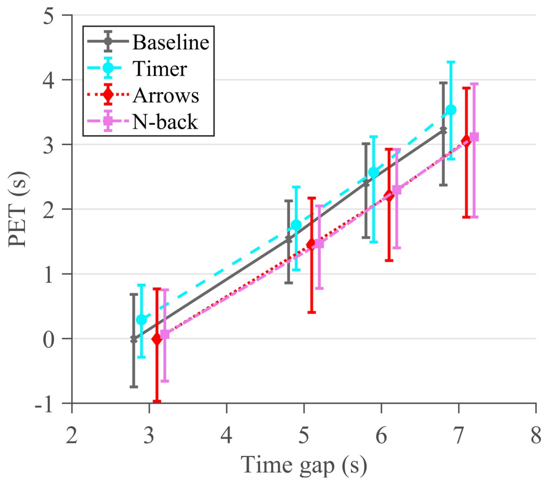

Figure 4.6: Means and 95 percentiles (error bars) of PET for each task and time gap.

decision category was divided by the number of trials with each secondary task. In other words, rather than looking at individual gaps, this analysis treats each full trial in the experiment (each line of time gaps as shown in Fig 2.2) as one measurement, where the obtained data point is the safety of the crossing that the participant eventually made in that trial, which thus depends both on which gap the participant chooses to cross in, as well as their crossing performance in that gap. The detailed results are summarised in Table A3.

A multinomial logit regression was applied to these crossing outcome data, with secondary tasks as independent variables. As the results show in Fig 4.7, whereas fewer participants made 'near-collision' crossing decisions (i.e., $9.9\% < 20.7\%$; Table A3) under time pressure ($Coef. = -0.71, z = -3.43, p < .001$), their 'unsafe' crossings were significantly increased (i.e., $44.3\% > 28.9\%$; Table A3; $Coef. = 5.19, z = 3.58, p < .001$). Since most participants under time pressure accepted the three-second gap, rather than waiting for larger gaps, it led some participants to miss out on safer opportunities (e.g., five-second gap) (Table A3). There was no significant difference in 'near-collision' decisions between the Arrows and baseline. However, the percentages of 'unsafe' decisions were bigger than the baseline (i.e., $34.0\% > 28.9\%$; Table A3), with a corresponding reduction in safe crossings ($Coef. = -0.53, z = -2.19, p < .05$). Regarding the N-back task, the performance of the participants was very similar to the Arrows task in that they had bigger percentages of 'unsafe' decisions (i.e., $36.4\% > 28.9\%$; Table A3) and smaller percentages of 'safe' decisions (i.e., $45.4\% < 50.4\%$; Table A3) than in the baseline ($Coef. = -0.46, z = -1.94, p < .05$). Fi-

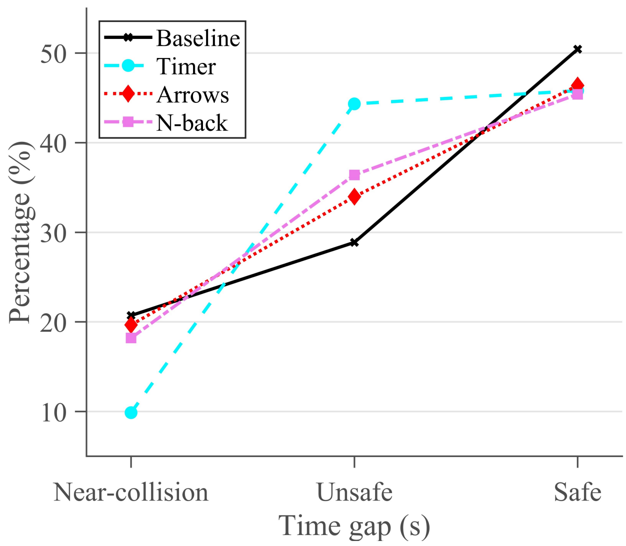

Figure 4.7: Percentages of decision categories for each task.

nally, according to the pairwise comparison, there were no differences between the Arrows and N-back tasks for all decision categories.

4.4 Discussion

In this section, a detailed discussion of the research results is presented. Table 4.3 summarises all the effects of secondary tasks on participants.

Table 4.3: Summary of influences of secondary tasks on participants, compared to the baseline. When an interaction with time gaps is mentioned, the stated interaction effect is for increasing time gaps.

Performance metric	Effect of secondary task, and interactions with time gap		
	Time pressure	Visual-manual distraction	Auditory-cognitive distraction
Gap acceptance	Smaller; No interaction	No significant difference; Decrease with time gaps	Smaller; Decrease with time gaps
Initiation time	Earlier; No interaction	Later: No interaction	Earlier; No interaction
Crossing duration	Shorter; No interaction	Longer; Increase with time gaps	Longer; Increase with time gaps
PET	Larger; No interaction	Smaller; Decrease with time gaps	No significant difference; Decrease with time gaps
Proportion of decision category	Fewer 'near-collision' decisions More 'unsafe' decisions Fewer 'safe' decisions	No significant difference More 'unsafe' decisions Fewer 'safe' decisions	No significant difference More 'unsafe' decisions Fewer 'safe' decisions

4.4.1 Time pressure

Our results demonstrated that participants tended to accept smaller time gaps in the Timer task than in the baseline, suggesting that time pressure makes them pursue riskier crossing opportunities, which is consistent with previous research that time pressure increases pedestrians' propensity to accept small gaps (Lobjois and Cavallo, 2007; Morrongiello and Corbett, 2015). At the same time, participants started earlier and walked faster under time pressure than when they crossed the road normally, which could be seen as a form of compensation for their acceptance of smaller gaps, to nevertheless achieve successful crossings (Kalantarov et al., 2018). This 'compensatory' behaviour also appeared to effectively cover some of the reduction in safety, whereby their PETs were bigger than in baseline across all time gaps. However, the increased PET for each time gap does not mean that their performance during time pressure was safer than that in the baseline. As noted in Section 3.4, by analysing the proportion of different decision categories, time pressure decreased the proportion of 'near-collision' decisions but increased the amount of 'unsafe' decisions and decreased the number of 'safe' decisions. Similar results were also reported by Kalantarov et al. (2018); Lobjois and Cavallo (2007). The possible explanation for this is that more participants accept small gaps (e.g., three-second) and thus lose opportunities to choose big time gaps (e.g., five-second). As a result, time pressure leads some participants who could have crossed the road at a safe gap to choose a smaller gap, thus compromising their safety.

Therefore, although the 'compensatory' strategy might mitigate seriously dangerous situations (e.g., the 'near-collision' decision), it is not sufficient to cover all reductions in safety. Time pressure can still impair participant safety by reducing the quality of crossing decisions. Generally, the time pressure (i) limits the pedestrians' options (i.e., they focus on the current choice at the expense of subsequent choices), (ii) reduces the time for judgment and reflection, and (iii) increases the propensity to take risky decisions (Coeugnet et al., 2019). Finally, unlike distractions (further discussed in Section 4.2), we found that the impacts of time pressure on participants' behaviour did not interact with the traffic gap. This could be taken to suggest that time pressure does not affect participants' perception of the traffic environment as such, but rather their actions in response to what they perceived.

4.4.2 Distractions

The results revealed significant impacts of distractions on pedestrian crossing behaviour. Regarding the visual-manual distraction (i.e., Arrows), we showed that its impacts on gap acceptance and crossing duration varied across the time gaps. With the increase in time gap, the tendency to accept gaps did not go up as much as in the baseline condition. A multimodal attention orientation theory (Davis et al., 2019) may provide explanations for this pattern in that participants allocate different proportions of attention on the crossing task and the visual-manual distraction, based on the gap size. Specifically, when the time gap is short, participants need to concentrate on the crossing task and give low priority to their cell phones. In contrast, the amount of attentional resources allocated to distraction tasks increases with a long time gap. Evidence in the case of driving tasks suggests drivers are able to compensate for the influences of distractions by self-regulating their engagement in a secondary task (Davis et al., 2019). Although limited pedestrian crossing behaviour studies have put forward similar results, relevant literature indicates that pedestrians walked slower and were more likely to accept bigger time gaps when using a cell phone (Neider et al., 2011; Vasudevan et al., 2020). Interestingly, only the participants in the Arrows task ever crossed in the four-second time gap. This behaviour would seem unreasonable because participants chose a riskier gap (i.e., four-second) after rejecting a safer gap (i.e., five-second) (Fig 2, Scenario 3 and 4). The potential mechanism is that the Arrows task involves both visual and manual components, which not only limits the frequency with which individuals scan the environment but also greatly affects their ability to allocate attentional resources for information processing (Jiang et al., 2018; Lin and Huang, 2017). In other words, due to the visual distraction, some participants seem to have missed the opportunity for crossing in the five-second gap, thus causing them to cross in the smaller and potentially less safe four-second gap succeeding it.

Regarding participant initiation time, in comparison to other studies indicating that cell phone use significantly slowed participants' initiation speed (Simmons et al., 2020), our study found a relatively weak effect. A potential reason for this could be that the artificial surrogate task we used (Arrows) may not be as difficult or as engrossing as real cell phone distraction (e.g., texting or reading) and may not have made participants concentrate as they do in reality. However, this pattern may also be in line with the multimodal attention orientation theory (Davis et al., 2019). The lifelike traffic flow scenario in the study might motivate pedestrians to self-regulate their attentional resources on the secondary task, thereby compensating for some of the effects caused by distraction.

With regards to the auditory-cognitive task (N-back), there were some ways in which its effects were similar to those of the visual manual task. The results indicated that the distraction could lead participants to walk slower than in the baseline condition. Meanwhile, its effects on gap acceptance and crossing duration varied across the time gap, suggesting a similar pattern as that observed in the visual-manual task, i.e., participants may have allocated different proportions of attentional resources on the crossing task and distraction based on size of time gap. However, in contrast to the Arrows task, participants' performances in the N-back task were somewhat unexpected. Whereas the Arrows task made participants accept bigger gaps and initiate slower crossings than in the baseline, the N-back task instead influenced them in the opposite way. In particular, the auditory-cognitive task not only failed to make participants conservative about their crossing but led them to accept smaller gaps and initiate earlier crossings. There are some possible explanations for these results. First, compared to visual-manual distractions, auditory-cognitive distraction does not require any pedestrian visual resources (Jiang et al., 2018; Pesic et al., 2016), such that basic visual monitoring of the oncoming traffic is left unaffected. Second, the cognitive control hypothesis (Engstrom et al., 2017), applied to the driving task may provide some insight into this behaviour pattern. It is argued that cognitive distraction could selectively impair main tasks that rely on cognitive control (e.g., brake response to the brake light of a lead vehicle) but leave well-practised and consistently mapped tasks unaffected, and even affected in the opposite way (e.g., brake response to looming stimulus of a lead vehicle may be enhanced by cognitive load). In the crossing task, pedestrians perceive the looming stimulus of approaching vehicles to make street crossing decisions similar to the braking task (Petzoldt, 2014; Tian et al., 2020). In light of the cognitive control hypothesis, pedestrian performance may not be negatively influenced by auditory-cognitive distraction since road crossing based on a looming stimulus is a well-practised task. (See also the literature on how cognitive load can improve drivers' lane-keeping performance, seemingly due to narrowing of the visual focus, increased arousal, or both) (Engstrom et al., 2017; Li et al., 2018). Moreover, due to the loss of auditory cues, pedestrians may enhance their visual perception or compensate for their decision-making to achieve a "risk homeostasis" (Walker et al., 2012), leading to more active decision-making behaviour. For instance, evidence from some simulator studies shows that participants accepted small gaps and initiated quickly when they omitted the noise of the vehicle (Soares et al., 2021, 2020). In addition, similar research showed that the pedestrian under auditory-cognitive distractions reacted quicker than the baseline (Siegmann et al., 2017).

Another important finding of the study was that the decision category analysis showed that both Arrows and N-back distractions increased participants' 'unsafe' decisions and reduced their 'safe' decisions. However, the reduced safety for Arrows and N-back distractions were associated with different road crossing performances. For the visual-manual distraction, greater initiation time and crossing duration compared to the baseline was the main reasons for reducing safety. By contrast, participants' safety under the auditory-cognitive distraction was mainly impaired because of the smaller accepted gap and greater crossing duration compared to the baseline. Based on these findings, we show that visual-manual and auditory-cognitive distractions affect pedestrian safety by influencing different crossing performance metrics.

4.4.3 Traffic flow

Interestingly, a significant effect of the traffic flow characteristics was found, indicating that fewer participants accepted a gap equal to or smaller than the maximum gap they previously rejected. Previous studies suggested that pedestrians tended to accept smaller gaps after missing several opportunities or waiting for a long time, thus negatively impacting their safety (Tiwari et al., 2007; Zhao et al., 2019). Contrarily, new findings from our research provide a different source and explanation of the traffic flow effect on crossing behaviour, indicating that pedestrians do not always become anxious when waiting for crossing opportunities. Instead, they can keep cautious and make rational cross decisions to maximise their safety and efficiency. Similar findings from Lobjois et al. (2013) indicated that pedestrians waiting for an available traffic gap was not accompanied by an increased risk of crossing. After rejecting several gaps, pedestrians could accurately estimate the approach of coming vehicles and think more carefully by comparing the current gap to previously rejected ones, thus avoiding unsafe behaviour.

4.4.4 Implications and limitations

The present results have several important implications in different areas. (1) Our findings have important meanings for understanding the influences of auditory-cognitive distractions and visual-manual distractions. First, the effect of distractions with different components on pedestrian crossing behaviour may not always be similar. Sometimes, they may work in an opposite way. The differences found in this study regarding the initiation and gap acceptance patterns of these two types of distractions have interesting parallels to the existing findings on how these distractions affect driving performance. Second, the impacts of distractions may not always be static. Pedestrians may actively self-regulate their engagement in the main and secondary tasks in terms of traffic scenarios (e.g., time gap). Moreover, (2) Existing research on traffic flow-related crossing behaviour is limited. Our results provide a novel perspective to understand pedestrian behaviour in complex traffic and can serve to help future research on this topic. (3) Based on these findings, our study may provide insights for researchers and policymakers to design appropriate interventions for pedestrians in different situations. For example, for pedestrians under visual-manual distractions, we could remind them to look more closely at the traffic. However, for the pedestrians doing auditory-cognitive distractions, the previous suggestion may not be sufficient to suppress the effects of distraction; instead, retaining the auditory cues from the traffic environment may be beneficial for their safety. In addition, (4) the results may also have significance in pedestrian behaviour modelling. Established safe and naturalistic traffic simulation or pedestrian-vehicle interactive models requires a deep understanding of pedestrian behaviour patterns. Our research results could provide insights into the improvement of crossing decision-making models related to distracted pedestrians and traffic flow.

Several limitations of the present study should also be borne in mind. One limitation is that while the Arrows and N-back tasks clearly single out visual-manual and auditory-cognitive aspects of distraction, respectively, this also means that these tasks are different from the real distracting behaviours that pedestrians engage with in real traffic. For this reason, the results cannot be directly generalized to pedestrians in actual traffic. Second, although similarly to many previous studies in simulated environments (Lin and Huang, 2017; Sobhani and Farooq, 2018) our results here were generally consistent with those from naturalistic studies on pedestrian distraction, and although the experimental apparatus we used here was arguably the most immersive used so far in a simulator study on pedestrian distraction (large walkable CAVE environment, handheld physical device), one must still assume that there are differences in behaviour between virtual and naturalistic settings. Finally, the scope of the study is limited to the studied experimental scenarios. We only considered constant-speed traffic flow, i.e., vehicles do not give way to participants, which is similar to crossing scenarios at unmarked crossroads. However, the crossing behaviour of distracted pedestrians at controlled crossings may be different, which needs to be further studied in the future.

4.5 Conclusion

In this study, we investigated the effects of distractions and time pressure on pedestrian crossing decisions in a road crossing environment with continuous traffic, using a CAVE-based pedestrian simulator. It was shown that time pressure and the two types of distractions affected different performance metrics of participants' crossing behaviour. Compared to the baseline task, the visual-manual distraction led to later initiation time, longer crossing duration, and a reduced tendency to accept a gap as the time gap increased. In comparison, participants under auditory-cognitive distraction tended to accept smaller gaps, had a longer crossing duration, and initiated their crossing earlier than in the baseline. This has interesting parallels to existing findings on how these two types of distractions affect driver performance. Furthermore, the influences of both distractions on gap acceptance and crossing duration changed over the time gap size, suggesting pedestrians self-regulate their engagement in the primary road-crossing task when compared to the secondary distraction task, as a function of the gap size. Both types of distraction impaired pedestrian safety but in different ways. Regarding time pressure, it caused participants to accept smaller gaps, initiate earlier, and use shorter crossing duration than in the baseline. Its safety impacts have two sides. On the one hand, participants under time pressure tended to take a risk and accept small gaps, causing them to lose the opportunity to cross in safe gaps. On the other hand, participants seemingly applied a 'compensatory' strategy to cover some of the reduction in safety caused by their risk-taking behaviour, by crossing earlier in the gap and walking faster.

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CHAPTER 5

Deconstructing pedestrian crossing decisions in interaction with continuous traffic: an anthropomorphic model

Deconstructing pedestrian crossing decisions in interaction with continuous traffic: an anthropomorphic model

ABSTRACT. As safe and comfortable interactions with pedestrians could contribute to automated vehicles' (AVs) social acceptance and scale, increasing attention has been drawn to computational pedestrian behaviour models. However, very limited studies characterise pedestrian crossing behaviour based on specific behavioural mechanisms, as those mechanisms underpinning pedestrian road behaviour are not yet clear. Here, we reinterpret pedestrian crossing behaviour based on a deconstructed crossing decision process at uncontrolled intersections with continuous traffic. Notably, we explain and model pedestrian crossing behaviour as they wait for crossing opportunities, optimizing crossing decisions by comparing the visual collision risk of approaching vehicles around them. A collision risk-based crossing initiation model is proposed to characterise the time-dynamic nature of pedestrian crossing decisions. A simulation tool is established to reproduce pedestrian behaviour by employing the proposed model and a social force model. Two datasets collected in a CAVE-based immersive pedestrian simulator are applied to calibrate and validate the model. The model predicts pedestrian crossing decisions across all traffic scenarios well. In particular, by considering the decision strategy that pedestrians compare the collision risk of surrounding traffic gaps, model performance is significantly improved. Moreover, the collision risk-based crossing initiation model accurately captures the timing of pedestrian crossing initiations within each gap. This work concisely demonstrates how pedestrians dynamically adapt their crossings in continuous traffic based on perceived collision risk, potentially providing insights into modelling coupled human-AV interactions or serving as a tool to realise human-like pedestrian road behaviour in virtual AVs test platforms.

Keywords: Pedestrian-AV interaction; Pedestrian road crossing; Decision-making model; Traffic flow; Simulation.

5.1 Introduction

Continued advances in vehicle automation have brought us great anticipation that society will adopt highly automated vehicles (AVs) in the near future. However, this vision faces many unresolved challenges. One of them is to achieve smooth interaction between AVs and other road users. The consensus suggests that in the transition from manual to fully automated driving, there will be mixed traffic with AVs and other road users on the road (Palmeiro et al., 2018). A typical case is the expansion of the deployment of AVs from a few confined areas of low risk to other road users to a range of operational design domains, which could inevitably increase conflicts with other road users (Connected, 2022). Failures in interactions between AVs and other road users may hinder the large-scale adoption and social acceptance of AVs

(Markkula et al., 2020; Rasouli and Tsotsos, 2019). This, therefore, leads to the research context of this study, which is to promote safe and smooth communication and interaction in traffic (Palmeiro et al., 2018; Markkula et al., 2020; Rasouli and Tsotsos, 2019). Pedestrians are generally regarded as the most vulnerable road users in modern transport systems, due to the lack of protective equipment and slow movement compared to other road users (El Hamdani et al., 2020). Given that pedestrians' actions and intentions are nondeterministic, and the diversity and dynamism of their behaviour, moving through this complicated environment is a challenge for AVs (Domeyer et al., 2022). Moreover, AVs' own behaviour can also affect pedestrian road behaviour, which introduces further uncertainties into interactions. In particular, the issues mentioned above become more pronounced at uncontrolled intersections where pedestrian behaviour is more unpredictable, and safety problems are more common than on other controlled road sections, as there are no traffic signals to coordinate the interaction process (Zhao et al., 2019). Additionally, most existing automated driving systems regard the driving task as a pure collision-free motion planning problem and view pedestrians in some contexts as rigid road obstacles, instead of social beings (El Hamdani et al., 2020; Schneemann and Gohl, 2016).

Against the above background, if AVs cannot properly understand the behaviour of pedestrians, they may not improve traffic efficiency and safety as expected, but rather increase traffic dilemmas and additional issues (Millard-Ball, 2018). Accordingly, much attention has been drawn to one pressing issue, namely computational models for pedestrian road behaviour, (Pekkanen et al., 2021; Giles et al., 2019; Domeyer et al., 2022; Zhang et al., 2020b; Predhumeau et al., 2021), which may help AVs to better anticipate pedestrian intentions or serve as a tool to implement realistic pedestrian behaviour in simulated scenarios, and thus be used in the validation and development of AVs (Markkula et al., 2020; Rasouli and Kotseruba, 2022). Existing computational models for pedestrian behaviour, particularly for pedestrian road-crossing decisions have been developed based on a wide range of theories and hypotheses, such as the cognitive models (Markkula et al., 2020; Pekkanen et al., 2021), data-driven approaches (Volz et al., 2016), discrete choice models (Zhang et al., 2020b), as well as game theoretical models (Camara et al., 2020a). However, those approaches have not yet bridged several gaps, as identified and discussed below.

Firstly, most of these approaches are rarely based on specific behavioural or psychological theories, such as pedestrian visual perception. Instead, external physical factors, like time to collision (TTC), have been often used. For example, Zhang et al. (2020a); Fu et al. (2018) developed a pedestrian crossing decision-making model based on the vehicle deceleration distance. Zhu et al. (2021); Rasouli and Kotseruba (2022) applied a minimum TTC as the threshold for pedestrian crossing decisions. Although TTC or distance from the vehicle has become the most used decision cue in crossing decision models (Zhang et al., 2020a), growing evidence has shown that the impacts of vehicle kinematics on pedestrians are multi-dimensional. For instance, at the same TTC condition, a higher vehicle speed induces more pedestrians to cross the street compared to a lower one (Lobjois and Cavallo, 2007). Therefore, the TTC or distance may not properly carry the risk information that pedestrians may perceive. As our previous research has shown, pedestrian crossing behaviour is highly correlated with their perceived visual cues (Tian et al., 2022a). Hence, existing models lack effort in characterising pedestrian perceived information, e.g., anthropomorphic visual cues (Pekkanen et al., 2021; Palmeiro et al., 2018).

Moreover, few computational models specifically characterise pedestrian decisions in the traffic flow scenario. In real situations, pedestrians usually face a fleet of vehicles and accept one traffic gap after rejecting some gaps. Thus, the decision-making in continuous traffic may not only be based on the collision risk, but also involve many trade-offs between safety and time efficiency (Sucha et al., 2017). Several previous studies indicated that with the increased waiting time, pedestrians tended to accept crossing opportunities with higher risk (Zhao et al., 2019). Rasouli and Kotseruba (2022) developed a model which hypothesised that pedestrians would change their obedience to the law when they waited a long time. However, there is much evidence that pedestrians who tended to wait were more cautious and less likely to accept risky gaps (Lobjois et al., 2013; Tian et al., 2022b; Yannis et al., 2013). A meta-study uncovered these conflicting results and noted that there was insufficient evidence to support a linear relationship between waiting times and pedestrians risking crossing the street (Theofilatos et al., 2021). On the one hand, the available findings support that pedestrians may dynamically adjust their crossing decision-making strategies in continuous traffic. On the other hand, it is unreasonable to assume that pedestrians always tend to accept more dangerous crossing opportunities as waiting time increases. Instead, we should treat each case on its own merits. Therefore, it is necessary to look into the details of pedestrian crossing behaviour when interacting with traffic flow.

Finally, very limited models pay attention to the time dynamic of pedestrian crossing decision-making. According to the cognitive decision-making theory, pedestrian crossing initiation time (or onset time) is a variable due to the noisy evidence in the human cognitive system (Markkula et al., 2021). In addition, it has been shown that pedestrian crossing initiation time can be affected by many factors. For instance, pedestrians may initiate quickly when facing a vehicle with a low speed (Lobjois and Cavallo, 2007) or with a small time gap from the approaching vehicle (Kalantarov et al., 2018). Accordingly, existing empirical observations highlight the time-dynamic nature of pedestrian crossing decision-making. Recently, a class of emerging models (Markkula et al., 2018; Giles et al., 2019; Pekkanen et al., 2021), namely the evidence accumulation model, detailed model pedestrian crossing decisions and their timing by simulating the cognitive process underlying crossing decision-making. However, given the complexity of those models, they focused more on the details of the cognitive process, and it is unclear whether it would be feasible to extend them to cover additional factors, such as vehicle kinematics.

Regarding the above discussion, several research questions in existing computational models of pedestrian crossing behaviour can be summarised:

- There is a lack of computational models that characterise pedestrian crossing decisions based on anthropomorphic behavioural theory.
- The decision pattern of pedestrians crossing the road when interacting with the traffic flow remains unclear.
- There is a lack of computational models that concisely consider the time-dynamic nature of road crossing decisions and relate them to vehicle kinematics.

In this study, a decision-making model for pedestrians interacting with continuous traffic at uncontrolled intersections is proposed to solve the above questions. The main contributions of this paper are as follows:

- We formally apply our findings (Tian et al., 2022a) and extend it to a relatively complex traffic scenario, demonstrating that pedestrian crossing decisions are dynamic and intrinsically linked to their perceived collision risk. Specifically, a visual collision risk model is introduced as the main decision cue accounting for pedestrian crossing decisions. Moreover, a novel decision strategy is proposed to interpret pedestrian crossing decisions in continuous traffic flow. In addition, a crossing initiation time model is developed and associated with the collision cue model to account for the pedestrian dynamic crossing initiation time.
- Two different datasets collected in a highly immersive pedestrian simulator are applied to calibrate and validate the model.

- A simulation tool is established to reproduce pedestrian crossing decisions in a customised traffic scenario based on the proposed model.

5.2 Methodology

5.2.1 Deconstructing the crossing decision-making process

During the decision-making process for road-crossing, several cognitive stages may be involved to establish pedestrian situation awareness (Palmeiro et al., 2018; Coeugnet et al., 2019). Normally, pedestrian perceived collision cues are the basis of their decisions, which contain vehicle distance, speed, TTC, and more. Based on those visual cues, pedestrians comprehend traffic situations and decide whether to cross the road or not by combining some prior knowledge and strategies. Finally, there is a reaction process before pedestrians start to move. Therefore, according to the deconstructed three-stage cognitive process, we propose a collision cue-based framework for road-crossing decision-making tasks (Fig 5.1), assuming that the crossing decision-making model consists of three constituent parts: visual collision cue, decision, and crossing initiation.

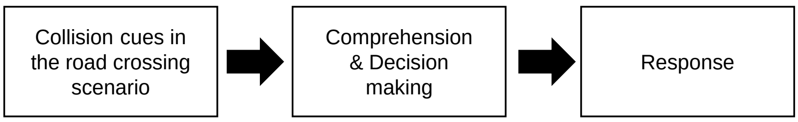

Figure 5.1: A simplified framework for pedestrians road-crossing decision-making process.

5.2.2 Visual collision cue model

Modelling pedestrian-vehicle interaction is challenging, partly because existing pedestrian models lack psychological underpinnings. According to psychological theory, when moving through the environment, people rely on their visual perception of the space around them (Gibson, 2014). Several human cognitive modelling studies have recently confirmed our assumptions, indicating that visual cues have the potential ability to characterise the PRD process (Markkula et al., 2018; Giles et al., 2019; Pekkanen et al., 2021). The road crossing task is a typical case that highly demands pedestrians to use visual cues to evaluate the collision risk from approaching vehicles and guide their movements. Relevant behavioural research has shown that the human visual system is sensitive to changes in some visual cues, which may be

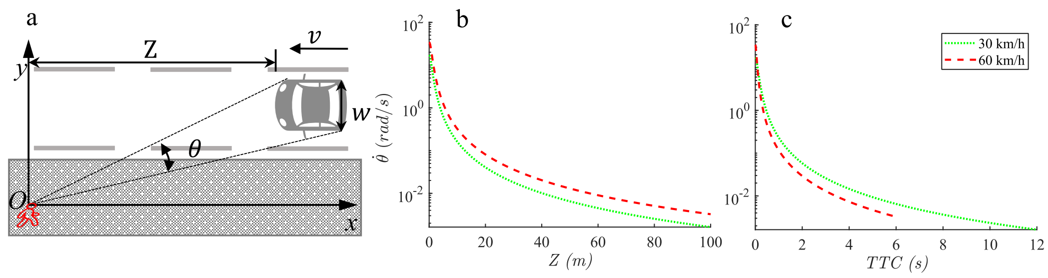

Figure 5.2: (a) Visual collision cue model in road crossing scenario. Collision cues are as a (b) function of distance from and speed of the vehicle or (c) TTC from and speed of the vehicle.

the source of collision perception. Specifically, one group of cues may provide reliable collision time information, such as Tau (Lee, 1976). Other cues, such as visual angle and its change rate (DeLucia, 2008), can efficiently convert information about the movement of objects into visual cues. Although most daily naturalistic road crossings involve all of the above visual cues (and possibly others), DeLucia (2008) has suggested that humans may rely on collision time-related cues when the scenarios include robust optical information or occur at a near distance. Conversely, when the optical information in the task is impoverished or occurs at a long distance, the visual angle and its first temporal derivative may play a dominant role. In light of this conceptual framework, we have previously identified that the first temporal derivative of visual angle, $\dot{\theta}$, is a critical collision cue for making crossing decisions at uncontrolled intersections. Chapter 2 has demonstrated that $\dot{\theta}$ not only well explains pedestrian crossing decisions across a wide range of traffic scenarios from two different datasets, but also reasonably characterises the impacts of vehicle speed and traffic gap on pedestrians (Tian et al., 2022a). Therefore, in this study, we formalised the pedestrian crossing decision model based on our previous findings. Typically, $\dot{\theta}$ refers to the change rate of the visual angle subtended by an approaching vehicle, θ, (Fig 5.2a) (Gibson, 2014). The following equations specify its physical model:

$$\theta = 2\tan^{-1}\frac{w}{2Z} \Rightarrow \dot{\theta}\,(Z, v, w) = \frac{wv}{(Z)^2 + w^2/4} \tag{5.1}$$

where v denotes the vehicle speed, Z and w are the distance to and width of the vehicle. To better interpret the collision cue model, an example is shown in Fig 5.2. Suppose that a vehicle ($w = 1.95$ m) approaches the pedestrian with two different constant speeds (30 km/h and 60 km/h) from 100 m. $\dot{\theta}$ is an approximately inversely exponential function of distance and TTC from the approaching vehicle (Fig 5.2b, c), showing that $\dot{\theta}$ increases slowly at long distances and rapidly at close 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 (Lobjois and Cavallo, 2007). Further, it can be noticed that speed effects vary across distance (Fig 5.2b) and TTC dimensions (Fig 5.2c). When $\dot{\theta}$ is a function of distance and speed, it increases with speed, which is opposite to the results in Fig 5.2c, suggesting that pedestrians may perceive a higher collision threat from the vehicle with higher speed at the same distance. However, the approaching vehicle with a slower speed gives pedestrians a bigger collision threat under the same TTC. The results tie well with the previous experimental observations on pedestrian crossing behaviour (Lobjois and Cavallo, 2007, 2009; Schmidt and Farber, 2009).

5.2.3 Decision model

Regarding crossing decisions at uncontrolled intersections, pedestrians typically make crossing decisions by judging and selecting the appropriate gaps between two consecutive vehicles, called gap acceptance behaviour (Zhao et al., 2019). In Chapter 2, it has proven that $\dot{\theta}$ is significantly negatively correlated with pedestrian gap acceptance behaviour, and a collision cue-based binary choice logit model predicts pedestrian gap acceptance well across different vehicle speeds and traffic gap experimental scenarios (Tian et al., 2022a). Furthermore, evidence from empirical observations and study in Chapter 4 indicated that individuals' judgments toward traffic gaps are not necessarily entirely static over time, especially in traffic streams (Woodman et al., 2019; Lobjois et al., 2013; Tian et al., 2022b). Due to certain learning or comparison strategies, pedestrians may estimate different utilities for the approaching vehicles with the same collision cues, thus adjusting their crossing decision to balance safety and efficiency. We, therefore, propose the following assumptions for the crossing decision-making in the traffic flow:

(i) Pedestrians make decisions mainly based on collision cues, i.e., $\dot{\theta}$, provided by approaching vehicles.

(ii) Pedestrians are unwilling to accept the current gap with a collision cue equal to or greater than the maximum collision cue previously rejected. For example, if pedestrians reject a 0.02 rad/s cue, they would be more likely to reject the same or bigger one upstream of traffic. The rule is given by:

$$X_1 = \begin{cases} 1, & \dot{\theta}_c \geq \dot{\theta}_{mr} \\ 0, & \dot{\theta}_c < \dot{\theta}_{mr} \end{cases} \tag{5.2}$$

where X_1 is the dummy variable for the rule. $\dot{\theta}_c$ and $\dot{\theta}_{mr}$ represent collision cues for the current gap and maximum rejected gap, respectively.

(iii) If pedestrians find that a gap next to the current gap has a smaller collision cue than the current gap, they may prefer to wait for this gap rather than accept a current gap with a greater collision threat, given the rule:

$$X_2 = \begin{cases} 1, & \dot{\theta}_c \geq \dot{\theta}_f \\ 0, & \dot{\theta}_c < \dot{\theta}_f \end{cases} \tag{5.3}$$

where X_2 is the dummy variable for the decision rule. $\dot{\theta}_f$ represents a collision cue of the gap following the current one. Therefore, the utility function of the decision model is formulated as:

$$V = \rho_0 \ln\left(\dot{\theta}\right) + \rho_1 X_1 + \rho_2 X_2 + \rho_3 \tag{5.4}$$

where ρ_0 to ρ_3 are estimated coefficients. In this study, every $\dot{\theta}$ only refers to the $\dot{\theta}$ value of the approaching vehicle at the time when the rear end of the previous vehicle just past the pedestrian (Fig 5.3a). Regarding the $\ln$ transformation, we have previously proven that it can efficiently increase the accuracy of model fitting in Chapter 2 (Tian et al., 2022a). Since crossing decisions at uncontrolled intersections are assumed to be a binary choice task, a logistic function is applied (Zhao et al., 2019). Then, a decision model for crossing tasks in the traffic flow is given by:

$$p(\dot{\theta}, X_1, X_2) = \frac{1}{1 + \exp\left(-V\right)} \tag{5.5}$$

where p is the probability of the gap acceptance. The (Eq 5.5) without the terms X_1 and X_2 degenerates to the model proposed in Chapter 2 (Tian et al., 2022a).

5.2.4 Crossing initiation model

In real traffic, the time at which pedestrians start to cross the road is a variable (Markkula et al., 2021). As illustrated in Fig 5.3a, crossing initiation time, t_{int}, is typically defined as

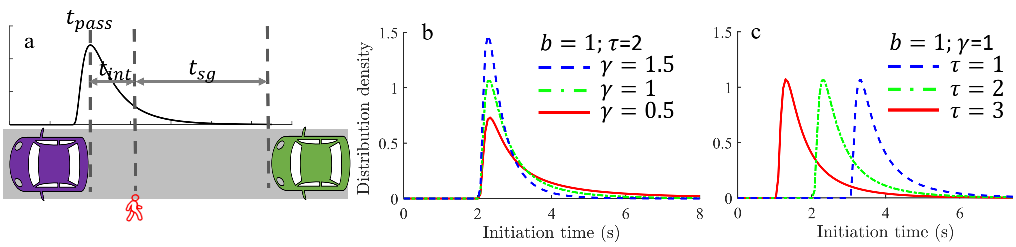

Figure 5.3: Illustration of the initiation model. (a) Initiation time t_{int} is the duration between t_{pass} and the time when the pedestrian start crossing. t_{sg} denotes the actual gap to the approaching vehicle when pedestrians initiate. (b) The shapes of the initiation model by changing γ. (c) The positions of the initiation model by changing τ.

the duration between the time when the rear end of the previous car passes the pedestrians' position, t_{pass}, and the time when pedestrians start their movements (Lobjois and Cavallo, 2007). Emerging cognitive models (Markkula et al., 2021; Giles et al., 2019; Pekkanen et al., 2021) have shown that the crossing initiation time distribution may arise from an underlying evidence accumulation process, but of a form that requires costly stochastic simulation of to estimate the distribution. However, the skewed, lognormal-like shape of the distribution is similar to those arising from simpler evidence accumulation processes, which can be written in a closed mathematical form, such as Ex-Gaussian, Shifted Wald (SW), and Weibull (Anders et al., 2016). Considering the similarities of those methods, we only apply the SW distribution instead of trying all of them. The SW distribution is a simple and concise distribution modelling tool, which can fully qualify the crossing initiation time distribution with three parameters: b (deviation around the mode), γ (tail magnitude) and τ (onset of the distribution). Its equation is defined as:

$$\begin{aligned} x &\sim \mathrm{SW}(b, \gamma, \tau) \\ \Rightarrow & \frac{b}{\sqrt{2\pi(x-\tau)^3}} \cdot \exp\left(\frac{-[b-\gamma(x-\tau)]^2}{2(x-\tau)}\right) \end{aligned} \tag{5.6}$$

An illustration of the distributional effect that occurs by changing each of the γ and τ parameters are shown in Fig 5.3 b and c. The tail becomes heavier as γ decreases, (Fig 5.3b). Changes in τ control the position of the distribution (Fig 5.3c) (Anders et al., 2016).

According to our assumptions in Fig 5.1, the crossing initiation time model is affected by collision cues, so we define the initiation time model as follows:

$$\begin{aligned} t_{int} &\sim \mathrm{SW}(b, \gamma, \tau) \\ \text{with } \gamma = \beta_1 \ln\left(\dot{\theta}\right) + \beta_2; \tau &= \beta_3 \ln\left(\dot{\theta}\right) + \beta_4 \end{aligned} \tag{5.7}$$

where t_{int} is the crossing initiation time. β_1 to β_4 are estimated coefficients. The idea behind these equations is that the strength of collision cues could affect the distribution pattern of pedestrian initiation time. For a more intensive collision threat, if pedestrians choose to cross, they tend to do so more quickly, so the distribution is concentrated and has a short tail. In contrast, when the collision threat is small, pedestrians tend to start crossing slowly, so the distribution is more likely to have a long tail (Lee et al., 2022). Accordingly, the SW model is not only a practical distribution model but also provides notable psychological significance for our decision model. In addition, b is assumed to be a coefficient not influenced by collision cues. Furthermore, since response time data are routinely assumed to be normally distributed in many studies (Lobjois and Cavallo, 2007; Oxley et al., 2005), another crossing initiation time model based on the Gaussian distribution is proposed as a comparison to the SW model, defined as the following equations:

$$\begin{gathered} t_{int} \sim \mathcal{N}(\mu, \sigma), \\ \text{with } \mu = \beta_1 \ln\left(\dot{\theta}\right) + \beta_2; \sigma = \beta_3 \ln\left(\dot{\theta}\right) + \beta_4 \end{gathered} \tag{5.8}$$

where μ and θ are parameters of the Gaussian model, $\mathcal{N}$.

5.2.5 Pedestrian road-crossing decision-making model in traffic flow

Finally, a pedestrian road-crossing decision-making model based on the SW distribution in the traffic flow (SW-PRD) is then established by employing (Eq 5.5 and Eq 5.7):

$$\begin{aligned} & f_{SW}(t_{\text{int}}) = \sum_{n=1}^{N} P_n \cdot \text{SW}\left(b, \gamma\left(\dot{\theta}_n\right), \tau\left(\dot{\theta}_n\right)\right) \\ & P_n = p\left(\dot{\theta}_n, X_{1,n}, X_{2,n}\right) \cdot \left(1 - P_{n-1}\right) \\ & P_0 = 0 \end{aligned} \tag{5.9}$$

where n is the position number of the gap in the traffic flow. $\dot{\theta}_n$, $X_{1,n}$ and $X_{2,n}$ represent the decision variables for the nth traffic gap. P_n means the recursive probability that pedestrians accept the nth gap, which is calculated based on p and P_{n-1}. Similarly, a road-crossing decision model based on Gaussian distribution (G-PRD) is given by:

$$f_G(t_{\text{int}}) = \sum_{n=1}^{N} P_n \cdot \mathcal{N}\left(\mu\left(\dot{\theta}_n\right), \sigma\left(\dot{\theta}_n\right)\right) \tag{5.10}$$

5.2.6 Simulation tool

In this subsection, an agent-based simulation tool is proposed using the established models to reproduce pedestrian crossing behaviour at uncontrolled intersections with traffic flow. The framework mainly includes three parts: the decision model, environment model, and pedestrian kinematics model. Regarding the traffic environment, as the intersections on multi-lanes are often separated by refuges (Davies, 1999), pedestrians actually cross one lane at a time. Therefore, a single-lane road with an uncontrolled intersection is considered. On the other hand, the model is possibly extended to a multi-lane situation, but the impacts of refuges should be further considered (Zhang et al., 2017). A fleet of vehicles travels on the lane at a constant speed, wherein the vehicle quantity, speed, and traffic gaps can be customised. Afterward, a basic social force model is applied as a pedestrian kinematics model (Farina et al., 2017), which considers the driving force towards the destination and repulsive force from the boundary of the crosswalk. Finally, according to the information provided by the traffic environment and kinematics model, each pedestrian's road crossing decision is generated through PRD models. The detailed process of the simulation tool is provided in the supplementary file (Appendix. C). A demonstration video of the simulation tool is also provided. Please see the attachment.

5.3 Model calibration and validation

In this study, two empirical datasets collected in a simulated environment, i.e., a CAVE-based highly immersive pedestrian simulator, were applied to calibrate and validate the PRD models. The following sections provide detailed information on the two datasets, calibration, and validation methods.

5.3.1 Empirical data

Dataset one. A virtual road scene with a 3.5 m wide single lane and 1.85 m wide pavement was created in the simulator. Two consecutive vehicles of 1.95 m in width were driven in the middle of the road at the same constant speed. Three vehicle speeds were selected, namely, 25 mph, 30 mph, or 35 mph. The first vehicle came into view 96 m away from the pedestrian, and the second vehicle maintained a specific time gap behind the first vehicle, i.e. 2 s, 3 s, 4 s, or 5 s (Fig 5.4a). Sixty participants were instructed to cross the road between the two cars if they felt comfortable and safe to do so. Otherwise, they could reject the gap. Three experimental blocks were created, and each of the 12 scenarios (4 time gaps $\times$ 3 speeds) were presented in random

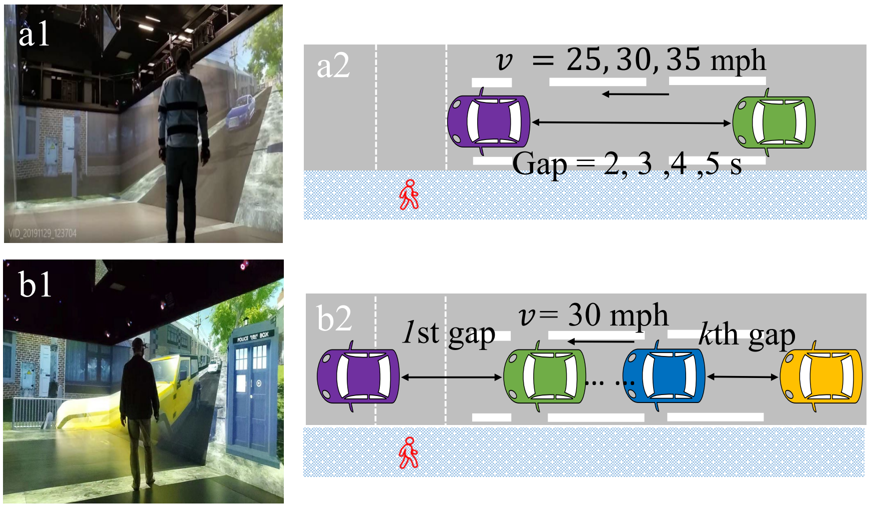

Figure 5.4: Schematic diagrams and photos of traffic scenarios in simulated experiments. The crossing scenarios and traffic of the (a) first dataset and (b) second dataset.

order and repeated once in each experimental block. Therefore, each participant experienced 72 trials, and 4270 trials of data were obtained in total.

The virtual environment and simulation process mentioned above were designed and controlled by the Unity3D platform. Internal code automatically recorded the positions and velocities of vehicles and participants on each time step. Two main metrics were applied: gap acceptance, u, and crossing initiation time, t_{int}. The gap acceptance data were the binary crossing decisions made by participants, i.e., $u = 1$ means pedestrians accepted the gap, while 0 indicated rejected the gap. The crossing initiation time was defined as described in Section 5.2.4 and Fig 5.3a. For more detailed information about this dataset, please refer to Lee et al. (2022).

Dataset two. To explore pedestrians' road crossing decisions in traffic flow, pedestrians were asked to cross a one-lane road with continuous traffic in the simulator (Fig 5.4b). The size of time gaps between every two consecutive vehicles varied, which provided pedestrians with different opportunities to make crossing decisions (Fig 5.4b). Four traffic scenarios with different sequences of gap sizes (in seconds) were designed as follows:

- Scenario one: 1 1 1 3 3 3 6 1 1 6;
- Scenario two: 1 1 1 1 3 3 7 1 1 3 8;
- Scenario three: 1 1 1 3 1 3 1 3 5 4 8;

- Scenario four: 2 3 1 1 3 1 1 1 5 4 7;

Among these scenarios, the one-second and two-second time gaps between vehicles were considered dangerous crossing opportunities that very few pedestrians would accept. For the three-second and four-second gaps, decisions were expected to significantly differ between participants due to their heterogeneity (e.g., age and gender). The time gaps longer than four seconds were considered safe gaps that most pedestrians were expected to confidently accept. In all scenarios, a range of compact, midsize, van, and SUV vehicles were driven at 30 mph. Since the types of the approaching vehicle were randomly selected, in the analyses here, the width of the vehicle was calculated by averaging the width of all vehicles in the corresponding gap in each scenario. 60 participants completed four crossing tasks in any of the four scenarios and repeated them once more (4 crossing tasks $\times$ 4 scenarios $\times$ 2 repetitions). We, therefore, collected data from 1920 trials. All the trials that participants experienced were in a randomised order. Similar to the first dataset, two main metrics were used: gap acceptance, u, and crossing initiation time, t_{int}. For more detailed information about this dataset, please refer to Tian et al. (2022b).

5.3.2 Data processing and parameter estimation

With regard to data processing, both datasets were divided into a training set and a validation set. Regarding dataset one, as controlled experimental variables were vehicle speed and time gap size, we separated the training and validation sets by choosing the data from different combinations of experimental variables (As illustrated in Section 5.3.1, there were 12 different combinations). To have enough data in the training and validation sets, data from 10 combinations were grouped into the training set, while the rest of the data belonged validation set. Moreover, in order to make sure the validation data were sufficiently different, the 2 combinations are not adjacent to each other in terms of speed or time gap size. Accordingly, the validation set included data in 4 s 25 mph and 5 s 35 mph conditions, approximately accounting for 23$\%$ of the initiation time data and 14$\%$ of the gap acceptance data (The data size of the two metrics was not the same as there was no initiation time data for participants who rejected the gap). The remaining data of all other conditions were grouped into the training set. Similarly, with respect to dataset two, the data from traffic scenario four were used as the validation set, accounting for 24$\%$ of gap acceptance data and 25$\%$ of initiation time data.

A Maximum Likelihood Estimation (MLE) method was used to calibrate the parameters in the models. Firstly, regarding the decision model (Eq 5.5), since it assumes that crossing decisions are drawn from a Bernoulli distribution, its likelihood function is given by:

$$\begin{gathered}\mathcal{L}_1(\omega)=\prod_{i=1}^{n} p(\Theta \mid \omega)^{u_i}\left(1-p(\Theta \mid \omega)^{1-u_i}\right) \\ \rho_1, \rho_2, \rho_3, \rho_4 \in \omega \\ \dot{\theta}_i, X_{1,i}, X_{2,i} \in \Theta\end{gathered} \tag{5.11}$$

where ω includes all the estimated parameters $\rho_1, \rho_2, \rho_3, \rho_4$. Θ denotes $\dot{\theta}_i, X_{1,i}, X_{2,i}$ for the ith trial. n is the size of the dataset. With respect to the initiation models, their likelihood functions are given by the following equations based on (Eq 5.7) and (Eq 5.8):

$$\begin{gathered}\mathcal{L}_2(\Delta)=\prod_{j=1}^{m} \mathrm{SW}\left(t_{int,j}, \dot{\theta}_j \mid \Delta\right) \\ \beta_1, \beta_2, \beta_3, \beta_4, b \in \Delta\end{gathered} \tag{5.12}$$

$$\mathcal{L}_3(\Delta)=\prod_{j=1}^{m} \mathcal{N}\left(t_{int,j}, \dot{\theta}_j \mid \Delta\right) \tag{5.13}$$

where Δ is the summary of the estimated parameters of crossing initiation models. $t_{int,j}$ is the jth crossing initiation time data. The data size is m. According to the MLE method, the maximization problem is equivalent to minimizing the negative log-likelihood. Thus, the optimal estimations for parameters are achieved when negative log-likelihood functions are minimised, e.g., $-\ln\left(\mathcal{L}_1(\omega)\right)$. We applied a built-in 'fminuc' function in MATLAB to find the solution to the above minimization problems (MATLAB, 2021).

Furthermore, there were some differences in the model estimates based on the two datasets. Firstly, since the traffic flow scenarios were not considered in dataset one, the models based on this dataset did not include the parameters ρ_1, ρ_2. Regarding dataset two, for comparison purposes, we manipulated the SW-PRD model so that it had the proposed decision rules for traffic flow, whereas the G-PRD model did not. The estimated parameters based on the two datasets are presented in Table 5.1 and Table 5.2. In addition, the parameters of the social force model are adopted from Farina et al. (2017).

5.3.3 Validation methods

After calibration, the predictions were compared with the validation set to verify the ability of the models. Two evaluation methods were applied to compare the performance of the

Table 5.1: Calibration results of models based on dataset one

Parameter	SW-PRD (Without flow)		G-PRD (Without flow)	
	Estimate	95 % C.I.	Estimate	95 % C.I.
β_1	0.03	[-0.19, 0.24]	-0.03*	[-0.05, -0.01]
β_2	4.48*	[3.35, 5.62]	0.15*	[0.07, 0.24]
β_3	-0.20*	[-0.26, -1.78]	-0.21*	[-0.24, -0.18]
β_4	-2.11*	[-2.43, 1.22]	-0.76*	[-0.91, -0.62]
b	6.06*	[4.43, 7.68]	-	-
ρ_0	-2.14*	[-2.28, -1.98]	-2.14*	[-2.28, -1.98]
ρ_3	-9.95*	[-10.64, -9.26]	-9.95*	[-10.64, -9.26]
LL	-108.43		-176.69	
BIC	252.37		381.79	

Note. LL: log-likelihood of the entire model, C.I.: confidence interval, *: significant at a 5% significance level
With/Without flow: consider/not consider decision strategies for traffic flow

proposed models, namely BIC and K-S test. The BIC is given by:

$$\text{BIC} = k \ln(n) - 2 \ln(L) \tag{5.14}$$

where k is the number of parameters in the model. n is the size of the dataset. L is the maximum likelihood. The preferred model is the one with the minimum BIC (Schwarz, 1978). K-S test is a nonparametric test, which is used to evaluate the goodness-of-fit of the predicted results by quantifying the distance between empirical and predicted distributions (Stephens, 1974). The main equation of K-S test is:

$$D_{n,m} = \sup |\boldsymbol{F}_n(x) - \boldsymbol{F}_m(x)| \tag{5.15}$$

where sup denotes the supremum function. $\boldsymbol{F}_n(x)$ and $\boldsymbol{F}_m(x)$ are the distribution functions of the observed data and predicted result. n and m represent the size of the samples. The K-S test rejects the null hypothesis, i.e., two samples are drawn from the same probability distribution if $D_{n,m}$ is bigger than the selected threshold. In addition, the R-squared, R^2, and Root Mean Square Error (RMSE) are also used in the model discussion.

Table 5.2: Calibration results of models based on dataset two

Parameter	SW-PRD (With flow)		G-PRD (Without flow)	
	Estimate	95 % C.I.	Estimate	95 % C.I.
β_1	0.47*	[0.29, 0.66]	-0.05*	[-0.06, -0.04]
β_2	7.36*	[6.15, 8.57]	0.01	[-0.05, 0.07]
β_3	0.04	[-0.02, 0.10]	-0.10*	[-0.13, -0.09]
β_4	-1.41*	[-1.70, -1.13]	-0.59*	[-0.68, -0.50]
b	7.76*	[5.6, 9.90]	-	-
ρ_0	-2.92*	[-3.16, -2.68]	-3.31*	[-3.55, -3.07]
ρ_1	-1.29*	[-1.56, -1.02]	-	-
ρ_2	-0.50*	[-0.84, -0.15]	-	-
ρ_3	-13.23*	[-14.30, -12.16]	-15.50*	[-16.56, -14.46]
LL(Decision model)	-1536.40		-1672.50	
LL(CIT model)	-36.35		-104.03	
BIC	3218.40		3600.40	

Note. LL(Decision model/CIT model): log-likelihoods of decision models /crossing initiation time models

5.4 Results and Analysis

In this Section, we first discuss the calibration results of the SW-PRD and G-PRD models. Afterward, the validation results of the two models were compared using the BIC and K-S test. Finally, the model with better performance is compared to two entire datasets, and the reproduced crossing behaviour patterns are discussed in detail. Additionally, regarding the first dataset, as it does not include the traffic flow scenario, we focus on the impacts of speed and time gap on pedestrian crossing behaviour, while the effect of traffic is discussed using the results based on the second dataset.

Table 5.3: Validation results of models based on dataset one

Condition	Model	LL	BIC	K-S test score	P value
25 mph 4 s	SW-PRD	-23.08	71.47	0.06	0.56
	G-PRD	-27.28	74.82	0.10	0.08
35 mph 5 s	SW-PRD	-13.19	54.81	0.05	0.31
	G-PRD	-24.83	72.41	0.09	0.02*

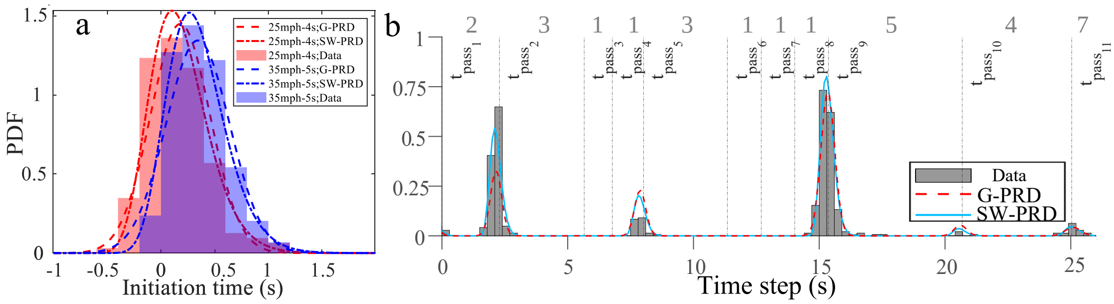

Figure 5.5: Validation results. Probability density functions and data based on datasets (a) one and (b) two. The vertical dash-dotted lines in (b) indicate the time when the rear end of the vehicle passes the pedestrian's position. The size of the time gap (in seconds) between every two vehicles is indicated at the top of the diagram.

5.4.1 Calibration results

Dataset one. The parameters of the SW-PRD and G-PRD models were calibrated using the first dataset. One thing to note is that as the first dataset did not include traffic flow scenarios, these two models thus did not implement decision strategies in traffic, which means ρ_1 and ρ_2 were not included in the models, and two decision models in the SW-PRD and G-PRD models were the same. The calibration results are shown in Table 5.1, where the maximum log-likelihood and BIC of the SW-PRD model based on the training set are -108.43 and 252.37, which are significantly better than those of the G-PRD model, i.e., -176.69 and 381.79, indicating that the SW-PRD model can better describe pedestrian crossing initiation time than the G-PRD model on the calibration set. Moreover, it can be found that the effect of ρ_0 is significantly negatively correlated with $\dot{\theta}$ (Est. $= -2.14, \text{C.I.} = [-2.28, -1.98]$), showing that pedestrian crossing gap acceptance decreases as the risk of collision increases. Additionally, the estimated effect of β_3 in the SW-PRD model is significantly correlated with $\dot{\theta}$ (Table 5.1), suggesting that pedestrian crossing initiation time is negatively related to the collision risk.

Dataset two. The calibration results based on the second dataset are shown in Table 5.2. As the SW-PRD model implemented the decision strategies in traffic flow, it included ρ_1 and ρ_2. However, the G-PRD model did not. Meanwhile, as both the decision model and initiation time model in the SW-PRD model and the SW-PRD model were different, we calculated the respective log-likelihood of the decision and initiation time models to facilitate the comparison of the results. Again, the SW-PRD model fits data better than the G-PRD model, where the SW-PRD model has larger log likelihoods for both the decision and crossing initiation time models, and its BIC is smaller than that of the G-PRD model. In particular, concerning the SW-PRD model, except for the significant effect of ρ_0 (Est. $=$

$-2.92, \text{C.I.} = [-3.16, -2.68]$), ρ_1 and ρ_2 also significantly affect the pedestrian gap acceptance ($\text{Est.} = -1.29, \text{C.I.} = [-1.56, -1.02]; \text{Est.} = -0.50, \text{C.I.} = [-0.84, -0.15]$), consistent with our assumed crossing decision strategies in traffic flow. In addition, although the effect of β_3 in the SW-PRD model is not significant, the positive effect of β_1 reduces the tail magnitude of the distribution of crossing initiation time as $\dot{\theta}$ increases and thus can reduce pedestrians crossing initiation time.

5.4.2 Validation results

The calibration results indicate that the SW-PRD model fits the training sets better than the G-PRD model. In this section, the validation sets of two datasets are compared with the predicted results of two models.

Dataset one. Regarding the validation results, as shown in Table 5.3, the SW-PRD model has better BIC values and K-S scores for all conditions. Specifically, in the 35 mph 5 s condition, the K-S test rejects the null hypothesis and indicates that the results of the G-PRD model are different from the observed data at a 5% significance level. As shown in Fig 5.5a, it can be found that the G-PRD model tends to overestimate the initial parts of the data, but the SW-PRD model does not.

Dataset two. The predicted results are compared to the validation set of the second dataset. The log-likelihood of crossing initiation time models of SW-PRD and G-PRD are presented separately for reasons explained previously (Table 5.4). Both SW-PRD and G-PRD models accurately capture the timing of pedestrian crossing decisions in the traffic flow, i.e., the peak location of the initiation time distribution (Fig 5.5b). The predicted peak shapes of both models are close to the data. However, the SW-PRD model has a relatively better performance than the G-PRD model because the log-likelihood of the crossing initiation time model for SW-PRD is bigger than the value for G-PRD in Table 5.4. The overall predictions of the SW-PRD model are closer to the data than these of the G-PRD model. Specifically, the SW-PRD model has a better BIC value and log-likelihood than the G-PRD model (Table 5.4). Also, the K-S test supports that the predicted density function of the SW-PRD model is similar to the empirical distribution. In contrast, the predicted result of the G-PRD model is rejected by the K-S test at a 5% significance level (Table 5.4). As shown in Fig 5.5b, it can be found that consistent with the empirical data, the SW-PRD model predicts a decrease in the gap acceptance from the first 3 s gap (at t_{pass_2}) to the second 3 s gap (at t_{pass_5}). By contrast, the G-PRD model calculates a constant value for both 3 s gaps, resulting in a significant underestimation of gap acceptance in

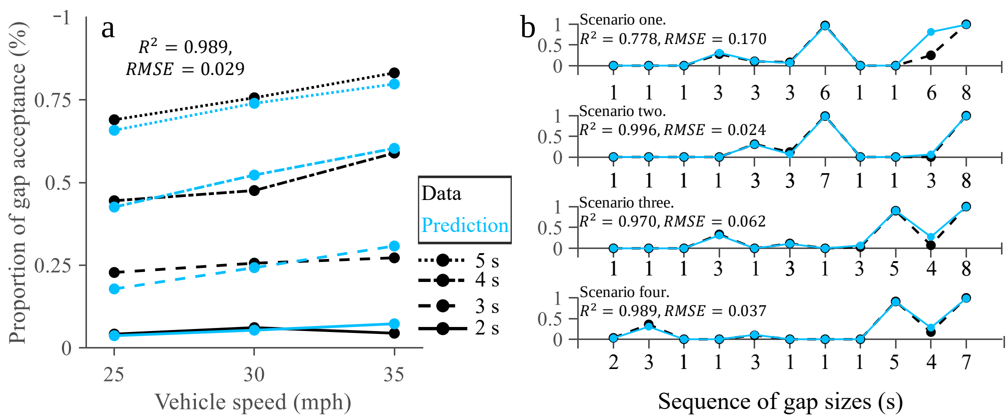

Figure 5.6: Predicted gap acceptance of the SW-PRD model for both datasets. The data and the predicted results are represented in black and blue respectively. (a) For dataset one, the proportion of gap acceptance is plotted as a function of vehicle speed and gap size (Gap sizes are indicated by different line styles). (b) For dataset two, the proportion of gap acceptance for each gap of each traffic scenario is presented.

the first 3 s gap. In general, the SW-PRD model has better performance than the G-PRD model on the validation set of dataset two.

Table 5.4: Validation results of models based on dataset two

Model	LL	LL(CIT model)	BIC	K-S test score	p value
SW-PRD	-578.37	-11.23	1193.10	0.08	0.10
G-PRD	-707.53	-52.76	1444.10	0.16	0.001*

5.4.3 Dataset one: Speed and time gap effects

The SW-PRD model predictions of crossing gap acceptance for each speed and time gap condition are compared with the observed data in Fig 5.6a. According to the empirical data, crossing gap acceptance increased with vehicle speed and traffic gap, aligning well with previous studies (Lobjois and Cavallo, 2007; Schmidt and Farber, 2009). The SW-PRD model reproduces these behavioural patterns very well ($R^2 = 0.890$, $RMSE = 0.050$), suggesting that pedestrians might adapt their crossing decisions based on the changes in collision cues.

Fig 5.7a shows a comparison between the predicted crossing initiation time and observed data. In line with the literature, (Lobjois and Cavallo, 2009), the empirical data showed that pedestrian crossing initiation time correlated with vehicle kinematics, i.e., it decreased as traffic gaps and vehicle speeds decreased. This behavioural pattern can be understood as a distance-dependent phenomenon whereby a reduction in vehicle speed and time gap leads to a reduction in spatial distance, resulting in an increase in the perceived risk of collision (Tian et al., 2022a). Hence, if pedestrians choose to cross, they tend to do so more quickly. Based on our modelling results, the proposed SW-PRD model captures this pattern with a good fit ($R^2 = 0.890$, $RMSE = 0.050$), again indicating that visual collision cues are associated with pedestrian crossing behaviour.

Moreover, a more detailed comparison between predictions and data is shown in Fig C.2 in Appendix C. It can be noticed that the SW-PRD model predicts pedestrian crossing behaviour qualitatively and quantitatively. It not only describes the distributions of pedestrian crossing initiation along the time axis but also captures the variation in the mean crossing initiation time.

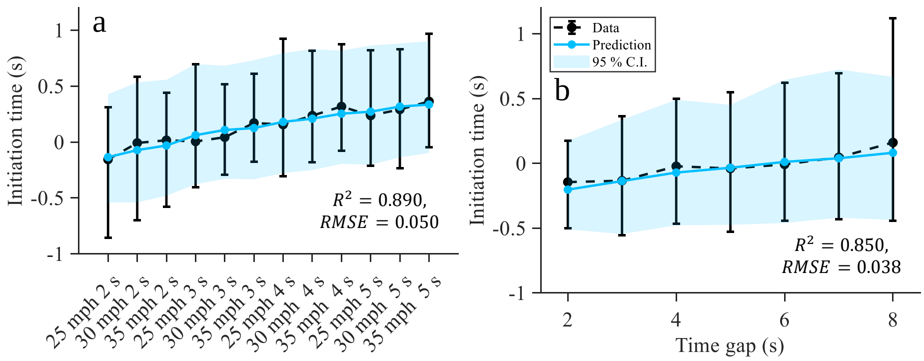

Figure 5.7: Predicted crossing initiation time of the SW-PRD model for both datasets. Error bars and the edge of blue areas indicate the 2.5% and 97.5% percentiles of the data and predicted results. (a) For dataset one, the crossing initiation time is plotted as a function of vehicle speed and gap size. (b) For dataset two, the crossing initiation time is a function of gap size.

5.4.4 Dataset two: Impacts of traffic flow

Predicted gap acceptances of the SW-PRD model in the traffic flow are compared to the observed data in Fig 5.6b. Firstly, it can be noticed that pedestrians in the traffic flow did not accept gaps of the same size equally. For instance, regarding the 4th gap and the 5th gap in traffic scenario one (The size of both traffic gaps is 3 s), the probability of crossing gap acceptance dropped significantly from 27.9% to 10.5%. When pedestrians faced the 6th gap, the decreasing trend became even stronger. The probability of crossing gap acceptance was 8.1%, more than three times smaller than the value of the 4th gap. Further looking at the predictions, the SW-PRD model reproduces this behavioural pattern across all traffic scenarios with reasonable goodness-of-fit (Fig 5.6b)).

Fig 5.7b plots the predicted crossing initiation time as a function of the time gap and compares it with the observed data. The SW-PRD model fits the crossing initiation time data well ($R^2 = 0.850$, $RMSE = 0.038$). Consistent with empirical observations (Kalantarov et al., 2018) and similar to the first dataset , the SW-PRD model predicts a smaller initiation time as the time gap decreases, again suggesting that pedestrians attempted to compensate for crossing risk in unsafe traffic gaps by initiating faster.

Furthermore, as shown in Fig C.3 in Appendix C, detailed model predictions are compared with the observed data. Across all traffic scenarios, the SW-PRD model accurately predicts the level, shape and location of peaks of the crossing initiation time distribution, showing that the model has a good ability to characterise pedestrian crossing decisions in a continuous flow of traffic.

5.5 Discussion and conclusion

This study demonstrates a novel approach to characterise pedestrian crossing decision-making at uncontrolled intersections with continuous traffic. We hypothesised that the crossing behaviour could be understood as depending on three stages of information processing (perceive, decide, execute), and thus proposed a model with three corresponding constituent parts: visual collision cue, crossing decision, and crossing initiation. Following is a summary of the detailed research results.

In our previous study (Tian et al., 2022a), we showed that the visual collision cue, $\dot{\theta}$, could capture the effects of vehicle kinematics on pedestrian crossing decisions in single gaps and explain why pedestrians tended to rely on distance from vehicles to make crossing decisions (Lobjois and Cavallo, 2007; Schmidt and Farber, 2009). In this study, this finding is formally applied to model crossing decisions and extended to a more complicated traffic scenario, i.e., a continuous flow of traffic. The modelling results support that $\dot{\theta}$ is capable of characterizing the risk perceived by pedestrians, at least at uncontrolled intersections with constant speed traffic.

Moreover, regarding our third hypothesis, i.e., pedestrian crossing initiation is time-dynamic and influenced by vehicle kinematics, we relate the proposed crossing initiation time model to $\dot{\theta}$. The modelling results support our hypothesis and show that pedestrians dynamically adjust their initiation time based on vehicle kinematics. Both the SW and Gaussian distributions can reasonably describe pedestrian initiation time, whilst the SW distribution has relatively better goodness-of-fit than the Gaussian distribution, which further indicates that the distribution of crossing initiation time is right-skewed.

Notably, to accurately reproduce pedestrian crossing behaviour in continuous traffic flow, we further hypothesise that pedestrians compare the risks of the gaps around them before making decisions, which is supported by the fact that the proposed crossing decision strategy for continuous traffic scenarios significantly improves the performance of the model. The study thus concludes with the following findings. Firstly, pedestrians may have a reduced tendency to accept a gap if they see an upcoming larger gap. Secondly, pedestrians may have a greater tendency to reject a gap if they have already rejected a gap of that size or larger. Although no other studies have yet found these patterns of crossing behaviour, some empirical observations provide indirect support. Kittelson and Vandehey (1991) showed that drivers who rejected the bigger traffic gap tended to incur a longer delay. Yannis et al. (2013) indicated that pedestrians who tended to reject the crossing opportunities would be more cautious and tend to accept longer gaps. Moreover, Lobjois et al. (2013) found that pedestrians who missed the first opportunity to cross the road would not compensate for their loss by accepting a shorter second opportunity to cross the road. The above studies reinforce our hypothesis that pedestrians who tend to wait for safer crossing opportunities are more cautious and more likely to optimise their crossing strategies by comparing crossing opportunities. Unlike several previous studies, which simply assumed pedestrians tend to accept smaller gaps with the increase in waiting time (Zhao et al., 2019; Rasouli and Kotseruba, 2022), the novelty is that we show that there may be other patterns in pedestrian crossing behaviour in terms of waiting for the crossing opportunity, which may provide an explanation for the non-significant effect of waiting time on pedestrian crossing decisions found in the meta-study (Theofilatos et al., 2021). Furthermore, this finding is interesting in that it reminds us that there may be a complex changing pattern in pedestrians' strategy toward waiting for crossing opportunities. Future research can further attempt to disentangle the effects of waiting time and traffic flow.

Overall, this work provides a new concept that pedestrian crossing decisions are dynamic and intrinsically closely linked to their perceived collision risk, and can be reinterpreted through a three-stage crossing decision-making process. The proposed model shows good predictive performance in different simulator datasets, and it could therefore be interesting to test the model on naturalistic traffic datasets as a next step. Furthermore, the idea of the deconstructed process may drive further study to involve more complicated perceptual, decision, and initiation models.

Regarding the practical implications of this study, there are many possible ways to extend these concepts and models to further improve research in pedestrian-AV interactions. First, as an increasing number of studies have been keen on using pedestrian behaviour models to promote safe and efficient interactions (Camara et al., 2020b), the proposed decision model may provide predictive information to help automated driving systems to better anticipate pedestrian crossing intentions and initiations. Early work is emerging where researchers are attempting to plan and coordinate the actions of AVs and pedestrians toward common goals by considering the visual collision risk of pedestrians (Domeyer et al., 2022). Another possible application case is future traffic scenarios involving AV platoons and pedestrians, where AV platoons may need to take into account the dynamic pedestrian crossing decisions along the length of the platoon and adopt the decision strategy of each AV. Moreover, there is an urgent need to train and evaluate AVs to perform well also in safety-critical interactions with human road users. However, due to the low frequency of critical traffic scenarios in real life, i.e., the corner case, and safety reasons, both academia, and industry have agreed on using simulation methods as a complementary way to validate AVs. Reliable simulation results rely on the behavioural authenticity of simulated road users (Rasouli and Kotseruba, 2022). Hence, another practical significance of this study is that the model can serve as a module in the microscopic transport simulation tools or virtual testing platforms to realise naturalistic pedestrian road crossing decisions.

However, several limitations of this study need to be addressed in the future. Since the results and model cover only scenarios with single-lane, constant-speed traffic, the model cannot be directly generalised to other scenarios without further development. For example, in situations with yielding vehicles, the collision cue model used in this study alone may not provide sufficient information to model crossing decisions. In addition, compared to the crossing behaviour in pedestrian simulators, in real traffic, pedestrians can flexibly adjust their behaviours and be affected by many potential factors. The pedestrian simulator allows exact experimental control of conditions but, therefore, naturally provides a less variable environment, and the virtual nature of the task may also affect the observed behaviour. Hence, an important future work should apply the model to a reliable naturalistic dataset. Furthermore, the model is developed based on current theories of human collision and does not assert that pedestrians exactly use the applied visual cues and perception strategy. As collision perception theory is further developed, the model can be improved accordingly.

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5. DECONSTRUCTING PEDESTRIAN CROSSING DECISIONS IN INTERACTION WITH CONTINUOUS TRAFFIC: AN ANTHROPOMORPHIC MODEL

CHAPTER 6

Pedestrians interact with yielding vehicles using a hybrid perception strategy: a modelling study

Pedestrians interact with yielding vehicles using a hybrid perception strategy: a modelling study

ABSTRACT. Humans rely on multiple visual cues to guide their actions and interact with the environment. A typical case in our daily life is the road-crossing task at an intersection. Understanding the mechanisms behind pedestrian road-crossing decisions is not only critical for traffic development but also helps to increase the safety and social acceptance of automated vehicles. However, most existing approaches to computational pedestrian road-crossing decisions ignore the role of visual cues, cannot account for crossing decisions in vehicle-yielding scenarios, and depict pedestrian behaviour at a coarse-grained level. Here, we propose a road-crossing decision-making model that uses specific visual cues and reproduces pedestrian crossing decisions across a wide range of vehicle-yielding scenarios. Specifically, a proposed hybrid perception strategy explains how pedestrians may apply visual cues to make crossing decisions. Simple discrete choice models based on the hybrid perception strategy combined with a crossing initiation model reproduce the details of crossing decisions: decision and its timing. An empirical dataset collected in a pedestrian simulator was used to validate the model. The results indicate that our model accurately predicts pedestrian road-crossing decisions across a range of vehicle-yielding scenarios. The proposed theory and approach bring insights into the computational pedestrian road-crossing behaviour and have practical implications in traffic modelling and automated vehicle development.

Keywords: Pedestrian road crossing; Hybrid perception strategy; Decision-making model; Visual cues; Vehicle-yielding scenario.

6.1 Introduction

In many situations, such as when catching objects, avoiding collisions, or simply moving through the environment, humans are required to decide how to interact safely and accurately with the environment. A concrete example of this in daily life is the road-crossing task at an intersection, where pedestrians must reach the opposite sidewalk while avoiding potential collisions with approaching vehicles. Understanding this road crossing decision-making process has critical implications for traffic safety, transportation management, and infrastructure development. As such, this has given rise to extensive modelling research of road-crossing behaviour across multiple disciplines, including perception, control theory, decision-making, human-machine interaction, and more (DeLucia, 2015; Hoogendoorn and Bovy, 2004; Markkula et al., 2020; Pekkanen et al., 2021; Tump et al., 2020). In recent years, with the development of automated vehicles (AVs) and the great expectations for highly autonomous vehicles (HAVs), more research has been drawn to this area (Camara et al., 2020; Rasouli and Tsotsos, 2019). The emerging concern is that extending the deployment of AVs from several confined areas, which have a much lower risk for pedestrians, to a range of operational design domains could inevitably increase the conflicts with pedestrians (Gräter et al., 2021). The failure of AVs to comprehend pedestrian behaviour and interact with them appropriately may not improve traffic efficiency and safety as expected but rather increase traffic dilemmas and additional issues (Jennings and Figliozzi, 2019; Markkula et al., 2020; Millard-Ball, 2018). Consequently, the lack of computational models of pedestrian behaviour could limit the deployment of AVs and hinder the development of HAVs.

Existing computational models for pedestrian behaviour, particularly for pedestrian road-crossing decisions (PRDs), have been developed based on a wide range of theories and hypotheses, such as cognitive models (Pekkanen et al., 2021; Markkula et al., 2020), data-driven approaches (Volz et al., 2018; Zhang et al., 2020b), choice models (Brewer et al., 2006; Pawar et al., 2016), game theoretical models (Camara et al., 2018), as well as socials force models (Farina et al., 2017; Moussaïd et al., 2011). Generally, existing approaches for PRD modelling share two limitations. Specifically, these approaches are rarely based on specific behavioural or psychological theories and do not describe perceived information from the pedestrian perspective. Instead, external physical factors which may not be directly available to the human pedestrian, like time to collision (TTC), vehicle distance from pedestrians (Rasouli and Kotseruba, 2022; Volz et al., 2015; Zhao et al., 2019; Zhu et al., 2021). Moreover, many models determine PRDs using critical thresholds and do not account for temporal information of PRDs (i.e., the delay between decision and action, known as crossing initiation time, response time or onset time). Hence, pedestrian behaviour in those models is established at a relatively coarse-grained level and ignores the details of decision (Fu et al., 2018; Lu et al., 2016; Rasouli and Kotseruba, 2022; Zhu et al., 2021). Consequently, the approaches mentioned above may not well characterise PRDs in some traffic scenarios where pedestrians may use multiple perceptual cues and have complicated initiation patterns.

To understand PRDs, we need to investigate the involved perceptual cues and identify their underlying behavioural mechanisms. When moving through the environment, people rely on their visual perception of the space around them. The PRD task is a typical scenario that puts high demands on human visual system. Vision cues have been demonstrated as the main source of information used by humans/pedestrians to interact with the traffic (DeLucia, 2015). Specifically, 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 appearance continues to expand and reaches a certain perceptual threshold, it suggests that observer can notice that the vehicle is approaching (Hoffmann and Mortimer, 1994). Chapter 2 has shown that this perceptual pattern, i.e., visual looming, is closely related to PRDs at uncontrolled intersections (Tian et al., 2020, 2022). Furthermore, prior studies have suggested that pedestrians could depend on different cues as the view distance changes (DeLucia, 2008, 2015). Based on this assumption, it is implied that since some visual cues become less reliable as viewing distance increases, pedestrians have to rely on alternative visual cues in those situations.

To the best of the authors' knowledge, very few computational approaches of PRD account for the limitations mentioned above, except for a recently emerged class of models, namely the evidence accumulation model based on visual cues (Giles et al., 2019; Markkula et al., 2020; Pekkanen et al., 2021). Those models have assumed that PRDs result from an accumulation process of visual cues and noisy evidence, and decisions are finalised after the accumulated evidence reaches a certain threshold. The resulting response time distribution details the crossing decisions and their corresponding timing. Although those models provide a powerful explanation tool for PRDs guided by visual cues, the paradigm for standard evidence accumulation theory, upon which these models are based, is developed for relatively simple experimental tasks with single-stimulus, such as judging the direction of moving dots which are interspersed with other randomly moving dots (Ball and Sekuler, 1982), comparing the random presented numbers to a given number (Schwarz, 2001). Due to this nature, evidence accumulation models may not currently be able to describe the decision processe perfectly without elaborate design. Moreover, due to the great complexity of those models, they are computationally demanding (Schwarz, 2001).

To address these shortcomings mentioned above, we developed a hybrid perception strategy of collision avoidance decision-making by focusing on pedestrian road-crossing decision-making, i.e., the HP-PRD model. As a basis, the proposed hybrid perception strategy drew on an established framework of visual space perception, in which humans in collision courses adopt different visual cues to evaluate risks during the vehicle approach (see Chapter 3). We extended this framework by showing how pedestrians selectively use visual cues to finalise their crossing decisions in complicated vehicle-yielding scenarios. Our approach captures well the rather subtle patterns seen in the empirical data, in terms of both crossing decisions and crossing initiation times. An empirical dataset collected in a highly immersive CAVE-based simulated environment was applied to test the model (For details on the dataset, please see Lee et al. (2022)). These results showed that the modelling decisions aligned with the observations well, suggesting that pedestrians can self-adjust the usage of different visual cues provided by approaching vehicles to successfully interact with complicated traffic scenarios.

6.2 Methodology: pedestrian road-crossing decision-making based on hybrid perception strategy

PRDs may involve several cognitive stages, such as perception, comprehension and decision making, and response execution (Palmeiro et al., 2018). Hence, developing a computational model of PRDs necessitates addressing two crucial questions. The first question is, what kind of perceptual information do pedestrians use? Prior studies have indicated that the perceived visual cues from the approaching vehicle play a dominant role in PRDs (Ackermann et al., 2019; Dey and Terken, 2017; Lee et al., 2022). Hence, a physical representation of the two visual cues that pedestrians may perceive is first established. However, knowing these visual cues is not enough to reproduce PRDs. How pedestrians apply these visual cues to make crossing decisions is necessary. A hybrid perception strategy based on these perceptual cues is proposed, determining when and how pedestrians use what cues. Finally, we show that simple discrete choice and initiation models based on the hybrid perception strategy are enough to characterise PRDs in vehicle-yielding scenarios.

6.2.1 Representation of visual information

Change rate of visual angle. When an object approaches an observer, its enlarged image on the observer's retina allows the observer to perceive it as an approaching object (Gibson, 2014). The expansion rate of the image is correlated to the sensation of collision threat (Gibson, 2014; Wagner, 1982), generally quantified as the change rate of the visual angle subtended by the approaching object at the observer's pupil (Lee, 1976). Suppose a road-crossing scenario, as shown in Fig 6.1a, a vehicle approaching a pedestrian at a speed v. The visual angle subtended by the car is specified by θ. Its first temporal derivative is given by:

$$\theta = 2\tan^{-1}(\frac{w}{2Z}) \Rightarrow \dot{\theta} = \frac{wv}{(Z)^2 + w^2/4} \tag{6.1}$$

where $\dot{\theta}$ refers to the change rate of visual angle. Z, w denote vehicle distance from the pedestrian and its width. According to the above equation, $\dot{\theta}$ is positively correlated with vehicle

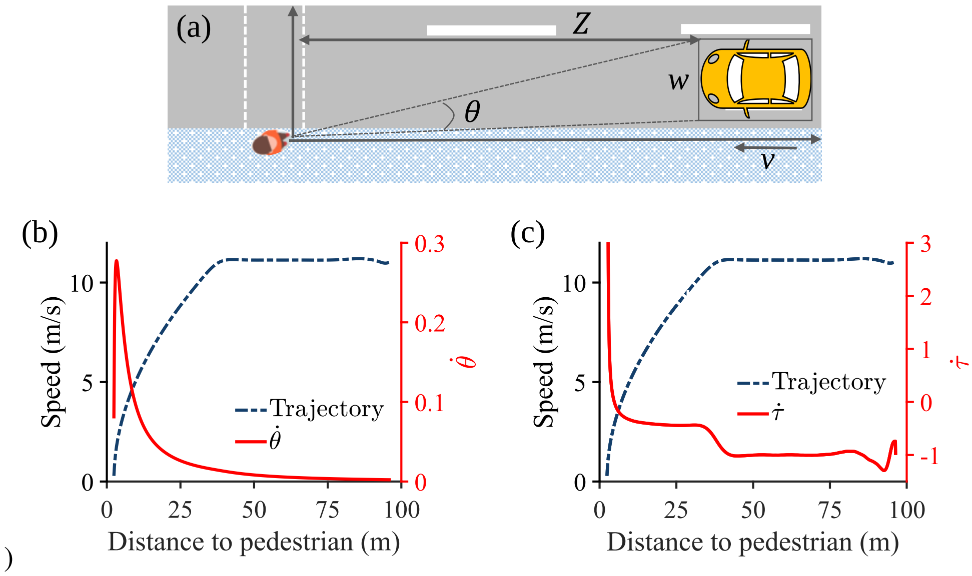

Figure 6.1: (a) Visual cues in road-crossing scenarios. (b) and (c) show curves of $\dot{\theta}$ and $\dot{\tau}$ in a specific scenario, where the vehicle drives at 25 mph (11.18 m/s), brakes at 38.5 m from the pedestrian with a constant rate of deceleration, -1.73 $\mathrm{m/s^2}$, and stops 2.5 m from the pedestrian. The corresponding $\dot{\theta}$ and $\dot{\tau}$ values are show in (b) and (c). For detailed information on traffic scenarios considered in this study, please refer to Section 6.3

speed and negatively correlated with vehicle distance, suggesting pedestrians perceive higher collision risk as vehicle speed increases (with a constant distance) or distance decreases (with a constant speed). Moreover, since the vehicle distance from the pedestrian equals the product of the time gap and vehicle speed, replacing the distance with the time gap and the speed reveals that the time gap and the speed have a negative impact on $\dot{\theta}$, suggesting pedestrians could perceive lower collision risk as vehicle speed decreases (with a constant time gap) or time gap decreases (with a constant speed). These deductions based on Eq 6.1 are discussed in detail in Chapter 2.

Change rate of τ. To avoid potential collision events, humans require both the spatial and temporal properties of objects. However, $\dot{\theta}$ does not provide veridical information on TTC of an approaching car (DeLucia, 2008). For instance, as shown in Fig 6.1b, it can be found that although the car slows down significantly for a while, $\dot{\theta}$ still increases and then dramatically decreases just a short while before the car comes to a full stop. Hence, $\dot{\theta}$ does not seem to be very informative and reliable cue for identifying deceleration. However, empirical observations (Ackermann et al., 2019; Dey et al., 2021) and the study in Chapter 3 both suggest that humans can recognise yielding behaviour in cars. In addition to $\dot{\theta}$, it would seem like pedestrians could benefit from using some visual cues that correspond to the TTC of the approaching vehicle.

Prior studies have demonstrated that there is one visual cue that specifies the TTC, i.e., τ, the ratio of visual angle to the change rate of visual angle (Hancock and Manster, 1997; Lee, 1976). Its first temporal derivative is given by:

$$\tau = \frac{\theta}{\dot{\theta}} \Rightarrow \dot{\tau} = \frac{ZD}{v^2} - 1 \tag{6.2}$$

where D is the deceleration rate of the vehicle. $\dot{\tau}$ has been found to be relevant for detecting whether a collision will occur (Lee, 1976). Suppose that at the t time point, a vehicle begins to brake with a constant D. According to a simple kinematics relationship, D is adequate to stop a vehicle safely in front of the pedestrian only if the following equation satisfies:

$$\frac{v^2}{2D} \leq Z \tag{6.3}$$

which means the distance the vehicle will take to stop should be less than, or equal, its current distance from the pedestrian. Afterwards, combing Eq 6.2 and 6.2, then we can get:

$$\dot{\tau} \geq -0.5 \tag{6.4}$$

Therefore, it has been mathematically proven that a value of $\dot{\tau} \geq -0.5$ represents that the current deceleration is adequate, and the collision events can be avoided. Further, look at Fig 6.1c, $\dot{\tau}$ equals to -1 when the vehicle maintains constant speed. As the car slows down with a constant deceleration rate and stops in front of the pedestrian, $\dot{\tau}$ dramatically rapidly exceeds -0.5 and then increases approximately exponentially. Therefore, $\dot{\tau}$ could be a visual cue characterise the yielding behaviour of the vehicle and judge if the collision events can be avoided.

6.2.2 Hybrid perception strategy

Suppose that a vehicle first travels at a constant speed or the vehicle brakes very lightly, and then slows down significantly at a distance from the pedestrian. Initially, the car maintains a constant speed, which means there may not be enough visual cues for vehicle deceleration behaviour detection, i.e., $\dot{\tau} \leq -0.5$. In this situation, pedestrians may rely on 'heuristic' visual cues, e.g., $\dot{\theta}$, that are easy to acquire and process (DeLucia, 2004). Consider another situation where a vehicle approaches pedestrians. However, the distance between pedestrians and vehicles is too great for pedestrians to tell if the vehicle is giving way to them. Hence, pedestrians in this situation may still tend to use 'heuristic' visual cues to judge if the collision

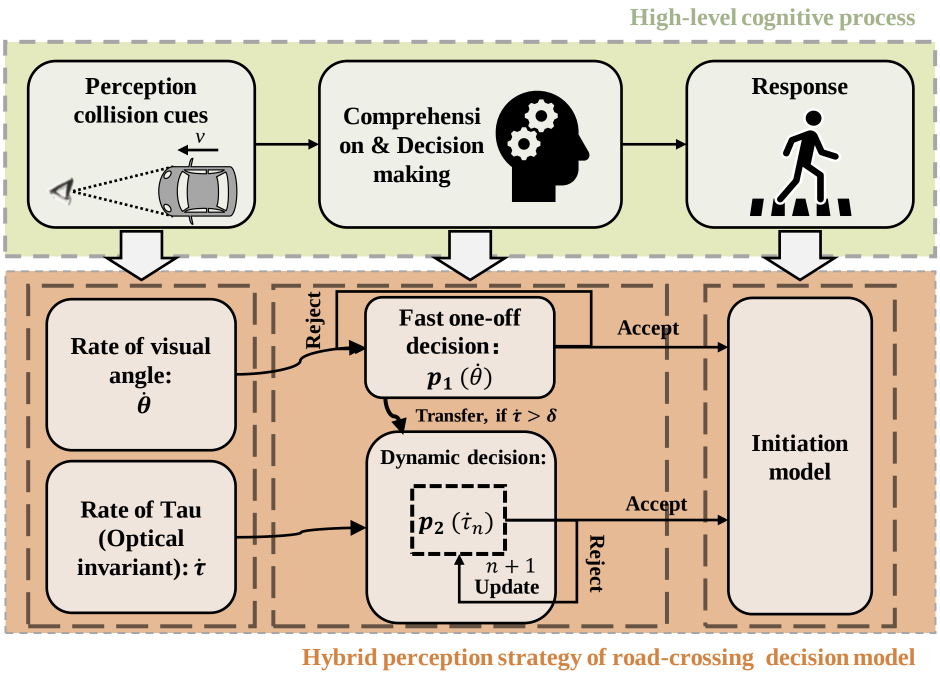

Figure 6.2: Framework of the pedestrian road-crossing decision-making model based on a hybrid perception strategy.

is imminent, rather than estimating the actual behaviour of the vehicle. The implication for above discussion is that when pedestrians observe the vehicle from a distance, the vehicle drives at a constant speed, or the vehicle brakes very lightly, visual cues provide too little information about vehicle behaviour. In these situations, pedestrians may rely on 'heuristic' visual cues to quickly judge collision risk, rather than the specific driving behavior of the vehicle. In contrast, when the vehicle drives close to pedestrians with obvious yielding behaviour, i.e., $\dot{\tau} \geq -0.5$, pedestrians then tend to rely on visual invariants, e.g., $\dot{\tau}$, to judge if the vehicle can slow down or stop in front of them. The optical invariants provide veridical and reliable information of the approaching vehicle at the time (DeLucia, 2004).

Moreover, in previous observations (Lee et al., 2022; Giles et al., 2019), it has been found that many pedestrians quickly finalised their crossing decisions based on the collision risk before they knew the yielding behaviour of the approaching vehicle. The study in Chapter 3 indicated that pedestrian crossing decisions and judgements of vehicle behaviour at the early stage of vehicle yielding scenarios are similar to the judgements and crossings in constant speed scenarios. These findings suggest that pedestrians may prioritise 'heuristic' visual cues for crossing decision-making.

The above discussion posits that pedestrians can flexibly use the perceived information based on a hybrid perception strategy. Specifically, first of all, pedestrians prioritise $\dot{\theta}$ for crossing decision-making. When pedestrians observe the vehicle from a distance, the vehicle drives at a constant speed, or the vehicle brakes very lightly, pedestrians still rely on $\dot{\theta}$. Only when $\dot{\tau} \geq \delta$, pedestrians instead use $\dot{\tau}$ as the main cue to their crossing decision. δ is a threshold indicating that pedestrians detect the yielding behaviour of the vehicle.

6.2.3 Formulations of the decision

Two concise road-crossing decision models are developed based on the proposed hybrid perception strategy:

Fast one-off decision. In light of the hybrid perception strategy, pedestrians prioritise $\dot{\theta}$ to evaluate the collision risk from the approaching vehicle. If there are no further cues that the approaching vehicle has slowed down, it would be irrational to make another decision to cross the road again after a previous rejection because $\dot{\theta}$ continues to increase, representing a continued increase in the risk of collision. Hence, the rational behaviour of pedestrians is either waiting for another crossing opportunity (let the vehicle pass first) or waiting for the vehicle to give way to them. Therefore, in this traffic situation, pedestrians should make their decision relatively quickly. Otherwise, they have to wait for the next opportunity or the yielding behaviour of the vehicle (Fig 6.2). According to the above assumption, the fast one-off decision based on $\dot{\theta}$ is given by:

$$p_1(\dot{\theta}) = \frac{1}{1 + \exp\left(-\beta_1 \ln\left(\dot{\theta}\right) - \beta_0\right)} \tag{6.5}$$

where $p_1(\dot{\theta})$ denotes pedestrian road-crossing probability for the approaching vehicle with a $\dot{\theta}$ value, which $\dot{\theta}$ only refers to the change rate of visual angle at the time point when a traffic gap is available, or pedestrians first observe the approaching vehicle. In is the natural logarithmic transformation. β_0 and β_1 are the model parameters needed to be estimated based on the data. The decision model is introduced in detailed in Chapter 2 (Tian et al., 2022).

Dynamic decision. However, when the fast one-off crossing decision is rejected by pedestrians and the deceleration behaviour of the vehicle is obvious, i.e., $\dot{\tau} \geq \delta$, pedestrians then turn to finalise their decision based on the yielding behaviour of the approaching vehicle. It is, therefore, assumed that pedestrians dynamically evaluate the crossing opportunity based on $\dot{\tau}$ until they finally make a decision to cross the road (Fig 6.2). Accordingly, the decision model based on $\dot{\tau}$ is dynamic, i.e., re-running after each rejection, given by:

$$\begin{aligned} P_n &= p_2\left(\dot{\tau}_n \mid \text{rejected before } n\right) \cdot \left(1 - P_{n-1}\right), P_0 = p_1(\dot{\theta}) \\ p_2\left(\dot{\tau}_n \mid \text{rejected before } n\right) &= \beta_3\dot{\tau}_n + \beta_2, p_2 \in [0,1] \end{aligned} \tag{6.6}$$

where P_n is the recursive crossing probability for the nth round of decisions, equals to the $n-1$th round of recursive rejection probability, $1 - P_{n-1}$, times the pedestrian road-crossing probability in nth round after rejecting all $n-1$th rounds of decisions, $p2$. P_0 equals $p_1(\dot{\theta})$ if the fast one-off decision has been performed previously. $p2$ is calculated using a linear equation, restricted to a range between 0 and 1. β_2 and β_3 are the model parameters needed to be estimated based on the data. Moreover, the dynamic decision can be further divided into two categories: dynamic decision (decelerating) and dynamic decision (stopped). The first kind of decision is mentioned above, where pedestrians continually update their choices based on $\dot{\tau}$. While the second decision category refers to the PRDs made after the vehicle has stopped. Theoretically, $\dot{\tau}$ is undefined when the car has stopped. Pedestrians thus do not make their decision based on the $\dot{\tau}$, and their crossing probability is 100%.

Initiation model. As shown in Fig 6.2, the third part of the HP-PRD model is the initiation model, accounting for the temporal information of crossing decisions. In this study, initiation time refers to the time duration between when the rear end of the previous car passes the pedestrian position and when pedestrians start crossing. We have previously demonstrated that the distribution of pedestrian initiation time could be represented using the Shifted-Wald model, also known as the Inverse Gaussian model (see Chapter 5, Section 5.2.4), given by:

$$\begin{gathered} x \sim W(a, \alpha, \gamma) \\ \Rightarrow x = \frac{a}{\sqrt{2\pi(x-\gamma)^3}} \exp\left(\frac{-[a - \alpha(x-\gamma)]^2}{2(x-\gamma)}\right) \end{gathered} \tag{6.7}$$

where the Shifted-Wald model is controlled by three parameters, namely a, α, and γ. a affects the deviation of the distribution around the mode. α influences the magnitude of the tail. γ represents the shift of the distribution (Anders et al., 2016). We further assume that different Wald models are responsible for the crossing initiation times of different crossing decisions (i.e., fast one-off decision, dynamic decision (decelerating), and dynamic decision (stopped)). Hence, combing Eq 6.5, 6.6, and 6.7, the density function of pedestrian crossing initiation time of the HP-PRD model is then proposed as follows:

$$f(t \mid \dot{\theta}, \dot{\tau}) = p_1(\dot{\theta}) \cdot W_1 + \sum_{n=1}^{N} (P_n \cdot W_{2;n}) + P_{n+1} \cdot W_3 \tag{6.8}$$

Wald models with three different sets of parameters are proposed to account for pedestrian initiation behaviour of different crossing decisions. Specifically, when pedestrians cross the road using the fast one-off decision, their initiation is represented by $W_1\left(a_1, \alpha(\dot{\theta}), \gamma(\dot{\theta})\right)$, where $\alpha(\dot{\theta}) = \rho_1 \ln\left(\dot{\theta}\right) + \rho_0$ and $\gamma(\dot{\theta}) = \rho_3 \ln\left(\dot{\theta}\right) + \rho_2$, which means pedestrians' initiation is affected by the visual cue. Our previous study has shown that pedestrian initiation pattern in constant speed scenario is correlated to $\dot{\theta}$ (Chapter 5, Section 5.2.4). When pedestrians use the dynamic decision and cross the road before the vehicle comes to a complete stop, their initiation time model is assumed to be $W_2\,(a_2, \alpha_2, \gamma)$. If they cross the road after the vehicle has fully stopped, they would use another initiation time model $W_3\,(a_3, \alpha_3, \gamma)$. The parameters in these two models are not dependent on the visual cue. The idea behind this manipulation is that if the vehicle is still moving close to pedestrians and has not come to a complete stop, the threat of collision is always present so that pedestrians would cross the road decisively. However, if the vehicle has stopped, pedestrians are free to cross because the collision threat is no longer there. Hence, for these two categories of crossing decisions, their initiation patterns are thus assumed to be characterised using two different Shifted-Wald models.

6.3 Material and methods

6.3.1 Empirical data

The empirical data used in this study was originally collected and applied to compare the impacts of different external human-machine interfaces on pedestrian road-crossing behaviour by (Lee et al., 2022) (Ethics approval number: LTTRAN-107). For detailed information on the experiment, please refer to that study. Here, a summary of the parts of the data we used is provided. The dataset was collected using a CAVE-based pedestrian simulator at the University of Leeds. Sixty participants (36 male and 24 female, aged 19 to 36) were recruited via the driving simulator database.

Apparatus and experiment design. The cave-based pedestrian simulator includes three wall projections and a floor projection. Eight 4K projectors project the images at 120 Hz. The walking environment in the simulator is 9 meters long and 4 meters wide, providing participants

Figure 6.3: Diagrams of experiment scenario. (a) Schematic top view of the road-crossing scenario. (b) A photo shows the traffic scenario in the HIKER simulator from a participant's perspective, where the first car is about to pass the participant and the second car comes into view (Lee et al., 2022)

with ample walking space. Ten cameras track the tracking glasses on the participant's head to adjust the images to fit the participant's perspective. Regarding the design of the experiment, A residential block scenario with a 3.5m wide one-lane road and an uncontrolled intersection was generated in the simulator using Unity (Fig 6.3). A row of trees was included on one side of the road to indicate the starting position for the pedestrian. For the traffic scenario, there were two vehicles, 1.95 m wide and 4.95 m long, driving in the centre of the road. The first car started 96 m away from the pedestrian, and the second car kept one of the four time gap sizes behind the first car, i.e., 2, 3, 4 or 5 s. In the beginning, both vehicles drove at one of the three constant speeds, i.e., 25, 30 or 35 mph. The first car always maintained the constant speed. However, the second car started decelerating at a constant rate when it arrived at 38.5 m from the participant and came to a stop at a distance of 2.5 metres from the participant (Fig 6.3a). Accordingly, the deceleration rates for 25, 30 and 35 mph were 1.73, 2.50 and 3.40 m/s^2, respectively.

Procedures. Initially, participants stood on the side of the road and held a button to trigger the scenario. Two vehicles then appeared on the road, and a crossing opportunity was available when the rear end of the first vehicle passed the participant (Fig 6.3a). Participants were asked to cross the road between two vehicles when they felt comfortable and safe to do so, meaning they could cross the road as soon as the first vehicle passed them or when the second vehicle slowed down or stopped. After they arrived at the opposite pavement, one trial was then completed. Three initial speed and four initial time gap conditions formed twelve traffic scenarios. All scenarios were presented in three different blocks so that each participant experienced 36 trials in a random order, resulting in a total of 2160 trials being recorded. It is important to note that the entire experiment also included additional experimental scenarios. However, the present data was only collected from the above-mentioned scenarios, where the approaching vehicle decelerated without external human-machine interfaces.

6.3.2 Data processing

Before fitting the model to the data and analysing the results, the data needed to be properly reduced and processed to meet our requirements. The crossing decisions fell into three categories: fast one-off decision, dynamic decision (decelerating), and dynamic decision (stopped). Fig 6.4 shows an example of data partitioning where data are grouped in terms of $\dot{\tau}$ value and the speed of the approaching vehicle. Specifically, those pedestrians who crossed the road when $\dot{\tau}$ was smaller than δ, were grouped into the fast one-off decision. Those who crossed the road when $\dot{\tau}$ was bigger than δ and before the car fully stopped were grouped into the dynamic decision (decelerating). The others who crossed the road after the car had come to a complete stop were sorted into the dynamic decision (stopped) group. According to Eq 6.6, we assume that in the dynamic decision process, pedestrians could recurrently evaluate the crossing opportunity until they feel comfortable crossing the road. Therefore, the data in the dynamic decision (decelerating) group were further sorted into a few subgroups to represent the above process. The division method is that the $\dot{\tau}$ curve of the approaching vehicle (ranging from δ to 20) was divided into 43 intervals. The length of intervals increased in increments according to the formula, $2\mathrm{e} - 8 \times i^5 + 0.003$. i denotes the number of the interval between 1 and 42. Finally, the data corresponding to the same $\dot{\tau}$ interval were classified as one subgroup.

Two main metrics were recognised for each group or subgroup of data: crossing initiation time and binary crossing decision. The crossing initiation time refers to the time point when pedestrians start their crossing decisions. The zero value of crossing initiation time was set to the time point when the first vehicle passed the pedestrian (Fig 6.4). Moreover, we used the following criteria to identify the onset of pedestrian crossing: (a) The longitudinal position of the participant should exceed the edge of the pavement. (b) The change in longitudinal position should be greater than 0.003 m over a simulated time step of 120 Hz. (c) To rule out incomplete crossings, where pedestrians start to cross the street but then realise that they cannot

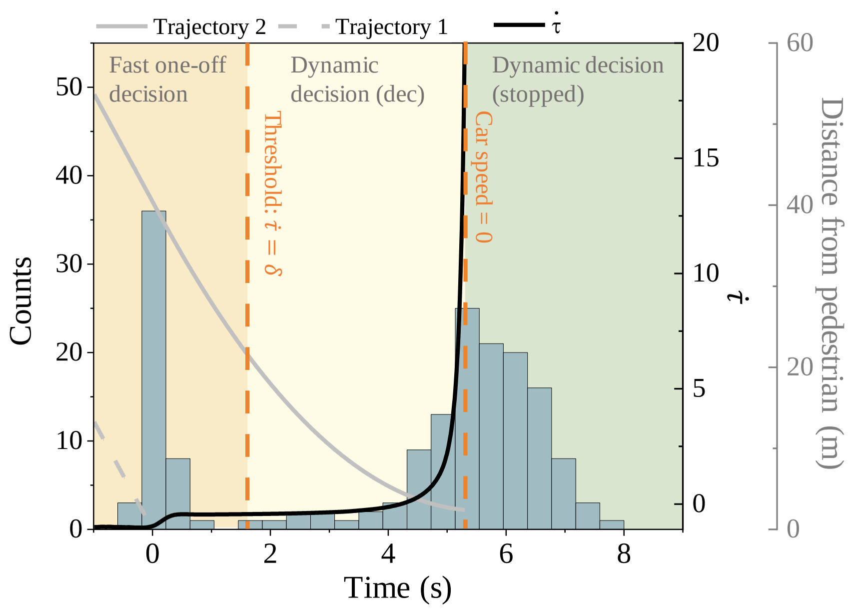

Figure 6.4: Example for data partitioning. The histogram figure of crossing initiation time is overlapped with the corresponding $\dot{\tau}$ curve (black solid) and distance curve of approaching vehicles (grey, dashed curve for the 1st car and solid curve for the 2nd car). Data is grouped into three parts, i.e., fast one-off decision, dynamic decision (decelerating), and dynamic decision (stopped), based on the criteria: $\dot{\tau} = \delta$ and the speed of the 2nd car is equal to $0\ m/s$. Moreover, the data in the dynamic decision (decelerating) are further divided into several subgroups based on consecutive $\dot{\tau}$ intervals.

and return to the pavement, participants must step out one metre from the edge of the pavement one second after the first two conditions had been met. The binary crossing decision represents whether pedestrians cross the road in a certain group or subgroup.

6.3.3 Model fitting

The decision models and initiation models fit different types of data. The fast one-off decision model, Eq 6.5, was fit to binary crossing decision data. The dynamic decision (decelerating) model, Eq 6.6, was fit to the road crossing probability. Regarding the initiation model, as crossing initiation time data of each group or subgroup has different scales, these data needed to be normalised to one scale first. The crossing initiation time data in the fast one-off decision group were normalised based on the time point where the rear end of the first vehicle passed the pedestrian. For dynamic decision (decelerating) and dynamic decision (stopped) groups, crossing initiation time data were normalised to one scale using time points corresponding to the low bounds of the relevant $\dot{\theta}$ intervals. Afterwards, three Wald models, i.e., W_1, W_2, and

Table 6.1: Estimated parameters of the model

β_0	β_1	β_2	β_3	ρ_0	ρ_2	ρ_3	ρ_4	a_1	a_2	α_2	a_3	α_3	δ
-10.344	-2.246	0.007	0.01	-0.238	2.477	-0.288	0.882	3.635	0.286	1.156	2.392	2.228	-0.44

W_3, were fit to normalised initiation time data of three groups, respectively.

Regarding parameter estimation, the optimal parameter set was found by maximising the likelihood of the model using the Maximum Likelihood Estimation (MLE) method. As the maximisation problem is equivalent to minimising the negative log-likelihood function. The log-likelihood functions of the decision models and Wald models can then be established according to Eq 6.5, 6.6, and 6.7. To solve the minimise problems, a 'fminuc' in MATLAB was applied (MATLAB, 2021). The estimated parameters are shown in Table 6.1. For detailed likelihood functions, please refer to Section 5.3.2 in Chapter 5.

Furthermore, although the deceleration perception threshold, δ, is suggested to be -0.5 (Lee, 1976), the model performance can be further improved by selecting the most appropriate threshold. Therefore, an exhaustive grid search method over δ was carried out by finding the minimum Root Mean Square Error ($RMSE$) of predicted road-crossing probability, given by:

$$RSME = \sqrt{\frac{1}{n}\sum (p_o - p_{pre})^2} \tag{6.9}$$

where p_0 and p_{pre} are the observed and predicted road-crossing probability of all groups. n is the number of all divided groups and subgroups. The δ range from -0.5 to -0.3 was uniformly divided into 20 grid values. The smallest RSME, i.e., 0.14, was found when δ equals -0.44.

6.4 Results

6.4.1 Empirical results

As pedestrian road-crossing decisions are categorised into three groups, i.e., fast one-off decision, dynamic decision (decelerating) and dynamic decision (stopped), a multinomial logistics regression model was applied to the crossing decision with initial speed and TTC as independents. In line with prior studies (Dey et al., 2019), pedestrian crossing decision in front of a yielding vehicle has a bimodal pattern (Fig 6.4, 6.5); that is, some pedestrians finalised their crossing decisions immediately when the traffic gap is available, while the rest crossed until the vehicle obviously slowed down or fully stopped. As shown in Fig 5, this pattern is affected by initial vehicle speed and TTC. More pedestrians made fast one-off decisions as initial TTC

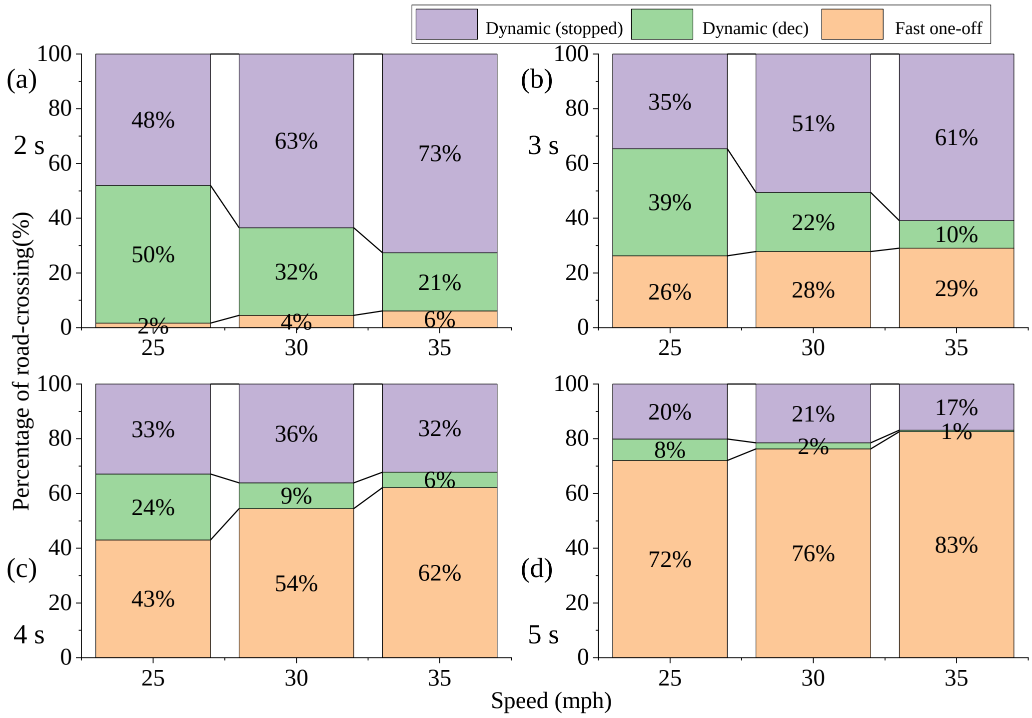

Figure 6.5: Observed proportion of pedestrian road crossing decisions in three groups. In each panel, the proportion of crossing decisions made by pedestrians in the fast one-off decision (orange), the dynamic decision (decelerating) (green), and the dynamic decision (stopped) (purple) groups are shown for three initial speed conditions, i.e., 25, 30, and 35 mph. Four panels depict pedestrian crossing decisions under different initial TTC conditions, i.e., 2, 3, 4, and 5 s.

($Odds = 4.693, p < 0.001$) and initial vehicle speed ($Odds = 1.478, p < 0.001$) increased. In the dynamic decision (decelerating) group, initial vehicle speed and initial TTC have significant negative effects on pedestrian crossing decision ($Odds = 0.712, p < 0.001; Odds = 0.704, p < 0.001$). Moreover, with an increase in TTC, fewer participants made dynamic decisions (stopped) ($Odds = 3.340, p < 0.001$). Overall, the empirical data indicates that the kinematics of the approaching vehicle has different impacts on pedestrians crossing probability in three groups, which may suggest that pedestrians rely on different cues to make their road-crossing decisions in vehicle-yiedling scenarios.

To investigate the potential correlation between pedestrian crossing decisions and visual cues, a binary logit regression model was applied to pedestrian crossing decisions in the fast one-off decision group with $\dot{\theta}$ as the independent variable. A significant negative correlation ($B = -2.246, tStat = -21.945, p < 0.001$) is found between the proportion of the road-crossing and $\dot{\theta}$, suggesting that the bigger the $\dot{\theta}$ is the fewer pedestrians make fast one-off

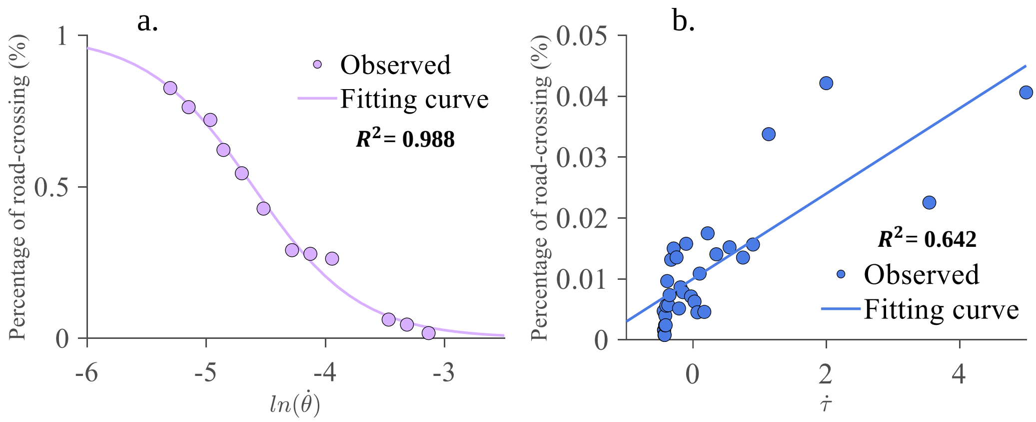

Figure 6.6: Proportion of the road-crossing decision versus visual cues. (a) The proportion of the crossing decision in the fast one-off decision group is plotted as a function of $\ln(\dot{\theta})$ (b) The proportion of the crossing decision in the dynamic decision (decelerating) group is plotted as a function of $\dot{\tau}$.

decisions (Fig 6.6a). Furthermore, a linear regression model was applied to the proportion of the crossing decision in the dynamic decision (decelerating) group with $\dot{\tau}$ as the independent variable. As shown in Fig 6.6b, there is a significant positive main effect of $\dot{\tau}$ on the proportion of road-crossing ($B = 0.01, tStat = 8.420, p < 0.001$), showing that, in dynamic decision (decelerating) group, more pedestrians crossed the road as $\dot{\tau}$ increased. Hence, the empirical results support our assumption (i.e., hybrid perception strategy) that during the vehicle approaching process, pedestrians may use $\dot{\theta}$ to quickly evaluate the traffic gap and use $\dot{\tau}$ to judge the yielding behaviour of the vehicle.

6.4.2 Modelling results

Crossing decision. As shown in Fig 6.7, the HP-PRD model quantitatively predicted the proportion of pedestrians crossing across all traffic scenarios, indicating that the HP-PRD model reasonably captures the proportion of crossing decisions in different groups. Moreover, the model details the impacts of initial vehicle speed and initial TTC on pedestrian crossing decisions. With the increase in initial TTC and speed, more pedestrians make the fast one-off crossing decisions. Moreover, pedestrians are more likely to cross the road before the vehicle fully stops (i.e., the dynamic decision (decelerating)) when the initial TTC and speed are small. Otherwise, they would prefer to cross the road immediately as the crossing opportunity is available or cross after the car has stopped. Accordingly, the predicted results show that the visual cues, i.e., $\dot{\theta}$ nd $\dot{\tau}$, have good ability to characterise pedestrian crossing decisions in the yielding scenario.

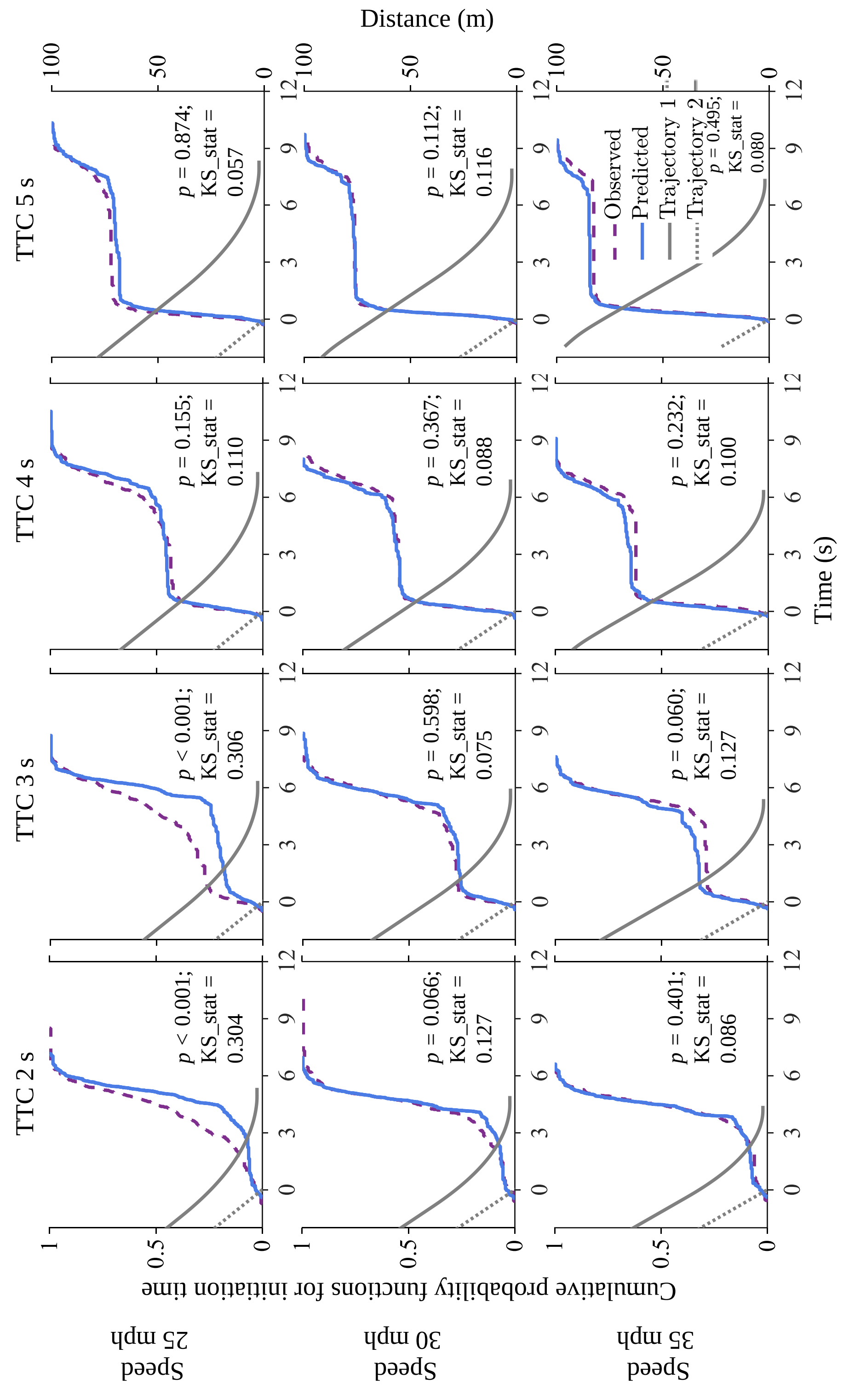

Figure 6.7: Comparison of empirical results and predictions of HP-PRD model. Twelve panels present cumulative probability functions for pedestrian initiation time in twelve traffic conditions. In each panel, empirical results and predictions are separately represented as purple dashed and blue solid curves. The distance of the first and second vehicles from the pedestrian at the corresponding time points is denoted by grey dotted and solid curves. The Kolmogorov-Smirnov test results, i.e., p-value and statistics, are presented in the figure.

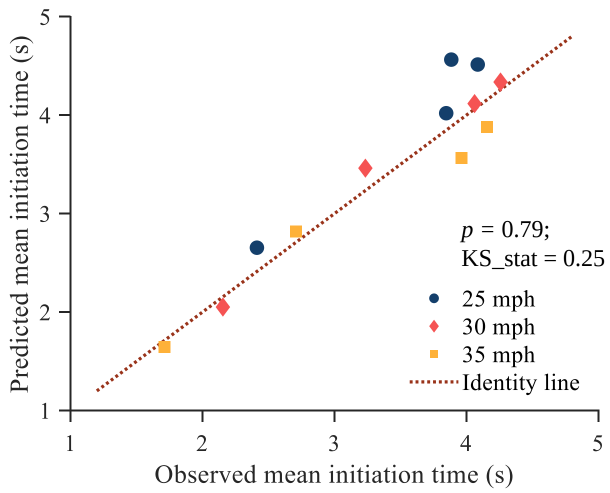

Figure 6.8: Comparison of observed and predicted mean initiation time. The results of Kolmogorov-Smirnov test, i.e., p value and statistics, are presented in the figure.

Initiation time. The detailed temporal information of pedestrian crossing decisions is shown in Fig 6.7 as a function of initial vehicle speed and initial TTC. Quantitatively, the HP-PRD model predicts pedestrian crossing onsets across a range of experimental conditions at a good level. Kolmogorov-Smirnov (KS) test is used to evaluate the goodness of fit of the modelling results. Except for the two scenarios, i.e., 2 s and 3 s of 25 mph, the KS test supports the modelling results have a similar distribution to empirical results for all other ten traffic scenarios, suggesting that the temporal information of pedestrian crossing decisions can be well characterised through the combination of multiple Wald models. The HP-PRD model clearly characterises the bimodal pattern by showing that some pedestrians quickly finalise their decisions when crossing opportunities are available, whereas others spend some time assessing the movement of the vehicle and then cross the road afterwards. Finally, the overall performance of HP-PRD models on mean initiation time is shown in Fig 6.8, the good agreement between observed and predicted results again indicates that the predictive power of the proposed model is acceptable.

6.5 Discussion

In this study, we have shown that pedestrian road-crossing decisions in complicated vehicle-yielding scenarios can be described using a sequence of simple discrete models based on a hybrid perception strategy, formalised by the HP-PRD model. Our model extends beyond the conventional crossing scenarios, where vehicles drive at a constant speed, to vehicle-yielding scenarios. Compared to the constant-speed scenarios, pedestrian road-crossing decisions in vehicle-yielding scenarios are much more complex, not only because pedestrian decisions in front of yielding vehicles have a complicated bimodal distribution , but also pedestrian decisions in deceleration scenarios are affected in real-time by the changing movements of the vehicle (Dey et al., 2019; Giles et al., 2019; Pekkanen et al., 2021). However, decisions at constant speed scenarios are mostly relatively decisive and do not take into account the details of the car's behaviour. The results show that our model accurately predicts pedestrian crossing decisions across a range of vehicle-yielding scenarios. A mechanistic explanation for pedestrian crossing decisions is given: pedestrian crossing decision-making is divided into three groups based on the availability of the visual cue accounting for detecting yielding vehicle behaviour. For the first phase, when the deceleration behaviour of the approaching vehicle does not exist or is not sufficiently obvious, pedestrians tend to rely on the simple optical expansion cues, i.e., $\dot{\theta}$, to make fast one-off decisions, which thus leads to these early crossing decisions. However, in the second and third groups, when the visual cues, $\dot{\tau}$, for vehicle yielding behaviour detection become available, pedestrians transfer to another decision strategy, which dynamically updates their decision based on the time-varying $\dot{\tau}$. This decision strategy therefore accounts for the later mode of crossing onsets. A detailed discussion of what new insights our study brings to computational pedestrian road-crossing decision-making is given below.

6.5.1 Hybrid perception strategy for road-crossing decision

In traffic, A typical example of a task requiring spatial visual perception is the road crossing task. As the vehicle's movements in the real world are complex, i.e., they can either drive at a constant speed or decelerate to yield, multiple kinematical cues of the vehicle are then required by pedestrians, such as TTC, speed, and distance, in order to cross the street. However, due to the limited sensitivity of the visual system, prior studies have demonstrated that pedestrians or humans are not good at judging the exact values of these kinematical cues (Lee et al., 2019; Petzoldt, 2014; Sun et al., 2015). Consequently, directly applying these kinematical cues to model pedestrian crossing decisions may result in unreal crossing behaviour, such as overestimating the sensitivity of the human perception system or overdependence on a certain kinematical cue (Fu et al., 2018; Zhang et al., 2020a). Therefore, we have thus demonstrated how to use visual cues to model pedestrian crossing decisions. We find a potential correlation between visual cues and decisions and show that two simple visual cues successfully account for the crossing behaviour in a wide range of scenarios with multiple kinematic cues, including speed, distance, TTC, or deceleration rate. Moreover, inspired by previous studies (DeLucia, 2008; Dietrich et al., 2019), one of the key notions highlighted by our results is that during a vehicle approach, pedestrians use different cues to make decisions depending on the visibility of deceleration behaviours, namely a hybrid perception strategy. Therefore, we propose a perceptual threshold of deceleration detection responsible for the transition between two perceptual strategies and show that our model captures bimodal patterns well. Our findings support the role of pedestrians' ability to deceleration detection in road-crossing decision-making (Ackermann et al., 2019). Moreover, our model shares similar assumption as the emerging evidence accumulation models that the pedestrian road-crossing decision process involves time-varying visual cues (Giles et al., 2019; Markkula et al., 2018; Pekkanen et al., 2021). However, instead of modelling the cognitive process underlying the crossing decision-making, we directly describe crossing decisions using simple computational models, so our model has lower complexity and better goodness of fit. Finally, future studies could test whether this perceptual threshold (or the transition between two strategies) is affected by vehicle kinematics and demographic and improve the model for more generalised traffic scenarios and populations.

6.5.2 Fast one-off and dynamic decisions

In addition to the hybrid perception strategy, another critical finding in this study is the proposed decision model, which formulated a sequence of simple discrete choice models based on the hybrid perception strategy. Specifically, when vehicles are travelling at a constant speed, or their yielding behaviour is not obvious, pedestrians tend to finalise their crossing decisions quickly. If vehicles do not give way to pedestrians, pedestrians are unlikely to change a non-crossing decision to a crossing decision. Hence, pedestrian crossing decisions in these situations are fast and one-off. In contrast, if pedestrians notice the vehicle's yielding behaviour, they tend to dynamically evaluate the situation based on visual cues until they feel they can cross. Our findings indicate that pedestrians involve not only multiple visual cues in their choices but also apply multiple decision strategies based, which thereby makes our model different from the latest approaches (Giles et al., 2019; Markkula et al., 2018; Pekkanen et al., 2021), which assumed one cognitive model accounts all decisions. Our proposed notion may have important implications for accumulation models. Further research could investigate if multiple accumulation models can better characterise crossing decisions or enable models to change with the situation, such as the collapsed threshold (Hawkins et al., 2015).

6.5.3 Temporal information of crossing decisions

Furthermore, our work goes beyond the conventional road-crossing models, such as critical gaps approaches and gap acceptance models(Brilon et al., 1999; Fu et al., 2018; Zhao et al., 2019). Those models only focus on pedestrians' final choices per traffic gap and do not consider the timing of road crossings (Pekkanen et al., 2021). However, the onset of road-crossing decisions has been demonstrated to have critical implications for traffic safety, simulation, and development of AVs (Faas et al., 2020; Hsu et al., 2018; Lobjois and Cavallo, 2007). Our model considers the entire road-crossing decision process and applies a Wald distribution model to account for the timing of road-crossing decisions. These ideas may drive the future computational pedestrian road-crossing models to a more fine-grain level. Several further mechanisms can be investigated in the future regarding the timing of crossing decisions, such as the effect of vehicle kinematics or pedestrian demographic.

6.5.4 Practical Implications

In addition to insights into the future of computational crosswalk models, the proposed model could have practical implications for other fields in several different ways. Since the HP-PRD model has successfully accounted for pedestrian behavioural phenomena across a wide range of traffic scenarios, it opens up new possibilities for studying various social interactions between pedestrians and vehicles. Intuitively, the HP-PRD model can be applied to the traffic simulation tools to generate human-like road-crossing decisions for pedestrian agents, which may improve the realism of traffic simulations for a better assessment of the traffic efficiency and safety involving pedestrians. Beyond the context of conventional traffic, our model has significance for the development of AVs. The model could provide predictive information from the perspective of pedestrians to help automated driving systems better anticipate pedestrian crossing intentions and initiations. If AVs make decisions concerning information from pedestrians, it will increase the safety and acceptance of AVs, thus advancing the introduction of self-driving cars into society. Moreover, the model could be applied to virtual testing platforms of AVs to control pedestrian behaviour in the simulated environment and therefore improve the realism of simulated traffic interactions.

6.5.5 Limitations

Although the proposed model captured patterns in pedestrian road-crossing decisions, several imperfections in the model need further improvement. First, the model fits are not perfect for all scenarios, i.e., 2 s and 25 mph and 3 s and 25 mph conditions (Fig 6.7). It can be found that the model predictions are relatively more conservative than empirical data, suggesting that pedestrians appear to involve other cues to strengthen their confidence in crossing decisions at low speed and short TTC conditions. Our previous study has demonstrated that pedestrians tend to suppose the near slow-speed vehicle is yielding to them even though it drives at a constant speed (see Chapter 4). The potential answer is that pedestrians tend to interpret the low-speed behaviour of vehicles as indicative of yielding.

Second, a more interpretable and rational approach to discretise dynamic decisions is needed. In the study, we partitioned the dynamic decisions into several intervals based on the visual cues $\dot{\tau}$. However, due to the different kinematics of the approaching vehicle, intervals with the same range of $\dot{\tau}$ have different time duration. Although the differences in time duration were usually very short, only a few tenths of a second.

Apart from the above limitations, the model can be further improved in other ways as well. For example, the model is developed based on the existing conceptional framework of human collision perception and does not assert that pedestrians exactly use the applied visual cues and perception strategy. As collision perception theory is further developed, the model can be improved accordingly

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CHAPTER 7

Discussion and conclusions

7.1 Overview

The work of this thesis aimed to observe pedestrian crossing decisions in different traffic scenarios, explore potential perceptual mechanisms underpinning their behaviour, and develop the computational model for pedestrian crossing decisions based on the observed results. Thus, the work focused on pedestrian crossing behaviour when interacting with an approaching vehicle (or vehicles), rather than the behaviour of drivers or vehicles. With this defined purpose in mind, in Chapter 1, several research gaps that need to be filled have been identified. In this chapter, the work and results of each chapter are mapped with the gaps by using defined objectives. All conclusions are supported by linking to the appropriate result. How each study led to the later ones is also discussed.

7.1.1 Gaps and objectives

Gap one: Lack of research on key visual cues for pedestrian crossing decisions

As perception, especially visual perception, underpins pedestrians' ability to establish the situation awareness during road-crossing tasks (Palmeiro et al., 2018; Coeugnet et al., 2019), it is vital to explore the visual cues underpinning pedestrian crossing decision-making, not only for modelling purposes, but also to facilitate the understanding of why pedestrians interact with vehicles in their way. As mentioned in Markkula et al. (2022), a range of psychological theories, such as perception and cognition, are required to describe human interaction on the road. However, according to the issues identified in Section 1.2, Chapter 1, existing studies only performed limited analysis to investigate visual perceptual mechanisms as well as the role of visual cues in road-crossing tasks. This work thus explored the potential visual cues and their functions by investigating pedestrian crossing behaviour in different traffic scenarios.

In Chapter 2, at specific uncontrolled intersections where vehicles were driven at constant speeds, this study answered two research questions. First, how does speed-induced unsafe crossing behaviour affect pedestrian road-crossing safety. Previous studies have shown that participants are less likely to cross the road in high vehicle speed conditions for a given distance gap and with slower crossing initiation, compared to low vehicle speed conditions. Conversely, the participants are more prone to initiate quickly and cross the road for a given time gap in higher speed conditions, resulting in a vehicle speed-induced unsafe (or 'distance-dependent') crossing behaviour (Lobjois and Cavallo, 2007; Schmidt and Farber, 2009; Petzoldt, 2014; Oxley et al., 2005). The study reproduced this crossing behavioural pattern and highlighted its negative safety impact. It showed that although participants attempted to walk faster in smaller time gap conditions, such a speed adaption strategy was insufficient to compensate for the reduction in safety margins caused by the speed-induced unsafe behaviour. Previous studies posited that pedestrians' over-reliance on the spatial distance from approaching vehicles might account for this pattern of behaviour, whereas our results showed that pedestrians had different gap acceptance and initiation times for conditions with similar spatial distances but different time gap size, suggesting that pedestrians relied on multiple sources of information from vehicle kinematics. To give a potential interpretation for our hypothesis, a second research question was proposed: can we use a psychological theory to describe and interpret speed-induced unsafe crossing behaviour? The mathematical expressions for the visual looming of an approaching vehicle in the studied traffic scenarios were derived. A looming-based crossing gap acceptance model was proposed, which quantitatively and qualitatively predicted speed-induced unsafe crossing behaviour. Hence, it potentially indicates that visual looming, as a critical visual cue, negatively relates to pedestrian crossing gap acceptance. Consistent with the literature, DeLucia (2008) showed that when visual cues were impoverished, humans might rely on visual heuristics, e.g., visual looming, to perceive collision risk. Therefore, the results support the possibility of pedestrians applying visual cues (i.e., visual looming) in simple road-crossing scenarios and achieve **O1** (Section 1.3, Chapter 1).

Moreover, beyond the simple road-crossing task, i.e., crossing at specific uncontrolled intersections where vehicles were driven at a constant speed, we also investigated pedestrian crossing in relatively complex scenarios, i.e., crossing when vehicles give way. Compared to constant-speed traffic scenarios, where pedestrians mainly rely on the gap from the approaching vehicles to finalise their decision, vehicle-yielding scenarios can involve more explicit and implicit communication signals between pedestrians and vehicles (Ackermann et al., 2019). For instance, in vehicle-yielding scenarios, explicit communication signals may include, but are not limited to, eye contact, hand gestures, light signals and eHMIs. Vehicle kinematics, such as speed, distance and deceleration, are implicit signals (Dey and Terken, 2017). Although several studies have pointed out that explicit signals can enhance communication between pedestrians and vehicles (de Clercq et al., 2019; Lee et al., 2022; Dey et al., 2021), especially in the context of the rapid development of AVs, there are some different opinions on explicit communication signals or eHMIs. On the one hand, the reliability of eHMIs has been questioned as its visibility may be affected by environmental factors. On the other hand, the existence of explicit signals may not significantly affect the quality of pedestrian crossing behaviour, and reasonable implicit signals are enough for pedestrians to interact with AVs safely (Moore et al., 2019). Hence, in Chapter 3, a study investigated how implicit signals of approaching vehicles affect pedestrian judgment and road-crossing decisions. An experiment was designed to identify the impacts of implicit signals on pedestrian crossing judgments and decisions at uncontrolled intersections with either yielding or constant-speed vehicles. It was found that the collision cue $\dot{\tau}$ was significantly correlated with the detection of yielding behaviour. That is, with the increase in $\dot{\tau}$, the yielding behaviour becomes more obvious to pedestrians. Our finding provided evidence to identify the role of $\dot{\tau}$ in pedestrian road-crossing and further supported the assumption proposed by the previous studies that $\dot{\tau}$ is an anthropomorphic cue that pedestrians might use to estimate vehicle-yielding behaviour (Bardy and Warren Jr, 1997; Pekkanen et al., 2021). Hence, in Chapter 3, by achieving **O2** (Section 1.3, Chapter 1), it indicated that pedestrian crossing decisions in vehicle-yielding scenarios was correlated to visual cue $\dot{\tau}$. In addition, the speed of approach of vehicles had an important impact on pedestrian crossing decisions.

In summary, two different studies were completed in Chapter 2 and 3 and identified $\dot{\theta}$ and $\dot{\tau}$ as the visual cues that pedestrians might use in the road-crossing scenarios. These findings contribute to filling the first research gap of this thesis, that is, critical visual cues for pedestrian crossing decisions in pedestrian-vehicle interactions.

Gap two: Lack of research on pedestrian crossing behavior in different traffic environments

Although there is a large body of studies in pedestrian-vehicle interaction research, those studies still have not shed light on several critical research questions as identified in Section 1.2, Chapter 1. Specifically, pedestrians often make road-crossing decisions in the face of complex traffic situations. For example, the approaching vehicles can either yield to pedestrians or not. Moreover, pedestrians may be confronted by a fleet of vehicles on a lane. Understanding the crossing behavioural patterns of pedestrians in these situations is valuable for traffic safety, planning, and management. On the other hand, investigating these issues can facilitate the development of more realistic computational models of pedestrian crossing decisions. Hence, two studies were designed to explore pedestrian crossing behaviour in different traffic environments.

In Chapter 3, considering the traffic scenario where the vehicle either yielded or not, two unsolved questions needed to be answered. Firstly, how do implicit signals of approaching vehicles affect pedestrian judgment and road-crossing decisions? Although there are several studies that have investigated pedestrian behaviour in vehicle-yielding scenarios (Ackermann et al., 2019; de Clercq et al., 2019), almost no study specifically investigated pedestrian ability to judge the behaviour of approaching vehicles. Moreover, no studies analysed how pedestrians coordinate their crossing decisions based on their judgments. Hence, the second question was what is the relationship between the pedestrian judgment of vehicle movement and road-crossing decisions? In this study, three different driving manoeuvres were designed for an approaching vehicle, including one non-yielding behaviour and two yielding behaviours. Participants randomly encountered one of three driving behaviours and then made their crossing decisions or reported judgements. The results indicated that pedestrians' detection of cars' yielding behaviour was stable, and their crossing behaviour was consistent with their judgments. A multiple-decision strategy was found that when the vehicle was far from pedestrians, their crossing decisions were mainly based on traffic gap size (e.g., distance or TTC to the vehicle). However, when pedestrians noticed the yielding behaviour of the approaching vehicle, their crossing decisions were mainly based on the kinematics of the vehicle (e.g., deceleration rate and speed). This finding was notable because it might not only explain why the distribution of pedestrian crossing initiations in front of a yielding vehicle is bimodal (Pekkanen et al., 2021), but also might provide evidence to support the hypothesis of DeLucia (2008) that humans could selectively rely on different visual cues to perceive collision events in terms of the perceived distance or the availability of these visual cues. Moreover, it was interesting that pedestrians had a tendency to suppose that vehicles would give way to them when the vehicle was travelling at low speeds.

In Chapter 4, a study was conducted to investigate the impacts of secondary tasks on pedestrian crossing decisions in crossing scenarios with continuous traffic flow. Two main research questions were answered, i.e., the influence of secondary tasks on pedestrian crossing decisions and safety, and the impacts of traffic flow. In this study, pedestrians were asked to perform a crossing task and one of three secondary tasks, i.e., time pressure, Arrows, and N-back. Our results showed that the two applied distractions affected pedestrian crossing safety in different ways. The visual-manual distraction led to a longer crossing duration and a reduced tendency to accept a gap as the time gap increased. In comparison, participants under auditory-cognitive distraction tended to accept smaller gaps, had a longer crossing duration, and initiated their crossing earlier than in the baseline. Moreover, we highlighted the dynamic pattern that the effects of the visual-manual distraction on pedestrians changed over the time gap size. This self-regulation pattern of distraction suggests that the distraction effect is not necessarily a binary measure but will instead change with the traffic environment (Larue and Watling, 2022). In addition, regarding time pressure, it caused participants to accept smaller gaps, initiate earlier, and use shorter crossing duration than in the baseline. Its safety impacts have two sides. On the one hand, participants under time pressure tended to take a risk and accept small gaps, causing them to lose the opportunity to cross the road in safe gaps. On the other hand, participants seemingly applied a 'compensatory' strategy to cover some of the reduction in safety caused by their risk-taking behaviour by crossing earlier in the gap and walking faster. Finally, an interestingly significant effect of the traffic flow characteristics was found, indicating that fewer participants accepted a gap equal to or smaller than the maximum gap they previously rejected. Prior studies often investigated the impacts of traffic flow from a perspective of 'waiting-time', suggesting that pedestrians tended to accept smaller gaps and exposed to more risk as waiting time increases (Zhao et al., 2019). Contrarily, new findings from our research provided a different source and explanation of the traffic flow effect on crossing behaviour, indicating that pedestrians did not always become anxious when waiting for crossing opportunities. Consistent with several previous studies, pedestrians who tended to wait were more cautious and less likely to accept risky gaps (Lobjois et al., 2013; Yannis et al., 2013; Theofilatos et al., 2021).

In brief, two studies conducted in Chapter 3 and 4 revealed pedestrian crossing decisions in diverse traffic situations, i.e., vehicle-yielding and continuous traffic flow scenarios. These findings contribute to filling the second gap of this thesis by achieving **O2** and **O3** (Section 1.3, Chapter 1).

Gap three: Lack of visual cue-based pedestrian crossing decision models

The above discussion naturally leads to the third research gap in this thesis: can we establish computational models to reproduce pedestrian road-crossing decisions based on behavioural patterns and the visual cues observed in pedestrians crossing the road (Chapter 2, 3, and 4)?

In Chapter 2, since visual looming $\dot{\theta}$ was significantly negatively related to the percentage of crossing gap acceptance, a psychophysics-based crossing gap acceptance model, called the PGA model, was proposed, which predicts crossing gap acceptance as a logit function of $\dot{\theta}$. The PGA model successfully characterised pedestrian gap acceptance behaviour across a range of experiment conditions. It replicated the speed-induced unsafe crossing and thus indicated that the mechanism behind this phenomenon is that higher speed situations provided weaker looming stimuli, leading to lower feelings of collision threat. Therefore, a notion was reinforced that looming may cause a sense of collision threat that affects pedestrian crossing decisions. This important mechanism underpinning pedestrian crossing decisions was also applied to model pedestrian decisions at uncontrolled intersections with continuous constant-speed traffic flow in Chapter 5 and vehicle-yielding scenarios in Chapter 6, which were covered in detail in the following sections.

In Chapter 6, the crossing decision model extended to a vehicle-yielding scenario. $\dot{\theta}$ investigated in Chapter 2 does not provide veridical information on TTC of an approaching car (DeLucia, 2008), and it alone may not be able to describe the yielding behaviour of the approaching vehicle. The visual cues $\dot{\tau}$ identified in Chapter 3 were then applied as the additional visual cues for pedestrian crossing decisions. Moreover, knowing only the physical representation of the visual information of approaching vehicles is not enough to understand pedestrian crossing decisions, and the decision-making strategy is also vital. In Chapter 3, our results indicated that pedestrians might apply a multiple-decision strategy: when the vehicle is far from pedestrians, their crossing decisions are mainly based on the traffic gap size. However, when pedestrians notice the yielding behaviour of the approaching vehicle, their crossing decisions are mainly based on the kinematics of the vehicle. Inspired by this, a hybrid perception strategy was proposed to account for pedestrian crossing decisions in Chapter 6, which assumed pedestrians could flexibly use different visual cues as vehicles approach. Specifically, pedestrians prioritise $\dot{\theta}$ for crossing decision-making. Moreover, When pedestrians observe the vehicle from a distance, the vehicle drives at a constant speed, or the vehicle brakes very lightly, pedestrians still rely on $\dot{\theta}$. However, when yielding behaviour is obvious, pedestrians instead used $\dot{\tau}$ as the primary cue of their crossing decisions. According to the proposed hybrid perception strategy, a sequence of simple discrete models was used to characterise pedestrian road-crossing decisions in complicated vehicle-yielding scenarios in Chapter 6. The results showed that our model accurately predicted pedestrian crossing decisions across a range of vehicle-yielding scenarios.

Furthermore, to model pedestrian crossing decisions at uncontrolled intersections with continuous constant-speed traffic flow, the PGA model was applied in Chapter 5. However, this model could not accurately capture pedestrian crossing decisions, as the crossing decisions in traffic flow appeared to be dynamic. Therefore, based on the findings on the impact of traffic flow in Chapter 4, a decision-making strategy was proposed that pedestrians compared the risks of observed gaps before making decisions, which means that pedestrians' current decisions were influenced by previously rejected crossing decisions and the oncoming crossing opportunities. This decision strategy significantly improved the performance of the PGA decision model in the continuous traffic flow.

Finally, as identified in Section 1.2, Chapter 1, exiting models characterised pedestrian crossing decisions at a relatively coarse-grained level, as they ignored the time dynamics of the crossing decision. Therefore, a crossing initiation model was proposed to account for this time-dynamic nature of crossing decisions in Chapter 5. Moreover, the crossing initiation model was internally linked to visual cue $\dot{\theta}$, suggesting that pedestrians could dynamically adjust their crossing initiation based on the perceptual risk. Two candidate distributions, i.e., Shifted Wald and Gaussian, were applied as crossing initiation models. The results indicated that the perceptual risk-based crossing initiation model could reasonably capture the time dynamics of pedestrian crossing decisions. The Shifted Wald model had a relatively better goodness-of-fit than the Gaussian distribution, showing that the distribution of pedestrian crossing initiation time is right-skewed.

In summary, this work bridges the third research gap by achieving four modelling goals, building on the findings of the three observational objectives (Section 1.3, Chapter 1).

7.2 Contributions

Understanding pedestrian road behaviour and its decision mechanism is a challenge. The studies in this thesis did not limit to experimental study and empirical data analyses but applied these observations to computational models that implement pedestrian crossing decisions. As a result, the work in this thesis thus has contributed to a wide range of traffic research in a diverse way. The following sections discuss the potential implications of this work from both a theoretical and practical perspective.

7.2.1 Theoretical implications

Psychological significance

First and foremost, this work has closed the gap between pedestrian road-crossing decision-making and human collision perception theory. In Chapter 2, it indicated that visual looming might engender a sense of collision threat, which might be a visual cue for pedestrians to make crossing decisions in crossing scenarios involving constant-speed vehicles. Chapter 3 provided further steps towards applying psychological mechanisms to vehicle-yielding scenarios by defining $\dot{\tau}$ as a visual cue of vehicle-yielding behaviour. Additionally, this chapter, as well as Chapter 6 proposed a hybrid perception hypothesis based on the identified visual cues. All the visual cues and perception hypotheses proposed above establish an explainable framework for the psychological mechanisms underpinning pedestrian crossing decision-making. In contrast to most existing studies on pedestrian road behaviour, which focus on purely observational research, this study's attempt to explain why and how pedestrians cross the road in their way is valuable. The findings of this work may also further encourage more studies to investigate pedestrian road behaviour by exploring its underlying psychological mechanisms.

Crossing behaviour in diverse traffic scenarios

This thesis has put much effort into investigating pedestrian crossing behaviour in different traffic scenarios, i.e., vehicles approaching at constant speeds, vehicles either yielding or not, or a fleet of vehicles travelling at constant speeds. It have attempted to deconstruct the logic of pedestrian crossing decision-making by tightly controlling traffic variables. Therefore, this work has demonstrated several novel theoretical findings regarding pedestrian crossing behaviour. Specifically, in Chapter 2, an unsafe pedestrian crossing behavioural pattern has been interpreted using a psychophysical-based model. Moreover, Chapter 3 has demonstrated the critical role of vehicle kinematics in pedestrian crossing judgments and decisions. An interesting behavioural pattern has been found, whereby pedestrians have a tendency to suppose that vehicles will give way to them when the vehicle travels at low speeds. In addition, Chapter 4 showed that pedestrians dynamically adjust their strategy when interacting with continuous traffic flow. An innovative interpretation has been made to this behavioural pattern that pedestrians optimise crossing decisions by comparing the collision risk of approaching vehicles. This finding partially answers previous observations that pedestrians are more cautious in their crossing decision-making when faced with traffic.

Computational models

Computational modelling is another focus of this thesis. In Chapter 5 and 6, pedestrian crossing decisions in continuous traffic flow and vehicle-yielding scenarios were characterised, respectively. These studies attempted to enhance the concept that pedestrian crossing decisions are dynamic and intrinsically closely linked to their perceived collision risk. Pedestrians have the flexibility to change their decision-making strategy or choose decision evidence depending on the situation. In addition, instead of emphasising the goodness-of-fit of data, this work valued the interpretability of the model. Compared to the data-driven approaches (Mainstream modelling approaches), this work has made at least two contributions to computational models of pedestrian road behaviour: (1) Provides mechanistic explanations for pedestrian crossing decisions. (2) Realises interpretable simulation of pedestrian crossing decisions in diverse crossing scenarios.

Impacts of secondary tasks

Beyond the investigation of the road behaviour of general pedestrians, this work has also tried to explore the crossing behaviour of heterogeneous pedestrians, i.e., the impacts of secondary tasks. It showed that the effects of distractions with different components on pedestrian crossing behaviour may be different, even in the opposite way. These differences have interesting parallels to the existing findings on how these distractions affect driving performance. Moreover, the impacts of distractions may not always be static. Pedestrians may actively self-regulate their engagement in the main and secondary tasks in terms of traffic scenarios. Hence, this situation-dependency of pedestrian distraction effects warrants considerable further research. Finally, regarding the time pressure, this work demonstrated that its safety impact has two sides. On the one hand, participants under time pressure tend to take a risk and accept small gaps, causing them to lose the opportunity to cross in safe gaps. On the other hand, participants seemingly apply a 'compensatory' strategy to cover some of the reduction in safety caused by their risk-taking behaviour by crossing earlier in the gap and walking faster.

7.2.2 Practical implications

Traffic management and safety

There are several ways these findings could benefit traffic management and improve traffic safety. In this work, several impacts of vehicle kinematics have been identified, some of which are negative. These findings suggest that necessary measures should be taken to increase the awareness of policymakers, road designers, and pedestrians. For example, to minimise the negative impact of vehicle speed on pedestrians (Chapter 2), a possible policy direction is to control vehicle speed by placing speed limit signs, indicators, or cameras at appropriate locations. Moreover, we can use signs to alert drivers to decelerate at a suitable distance from intersections to facilitate pedestrian crossing decisions. Additionally, to avoid the misinterpretation caused by low vehicle speed (Chapter 3), pedestrians need to be educated about the fact that low-speed AVs do not necessarily give way to them when they are not given explicit signals of yielding. Finally, regarding distracted pedestrians, our study may provide insights for researchers and policymakers to design appropriate interventions for pedestrians in different situations. For example, for pedestrians under visual-manual distractions, we could remind them to look more closely at the traffic. However, for the pedestrians doing auditory-cognitive distractions, the previous suggestion may not be sufficient to suppress the effects of distraction; instead, retaining the auditory cues from the traffic environment may be beneficial for their safety.

Development of automated vehicles

In addition to the significance of this work on traffic management and safety, the practical contribution to the development of AVs needs to be highlighted. At least this thesis demonstrates its practical implications for AVs in three aspects: eHMI, traffic simulation, and decision-making. Firstly, previous studies have shown that pedestrians highly rely on vehicle kinematics to guide their crossing decisions (Dey and Terken, 2017; de Clercq et al., 2019). However, in situations, where vehicle kinematics information is ambiguous, even misleading, eHMI can then be applied to enhance the communication between pedestrians and AVs. As shown in Chapter 2 and 3, variation in vehicle speed may engender pedestrians' misunderstanding of AVs' intention. In these situations, researchers and engineers may, therefore, develop an eHMI interface to provide explicit information on vehicle behaviour for pedestrians and thus reduce the potential negative effects of vehicle speed. Moreover, regarding traffic simulation, there is an urgent need for data to train and evaluate the functions of AVs. However, due to the low frequency of critical traffic scenarios in real life (i.e., the corner case) and safety reasons, both academia and industry have agreed on using simulation methods as a complementary way to validate AVs. Reliable simulation results rely on the behavioural authenticity of the simulated road user. Hence, another practical significance of this study is that the models serve as a module in the microscopic transport simulation tools or virtual testing platforms to realise naturalistic pedestrian road-crossing decisions. Finally, as recent studies have been keen on using pedestrian behaviour models to implement human-like pedestrian-AV interactive processes (Markkula et al., 2022; Domeyer et al., 2022), the proposed decision model may provide predictive information from the perspective of pedestrians to automated driving systems to better anticipate pedestrian crossing intentions and initiations.

7.3 Outlook

This thesis has investigated pedestrian road-crossing behaviour across a range of traffic scenarios. Several decision-making models have been developed to characterise pedestrian road behaviour in these scenarios. However, I have also seen a number of further steps for future research. In this section, these potential further research directions were summarised, concerning the research gaps identified in Section 1.2, Chapter 1.

Regarding the first research gap, whilst our work has identified two critical visual cues that pedestrians might use to make crossing decisions and proposed a hybrid perception strategy to determine the role of these visual cues, there is still much work left to do. Firstly, although previous studies (DeLucia, 2008; Pekkanen et al., 2021) and our work indicated that pedestrians might adopt different strategies and visual cues based on the availability of visual cues during the course of vehicles approaching pedestrians, there is a lack of rigorous psychological experiments to demonstrate the correlations between pedestrian behaviour, strategies, and visual cues. For instance, do pedestrians change from relying on one visual cue to relying on another? Does there exist a perceptual threshold that separates these strategies? Moreover, in Chapter 3, the tendency of pedestrians to interpret slow moving speed of vehicles as yield behaviour suggests that in addition to the visual cues of yielding behaviour, pedestrians may take other simple cognitive process into account. Potentially, pedestrians involve multiple visual cues or strategies to judge vehicle-yielding behaviour. Furthermore, as shown in Petzoldt (2016), the size of a vehicle could also affect pedestrian road-crossing decisions. It is, therefore, essential to identify the visual cues associated with the size of vehicles. Finally, pedestrian perceptual cues or strategies remain unstudied in other traffic scenarios, such as multiple lanes and two-way lanes scenarios.

Regarding the second research gap, firstly, whilst this work and existing studies have investigated pedestrian crossing behaviour in some traffic scenarios where vehicles are driven in different manoeuvres, these traffic scenarios are still too simple and very different from real traffic. For example, in Chapter 3, the vehicle only decelerated at a constant deceleration rate. However, in real situations, drivers often change the deceleration rate in the course of yielding. In Dey et al. (2021), it was found that there was an up and down pattern in pedestrian crossing willingness when the approaching vehicle's deceleration rate was not constant. Hence, it is valuable to investigate pedestrian crossing behaviour in those scenarios. Not limited to that, for a comprehensive understanding of pedestrian crossing behaviour, other traffic scenarios, such as two-way lanes or multiple lanes, are also interesting. Secondly, Chapter 4 did not capture the waiting time effect on pedestrian crossing behaviour, potentially because the length of the traffic scenarios was not long enough for us to observe changes in pedestrians' compliance with the law. Hence, further studies may consider the temporal length of traffic scenarios. Finally, with respect to the distracted pedestrian in Chapter 4, it showed that pedestrians may self-regulate their engagement in crossing tasks and distraction tasks based on the traffic scenario by analysing their crossing behaviour. However, participants' performance on the distraction tasks was not analysed. Accordingly, this aspect could be a further step in the future, which may provide insights into the impacts of traffic factors on distraction effects.

Last but not least, regarding the third gap of this thesis, since the results and models considered only specific traffic scenarios, they could not be directly generalised to other scenarios without further development. Accordingly, many challenges still exist to characterise pedestrian crossing behaviour in some traffic scenarios, like crossing the road in multiple lanes, two-way lanes, or continuous traffic flow. Moreover, there are also many unsolved issues in terms of the impacts of vehicle kinematics on pedestrians. For example, how to describe the behavioural pattern that pedestrians tend to interpret low vehicle speed as a yielding behaviour. Again, for example, what are the patterns of pedestrian crossing behaviour when interacting with vehicles with naturalistic driving manoeuvres? There are many, many more questions like this. In addition to the problems of the transport environment, modelling the crossing behaviour of different types of pedestrians (heterogeneous pedestrians) is also essential. Reliably reproducing the influences of age, gender, secondary tasks, culture, and more remains a considerable challenge. Furthermore, all models developed in this thesis are based on the premise that humans apply certain existing visual cues and strategies to perceive environments. However, I do not assert that humans exactly use the applied visual cues and perception strategy. With further development in human collision perception theory, the model can be improved accordingly. Finally, compared with the crossing behaviour in the simulated environment, pedestrians can flexibly adjust their behaviours and be affected by many potential factors in real traffic. As all the datasets applied in this thesis were collected in the virtual environment as well as the highly controlled experiments, the absolute human behaviour may not be identical to what would have been observed in the same situations in the real world. Hence, in future work, it will be important to apply the model to reliable naturalistic datasets.

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APPENDIX A

Chapter three: Supplementary file

A.1 Visual information for vehicle behaviour judgement

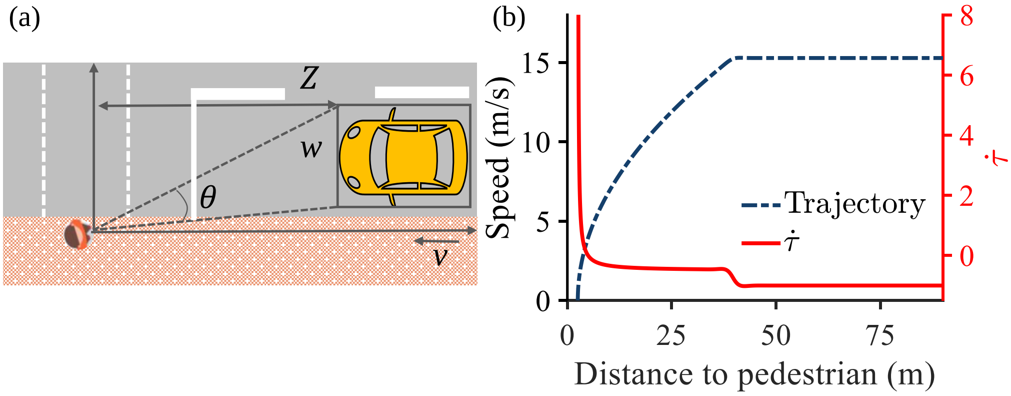

Figure A.1: Visual cues in road-crossing scenarios. (a) Diagram of the vehicle yielding scenario. (b) $\dot{\tau}$ curve and its corresponding vehicle trajectory.

In the road crossing scenario (Fig. A.1a), the pedestrian acquires the vehicle's movement information through the optical variables that change on the retina, which usually refers to the 'optic flow field' (Gibson, 2014). As the vehicle drives close, its image on the pedestrian's retina increases continuously. This optical expansion variable and its first temporal derivative are correlated to the sensation of collision threat, which the following equations can specify (Gibson, 2014; Lee, 1976):

$$\theta = 2\tan^{-1}(\frac{w}{2Z}) \Rightarrow \dot{\theta} = \frac{wv}{(Z)^2 + w^2/4} \tag{A.1}$$

where θ is the visual angle subtended by the approaching vehicle at the pedestrian's pupil. Its first temporal derivative is $\dot{\theta}$. Z, w denote vehicle distance from the pedestrian and its width. The ratio of visual angle to its first temporal derivative, τ, specifies the TTC of the approaching vehicle to the pedestrian, called Tau (Lee, 1976), and its rate of change over time is given by:

$$\tau = \frac{\theta}{\dot{\theta}} \Rightarrow \dot{\tau} = \frac{ZD}{v^2} - 1 \tag{A.2}$$

where D is the deceleration rate of the vehicle. Previous literature has demonstrated that $\dot{\theta}$ is correlated to the judgment of collision events in the course of vehicle yielding (Bardy and Warren Jr, 1997), which can be a variable that pedestrians use to judge whether the deceleration rate is enough to stop the vehicle in front of them and avoid the collision events as following equations:

$$\frac{v^2}{2D} \leq Z \Rightarrow \dot{\tau} \geq -0.5 \tag{A.3}$$

If the deceleration rate is enough to stop the vehicle in front of pedestrians, the distance the vehicle will take to stop, $v^2/2D$, should be less than or equal to its current distance, Z, from the pedestrian (Eq. A.3). let's substitute $\dot{\theta}$ into this equation, and we get the condition of collision avoidance: $\dot{\theta}$ should be equal to or bigger than -0.5. Now, suppose a concrete example, as shown in Fig. A.1b, that a vehicle approaches the intersection, and a pedestrian intends to cross the road. The trajectory of the vehicle is given, i.e., the car maintains a constant speed, 55 km/h, for a while and then decelerates at a constant rate, -3.135 $\mathrm{m/s^2}$, at a distance of approximately 40 m from the pedestrian and finally stops at a distance of 2.5 m from the pedestrian, as shown in Fig. A.1b. In the beginning, when the vehicle approaches at a constant speed, $\dot{\theta} = -1$, suggesting that pedestrians cannot perceive any deceleration behaviour of the approaching vehicle. As the car decelerates, $\dot{\theta}$ quickly increased to -0.5, representing that the deceleration rate is enough to stop the vehicle in front of the pedestrian. Afterwards, $\dot{\theta}$ increases approximately exponentially, which means that the closer the distance, the more obvious the collision avoidance cues become. Therefore, we then assumed that $\dot{\theta}$ may be the anthropomorphic implicit cue associated with pedestrian crossing decisions in vehicle-yielding scenarios.

A.2 Parameters of segments of traffic scenarios

Bibliography

Bardy, B. G. and Warren Jr, W. H. (1997). Visual control of braking in goal-directed action and sport. *J. Sports Sci.*, 15(6):607–620.

Gibson, J. J. (2014). *The ecological approach to visual perception: classic edition*. Psychology Press.

Lee, D. N. (1976). A theory of visual control of braking based on information about time-to-collision. *Perception*, 5(4):437–459. Number: 4.

Table A.1: Parameters of segments of traffic scenarios. The duration of scenario segment, vehicle distance to the participant, and $\dot{\tau}$ are included. All parameters correspond exactly to scenarios at the end of segments.

Condition		1st Segment	2nd Segment	3rd Segment	4th Segment
Const_3s_25 km/h	Duration (s)	1.00	1.33	1.98	2.64
	Distance (m)	13.79	11.61	7.06	2.50
Const_3s_40 km/h	Duration (s)	1.00	1.39	2.08	2.78
	Distance (m)	22.06	17.83	10.17	2.50
Const_3s_55 km/h	Duration (s)	1.00	1.43	2.13	2.84
	Distance (m)	30.32	24.05	13.28	2.50
Const_6s_25 km/h	Duration (s)	1.42	2.83	4.23	5.64
	Distance (m)	31.80	22.03	12.27	2.50
Const_6s_40 km/h	Duration (s)	1.46	2.90	4.34	5.78
	Distance (m)	50.50	34.50	18.50	2.50
Const_6s_55 km/h	Duration (s)	1.47	2.93	4.38	5.84
	Distance (m)	69.20	46.97	24.73	2.50
Decel_3s_25 km/h	Duration (s)	1.62	2.92	4.16	5.28
	Distance (m)	11.29	6.15	3.32	2.50
	$\dot{\tau}$	-0.36	-0.16	1.01	$> 10e4$
Decel_3s_40 km/h	Duration (s)	1.81	3.17	4.31	5.52
	Distance (m)	16.46	8.15	4.03	2.50
	$\dot{\tau}$	-0.41	-0.28	0.31	$> 10e4$
Decel_3s_55 km/h	Duration (s)	1.93	3.33	4.43	5.61
	Distance (m)	21.31	9.86	4.03	2.50
	$\dot{\tau}$	-0.44	-0.33	0.15	$> 10e4$
Decel_6s_25 km/h	Duration (s)	3.80	6.56	8.79	11.28
	Distance (m)	19.70	9.34	4.40	2.50
	$\dot{\tau}$	-0.43	-0.32	0.15	$> 10e4$
Decel_6s_40 km/h	Duration (s)	4.16	7.01	9.12	11.55
	Distance (m)	28.73	12.39	5.33	2.50
	$\dot{\tau}$	-0.45	-0.37	-0.06	$> 10e4$
Decel_6s_55 km/h	Duration (s)	4.40	7.30	9.34	11.67
	Distance (m)	37.07	14.98	6.05	2.50
	$\dot{\tau}$	-0.46	-0.40	-0.15	$> 10e4$
Mixed_3s_25 km/h	Duration (s)	1.36	2.23	3.04	3.78
	Distance (m)	11.30	6.17	3.36	2.50
	$\dot{\tau}$	-1.00	-0.16	0.99	$> 10e4$
Mixed_3s_40 km/h	Duration (s)	1.51	2.43	3.21	4.05
	Distance (m)	16.47	8.17	4.06	2.50
	$\dot{\tau}$	-0.65	-0.28	0.31	$> 10e4$
Mixed_3s_55 km/h	Duration (s)	1.61	2.56	3.31	4.17
	Distance (m)	21.24	9.89	4.06	2.50
	$\dot{\tau}$	-0.45	-0.33	0.08	$> 10e4$
Mixed_6s_25 km/h	Duration (s)	3.15	4.91	6.31	7.88
	Distance (m)	19.72	9.36	4.44	2.50
	$\dot{\tau}$	-1.00	-0.32	0.15	$> 10e4$
Mixed_6s_40 km/h	Duration (s)	3.41	5.24	6.59	8.15
	Distance (m)	28.72	12.41	5.36	2.50
	$\dot{\tau}$	-0.67	-0.36	-0.06	$> 10e4$
Mixed_6s_55 km/h	Duration (s)	3.57	5.44	6.76	8.27
	Distance (m)	37.06	15.02	6.09	2.50
	$\dot{\tau}$	-0.45	-0.40	-0.16	$> 10e4$

APPENDIX B

Chapter four: Statistics of the data

B. CHAPTER FOUR: STATISTICS OF THE DATA

Table B.1: Gap acceptance for tasks and traffic scenarios.

Task	Scenario	Decision	Position of the gap in traffic flow										
			1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	11th
Baseline	One	Accept	0	0	0	29	6	10	73	0	0	0	2
		Reject	120	120	120	91	85	75	2	2	2	2	0
	Two	Accept	0	0	0	0	33	10	77	-	-	-	-
		Reject	120	120	120	120	87	77	0	-	-	-	-
	Three	Accept	0	0	0	31	0	13	0	1	68	0	6
		Reject	119	119	119	88	88	75	75	74	6	6	0
	Four	Accept	3	39	0	0	6	0	0	0	68	0	4
		Reject	117	78	78	78	72	72	72	72	4	4	0
Timer	One	Accept	0	0	0	47	8	6	57	0	0	0	2
		Reject	120	120	120	73	65	59	2	2	2	2	0
	Two	Accept	0	0	0	0	49	7	64	-	-	-	-
		Reject	120	120	120	120	71	64	0	-	-	-	-
	Three	Accept	0	0	0	52	0	7	0	2	55	0	4
		Reject	120	120	120	68	68	61	61	59	4	4	0
	Four	Accept	4	53	0	0	6	0	0	0	54	0	3
		Reject	116	63	63	63	57	57	57	57	3	3	0
Arrows	One	Accept	0	0	0	26	11	5	72	0	0	3	-
		Reject	117	117	117	91	80	75	3	3	3	0	-
	Two	Accept	0	0	0	0	32	10	73	0	0	0	2
		Reject		117	117	117	85	75	2	2	2	2	0
	Three	Accept	0	0	0	34	0	9	0	5	58	2	9
		Reject	117	117	117	83	83	74	69	11	9	0	-
	Four	Accept	7	31	0	0	9	0	0	0	59	4	8
		Reject	111	80	80	80	71	71	71	71	12	8	0
N-back	One	Accept	0	0	0	31	11	4	71	0	0	1	2
		Reject	120	120	120	89	78	74	3	3	3	2	0
	Two	Accept	0	0	0	0	34	12	73	0	0	0	1
		Reject	120	120	120	120	86	74	1	1	1	1	0
	Three	Accept	0	0	0	42	0	8	0	1	62	0	7
		Reject	120	120	120	78	78	70	70	69	7	7	0
	Four	Accept	2	43	0	0	7	0	0	0	60	0	4
		Reject	118	75	75	75	68	68	68	68	8	8	4

Table B.2: Means and S.D. of the initiation time and PET for tasks and time gaps

Condition		Time gap (s)						
		2	3	4	5	6	7	8
IT	Baseline	-0.27 (0.22)	-0.05 (0.16)	-	-0.00 (0.20)	0.02 (0.20)	0.11 (0.22)	0.17 (0.26)
	Timer	-0.09 (0.27)	-0.24 (0.19)	-	-0.16 (`0.23)	-0.10 (0.23)	-0.12 (0.20)	0.01 (0.25)
	Arrows	-0.09 (0.16)	-0.05 (0.26)	-0.02 (0.32)	0.05 (0.44)	0.05 (0.34)	0.12 (0.34)	0.12 (0.40)
	N-back	-0.22 (0.19)	-0.15 (0.19)	-	-0.06 (0.21)	-0.02 (0.25)	0.06 (0.41)	0.32 (0.45)
CD	Baseline	2.58 (0.22)	3.07 (0.30)	-	3.47 (0.34)	3.58 (0.33)	3.67 (0.36)	3.69 (0.26)
	Timer	2.46 (0.11)	2.95 (0.35)	-	3.40 (0.35)	3.53 (0.43)	3.58 (0.42)	3.83 (0.39)
	Arrows	2.48 (0.30)	3.06 (0.33)	3.57 (0.73)	3.49 (0.34)	3.74 (0.42)	3.84 (0.47)	4.25 (0.86)
	N-back	2.45 (0.14)	3.09 (0.34)	-	3.59 (0.35)	3.71 (0.38)	3.80 (0.39)	4.15 (0.48)
PET	Baseline	-0.31 (0.86)	-0.01 (0.33)	-	1.53 (0.33)	2.40 (0.38)	3.22 (0.35)	4.04 (0.24)
	Timer	-0.36 (0.24)	0.29 (0.35)	-	1.76 (0.32)	2.57 (0.40)	3.53 (0.39)	4.14 (0.43)
	Arrows	-0.37 (0.43)	-0.01 (0.41)	0.45 (0.81)	1.45 (0.46)	2.21 (0.46)	3.05 (0.51)	3.60 (0.73)
	N-back	-0.23 (0.24)	0.07 (0.35)	-	1.47 (0.34)	2.30 (0.39)	3.12 (0.55)	3.50 (0.71)

Note. IT: initiation time (s); CD: crossing duration PET: post encroachment time (s)

Table B.3: Proportion of crossing decision categories for time gaps and tasks.

Time gap (s)	Decision category	Baseline		Timer		Arrows		N-back	
		Freq.	Pct.	Freq.	Pct.	Freq.	Pct.	Freq.	Pct.
2	Near-collision (PET 0)	3	100	4	100	5	100	2	100
	Unsafe (0 PET 1.5)	0	0	0	0	1	0	0	0
	Safe (PET 1.5)	0	0	0	0	0	0	0	0
3	Near-collision	96	54.2	43	18.5	84	48.8	85	44.0
	Unsafe	81	45.7	190	81.5	88	51.2	108	56.0
	Safe	0	0	0	0	0	0	0	0
4	Near-collision	0	0	0	0	1	16.7	0	0
	Unsafe	0	0	0	0	5	83.3	0	0
	Safe	0	0	0	0	0	0	0	0
5	Near-collision	0	0	0	0	2	1.4	0	0
	Unsafe	57	41.9	20	18.3	58	50.4	61	50
	Safe	79	58.1	89	81.7	57	49.6	61	50
6	Near-collision	0	0	0	0	0	0	0	0
	Unsafe	0	0	1	1.8	6	6.8	4	5.0
	Safe	73	100	56	98.2	69	93.2	68	95.0
7	Near-collision	0	0	0	0	0		0	
	Unsafe	0	0	0	0	1	1.3	1	1.3
	Safe	81	100	67	100	80	98.7	76	98.7
Overall	Near-collision	99	20.7	47	9.9	92	19.6	87	18.2
	Unsafe	138	28.9	211	44.3	159	34.0	174	36.4
	Safe	241	50.4	218	45.8	217	46.4	217	45.4

Note. PET: post encroachment time (s); Freq.: frequency; Pct.: percentage (%)

APPENDIX C

Chapter five: Supplementary file

C.1 Simulation tool

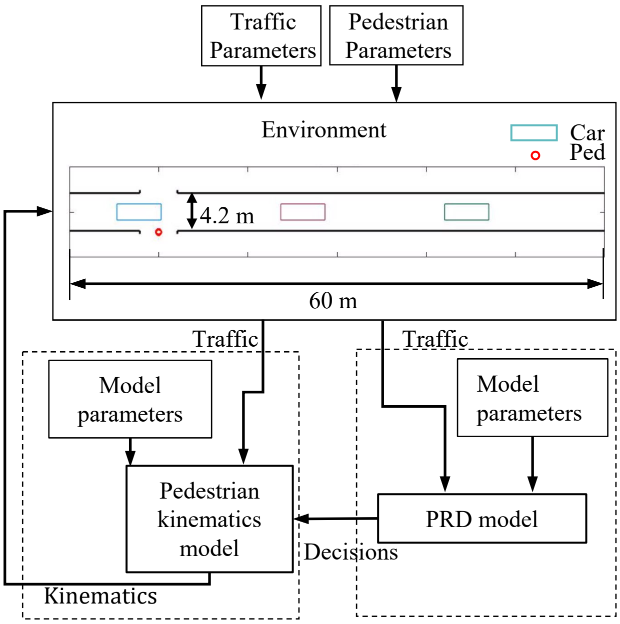

Figure C.1: Structure of the simulation tool. The traffic environment contains a single lane (60 m long and 4.2 m wide) and a fleet of vehicles (colored rectangles).

In this study, an agent-based simulation tool is proposed using the established PRD models for reproducing pedestrian crossing behaviour at uncontrolled intersections with traffic flow. The framework mainly includes three parts: PRD model, environment model, and pedestrian kinematics model (Fig C.1). The detailed process of the simulation tool is as follows:

(i) Generate the traffic environment using the given traffic and pedestrian parameters.

(ii) Generate a pedestrian agent at a random location on the pavement near the crosswalk. After that, the pedestrian walks to the edge of the pavement. Since this study focuses on the crossing decisions in the traffic flow, the pedestrian performs the PRD model after the first vehicle has passed him/her (Algorithm 1).

(iii) The PRD model generates each pedestrian's decision and initiation time through a Monte Carlo sampling method (Algorithm 2).

(iv) Pedestrians cross the road and walk to the opposite side of the road. The simulation model stops when the traffic scenario ends or all pedestrians cross the road.

A demonstration video of the simulation tool is also provided via link.

Algorithm 1 Simulation model based on the model

Input: Model parameters $\rho_0, \rho_1, \rho_2, \rho_3, \beta_1, \beta_2, \beta_3, \beta_4, b$
Output: $\boldsymbol{u}, \boldsymbol{t}_{int}$

$I_r = I$ // Number of remaining participants I_r and total number participants I
for nth gap in traffic N **do**
  $\dot{\theta}_n \leftarrow$ Eq.5.1
  $X_{1,n}, X_{1,n} \leftarrow$ Eq.5.2 and Eq.5.3
  $p_n \leftarrow$ Eq.5.5
  $P_n = p_n \cdot (1 - P_{n-1}) \leftarrow$ Eq.5.9
  for ith pedestrian in I_r **do**
    $u_i \leftarrow Binomial(1, P_{n,i})$ // Sampling: crossing decision
    if $u_i == 1$ **then**
      $f(t_{int}) \leftarrow$ Eq.5.9 or Eq.5.10 // Caulculate probability density function of crossing decision
      $t_{int,i} \leftarrow$ Algorithm. 2 // Sampling: crossing initiation time
    else
      Continue
    end if
  end for
  $I_r = I_r - \text{length}(\boldsymbol{t}_{int})$ // Update remaining participants
end for

Algorithm 2 Monte Carlo sampling of the model

Input: $f(t_{int})$
Output: $t_{int,i}$

Initialise $s = 1$
while $s \neq 2$ **do**
  $\pi(x) = f(x)$
  $s \leftarrow \text{Uniform}(0, 1)$;
  $y \leftarrow Q(x|y)$ // Arbitrary probability density
  if $u \leq \min(\frac{pi(y)Q(x|y)}{pi(x)Q(y|x)}, 1)$ **then**
    $t_{int,i} = y$
    $s = s + 1$
  else
    $s = 1$
  end if
end while

C.2 Detailed modelling results

Detailed comparisons between modelling results and observations are shown in Fig C.2 and Fig C.3. In Fig C.2, the probability density functions of crossing initiation time are plotted against time gaps and vehicle speeds. While, In Fig C.3, the probability density functions of crossing initiation time are plotted as a function of traffic scenarios and crossing initiation time.

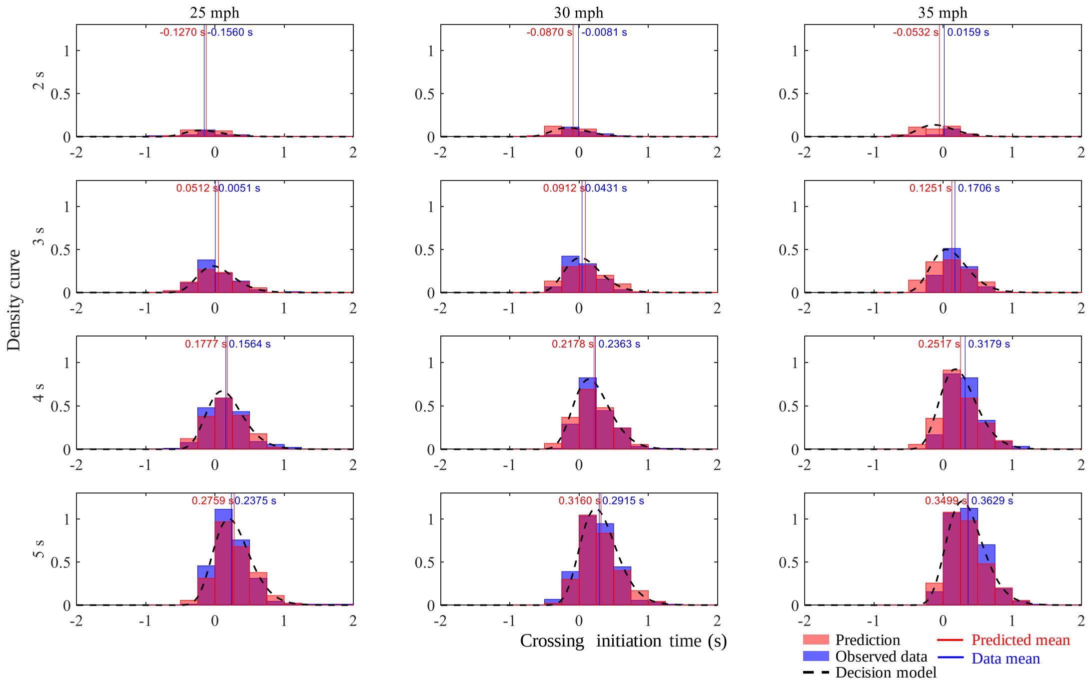

Figure C.2: Predicted density function of crossing initiation time of the SW-PRD model based on dataset one. The predicted results, including density function, samplings and mean values of crossing initiation time, are compared with the observed data in terms of vehicle speed and traffic gap size.

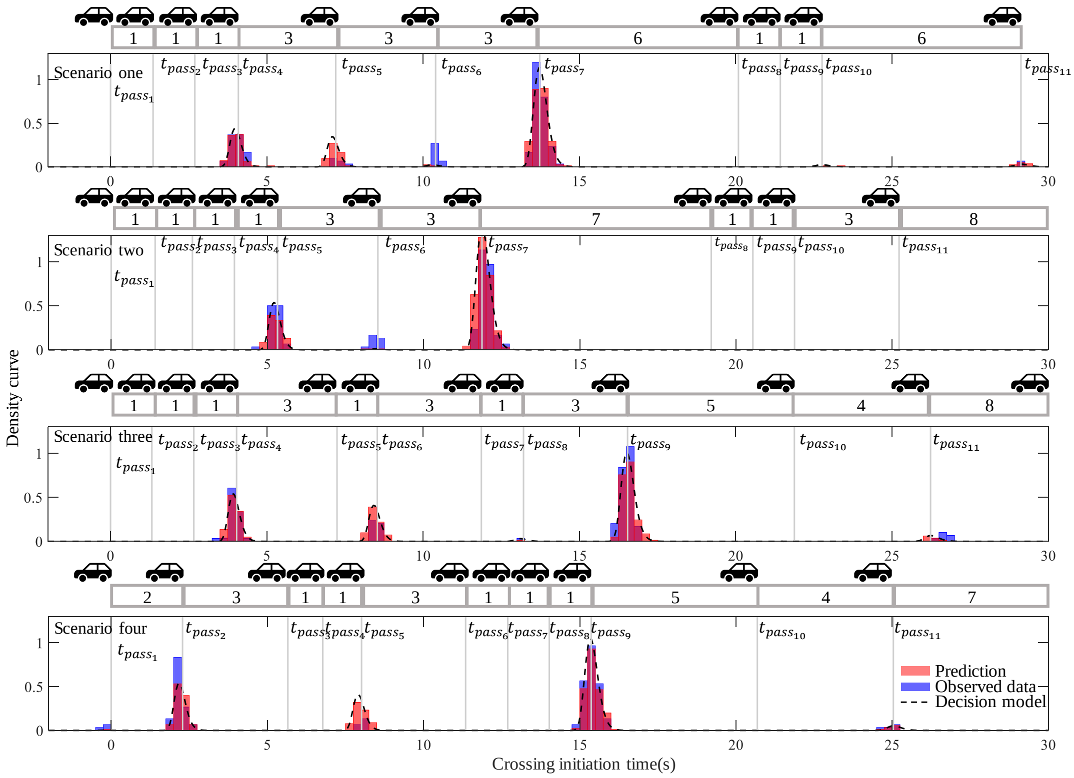

Figure C.3: Predicted density function of crossing initiation time of the SW-PRD model based on dataset two. The predicted density functions and samplings are compared with the observed data. Regarding each traffic scenario, the order of traffic gaps is indicated above each sub-figure. The vertical lines represent the time when the rear end of the related vehicle passes the pedestrian's position, i.e., t_{pass}.