Modelling vehicle-pedestrian interactions at unsignalised locations employing game-theoretic models

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The candidate affirms that the submitted work is his own, with the exception of contributions from jointly authored publications. In cases of joint authorship, the specific collaborators are named, and the contributions of each party are explicitly detailed below. The candidate further confirms that due credit has been appropriately given within the thesis to acknowledge the work of others.

This PhD project has three interconnected parts resulting in three journal papers: one for computational modelling, one for an experimental study and another for a naturalistic study of road user interactions. The focus of the first journal paper is a methodology that was developed for the experimental study with subsequent statistical analyses. This paper constitutes the second chapter of the thesis. The second paper deals primarily with the mathematical modelling of the dataset obtained from the experimental study and is included as the third chapter of the thesis. The third paper involves both a comparison of the findings of the two methodologies (experimental versus naturalistic) and testing the computational models developed in the second paper, this time using a naturalistic dataset. The fourth chapter is dedicated to this paper. 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 4 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:

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

The candidate developed the main idea for this work, under the guidance of Gustav Markkula, and Natasha Merat. The design of the experiment was led by the candidate but all the authors contributed to that. The experiment was conducted by the candidate and Yue Yang. The candidate performed the analysis and modelling and wrote the paper. The results were reviewed by Gustav Markkula, Natasha Merat and Yee Mun Lee. The manuscript was improved by comments from Gustav Markkula, Natasha Merat, Yee Mun Lee, Yue Yang and Albert Solernou.

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The candidate developed the main idea for this work, under the guidance of Gustav Markkula and Natasha Merat. The design of the experiment was led by the candidate but all the authors contributed to that. The experiment was conducted by the candidate and Yue Yang. The candidate performed the modelling work and data analysis, and wrote the manuscript. The general results were reviewed by Gustav Markkula and Natasha Merat. The modelling results were reviewed by Gustav Markkula. The manuscript was improved by comments from Gustav Markkula and Natasha Merat.

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The candidate developed the main idea for this work, under the guidance of Gustav Markkula and Natasha Merat. The study was conducted by the candidate with the help of Yi-Shin Lin. All the authors contributed to the methodology of the work. The candidate performed the modelling work and data analysis, and wrote the manuscript. The results were reviewed by Gustav Markkula and Natasha Merat. The manuscript was improved by comments from Gustav Markkula.

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

- Yang, Y., Lee, Y. M., **Kalantari, A. H.**, de Pedro, J. G., Horrobin, A., Daly, M., Solernou, A., Markkula, G., & Merat, N. (2023, September). The effect of different infrastructures on driver response to a crossing pedestrian: A distributed simulation study. The 22nd Driving Simulation Conference. Antibes, France.

- Markkula, G., Lin, Y. S., Srinivasan, A. R., Billington, J., Leonetti, M., **Kalantari, A. H**., ... & Merat, N. (2023). Explaining human interactions on the road by large-scale integration of computational psychological theory. *PNAS nexus*, *2*(6), pgad163.
- Zhang, C., **Kalantari, A.H.**, Yang, Y., Ni, Z., Markkula, G., Merat, N. (2023). Cross or Wait? Predicting Pedestrian Interaction Outcomes at Unsignalized Crossings. 2023 IEEE Intelligent Vehicles Symposium (IV), Anchorage, AK, USA, 2023, pp. 1-8. DOI: 10.1109/IV55152.2023.10186616
- **Kalantari, A. H.**, Yang, Y., Garcia de Pedro, J., Lee, Y. M., Horrobin, A., Solernou, A., & Öztürk, Í. (2022, August). A distributed simulator study of car-pedestrian interaction. 7th International Conference on Traffic and Transport Psychology, Gothenburg, Sweden.
- **Kalantari, A. H.**, Markkula, G., Uzondu, C., Lyu, W., Garcia de Pedro, J., Madigan, R., Lee, Y. M., Holmes, C., & Merat, N. (2022). Vehicle-Pedestrian Interactions at Uncontrolled Locations: Leveraging Distributed Simulation to Support Game Theoretic Modeling. Transportation Research Board 101st Annual Meeting. DOI: 10.13140/RG.2.2.15469.72165

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Abstract

There are some aspects of driver-pedestrian interactions at unsignalised locations that remain poorly understood. Understanding these aspects is vital for promoting road traffic safety in general which involves the interaction of human road users. Recent developments in vehicle automation have called for investigating human-robot interactions before the deployment of highly automated vehicles (HAVs) on roads so that they can communicate effectively with pedestrians making them trustworthy and reliable road users. To understand such interactions, one can simulate interactive scenarios studying various factors affecting road user decision-making processes through lab and naturalistic studies. To quantify such scenarios, mathematical models of human behaviour can be useful. One of these mathematical models that is capable of capturing interactions is game theory (GT). GT can provide valuable insights and strategies to help resolve road user interactions by analysing the behaviour of different participants in traffic situations and suggesting optimal decisions for each party. Thus, the current doctoral thesis aimed to investigate vehicle-pedestrian interactions at unsignalised crossings using GT models, applied to both lab-based and naturalistic data. One of the main aims of the current thesis was to understand how two or more human road users can communicate in a safe and controlled manner demonstrating behaviours of a game-theoretic nature. Thus, an experimental paradigm was created in the form of a distributed simulator study (DSS), by connecting a motion-based driving simulator to a CAVE-based pedestrian simulator to achieve this goal. It was found that the DSS could generate scenarios where participants interact actively showing similar communication patterns to those observed in real traffic. Another prominent finding was the stronger role of vehicle kinematics than personality traits for determining interaction outcomes at unmarked crossings, i.e. whether the pedestrian or driver passed first. To quantify the observations made from the DSS, five computational models namely four GT and one logit model were developed, tested and compared using this dataset. The GT models were obtained from both conventional and behavioural GT literature (CGT and BGT, respectively). This was done to bridge a gap in the previous research, specifically the lack of a comparison between these two modelling approaches in the context of vehicle-pedestrian interactions. Overall, the findings showed that: 1) DSS is a reliable source for the testing and development of GT models; 2) there is a high behaviour variability among road users highlighting the value of studying individualised data in such studies; 3) the BGT models showed promising results in predicting interaction outcomes and simulating the whole interaction process, when compared to the conventional models. These findings suggest that future studies should proceed to adopt, test, and develop BGT approaches for future HAV-human road user interaction studies. To validate the findings of the first two studies, a naturalistic study was conducted in the city of Leeds using state-of-the-art sensors. The sensors gathered road user data including their trajectory and speed over time. The findings from observations revealed similar communication patterns between drivers and pedestrians as in the DSS, suggesting a high degree of relative validity of the experimental paradigm. The results for the computational models were similar but the differences among the models were less noticeable compared to when the models tested against the controlled dataset. Overall, this thesis illustrates that the experimental paradigm and BGT models developed as part of the PhD programme have potential applications for HAV decision-making and motion planning algorithms, as well as traffic safety in general.

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List of Abbreviations

ABM – Agent based model

ADAS - Advanced driver-assistance system

AISS - Arnett Inventory of Sensation Seeking

BGT - Behavioural game theory

CA – Cellular automata

CAVE - Cave Automatic Virtual Environment

CFM - Centrifugal force model

CGT - Conventional game theory

CIT - Crossing initiation time

DA - Dual accumulator

DRL - Deep reinforcement learning

DRT - Detection response task

DT - Decision time

DSS - Distributed simulator study

EAM - Evidence accumulation model

eHMI - External human-machine interface

FVD - Full velocity difference

GAM - Gap acceptance model

GT - Game theory

HAV - Highly automated vehicle

HD - Human driven

HIKER - Highly Immersive Kinematic Experimental Research Lab

HMD - Head mounted display

HMM - Hidden Markov model

iHMI - Internal human machine interface

LATER - Linear approach to threshold with ergodic rate

LBA - Linear ballistic accumulator

LCA - Leaky-competing accumulator

MDP - Markov decision process

MLM - Maximum likelihood method

PEM - Probability equilibrium method

POMDP - Partially observed Markov decision process

PVT - Psychomotor vigilance test

RMS - Root mean square

SS - Sensation seeking

SFM – Social Force Model

SVO - Social value orientation

TTA - Time-to-arrival

UoLDS - University of Leeds Driving Simulator

VDDM - Variable-drift diffusion model

VR - Virtual reality

VRU - Vulnerable road user

Chapter 1

Introduction

Pedestrians constitute a great proportion of road users as many people may play this role on a daily basis. Therefore, their interaction with other road users including their crossing behaviours has been a topic of interest for road safety experts, traffic engineers and human factor specialists for decades. With the advent of automated vehicles (AVs), particularly highly automated vehicles (HAVs) – referring to level 4 and 5 in SAE's automation level definitions (Society of Automotive Engineers, 2021)– studying road crossing behaviours has become even more crucial. HAVs could solve the problems associated with trip duration and traffic jams with better route planning and more efficient vehicle operation, decrease fatalities and injuries by reducing human error, and address the lack of possibility for elderly/disabled people to drive by providing a new travelling option for them (T. Zhang et al., 2019). However, it is still unclear how these autonomous systems are going to share the road with other road users and especially pedestrians in future urban scenarios, highlighting the importance of understanding their role in the road traffic context (Alvarez et al., 2019) before they get deployed on the roads. The current thesis aims to understand and model vehicle-pedestrian social interactions at unsignalised locations to support efforts toward safe and automated road traffic.

However, social interaction is not a trivial concept. In the research literature, this term generally refers to the various ways in which drivers, pedestrians, cyclists, and passengers, communicate, cooperate, and respond to each other while navigating the road environment. It involves the dynamic interplay of behaviours, gestures, signals, and decisions that influence the flow of traffic and safety on the roadways (Markkula et al., 2020). Social interaction is a complex phenomenon where individuals' actions and reactions are influenced by a combination of rules, norms, expectations, and situational factors. This type of interaction plays a crucial role in maintaining orderly and safe traffic movement, preventing collisions, and ensuring efficient transport systems. In order to interact socially, road user needs a sense of social intelligence which can be described as an individual's state of knowledge and ability to understand social situations (Kihlstrom & Cantor, 2000). The need for social intelligence has to do with different skills, preferences, and walking behaviour/driving style of road users (K. Brown et al., 2020). But how can one make sense of such interactions considering these different skills and preferences?

One promising approach for understanding human behaviour in general is mathematical modelling of the behaviour in question (Calder et al., 2018). Modelling and simulating road user behaviour in different traffic scenarios would it be in the lab or real traffic can help us understand social interaction. These models can serve as the foundations for conceptual notions, and aid researchers in generating inquiries related to the behaviours under observation (Calder et al., 2018). One of these mathematical models that is capable of capturing social interactions is game theory (GT) which in general can be defined as the study of strategic interactions between rational decision-makers, often referred to as 'players' (Novikov et al., 2018). GT can provide valuable insights and strategies to help resolve road user interactions by analysing the behaviour of different participants in traffic situations and suggesting optimal decisions for each party. By utilising proper models and studying critical parameters in the related traffic scenarios, a better account of road user behaviour would be achievable. This could help researchers to develop better algorithm designs in this field. Additionally, this will serve a purpose in the virtual testing of HAVs. This holds particular significance in the context of vehicle-pedestrian interaction at unsignalised locations, as evidenced by prior research indicating that the heterogeneity among drivers, pedestrians, vehicles, and road environments has often been overlooked in the formulation of models within previous studies (Amado et al., 2020). In the rest of this chapter, a comprehensive literature review is conducted to help us understand what aspects should be taken into account when designing and modelling vehicle-pedestrian interactions for future urban scenarios. Then, the main research gaps and questions are discussed. The section concludes with the thesis objectives and outline.

1.1 Literature review

This section undertakes a review of the literature pertaining to methods employed thus far in the study of road user behaviour, particularly interactions involving vehicles and pedestrians. Subsequently, factors influencing road user interactions, with a specific emphasis on decisions related to pedestrian crossings are reviewed. Afterwards, computational models of road user behaviour and interaction are reviewed.

1.1.1 Empirical studies on (automated) vehicle-pedestrian interaction

This section discusses different approaches to study road user interaction, namely naturalistic and controlled studies expressing the identified research gap in each section.

Naturalistic studies

Naturalistic studies are referred to as those studies undertaken to provide insight into road user behaviour during everyday trips in the real-world by recording details of the road user, vehicles and the surroundings through unobtrusive data collection methods. These studies are usually divided into on-site studies and studies with instrumented vehicles. On-site studies are conducted using different types of sensors including the ones from drones (Bock et al., 2020; Laksham, 2019) and static video cameras installed near the road facility (Ismail et al., 2009). Instrumented vehicles are usually equipped with GPS devices, accelerometers, radar and LiDAR sensors, onboard diagnostics (OBD), video cameras, eye-tracking devices, etc (Singh & Kathuria, 2021). Using instrumented vehicles allows researchers to study driver behaviour for a longer time, with high quality and to follow a large set of parameters including those related to eye movement (Uchida et al., 2010), lateral and longitudinal acceleration (Singh & Kathuria, 2021) and the vehicle's angular rate, angular altitude, and yaw rate (Mahapatra & Maurya, 2013). Nevertheless, this approach comes with a drawback, as it can be costly, and drivers are typically conscious of being under observation (Ehsani et al., 2021), potentially leading to altered behaviour (van Haperen et al., 2019). Conversely, video and sensor-based studies provide the advantage of discreetly recording road user behaviour, allowing for a deeper understanding of road user behaviour and its characteristics while avoiding behavioural adjustments (van Haperen et al., 2019).

Overall, site-based studies have been used to study vehicle-pedestrian interactions at roundabouts (C. Li et al., 2022) and at intersections with various objectives including investigating driver-pedestrian secondary interactions, i.e. interactions between vehicles exiting the intersection and crossing pedestrians; Fu et al., 2019; see also Cloutier et al., 2017, 2019; Ismail et al., 2009; Stipancic et al., 2021 for more studies at intersections. They have been used also to study pedestrian dangerous behaviours like red light running (Brosseau et al., 2013; Zhu et al., 2021) and child pedestrian rule compliance (Cloutier et al., 2022) at signalised crossings. Moreover, they have been considered for unsignalised crossings (Y. Zhang, 2019) to understand pedestrian crossing route choice (Z. Zhang et al., 2023), the effect of yielding cameras on road user conflicts (H. Li et al., 2023), the effect of driver yielding behaviour as a function of vehicle heterogeneity (Wang et al., 2021) and the effect of pedestrian social groups on different phases of road crossing (Barón et al., 2023). Finally, they have served a purpose for courtesy crossings to understand driving yielding behaviours (Anciaes et al., 2020).

Instrumented vehicle studies have been conducted to understand driver behaviour and performance in different scenarios such as car-following (Hammit et al., 2018; James et al., 2019; Kusano et al., 2014), lane change (Das & Ahmed, 2021; Doshi & Trivedi, 2009), gap acceptance (Hutton et al., 2015; Yang et al., 2019), speed selection (Ghasemzadeh et al., 2018; Khan & Ahmed, 2020), crash and near-crash causation (Charly & Mathew, 2020; Montgomery et al., 2014; Papazikou et al., 2019) and prediction (Jovanis et al., 2011; Ryder et al., 2019), distraction (Owens et al., 2018; Risteska et al., 2018) and also their interaction with pedestrians and cyclists (Feng et al., 2018; Habibovic et al., 2013).

Overall, although naturalistic data hold significance, its primary contribution lies in providing correlational information (Carsten et al., 2013) rather than establishing causal relationships between different factors. Additionally, no existing open datasets has ever provided extensive data specifically on vehicle-pedestrian interactions at unsignalised locations.

Controlled studies

To comprehend and model the causal mechanisms behind the road user behaviour, controlled studies are proved to be more advantageous. Controlled studies regarding vehicle-pedestrian interaction can be divided into two categories: virtual reality (VR) and test track studies. Both types of studies provide a safe and controlled environment, where the experimenter(s) can manipulate the conditions of the study to investigate the influence of various traffic scenarios on road users' behaviours and interaction outcomes. Additionally, this technique enables the observation of participants on multiple occasions. Lastly, investigating road user personality traits and psychophysical states is possible via this method providing valuable insights into interindividual differences.

VR studies are usually conducted using head-mounted displays (HMDs), screen-based setup and CAVE (Cave Automatic Virtual Environment; Cruz-Neira et al., 1992) for pedestrians (Tran et al.,

2021) and driving simulators for drivers (Bruck et al., 2020). HMDs offer a cost-effective and convenient option, as they only require a helmet with 3D goggles projecting high-quality images and some walking space (Mestre, 2017). Moreover, HMDs exhibit a different field of view pattern compared to other displays. While they have a limited field of view (approximately 110◦ vertically and 100◦ horizontally), they provide a 360◦ field of regard, creating a heightened sense of immersion by isolating the viewer from the real world (LaViola Jr et al., 2017). The CAVE system (Fig 1.1) comprises large surrounding screens that project high-resolution computer-generated images, creating an immersive experience for the user. This setup allows for realistic street crossing scenarios to be easily observed and measured in a naturalistic manner (Pala et al., 2021b). Both HMDs and CAVE-based simulators have their own downsides: compared to CAVE, HMDs have been found to cause motion sickness (Deb et al., 2017) and postural instability (Robert et al., 2016) more frequently. On the other hand, implementing the CAVE technology is a considerable expense, and it demands a substantial amount of space due to the large screens and rear projectors involved. Plus, unlike HMDs, the immersive experience of the viewer is interrupted when they look at the ceiling or areas where screens are absent (Pala et al., 2021a).

Figure 1.1. The CAVE-based pedestrian simulator at University of Leeds

Overall, previous research has shown that about two-thirds of experimental tasks in VR regarding pedestrians are related to road crossing scenarios (Schneider & Bengler, 2020). Regarding the comparison of these two simulators, pedestrians using HMDs have been found to cross more and accept smaller gaps, take less time to cross, and have a larger safety margin compared to the CAVE group (Mallaro et al., 2017; Pala et al., 2021b, 2021a).

Driving simulators are in charge of giving the illusion of driving in the real world to the participants as much as possible. Fig 1.2 shows the diagram of a typical driving simulator (left) and the University of Leeds driving simulator (right). The vehicle model uses driver input to calculate vehicle dynamics, which are then utilised by feedback systems to provide necessary cues to the driver. The scenario control incorporates environment definitions (terrain) and vehicle dynamics to generate visual and sound cues. Furthermore, haptic feedback mechanisms, including dynamic seats and belts and steering torque, are utilised to provide cues derived from the vehicle's dynamics. In instances involving the use of multiple projectors to generate a seamless image on curved screens within simulators, pre-projection tasks encompass image warping and blending (Bruck et al., 2020).

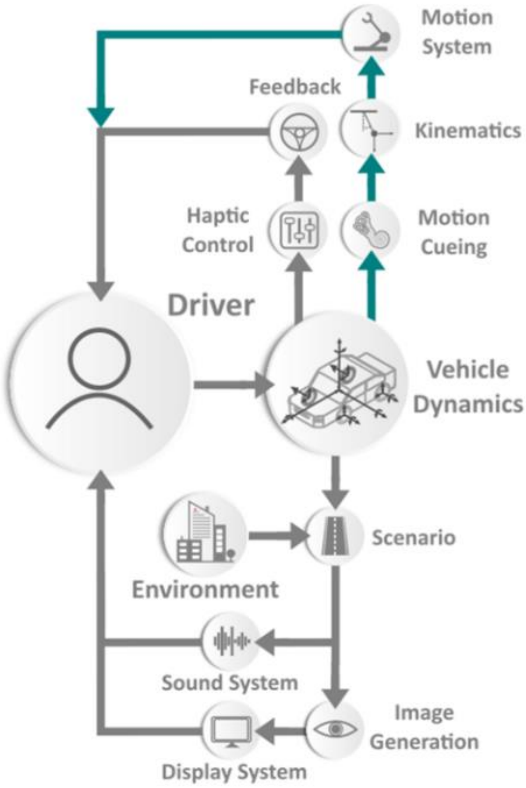


Figure 1.2. Left: A diagram of a driving simulator, the presence of green arrows within the sequence indicates the inclusion of optional systems designed to facilitate motion within driving simulators, (Bruck et al., 2020; reprinted under a CC-BY license). Right: The University of Leeds Driving Simulator (UOLDS).

An important point regarding the driving and pedestrian simulators is their ‘fidelity’ which usually refers to the degree to which they replicate real-world driving (Wynne et al., 2019) and walking experiences, respectively. This could be explained in terms of psychological fidelity, concrete fidelity, perceptual fidelity, behavioural fidelity, task fidelity, functional fidelity, and motion fidelity (De Winter et al., 2007; Goode et al., 2013). However, as stated by Wynne et al. (2019), a more proper approach would be to divide these into three groups: fidelity of vehicle controls (physical), field of view (visual), and the kinaesthetic feedback (motion) provided to the driver. Thus, when talking about ‘high fidelity’ simulators, these three aspects are the targets of the current thesis. Overall, driving simulators have been used to investigate drivers’ fatigue and drowsiness (G. Matthews et al., 2019; Soares et al., 2020), alcohol consumption (Yadav & Velaga, 2021), distraction (Boboc et al., 2022; Voinea et al., 2023), their interaction with other road users (Farah et al., 2019; Lindner et al., 2022) and especially pedestrians (Obeid et al., 2017; Tran et al., 2021), developing human-machine interface (HMI) (Large et al., 2019) and autonomous systems such as advanced driver assistance systems (ADAS) (Cohen-Lazry et al., 2019) and studying the effect of road infrastructure on driving performance (Bobermin et al., 2021).

Driving in a simulator (even in a high fidelity one) will never be the same as driving in reality. Thus, one main concern with laboratory-based experiments is the reliability and validity of the apparatus in replicating real-world performance. Reliability refers to the simulator's capability to produce consistent results over time. In driving research, reliability studies may involve participants completing the simulator task multiple times, with subsequent analyses comparing driving performance across these sessions (see Contardi et al. 2004; Davenne et al. 2012; Iwata et al. 2021 as examples). On the other hand, validity pertains to how faithfully the simulator represents real-world driving (Wynne et al., 2019). Reliability is solely affected by unsystematic errors of measurement, whereas validity can be influenced by both unsystematic and systematic (constant) errors. In essence, reliability is a necessary but not sufficient condition for establishing validity (Blana, 1996). The behavioural validity of a driving simulator can be explained in terms of absolute validity and relative validity. While absolute validity is attained when the numerical values of driving behaviour measures observed in both the simulated world and real-world are the same in absolute terms (Wynne et al., 2019), relative validity assesses how closely the variation of a factor in the simulated world corresponds to its influence in the real-world (Branzi et al., 2017) and it is realised when the difference in driving behaviour measures between experimental conditions is of the same order and direction (Kaptein et al., 1996; Wynne et al., 2019). Overall, although several studies have attempted to validate driving simulator research, there is limited research on the validity of pedestrian simulators, including CAVEs. This raises the question of whether pedestrians perform similarly in a VR environment compared to the real world.

Test track studies are also controlled studies that have been used to understand pedestrian-vehicle interactions including HAVs. As HAVs are currently not available for the general public and independent researchers, Wizard-of-Oz (WoZ) techniques have been used enabling researchers to prototype interactions between HAVs and pedestrians using conventional vehicles with minor physical modifications making them appear automated. Some methods include Ghostdriver (with a driver underneath a costume) and right-hand drive vehicles with fake steering wheels (Moore et al., 2019). That said, very few studies have used real HAV to investigate such interactions (Horn et al., 2023). WoZ method has been used for understanding the effects of different external HMI (eHMI) on pedestrian crossing decisions (Bindschädel, Weimann, and Kiesel 2023; Faas and Baumann 2019; Faas, Stange, and Baumann 2021; Hensch et al. 2019; Wang et al. 2021), comparing pedestrians' behaviour in front of conventional versus automated vehicles (Palmeiro et al., 2018), investigating pedestrian behaviour and interaction related metrics (Bindschädel et al., 2023; Bindschädel & Kiesel, 2022; Fuest et al., 2020; Rothenbücher et al., 2016) and validating the studies of the same nature in VR (Schneider et al., 2022). WoZ studies have been mostly utilised to study crossing intention rather than actual crossing most of the time because pedestrians are not allowed to actually walk in front of the vehicle for ethical reasons (Palmeiro et al., 2018) which makes the application of this method rather limited.

Overall, a key takeaway from this section is that controlled studies offer much greater flexibility in studying various traffic scenarios within a safe and controlled environment, making it possible to test causal hypotheses. However, there is a need for validation studies to evaluate their validity and reliability. Additionally, most of these studies lack actual interaction between two or more humans, as explained below.

Distributed simulation

All the VR studies that were mentioned in the last section concern the interaction of a human road user (driver/pedestrian) with a pre-programmed computer agent (driver/pedestrian) which lacks the true nature of the interaction. This could make the results coming out of the lab questionable as it is not quite clear whether human behaviour would have been the same if they interacted with another human agent. To address this shortcoming, a rather novel methodology has been introduced named distributed simulation (also known as co-simulation and/or coupled/linked simulation; Andersson, 2019). In this method, two or more road user simulators are connected over a network where two or more human road users can communicate with each other in a VR environment. Thus, in addition to the advantages that VR studies offer such as controllability, repeatability and safety, the aspect of interactive communication will be also added to the study.

Coupling the simulators in the road traffic context dates back to 2003 when Hancock & De Ridder (2003) conducted a behavioural analysis of drivers' response in the final seconds before a collision using two adjacent, full-vehicle simulators, both operating within a common virtual world. The vehicles were visible to each other, allowing the drivers to interact with one another in the virtual environment. After that, a few other researchers conducted distributed simulation studies connecting two or more driving simulators to each other (Houtenbos et al., 2017; Maag et al., 2012; Mühlbacher et al., 2011; Yasar et al., 2008). However, the first instance of studying vehicle-pedestrian communication patterns can be found in a work by Lehsing et al. (2016) where they connected a desktop driving simulator to a desktop pedestrian simulator. Both programmed and human-controlled pedestrians crossed a zebra and non-zebra crossings while the latter had an additional scenario where pedestrians crossed behind an object. Vehicle time-to-arrival (TTA), braking pressure, and average speed were collected and compared between human-human interaction and human-bot interaction scenarios (Lehsing et al., 2016; Lehsing & Feldstein, 2018). Later a similar methodology was employed by Bazilinskyy et al. (2020) where a human-controlled (by keyboard) passenger in an HAV interacted with both a human driver behind a desktop driving simulator and a human pedestrian equipped with an HMD. The objective of the study was to provide an open-source linked-simulator software helping the advancement of human factors research into interactions between pedestrians and HAVs. Hence, the authors did not investigate interaction-related metrics. In 2022, however, a human pedestrian on HMD interacted with a human driver behind a desktop driving simulator to understand if the presence of eHMI, displaying the direction for the pedestrian to move, resulted in safer and more predictable interactions in near-collision scenarios compared to the eHMI being turned off. This time both road users' trajectories and kinematics were analysed regarding the eHMI conditions (Bazilinskyy et al., 2022).

Sadraei et al's (2020) study together with the study at NADS (The National Advanced Driving Simulator) (Kearney et al., 2020) are the only studies that connected a CAVE-based pedestrian simulator to a driving simulator. To better understand the mechanism of this type of simulation, Sadraei et al's study (2020) is used as an example as a similar mechanism is utilised in the study of Chapter 2. In Sadraei et al.'s study (2020), a desktop driving simulator was connected to the HIKER (Highly Immersive Kinematic Experimental Research) pedestrian lab to study the interactive behaviour of pedestrians and drivers under automated and human-driven (HD) conditions. The distributed simulation mechanism and the network components can be seen in Fig 1.3. Unit B facilitated the experimenter's control over the experimental scenario, allowing real-time observation of both the pedestrian and driver. On the other hand, Unit-A was the machine where the driver interacted with the desktop driving simulator. Inside Unit-A, SimulatorD (i.e. an in-house developed software at the University of Leeds) was receiving the driver's control inputs (steering, gas, and brake) from the driving simulator device and forwarded them to Unit B. Furthermore, SimulatorD was receiving pedestrian states from Unit B and sending them to Turner in Unit A, where they were combined with car states coming from Unit B to render the information to the driver (Sadraei et al., 2020). During the experiment, the pedestrian was instructed to cross between two vehicles: a white car and a blue car. The white car's actions were consistently controlled by software, whereas the blue car was operated by a human driver in 50% of the trials and by an automated vehicle in the remaining 50% of the trials. Overall, interaction outcomes and vehicle speed and deceleration profiles were analysed (Kalantari et al., 2022).

Overall, this section suggests that the past distributed simulation studies mostly used low-fidelity driving and pedestrian simulators with the scenarios being mostly simple and far from the actual interactions that happen in real traffic. Additionally, the causal effect of road user kinematics on interaction outcomes has not been well studied.

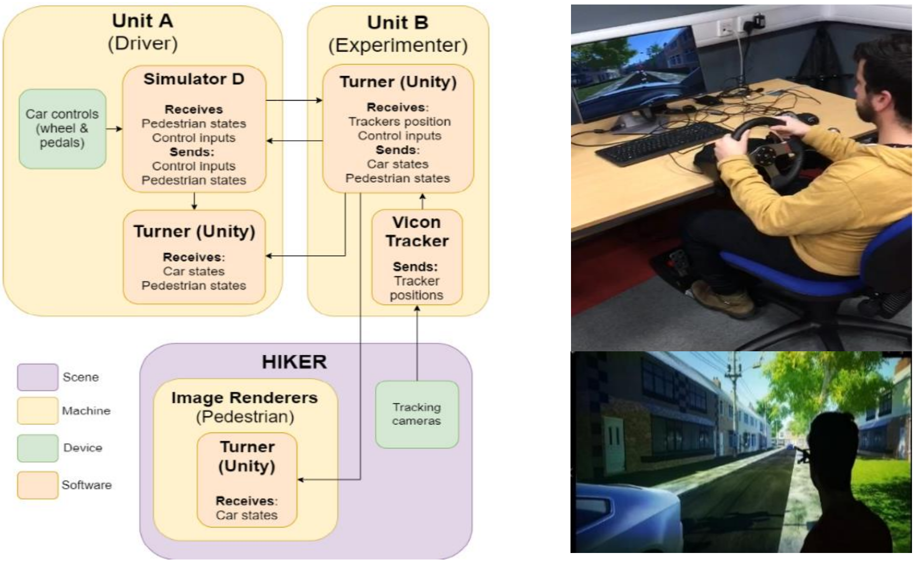


Figure 1.3. Distributed simulation mechanism (left) and the desktop driving simulator (top right) and the pedestrian in the HIKER lab (bottom right) at Virtuocity, University of Leeds (Sadraei et al., 2020).

1.1.2 Road user characteristics and interaction outcome factors

In this section, first, the role of pedestrian characteristics in crossing behaviour is reviewed and then other factors such as pedestrian walking behaviour regarding environmental factors, etc. are discussed. Finally, a section with respect to implicit and explicit communication is dedicated to shed light on elements which can describe the quantity/quality of crossing decisions.

Pedestrian characteristics

Here, characteristics refer to pedestrian age, gender, country of residence and its associated culture. Studies show that older adults (mostly above 65 in the literature) have slower walking speed and longer crossing durations (Ishaque & Noland, 2008; Rasouli & Tsotsos, 2019; Wilson & Grayson, 1980), variable walking pattern (Goldhammer et al., 2014), more risky crossing behaviour in complex traffic (J. Oxley et al., 1995), higher accident rates (Olszewski et al., 2015; Pour-Rouholamin & Zhou, 2016) and have more problem in estimating the vehicle speed (Camara et al., 2020; Rasouli & Tsotsos, 2019). Moreover, children’s unpredictable behaviours, distraction, and threat perception have been found to be the main reasons for child pedestrian accidents (Amini et al., 2019) as they are less capable of assessing vehicle speed correctly (Rasouli & Tsotsos, 2019). Riskier behaviours (passing in the red phase, passing between moving vehicles also known as accepting rolling gaps, etc.) have been observed in younger pedestrians (Granié et al., 2013; Narváez et al., 2019; Zafri et al., 2020) and they have been found to be less predictable (Rasouli & Tsotsos, 2019).

Generally, it has been observed that women have higher risk perception (Amini et al., 2019; Rasouli & Tsotsos, 2019), although no significant difference has also been found in some studies (Alver & Onelcin, 2018; Narváez et al., 2019; Papadimitriou et al., 2016), are more concerned about social values (Rasouli & Tsotsos, 2019), have lower crossing speed (Amini et al., 2019; Deb et al., 2017; Rasouli &

Tsotsos, 2019), have different attention patterns (Tom & Granié, 2011) and experience lower rates of severe injuries or fatalities (Olszewski et al., 2015; Pour-Rouholamin & Zhou, 2016). Men, on the other hand, have been found to violate traffic laws more (Lipovac et al., 2013; O'Hern et al., 2020; Tom & Granié, 2011).

Previous research has shown that instances of walking on red are significantly influenced by the pedestrians' country of residence and its culture (Pelé et al., 2017) and the findings about age and gender is country-dependent at least with respect to signalised intersections (Pelé et al., 2019a, 2019b). It has been also revealed that even neighbouring developed countries may have different attitudes towards crossing behaviour due to their culture (Papadimitriou et al., 2013; Pucher & Dijkstra, 2003).

Standing/walking behaviour

While it has been suggested that walking pedestrians (towards the crossing location) are less conservative (compared to standing ones) when it comes to crossing the road because of having a better grasp of kinematic cues (Oudejans et al., 1996), later, some evidence proved the opposite (Fajen, 2013) stating that standing still pedestrians can better estimate the kinematic cues. Pedestrians tend to walk faster at signalised intersections and when they are alone, the vehicle has the right of way, or when the traffic volume is high (Amini et al., 2019; Rasouli & Tsotsos, 2019). Walking speed is influenced by road structure, group size, age, gender, time of day, country and weather (Amini et al., 2019; Rasouli & Tsotsos, 2019).

Group size

In terms of the effect of group size, drivers have been found to be more likely to yield to pedestrians in group (Anciaes et al., 2020); when the number of waiting pedestrians increases from three to six, the yielding probability is two times greater (Sucha et al., 2017; Sun et al., 2003). The probability of a group of four pedestrians attempting to pass a crossing is 70% higher than a single pedestrian (Himanen & Kulmala, 1988). Besides, pedestrians are less cautious when crossing in group and pay less attention to vehicles (Rasouli & Tsotsos, 2019). Group size influences the pedestrian flow and as a result walking speed (Rasouli and Tsotsos, 2019). Moreover, the proportion of '*hard-yield and stop*' grows significantly if the group size becomes bigger (Amini et al., 2019). Concerning social connections, three strangers in a group are less likely to assert themselves in a crossing than three friends (Camara et al., 2020). Pedestrians make crossing decisions earlier when other pedestrians also crossed slightly earlier, compared to when there were no other pedestrians (Mahadevan et al., 2019); this can be explained by the theories behind conformity stating the more conformist a pedestrian is, the more likely they are to cross the road if another pedestrian does (R. Zhou et al., 2009).

Waiting time

Research suggests that waiting time is a key element in pedestrians' willingness to violate traffic signals (Brosseau et al., 2013; Van Houten et al., 2007; Zhuang et al., 2018) and an increase in waiting time would increase the chances of accepting lower gaps, however, this should be examined in the context of pedestrian characteristics, road geometry and vehicle features (Amini et al., 2019; J. A. Oxley et al., 2005; Palmeiro et al., 2018; Rasouli & Tsotsos, 2019). As stated by Cœugnet et al. (2019), waiting time can simultaneously sustain safe decision-making as it allows comprehension of the road situation among the more cautious or hesitant pedestrians. It has also been found that pedestrians tend to wait longer before they violate traffic signals at intersections with countdown signals and during peak hours (Xiong et al., 2019). Nonetheless, prior studies have indicated that it may not be a valid assumption to assume that pedestrians consistently choose riskier crossings as their waiting time increases (Tian, 2023). Hence, previous research has presented somewhat contradictory findings concerning the role of waiting time in pedestrians' crossing decisions. Furthermore, another factor relating to time, time pressure, might have deleterious effects by reducing the quality/quantity of the information considered, thus elevating the risk-taking (Morrongiello et al., 2015); for instance, it has been observed that pedestrians under time pressure make risky decisions in nearly 65% of their road crossings (Cœugnet et al., 2019) which is in relation to the feeling of irritation and anger (Cœugnet et al., 2013).

Pedestrians accept a shorter gap when they are waiting on central refuge islands (where they have the lowest irregular movements; Mako 2015), in comparison with the kerb side, or in narrow streets rather than wide ones (Amini et al., 2019). They also seek rolling gaps (i.e. the minimum acceptable gap when crossing a multi-lane road, determined by varying crossing speed and direction.) in high traffic volume and narrower medians (Brewer et al., 2006; Dutta & Vasudevan, 2017; Zafri et al., 2020). The number of lanes has also been identified as a critical factor influencing pedestrians' waiting time at unsignalised midblock crosswalks (J. Zhao et al., 2020).

Vehicle size/colour

Pedestrians tend to be more cautious when facing bigger vehicles and the probability of crossing becomes lower if the vehicle is a lorry or a truck (Amini et al., 2019; Rasouli & Tsotsos, 2019). This can be explained in terms of utility functions in asymmetric games (Fox et al., 2018) or the size-arrival effect which has been shown to affect distance/speed estimation (DeLucia, 2013). To support this, it has been indicated that vehicle size affects judgments specifically for the larger actual TTAs (2 and 3 s), with double-sized cars being estimated as arriving sooner than normal-sized cars (Mathieu et al., 2017). In addition, the colour of the vehicle has been found to be relevant in crossing decisions where pedestrians judged dark vehicles to be a more imminent threat compared to light ones (either by moving faster or being closer) (Feldstein & Peli, 2020).

The role of communication in crossing decisions

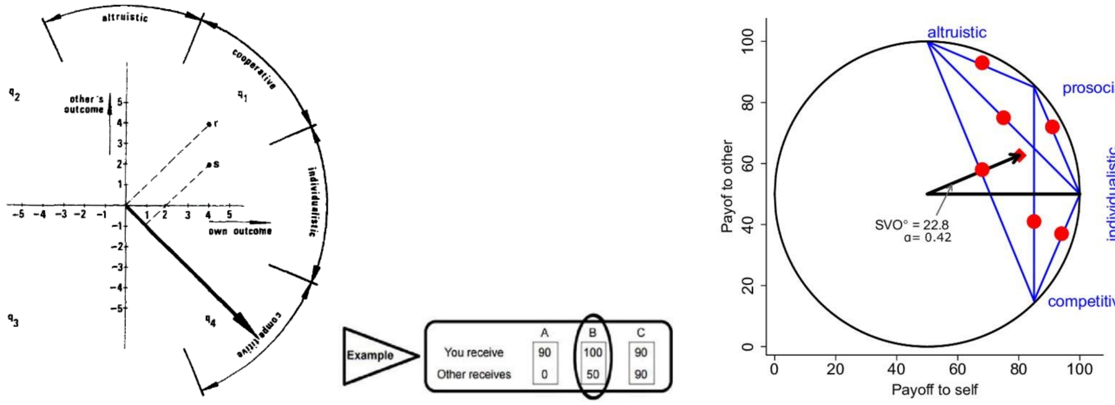
HMI can be divided into implicit and explicit communication. According to Markkula et al. (2020), implicit communication is: 'A *road user behaviour which affects own movement or perception, but which can at the same time be interpreted as signalling something to or requesting something from another road user*.' and accordingly explicit communication is: '*A road user behaviour which does not affect own movement or perception, but which can be interpreted as signalling something to or* *requesting something from another road user*.' Implicit communication in terms of vehicle-pedestrian interaction can be explained as kinematic cues (acceleration, deceleration, etc.), head/gaze orientation/direction of pedestrians or their gate or presence at the kerb (Amini et al., 2019). Explicit communication with respect to conventional cars can be defined by turn indicators, brake lights, emergency lights, warning lights, horns and labelling a vehicle (Amini et al., 2019). Regarding AVs, both external-and-internal HMIs (eHMI-and-iHMI) are important in an interaction. External refers to any communication process happening in the surrounding of the vehicle and internal refers to the communication processes that happens between the driver and the vehicle. Instances of eHMI encompass visual cues (comprising text-based directions, symbolic icons, animated human-like figures, etc.) as well as multi-modal communication and overloading of information (a combination of recurring visual and auditory signals from the vehicle, along with the integration of contextual awareness into the urban landscape).

Regarding implicit communication, vehicle speed is one of the most important factors in pedestrian decision making (Amini et al., 2019; Theofilatos et al., 2021); an increase in vehicle speed deteriorates pedestrians' ability to assess it (Rasouli and Tsotsos, 2019). The impact of speed on interaction outcomes seems to be different between naturalistic and VR studies: some VR studies suggest that at higher speeds pedestrians tend to behave more recklessly and accept smaller gaps (S. Schmidt & Faerber, 2009; Tian et al., 2022; Velasco et al., 2019) whereas naturalistic studies found s reverse relationship between approaching vehicle's speed and the likelihood of pedestrians' crossing first (Theofilatos et al., 2021). Overall, in complex and busy traffic scenarios with low visibility conditions such as adverse weather the role of implicit communication is more critical (Ackermann et al., 2018; Rasouli & Tsotsos, 2019) as the growth in the number of AVs could result in information overload (S. K. Jayaraman et al., 2019). It also has been suggested that the most comfortable deceleration type is the one with a smooth speed reduction and proper distance (Palmeiro et al., 2018; Pillai, 2017); a defensive deceleration strategy results in earlier crossing decisions (Schieben et al., 2019). Also, there is no 'one-fits-all' solution for comfortable braking; vehicle speed and daytime are important as well (Beggiato et al., 2017). Additionally, some argue that a vehicle is considered simply as a moving obstacle to pedestrians (Rasouli & Tsotsos, 2019) but it has been shown that pedestrians might employ vehicle kinematic cues to infer social intentions and not only as the state of a moving entity (H. Schmidt et al., 2019). Overall, there is enough evidence to support that pedestrians mostly use implicit cues when deciding to cross the road (Dey & Terken, 2017; Fridman et al., 2017; Jayaraman et al., 2019; Lee et al., 2021; Palmeiro et al., 2018) and have more trust in defensive AV (Ackermann et al., 2018; Jayaraman et al., 2019; Pillai, 2017).

On the other hand, explicit communication has been mostly observed in the absence of traffic regulation (e.g. no traffic light) (Amini et al., 2019) and to be more precise when the AV/vehicle does not behave as expected by the other road users (Dey & Terken, 2017). It has been found that pedestrians' perceived safety is increased when there is an eHMI to communicate with (Chang et al., 2017; De Clercq et al., 2019; Habibovic et al., 2018) and it could decrease the crossing duration in case AV wants to give the right of way or make the situation clear for the pedestrian in deadlock scenarios (M. Matthews et al., 2017).

Social value orientation

To effectively handle social dilemmas in the road traffic context, road users must construct mental models of their social surroundings and adjust their behaviour based on the decisions made by others. One of the constructs that helps explain these mechanisms is social value orientation (SVO). SVO formalises one's concerns about others' welfare and usually refers to an individual's preference about how to allocate resources (e.g. money) between the self and another person. There are several ways to measure SVO but among them, ring measure (Liebrand, 1984), triple-dominance measure (Van Lange et al., 1997) and SVO slider measure (Murphy et al., 2011) are more commonly used. Ring measure is based on SVO geometric framework suggested by Griesinger & Livingston Jr (1973) (See Fig 1.4-a). Participants are presented with 24 pairs of options that involve allocating money between themselves and an 'other' individual. Through an examination of the participant's 24 decisions, a motivational vector is formed, characterised by a specific magnitude and direction. The length and the angle of this vector indicate the coherence of the participant's decision-making patterns and SVO, respectively (Fig 1.4-a) (Liebrand, 1984). The triple-dominance measure comprises nine items, each presenting the subject with a choice among three own-other-outcome allocations. To evaluate a participant's SVO using this metric, their decisions in a minimum of six out of the nine scenarios are taken into account (Fig 1.4-b) (Van Lange et al., 1997). The SVO slider measure is a choice task that can be administered online or on paper. It consists of six primary and nine secondary items. In these items, participants make resource allocation choices, dividing money between themselves and another fictional person along a continuum of joint rewards. The SVO angle can be computed from the primary items whereas the secondary items serve the purpose of distinguishing between the motivations to maximise the joint outcome and to minimise the difference in outcomes (inequality aversion) among prosocial subjects (Fig 1.4-c) (Murphy et al., 2011). This measure is used in Chapter 2 to quantify both drivers' and pedestrians' SVO. Overall, high SVO values signify an altruistic disposition, while progressively lower values correspond to prosocial, individualist, and competitor tendencies, in that order.



a b c

Figure 1.4. Different measures of SVO: a) Ring Measure (© 2006 John Wiley and Sons, reprinted with permission from European Journal of Social Psychology; Liebrand, 1984), b) Triple Dominance (Van Lange et al., 1997) and c) Slider Measure (Murphy et al., 2011 under a CC-BY license).

To date, some studies have employed SVO in their models and algorithms to predict and understand road user interaction with most of them studying HAV-HD interaction. Schwarting et al. (2019) found that incorporating SVO into driver models would result in a 25% reduction in errors in human trajectory predictions by HAVs in challenging traffic scenarios such as merging lanes and unprotected left turns. Valiente et al. (2022) showed that altruistic HAVs have the capability to learn the decision-making process through experience, taking into account the interests of all vehicles while giving priority to safety. As a result, they can effectively utilise social coordination to enhance safety and reliability on the roads. SVO has also been employed to tackle the motion planning problem in mixed traffic scenarios involving interactions between HAVs and human drivers. This approach generated an objective function that enabled the HAV to adjust its behaviour appropriately based on the level of cooperation exhibited by the human driver (Le & Malikopoulos, 2022). X. Wang et al. (2021) created a safety evaluation framework for HAVs regarding highly-interactive driving scenarios such as roundabout entering and highway merging showing that the SVO-enabled framework outperformed other conventional sampling methods. Another study indicated that the use of SVO to characterise drivers allows the generation of unique interaction evolution patterns based on their individual social attributes. The agents' social preferences influence the temporal consistency of their behaviours, which, in turn, impacts the quality of interactions, including driving progress (X. Zhao et al., 2021). Very few studies also investigated HAV-pedestrian interactions employing SVO. Crosato et al. (2021) demonstrated that incorporating SVO in the deep reinforcement learning (DRL) reward function design resulted in the trained vehicle agent exhibiting humanlike behaviour. The SVO value directly affects the likelihood of the trained agent yielding to pedestrians. Later, they presented a novel pedestrian model for computer simulations, integrating a risk assessment based on situational awareness to predict pedestrians' crossing behaviour. Their work demonstrated SVO as a valuable tool in creating DRL algorithms for applications involving human-machine interaction (Crosato et al., 2022).

All in all, SVO has been used in various computational models and engineering frameworks for AV development, but it has not actually been studied in empirical research on road user interactions – to see if road user SVO affects interactions.

1.1.3 Models of human decision-making and behaviour prediction

Many real-world road user interactions can be framed as dynamic exchanges involving competitive entities. In this context, agents' physical attributes (i.e. position, orientation, and speed) and internal conditions (including navigation goals, behavioural traits, and their mental representation of the environment) can be integrated within a mathematical framework (K. Brown et al., 2020). Within this framework, it becomes possible to model and study various tasks related to road users, particularly HAVs. These tasks encompass the estimation of states, intentions, risks, and traits, as well as the prediction of motion and the emulation of behaviours (K. Brown et al., 2020). In the domain of modelling road user behaviour, two types of architectures are commonly distinguished: glass-box and black-box models (Rai, 2020). Black-box models, including deep learning models, are valued for their generalisability and high accuracy in simulating the behaviour of multiple interacting agents (Mozaffari et al., 2020). However, these models lack interpretability due to the unknown underlying mechanisms and limited understanding of the connections between inputs and outputs (Gilpin et al., 2018). This lack of interpretability also hinders their alignment with human psychological theories (Markkula et al., 2023), making them challenging to interpret. On the other hand, glass-box models offer the advantage of interpretability and transparency by providing detailed explanations for their mechanisms. Hence, in the current thesis, the focus is on glass-box models but the application of black-box models in combination with glass-box models in previous research is also mentioned. The review of glass-box interactions models below will divide existing models into agent-based models (force-and-cellular-based models), gap acceptance models, evidence accumulation models, Markovian process models, game-theoretic models and finally hybrid models.

Agent-based models (ABMs)

Agent-based models (ABMs) (also known as individual-based models, IBMs) consist of a collection of autonomous decision-making agents and the relationships between them where each agent evaluates its situation separately and makes choices according to a set of rules (Bonabeau, 2002). ABM assumes pedestrian crowds as independent and intelligent entities who are capable of reacting to certain events adapting themselves to a complex dynamic environment (El Helou, 2016). While some studies assume pedestrians as point masses [e.g. (Adamey, Kurt, and Özgüner 2013)], others considered other factors like pedestrian characteristics [e.g. (El Helou, 2016)] to produce more realistic crowds and concentrate on one-on-one pedestrian interaction. All in all, ABMs have the shortcoming of focusing on the level of the constituent units rather than the aggregate level. Moreover, simulating all units can be a computationally intensive job to do and as a result, time consuming (Bonabeau, 2002).

ABM can be defined in different forms and with the help of different models; here force-based and cellular-based models are described briefly.

Force-based models which are continuous in space, take Newton's second law of dynamics as their guiding principle and simulate the trajectories of pedestrians based on their reaction to the surroundings. In these models, pedestrians' movements are due to external forces acting on them which can be split into repulsive and driving forces (Chraibi et al., 2011). While the former simulates the collision-avoidance behaviour of pedestrians, the latter seeks to model pedestrians' intention to move to a certain destination with a desired speed (Chraibi et al., 2011). Fig 1.5 shows the application of SFM in modelling pedestrian crossing behaviour. The models are generally divided into social-and-centrifugal force models (Helbing & Molnar, 1995; W. J. Yu et al., 2005). The social-force model (SFM) suggests that 'social forces' like the interaction with other pedestrians, paths without detours and the effect of the environment (Helbing and Molnar, 1995) are chosen by pedestrians due to certain preferences and are not exerted directly and externally by the surroundings of the individuals (El Helou, 2016). SFM has been used so far for shift tracking algorithms (i.e. algorithms that iteratively move a data point to a position where the neighbourhood's average of data points is centred) for collision avoidance (X. Zhang et al., 2016), simulating pedestrian evacuation route choice in different evacuation scenarios (J. Zhou et al., 2019), describing vehicle crowd interaction scenarios (pedestrian tracking in complex interaction scenarios and vehicle trajectory planning) (Yang, Maroli, et al., 2018; Yang, Özgüner, et al., 2018; Yang & Özgüner, 2019) and road user interactions in shared spaces (Johora et al., 2020; Johora & Müller, 2018, 2020; Rinke et al., 2017; Schönauer, 2017; Schönauer et al., 2012; Yang et al., 2017) also with respect to pedestrian crossing (Yang et al., 2020; Zeng et al., 2014) and right-turn scenarios (P. Chen et al., 2019).

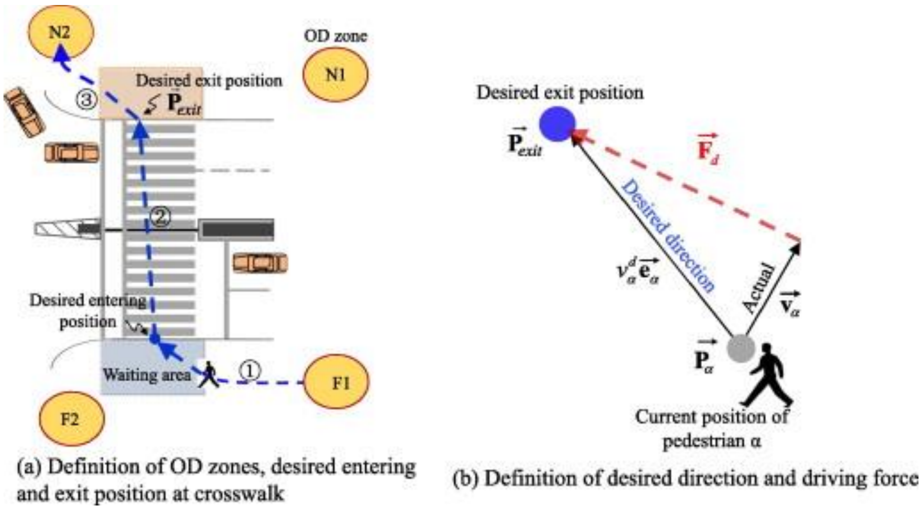


Figure 1.5. Application of SFM in modelling pedestrian crossing behaviour © 2014 Elsevier. Reprinted, with permission from Transportation Research Part C: Emerging Technologies (Zeng et al., 2014).

The centrifugal force model (CFM) incorporates factors such as relative velocity (meaning a faster individual in front of a slower one will not affect their motion) and headway among pedestrians when specifying the force. In contrast to the social force model (SFM), CFM makes different assumptions, such as the force being anisotropic to account for pedestrians' visual range, which is typically 180° (Chraibi et al., 2011). (Chraibi et al., 2011). It also provides a 'collision detection technique' which addresses the problem of overlapping pedestrians which can be explained as a failure of the avoidance mechanism in terms of repulsive forces (Chraibi et al., 2011).

Overall, despite the wide range of applications of force-based models, these models face challenges such as a trade-off between increasing the repulsive force with the aim of removing overlapping and/or decreasing this force to avoid any oscillations in simulation which is not an easy task to be accomplished. Additionally, in force-based models pedestrians continue their movement without stopping, leading to oscillations, while in reality, pedestrians may stop or change direction when they perceive that the path is blocked (Chraibi et al., 2011).

Cellular automata (CA) is a discrete, time-based model of computation that represents pedestrians as occupied cells within a field of empty cells arranged side by side (Camara et al., 2020; El Helou, 2016). A cell can be occupied provided it is empty and a pedestrian usually has three possible movements: frontal, lateral or mitigation of the conflicts (Camara et al., 2020). Each cell defines its 'neighbourhood' by identifying a collection of cells associated with that specific cell (Fig 1.6). At time t = 0, an initial state is assigned to each cell. Using a predefined mathematical function or rule, the subsequent generation (incrementing t by 1) is generated. This new generation dictates the updated state of each cell, taking into account the present state of the cell, as well as the states of the adjacent cells in its vicinity (reflecting awareness of the environment) (Toffoli & Margolus, 1987).

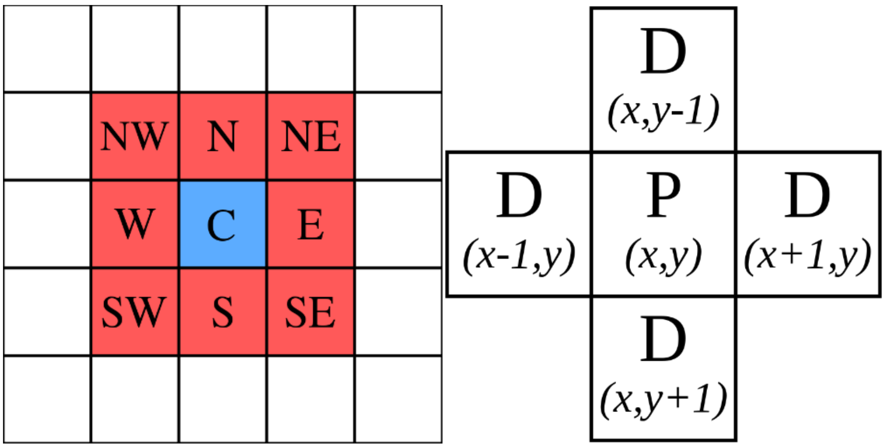


Figure 1.6. The two classical neighbourhoods used in CA: Moore is composed of nine cells consisting of a central cell and the eight cells which surround it (left) while von Neumann neighbourhood excludes the corner cells (right).

To date, different types of CA with different modifications have been proposed, some of them are behaviour-based (involving neighbour's behaviour and environmental characteristics) (Huang et al., 2017; Y. Li et al., 2020), extended (J. Hu et al., 2018) and adaptive (i.e. using traditional CA and a set of extensions to reconfigure pedestrians own internal structure and behaviour regarding observable events and rules which allows them to adapt and respond to environment changes) (Padovani et al., 2018). Overall, CA has been used for modelling vehicle-pedestrian conflicts in multi-lane roundabouts (Layegh et al., 2020), modelling traffic conflicts and driver behaviour in single-lane roundabouts (Dong et al., 2014; Echab et al., 2016; X. P. Yu et al., 2012), modelling vehicle/pedestrian behaviour at signalised intersections (Alhajyaseen & Iryo-Asano, 2017; Iryo-Asano & Alhajyaseen, 2017; X. Li et al., 2012), modelling vehicle/pedestrian interaction/conflict at unsignalised intersections/mid-blocks (Almodfer et al., 2016; P. Chen et al., 2016; Feng et al., 2019; Khallouk et al., 2018; Lu et al., 2016; Y. Wang et al., 2018; Wu et al., 2019; C. Zhang et al., 2017) and modelling vehicle-pedestrian conflicts at right-turns (Rao & Ni, 2016).

In general, both SFM and CA models operate under the assumption that pedestrians are mobile entities, disregarding their mutual intentions within each action and neglecting the interdependencies among them. Consequently, these models are less suitable for representing road users as highly intelligent agents as humans usually are.

Pedestrian gap acceptance models (GAMs)

In places where pedestrian infrastructure is lacking and compliance with traffic rules is low, gap acceptance becomes a critical factor affecting pedestrians' crossing choices. It has been suggested that pedestrians might have a critical gap in mind for crossing attempts which can be explained by the crossing length, their average walking speed and a safety margin (in seconds) which represents pedestrians’ risk acceptance, i.e. lower risk perception results in smaller safety margins (Yannis et al., 2013). Overall, traffic gap acceptance can be estimated by three approaches namely deterministic, i.e. where gap acceptance only depends on the (mean) gap sizes, modelling, i.e. which correlates the minimum gap from the vehicle accepted by pedestrians who want to cross the road with different parameters and probabilistic approach, i.e. where the probability of gap acceptance is computed as a random variable from a distribution that best fits the data (Sun et al., 2003).

In practice, a great proportion of existing literature has made use of the probabilistic approach, and the most common approach to modelling probabilistic decisions is a binary logit model. The logit model can be expressed as the following formulation:

$$ln(\frac{p}{1-p}) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n \quad (1.1)$$

where p is the probability of the event occurring (e.g. success in a binary choice), x_1,x_2, … , x_n are the independent variables (predictors) influencing the outcome, $\beta_0, \beta_1, \beta_2, \dots \beta_k$ are the coefficients corresponding to the respective independent variables and ln represents the natural logarithm.

In this formulation, the log odds of the event occurring (the left-hand side of the equation) is modelled as a linear combination of the predictor variables (the right-hand side of the equation) through the coefficients. The logit transformation allows the linear relationship to be mapped to a bounded range between 0 and 1, which is suitable for representing probabilities.

Using the binary logit technique and non-intrusive observations from real pedestrian-vehicle interaction scenarios, Wang et al. (2010) modelled and analysed the pedestrians' gap acceptance behaviour when jaywalking outside crossing facilities. Binary logit models along with a cross-validation method have also been developed to account for pedestrian gap acceptance behaviour regarding different roadway characteristics (Kadali & Vedagiri, 2020). Moreover, a combination of a lognormal regression and binary logit model has been used to analyse pedestrian gap acceptance at midblock crossings (Yannis et al., 2013). Employing a combination of multiple regression model and artificial neural network, Kadali, Vedagiri, and Rathi (2015) assessed the significant contributing factors for pedestrians' gap acceptance behaviour at uncontrolled midblock crossings under mixed traffic conditions. The logit model has also been compared to Maximum Likelihood Method (MLM), which considers the log-normal distribution of maximum rejected and accepted gaps, Raff's method, which is a deterministic approach using an empirical distribution function of accepted and rejected gaps, Root Mean Square (RMS) Method, which estimates a critical gap by minimising the sum of the root-mean-square function values and Probability Equilibrium Method (PEM), which relies on the probability equilibrium between the rejected and accepted gaps. The logit model has been found to be the most appropriate model for estimating the critical gaps (Vinayaraj et al., 2020). Other than logistic regression (Malenje et al., 2019), an extended full velocity difference (FVD) model, which integrates the probabilistic models of vehicle yield and pedestrian gap acceptance into the car-following model, has been developed to assess the impact of traffic and geometric factors on the functioning of these types of pedestrian crossings (J. Zhao et al., 2020).

In terms of signalised intersections, a Cumulative Weibull distribution function for accepted/rejected lags and gaps was used to predict how a driver considers the position of the pedestrian in a left turn (Alhajyaseen et al., 2013). Four left-and-right turn scenarios, data mining methods (i.e. decision tree and instance-based and random forest models) have also been used (Mafi et al., 2018). In addition, decision tree models have been employed to investigate the non-yielding, risky behaviour of turning drivers towards pedestrians and cyclists at signalised intersections (IASMIN, 2016). Concerning pedestrian behaviour at overpass locations, Raff's method and a binary logit model have been utilised to estimate the critical gap and time gaps, respectively (Alver & Onelcin, 2018).

Overall, while GAMs have shown promising results when it comes to vehicle-pedestrian interaction, they tend to fall short in capturing the intricate interdependencies among road users. They also, similar to many traditional modelling approaches, lack the concept of time making them good models for vehicle-pedestrian interaction outcomes prediction but not for simulating the decision-making process in drivers and pedestrians. In the next section, models that are capable of doing so are explained.

Evidence accumulation models (EAMs)

Evidence accumulation models (EAMs) (also known as sequential-sampling models) offer a good depiction of behaviour for specific kinds of decisions (Purcell & Palmeri, 2017) and suggest that evidence favouring a particular response gets synthesised through one or more accumulators over time, influenced by a rate termed the 'drift rate.' This drift rate signifies how swiftly sensory information reaches a decision threshold, which is influenced by the strength of evidence extracted from the stimulus or memory (Ratcliff et al., 2016) (see Fig 1.7). The accumulation process is characterised by noise, meaning that at each time step, evidence may guide attention towards either of the two boundaries (or two ends/poles of a single boundary). The boundary indicates the amount of evidence required to be reached before a response is triggered (Ratcliff et al., 2016). The time variation for accumulated evidence to reach threshold represents variability in observed response times and choice probabilities in a wide range of decision-making tasks (Evans & Wagenmakers, 2020; Purcell & Palmeri, 2017). In order for the models to reveal the mechanisms underlying decision-making variations across different experimental conditions, one can identify parameter values (i.e. speed-accuracy, experience and stimulus strength; Purcell and Palmeri 2017) that maximise the correspondence between observed and predicted behaviour (Vandekerckhove & Tuerlinckx, 2007).

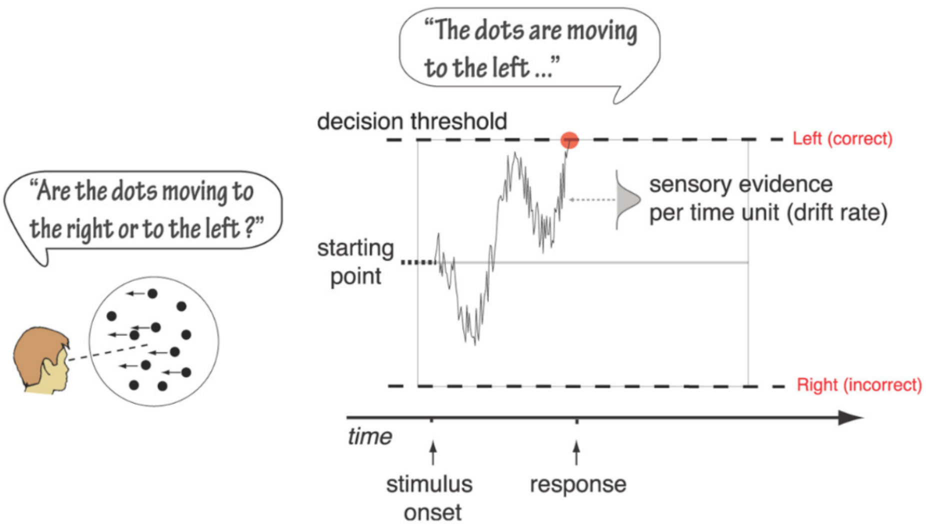


Figure 1.7. Schematic representation of the EAM model (Mulder et al., 2012; reprinted under a CC-BY-NC-SA licence).

To date, different types of accumulator model architectures with specific assumptions about the form of evidence accumulation and also value-based decision-making (also known as preferential choice) have been proposed. These include but are not limited to the diffusion model with single (Ratcliff & Rouder, 1998) and multiple accumulators (Bogacz et al., 2006; Ratcliff et al., 2007), attentional drift diffusion model (Krajbich et al., 2010; Krajbich & Rangel, 2011), linear ballistic accumulator (LBA) (S. D. Brown & Heathcote, 2008), multi-alternative linear ballistic accumulator (Trueblood et al., 2014), linear approach to threshold with ergodic rate (LATER) (Reddi & Carpenter, 2000), leaky-competing accumulator (LCA) (Usher & McClelland, 2001), selective integration model (Tsetsos et al., 2012), the associative accumulator model (Bhatia, 2013) and multi-alternative leaky-competing accumulator (Tsetsos et al., 2010; Usher & McClelland, 2004). Moreover, while accumulator and threshold models are sometimes used interchangeably, they are distinct concepts (Simen, 2012). For instance, in a driving context, the threshold model assumes a specific response threshold at which drivers initiate their reaction to a threat. In contrast, accumulator models involve the integration of sensory evidence before a driver's action (Kovaceva, 2020). Xue et al. (2018) compared the threshold and accumulator models in their ability to model distributions of brake response times and showed that the decision-making process underlying drivers' brake onset is more likely based on evidence accumulation than a particular threshold and threshold model failed to account for behaviour in the weakest and strongest looming scenarios (i.e. object moving towards the subject indicating an impending collision). In addition, variable-drift diffusion models (VDDMs) were introduced to answer the question 'How different cues should contribute to the drift rate in more complex decisions with possibly multiple types of sensory cues?' (Xue et al., 2018; Markkula et al., 2018a; Schieben et al., 2020).

EAMs have been used so far in simple driving tasks like response time and psychomotor vigilance test (PVT) (Ratcliff & Strayer, 2014), brake response (Engström et al., 2018; Markkula, 2014; Markkula et al., 2016; Ratcliff, 2015; Svärd et al., 2017, 2021; Xue et al., 2018), HAV-human interactions in take over and crossing scenarios (Markkula et al., 2018b), collision threat detection task and TTA estimation (Daneshi et al., 2020; Markkula et al., 2021), driver gap acceptance in turns (Zgonnikov et al., 2022), pedestrian crossing decision (Giles et al., 2019; Pekkanen et al., 2022; Sargoni & Manley, 2020), detection response task (DRT) (Howard et al., 2020; Innes et al., 2019; Palada et al., 2018), and modelling cognitive load in driver distraction context (Castro et al., 2019).

Overall, although EAMs offer detailed insights into decision-making, their scope is limited to specific tasks, functioning predominantly as single-decision models. This raises concerns about their suitability for various interaction scenarios. Moreover, these models often overlook the interdependencies among road users.

Markovian Decision Processes (MDPs)

A Markov decision process (MDP) is a random process that abides by the Markov property. This property implies that the future state of the system depends solely on the present state and the action taken, independent of the sequence of past states and actions (Gagniuc, 2017). The alterations in the system's state are termed transitions, and the probabilities linked with these state changes are recognised as transition probabilities. This process is defined by a state space, a transition matrix outlining the likelihood of distinct transitions, and an initial state (or initial distribution) encompassing the entire state space (Gagniuc, 2017). A standard assumption is that the process definition covers all conceivable states and transitions, guaranteeing the existence of a subsequent state at all times and preventing the process from concluding abruptly.

A number of studies used different variants of MDP to simulate road user interactions. Hsu et al. (2018) examined the impact of velocity-based signalling on vehicle-pedestrian interaction in a basic scenario and showed that the MDP model can account for adversarial agents leading to reduced efficiency in less challenging scenarios. Both MDPs and Partially Observed MDPs (POMDPs) have been applied to predict pedestrian positions (Ziebart et al., 2009), plan for autonomous driving in crowded environments (Bai et al., 2015) and study human-HAV interactions in crossing scenarios (Deshpande et al., 2020; El Hamdani et al., 2021; Hsu et al., 2020; D. Li et al., 2022) , including collision avoidance mechanisms (De Moura et al., 2020; Nasernejad et al., 2022; Toytziaridis et al., 2019). Additionally, different variants of hidden Markov models (HMMs) have been utilised in the road traffic context. These models outline the probability of a sequence of observations being generated from certain 'hidden' states of a Markov process. Estimating driver awareness of pedestrians (Phan et al., 2015), predicting pedestrians' trajectory and position (Vasishta et al., 2018) and understanding drivers' behaviour and their associated intentions when interacting at midblock crosswalks (Guo & Boyle, 2022) are among the applications of HMMs.

Overall, MDPs may encounter challenges in accurately capturing sudden shifts in pedestrian behaviour due to external influences. Also, although the present state of a driver, like maintaining a specific distance behind another vehicle, might impact the subsequent state, the model might struggle to capture complex, long-term decision-making processes or incorporate novel information. Furthermore, traffic patterns can undergo substantial changes due to variables such as the time of day, weather conditions, or special occasions. This departure from assumptions of stationarity could lead to notably inaccurate predictions. Adding to these complexities, pedestrians and human drivers frequently derive their decisions from historical data, such as recent traffic conditions, while simultaneously anticipating forthcoming events. However, the memoryless trait of Markov models might not align with these intricate behavioural patterns. In the coming section, a modelling approach that addresses most of the above challenges is discussed.

Game theory (GT)

GT is a branch of applied mathematics that conceptualises interactions in social settings among intelligent and rational decision-makers. It operates under the premise that rational agents construct their beliefs based on expectations of other players' actions (strategic reasoning). Subsequently, they make decisions that align with these beliefs (optimisation). Participants can iteratively adjust their decisions and beliefs until they converge, eventually reaching the state known as the Nash equilibrium. The Nash equilibrium involves decision strategies where individuals cannot enhance their outcomes by unilaterally altering strategies in non-cooperative games. GT builds upon optimal control theory, which seeks to optimise an objective function (i.e. reward/payoff/utility) by finding suitable controls for a dynamical system over a period of time (Ross 2015). GT extends this concept to address decentralised multi-agent decision problems (Başar & Olsder, 1998), providing an explanation for interactions among multiple agents with divergent interests. The outcomes or payoffs/utility of each agent generally depend on the collective actions of all involved (Novikov et al., 2018). The following example obtained from the GT literature (Wu et al., 2019) shows how the Nash equilibria for a 2×2 game between a driver and a pedestrian are calculated. Table 1.1 shows the payoff matrix of the game:

Table 1.1. Wu et al. Payoff matrix (Wu et al., 2019)

	Pedestrian pass	Pedestrian wait
Vehicle pass	$-k - act_v,\ -k - act_p$	$k + at_v,\ k - at_p$
Vehicle wait	$k - at_v,\ k + at_p$	$k - at_v,\ k - at_p$

In the table, each cell represents two mathematical expressions that refer to the vehicle and pedestrian utility functions, respectively. The game has no unique Nash equilibrium and has two possible outcomes which are named dominant strategies: {(pedestrian pass, vehicle wait), (pedestrian wait, vehicle pass)}. The probabilities of these dominant strategies can be calculated using a mixed strategy algorithm which equates expected utilities of each player (Spaniel, 2014). Initially, if one considers σ as the probability that an agent plays a specific pure strategy, let's say, here σ_{pp} as the probability that the pedestrian passes. Using this notation, one can then write the vehicle's expected utility of passing as a pure strategy as a function of the pedestrian's mixed strategy:

$$EU_{vp} = \sigma_{pp}\,(-k - act_v) + \sigma_{pw}\,(k + at_v) \tag{1.2}$$

Similarly:

$$EU_{vw} = \sigma_{pp}\,(k - at_v) + \sigma_{vw}\,(k - at_v) \tag{1.3}$$

As we are looking for the mixed strategy from the pedestrian that leaves the driver indifferent between their pure strategies, we have:

$$EU_{vp} = EU_{vw} \tag{1.4}$$

from (1.3), and by substituting $\sigma_{pw} = 1 - \sigma_{pp}$, both probabilities will be obtained. The same calculation goes for EU_{pp} and EU_{pw} and finally, we have the following probabilities of the dominant strategies:

$$P_{pp}, P_{vw} = \left(\frac{2at_v}{2k+(1+c)at_v}, 1 - \frac{2at_p}{2k+(1+c)at_p}\right) \tag{1.5}$$

$$P_{pw}, P_{vp} = \left(1 - \frac{2at_v}{2k+(1+c)at_v}, \frac{2at_2}{2k+(1+c)at_p}\right) \tag{1.6}$$

where P_{pp} and P_{pw} are probabilities for the pedestrian to pass and wait, respectively and P_{vp} and $P_{vw,}$ are probabilities for the vehicle to pass and wait, respectively.

Unlike most computational models, GT provides some tools to analyse problems such as infinite regress; most interaction models are firstly built based on a finite order: At first, A's belief about B's future action is modelled and in the second order A's belief about B's belief about A's future action will be modelled and so on. This eventually will result in a need for an infinite order of models to consider all possibilities which is called infinite regress (T.-W. Hu & Kaneko, 2014). In games, this can be explained as the act of continuous recognition of the fact that the opponent is clever too and is going to do the same thing endlessly. GT does not suffer from infinite regress as it integrates reasoning about probable actions of others and interdependencies, known as interaction awareness (Turnwald et al., 2016): A fundamental element in human-like navigation that results in conditionally cooperative behaviour (Turnwald & Wollherr, 2019).

Until now, predominantly conventional game theory (also referred to as orthodox or traditional) - denoted as CGT - has been the prevailing approach in prior traffic studies. This method has undergone subtle modifications and extensions to address certain limitations, striving to emulate the performance of behavioural models (Amini et al., 2020; Astarita et al., 2019; Bjørnskau, 2017; Camara et al., 2021; Y. Chen et al., 2021; Fox et al., 2018; Geary & Gouk, 2020; Ji & Levinson, 2020; Johora & Müller, 2020; Michieli & Badia, 2018; Rahmati et al., 2020; Sadigh et al., 2018; Wu et al., 2019). CGT generates the best outcomes and equilibria for each scenario, assuming that preferences are consistent, or in other words, decisions are all rational suggesting that people are self-interested and they do not care about the others' payoffs (Camerer, 2010) and that players can react to relevant information and abandon the irrelevant ones all the time and then predicts which scenario and outcome are the most likely. However, first of all, preferences are more complicated than simple self-interest and they are, along with concern for fairness, highly context-dependent (Camerer, 2010). Second, as suggested by Kahneman and Tversky (2013) people appraise choices in varying ways depending on the framing of options. This means that decisions are not solely guided by absolute outcomes, but are influenced by a heuristic assessment of potential gains and losses, giving rise to prospect theory. Heuristics are mental shortcuts that facilitate quick decision-making and inference, allowing individuals to avoid lengthy analysis of information (Dale, 2015). This theory and some others which will be mentioned later have contributed to the development of behavioural models and their application in many areas such as GT.

Behavioural game theory (BGT)

Through the use of experimental evidence, behavioural game theory (BGT) creates computational models that integrate human cognitive limitations, social utility, and learning rules aware of '*how people actually behave in strategic situations*' (Camerer, 2003). An essential aspect of this model focuses on the theory of decision-making by individuals in one-shot games or the first round of a repeated game. Studies in this context highlight that the Nash equilibrium often inadequately captures human players' behaviour, especially in non-repeated normal-form games (Wright & Leyton-Brown, 2017). A simple example could be the 'p-beauty contest game' where players are asked to choose numbers from 0 to 100 simultaneously. The average will be calculated and multiplied by 2/3. The individual whose selected number is closest to 2/3 of the average, will win a prize (Camerer & Fehr, 2006). The only equilibrium of the game is when all select 0. Players should choose (2/3)X, if they believe the average will be the number X. Nevertheless, if they think others speculate with accuracy, then other players will choose (4/9)X which is the best possible response to (2/3)X and so on. The unique combination of accurate belief and optimal response is when all choose zero and this gives a poor prediction about what actually happens when humans play this game. Strategies, here, are complements and because of that the Nash equilibrium is an inaccurate prediction: If a player believes others will choose high numbers, they should choose a high number as well, which suggests that if a limited number of players were 'irrational' by picking numbers that are above the equilibrium of zero, then even they themselves should deviate from the equilibrium by picking high numbers too. The two associated ideas behind this are *Strategic Complementarity,* i.e. *'Strategies are complements if agents have the incentive to match the strategies of other players'* (Camerer & Fehr, 2006) and *Bounded Rationality,* i.e. being biased about other's behaviour or deviating from the action that satisfies the preferences systematically (Camerer et al., 2004; Camerer & Fehr, 2006; Stahl & Haruvy, 2008). Some other phenomena can explain the divergence from the Nash equilibrium and the question that why the behavioural game theory has the potential to predict and simulate human behaviour better; these include but are not limited to:

- Theories of *Team Reasoning*: Players attempt to maximise collective rather than individual payoffs (Colman et al., 2014).
- Theories of *Social Projection*: Individuals tend to project their intentions and preferences onto others and particularly '*most people have a strong expectation that members of their own groups will act as they themselves do'* (J. Krueger, 2008; J. I. Krueger et al., 2012).
- *Strong Stackelberg Reasoning*: Individuals choose their strategy based on the belief that other players could anticipate their choices and give the best response to them while maximising their own payoff accordingly (Colman et al., 2014).
- *Bidirectionality*: Evidence in a judgement task (i.e. mental objects that induce a response in high-level cognitive tasks) affects decision makers' conclusions, and these conclusions, in turn, affect how decision-makers use this evidence over a dynamic relationship (Bhatia, 2016; Golman et al., 2020).

There exist several types of BGT models but among them, Quantal response equilibrium (McKelvey & Palfrey, 1995), Level-k reasoning (Stahl & Wilson, 1995), Cognitive hierarchy reasoning (Camerer et al., 2004) and noisy introspection (Goeree & Holt, 2004) are more commonly known and used.

Besides, Golman et al. (2020) introduced the Dual Accumulator (DA) model of decision making which combines the properties of EAMs with those in the GT context. This model is one of the most advanced decision-making models considering its potential for accommodating different parameters and the ability for its extension/modification according to different use cases and scenarios. In this model, decision-makers engage in dynamic preference construction for their available strategies while incorporating beliefs about the opponents' preferred strategies. This process involves a stochastic sampling approach with a finite number of accumulation steps in payoffs, following established models of preferential choice and evidence. As can be seen in Fig 1.8, the model has two accumulator layers:

one is for own preferences and the other for beliefs about the opponent's preferences. At each time step, the decision maker samples one of their opponent's strategies and updates their tendencies to pick their own strategies based on the payoffs they provide conditional on the opponent playing the sampled strategy. The decision maker samples one of their own strategies afterwards and updates their beliefs regarding the opponent's preferences correspondingly. Strategy sampling probabilities depend on their activation and salience. Decisions are made in favour of the most highly activated strategy until reaching an exogenous time limit. Through a hold-one-out analysis, the model was compared to existing BGT models, namely Level-k reasoning, cognitive hierarchy theory, logit quantal response equilibrium, and noisy introspection. The results revealed that the proposed model outperformed the others in making accurate out-of-sample predictions in one-shot, simultaneous-move games with complete information (Golman et al., 2020).

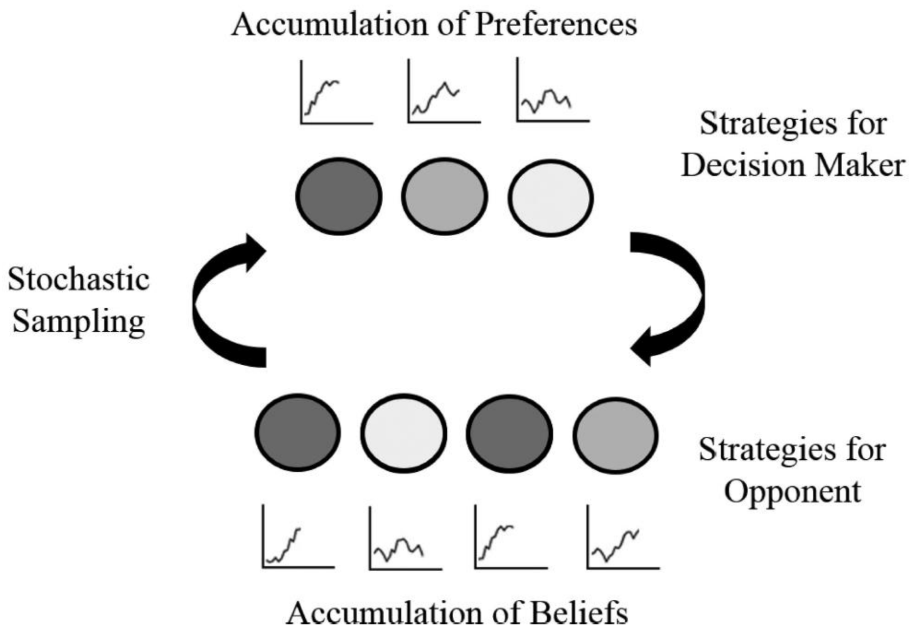


Figure 1.8. The dual accumulation process © 2020 APA. Reprinted, with permission from Psychological Review (Golman et al., 2020).

A number of studies have utilised the mentioned models to investigate road user interactions. For instance, logit quantal response equilibrium has been employed in vehicle-pedestrian interactions (Y. Zhang & Fricker, 2021), while Level-k reasoning (Albaba & Yildiz, 2021; Oyler et al., 2016; S. Zhang et al., 2020) and cognitive hierarchy reasoning (S. Li et al., 2019) have been used in vehicle-vehicle interactions, including those involving AVs. These models have proven effective in capturing road user behaviour. In another investigation by Alsaleh & Sayed (2022), two different multiagent Markov Games were utilised, one based on the Nash equilibrium and the other on logit quantal response equilibrium. Through a multiagent DRL approach, the authors estimated cyclist-pedestrian strategies and observed that the logit quantal response equilibrium model demonstrated higher accuracy in predicting road user trajectories.

All things considered, there has been no study that directly compares CGT with BGT in the domain of vehicle-pedestrian interactions to show why using BGT might be beneficial. This leaves uncertainty about whether CGT models are sufficient to capture road user interactions, particularly in vehicle-pedestrian scenarios, or if the added complexity provided by BGT is necessary. Also, most of the past studies used naturalistic data to test and validate their GT models which might suffer from unknown confounders. Therefore, a comparison of these two theories is necessary in this context to establish the foundation for further behavioural modelling. Also, no study has attempted making use of the DA model in the road user interaction context. This has particular interest since it incorporates an element of time, which is highly relevant in the road traffic context.

Hybrid models

For the past few years, developing and utilising hybrid models for understanding human decision-making in general and with regard to traffic interactions has become popular. A hybrid approach is generally useful when a single type of model cannot account for all the mechanisms behind agents' actions and to offset the shortcomings of one model with the help of another which is believed to have more strengths in that domain. The remaining part will mention some examples of this domain.

Johora and Müller developed a SFM layer to generate free-flow movement and simple interactions and a GT decision layer to handle complex situations in shared spaces (Johora and Müller, 2018; Johora and Müller, 2020). Later on, Johora and colleagues combined their past model with an expert-based and a deep learning model (known as GSFM-w-LSTM) for trajectory prediction in shared space and showed that it can outperform other pure approaches in predicting realistic and collision-free trajectories (Johora et al., 2020). In addition, a hybrid approach with promising results including the combination of model predictive control (MPC) and SFM to regulate the longitudinal speed of the AV confronting a crowd of crossing pedestrians has also been developed (Yang and Özgüner, 2019). Chen, P. et al. (2016) used a hybrid framework consisting of a GT model (the decision model to describe the perception and judgment of pedestrians and drivers) and a CA (the motion model which determines the microscopic movements of pedestrians and vehicles) for simulating the interactions at unsignalised intersection. The relatively same approach with some simplifications has been utilised by Wu et al. (2019). Both studies validated their models using actual video footage and showed promising results.

Overall, while these models provide valuable insights into road user behaviour, there remains a need for additional exploration in terms of different combinations, refining methodologies, and validating them across a spectrum of real-world situations. Furthermore, addressing specific challenges like scalability and applicability to varied contexts is necessary. Some of the computational models used in the current thesis are also developed using the same approach while taking the above points into account.

1.2 Research gaps

As explained in the previous part, although there is a growing body of research concerning both behavioural observations and modelling of (automated) vehicle-pedestrian interactions, there are still some aspects that remain poorly understood. The following research gaps are addressed in this thesis:

G1: A comprehensive experimental paradigm in distributed simulation

Distributed simulation is still in its infancy in the road traffic context. The studies that have been conducted so far mostly used low-fidelity driving and pedestrian simulators and the scenarios were quite simple compared to the real traffic. Additionally, the causal effect of road user kinematics on interaction outcomes has not been studied well. Also, previous research lacks the investigation of road user personality traits such as SVO on interactive behaviours empirically to confirm the previous findings of the DLR algorithms.

Linking two or more road user simulators and conducting a co-simulation study can be a demanding task, given the challenges posed by considerations such as how to design a scenario to actually make an interaction happen, how to control the initial conditions, how to make it reasonably natural, etc. A great proportion of the mentioned challenges could be addressed by proposing a comprehensive experimental paradigm allowing social interactions among road users that utilises high fidelity apparatuses and considers participant characteristics. Hence, the first research question is: **RQ1: How can one design a distributed study that allows pedestrian and driver participants to repeatedly interact with each other, in a manner that is both controlled yet still as close as possible to real-life interaction? Subsequently, RQ2 is: What does the interaction behaviour look like as a function of time gaps and crossing types, SVO and sensation seeking (SS)?**

G2: Lack of lab data to test GT models and BGT-CGT comparison

As mentioned in Section 1.1.3, unlike most of the computational models of road user interaction, GT has the distinctive advantage of taking into account interdependencies among agents which helps simulate social interactions with high levels of precision. However, almost all previous studies utilised naturalistic data to test these models which mostly present correlational data. In co-simulation, the observed effects of various influencing variables can be disentangled from potential confounding variables, ensuring more confident causal inferences. This improvement supports the rationale for including or excluding the variables into/from the payoff formulations. Thus, this question arises which is directly related to G1: **RQ3: Is distributed simulation a good alternative as a validation tool for GT models?** Furthermore, as discussed earlier, BGT has shown promising results in simulating and predicting human behaviour by modelling how people actually behave rather than how they ought to behave. However, there is a lack of comparison between CGT and BGT in the road traffic context and specifically vehicle-pedestrian interaction domain. Thus, **RQ4** is: **Are conventional models, such as traditional game theory (the Nash equilibrium), sufficient for predicting vehicle-pedestrian**

interaction outcomes at unsignalised locations, or is it essential to consider more complex models like behavioural game theory?

G3: Distributed simulation validation

As explained in Section 1.1.1, validating the lab data is important because even with using high fidelity simulators, road user behaviour is different in VR compared to real traffic not least with respect to how they respond to stimuli between the two environments. While there are many driving simulator validation studies (Wynne et al., 2019), the ones for pedestrian simulators are very rare (Schneider et al., 2022) and there has been no study to validate road user behaviour in a connected virtual environment (i.e. distributed simulation). Thus, it is still unknown to what extent the data that comes out of distributed simulation is representative of the real world. Therefore, **RQ5** is: **To what extent are the findings from a distributed simulator study comparable to real traffic data in terms of both behavioural findings and computational models?**

1.3 Thesis objectives and outline

The main objective of this thesis is to investigate vehicle-pedestrian social interactions at unsignalised locations using GT models and both lab and naturalistic data. To showcase how this work has effectively addressed the stated objective and filled the research gaps, this section provides a concise overview of each chapter. These chapters have either been published, submitted for publication, or prepared as journal papers (please refer to the Intellectual Property Statement for verification). Additionally, this section illustrates how each study has laid the foundation for subsequent ones, creating a coherent progression of research.

Chapter 2 presents a paper entitled '*Who goes first? A distributed simulator study of vehicle–pedestrian interaction*' which has been published in *Accident Analysis & Prevention* journal. The aim of this study was to propose an experimental paradigm where two human road users can interact with each other in a safe and controlled manner to address G1 and answer RQ1 and RQ2. To achieve this goal, a high fidelity motion-based driving simulator was connected to a CAVE-based pedestrian simulator. A distributed simulator study (DSS) was designed in a way that both agents (driver and pedestrian) can interactively decide whether to pass first or wait for the other in different traffic scenarios. The study sought to investigate how the approaching vehicle's time gap, different crossing types, and road user personality traits such as SVO and SS affect interaction outcomes, pedestrians' crossing initiation/duration time as well as the delay that drivers might experience as a result of yielding. The dataset obtained from this work was used in Chapter 3 for testing the computational models and in Chapter 4 for a comparison to naturalistic data and the validation of the lab study itself.

In Chapter 3, the paper entitled '*Driver-pedestrian interactions at unsignalized crossings are not in line with the Nash equilibrium*' is proposed. This paper has been published in *IEEE Access* journal. Four game-theoretic models based on two different payoff formulations and two solving algorithms obtained from the CGT and BGT literature were compared using the DSS dataset to answer RQ3 and 4 and address G2. Overall, this work showed how beneficial the DSS could be for testing and validation of GT models. But, will the models perform similarly when tested against naturalistic data?

To validate the findings and models that were developed in Chapter 2 and 3, a naturalistic study was conducted to provide real traffic data and compare the previous findings with them. Thus, in Chapter 4, the paper entitled '*Driver-pedestrian interactions at marked crossings: A comparison of two methodologies*' is presented. In this paper, data collection was carried out at two distinct marked crossings: a normal zebra and a staggered crossing. For this purpose, advanced sensors were employed to capture crucial information such as the type of road users, their trajectories, and speeds over discrete time stamps. Similar analyses conducted in Chapter 2 were applied to this dataset and the findings between the two studies were compared. Moreover, the models developed in Chapter 3 were tested against this dataset.

Finally, Chapter 5 presents a summary of the thesis. It discusses the identified research gaps and how they have been addressed through the PhD project and the three studies, highlighting contributions, limitations, and areas for improvement. Moreover, the chapter delves into the practical applications of the research followed by a discussion of future work and potential research directions and concludes with concluding remarks.

Figure 1.9 provides an overview of the PhD project, highlighting research gaps, questions and objectives addressed in each thesis chapter, and their interconnections.

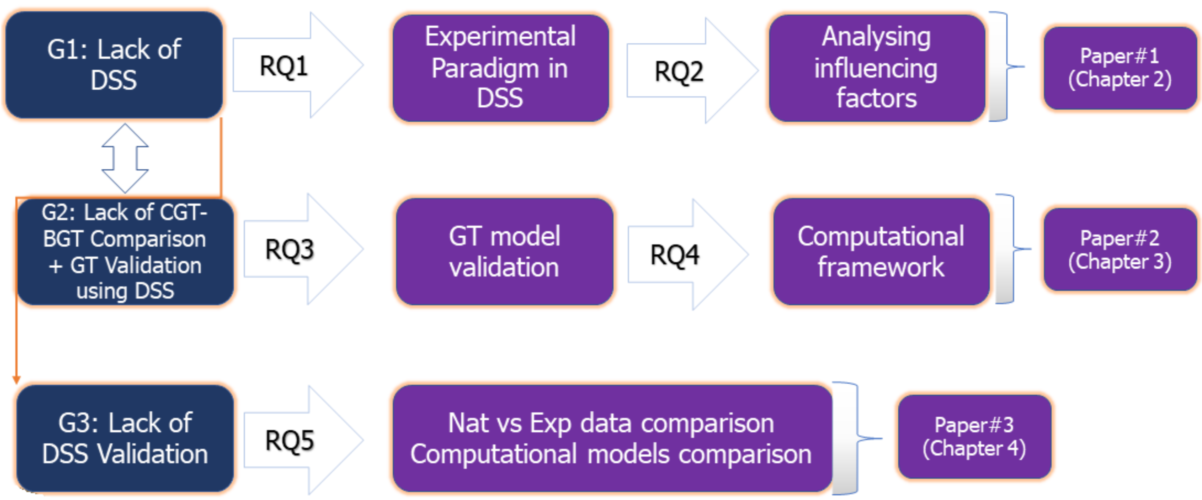


Figure 1.9. An overview of the PhD thesis

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Chapter 2

Who goes first? A distributed simulator study of vehicle–pedestrian interaction

Who goes first? A distributed simulator study of vehicle–pedestrian interaction

Abstract

One of the current challenges of automation is to have highly automated vehicles (HAVs) that communicate effectively with pedestrians and react to changes in pedestrian behaviour, to promote more trustable HAVs. However, the details of how human drivers and pedestrians interact at unsignalised crossings remain poorly understood. We addressed some aspects of this challenge by replicating vehicle-pedestrian interactions in a safe and controlled virtual environment by connecting a high fidelity motion-based driving simulator to a CAVE-based pedestrian lab in which 64 participants (32 pairs of one driver and one pedestrian) interacted with each other under different scenarios. The controlled setting helped us study the causal role of kinematics and priority rules on interaction outcomes and behaviour, something that is not possible in naturalistic studies. We also found that kinematic cues played a stronger role than psychological traits like sensation seeking and social value orientation in determining whether the pedestrian or driver passed first at unmarked crossings. One main contribution of this study is our experimental paradigm, which permitted repeated observation of crossing interactions by each driver-pedestrian participant pair, yielding behaviours which were qualitatively in line with observations from naturalistic studies.

Keywords: Zebra crossing, Autonomous Vehicles, Gap acceptance, Mixed-effects model, Traffic psychology

2.1 Introduction

Pedestrians constitute a great proportion of the traffic ecosystem and their interaction with other road users, especially vehicles, has a great impact on traffic safety and efficiency. With the deployment of highly automated vehicles (HAVs) on roads in the future, they will share the road space with other road users, such as pedestrians and conventional vehicles. Hence, HAVs need to communicate their intent and be able to negotiate different driving strategies such as right of way (Koopman & Wagner, 2018). Those HAVs that communicate effectively with pedestrians and react to changes in pedestrian behaviour may promote greater acceptance of their driving performance and make them seem more trustable (J. E. Domeyer et al., 2020). To this end, understanding competing as well as communication strategies that exist between pedestrians and drivers/vehicles is necessary to achieve a safe, efficient and transparent traffic flow.

Research suggests that the safety and efficiency of interactions can be defined by movement, distance and time-based factors (J. E. Domeyer et al., 2020; Ismail et al., 2009). The literature suggests that road user communication is predominately achieved by factors such as implicit cues, and explicit communication (such as hand gestures) is rarely used in vehicle–pedestrian interaction (Amini et al., 2019; Dey & Terken, 2017; Fridman et al., 2017; Jayaraman et al., 2019; Lee et al., 2021; Palmeiro et al., 2018; Rasouli and Tsotsos, 2020). For instance, a study on six observation sites (including both marked and unmarked crossings) across three European countries revealed that both pedestrians and drivers used explicit cues quite rarely in crossing situations and this was in correspondence with the results of the post-crossing questionnaire on the cues that were used by the pedestrians to cross the road (Lee et al., 2021). Some of the most commonly reported implicit cues in the literature are time-to-arrival (TTA) or time gap (J. Domeyer et al., 2019; Gorrini et al., 2018; Velasco et al., 2021) and vehicle's speed and deceleration profile (Ackermann et al., 2018, 2019; Palmeiro et al., 2018; H. Schmidt et al., 2019; Sucha et al., 2017). Besides, other factors such as delay or waiting time for both agents (J. Domeyer et al., 2019; Sucha et al., 2017; Y. Wang et al., 2021; W. Wu et al., 2019), demographics (Amini et al., 2019; Rasouli and Tsotsos, 2020) and type of conflict zone/crossing (Cloutier et al., 2017; Habibovic et al., 2018; R. Tian et al., 2019) have been found to affect crossing behaviour. However, research suggests that the causal impact of these various factors on interaction outcomes is not well understood.

There are cultural, geographic and legal differences regarding road user behaviour at locations with right of way such as marked crossings. In the UK, drivers should give way to pedestrians waiting to cross as well as those on a zebra crossing (see Rule H2 in The Official Highway Code, 2023). This is similar to many western European countries. A study in the UK found that people have a higher tendency to use a zebra crossing to pass the road, spend significantly less time waiting to cross, and cross more slowly compared with unmarked crossings (Havard & Willis, 2012). It has also been found that pedestrians in the UK feel much safer and have a higher perceived behavioural control when interacting at marked crossings (Havard & Willis, 2012; O'Dell et al., 2022). That said, drivers might not always yield to pedestrians even though they know they should (Dąbrowska-Loranc et al., 2021; Varhelyi, 1998), for instance, to reach their destination sooner as a matter of urgency or when they fail to see the pedestrian in time making the pedestrians abort the crossing and step back (Dąbrowska-Loranc et al., 2021).

In addition to the use of objective metrics such as implicit cues, subjective reports like perceived safety and trust are shown to be useful in assessing the intentions behind road user encounters (Habibovic et al., 2018; Liu et al., 2021). However, there is less known about the role of personality traits such as sensation seeking (SS) and social value orientation (SVO) in interactions as they can explain some of the mechanisms of human decision-making. SS is defined as the inclination to look for intense, varied, complex, and novel experiences (Arnett, 1994). SS is reported to be associated with risky traffic behaviours (Rosenbloom, 2006; A. Wang & Wang, 2021) and pedestrians with low SS have been found to miss more road-crossing opportunities compared to high sensation seekers (H. Wang et al., 2022). Additionally, adolescents have been found to be the age group influenced more by SS (Wang et al., 2019; Wang et al. 2022). SVO formalises one's concern for the welfare of others and is an individual's preference about how to distribute resources (e.g. money) between the self and another person. SVO has been found to be capable of imitating human driver behaviour when integrated into automated vehicle (AV) motion controller design. This integration was found helpful when AV interacted with other cars (Geary & Gouk, 2020; Le & Malikopoulos, 2022; Schwarting et al., 2019) and pedestrians (Crosato et al., 2021; Crosato et al., 2022). This past work all rests on the idea that the SVO of road users involved in interaction has an impact on the interaction outcomes, but as far as we are aware this hypothesis has never been tested empirically.

To investigate road user interactions, many studies have used naturalistic data (Brosseau et al., 2013; J. Domeyer et al., 2019; Gorrini et al., 2018; Ismail et al., 2009; Madigan et al., 2021; Sucha et al., 2017; Zhao et al., 2020) in which the initial conditions of the scenarios in questions are not controlled. This means even by selecting certain subsets of naturalistic data, e.g. certain ranges of initial conditions, one could never know for sure if there are no correlations with various latent factors (e.g. road user personalities) which simultaneously affect both initial conditions and outcomes. This is especially important for testing and validating the models of road user interaction as using naturalistic data could be less helpful for the development of these models which seem necessary for understanding road user interactions in automation (Markkula & Dogar, 2022; Markkula et al., 2022).

Controlled studies provide an opportunity for traffic scenarios to be tested in a way not possible in reality, not least with respect to safety (Dey & Terken, 2017; Dommes et al., 2021; Sadraei et al., 2020`), by allowing traffic conditions to be controlled to a high degree of accuracy and traffic scenarios to be repeated between and within participants. Controlled studies can be represented as test track studies (Habibovic et al., 2016; Palmeiro et al., 2018) and studies in virtual reality (VR) (Tran et al., 2021) either using head-mounted displays (Dey & Terken, 2017; Morrongiello et al., 2015), CAVE-based pedestrian simulators (Dommes et al., 2021; Lee et al., 2022; Velasco et al., 2021) and/or driving simulators (Ali et al., 2020; Bella & Silvestri, 2015; J. Wu et al., 2018). Because pedestrians cannot cross the road in front of AVs in test track studies, for ethical reasons, VR-based studies are considered a safer alternative. However, most previous VR studies involved human interaction with a pre-programmed computer agent. For instance, a human agent (driver/pedestrian) encountered a computer-programmed agent (driver/pedestrian) and this made it less possible to consider the computer-programmed agent as an interactive participant. Thus, it is less clear if the decision made by the human agent would be the same if they were interacting with another human in the real life. Distributed simulation in the road traffic context in which two or more human agents can interact in a controlled manner is a potential solution to address the mentioned shortcomings (Andersson, 2019). In distributed simulation, one can collect data from both pedestrians and vehicles simultaneously which can be used to explore the interactions precisely, repeatably, and controllably. This will help identify the communication pattern between road users (Sadraei et al., 2020).

To date, very few studies have employed this method to understand vehicle–pedestrian interactions (Kearney et al., 2020; Lyu et al., 2021; Sadraei et al., 2020). In a study by (Kearney et al., 2020), pedestrians wearing a head-mounted display interacted with both simulated and human-driven cars at two locations: an intersection and a midblock with a crosswalk. In both cases, the drivers are required to yield to the pedestrian in many US states such as Iowa (the location of the experiment) (The Iowa Legislature, 2022) and Illinois (Illinois Legal Aid, 2023). The pedestrians were told that they would see three oncoming cars, and they need to see how many times they can cross the road (back and forth) without being hit. The authors studied the crossing and yielding behaviours of the agents and also pedestrians' looks and gestures towards the vehicles. The results showed that pedestrians crossed more in front of both human-driven and simulated cars when at intersections, compared to midblock crossings. Drivers also had a lower yielding rate at midblock crossings, compared to intersections. Lyu et al. (2021) studied pedestrians' head-turning frequency and the change in head-turning angle before and during the actual road crossing. This was done by connecting a desktop driving simulator to a CAVE-based pedestrian simulator. The drivers experienced two types of scenarios: (1) braking trials when the driver was asked to stop the car from a specific distance to the pedestrian or the AV decelerated from a specific distance and stopped before reaching the pedestrian and (2) non-braking trials: when the driver was asked to yield to the pedestrian if they stepped into the road or the AV did not brake and passed the pedestrian. They found that pedestrians crossed less in front of the AV in the non-braking trials and the peak value for the head-turning behaviour was achieved at the crossing initiation. Moreover, the vehicle's stopping/braking distance to the pedestrian was the prominent factor in the pedestrians' crossing decisions and head-turning behaviour.

That said, the following research gap still exists: there has been no controlled study where two road users can interact with each other, to investigate how time gap, different crossing types, and personality traits affect interaction outcomes. Additionally, none of the previous controlled studies explicitly considered whether their results were comparable to the knowledge about pedestrian-vehicle interactions from naturalistic data.

This distributed simulator study was conducted with the aim of understanding vehicle–pedestrian interactions by showing the specific impact of crossing type, time gap, SVO and SS on a number of interaction-related metrics including pedestrians' decision to pass first. This work became possible by connecting a high-fidelity motion-based driving simulator to a CAVE-based pedestrian lab. The following research questions were of interest:

1. What does the interaction behaviour look like as a function of time gaps and crossing types, SVO and SS?

2. What factors play a role in determining the interaction's outcome (who goes first)?

The rest of the paper consists of the following sections: Section 2.2 explains the methodology, Section 2.3 describes the results, Section 2.4 is the general discussion of the findings and Section 2.5 is conclusion.

2.2 Methods

2.2.1 Participants

Sixty-four participants (32 drivers: M = 31.53, R = 21–50, SD = 1.72; paired with 32 pedestrians: M = 25.09, R = 19–34, SD = 0.87) with 8 pairs for each possible combination of genders (i.e. male-male, male–female, female-male and female-female in the driver and pedestrian roles, respectively) took part in the study. Participants were recruited via adverts using different social media platforms, and also via an existing University of Leeds Driving Simulator e-mail distribution list. They received £20 compensation for their participation in the study. The pedestrians had lived in the UK for at least one year, and drivers had at least three years' UK/EU driving experience with an average annual mileage of 7384.59. The study was approved by the University of Leeds Ethics Committee (Reference No AREA 21–022).

2.2.2 Apparatus

The study was conducted by connecting a CAVE-based pedestrian simulator - the Highly Immersive Kinematic Experimental Research (HIKER) pedestrian lab, to a high-fidelity driving simulator known as the University of Leeds Driving Simulator (UoLDS). HIKER is a 9 × 4 m CAVE simulator that consists of a wooden floor and four glass walls (Fig 2.1d). Eight Barco F90 4k projectors are used to project virtual scenes at 120 Hz to the floor and walls. Two designated points depicted by markers were considered on the HIKER floor which showed the standing point and the point for the 'move on' for the pedestrians, respectively which will be explained below (Fig 2.2b).

UoLDS (Fig 2.1a) is a controlled and safe environment for studying drivers' behaviour. The simulator consists of a Jaguar S-type cab, housed in a 4 m-diameter spherical projection dome, with a 300° field-of-view projection system. The simulator also incorporates an eight degree-of-freedom motion base consisting of a 5x5 m long x-y table and a hexapod.

Fourteen body markers (Fig 2.1b) were attached to the head, arms, chest, pelvis, elbows, hands, thighs, ankles, and feet of the pedestrian, to track their position as they moved freely during the experiment. The head and body movements were captured in the HIKER with ten VICON Vero v2.2 (2.2MP) cameras placed on top of the glass walls, with their signal processed by a VICON Tracker (v 3.7). The entire scene responds to the participant's head movements using the HIKER glasses to show a perspective-correct virtual reality. The tracking system was used to constantly feed real-time positions and orientations to SimulatorD, our in-house developed simulation software. SimulatorD is designed with a service-oriented architecture, and runs different nodes, distributed over different machines. The virtual environment was rendered in Unity 3D-based nodes, integrated into the SimulatorD message-bus, using the UniCAVE plugin in the HIKER, ProNET for the warping, and projector blending in the UoLDS dome. The resulting set up allowed pedestrians in the HIKER lab and drivers behind the wheel of the UoLDS to experience the environment simultaneously, from their respective perspectives. To the driver, the pedestrian was represented by pink spheres (Fig 2.1c), corresponding to the body tracking markers, yielding an effective representation of pedestrian position, pose, and movement (Sadraei et al., 2020).

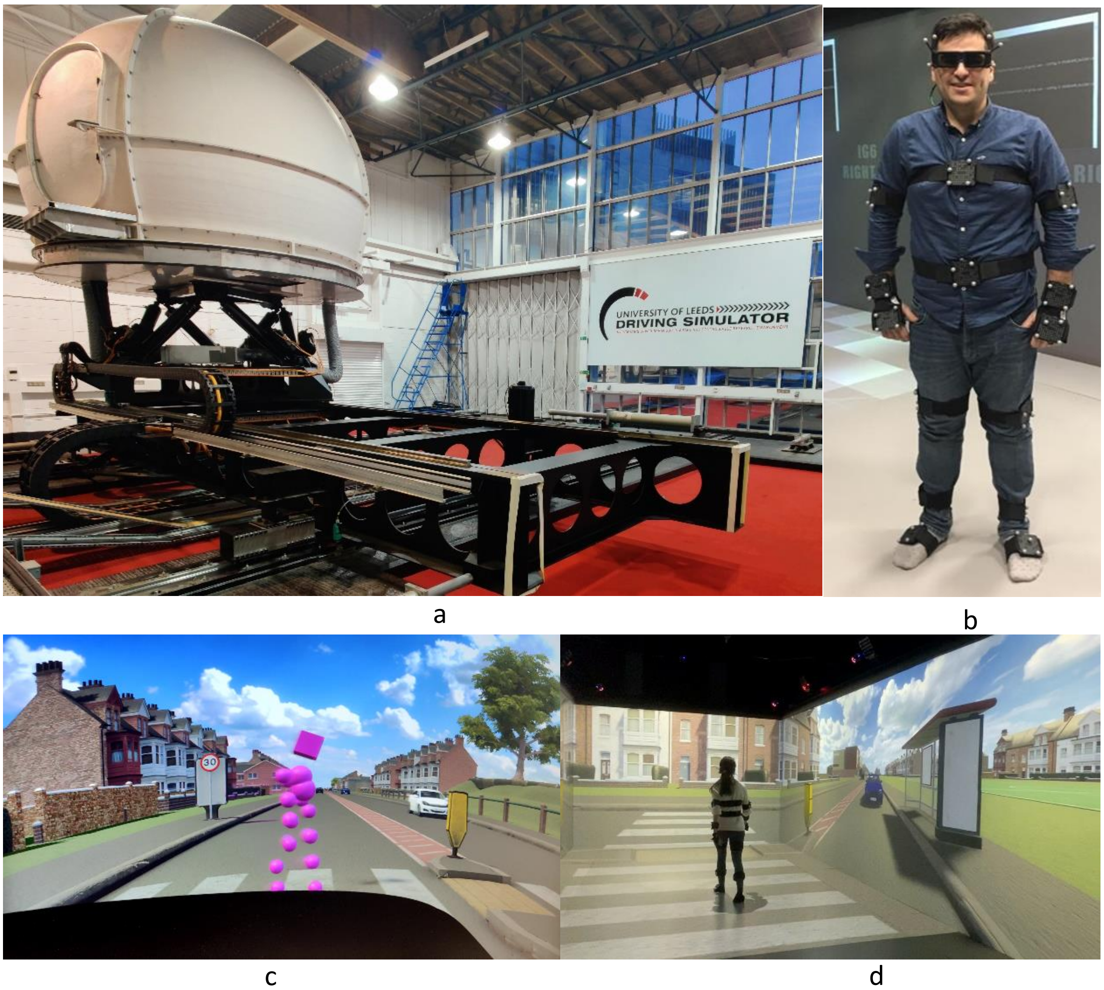

Figure 2.1. (a) The high fidelity driving simulator (b) The motion trackers (c) The driver's view of the pedestrian: the driver is stationary on the road, and the pedestrian is the pink bubbles (d)The pedestrian's view of the vehicle in the CAVE-based pedestrian lab: the pedestrian is crossing the zebra and the vehicle is to their right.

Two personality trait questionnaires were used in this study namely the 20-item Arnett Inventory of Sensation Seeking (AISS) (Arnett, 1994) and the SVO slider measure (Murphy et al., 2011). The AISS is designed to measure the personality trait of SS in two subscales of novelty and intensity, which is believed to contribute to risk-taking (Arnett, 1994). The SVO slider measure is an online/paper-based choice task with six primary items and nine secondary items. The items are all resource allocation choices dividing money between oneself and another (fictional) person over a continuum of joint rewards. Hence, the SVO measure quantifies the degree to which individuals have concern for others' reward/outcome. At lower SVO values, individuals care less about others' outcomes. High SVO values indicate an altruistic personality and successively lower values indicate prosocial, individualist and competitor types, respectively (Murphy et al., 2011).

2.2.3 Experiment and road scene design

In this study, a two-way, straight section of urban road (890 m long) with traffic in both directions (each lane had 4.5 m width) and with four crossing locations (two zebra and two non-zebra) as shown in Fig 2.2 a-b was created in Unity. The start and end of the road were identical, making it possible to create an endless loop for the driver. A number of vision obstructions (i.e. bus stops) were presented at the roadside. Drivers could see that sometimes the pedestrians stepped out from one of the obstructions and they needed to decide whether to yield to the pedestrians or to pass the crossing first. Pedestrians, on the other hand, were standing behind a vision obstruction until an auditory cue prompted them to step up to the kerb and look for oncoming traffic and cross the road if they felt safe to do so. This auditory cue was triggered based on the temporal distance of the subject vehicle to the centre of the crossing (3, 4, 5, 6, or 7 s), providing experimental control over the initial time gap in each interaction. The auditory cue was only audible by the pedestrian in the HIKER lab and the driver could not hear it thus preventing them from changing their driving behaviour such as speed before observing the pedestrian. The choice of the specific time gaps was made based on the related literature (Lobjois & Cavallo, 2007), our previous experience regarding several experiments with similar scenarios in the HIKER (Lee et al., 2022; Velasco et al., 2021) and pilot sessions. We wanted to have time gaps starting from simulating a situation where road users can only see each other quite late before taking an action, due to visual obstructions, distractions, etc. (3 s) to a situation where pedestrians feel comfortable crossing the road even at unmarked crossings (7 s). The end of each trial for the pedestrian was indicated by briefly greying out the virtual scene before moving the pedestrian to the location for the next trial.

Each of the ten different crossing conditions (five time gaps, with and without a zebra crossing) was repeated twice resulting in 20 randomised trials in each block, per participant pair. The complete road scene for the driver with the placements of the crossings is depicted in Fig 2 a-b.

a

b

Figure 2.2. (a) Road environment created in Unity: the arrow shows the distance from the start to the end point of the loop for the driver (b) Top view of the zebra (left) and non-zebra crossing (right) in Unity including the designated stand points (blue markers): the first one shows the pedestrian's standing point, the second point shows the point where the pedestrian needed to move on, which was the kerb of the virtual road, the grey rectangles: visual obstruction (bus stop) and the blue circle: the centre of the zebra crossing.

2.2.4 Procedure

Both participants: The specific information sheets describing the simulator and the experiment procedure regarding each role (one for the driver and one for the pedestrian) were sent to the participants before they arrived for the study. Upon arrival, they were asked to sit in their respective briefing areas in two separate rooms and read and sign the consent form. Thus, although both participants were told that they would interact with a human participant, they did not meet or see each other. While road user interactions in real traffic may be affected by factors such as the age, gender, ethnicity of others (Sullman & Mann, 2009), in this experiment this source of variability was excluded. Both participants were asked to have the following mindset in the experiment: '*Please assume that you are late for an important meeting, such that you want to avoid any unnecessary delays, but of course, you also want to stay safe*.' They were also reminded that at zebra crossings, pedestrians have the right of way. The study had one practice block for the driver to get used to the vehicle controls, one interactive practice block involving both agents (with ten randomised trials), and two identical blocks (with 20 randomised trials each) for the main experiment.

The procedure for each agent was as follows:

Drivers: The driver participants were asked to sit behind the wheel of the simulator and get prepared to drive. They were told that they will experience a practice session designed to allow them to become familiar with the equipment, virtual environment and speed management. The practice session stopped as soon as participants confirmed that they became accustomed to the equipment and the road environment. After completing this first practice block, the interactive practice block (ten trials), which included the pedestrian participant, began. Drivers were told that they would be driving on a two-way road with traffic on both lanes, and interacting with a pedestrian at a number of locations, with and without a zebra crossing. They were also asked to drive as they normally would and maintain the designated speed limit (30 mph). After completing the interactive practice block, the main experiment consisting of two blocks (40 trials) started.

Pedestrians: Once they signed the consent form, pedestrian participants were fitted with the motion trackers and HIKER glasses. The pedestrians were asked to initially stand at the first marker (Fig 2.2b). From this position, they could see that vehicles were driving in both directions on the road, but they could not see the approaching vehicles in the nearest lane, due to a vision obstruction (bus stop), i.e. they were not able to anticipate when the human-driven vehicle was approaching. The participants were instructed to wait at the first floor marker until they heard an auditory tone, and then step up to the second marker (which was at the kerb of the virtual road), evaluate the situation and cross if they felt safe to do so (Fig 2.2b). After the end of each trial which happened when the vehicle passed the centre of the crossing, they were asked to wait for the HIKER screens to fade out in grey, and then return to the starting point, waiting for the start of the next trial.

Upon completion of the experiment, participants were asked to fill out post-experiment questionnaires which included demographics (e.g. age, gender, nationality, driving experience, etc.), questions about the interactions with the other road user (e.g. what cue they used when deciding to cross/pass through or wait for each other) and their experience about being in a virtual reality environment. They were then asked to fill in the two personality trait questionnaires probing their psychosocial profiles as mentioned above. Doing the experiment before the questionnaires could affect responses in the questionnaires, and vice versa. However, it was more important for us to ensure that we would not affect the behaviour in the experiment itself by, for example, making the participants think that a key research interest of ours was their fairness in traffic interactions. Therefore, we administered the personality surveys after the experiment.

The duration for the whole experiment was about 1.5 h with the two practice sessions taking 20–25 min followed by two experimental blocks of 20 min with a 10-min break between them for the main experiment. Completing the questionnaires, on average, took about 20 min.

2.2.5 Data preparation

Data from 32 participant pairs, each completing 40 trials, except for the last trial of the last session, which was not recorded due to technical issues, resulted in a total of 1279 recorded trials. Out of 1279 trials, no collision was recorded but there were a few instances (<1 % of trials) where the pedestrians stepped out into the road at a time such that the drivers had to brake harshly, or increase their lateral deviation to avoid a collision. Table 2.1 shows all the variables and metrics used in this study, with a short description of each. To investigate the role of AISS and SVO metrics in the interactions, we calculated the relative values (differences in values between each role) for each participant pair, as shown in Table 2.1. The motivation for taking these differences was the assumption that the interactions are affected by the relative differences, between participants, in AISS and SVO, more than by the absolute levels of these traits.

2.2.6 Statistical analysis

A generalised linear mixed-effects model with a binary response variable of interaction outcomes (1 = pedestrian crossed fist, 0 = vehicle crossed first) was used to investigate which factors affected which participant crossed first. Also, three linear mixed-effects models were built to account for CIT, crossing duration and vehicle delay. The full model of potential predictors based on theoretical reasoning (Maxwell et al. 2017) is proposed in Eq (2.1) which is written using Wilkson notation (Wilkinson and Rogers 1973).

$$\textit{Outcome variable}\ (\mathrm{Ppc/CIT/CD/VD}) \sim T + L + W + A(p) + G(p) + \Delta SVO + \Delta AISS + (1|\textit{Participant pair}) \tag{2.1}$$

The above Eq was used to fit generalised linear mixed-effects models to the data using R package lme4.

2.3 Results

2.3.1 Personality traits, roles and gender

We conducted independent t-tests to see if there is any difference between the roles and genders regarding the personality traits. The results showed while the drivers had higher AISS scores than the pedestrians, 53.77 vs 50.18; $t(62) = -2.02$, $p = 0.04$, SVO values for both roles were not significantly different, 53.16 vs 53.67; $t(62) = 0.24$, $p = 0.88$. The results for gender showed that the mean score for AISS was significantly higher for men in both roles, 55.95 vs 51.38; $t(30) = 5.83$, $p < 0.001$ for pedestrians and 55.09 vs 51.23; $t(30) = 10.92$, $p < 0.001$ for drivers, suggesting that they were high sensation seekers compared to the women participants which is in correspondence with previous research (Rahmani & Lavasani, 2012; W. Wang et al., 2000). Also, men, on average, had significantly higher SVO values in both roles, $t(30) = 8.35$, $p < 0.001$ for pedestrians and $t(30) = 5.83$ $p < 0.001$ for drivers, suggesting that they were closer to an altruistic profile, whereas females were, on average, more prosocial (Murphy et al., 2011).

Table 2.1. Variables used in the study and for data analysis

Variable	Type	Description	Symbol	Unit
Time gap	Independent	Temporal gap of the approaching vehicle to the centre of the crossing.	T	Seconds
Waiting time	Independent	Defined as the total time waiting time of the pedestrian and was calculated in two ways: a) In the first trial of each block (when there was no previous trial): from the time that the pedestrian stood at the first marker on the HIKER's floor to the time the auditory tone was triggered. b) In all other trials (when there was a previous trial): from the time the pedestrian started moving towards the first marker in the previous trial to the time the auditory tone was triggered in the current trial.	W	Seconds
Age	Independent	For both agents; only pedestrian age 'A (p)' was considered for the analysis as the response variable is for the pedestrian.	A	Years
Gender	Independent	For both agents; only pedestrian gender 'G (p)' was considered for the analysis as the response variable is for the pedestrian.	G	n/a
Crossing type	Independent	Two categories: zebra & non-zebra.	L	n/a
ΔSVO	Independent	The difference in SVO values between the two participants (degree): $(SVO_{ped} - SVO_{driver})$.	ΔSVO	Degree
$\Delta AISS$	Independent	The difference in AISS scores between the two participants: $(AISS_{ped} - AISS_{driver})$.	$\Delta AISS$	n/a
Crossing Initiation time (CIT)	Dependent	Calculated from the time the auditory tone was triggered to the time pedestrians stepped off the kerb and started crossing the road.	CIT	Seconds
Crossing duration	Dependent	Calculated from the time pedestrians started crossing to the time they reached the central hatch.	CD	Seconds
Vehicle delay	Dependent	The time it took the driver to reach the centre of the pedestrian crossing in the trial, minus the time this would have taken if the driver had just continued at constant speed. This shows how much time was lost for the driver due to slowing down for the pedestrian.	VD	Seconds
Interaction outcomes (1 = pedestrian crossed first, 0 = waited)	Dependent	The pedestrian was considered to have crossed first when they stepped out of the kerb after the auditory tone had played but before the car had reached the crossing, and then continued walking until reaching the other end of the crossing location (i.e. the pedestrian did not abort the crossing).	Ppc	n/a

2.3.2 Participants trajectories

Fig 2.3 provides an overview of the entire dataset in which both pedestrians and vehicles' distance to the centre of the crossing are illustrated, for all trials. The darker (green and orange) lines show trials where the pedestrian crossed first, and the lighter lines (light green and yellow) show trials where the vehicle passed first. A number of different qualitative patterns of interaction are discernible in this figure, for example: (1) in trials when the vehicle passed first, we can see how the pedestrian remains standing at the kerb (the light green lines), whereas the car continues on (yellow lines.) (2) When time gaps were lower, i.e. 3 or 4 s (the four panels on the left), there are more horizontal orange lines showing vehicle's position (with higher duration) compared with higher time gaps, i.e. 6 and 7 s (the four panels on the right). This suggests that for the lower time gaps, drivers who passed second (the orange lines) needed to slow down or stop completely more often before the pedestrian crossing in front of them (the dark green lines). The following sections provide quantitative analyses of this dataset.

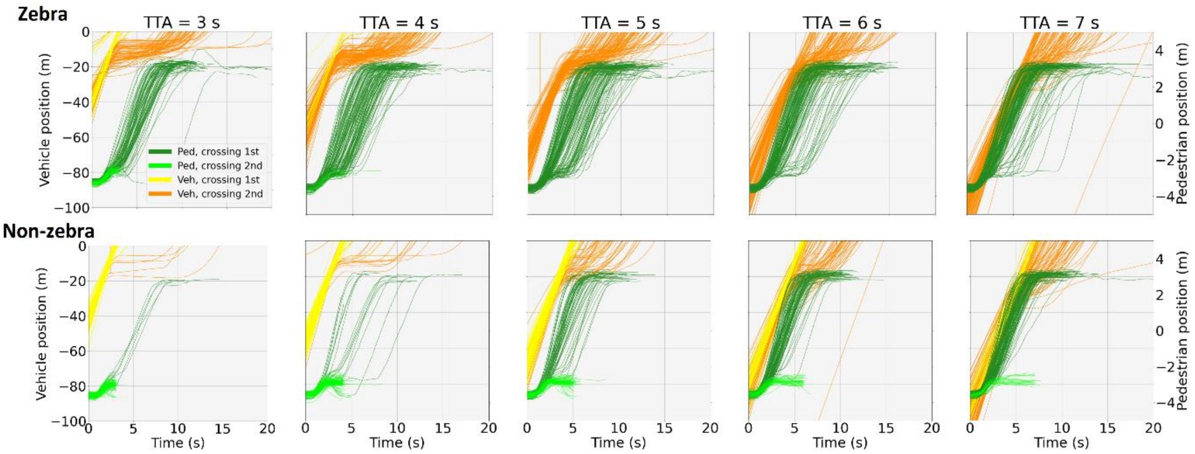

Figure 2.3. Pedestrian and vehicle position measured as distance to the centre of the crossing as a function of time, for all trials, separated into panels by initial time gap (columns) and crossing type (rows). Time zero is at the auditory cue to the pedestrian, and all lines end at the time the vehicle passed the centre of the crossing. The y-axis on the left and right indicate the position of the vehicle and pedestrian, respectively. Orange and dark green lines show the vehicle and pedestrian position, respectively, in trials where the pedestrian crossed first, and yellow and light green lines show the same agents' positions in trials where the vehicle passed first.

2.3.3 Interaction outcomes

Table 2.2 shows the results of the generalised linear mixed-effects model for the interaction outcomes.

Table 2.2. Results for mixed-effects logistic regression of interaction outcomes (1 = pedestrian crossed first, 0 = waited)

		Estimate	Std. Error	z value	Pr(>|z|)	95% CI	
						L	U
(Intercept)		-0.553	1.737	-0.319	.000	-3.958	2.851
Time gap		**1.855**	**0.135**	**13.723**	**.000**	1.590	2.119
Crossing type (Non-zebra)		**-5.077**	**0.369**	**-13.755**	**.000**	-5.801	-4.354
$\Delta \boldsymbol{AISS}$		**-0.079**	**0.032**	**-2.469**	**0.01**	-0.142	-0.016
ΔSVO		0.007	0.023	0.326	0.74	-0.039	0.054
Age		-0.087	0.071	-1.230	0.21	-0.227	0.052
Gender (Male)		1.111	0.680	.632	0.10	-0.223	2.445
Waiting time		**-0.052**	**0.006**	**-7.494**	**.000**	-0.064	-0.038
AIC 662.2	BIC 708.6	logLik -322.1	Deviance 664.2	df.resid 1270	ICC 0.43	Observations 1279	

As can be seen in Table 2.2 both time gap of approaching vehicle and crossing type played a significant role in the pedestrian's decision to cross first. As expected (Dommès *et al.* 2021, Theofilatos *et al.* 2021), pedestrians crossed first more often at higher time gaps and in the presence of a zebra crossing (see Fig 2.4). The left panel of Fig 2.4 shows that while all pedestrians crossed before the vehicle in the zebra conditions, for time gaps of 5 s and higher, this was not the case for lower time gaps. For the no-zebra conditions, the probability of crossing at the highest time gap (7 s) was just above 0.8. Fig 2.3 shows that many pedestrians crossed at the no-zebra locations when the time gap was 6 s or more, probably because they had more than enough time to cross the road.

Waiting time had a negative relationship with pedestrian crossing decisions, suggesting that pedestrians who had waited longer since their previous crossing had a lower probability of crossing before the vehicle. Finally, $\Delta AISS$ was found to have a negative relationship with the pedestrian's choice to cross first. As shown in the right panel of Fig 2.4, interestingly, when pedestrians had lower SS scores compared to drivers, they crossed first more often, especially at non-zebra which seems counterintuitive to the reported role of SS in risky traffic behaviours. However, higher vehicle speed has been found to decrease pedestrians' odds of crossing the road (Theofilatos et al. 2021).Therefore, we checked the vehicle's speed distribution as a function of crossing type and AISS groups to see if there was any difference between the groups. Fig 2.5 shows the box plots of the vehicle's speed based on the crossing types and the two groups of AISS: when the AISS scores for the pedestrians were higher than the drivers (higher values, n = 10, denoted by $AISS_{Ped} > AISS_{Driver}$) and when it was the other way around (lower values, n = 21, denoted by $AISS_{Driver} > AISS_{Ped}$). The figure shows that the average vehicle speed was higher for the first group, suggesting that this might have a stronger effect than $\Delta AISS$ on the interaction outcomes. It is worth noting that speed outside the interaction time interval, i.e. from the time the auditory tone was triggered to the time the vehicle passed the centre of the crossing, had an average of 13.47 m/s (SD = 1.72 m/s) for all trials. Within the interaction time interval, the average vehicle speed was 8.59 m/s (SD = 5.29 m/s).

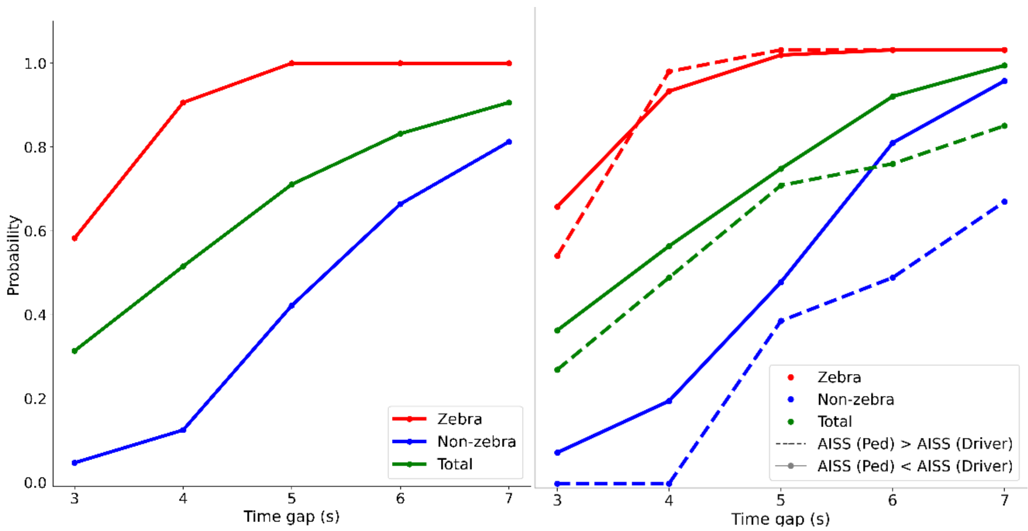

Figure 2.4. The probability of pedestrian crossing first as a function of time gap and location (left) and for AISS groups (right).

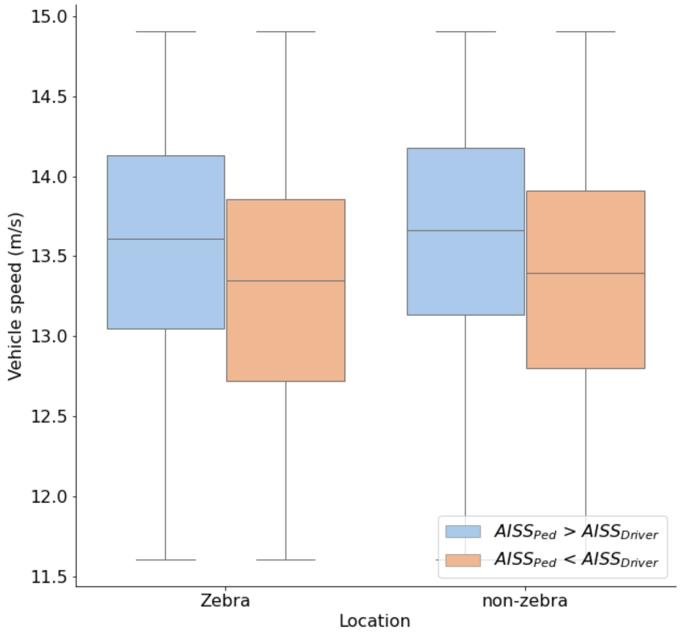

Figure 2.5. Box plots of vehicle speed for the AISS groups

Although ΔSVO was not significant in the model, due to the strong previous interest in SVO as a potential factor in road user interactions (Crosato *et al.* 2021), we conducted a follow-up analysis: Fig 2.6 shows the probability of pedestrian crossing first as a function of time gap and crossing type for the top and bottom 16 values of ΔSVO (i.e. the participant pairs were dichotomised into two groups by ΔSVO). As shown in Fig 2.6, while the impact of ΔSVO at zebra crossings was negligible, at non-zebra crossings with time gaps of 3 s or higher, there was a trend of higher probabilities of pedestrian crossing first when ΔSVO was low, i.e. when the driver was more altruistic than the pedestrian.

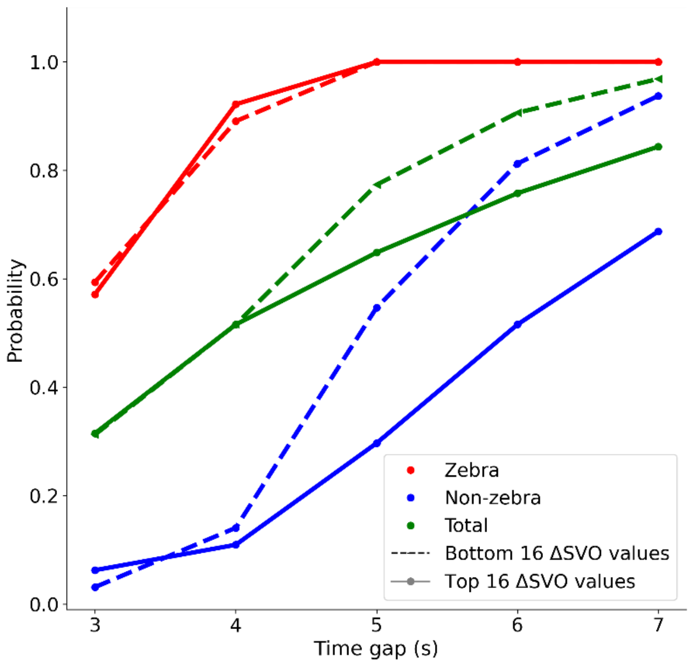

Figure 2.6. Pedestrian's probability of crossing first as a function of the time gap, dichotomised by 16 highest (top) and lowest (bottom) values of ΔSVO.

2.3.4 Crossing initiation time (CIT)

Table 2.3 shows that time gap had a negative effect on CIT meaning that, with increasing time gap, CIT decreased, i.e. pedestrians were less hesitant to start their crossing behaviour. Moreover, they had lower CITs at non-zebra compared with zebra crossings. These two findings can be seen visually in Fig 2.7. Finally, ΔSVO also had a significant positive effect on CIT, suggesting that for more positive ΔSVO, i.e. when pedestrians tended more toward altruism than the drivers, they spent more time screening the situation before crossing.

Table 2.3. Results for linear mixed-effects modelling of CIT

	Estimate	t value	P-value	95% CI	
				L	U
(Intercept)	2.391	3.078	**0.004**	0.868	3.914
Time gap	**-0.146**	**-7.287**	**<0.001**	-0.186	-0.107
Crossing type (Non zebra]	**-0.145**	**-2.417**	**0.01**	-0.263	-0.027
$\boldsymbol{\Delta SVO}$	**0.018**	**1.996**	**0.04**	0.003	0.03
$\Delta AISS$	0.020	1.609	0.11	-0.004	0.04
Age	0.052	1.862	0.07	-0.002	0.107
Gender (Male)	0.399	1.503	0.14	-.121	0.920
Waiting time	0.002	1.784	0.07	-0.000	0.005
Marginal R^2 0.189 / Conditional R^2 0.555	ICC 0.45	N 32	Observations 836		

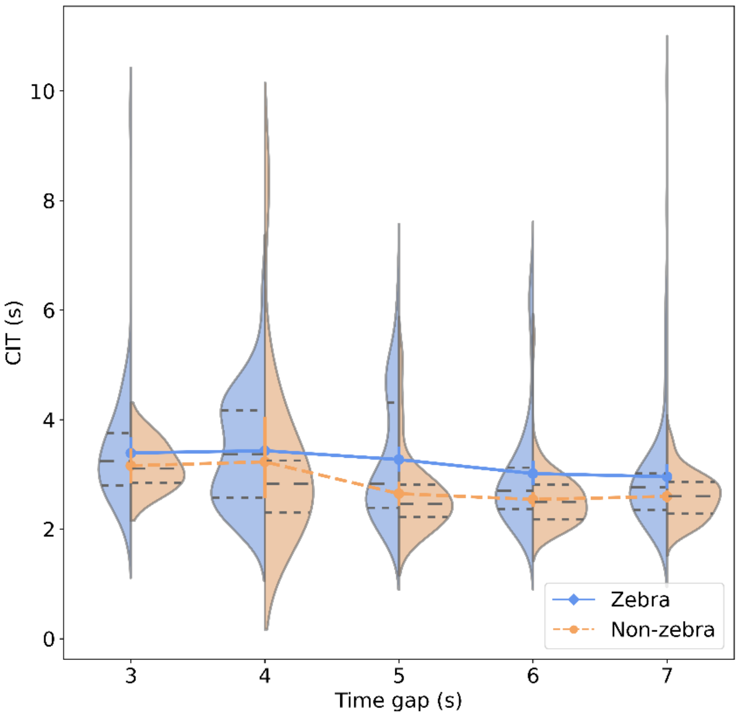

Figure 2.7. Violin plots of CIT: The connected dots show the means for each category and the dashed lines show the quartiles.

2.3.5 Crossing duration

Table 2.4 shows the results of the mixed-effects modelling for the crossing duration. As shown in Table 2.4, crossing type had an effect on the crossing duration in which longer crossing durations were observed at zebra crossings. This effect can be seen in Fig 2.8, where the distribution of this variable is depicted and the means of crossing duration are higher for zebra except for time gap 3 s. Also, men had longer crossing durations than women.

Table 2.4. Results for linear mixed-effects modelling of crossing duration

	Estimate	t value	P-value	95% CI	
				U	L
(Intercept)	2.873	4.258	0.000	1.550	4.207
Time gap	-0.001	0.097	0.92	-0.020	0.020
Crossing type (Non zebra)	**-0.288**	**-9.026**	**0.000**	-0.350	-0.230
$\Delta AISS$	0.010	0.558	0.58	-0.020	0.030
ΔSVO	0.011	1.380	0.17	-0.020	0.030
Age	0.025	1.022	0.31	-0.020	0.070
Gender (Male)	**0.280**	**1.228**	**0.02**	-0.170	-0.740
Waiting time	-0.000	-0.700	0.48	-0.000	0.000
Marginal R^2 0.130	Conditional R^2 0.706	ICC 0.66	N 32	Observations 836	

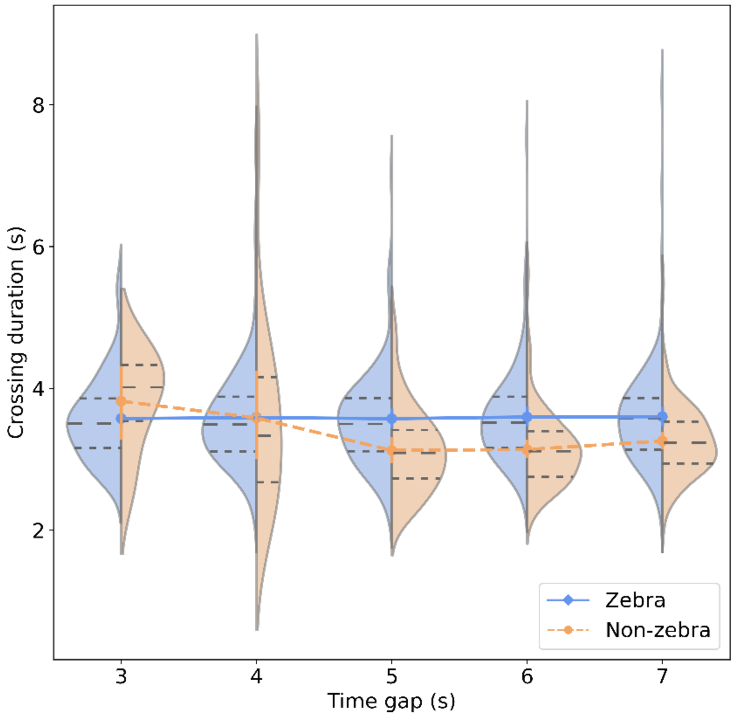

Figure 2.8. Violin plots of crossing duration

2.3.6 Vehicle delay

Table 2.5 shows the results of the mixed-effects modelling for the vehicle delay. From the table, it can be seen that both time gap and non-zebra location had negative relationships with the vehicle delay. This suggests that with a rise in time gap and while interacting at non-zebra crossings, the driver waited less for the pedestrian to cross the road. These findings can be confirmed in Fig 2.9 where the means of vehicle delay at the zebra crossing are more than those for non-zebra except for time gap 3.

Table 2.5. Results for linear mixed-effects modelling of vehicle delay

	Estimate	t	P-value	95% CI	
				L	U
(Intercept)	7.379	3.398	.000	3.121	11.640
Time gap	**-0.963**	**-20.000**	**.000**	-1.059	-0.870
Crossing type (Non-zebra)	**-0.863**	**-6.212**	**.000**	-1.135	-0.590
$\Delta AISS$	0.023	0.681	0.68	-0.501	0.090
ΔSVO	0.507	1.934	0.06	-0.001	0.100
Age	0.086	1.103	0.27	-0.071	0.240
Gender (Male)	1.147	1.539	0.13	-0.321	0.269
Waiting time	0.003	1.034	0.30	-0.001	0.010

Marginal R^2	Conditional R^2	ICC	N	Observations
0.326	0.686	0.53	32	836

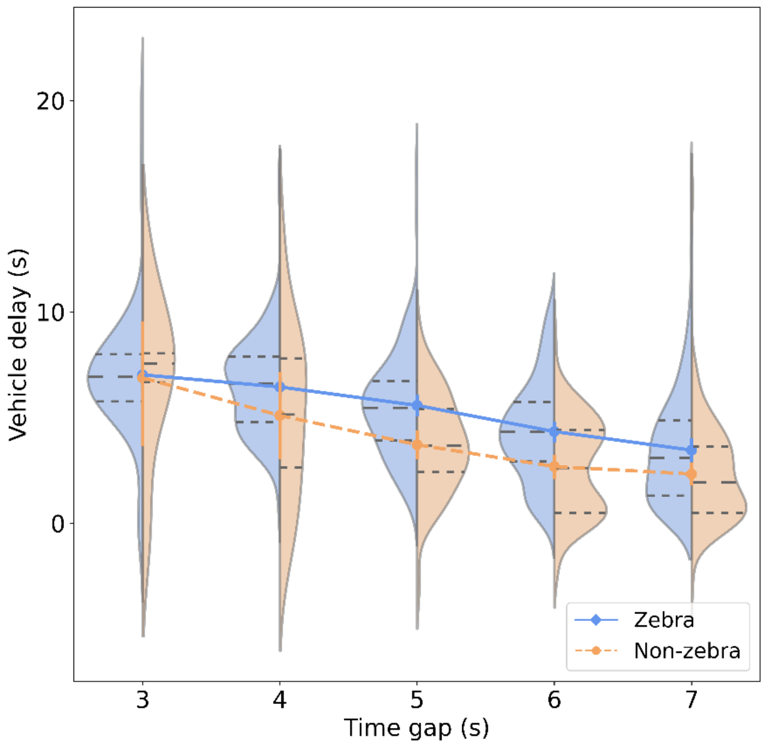

Figure 2.9. Violin plots of vehicle delay

2.4 Discussion

In this study, we sought to investigate vehicle-pedestrian interaction by specifically showing the impact of crossing type, time gap, AISS and SVO on interaction outcomes. This was done by conducting a distributed simulation study, where two actors (a driver and a pedestrian) interacted via two connected high fidelity simulators. Apart from the technical challenge of connecting the simulators to each other in these types of studies, there is also the matter of having the participants together at the same place at the same time, ideally with experimental control over the initial conditions, in a way which permits natural interaction behaviour. This methodology could be an important step for providing validation tools for the models of road user interaction like game-theoretic models in which variables should be controlled with a high degree of accuracy for determining exactly how to formulate the payoffs (Kalantari, Markkula, et al., 2022).

The results showed that time gap, location, waiting time and $\Delta AISS$ had a significant effect on pedestrians' probability of crossing first. In line with the current literature in this context, increasing the time gap led to higher probabilities of crossing which has been shown in both naturalistic (Theofilatos et al., 2021) and controlled studies (Dommès et al., 2021; Lee et al., 2022; Velasco et al., 2021).

Our findings for waiting time and ΔAISS were both interesting and unexpected. In this study, we investigated the effect of the total waiting time of the pedestrian on crossing decisions. According to the literature, the general belief is that the longer pedestrians wait at the kerb, the higher the chance of accepting lower time gaps (Theofilatos et al., 2021; Wu et al., 2019; J. Zhao et al., 2019). However, we observed the opposite behaviour in our study: by increasing the waiting time, pedestrians were less inclined to cross the road first. This may be because our definition of waiting time is not identical to that used in previous, naturalistic studies. In the previous studies waiting time is defined as the time that a pedestrian takes to wait for a gap size that is safe to cross while there is a stream of cars approaching and passing, suggesting that the pedestrians were actively and continuously looking for a chance to cross, which could lead to frustration after a while (J. Zhao et al., 2019). That said, our findings are consistent with (Yannis et al., 2013) who observed that pedestrians who had waited for a longer time, were more inclined to be cautious and less likely to engage in risk-taking by accepting smaller gaps.

Results regarding ΔAISS showed that while no clear pattern was observed at zebra crossings, pedestrians with lower AISS scores than drivers crossed first more often, when interacting at non-zebra crossing locations. There are two possible explanations for this: First, although SS is seen to be associated with risky traffic behaviours (Jonah, 1997; Rosenbloom, 2006), it was not the strongest predictor of road crossing intentions in some studies (e.g. see Zhou & Horrey, 2010). Second, as shown in Fig 2.5, this could be because the drivers of this group, on average, drove faster replicating the findings in the literature that pedestrians are less likely to cross the road when the speed of approaching vehicle is higher (Cherry et al. 2012, Pawar and Patil 2015, Kaparias et al. 2016). Overall, this confirms the stronger role of kinematic cues for pedestrians when crossing the road. As mentioned in Methods, speed was not part of the study design, and since all drivers were expected to follow the same speed limit of 30 mph we did not include speed in our statistical models. However, it could be argued that natural variations in speed between drivers and trials may have affected the interaction outcomes (and indeed, we saw some possible indications of this in relation to AISS as discussed above). Therefore, we reran our mixed-effects models also including the vehicle's speed 1 s after the auditory tone (to allow time for the pedestrian to have reached the kerb), but did not find any statistically significant effect of this variable on interaction outcomes. Moreover, other metrics such the distance from the vehicle to the conflict point and pedestrian could help predict pedestrians' decisions to cross the road (Y. Zhang & Fricker, 2021). Future studies could investigate the role of spatial distance, by including it as a controlled variable.

CIT results showed that pedestrians were less hesitant to cross the road at higher time gaps. This is in line with previous lab studies (Dommès et al., 2021; Velasco et al., 2021) and can be confirmed by looking at Fig 2.3. CIT is reported to be an important factor for predicting pedestrians' perceived safety and trust, when crossing in front of AVs and conventional vehicles (Dommès et al., 2021) and also a good predictor for assessing the application of human-machine interface (Lee et al., 2022). Also, both CIT and crossing duration were found to be longer for the zebra crossing locations in this study. The longer CIT at zebra crossings was likely because there were more unresolved interactions suggesting that the incentive to save time and conform to the priority rules might put the two agents into a dilemma. This could happen also in real traffic: when a pedestrian is in hurry, they would expect the driver to yield to them at a marked crossing, while at the same time the driver wants to reach their destination sooner also as a matter of urgency, they both will be placed in a situation where the driver might at first slow down a little bit and when they see that the pedestrian might be a bit hesitant they accelerate shortly right after that or continue to approach the crossing with the same speed, making the pedestrian doubtful if their crossing will be safe or not; eventually, the driver decides to yield resulting in delays.

Although we saw only limited effects of ΔSVO, there was an interesting trend for interaction outcomes at non-zebra crossings at higher time gaps and its effect on the pedestrians' hesitation to cross the road. This is in line with the theory stating that larger differences in SVO values would usually lead to a situation where an agent with the higher SVO value shows more cooperative behaviour, and as a result, it is more likely for them to give the right of way to an agent with the lower SVO values (Schwarting et al., 2019). That would need confirmation in future studies by using larger and more inclusive datasets. One possible reason for the limited observed effect of SVO could be that our sample did not include more extreme SVO profiles, such as individualists and competitors. Research suggests prosocials (who were the extreme case of considering self-benefits in our study) exhibit more fairness and are less demanding compared to individualists and competitors who were absent in this study (De Dreu & Van Lange, 1995). Hence, to include a wider range of SVO categories in an experiment and see, for example, what would happen if competitor pedestrians and drivers interact with each other and also with other SVO categories, one might try non-probability sampling techniques such as purposive sampling. That said, while the inclusion of such profiles could lead to observing more substantial effects of SVO on interactions, these profiles are less common in the general population (Zhen et al., 2015). Thus, the applied importance of more extreme SVO profiles may still be limited.

Finally, vehicle delay which can be viewed as the amount of time added by the pedestrian to the vehicle's journey was higher at zebra crossings and lower time gaps. These findings can be explained by looking at the results of both CIT and crossing duration. As stated by Domeyer et al. (2020) when it comes to 'Nonintersection encounters', the amount of waiting time for the driver is solely pedestrian-dependent, that is what we also observed in our study.

This study had several limitations: First, we did not include pedestrian approach phase, whereas past naturalistic studies (Domeyer et al., 2022; Gorrini et al., 2018; Varhelyi, 1998) suggest that interaction takes place already during this time, if the vehicle and pedestrian can see each other during the approach. Second, due to the size limit of the CAVE-based system, we could not account for multiple pedestrians to investigate the effect of group size on interaction outcomes (head-mounted displays will be preferred in this instance). Third, we also did not account for the scenarios including encountering at least two vehicles from both directions as this seems to cause relatively different crossing behaviours (Dommès et al., 2021). Fourth, instead of using spheres to represent pedestrians and presenting the vehicle as an entity without a driver behind its wheels, having calibrated avatars of both agents would help to truly examine how drivers and pedestrians see each other in the virtual environment. This would help to further investigate aspects such as eye contact and gaze under different traffic scenarios, which could be an important aspect to address in future studies.

2.5 Conclusions

This study showed that, overall, distributed simulation can simulate scenarios where traffic agents interactively communicate with each other, demonstrating behaviours that are qualitatively in line with those observed in naturalistic studies. Some of these important observed patterns were the higher probability of pedestrians' crossing first at higher time gaps and also at marked crossings. The controlled nature of the study made it possible to draw the conclusion that these behavioural patterns are due to causal links between the independent and dependent variables, rather than spurious correlations. Our findings also showed that kinematic cues, including vehicle speed and time gap, had a stronger influence on pedestrians' crossing behaviours at unmarked crossings, than psychological traits such as AISS and SVO. The findings of this study could provide further insights into how to study a large number of vehicle-pedestrian interactions in a controlled manner, which is an essential part of the design and testing of AVs.

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Chapter 3

Driver-pedestrian interactions at unsignalised crossings are not in line with the Nash equilibrium

Driver-pedestrian interactions at unsignalised crossings are not in line with the Nash equilibrium

Abstract

Recent developments in vehicle automation require simulations of human-robot interactions in the road traffic context, which can be achieved by computational models of human behaviour, such as game theory. Game theory provides a good insight into road user behaviour by considering agents' interdependencies. However, it is still unclear whether conventional game theory is suitable for modelling vehicle-pedestrian interactions at unsignalised locations or if more complex models like behavioural game theory are needed. Hence, we compared four game-theoretic models based on two different payoff formulations and two solving algorithms to answer this question. Unlike the previous studies that employed naturalistic datasets to test and validate such models, this study utilised a distributed simulation dataset to test and compare the models. The study was conducted by connecting a CAVE-based pedestrian simulator to a motion-based driving simulator to replicate the traffic scenarios for 32 pedestrian-driver pairs. The findings demonstrated that there is a high variability between participant pairs' behaviours. Our proposed behavioural game-theoretic model outperformed other models in predicting the interaction outcomes. The model can also predict which interaction will take the longest time to resolve. According to our results, road users cannot be expected to behave in line with the Nash equilibrium of conventional game theory that underscores the complexity of human behaviour with implications for the testing and development of automated vehicles.

Keywords: Game theory, mathematical modelling, road user interaction, vulnerable road users, decision

3.1 Introduction

Road user interaction has been a topic of interest for years from a safety perspective for human-human interaction (Bjørnskau & Sagberg, 2005) and has become popular in recent years due to successive improvements in vehicle automation bringing the challenges of human-robot interaction into the topic (Koopman & Wagner, 2018; Markkula et al., 2020; Turnwald & Wollherr, 2019). Among different types of interactions, the interaction of pedestrians as vulnerable road users (VRUs) with drivers and automated vehicles (AVs) has a great impact on traffic safety and efficiency as pedestrians constitute a great proportion of the traffic ecosystem (World Health Organization, 2013). They are also known to exhibit unpredictable behaviours (de Lavalette et al., 2009). To this end, previous research has strived to understand (Amado et al., 2020; Ezzati Amini et al., 2019; Tran et al., 2021; W. Wang et al., 2022) and quantitatively model (Camara et al., 2020) how VRUs and vehicles/AVs interact with each other with the latter becoming an essential part of the test and development procedure for the future deployment of AVs (Markkula & Dogar, 2022).

Existing modelling approaches to road user behaviour are often separated into two types of architecture: glass-box and black-box models (Rai, 2020). Black box models such as deep learning models offer a generalisable approach where the behaviour of several agents can be simulated with high accuracy (Mozaffari et al., 2020) but the underlying mechanisms of the model components are unknown: there is a lack of interpretability in the connection between the inputs and outputs of the model (Gilpin et al., 2018) and with human psychological theories which makes the model interpretation difficult. On the other hand, glass box models offer the advantage of interpretability and transparency by providing explanations for the mechanisms in relatively great detail. These models rely on different modelling paradigms including agent-based modelling (Bonabeau, 2002; Prédhumeau et al., 2022), optimal control theory (Le & Malikopoulos, 2022; Ross, 2015), Markovian processes (Bellman, 1957; Hsu et al., 2018), evidence accumulation (Pekkanen et al., 2022; Ratcliff et al., 2016), proxemics (Domeyer et al., 2019), discrete choice modelling (Hensher & Johnson, 2018; Zhao et al., 2019) and game theory (Elvik, 2014).

From the above modelling approaches, agent-based and discrete choice models have a long and rich history in predicting road user behaviour. Agent-based models have been used for modelling different traffic scenarios such as two-dimensional trajectory modelling of vehicular movements at intersections where one-dimensional simplification is not enough to capture road user behaviour and distance-based factors play a more important role than time-based variables (Zhao et al., 2020). The downside of these models is that road users are generally assumed to act mostly like moving objects without considering each other's intentions before taking every decision. Logit models are among the most commonly used models for modelling pedestrians' gap acceptance behaviour (Kadali & Vedagiri, 2020; Sun et al., 2003; Yannis et al., 2013; Zhao et al., 2019) due to the binary nature of pedestrian crossing decisions, the convenience in utilising them and the flexibility of their application together with other models (Papadimitriou et al., 2009). They have been compared to a number of statistical methods namely maximum likelihood method, Raff's method, root mean square method and probability equilibrium method and have been found to be the most appropriate model for estimating the critical gaps of pedestrians (Vinayaraj et al., 2020). Moreover, their ability to be incorporated into other modelling approaches such as microscopic traffic flow models (Zhao et al., 2020) and artificial neural networks (Kadali et al., 2015) make them an attractive choice. Having said that, the discrete nature of these models provides no concept of time such as time-varying utility functions and the ability to fully capture traffic agents' interdependencies. To this end, other modelling approaches such as evidence accumulation and game theory have become popular for road user behaviour modelling studies, over recent years.

Evidence accumulation offers a well-established depiction of human behaviour for some specific decisions (Markkula et al., 2021; Purcell & Palmeri, 2017) and suggests that evidence for a particular response is integrated by single or multiple accumulators over time and by a rate known as drift rate which is the rate at which sensory information reaches a bound (a decision boundary) (Ratcliff et al., 2016). This model has been used for simulating and predicting driver gap acceptance in left-turns (Zgonnikov et al., 2022), pedestrian crossing decisions (Giles et al., 2019; Pekkanen et al., 2022) and AV-human interactions in take-over and crossing scenarios (Markkula et al., 2018). That said, while evidence accumulation models provide ample detail about the decision-making process, they do so for a very constrained set of tasks and are typically considered single-decision models suggesting they may not be able to account for all types of interaction scenarios. Also, as opposed to game-theoretic models, these models are mostly incapable of capturing road users' interdependencies.

Game theory extends optimal control theory to a decentralised multi-agent decision problem (Başar & Olsder, 1998) and explains the interaction of multiple agents whose interests do not coincide, and their decisions, generally, depend on the actions of all (Novikov et al., 2018). In this model, agents keep revising their decisions and beliefs until they become mutually consistent, that is until (the Nash) equilibrium is reached. This is the core idea in conventional (also known as orthodox/traditional) game theory which relies on perfect rationality of players who are always assumed to be self-interested and choose optimal choices. Overall, conventional game theory has the advantage of accounting for interdependencies, unlike agent-based, logit and evidence accumulation models (Evans & Wagenmakers, 2019). Thus, it has been used in several vehicle-pedestrian interaction studies (Camara et al., 2021; Fox et al., 2018; Johora & Müller, 2020; H. Li et al., 2023; Wu et al., 2019). However, behavioural economics suggests that agents' preferences, along with concern for fairness, are highly context-dependent (Camerer, 2010): individuals make decisions based on a heuristic estimate of the potential value of losses and gains (Kahneman & Tversky, 2013) and they do not usually play the Nash equilibrium in strategic situations such as unrepeated normal-form games (Wright & Leyton-Brown, 2017). This is due to different reasons, including bounded rationality (Camerer & Fehr, 2006; Stahl & Wilson, 1995) and positive theory (Colman, 2003) which are the backbones of behavioural game theory. Behavioural game theory utilises experimental evidence to create computational models of human cognitive limitations, social utility and preferences, and learning rules aware of '*how people actually behave in strategic situations*' (Camerer, 2003). To date, several behavioural game-theoretic models have been introduced and tested using economic games. For instance, the dual accumulator (DA) model that combines the knowledge of evidence accumulation paradigm with game theory is a promising approach to simulating human decision-making (Golman et al., 2020). The authors compared their model to several existing behavioural game theory models, i.e. noisy introspection (Goeree & Holt, 2004), logit quantal response equilibrium (McKelvey & Palfrey, 1995), Level-k reasoning (Stahl & Wilson, 1995), and cognitive hierarchy theory (Camerer et al., 2004), employing a hold-one-out analysis. They showed that the model makes the most accurate out-of-sample predictions (Golman et al., 2020). However, this model has not previously been tested in the context of road user modelling, highlighting a gap in the literature. Some studies have employed other behavioural game theory models for the road traffic context, such as logit quantal response equilibrium in vehicle-pedestrian interactions (Y. Zhang & Fricker, 2021) and Level-k reasoning (Albaba & Yildiz, 2021; Oyler et al., 2016; S. Zhang et al., 2020) and cognitive hierarchy reasoning (S. Li et al., 2019) in vehicle-vehicle (including AVs) interactions showing that the models can capture road user behaviour well. Using two different multiagent Markov-Games, i.e. one based on the Nash equilibrium and one based on logit quantal response equilibrium, Alsaleh & Sayed (2022) estimated cyclist-pedestrian strategies using a multiagent deep reinforcement learning approach and found that the latter predicted road user trajectories with higher accuracies.

All things considered, to the best of our knowledge, no study has ever directly compared conventional game theory to behavioural game theory in the vehicle-pedestrian interaction domain. Hence, it is currently unclear whether conventional game theory models are sufficient for road user interaction and especially vehicle-pedestrian interactions, or whether higher complexity in modelling provided by behavioural game theory is needed. There is also a lack of comparison between game-theoretic models and logit models. The main contribution of this study is a comparison of these two types of game theory models also with logit models (representing the popular modelling approach in this area). This was done by using a dataset from a controlled distributed simulator study. Unlike naturalistic studies which are the common validation tools for the models of road user behaviour (van Haperen et al., 2019), controlled studies provide a safe environment where one can directly control the interactions between agents, varying the conditions of interest to study their causal (rather than correlational) impact on behaviours and outcomes. Also, this technique enables multiple observations for each participant, allowing a better understanding of interindividual differences.

Our main research question is as follows:

- Are traditional models such as logit and conventional game theory (the Nash equilibrium) enough to predict vehicle-pedestrian interaction outcomes at unsignalised locations or are more complex models such as behavioural game theory needed?

3.2 Methodology

This section describes all the methods used in the study, beginning with a description of the controlled distributed simulation empirical study, followed by a definition of each computational model, and details of the model fitting.

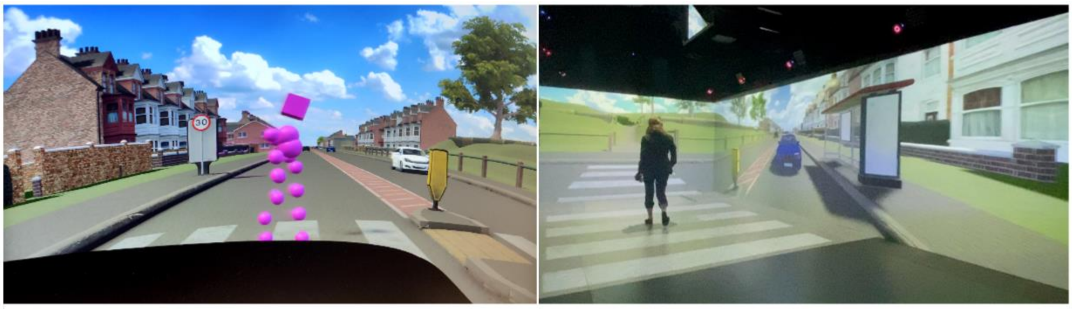
3.2.1 Empirical study

A distributed simulator study was conducted to investigate road user interactions in a safe and controlled environment, providing a large dataset of vehicle-pedestrian interactive behaviours to test and validate the computational models of this study. The full details of the study can be found in (Kalantari, Yang, et al., 2023). Here, we provide a summary of the study.

The study was conducted by connecting the University of Leeds Driving Simulator (UoLDS) to the HIKER (Highly Immersive Kinematic Experimental Research) pedestrian lab. UoLDS is a high-fidelity motion-based driving simulator with an eight degree-of-freedom motion platform carrying a Jaguar car housed in a 4 m-diameter spherical projection dome, with a 300° field-of-view projection system. HIKER is a 9 × 4 m CAVE simulator consisting of eight 4K projectors that are used to project virtual scenes at 120 Hz to the floor and walls. Fourteen body markers were attached to different parts of the pedestrian's body, represented as pink spheres to the driver (Fig 3.1-a). The pedestrian could also see the vehicle as shown in Fig 3.1-b.

In this experiment, 64 participant pairs (PPs) (32 drivers [Age: M = 31.53, R = 21−50, SD = 1.72]; paired with 32 pedestrians [Age: M = 25.09, R = 19−34, SD = 0.87]) interacted with each other under different traffic scenarios. The study was approved by the University of Leeds Ethics Committee (Reference No AREA 21-022). The scenarios were defined based on different crossing types (i.e. zebra and non-zebra crossings; see Fig 3.1-c) and five different vehicle time-to-arrival conditions (TTAs, i.e. the temporal distance of the vehicle to the centre of the crossing, 3−7 s) resulting in 10 conditions that were repeated two times in each experimental block. There were two blocks resulting in 40 randomised trials per PP.

Upon arrival, both participants were asked to sit in their respective briefing areas in two separate rooms and read and sign the consent form. The instruction to the pedestrian was to stand at a marker on the HIKER's floor (the first blue cross in Fig 3.1-c) where they could see that cars are going both ways but they could not tell when the subject vehicle was approaching due to a visual obstruction (a bus stop; Fig 3.1-c). After hearing an auditory tone, they were asked to step to a second marker which was the kerb of the virtual road where the driver could see them, at which point the interaction started. The participants (driver and pedestrian) could decide whether they wanted to wait for the other to pass first or they themselves passed. Both participants were told: '*Please assume that you are late for an important meeting, such that you want to avoid any unnecessary delays, but of course, you also want to stay safe.*' Drivers were told to maintain the speed limit (30 mph) as they would in their normal driving and were also reminded that pedestrians have priority at zebra crossings. Upon completion of the experiment, participants were asked to fill out post-experiment questionnaires for demographic information and personality traits (not reported here, see Kalantari, Yang, et al., 2023).



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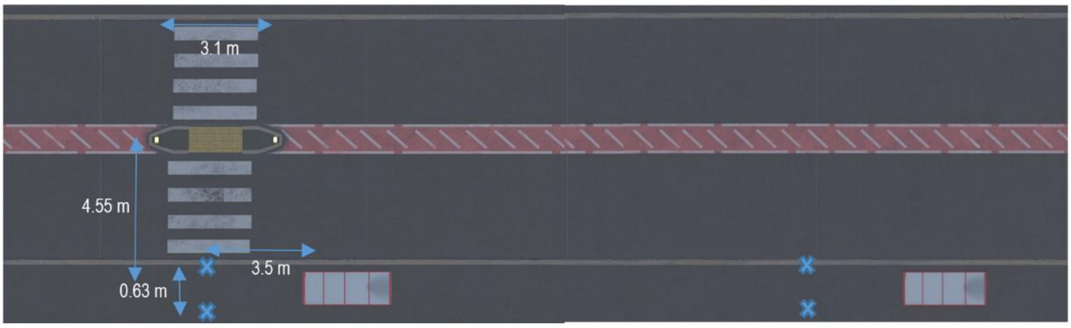

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Figure 3.1. (a) The driver's view of the pedestrian: the driver is stopping, and the pedestrian is shown by pink spheres, (b) the pedestrian's view of the vehicle in the pedestrian lab: the pedestrian is crossing the zebra and the subject vehicle is to their right and (c) top view of the zebra (left) and non-zebra crossing (right) in Unity including the designated standpoints (blue markers.)

3.2.2 Computational models of vehicle-pedestrian interaction

This section describes the five computational models that were tested in this study.

Logit model (Logit)

A logistic model was tested assuming the utilities to be the linear function of TTA and pedestrians' total waiting time which is in line with the literature (J. Zhao et al., 2019). Two different intercepts were considered for each crossing:

$$U = \beta_{0z/nz} + \beta_1 TTA + \beta_2 WT \tag{3.1}$$

As the probability of the pedestrian passing first or waiting can be denoted by $P(U)$ and $P(1-U)$, respectively, the probability of pedestrian passing first can be defined using the Logit function (J. Zhao et al., 2019):

$$P(U) = \frac{1}{1+e^{-U}} \tag{3.2}$$

where U is the utility of waiting/passing for the pedestrian, β_{0z} and β_{nz} are intercepts for the unmarked and marked crossings, respectively and β_1 and β_2 are coefficients for TTA and waiting time of pedestrians, respectively.

Original conventional game-theoretic (OCGT) model

A conventional game theory model by Wu et al. which considers the two-agent game of vehicle-pedestrian was chosen and slightly modified (Wu et al., 2019). This model was chosen due to a well-balanced integration of road user safety and efficiency metrics, the ease of working with its payoff formulation and the fact that it is one of the few game-theoretic models in the literature with an explicitly stated payoff formulation. The model was established as the baseline for comparison against other models utilizing more complex payoff formulations and solving algorithms.

Table 3.1 shows the parameters of the study including the Wu et al. (2019) model's parameters.

Table 3.1. Parameters of the study

Scenario-based parameters (parameters of the experiment)		
Parameter	*Description*	*Unit*
v	The approaching vehicle's speed.	m/s
l	The direct distance between the vehicle and pedestrian.	m
$k = \frac{v}{l}$	Risk perception for pedestrians/vehicles.	1/s
t	Total waiting time of pedestrians. This was defined from the time the previous trial ended (for the first trial: from the start of the experimental block) to the time the auditory tone was triggered.	s
t_{v}	Temporal gap of the approaching vehicle to the centre of the crossing minus one second to account for the average time that it took for the pedestrians to step up to the second marker on the HIKER's floor which was at the kerb of the virtual road.	s
t_{p}	The estimated crossing duration of pedestrians, from the kerb to the central hatched area: For simplicity, this was fixed to the average of all crossing durations observed in the study.	s
Model parameters		
$\boldsymbol{c}$	A multiplier for the negative utility of delay to compensate for the extra waiting time required when both agents decide to pass simultaneously and thus need to avoid collisions, e.g. by braking suddenly (Wu et al., 2019).	1/s
t_0	Tolerable waiting time of pedestrians (s); this usually has been reported within the 40-60 s range in the literature (Wu et al., 2019).	s
a = $\frac{\boldsymbol{\alpha * e^{[\delta(t_0-t)]}}}{\boldsymbol{1+e^{[\delta(t_0-t)]}}}$	Weight coefficient: Varies from scenario to scenario.	1/s
n	A multiplier in the *alternative formulation* helps the model distinguish between the crossing types (zebra vs no zebra) and is relative to the risk perception of the road user with no priority (≥ 1).	-
m	A multiplier in the *alternative formulation* discourages both agents to wait when they think that the other one is waiting (≥ 1).	1/s

Table 3.2 shows the Wu et al. (2019) model's payoff formulation. The model's payoffs are defined as a summation of utilities relating to (i) the perceived risk of being involved in a conflict with another road user modelled as $k = 1/TTA$, and (ii) the time spent as a result of one waiting for another, which is equal to the time that the passer takes to pass the crossing ($\mathrm{t_i}$). The presence of these utility values in all outcomes with a negative sign when they have a negative influence on a road user, or a positive sign otherwise, is the main assumption of the formulation. Additionally, a weight coefficient was considered for the total waiting time of the pedestrians with the following assumption: pedestrians who have waited for a longer time, are more inclined to be cautious and less likely to engage in risk-taking by accepting smaller gaps (Yannis et al., 2013). This was assumed in the opposite direction in the original paper (Wu et al., 2019) as the authors' definition of waiting time was different from our study.

Table 3.2. Wu et al. Payoff matrix (the vehicle is the row player and the pedestrian is the column player)

	Pedestrian pass	Pedestrian wait
Vehicle pass	$-\mathrm{k} - \mathrm{act}_{\mathrm{v}},\ -\mathrm{k} - \mathrm{act}_{\mathrm{p}}$	$k + \mathrm{at}_{\mathrm{v}},\ \mathrm{k} - \mathrm{at}_{\mathrm{p}}$
Vehicle wait	$\mathrm{k} - \mathrm{at}_{\mathrm{v}},\ \mathrm{k} + \mathrm{at}_{\mathrm{p}}$	$\mathrm{k} - \mathrm{at}_{\mathrm{v}},\ \mathrm{k} - \mathrm{at}_{\mathrm{p}}$

Table 3.2 suggests that there is no unique Nash equilibrium, and the game has two dominant strategies {(*pedestrian pass, vehicle wait*), (*pedestrian wait, vehicle pass)*} which can be obtained using the mixed strategy algorithm by equating the expected utilities of each player (Spaniel, 2014).

$$P_{pp}, P_{vw} = \left(\frac{2a\mathrm{t_v}}{2k+(1+c)a\mathrm{t_v}}, 1 - \frac{2at_p}{2k+(1+c)at_p}\right) \tag{3.3}$$

where P_{pp} and P_{vw} are the probability of pedestrian passing first and vehicle waiting, respectively (Wu et al., 2019). Another dominant strategy (P_{pw}, P_{vp}) can be obtained as one minus the probabilities in Eq (3.3). In this study, we present all the results based on the pedestrian's probability of passing first.

Alternative conventional game-theoretic (ACGT) model

An alternative payoff formulation was proposed, based on Wu et al.'s original payoff. The formulation was provided to correct some of the assumptions of the original payoff which we suspected did not correctly capture road users' perceived utilities of the different outcomes. For instance, road users' utility functions were modified to help the model distinguish between marked and unmarked crossings as shown in Table 3.3. According to traffic regulations in the UK, similar to many western European countries, drivers should give way to pedestrians waiting to pass as well as those at a zebra crossing (see Rule H2 in The Official Highway Code, 2023). Thus, while based on the regulations pedestrians have priority at a zebra crossing, the driver (vehicle) was also assumed to have priority at non-zebra locations, as there was no refuge for this crossing type and the crossing behaviour could be considered as an instance of jaywalking (T. Wang et al., 2010) in the experiment.

The following modifications were made to the original payoff formulations:

I) The utility of risk perception is not considered when a road user is waiting for the other to pass first, thus removing k from their utilities in these instances.

II) When road users with no right of way want to pass first, they get a higher negative score for risk perception (knR_p, knR_v where $R_p = 1$ and $R_v = 0$ if pedestrians have right of way (i.e. at zebra crossing), and vice versa).

III) When a road user waits for the other to pass first, they do not only lose the approaching vehicle's TTA but also the pedestrians' estimated crossing duration$[-\mathrm{a}(t_v + t_p)]$.

IV) When a road user waits for the other to pass but none of them passes immediately, they will lose their own passing time with a multiplier (m) which can make it worse than waiting for the other to pass first.

V) When a vehicle waits for a pedestrian, the pedestrian gains the vehicle's TTA (t_v) instead of their crossing duration (t_p).

Table 3.3. Alternative payoff formulation

	Pedestrian pass	Pedestrian wait
Vehicle pass	$-k(nR_p + R_v)$ – act_v, $-k\,(nR_v + R_p)$– act_p	$k(nR_p - 2nR_p + R_v) + at_v, -a(t_v + t_p)$
Vehicle wait	$-a(t_v + t_p)$, $k(nR_v - 2nR_v + R_p) +\ at_v$	$-amt_v,\ -amt_p$

Similar to the original model, the above formulation was solved using the mixed-strategy Nash equilibrium and Eqs 3.4 and 3.5 show pedestrians' and vehicles' probabilities of passing first and waiting for zebra and non-zebra crossings, respectively.

$$P_{ppz}, P_{vwz} = \left(\frac{a(t_v+mt_v)-kn}{a(ct_v-t_p+mt_v)}, 1 - \frac{a(t_v+mt_p)+k}{2k+a(ct_p+mt_p-t_p)}\right) \tag{3.4}$$

$$P_{ppnz}, P_{vwnz} = \left(\frac{a(t_v+mt_v)+k}{2k+a(ct_v-t_p+mt_v)}, 1 - \frac{a(t_v+mt_p)-kn}{a(ct_p+mt_p-t_p)}\right) \tag{3.5}$$

Behavioural game-theoretic models

Both original and alternative payoff formulations were solved by a model from the behavioural game theory category creating OBGT [original (solved by) behavioural game theory] and ABGT [alternative (solved by) behavioural game theory] models, respectively. The DA model (Golman et al., 2020) from the behavioural game theory category was chosen and utilised as an alternative game solution to the mixed-strategy Nash equilibrium. According to the model, agents generate preferences by considering the conveniently available strategies with assumptions about opponents' preferred strategies using evidence and stochastic sampling, i.e. the process of a finite number of accumulation steps in payoffs inspired by existing cognitive models of preferential choice (Golman et al., 2020).

The following equations show the model formulation:

$$\widehat{V_{D,c_D}}(t) = \gamma \widehat{V_{D,c_D}}(t-1) + \ \omega \textstyle\sum_w P_{P,w_P}\,(t-1) v_{D,c_D,c_P} \tag{3.6}$$

$$\widehat{V_{P,w_P}}(t) = \gamma \widehat{V_{P,w_P}}(t-1) + \ \omega \textstyle\sum_c P_{D,c_D}\ \,(t-1) v_{P,w_P,w_D} \tag{3.7}$$

$$P_{D,c_D}\,(t) = \frac{e^{\lambda \widehat{V_{D,c_D}}(t)}}{\sum_c e^{\lambda \widehat{V_{D,c_D}}(t)}} \tag{3.8}$$

$$P_{P,w_P}\,(t) = \frac{e^{\lambda \widehat{V_{P,w_P}}(t)}}{\sum_w e^{\lambda \widehat{V_{P,w_P}}(t)}} \tag{3.9}$$

where $\widehat{V_{D,c_D}}(t)$ and $\widehat{V_{P,w_P}}(t)$ are the values of action $c = cross$ for driver and action $w = wait$ for pedestrian, respectively. $P_{D,c_D}\,(t)$ and $P_{P,w_P}\,(t)$ are the estimated action probabilities for c and w, respectively and finally v_{D,c_D,c_P} (value for driver of action c if pedestrian plays c) and v_{P,w_P,w_D} (value for pedestrian of action w if driver plays w) are the payoffs as defined in the two-agent game under study. By increasing λ, agents are more likely to choose the option with the highest value while the lower values of this parameter represent agents with a greater degree of 'randomness' in their decisions.

The model was slightly modified and named the *generalised DA* model. To this end, a distinction mechanism was added to the model which explains how rapidly activations and beliefs are updated by an agent, and how long it takes to perform such an update. This was done by setting the parameters (ω and γ in Eqs 3.6 and 3.7) that define the rate of change during an update of the agents' activations (preferences) and beliefs as follows: $\omega = 1 - \gamma$ while in the original DA model, it was assumed that $\omega = \gamma = 1$. Both ω and λ parameters are called 'DA parameters' in this paper. Also, while in the original model, the first agent (driver) samples one of the other second agent's (pedestrian's) actions w with probabilities P_w at each time step, and updates their own value based on that sample, a weighted average across all possible actions w is taken in the generalised model. This is also true for the other agents' possible actions.

The model has a concept of decision-making over time. This time is known as model convergence time. The criterion for the convergence was to consider a threshold of 0.001 for the change in the two consecutive probabilities of actions for both agents.

Fig 3.2 illustrates how road users decide whether to pass first or wait for each other using the DA model under the following conditions: a) $t_v = 6\ s$, $t = 30\ s$ and at a zebra crossing and b) $t_v = 5\ s$, $t = 45\ s$ and at a non-zebra crossing. As can be seen from the figure, the model assumes that both the driver and pedestrians' values of actions are the same at the first time step and in panel ***a*** as time goes by, the value of passing first for the driver becomes lower while it increases for the pedestrian. This happens because both agents' information about the priority rules and available safety margin is being updated over time. As a matter of this deliberation process, the probability of passing first for the pedestrian increases and converges to a constant value. The opposite of this situation happens to the driver. Panel ***b*** shows the alternative, although with a slight difference, just after the first time step and at the beginning the values of both actions for the driver (pass, yield) tend to decrease and as a result, the probability of yielding to the pedestrian becomes higher. However, quite soon the probabilities of actions swap places and the driver decides to pass first probably when observing the pedestrian is less assertive in crossing the road. This happens because the pedestrian feels less safe at an unmarked crossing although the safety margin seems to be enough for them to pass first.

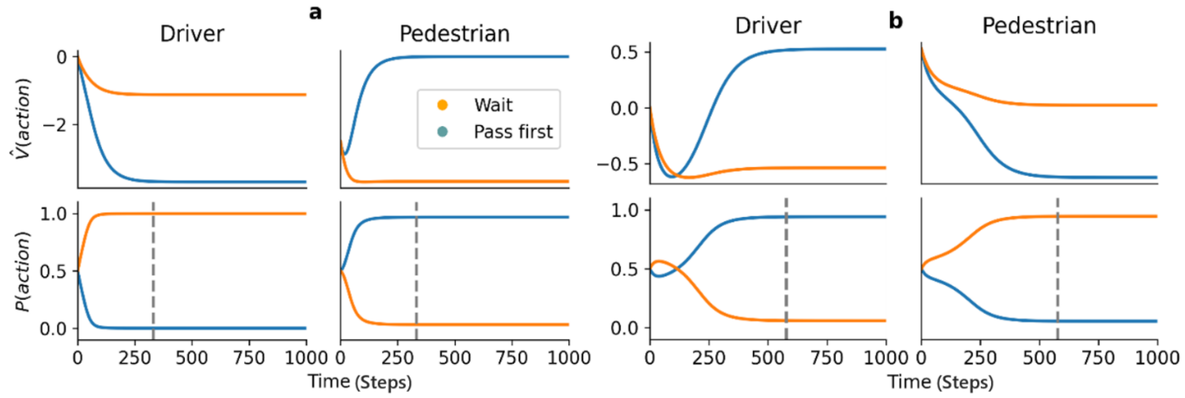

Figure 3.2. An example of how the DA model works: the estimated value and probability of pass/wait of both agents when the pedestrian passed first (a) and when they wait for the driver to pass first (b). The horizontal dashed lines show the time that model converged according to the defined threshold.

3.2.3 Model fit

All the models were fitted to the experiment dataset using maximum likelihood estimation method by computing likelihood and log-likelihood functions as follows:

$$\mathbf{L_{ij}} = \begin{cases} p(X_{ij,\theta}) & \text{If the pedestrian } i \text{ crossed in trial } j \\ 1 - p(X_{ij,\theta}) & \text{Otherwise} \end{cases} \tag{3.10}$$

$$LL(\theta) \ = \sum_{i=1}^{n} \sum_{j=1}^{m} log\, L_{ij} \tag{3.11}$$

where $n = 32$ is the number of PPs and p is the model-predicted probability of the pedestrian crossing first in trial j of participant i, where X_{ij} specifies the experimental condition on that trial, given model parameters θ.

Both DA models (i.e. ABGT and OBGT) were fitted with three different assumptions about the parameters:

a) Using both DA parameters (i.e. ω, λ) and the game-theoretic model's payoff parameters as free parameters, separate per participant pair.

b) Fixing DA parameters, i.e. choosing two constant values for λ representing high $= 1$ and low randomness $= 18$ and a predefined value for ω (i.e. 0.9; Golman et al., 2020), and using payoff parameters as free parameters.

c) Having DA parameters shared across all participants and letting the payoff parameters be free per participant pair; in this method, alternating minimisation (Csiszár, 1984) was used to account for varying payoff (free) parameters with shared DA model parameters across the PPs with the following form:

$$max_{\theta_{PO},\theta_{DA}} LL(\theta_{PO}, \theta_{DA}) \tag{3.12}$$

where $LL(\theta_{PO}, \theta_{DA})$ is the total negative log-likelihood function, θ_{PO} is the vector of payoff parameters and θ_{DA} is the vector for the DA model parameters. This method solves the problem by fixing θ_{PO} and minimising in θ_{DA}, and then fixing θ_{DA} and minimising in θ_{PO}.

This method helps the function converge to a global minimiser, which in our case is the total (sum of) negative log-likelihood across all PPs.

All models were fitted to both crossing locations at the same time and thus the parameters were shared between the two crossing types. The above procedure was used for all models using Powell's method implemented in *Scipy* (Virtanen et al., 2020).

Table 3.4 shows the parameter ranges of all game theoretic models used in the study. The parameter space was chosen in a way that guaranteed the best fit for each model after several rounds of manual testing regarding the optimisation algorithm. The parameter bound criterion for all models was to conform with the theoretical reasoning, for example, by limiting the lower bounds of multipliers (c , m & n) to 1 or keeping a and δ between 0 and 1. The main criterion for choosing the bounds for conventional game-theoretic models was to discard any parametrisation that yields probabilities outside the range of 0−1. Also, for all models, the bounds were set in a way that expanding them could make the algorithm choosing values resulting in a worse fit.

Table 3.4. Parameter ranges for all game-theoretic models

Model / Parameter	ABGT		ACGT		OBGT		OCGT	
	L	U	L	U	L	U	L	U
a	0.1	0.99	0.2	0.5	0.1	0.99	0.1	0.99
δ	0.01	0.099	0.009	0.020	0.010	0.099	0.010	0.099
c	1.42	5	1.54	2	1	2	1	2
m	1	1.4	1	1.4	N/A			
n	1	1.4	1	1.4				
ω	0.1	0.99	N/A		Fixed at 0.9			
λ	0.1	20			Fixed at 1 & 18			

All the models were compared using information loss criteria, i.e. Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), as well as error indicators, including the Mean Absolute Error (MAE) and the Root Mean Squared Error (RMSE). Here are the formulations for these metrics:

$$AIC = 2k - 2ln(LL(\theta_{PO}, \theta_{DA})) \tag{3.13}$$

where k is the number of estimated parameters in the model.

$$BIC = kln(n) - 2ln(LL(\theta_{PO}, \theta_{DA})) \tag{3.14}$$

where: n is the sample size.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |actual - predicted| \tag{3.15}$$

where: |actual - predicted| is the absolute difference between the actual and predicted probabilities and n is the number of data points.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(actual - predicted)^2} \quad (3.16)$$

3.3 Results

In this section, first, the observed behaviours of participant pairs at both crossings are presented followed by the modelling results for the individual and aggregated data.

3.3.1 Observed behaviour at both crossings

Figs 3.3 and 3.4 show the crossing behaviour as well as the probability of pedestrian crossing first as a function of time gap, for all 32 PPs, for all models. Looking at the panels in Fig 3.3, it can be seen that while different PPs behaved differently for TTAs equal to two and three seconds, all of them passed the crossing first at higher time gaps. Also, 28% (nine out of 32) of the pedestrians crossed first in all trials, irrespective of the available safety margin (TTA). Looking at the observed data in Fig 3.4, one can see the crossing behaviour at non-zebra was quite different compared to the zebra crossing among the pedestrians: first, very few pedestrians passed before the driver, at the 2-second TTA (i.e. 11, 12, and 29). Second, the crossing probability increased for the 3-second time gaps, but was still low. This was due to the crossing behaviour of PP 3, 11, 12, 20, 23, 24 and 29. Third, data of some pedestrians, i.e. 17, 20 and 22 showed fluctuations (rises and dips) as TTA increased. Finally, three out of 32 pedestrians (i.e. PPs 4, 25 and 28) did not pass at all, suggesting they were risk-averse.

3.3.2 Model performance for both crossings

Fig 3.4 shows that the two conventional game-theoretic models, i.e. ACGT and OCGT performed comparatively weakly in almost all cases. This can be confirmed by looking at Table 3.5 which shows the model comparison for both crossing types including information loss criteria (AIC, BIC) and error indices (MAE, RMSE). However, when Wu et al.'s payoff formulation was solved with the DA model (OBGT), a clear improvement can be seen in all cases, according to the plots in Fig 3.3 and the values in Table 3.5.

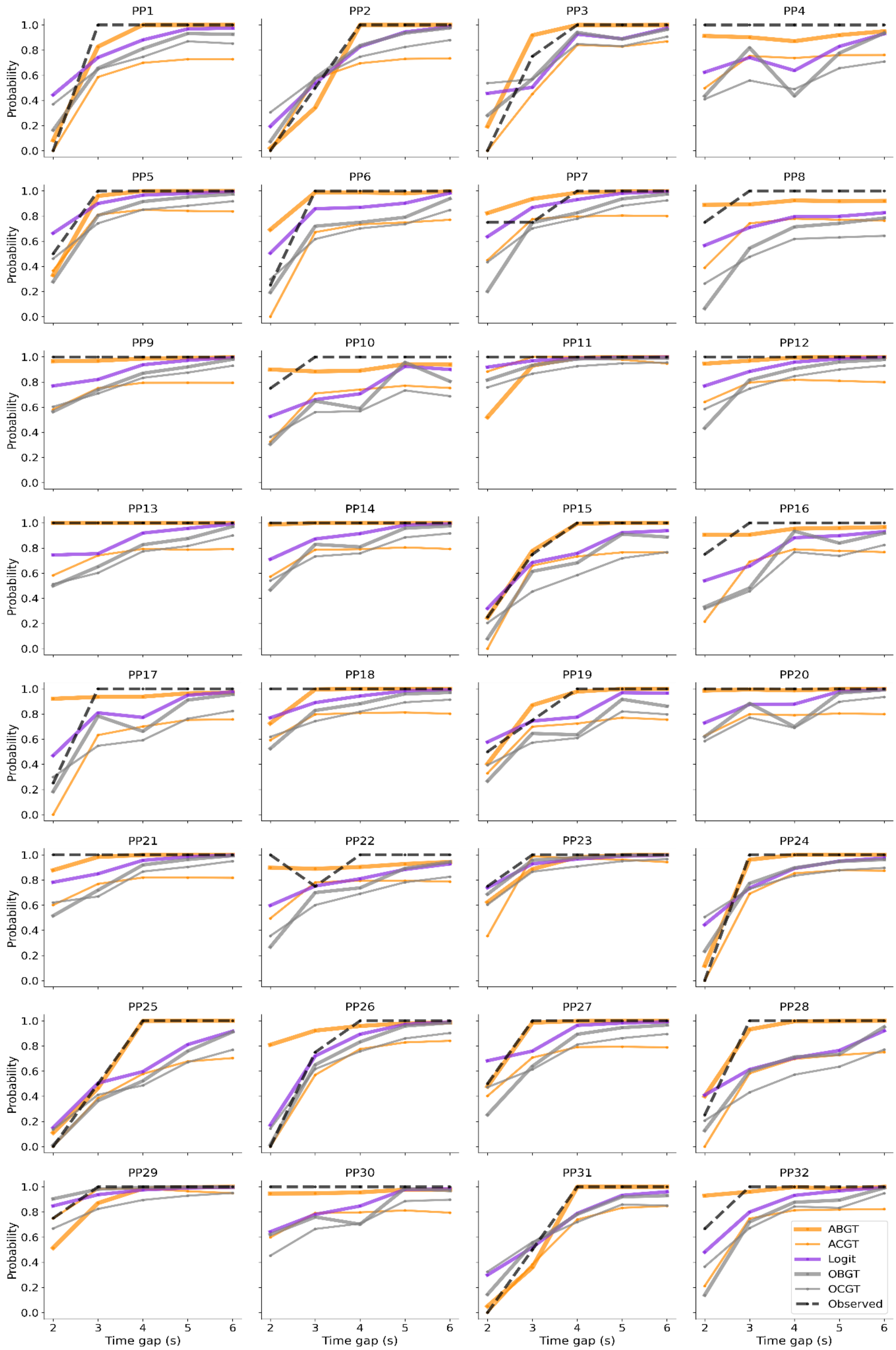

Figure 3.3 Pedestrian's probability of crossing first over time gap at zebra for all models.

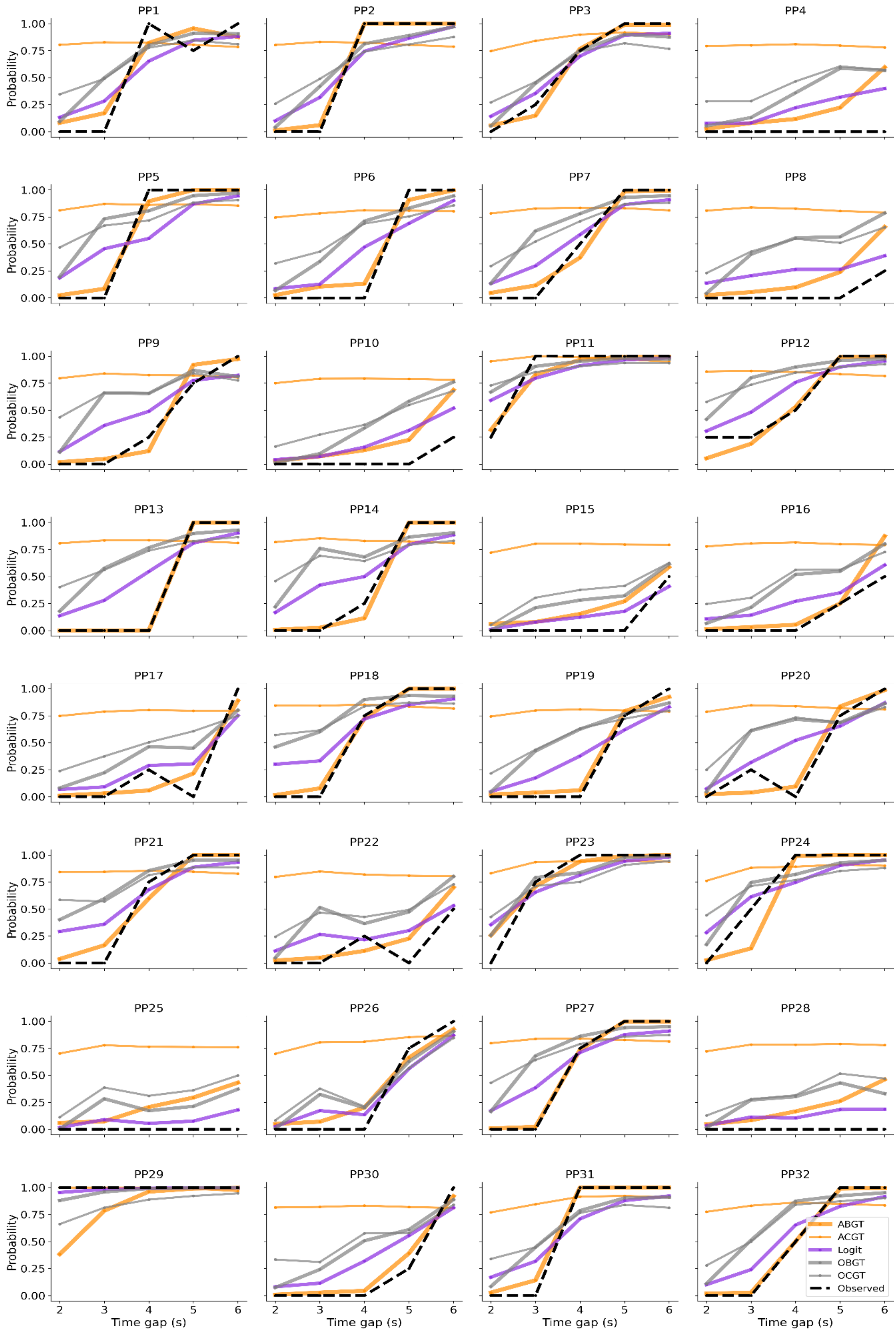

Figure 3.4. Pedestrian's probability of crossing first over time gap at non-zebra for all models.

Table 3.5. Model comparison

Model	ABGTZ	ABGTNZ	ACGTZ	ACGTNZ	LogitZ	LogitNZ	OBGTZ	OBGTNZ	OCGTZ	OCGTNZ
MAE[1]	**0.058**	**0.087**	0.2121	0.4996	0.1226	0.1635	0.172	0.230	0.231	0.297
RMSE[2]	**0.088**	**0.139**	0.2372	0.5676	0.1497	0.195	0.209	0.290	0.262	0.339
AIC[3]	**705.949**		1984.913			884.607	1156.695		1283.619	
BIC[4]	**1540.870**		2809.527			1544.298	1666.925		1778.387	
NLL[5]	**190.974**		832.456			314.303	479.347		545.809	
NO params[6]	162		160			128	99		96	

[1] *Mean absolute error* [2] *Root mean squared error* [3] *Akaike information criterion*
[4] *Bayesian information criterion* [5] *Negative log-likelihood* [6] *Number of free parameters*

Fig 3.4 and Table 3.5 show that similar to the zebra crossing, overall, the Wu et al. model combined with the DA model, i.e. OBGT, performed better than the original model (OCGT) but the differences were subtle for the non-zebra crossing. Also, the logit model performed second-best with a weaker performance compared to the zebra crossing. Unlike the zebra crossings, the differences between the ACGT and ABGT are much more obvious. Although the two models utilise the exact same payoff formulations, the ABGT model outperformed all other models in almost all cases while it is clear that the ACGT model was not capable of exhibiting the observed pattern of probabilities. For ABGT, the model's capability to capture the more complex crossing behaviours of pedestrians No 3, 6, 8, 13, 14, 18, 19, 27 and 30 is specifically noticeable compared to other models. Overall, Table 3.5 shows that when moving from conventional to behavioural game-theoretic models, the improvements in all criteria, including negative log-likelihood are observable which firmly confirms the observations of Figs 3.3 and 3.4.

3.3.3 Overall results for both crossing types

Fig 3.5 shows the average of all 32 pedestrians' crossing probabilities over time gaps for both crossing types. In line with the individual data, the overall fine performance of the ABGT model and the better performance of the Wu et al. combined with the DA model (OBGT) compared to the original model (OCGT) is evident for both crossing types.

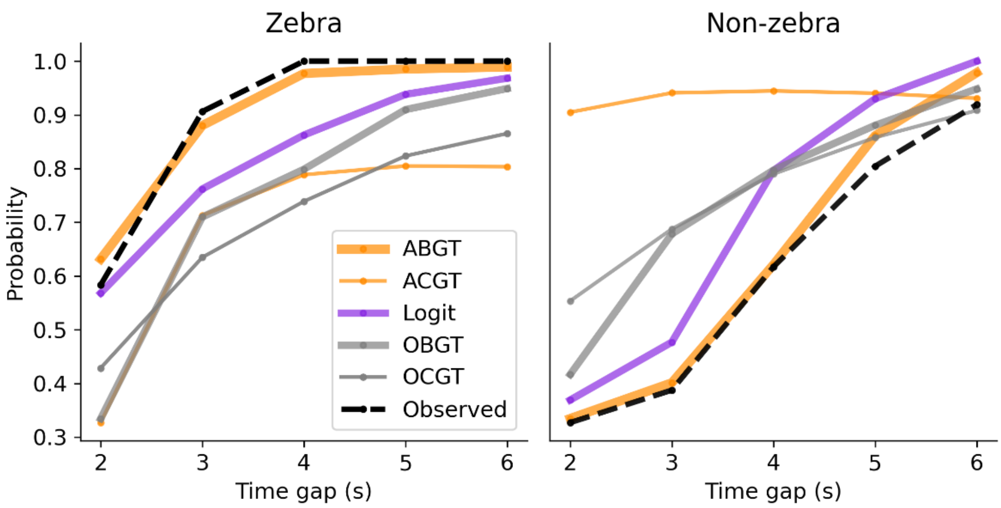

Figure 3.5. Average probability of pedestrian crossing first over time gap for all models

3.3.4 ABGT model decision time

As shown in Fig 3.2, the dual accumulation process in the DA model corresponds to a deliberation process that unfolds over time such that we can define a model convergence/decision time. Thus, we conducted a correlation test to understand if there is a relationship between the ABGT model's decision time (DT) and pedestrians' crossing initiation time (CIT) (i.e. from the time the auditory tone was triggered to the time the pedestrian started crossing the road, minus one second). Table 3.6 shows that there is a weak, yet significant correlation ($r(821) = .213$, $p = .000$), between the ABGT model's DT and CIT, which also can be confirmed by Fig 3.6. From the figure, it can be seen that most of the initiation times are concentrated in the 1−2 second range. The Figure also shows that the model had a hard time predicting DT within this range. By increasing CIT, more instances of successful estimations are observable. Three different points were chosen to show how the model predicted the interaction outcomes over time which can be seen by the respective insets. Fig 3.6 shows that in points C: [1.5,290] and B: [5,490] the model performed well. Point C belongs to PP 29 with the following experimental conditions: non-zebra, TTA of 6 s, both female and the waiting time of 80 s and point B is for PP 8 at zebra, with a TTA of 5 s, with a male driver and female pedestrian, and a waiting time of 78 s. Hence, probably the most obvious difference between these two points is the crossing type that led to different CITs and DTs. Finally, in point A: [1.2, 895], it can be seen that the pedestrian's probability of passing and waiting swapped places after a few time steps which made the model predict the interaction outcomes incorrectly, and over a longer time. This point refers to PP 1 at non-zebra, with a TTA of 4 s, with a female driver and male pedestrian, and a waiting time of 64 s. Although both the TTA and crossing type made the model predict lower values and subsequently lower probabilities of passing first for the pedestrian over time, the pedestrian passed first suggesting that there might be other influencing factors such as gender and personality traits that were not considered for calculating the probabilities.

Table 3.6. Correlation between ABGT's DT and CIT in the experiment

Variables			CIT
Spearman's rho	DT	Correlation Coefficient	.213
		Sig. (2-tailed)	.000
		N	823

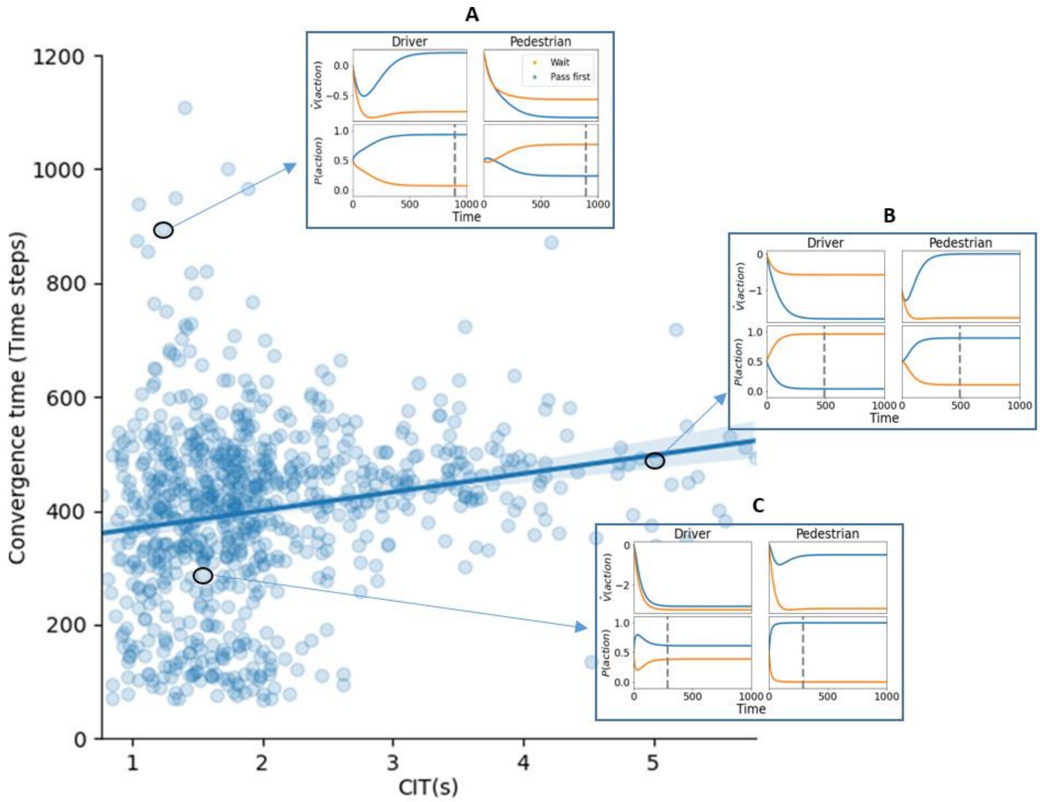

Figure 3.6. The relationship between the ABGT model's DT and CIT in the experiment.

3.3.5 ABGT model parameterisation results

Fig 3.7 shows the pairwise distribution of the best-fitted model, i.e. ABGT parameterisation as a function of the average probability of pedestrian crossing first in each PP. Thus, each point in the figure is representative of a PP. From the figure, it can be seen that there is a positive correlation between the values of $\boldsymbol{a}$ and the average crossing probability suggesting that higher values of this parameter resulted in higher average probabilities. Also, a moderate negative correlation can be seen between $\boldsymbol{a}$ and $\boldsymbol{c}$ suggesting that fixing one parameter (e.g. $\boldsymbol{a}$) and leaving the other one to vary freely could improve the model fit results. However, it is quite debatable what would be the exact value of the fixed parameter as there is no theoretical reasoning for choosing a specific value for either of these parameters. One can try different values and see which value would yield the best results. Finally, several instances of hitting bounds can be seen but as we explained above, broadening the bounds did not result in a better model fit.

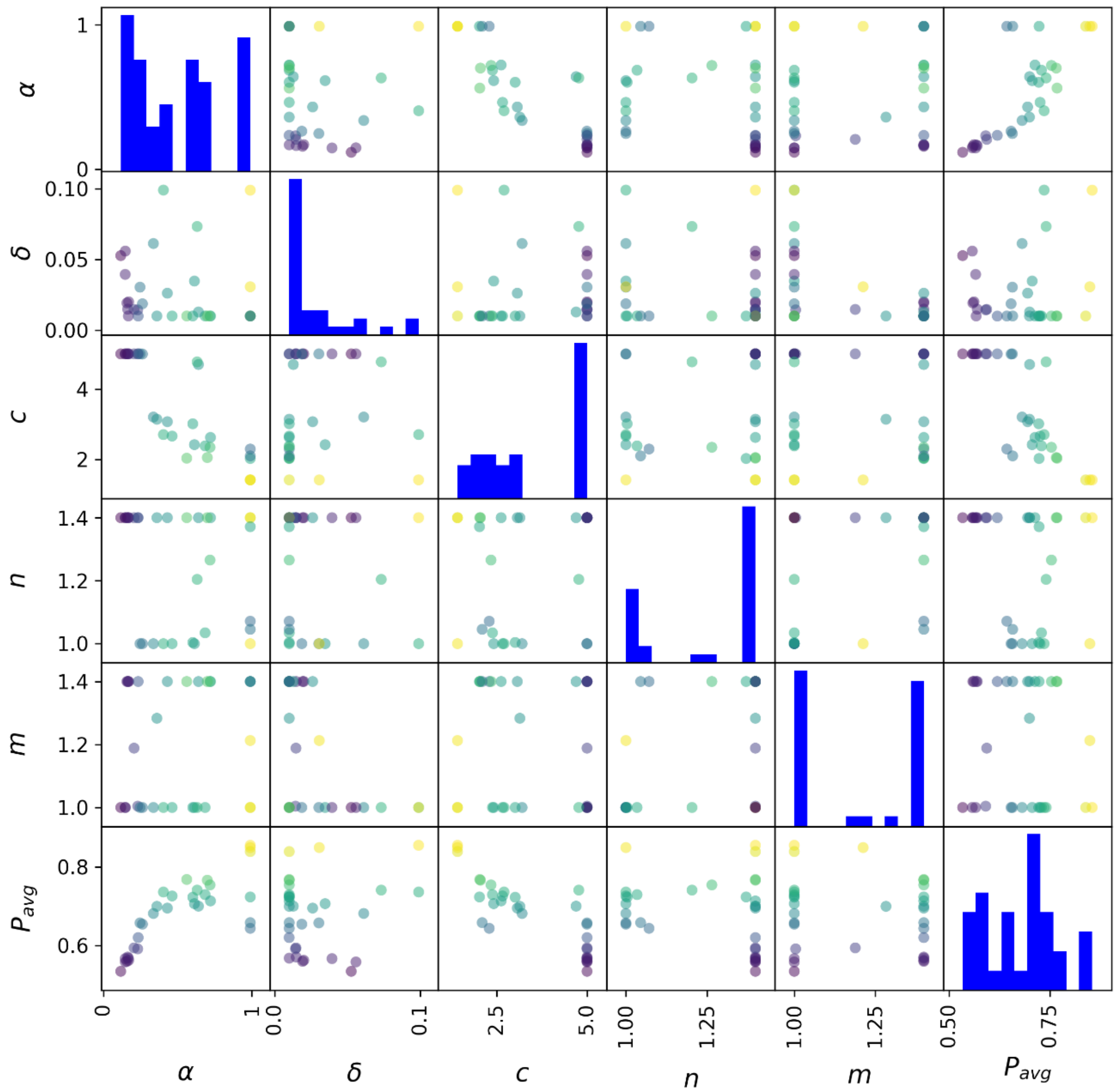

Figure 3.7. Pairwise distributions of parameters for ABGT model as a function of average crossing probability in each PP.

3.4 Discussion

In this study, we compared a number of computational models of road user interaction, namely a logit model and four game-theoretic models, using a controlled study. The findings showed that our proposed model, which was based on behavioural game theory outperformed all others for almost all PPs' data, for both crossing types. The second-best performing model was the Logit model confirming the findings of many studies that relied on this type of modelling to predict vehicle-pedestrian interaction outcomes (Perumal, 2014; Vinayaraj et al., 2020; J. Zhao et al., 2019). Moreover, a huge improvement was observed by switching from mixed-strategy Nash equilibrium to dual accumulation to solve the same payoff matrices. This was especially noticeable for our ACGT versus ABGT models and for the non-zebra crossing which constituted the worst and the best models for this crossing type, respectively. This helps us answer our main research question: In line with behavioural economics, people do not play the

Nash equilibrium in their daily life (Wright & Leyton-Brown, 2017a), which may also be true about road users. As stated by (Mailath, 1998), people are usually not aware that they are playing a game. They have some beliefs about their surroundings, other potential players and their available strategies and the possible outcomes of each chosen strategy. Hence, they use heuristics and the rule of thumb to take an action. Road users' divergence from Nash equilibrium has been reported in cyclist-pedestrian interactions (Alsaleh & Sayed, 2022) and is observed here for vehicle-pedestrian interactions. Alsaleh & Sayed (2022) suggested that this might be due to the possible Nash equilibrium's inability to consider suboptimal road user behaviour. While one could argue that the performance difference between ACGT and ABGT models can be attenuated by formulating a different payoff matrix, we tend to believe that it is less possible to propose a model based on a different payoff formulation and solve it by mixed-strategy algorithms, which works better than the ABGT model. This is due to the inherent limitation of the mixed-strategy algorithm with respect to only considering the opposing player's utilities. Overall, the results of this study can be beneficial for the testing and development of AVs when there is a need for studying a large number of vehicle-pedestrian interactions in a safe and controlled manner with subsequent computer simulations and mathematical modelling.

Unlike other models used in the study, the behavioural game-theoretic models provide a concept of time and suggest that the initial conditions (i.e. kinematics and crossing type) are processed over time. The time it takes for the model to process those initial conditions correlates with the actual time it takes for PPs to reach a point where one of the agents can go ahead and pass first (Fig 3.6). That said, the agents may be adjusting their behaviour at multiple points in time during the interaction. Hence, the key simplification in the model is that the interaction is modelled as a single decision-making process making it a simple model capable of predicting interaction outcomes, which could be quite useful in some types of applications. Also, the DA model relaxes this single decision simplification a little more, as there can be many steps of deliberation in the DA process, even though in this model those steps of deliberation in the model are not connected to how the external world is developing over time.

Moreover, checking the participant features and traffic conditions of the three selected points in Fig 3.6 revealed that there was a difference in traffic conditions between the points where the model performed well (i.e. B and C in Fig 3.6); longer CIT and DT were observed at a zebra crossing (***B***) compared to a non-zebra crossing (***C***). We have previously shown that pedestrians had considerably longer CITs at zebra crossings (Kalantari, Yang, et al., 2023). Also, investigating the third point, i.e. ***A***, where the model performed poorly suggested that other factors such as personality traits could play a role in the pedestrians' CIT (see Kalantari, Yang, et al., 2023). Therefore, the observed discrepancy between the model's DT prediction and the pedestrian CIT could be due to the lack of consideration of such variables. A more complete account of this negotiation process could include these variables (e.g. personality traits) in future studies.

We used a novel approach in model fitting employing a distributed simulation dataset to test and validate the models. The controlled nature of the study allowed us to understand and pinpoint each and every PP behaviour, individually as well as evaluate each model's performance with respect to the individual data, something that is not possible in naturalistic studies. It also helped us formulate the alternative payoff matrix having the confidence that there are no unknown correlations between the studied variables. Previously, we showed that distributed simulation can generate pedestrians' gap acceptance behaviours, using a desktop driving simulator connected to the HIKER lab (Kalantari, Markkula, et al., 2022). This paper tried to a take step forward in this direction by replicating game-theoretic interactions using two high fidelity simulators to maximise the validity of the experiment. That said, naturalistic data still provide some advantages over simulator data which should not be overlooked: studying road user behaviour over a longer period to understand, for example, driving patterns (Balsa-Barreiro et al., 2020), giving a truthful representation of road users' 2D movement on the road for vehicle-vehicle (Zhao et al., 2020) and vehicle-pedestrian interactions (Camara & Fox, 2021) and the capability of tracking a large number of road user parameters, especially those related to driving performance (Balsa-Barreiro et al., 2019) are some of the aspects that still make the naturalistic data a necessary tool for a successful traffic microsimulation.

Another strength of this modelling approach is that the inputs of the proposed model (the agents' kinematics) are usually easy to record and extract and unlike many models, it does not demand metrics such as vehicle's deceleration, dimensions, etc. which are usually more difficult to achieve when using naturalistic video data. Moreover, while the modelling framework of this study is both computationally less expensive and intensive than most machine-learned models, we do not consider it quite a substitute for these black box models, rather, we think the combination of these two would generate an even more powerful computational framework which balances interpretability and generalisability.

Several improvements can be made to this study. First and considering the empirical study, we did not account for the interaction approach phase while research showed that the interaction commences as soon as road users see each other even before the time pedestrians reached the kerb (Gorrini et al., 2018). Second, making the utility functions time-varying would yield a more complete picture of the whole interaction from the approach phase to the time that both agents passed the crossing. Third, from both the experimental and modelling perspective, there is a need to further develop a methodology to consider situations where multiple pedestrians are interacting with multiple vehicles. This could be done by using head-mounted displays where several pedestrians wear these devices connected over a network. Fourth, our ABGT model currently uses some of the features of behavioural game theory while there are more aspects associated with this theory that distinguishes itself from its conventional counterpart concerning collective behaviour, which have not been investigated in a road traffic setting. These include theories of strategic complementarity (Camerer & Fehr, 2006), theories of team reasoning (Colman et al., 2014) and theories of social projection (J. I. Krueger, 2008; J. I. Krueger et al., 2012).

To this end, extending the framework to a multi-agent problem is one of the most important future research directions. Finally, due to the nature of the experimental work, the behaviour of a limited number of people was studied and the models' performance including the proposed ABGT model was judged accordingly. Future studies should test and validate the framework using large naturalistic datasets to both confirm and improve its performance and generalisability.

3.5 Conclusions

In this study, we compared several computational models of road user interaction using data from an experimental setting. The results showed that drivers and pedestrians do not play Nash equilibrium when interacting at unsignalised crossings and more complex behavioural modelling paradigms like behavioural game theory are needed to fully capture the pedestrians crossing decisions at these locations. The ABGT model was successful in replicating these interactions by taking into account how agents negotiate their available strategies and gains and losses over time which sometimes results in choosing a suboptimal decision as opposed to the assumed rationality of players in conventional game theory. These findings are especially a pivotal point for the virtual testing and development of AVs where they need to take over human driver tasks to a great extent taking the unpredictability of VRUs into account.

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Chapter 4

Investigating driver-pedestrian interactions at marked crossings: A comparison of two methodologies

Investigating driver-pedestrian interactions at marked crossings: A comparison of two methodologies

Abstract

Understanding driver-pedestrian interactions at unsignalised locations has gained additional importance due to recent advancements in vehicle automation. To investigate these interactions, we previously developed a novel experimental study paradigm and a set of computational models, including four game-theoretic models (two conventional and two behavioural game-theoretic models). This study aims to validate lab and model results with naturalistic data to assess their comparability with real traffic data. In the experimental study, several pairs of one driver and one pedestrian interacted under various kinematic conditions in a connected virtual environment. Naturalistic data collection occurred at two marked crossings (normal versus staggered zebra crossings) using state-of-the-art sensors to capture road user type, trajectory, and speed over time. Overall, the results indicated a fine relative validity of the experimental study, where road users showed similar non-verbal communication patterns in both studies. Like the lab data, crossing type influenced interaction metrics, including pedestrian crossing speed and vehicle delay. Pedestrians crossed more often and walked faster at staggered zebra compared to normal zebra in real traffic. In both studies, vehicle delay was affected by kinematics and location. However, vehicle delay was longer in the lab compared to real traffic. Also, unlike the lab study, pedestrian approach speed was measured and found to be a predictor of their crossing speed and the delay of the drivers. All computational models performed well, with behavioural game-theoretic models slightly outperforming others in prediction accuracy, highlighting the complexity of road user behaviour in the context of virtual testing for automated vehicles.

Keywords: Validation study, mathematical modelling, site-based study, autonomous vehicles

4.1 Introduction

Negotiating right-of-way at unsignalised locations and shared spaces has become a topic of interest over recent years. This happened mostly due to the recent advances in vehicle automation in which highly automated vehicles (HAVs) are expected to take over most (if not all) of the human driver tasks (Koopman & Wagner, 2018). This requires an in-depth understanding of human road user interaction and its challenges in the first place so that HAVs become completely prepared before their full deployment on the roads. If not, they may face the challenge of having non-transparent driving behaviour due to associated complexities with their architecture and different decision-making mechanisms compared to humans (Koopman & Wagner, 2017); this can eventually lead to mistrust among human road users. The problem is exacerbated when interacting with vulnerable road users, especially pedestrians, as they are omnipresent (World Health Organization, 2013) and unpredictable in their crossing behaviours (de Lavalette et al., 2009) which targets safety and efficiency in future urban traffic scenarios. This situation has led researchers to both investigate (Gorrini et al., 2018) and quantitatively model (Camara et al., 2020; Markkula et al., 2022) competing as well as communication strategies that exist between pedestrians and vehicles.

To understand each other's intentions, road users employ a wide range of communication strategies to convey information about their position, trajectory and intention. A growing body of research suggests that this heavily relies on implicit communication (Lee et al., 2021; Markkula et al., 2020) which consists of time-based (e.g. time-to-arrival [TTA]) (Dozza et al., 2020; Rasouli & Kotseruba, 2022) and movement-based (e.g. vehicle speed) (Theofilatos et al., 2021; Tran et al., 2021) factors. Other situational factors such as crossing location type (e.g. presence of zebra) (Kalantari, Yang, Pedro, et al., 2023; Madigan et al., 2022) and vehicle distance at interaction onset (Velasco et al., 2021b) have also been found to play an important mediating role (Domeyer et al., 2020). For instance, pedestrians have been found to cross less often at an unmarked crossing compared to a zebra crossing for the same TTA (Kalantari, Yang, Pedro, et al., 2023). Additionally, age and gender have been found to be associated with interaction outcomes and pedestrian crossing behaviours (Amini et al., 2019; Rasouli & Tsotsos, 2019).

Previous research has relied on either controlled or naturalistic studies to investigate and model vehicle-pedestrian interactions. Naturalistic data constitute a greater proportion of past studies where most previous studies utilised them as their validation tools for the mathematical models of road user behaviour. Naturalistic studies are usually conducted either using instrumented vehicles (Ehsani et al., 2021) or traffic data collection devices including drones (Bock et al., 2020) and installed cameras on fixed objects like light poles (Kloeker et al., 2021). Using instrumented vehicles provides the advantage of studying road user behaviour over a longer period of time and with high quality and the capability of tracking a large number of road user parameters (Boda, 2017). However, the downside is that this method is expensive and drivers are usually aware that they are being watched (Ehsani et al., 2021) and this might make them alter their behaviour (van Haperen et al., 2019). On the other hand, video and sensor-based studies offer this opportunity to record road user behaviour in an unnoticed manner, gaining more knowledge of road user behaviour and its features while avoiding behavioural adaptation (van Haperen et al., 2019).

While naturalistic data are important, they primarily offer correlational information and do not establish causal relationships between different factors. To comprehend and model the causal mechanisms underlying behaviour, controlled studies are more helpful. Controlled studies are divided into two categories: test track studies (Palmeiro et al., 2018) and studies in virtual reality (VR) (Tran et al., 2021). In both categories, one can study traffic scenarios in a way not possible in reality, not least with respect to safety. However, distributed simulation (also known as coupled simulation) is the only method that can help investigate road user interactive communications precisely, repeatably, and controllably (Kalantari, Yang, Pedro, et al., 2023; Mok et al., 2022; Sadraei et al., 2020). In this type of study two or more simulators (e.g. a driving and a pedestrian simulator) are connected over a network where two or more human participants can interact in a safe and controlled environment and the experimenter(s) can manipulate the conditions of interest to study the impact of traffic conditions regarding interactive behaviours and outcomes. The technique also allows participants to be observed multiple times, offering a deeper understanding of inter-individual differences (Kalantari, Yang, Merat, et al., 2023). These features are undoubtedly beneficial (if not necessary) for developing human behaviour models for vehicle automation such as those in the game theory category (Kalantari, Yang, Merat, et al., 2023). Game-theoretic models provide a well-established image of road user interactions by considering interdependencies suggesting optimal decisions for each party (Novikov et al., 2018).

Nonetheless, distributed simulation is expensive and requires advanced hardware and software installations plus a comprehensive experiment design. Moreover, it is still unclear to what extent the findings from the lab are comparable to real traffic data to determine, for example, whether the computational models that are tested against these datasets are capable of capturing human behaviour under uncertainty and risky conditions in real traffic. While there are many driving simulator validation studies (Wynne et al., 2019), the ones for pedestrian simulators are very rare (Schneider et al., 2022) and there has been no study to validate road user behavior in a connected virtual environment (i.e. distributed simulation). Thus, there is a gap in the literature regarding the validity of the data that come out of the lab with respect to pedestrian simulators and distributed simulation (Feldstein et al., 2018). Validity in the context of simulators pertains to how faithfully they replicate real-world driving or walking behaviour. Researchers have identified different types of validity (Annett, 2002; Stanton, 2016), with the most common ones being absolute validity and relative validity, which are often evaluated in studies (Blaauw, 1982). While absolute validity happens when measured metrics in the lab match those in real traffic, relative validity occurs when the observed patterns and/or effects from the lab are similar to the ones in a naturalistic setting (Wynne et al., 2019). Overall, the practice of connecting simulators has the potential to enhance the validity of simulator data by incorporating an interaction channel that enables non-verbal communication, thereby promoting more realistic behaviour (Feldstein et al., 2018).

The main objective of this study is to validate both findings of a distributed simulator study (DSS) (Kalantari, Yang, Pedro, et al., 2023) and a set of computational models that were tested against this type of data, previously (Kalantari, Yang, Merat, et al., 2023). This validation is achieved by comparing the findings of both studies with the real traffic data presented in this paper.

In the DSS, several driver-pedestrian pairs interacted with each other in different crossing scenarios. To maximise experimental control, the simulator study only had participants cross a single lane. In practice, this was achieved by making the crossing location staggered, letting the participants cross only a single lane, to a refuge in the middle of the simulated road. Many crossings in the real world are not of this nature, but to the best of our knowledge, there are no existing comparisons of pedestrian crossing behaviour between staggered and normal (non-staggered) two-lane zebra crossings. Thus, it remains uncertain whether road user behaviour would have been the same if the pedestrians had the opportunity to cross both parts of the crossing, something that this study can help us resolve. Therefore, a secondary objective of this paper is to compare naturalistic pedestrian crossing between these two types of crossing locations, to provide additional insight about the generalisability of the findings from our DSS.

4.2 Methods

This section describes all the methods used in the study, beginning with a description of the DSS, data collection locations and data extraction algorithms, followed by data preparation and modeling details.

4.2.1 Experimental study

In the DSS, 32 pairs of one driver and one pedestrian (32 drivers [Age: M = 31.53, R = 21−50, SD = 1.72]; paired with 32 pedestrians [Age: M = 25.09, R = 19−34, SD = 0.87]) interacted with each other in a VR environment. The VR environment was built by connecting a motion-based driving simulator to a CAVE-based pedestrian lab. In this setup, participants (both drivers and pedestrians) had the choice to decide whether they would wait for the other to pass first or proceed themselves. Each pair experienced 40 trials which were designed as a combination of the approaching vehicle's TTA and the presence of zebra. A number of interaction-related metrics including interaction outcome, pedestrians' crossing duration and vehicles' delay as the result of yielding to pedestrians were recorded and analyzed. Also, participants' demographics and personality traits were collected. The DSS also included trials where the pedestrian crossed at unmarked locations, i.e. jaywalking. This type of pedestrian crossing location is left outside of the scope in this paper (Kalantari, Yang, Pedro, et al., 2023).

4.2.2 Data collection

Two marked crossings in the city of Leeds, England were surveyed to collect real-time traffic data. Following several roadside observations by two independent observers and consultations with Leeds City Council regarding each location's crash history, the crossings were chosen based on safety concerns and the prevalence of one-to-one interactions between vehicles and pedestrians. A staggered crossing on Belle Isle Road (53°46′07″N, 001°31′48″W) and a zebra crossing on Queensway Road (53°44′45″N, 001°36′16″W) were chosen. Two Viscando camera sensors known as OTUS3D were used to collect data over 14 days (seven days for each location). The sensors detect the type of road users (light vehicles, heavy vehicles, cyclists, pedestrians) and track their trajectory and speed over discrete time stamps. The camera sensors were set up on two light poles at Belle Isle Road and the Queensway with heights of 6.46 m and 8.3 m, respectively. The traffic data were recorded from the 9th of May to the 15th at the first site. For the second site, the road user data were recorded from the 17th of May to the 23rd of May, 2022. Fig 4.1 shows the bird's-eye view of the two locations.

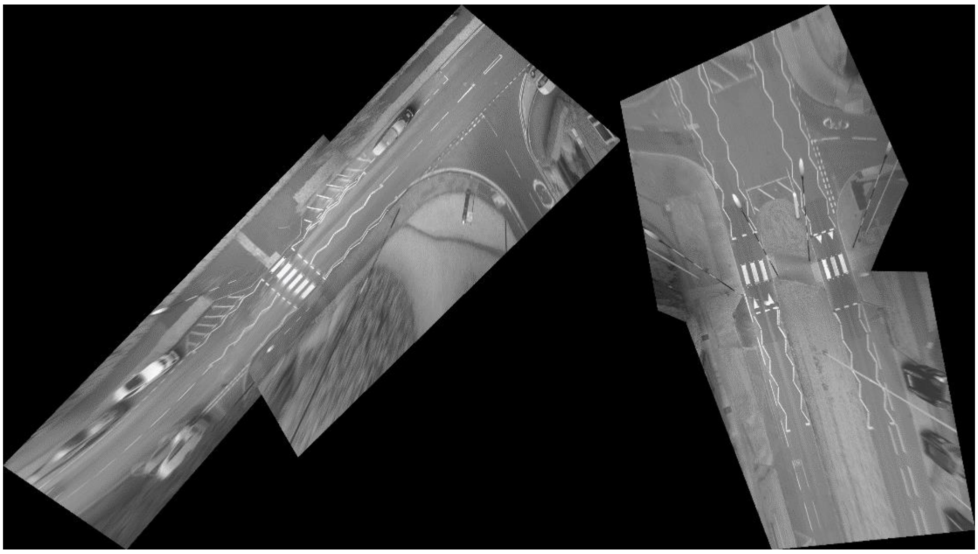

Figure 4.1. Bird's eye view of Queensway (left) and Belle Isle roads (right)

Fig 4.2 (top and bottom) shows the rotated trajectory map of cars and pedestrians at the two crossing locations and their *potential conflict zones* depicted by black rectangles. The potential conflict zone was defined from 1 m before the kerb on one side to 1 m after the kerb to the other side of each crossing location as it is shown in their respective insets in the figure. Potential interaction was defined as the time that both pedestrian and car entered the potential conflict zone within a specific temporal distance of ± 7 s and a car was approaching the pedestrian on the near lane. If there were multiple vehicles interacting with a pedestrian, only the nearest car that interacted with the pedestrian was considered. This was done by selecting the car that had a minimum time difference of entering the potential conflict zone after which the pedestrian entered the zone. An algorithm was developed to detect the potential interactions and extract and store the interaction-related metrics according to Fig 4.3.

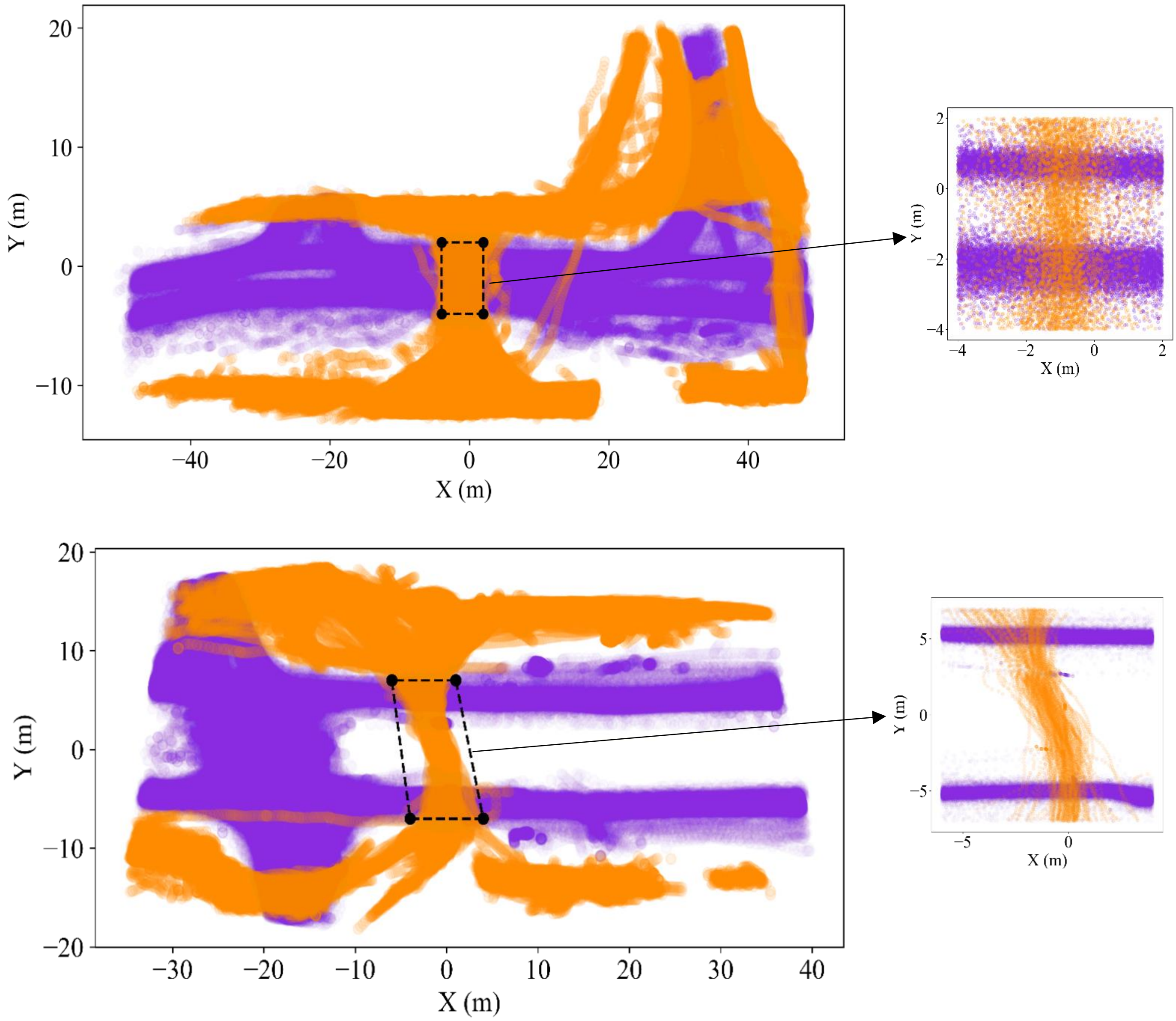

Figure 4.2. Trajectory map of (top) Queensway and (bottom) Belle Isle Road; the orange and violet dots show pedestrians and cars, respectively.

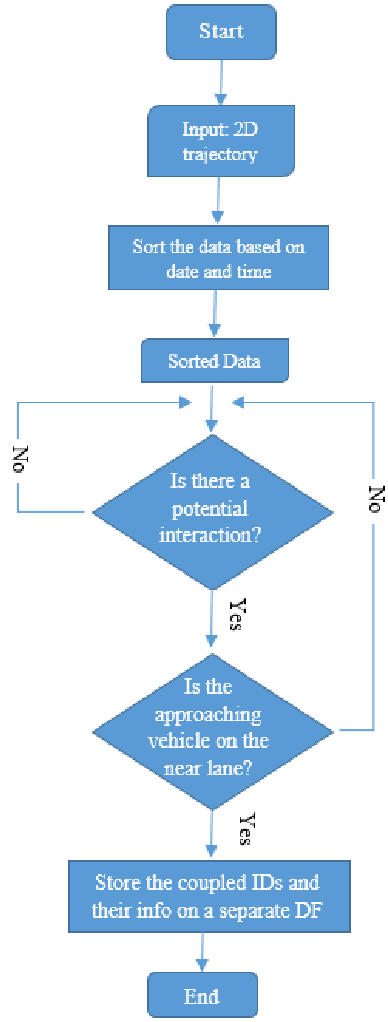

Figure 4.3. Flowchart for extracting the potential interactions (ID= identification; DF = data frame)

A total of 813 potential interactions were detected using the above algorithm. Afterwards, to verify and extract the actual one-to-one interactions, the related video clips were watched according to the timestamps obtained by the algorithm and the following exclusion criteria were applied to the data:

- There were some cases in that interaction took place between a bus/truck and a pedestrian; in these instances, trucks were detected as cars (e.g. two cars) by the sensors, erroneously. Twenty-six events were removed.
- In some cases where the vehicle passed first, the pedestrians did not change their direction toward the crossing nor did they turn their head towards the crossing before the vehicle reached the crossing suggesting a lack of interaction. Thus, 131 events were removed.
- Every potential interaction that had a group of three or more pedestrians interacting with a car was removed. As the time of reaching entering and exiting the potential conflict zone for the couples was roughly the same, they were considered in the analysis. The sensors almost always considered these cases as a single pedestrian. Sixty-two events were removed.

- There were a few instances where there was no direct car-pedestrian interaction: although there was a car on the near lane approaching satisfying the potential interaction definition, the car was behind a bus/truck and the pedestrian interacted with the bus/truck, not the car. Twenty events were discarded.
- There were some instances that sensors detected pedestrian presence but in the corresponding video clip, no pedestrian was present in the scene. Twelve events were removed.

After applying the aforementioned criteria, 562 (i.e. 243 for the normal and 319 for the staggered zebra crossing) interactions (events) were identified and used for the statistical analysis and modelling.

4.2.3 Data preparation

Table 4.1 displays the variables and parameters utilised in the study for analysis, including their type, description, symbol, and the source from which each variable is defined. The criteria for categorising the variables as either dependent or independent were determined based on both the related literature and the DSS.

4.2.4 Inferential testing

Similar to (Kalantari, Yang, Pedro, et al., 2023), a logistic regression and a linear regression model were used to predict interaction outcomes and vehicle delay, respectively. To provide a more precise comparison, regression analyses were conducted on pedestrian walking speed instead of crossing duration for both studies. This is due to the difference in the length of the staggered crossings in the two studies (2.5 m in this study versus 4.55 m in the DSS). Also, only the trials in which the pedestrian crossed first were considered in the models for walking speed and vehicle delay similar to the DSS. The full model of potential predictors based on theoretical reasoning (Maxwell et al., 2017) is proposed in Eq 4.1 which is written using Wilkson notation (Wilkinson & Rogers, 1973).

$$Outcome\ variable\ (IO/WS/VD) \sim C(Gender) + Age + v_p + L + v_{vo} + Location \tag{4.1}$$

Eq 4.1 was used to fit the regression models to the data using `statsmodels` in Python. Note that, we did not consider TTA as a predictor in the models to avoid multicollinearity which undermines the statistical significance of both speed and distance of the vehicles at interaction onset. However, TTA was used for the Logit model and also to interpret the results throughout the paper.

Table 4.1. Parameters of the study

Variable	Type	Description	Symbol	Unit	Source
Interaction onset time	Independent	Defined as 2 s before the pedestrian entered the potential conflict zone.	T_o	s	Trajectory data
Vehicle arrival time	Independent	The time at which the vehicle reached the edge of the crossing.	T_a	s	Trajectory data
Vehicle distance	Independent	The distance of the vehicle to the edge of the crossing at interaction onset time.	L	m	Trajectory data
Vehicle speed (onset)	Independent	The speed of the vehicle at interaction onset time.	v_{vo}	m/s	Trajectory data
Time gap	Independent	$TTA = L/v_{vo}$	t_v	s	Trajectory data
Pedestrian approach speed	Independent	The speed of the pedestrian when they entered the potential conflict zone.	v_p	m/s	Trajectory data
Age group	Independent	The age group of pedestrians: (1: <20, 2: 20-60, 3: >60).	Age	-	Video
Gender	Independent	The detected gender of the pedestrians.	$Gender$	-	Video
Location	Independent	The type of crossing (1 = normal zebra, 2 = staggered zebra).	$Location$	-	Video
Crossing duration	Independent	The time it took the pedestrians to cross their nearest driving lane (i.e. half of the normal, two-lane zebra crossing, and the first of the two single-lane crossing in the staggered zebra).	t_p	s	Trajectory data
Walking speed	Dependent	The average walking speed of pedestrians during the crossing behaviour. This was obtained by dividing the width of each driving lane by crossing duration.	WS	m/s	Trajectory data
Interaction outcome	Dependent	The pedestrian was considered to have crossed first when they crossed before the car had reached the crossing, and then continued walking until reaching the other end of the crossing location, i.e. the pedestrian did not abort the crossing (1 = pedestrian crossed first, 0 = waited).	IO	-	Video
Vehicle delay	Dependent	The time the driver lost as a result of yielding to the pedestrian is defined as the difference between the time that it actually took the vehicle to reach the edge of the crossing (i.e. $T_a - T_o$) and the time it would have taken if the driver had kept their initial speed (i.e. t_v).	VD	s	Trajectory data

4.2.5 Computational models

The five computational models introduced in (Kalantari, Yang, Merat, et al., 2023) were tested and fitted to the naturalistic dataset to predict the interaction outcome. These were original formulation (solved by) conventional game theory (OCGT), alternative formulation (solved by) conventional game theory (ACGT), original formulation (solved by) behavioural game theory (OBGT), alternative formulation (solved by) behavioural game theory (ABGT), and a Logit model. To achieve this objective, we considered both an original payoff formulation from the game theory literature and an alternative formulation, both based on road users' risk perception and efficiency in interactions. The payoff formulations were then solved by two algorithms from conventional game theory (i.e. mixed-strategy Nash equilibrium) and behavioural game theory (i.e. dual accumulation; Golman et al., 2020) resulting in OCGT, ACGT, OBGT and ABGT models, respectively. Mixed-strategy Nash equilibrium assumes that agents have complete information about the game, act completely rational and they always make optimal choices in each game. On the other hand, the dual accumulation paradigm presumes agents generate preferences with assumptions about opponents' preferred strategies using evidence and stochastic sampling which accounts for their suboptimal behaviour (Golman et al., 2020). Two key takeaways from the study were the following: a) A huge improvement was observed moving from conventional to behavioural game theoretic models in all modelling comparison criteria (prediction accuracy and model parsimony) although both types of models utilised the same payoff formulations and b) Our proposed behavioural game theoretic model (i.e. alternative payoff formulation solved by behavioural game theory) outperformed others for both individual and average road user data (Kalantari, Yang, Merat, et al., 2023). The current study aimed to verify if these results held up when using real traffic data.

Slight modifications were made to the Logit model and the payoff formulation of the ABGT/ACGT model. The logit model was defined as a linear function of TTA, L and v_{vo} as there was no concept of pedestrian waiting time like the study in (Kalantari, Yang, Merat, et al., 2023) and both distance and speed of the vehicles at interaction onset were significant in the interaction outcome model (see Table 4.4). The following equation shows the model formulation:

$$U = \beta_0 + \beta_1 TTA + \beta_2 L + \beta_3 \mathrm{v_{vo}} \tag{4.2}$$

where β_0 and β_{1-3} are model intercept and coefficients and U is the utility of waiting/passing for the pedestrian. The probability of pedestrian passing first can be defined using the Logit function:

$$P(U) = \frac{1}{1+e^{-U}} \tag{4.3}$$

The alternative payoff formulation in AB(C)GT model was also modified slightly. Table 4.2 shows the payoff parameters of this model.

Table 4.2. Payoff parameters of the game-theoretic models

Parameter	Description	Unit
$k = \frac{v_{vo}}{L}$	Risk perception for pedestrians/vehicles.	1/s
c	A multiplier for the negative utility of delay to compensate for the extra waiting time required when both agents decide to pass simultaneously and thus need to avoid collisions, e.g. by braking suddenly (Wu et al., 2019).	1/s
a	Weight coefficient: In the original paper, the model assumes that the value of factor a varies depending on the cumulative waiting time of pedestrians. However, waiting time is not considered here, since the present analyses only consider the interaction with the first vehicle arriving after the pedestrian entered the potential conflict zone.	1/s
m	A multiplier in the alternative payoff formulation discourages both agents to wait when they think that the other one is waiting (≥ 1).	-

As the naturalistic dataset did not include crossings events at unmarked locations, we removed the multiplier $\boldsymbol{n}$ relating to this aspect of the crossing (Kalantari, Yang, Merat, et al., 2023), resulting in the payoff matrix shown in Table 4.3:

Table 4.3. The revised alternative formulation for AB(C)GT models

	Pedestrian pass	Pedestrian wait
Vehicle pass	$-\mathrm{k} - \mathrm{act_v},\ -\mathrm{k} - \mathrm{act_p}$	$k + \mathrm{at_v}, -\mathrm{a}(t_v + t_p)$
Vehicle wait	$-\mathrm{a}(t_v + t_p),\ \mathrm{k} + \mathrm{at_v}$	$-amt_v,\ -amt_p$

Eq 4.4 shows pedestrians' and vehicles' probabilities of passing first, respectively which was obtained based on mixed strategy Nash equilibrium.

$$P_{ppz}, P_{vwz} = \left(\frac{a(\mathrm{t_v} + m\mathrm{t_v} + m\mathrm{t_p}) + k}{2k + a(c\mathrm{t_v} - \mathrm{t_p} + m\mathrm{t_v} + m\mathrm{t_p})}, 1 - \frac{a(\mathrm{t_v}(1-k) + m\mathrm{t_p}) + k}{2k + a(ct_p - t_v - t_p + mt_p)}\right) \quad (4.4)$$

All the models were fitted to the dataset using maximum likelihood estimation and Powell's method implemented in Scipy similar to (Kalantari, Yang, Merat, et al., 2023).

4.3 Results

4.3.1 Interaction outcome

Fig 4.4 shows the probability of pedestrian crossing first over time gap with 95% CI at both marked crossings of the current study and the staggered crossing in the DSS (Kalantari, Yang, Merat, et al., 2023). From the figure, it can be seen that the crossing pattern is close between the two datasets and especially between the two staggered crossings, except for the dip in the curve for the naturalistic staggered crossing at TTA of 5 s. Also, the pattern for the normal zebra crossing is close to what has been observed in the lab. Overall, the positive effect of time gap on pedestrian crossing first is evident among the crossings.

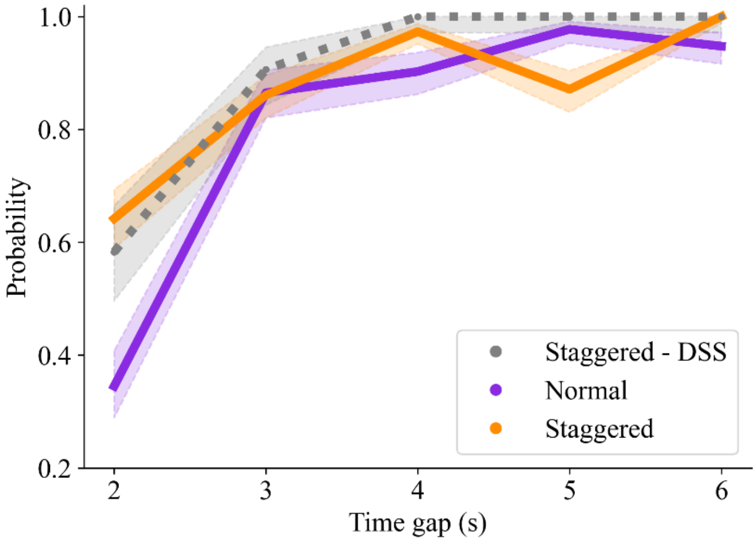

Figure 4.4. Percentage of pedestrians crossing first among three crossing locations and two datasets with 95% confidence intervals.

Table 4.4 shows the results for logistic regression of interaction outcome. The distance of the vehicle at the interaction onset had a significant positive relationship with the pedestrian's choice to pass first meaning that at greater distances pedestrians crossed more often. The speed of the vehicle, on the other hand, showed a negative association with the interaction outcomes, meaning that at higher speeds, pedestrians were less inclined to cross first which is in line with previous naturalistic studies (Theofilatos et al., 2021). The combined results of both distance and speed of the vehicle at interaction onset correspond well with our previous lab study' (DSS) finding regarding TTA (Kalantari, Yang, Pedro, et al., 2023). Additionally, the pedestrians behaved differently between the two locations with the staggered crossing showing a higher probability of crossing as shown in Fig 4.4. Finally, similar to the DSS, both age and gender did not show any association with interaction outcomes.

Table 4.4. Logistic regression results of interaction outcomes (1 = pedestrian crossed first, 0 = waited)

<table>
<tr><th colspan="2" rowspan="2"></th><th rowspan="2">Estimate</th><th rowspan="2">Std. Error</th><th rowspan="2">z value</th><th rowspan="2">Pr(>|z|)</th><th colspan="2">95% CI</th></tr>
<tr><th>L</th><th>U</th></tr>
<tr><td colspan="2">(Intercept)</td><td>2.349</td><td>0.767</td><td>3.062</td><td>0.002</td><td>0.845</td><td>3.853</td></tr>
<tr><td colspan="2">Gender</td><td>-0.164</td><td>0.221</td><td>-0.744</td><td>0.457</td><td>-0.596</td><td>0.268</td></tr>
<tr><td colspan="2">Age</td><td>-0.294</td><td>0.186</td><td>-1.585</td><td>0.113</td><td>-0.658</td><td>0.070</td></tr>
<tr><td colspan="2">Pedestrian approach speed</td><td>-0.046</td><td>0.056</td><td>-0.829</td><td>0.407</td><td>-0.157</td><td>0.064</td></tr>
<tr><td colspan="2">Distance</td><td>0.036</td><td>0.007</td><td>5.054</td><td>0.000</td><td>0.023</td><td>0.051</td></tr>
<tr><td colspan="2">Speed</td><td>-0.269</td><td>0.037</td><td>-7.203</td><td>0.000</td><td>-0.342</td><td>-0.196</td></tr>
<tr><td colspan="2">Location</td><td>1.032</td><td>0.311</td><td>3.322</td><td>0.001</td><td>0.423</td><td>1.642</td></tr>
<tr><td>AIC
538.29</td><td>BIC
568.61</td><td>logLik
-262.15</td><td>R-squ.
0.144</td><td colspan="2">df.resid
555</td><td colspan="2">Observations
562</td></tr>
</table>

4.3.2 Walking speed

As mentioned in Section 4.2.4, we considered the average walking speed of pedestrians instead of their crossing duration which was reported in the DSS paper (Kalantari, Yang, Pedro, et al., 2023) to provide a more direct comparison between the two studies. Table 4.5 shows the results of linear regression for the walking speed of pedestrians. From both the table and Fig 4.5 (left), it can be seen that those pedestrians who approached the crossing with a higher speed tended to keep their high speed during the crossing. They also walked faster at staggered compared to the normal zebra crossing. From the table and Fig 4.5 (right), an effect of age group can be seen where the older pedestrians walked significantly slower compared to younger pedestrians which is in correspondence with the literature (Fitzpatrick et al., 2006; Montufar et al., 2007). Table 4.6 shows the results of linear mixed-effects modelling of the pedestrians' average walking speed in the DSS. Similar to the current study, kinematics did not affect the pedestrians walking speed and only the type of crossing was important suggesting that pedestrians walked faster at unmarked crossings compared to marked crossings which is obviously in line with the crossing duration analysis in the DSS paper. Also, unlike real traffic interactions, the age of participants was not a predictor for their walking behaviour in the lab. From Fig 4.5, it can be seen that the pedestrians in the lab walked slower and had a narrow range of age compared to the naturalistic data.

Table 4.5. Linear regression results of walking speed

	Estimate	Std. Error	t value	Pr(>|z|)	95% CI	
					L	U
(Intercept)	**0.501**	**0.177**	**2.818**	**0.005**	**0.153**	**0.850**
Gender	0.005	0.042	0.132	0. 924	-0.076	0.087
Age	**-0.114**	**0.036**	**-3.197**	**0.001**	**-0.184**	**-0.044**
Pedestrian approach speed	**0.828**	**0.065**	**12.709**	**0.000**	**0.700**	**0.957**
Distance	0.000	0.001	-0.368	0.746	-0.003	0.002
Speed	-0.011	0.007	-1.632	0.091	-0.025	0.002
Location	**0.184**	**0.059**	**3.112**	**0.002**	**0.068**	**0.300**
AIC 496.6 / BIC 525.0	logLik -241.30	R-squ. 0.344	df.resid 422		Observations 429	

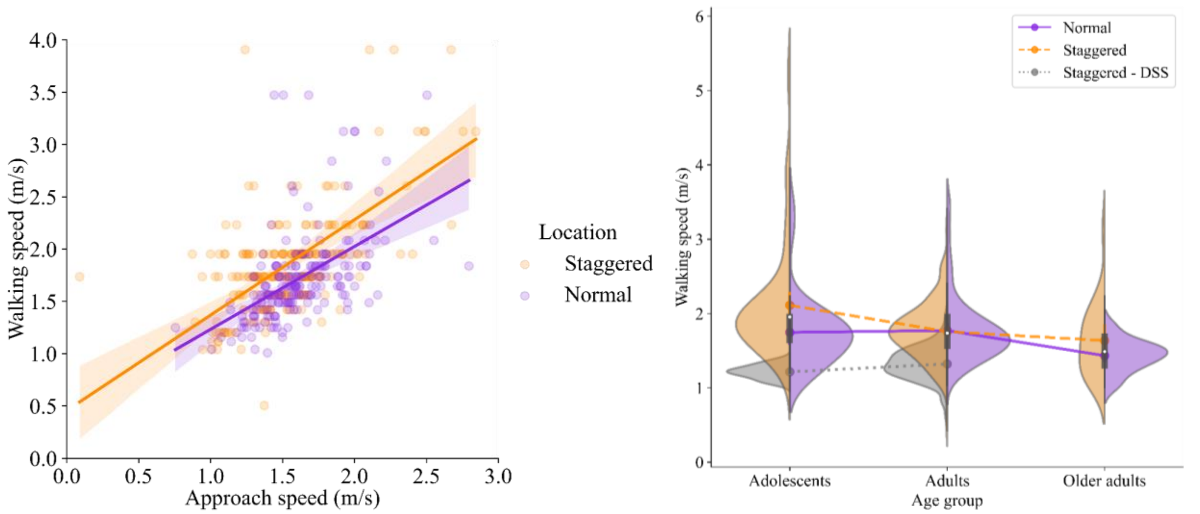

Figure 4.5. The relationship between pedestrians' approach speed and walking speed (left) and violin plots of walking speed as a function of age group and crossing type (right); connected dots show the means for each category.

Table 4.6. Linear mixed-effects modelling for walking speed in the DSS

		Estimate	Std. Error	z value	Pr(>|z|)	95% CI	
						L	U
(Intercept)		**1.372**	**0.208**	**6.585**	**0.000**	**0.964**	**1.780**
Gender		-0.113	0.072	-1.557	0.119	-0.254	0.029
Age		-0.005	0.007	-0.686	0.493	-0.020	0.009
TTA		-0.004	0.004	-0.883	0.377	-0.011	0.004
Location		**0.132**	**0.012**	**11.289**	**0.000**	**0.109**	**0.155**
AIC -712.9	BIC -679.8	logLik 363.486	Marginal R^2 0.107	Conditional R^2 0.659	df.resid 831	Observations 836	

4.3.3 Vehicle delay

Table 4.7 shows the results of linear regression for vehicle delay. The table shows that when the vehicle speed was higher at interaction onset, the driver waited longer for the pedestrian to pass first. Fig 4.6-a shows this relationship and that different vehicles had different speeds at interaction onset (mostly in the range of 0-12 m/s). In the DSS, however, this was different: As shown in Fig 4.6-b, most drivers had a speed of 12-15 m/s at interaction onset and the relationship between vehicle delay and speed was almost nonexistent. Moreover, drivers experienced a significantly longer delay at the normal zebra crossing compared to the staggered one which can be confirmed by looking at Fig 4.6-c: vehicle delay was longer at lower time gaps and the normal zebra crossing. The figure also shows the violin plots for the DSS at the staggered zebra. Similar to the lab data, a trend of decreasing vehicle delay by increasing time gap can be seen. However, compared to the naturalistic setting, drivers experienced longer delays in the lab (M = 2.56 s versus M = 4.49 s). Finally, the speed at which the pedestrians approached the crossings was negatively associated with the delays the drivers experienced (Fig 4.6-d).

Table 4.7. Linear regression results of vehicle delay

		Estimate	Std. Error	t value	Pr(>|t|)	95% CI	
						L	U
(Intercept)		**4.8207**	**0.674**	**7.153**	**0.000**	**3.496**	**6.145**
Gender		0.008	0.158	0.051	0.960	-0.303	0.319
Age		-0.092	0.136	-0.682	0.496	-0.359	0.174
Pedestrian approach speed		**-0.710**	**0.248**	**-2.866**	**0.004**	**-1.197**	**-0.223**
Distance		-0.008	0.005	-1.617	0.107	-0.018	0.002
Speed		**0.220**	**0.026**	**8.485**	**0.000**	**0.170**	**0.272**
Location		**-1.535**	**0.225**	**-6.834**	**0.000**	**-1.977**	**-1.094**
AIC 1642	BIC 1671	logLik -814.15	R-squ. 0.196	df.resid 422		Observations 429	

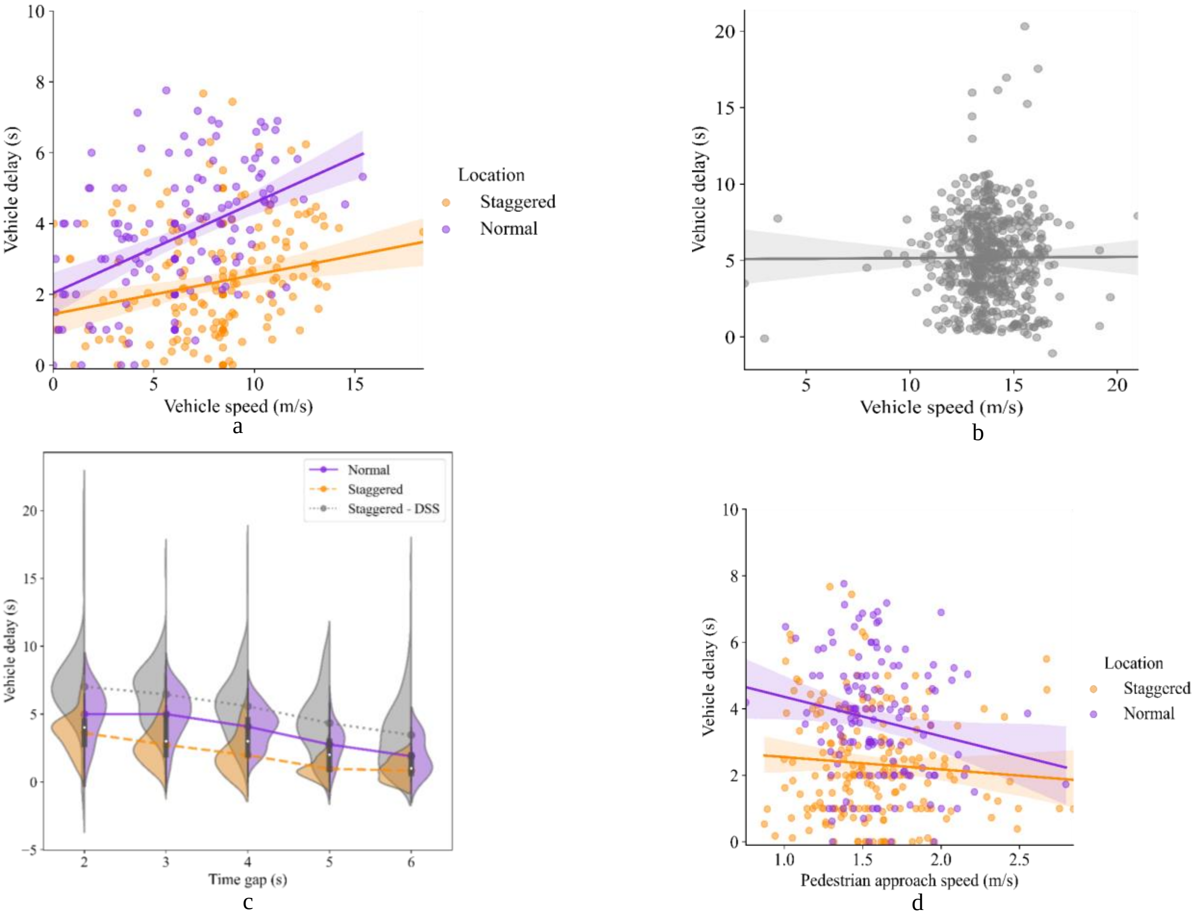

Figure 4.6. Relationship between vehicle delay and speed at interaction onset in the naturalistic study (a) and DSS (b), violin plots of vehicle delay as a function of time gap and crossing type (c), and relationship between vehicle delay and pedestrian approach speed as a function of crossing type (d).

4.3.4 Computational models

Fig 4.7 shows the pedestrians' probability of crossing first over time gap at the normal zebra (a), the staggered zebra (b) and the total data (c) for all the computational models. Table 4.8 shows information loss criteria (AIC, BIC) and error indices (MAE, RMSE) for all models and datasets (S for staggered, N for Normal zebra and T for total data). Both from the figure and table, it is evident that all the models except for ACGT, performed close to each other and well. However, it can be seen that both behavioural game-theoretic models performed best for the normal zebra crossing with the OBGT in lead. That said, the situation for the staggered crossing is more complex: in terms of model parsimony, the Logit and OCGT models performed better but when it comes to prediction accuracy, again behavioural game-theoretic models did a better job. Finally, for the total data, the ABGT model performed best replicating our previous findings for the DSS. Overall, while there were quite substantial differences in performance between the models using the DSS dataset (Kalantari, Yang, Merat, et al., 2023), this was not the case when fitting the models to the naturalistic data.

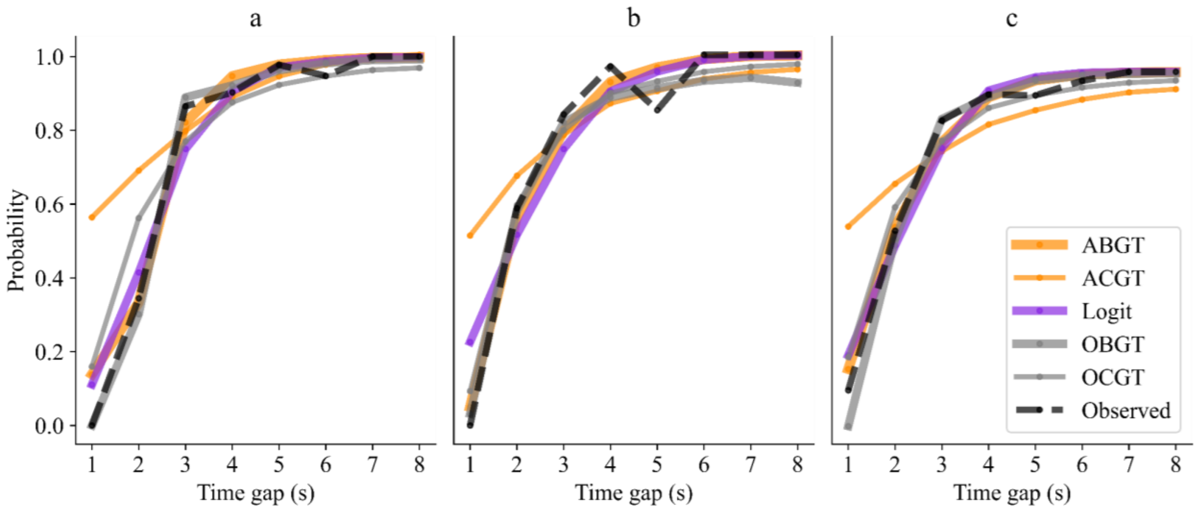

Figure 4.7. Pedestrians' probability of passing first over time gap for all models and for (a) Normal zebra, (b) Staggered zebra and (c) Total data.

Furthermore, as a model-based comparison of the interaction behaviour in the two datasets, we also directly tested the model parameterisations obtained from the 32 participant pairs in the DSS and used them to predict outcomes for the initial situations in the current naturalistic data. Thus, for each model, 32 curves of the probability-time gap were obtained as if each participant pair experienced the 562 initial conditions in this naturalistic study. As the pedestrians did barely wait for more than 5 s in real traffic, we set their waiting time to zero to calculate ***a*** in Table 4.3. Fig 4.8 (left) shows the 32 curves for the OCGT model as an example. Fig 4.8 (right) shows the average of 32 curves obtained from the DSS parametrisations for each model. As it is evident from the figure, none of the models could capture the road user behaviour well but OCGT and ABGT models performed slightly better. These findings suggest that while the general forms of the models developed based on the simulator data work well also for the naturalistic data, it was not possible to make accurate predictions about interaction outcomes in the naturalistic data from the models fitted to the simulator data.

Table 4.8. Model comparison

Model		ABGT			ACGT			Logit			OBGT			OCGT		
Crossing type		N	S	T	N	S	T	N	S	T	N	S	T	N	S	T
MAE[1]	Case by case	**0.130**	**0.227**	0.188	0.197	0.296	0.279	0.137	0.247	0.219	**0.115**	**0.231**	**0.151**	0.179	0.238	0.212
	Average	**0.036**	**0.028**	**0.019**	0.132	0.103	0.125	0.041	0.062	0.048	**0.019**	**0.040**	0.025	0.077	0.042	0.040
RMSE[2]	Case by case	0.252	0.339	**0.305**	0.320	0.379	0.356	**0.250**	0.335	0.314	0.252	0.337	**0.300**	0.270	0. 335	0.310
	Average	**0.056**	**0.039**	**0.025**	0.235	0.163	0.178	0.053	0.086	0.082	**0.023**	0.044	0.040	0.104	0.048	0.049
AIC[3]		**116.178**	273.544	**366.74**	159.7	289.088	459.13	119.822	**242.92**	376.934	**111.622**	271.838	**371.3**	129.576	247.34	375.442
BIC[4]		**126.657**	284.839	**379.734**	170.179	300.383	472.124	133.794	257.980	394.260	**118.608**	280.501	**379.963**	136.562	**254.870**	384.105
NLL[5]		**55.089**	130.772	**180.370**	76.850	141.544	226.565	55.911	117.460	184.467	**53.811**	130.919	**183.65**	62.788	121.670	185.721
NO params[6]		3			3			4			2			2		

[1] Mean absolute error [2] Root mean squared error [3] Akaike information criterion [4] Bayesian information criterion [5] Negative log-likelihood [6] Number of free parameters

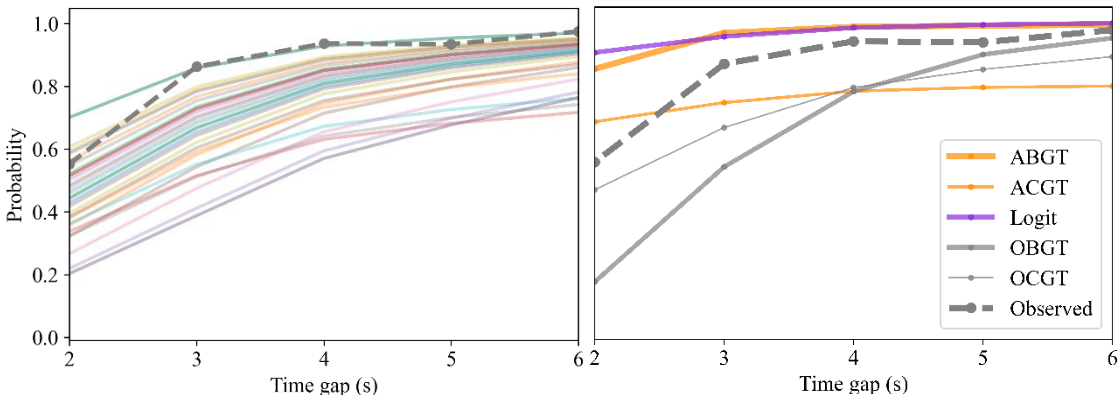

Figure 4.8. Thirty-two curves of pedestrian probability-time gap obtained from OCGT model parameterisation in the DSS (left) and the average of 32 DSS parameterisations for each model (right).

4.4 Discussion and Conclusions

In this study, we compared our analyses and modelling findings from the DSS to naturalistic data. Overall, the findings of this paper suggest a good match between the two methodologies, especially regarding behavioural observations. We found a well-established relative validity of what has been observed in the lab which is a promising achievement. This is because simulating pedestrian and driver behaviour simultaneously in a VR environment has the potential to radically change how we study and understand traffic safety, including with the development of HAVs. However, it is worth noting that driving in a simulator, for example, will never be exactly the same as driving in reality (De Winter et al., 2012), both from the exact sensory stimuli perspective (Blaauw, 1982) and the sense of awareness of driving in a virtual environment.

We found that road infrastructure plays an important role in driver-pedestrian interaction metrics. This is because crossing location type not only conveys the regulatory messages (e.g. the right of way) but also acts as a mediating factor influencing road users' kinematics which is the pivotal point of interactions. The pedestrians crossed first more often at staggered zebra versus normal zebra and normal zebra versus unmarked crossing suggesting a difference in risk perception even between the two types of marked crossings. Also, there was a good match between the data of the two studies for staggered zebra: a similar pattern was observed except for a time gap of 5 s in which a dip in the naturalistic dataset was seen (Fig 4.4). We tend to believe that this might be due to the limitations associated with this type of data (including some unknown confounding variables or the errors associated with the sensors regarding the road users' trajectories) rather than a fundamental behavioural phenomenon.

We did not find a study regarding a comparison of unsignalised crossings including staggered crossings but very few papers studied pedestrians' preferences and behaviour at different types of signalized crossings; among them, Anciaes & Jones (2018) found that pedestrians gave higher ratings to staggered crossings compared to straight crossings, primarily because they perceived the former as offering greater safety. The preference could be strengthened in the case of unsignalised staggered crossings as road users have usually a higher risk perception.

The crossing location also played a role in the pedestrians' walking speed and the vehicles' delay. A novel finding here was that there is a correlation between pedestrian approach and crossing speed and that this correlation is stronger for the normal zebra crossing ($r(243) = 0.633$, $p = 0.000$, [0.529, 0.714] compared to the staggered crossing $r(319) = 0.557$, $p = 0.000$, [0.439, 0.653]) something that was not possible to investigate in the DSS (Kalantari, Yang, Pedro, et al., 2023). Previous research has shown pedestrian approach phase (Madigan et al., 2021) plays an inevitable role in interaction outcomes (Gorrini et al., 2018) and a higher velocity in approaching suggests a higher likelihood of pedestrians passing first (Zhang & Fricker, 2021). Additionally, the pedestrian approach speed has been found to strongly correlate with their aggressiveness (Zhang & Fricker, 2021) suggesting they are more assertive to keep their speed and pass first irrespective of the other agent's status. This is an important finding for the virtual testing of HAVs as they need to continuously track and react to pedestrians' behaviour as soon as they are detectable and do not wait, for instance, until they reach the kerb which might be too late to react in some cases.

Vehicle delay was longer for the normal crossing compared to the staggered one. This is in line with the primary applications of such crossings where they are being used to minimise clearance time in wider roads like dual carriageways. Also, the speed of the pedestrians approaching the crossing could predict the vehicle delay. This novel finding can be explained by looking at Figs 4.5 and 4.6-d. By comparing the results of this study and the DSS, it becomes evident that, firstly, drivers waited less for pedestrians in real traffic compared to the DSS (Fig 4.6-c). This could be because in the DSS both participants were told that they should assume they are in a rush and this could make interactions more competitive where both agents were more assertive to pass first resulting in longer delays for the vehicle (Kalantari, Yang, Pedro, et al., 2023). Another reason could be the simulated driving, which might have resulted in a different deceleration or acceleration behaviour by the drivers compared to a real vehicle. Second, unlike this study, vehicle speed had a dense distribution at interaction onset and was not a predictor of vehicle delay in the DSS. This is not surprising as the definition for interaction onset was different between the two studies: in this study, this was defined about three seconds before the pedestrian reached the kerb (accounting for the pedestrian approach phase), whereas in the DSS, road users could only see each other after the pedestrian had reached the kerb which was set in this way to control for TTAs (Kalantari, Yang, Pedro, et al., 2023). Hence, much less speed variation was observed in the DSS.

At least one of the vehicle kinematics including TTA, distance and speed at interaction onset was a significant predictor of interaction outcome and vehicle delay. This is in correspondence with both the DSS (Kalantari, Yang, Pedro, et al., 2023) and previous research (Theofilatos et al., 2021; Velasco et al., 2021). Higher vehicle speeds were associated with longer delays for the drivers probably because they had to brake more harshly and stop completely before having the chance to accelerate again and pass the crossings in these instances. Also, lower time gaps imposed longer delays for the drivers in both studies. Moreover, similar to the DSS, the lack of the effects of kinematics on both pedestrians' crossing duration and walking speed was proved. Finally, age was a predictor of walking speed in this study confirming the previous research that older adults walk more slowly than the other age groups (Fitzpatrick et al., 2006; Liu & Tung, 2014; Wilmut & Purcell, 2022). However, age did not show an association with either the average walking speed or crossing duration of the pedestrians in the DSS. The most obvious reason was the limited age range (18-34 years) in that study, which was not representative of the whole population (Kalantari, Yang, Pedro, et al., 2023). Also, no effect of gender on walking speed was found in either study.

The results for the five computational models developed previously suggested the following points: first, a better fit was obtained for all the models compared to the lab data and the differences in the models' performance were much less noticeable. One possible reason for the smaller difference in model performance is that here, the model was fitted to the average population, while in the previous study, each model was fitted to the individual data, thus accounting for inter-individual differences. Second, the behavioural game-theoretic models performed slightly better than the others in terms of prediction accuracy. This replicates our previous findings that more complex behavioural models are probably needed to predict driver-pedestrian interaction outcomes at unsignalised locations. Moreover, improved performance was observed moving from mixed-strategy Nash equilibrium to dual accumulation solving algorithms (Kalantari, Yang, Merat, et al., 2023). Third, when the models were used to predict the pedestrians' behaviour in this study using the fitted parameters from the DSS, they failed to capture the observed data well. A reason for this discrepancy can be found in the way that parameter ***a*** was being treated: the waiting time of the pedestrians was an important parameter influencing interaction outcomes in the DSS dataset to the extent we observed entirely different behaviours for the same TTA and crossing type but for a different waiting time among the participants (Kalantari, Yang, Merat, et al., 2023). However, in this study, the pedestrians barely waited for over 5 s before having the chance to cross which made us set this parameter to zero to make the two datasets more comparable. Also, the models' parameters obtained for the DSS were shared between two totally different crossings whereas in this study the crossing locations were more similar in terms of regulations which can explain the nature of the mismatch.

This study is not without limitations. For modelling purposes, only one-on-one interactions were considered and used in the analyses. Hence, the effect of variables such as pedestrian group size (Amini et al., 2019) on interaction-related metrics was not investigated. Also, road user behaviour was investigated for one driving lane and direction whereas previous research suggests pedestrians behave differently on two-way streets (Dommès et al., 2021; Song et al., 2023). The road infrastructure including the crossing locations between the two studies was not exactly the same hindering more specific comparisons. For example, we could not compare the two datasets in terms of pedestrians' waiting and crossing initiation time. Demographic information was extracted by a human observer and from GDPR-compliant videos, and therefore, errors and mistakes are probable.

All in all, the findings of the current study suggest that distributed simulation could be a proper methodology to study and model road user behaviour and can be used as an alternative method to naturalistic studies for some applications. This method is especially helpful for simulating critical traffic scenarios such as near-misses and crashes which do not happen in real traffic very often and are a must for HAVs' virtual testing and development. We found that drivers and pedestrians showed similar patterns of non-verbal communication between the two studies, overall. While there are some potential limitations with conducting studies in a virtual environment, including the fact that pedestrians may not exactly experience traffic scenarios in the CAVE as they do in the real world (e.g. under or overestimation of speed), it is possible to attribute the observed differences more to the study design rather than inherent limitations of the simulator itself. This is promising, as it suggests that optimising the study design can lead to better results in alignment with one's objectives.

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Chapter 5

Discussion and conclusions

5.1 Overview

The current thesis has aimed to shed light on vehicle-pedestrian social interactions at unsignalised locations. This aim was pursued by conducting controlled and naturalistic studies and studying road user behaviour through different statistical analyses and computational models. Although the behaviour of drivers was also under scrutiny, the primary emphasis of the present thesis was on investigating pedestrian crossing behaviour. In Chapter 1, several research gaps and questions in this domain were raised. Within this chapter, the findings of Chapters 2-4 are connected with the identified gaps and the research questions are answered. Then, research implications are discussed followed by future work and concluding remarks.

5.2 Research gaps and questions

G1: A comprehensive experimental paradigm in distributed simulation

The aim of Chapter 2 was to answer two fundamental questions including RQ1: **how can one design a distributed study that allows pedestrian and driver participants to repeatedly interact with each other, in a manner that is both controlled yet still as close as possible to real-life interaction?**

An experimental paradigm was proposed to address the question above while considering the below challenges.

Conducting a DSS using two or more (high fidelity) road user simulators is a burdensome job due to the following reasons: 1) The complexity of recruiting the required participants not least with respect to counterbalancing demographics, personality traits, etc. as, for example, the degree of social similarity or antipathy/sympathy among them may influence the interaction (Lehsing & Feldstein, 2018). 2) The tasks for the experimenters in these studies are multiplied by the number of participants in the scene compared to conventional studies and thus a higher number of experimenters are usually needed with a high degree of collaboration between them. The experimenters also need to monitor the scene and make sure that social interactions happen throughout the study which is a challenging task. 3) The technical complexity of connecting two or more simulators to each other with the lowest latency possible in rendering the traffic scene is another aspect. 4) The situation in which one or more human road users could become passive after a number of trials due to the differences between the two environments including the stimuli and the incentive of participants in an experiment versus real traffic.

While the third challenge was addressed, it was not part of the research thesis and thus the solution to address that is not explained here (see Sadraei et al., 2020). The following statements briefly outline how the remaining challenges were addressed. To address challenge 1, there was a recruiter in charge of grouping the pedestrians and drivers regarding both their availability and gender distribution. The recruiter was also in charge to ensure the participants do not meet each other before the experiment affecting their interactive behaviours. For challenge 2, two trained experimenters were in charge of setting up the equipment, briefing participants, providing instructions, and closely overseeing their activities in the UoLDS and the HKER lab, respectively. To facilitate communication between them, they used both walkie-talkies and a voice call service over WhatsApp to leverage the coordination as much as possible. The voice call was used to inform one another about their progress with preparation, etc. without notifying the participants. As for challenge 4, the concept of time pressure was contextualised as an 'instruction of being in a hurry' to avoid the potential of passiveness after a number of trials while ensuring that participants keep concerned about their safety when interacting with each other. A trade-off in highlighting the efficiency versus safety in the instructions to participants is a critical factor as significant time constraints could result in pedestrians stepping onto the road too late, causing drivers to suddenly brake in order to prevent a collision. This could potentially lead to issues involving subsequent behavioural adjustments, discomfort for the driver due to the driving simulator, or a combination of these factors.

Overall, the findings suggested that the proposed experimental paradigm could generate scenarios where both driver and pedestrian communicate interactively with each other showing behaviours that are both qualitatively (Chapter 2) and quantitatively (Chapter 3 & 4) in line with those observed in a naturalistic setting.

The second research question, RQ2, was 'What does the interaction behaviour look like as a function of time gaps and crossing types, SVO and SS?' In line with the previous research (Amini et al., 2019; Madigan et al., 2022; Theofilatos et al., 2021), higher time gaps and the presence of zebra, resulted in pedestrians crossing first more often and the impacts of these variables on interaction outcome (1 = pedestrian crossed first, 0 = waited) was stronger than road user personality traits such as SS and SVO. This highlights the role of kinematics in interactions. To this end, it was found that when the drivers had higher speeds, on average, the pedestrians tended to cross less often especially at unmarked crossings even though they had higher AISS scores.

Further considering the results across Chapters 2-4, there are other interesting observations that can be made about the DSS. The first of these relates to the effect of vehicle speed on interaction outcomes. The speed-interaction outcome relationship in previous research showed somewhat contradictory results and could be divided into two groups: the first group of studies (mostly in the VR environment) indicated that pedestrians have an inclination to accept smaller time gaps when the approaching vehicles speed was higher (S. Schmidt & Faerber, 2009; Tian et al., 2022; Velasco et al., 2019) whereas the second group of studies found that the higher the vehicle speed, the lower the pedestrian tendency to accept a specific gap and cross first (Kadali & Vedagiri, 2020; Sheykhfard & Haghighi, 2020). The findings of the first group of studies could be interpreted as pedestrians' tendency to overestimate a certain TTA when faced with higher vehicle speeds, in contrast to situations with lower speeds (Hancock & Manster, 1997; Petzoldt, 2014). However, the findings of the second group of studies could be linked to pedestrians' risk perception and the claim that higher speeds result in higher risk perception and consequently lower gap acceptance (Theofilatos et al., 2021). What has been found in this thesis was in correspondence with the second group of studies, where the negative speed-interaction outcome relationship was shown in both the controlled (Chapter 2) and naturalistic studies (Chapter 4). A possible explanation for this could be the interaction aspect of the two studies; unlike the DSS, the VR studies of the first group consisted of more pure gap acceptance scenarios, where the pedestrians were not expecting an interaction, and they only judged whether the existing gap is large enough to cross first.

One of the aims of the DSS was to learn how drivers and pedestrians avoided collisions while showing their intention through employing different strategies. As mentioned before, crashes and near-crashes are not that common in naturalistic datasets. In the VR environment, however, participants may have lower risk perception and thus they may engage in more risky situations especially when they have incentives to save time as they did in the DSS. Generally, it is assumed that drivers' and pedestrians' state of action when interacting at crossings consists of two choices namely either to pass first or wait for the other(s) to pass. However, drivers sometimes accelerate or increase their lateral deviation to convey the message that they are not giving the right of way while avoiding colliding with pedestrians irrespective of their legal rights (Fuest et al., 2018). Both types of these behaviours were observed in the DSS: negative values of vehicle delay depicted in Fig 2.9, showed the mentioned instances of acceleration, especially at lower TTAs. Increasing lateral deviation was also observed on further analyses of the DSS which was higher at unmarked crossings and lower time gaps (Yang, Yue et al., 2023). Furthermore, pedestrians were granted the opportunity to run in the HIKER lab, provided that their actions reflected real-world traffic behaviour. As a result, the observation of running behaviour, especially among female participants, underscores the participants' earnest commitment to the experimental tasks. Exhibiting such behaviour in the DSS suggests that this methodology could be a reliable source for the virtual testing of HAVs as it can cover a wide range of scenarios capturing the naturalistic notion of interactions.

In general, various aspects of the DSS could have been approached differently. A notable factor was the recognition of the pedestrians' approach phase in interactions. As explained in Chapter 2, the DSS was designed in a way that both agents could not see each other (due to the visual obstruction) until the pedestrians reached the kerb of the road. This was done to control the time gaps of the approaching vehicle at the expense of overlooking the pedestrian approach phase. In Chapter 4, it was shown that pedestrian approach speed correlated with their crossing speed and consequently the delay imposed upon the drivers as a matter of yielding to them. The same finding was reported in Gorrini et al., (2018) study where they found the difference between pedestrians' approach and crossing speed is negligible. Hence, one main finding of Chapter 4 was that including or excluding the approach phase could impact the way agents interact with each other not least regarding their kinematics and this would be a suitable topic for investigation in future distributed simulator studies.

Furthermore, the definition of pedestrian waiting time in Chapter 2 was somewhat different to most previous studies and it is possible that the negative relationship between this variable and interaction outcome was obtained due to this difference in definitions. The basic idea for defining the waiting time was to consider how long the pedestrian did wait after completing their crossings in the previous trial (if any) to the time that they were prompted to cross (auditory tone) in the current trial. That said, a definition closer to that in previous research could have improved the ability to compare the impact of this factor on agents' interactive behaviours. This, in turn, might have allowed the computational models to show a better performance (Chapter 3). This requires further modifications to the experiment design such that pedestrians could interact with continuous traffic deciding to accept a proper gap between two oncoming vehicles. However, previous research has shown that it is less reasonable to presume that pedestrians consistently opt for riskier crossings as their waiting time grows (Tian, 2023). Additionally, as discussed in Chapter 4, pedestrians do not consistently wait for an ideal gap at marked crossings; rather, they often proceed with their crossing behaviour without significant interruptions. Thus, it is more sensible for human factors researchers to evaluate each situation individually and examine the specific aspects of pedestrian crossing behaviour while engaging with traffic flow.

Another point of improvement for the DSS could involve expanding the participant pool to encompass a wider age range, including both children and the elderly. While there are some discrepancies regarding the role of gender in interaction outcomes in previous studies, most of the past papers found a relationship between pedestrians' age (group) and interaction-related metrics such as walking (crossing) speed as explained in Section 1.1.2 and in line with the findings of Chapter 4; older adults crossed significantly slower than younger ones. Therefore, the design of the experimental paradigm could have benefited from slightly different crossing scenarios to study both children, adolescents (Pala et al., 2021b) and older adults (Pala et al., 2021a) walking speed and pattern, risky crossing behaviours, and their difference in estimating the vehicle kinematics compared to other age groups. To this end, the assumption of 'being in a rush' as a matter of an important meeting would have probably not worked in these age groups and alternative assumptions appropriate for each age group might have been considered.

In brief, all three studies conducted in the current PhD project and especially the studies in Chapter 2 and 4 showed that the experimental paradigm (DSS) worked as intended setting a new milestone of how researchers can study road user interaction with promising similar patterns observed in real traffic to provide a controlled and safe environment to replicate more risky scenarios.

G2: Lack of lab data to test GT models and BGT-CGT comparison

As outlined in Section 1.1.3, nearly all preceding studies assessed and verified their GT models using real-world data. The main reason for this was that past controlled studies lacked the interactive nature of road user communication and thus were not a proper choice for testing these models. Within Chapter 2, a comprehensive research paradigm was introduced to bridge the identified gap. Notably, a key achievement of Chapter 2 was the identification of factors influencing interaction outcomes. Importantly, the observed effects of these factors were studied disentangled from potential confounding variables, ensuring more confident causal inferences. These findings about causality strengthened the rationale for integrating the input variables of the GT models in Chapter 3. In this chapter, it was shown that the DSS could be a beneficial validation tool for the computational models of road user behaviour such as GT. This answered RQ3: **Is distributed simulation a good alternative as a validation tool for game-theoretic models?** This is especially crucial as the DSS can provide multiple data per individual giving the credence that it is highly likely for an individual to exhibit similar behavioural patterns when a traffic scenario with some specific initial conditions is repeated and thus the model's predictions derived from this dataset appear to possess greater reliability.

Another gap in the existing literature was the lack of CGT-BGT comparison in general and specifically in the field of vehicle-pedestrian interactions in the literature. Chapter 3 demonstrated that, beyond the formulation of agents' payoffs, the method employed for solving the game holds equal significance. Notably, the models exhibited substantial enhancements when their payoff formulations were solved through the BGT methodology in comparison to the CGT approach. This underscored the underlying hypothesis that, similar to strategic decision-making in everyday scenarios, individuals might not adhere to the Nash equilibrium when engaging in interactions at uncontrolled crossings. It is worthwhile noting the term ‘strategic’ refers to agents who act with the objective of maximising their personal utilities based on explicit probabilistic beliefs concerning the actions of other agents whereas the opposite ‘nonstrategic’ is generally used to refer to agents who adhere to established and known decision-making rules (Wright & Leyton-Brown, 2020). In behavioural economics, both bounded iterated reasoning and errors proportionate to costs constitute significant components in a predictive model of human game-theoretic conduct with iterative reasoning delineating an authentic cognitive process (Wright & Leyton-Brown, 2017). Iterative reasoning is the backbone of the DA model that was used as the solving algorithm for the BGT models. Chapter 4 unveiled parallel findings in the comparison between CGT and BGT models, corroborating the conclusions drawn in Chapter 3, albeit with relatively minor differences in model performance. One important factor accounting for this inconsistency lay in the distinction between fitting the model to average population data versus individual data within the two datasets. However, it remains challenging to definitively attribute the variation in model performance between the two studies solely to the fitting of the models and the nature of the data. Thus, a definitive conclusion cannot be reached unless it becomes feasible to continuously monitor and record the interactions of every pedestrian-driver pair within the naturalistic dataset (Chapter 4), similar to the methodology employed by the DSS (Chapter 2). Overall, the answer to RQ4 that: **Are conventional models, such as traditional game theory (the Nash equilibrium), sufficient for predicting vehicle-pedestrian interaction outcomes at unsignalised locations, or is it essential to consider more complex models like behavioural game theory?** is *probably not and there is a need for BGT!* Thus, it is highly likely that more complex models like those in the BGT category are needed for a successful simulation and prediction of road user interaction at unsignalised crossings.

Overall, some believe that the incapability of the Nash equilibrium in capturing the human suboptimal behaviour lies in the Nash equilibrium's assumption of agents with perfect information about each other and their fully rational behaviour which always results in picking the best strategies. But what if road users tend to be more cooperative when communicating at unsignalised locations, something which is not in line with the underlying assumptions of CGT? Conducting a more in-depth examination of the model parameters and subjecting the models to a varied array of scenarios could provide insights to address this question.

Certain aspects of the investigation conducted in Chapter 3 could have been approached differently to potentially yield enhanced results. For instance, incorporating both drivers' and pedestrians' SVO into their utility functions could elevate the models' performance. This was shown in a study as a part of the current project where the SVO-extended GT model almost always outperformed the baseline model (Kalantari et al., 2022). However, the extension was applied to the simplest payoff formulations (Table 3.2) in which calculating the probabilities was straightforward. Solving the game for the SVO-extended alternative formulation (Table 3.3) using the DA model would be a rather computationally intensive task. Thus, to keep the computations simple enough, the SVO-extended versions were excluded from the current work but it is a promising research direction for the future. Furthermore, Chapter 3 indicated that factors such as the gender of the road users could affect the interaction outcome under the same initial conditions (same crossing type and TTA). Thus, considering these variables could paint a better picture of road user behaviour. Additionally, potential exists to transform the current functions of the DA model into time-varying utility functions, incorporating real-time units to emulate genuine traffic interactions. This adjustment would lead to utilities fluctuating over time as the vehicle approaches the pedestrian crossing while agents deliberate their actions. A subsequent comparison between the outcomes of the two models would determine the model better suited to encapsulate this form of interaction.

G3: Distributed simulation validation

In Section 1.1.2, it was mentioned that validation studies are quite rare for pedestrian simulators and non-existent for co-simulation studies. In Chapter 4, initiatives were taken to test and validate the findings of the experimental paradigm introduced in Chapter 2 by comparing them to the naturalistic setting. Hence, in addressing RQ5, the question of '**To what extent are the findings from a**

distributed simulator study comparable to real traffic data in terms of both behavioural findings and computational models?' a favourable degree of relative validity for the DSS was established, effectively emulating the behavioural patterns of road users within the laboratory setting; in both studies, the type of crossing influenced the dynamics of interactions, affecting pedestrian crossing speed and vehicle delay as well as interaction outcomes. Additionally, vehicle kinematics played a significant role in both datasets, with an increase in time gap leading to reduced driver delay. As mentioned in the previous section, the results of the computational models were consistent between the studies, underscoring the viability of the DSS as a valuable alternative for testing models of road user interaction, including those involving HAVs.

Overall, one of the main contributions of the current thesis was the application and comparison of two key methodologies in traffic studies to examine communication patterns between drivers and pedestrians. The advantages and limitations of each methodology were uncovered and emphasised throughout the course of this doctoral research, underscoring the necessity of employing both methodologies for a comprehensive traffic microsimulation. In essence, the limitations inherent in each methodology (e.g. the constrained participant count and the focus on a consistent vehicle speed and its fluctuations in Chapter 2 for the DSS) were complemented by the other approach (e.g. offering a substantial number of cases and encompassing varying vehicle speeds at interaction initiation in Chapter 4). Furthermore, for instance, solely relying on experimental data would not instil confidence in determining the influence of pedestrians' age on interaction outcomes due to the narrow age range of the participants in the DSS as well as of inherent limitations in behavioural validity of the controlled experiments. Or, it would be challenging to definitively ascertain the influence of the zebra crossing on vehicle delay solely through the use of naturalistic data, as such data often involves numerous unknown confounders. Therefore, a key takeaway here is that employing a mixed-method approach that integrates different data collection techniques and analytical strategies is necessary to provide a more comprehensive and well-rounded understanding of road user behaviour.

The validation study could have taken diverse approaches to achieve more refined outcomes. For instance, a pivotal factor that could have facilitated a closer comparison between the two studies would have been the incorporation of unmarked (midblock) crossings and pedestrian jaywalking behaviour into the dataset. However, most of the critical locations regarding crash history in the city of Leeds were either signalised or marked and those few unmarked crossings that were on the list did not meet the criteria of an ample number of one-one vehicle-pedestrian interactions per hour, thus limiting the choices. That said, several instances of jaywalking in the vicinity of the marked crossings were observed both in the trajectory data and the related videos. Modifying the data extraction algorithms to capture such illegal behaviour could address this objective which is a quite challenging task as there is no specific spatial information to help the algorithm detect an interaction. Considering these types of interaction, could provide an avenue to factor in metrics such as pedestrian waiting time and CIT, which are particularly common in more straightforward gap acceptance scenarios, similar to non-zebra crossing scenarios within the DSS.

5.3 Research implications

Understanding road user behaviours and their decision-making mechanisms presents a formidable challenge. The scope of the studies within this thesis extends beyond mere experimental and naturalistic data analysis. Instead, these observations are integrated into computational models that emulate road user interactive behaviours such as pedestrian crossing decisions. As a result, the work in this thesis yields contributions that span a wide range of traffic research domains. The subsequent sections delve into the potential implications of this research, addressing both theoretical and practical considerations.

5.3.1 Computational models and HAVs

One of the primary goals of the current thesis was to underscore the significance of glass-box models as a mean to gain a deeper understanding of road user behaviour in the context of vehicle automation. A plethora of research studies have instead focused on black-box, machine-learned models for simulating and predicting interactions between HAVs and human road users (Lim & Taeihagh, 2019; Sana et al., 2023). This is also the main modelling approach for the HAVs decision-making algorithms in the industry today (Coffin et al., 2019). Utilising these black-box models could bring two fundamental challenges: First, these models rely on large naturalistic datasets to get trained and learn the relationships among different variables. As a result, bias in the data can arise due to the over or under representation of specific groups in the dataset (Zarsky, 2016) and mathematical correlations (Citron & Pasquale, 2014) derived from that dataset (discussed in Chapters 2-4). Hence, HAVs might allocate more risks to certain groups of individuals over others which is problematic regarding ethical considerations; lessening this bias in machine learning algorithms is challenging as they are opaque and hard to interpret, trained based on data that changes over time and there is an 'automation bias' problem (i.e. the inclination to overrely on automated decision-making systems) (Liu, 2017). Second, the training data in machine-learned systems can contain accidental correlations that lead to inaccurate predictions (overfitting) (Schwarting et al., 2018). Additionally, these algorithms are prone to exhibiting erroneous corner-case behaviours that have already led to fatal accidents in HAV trials (Stilgoe, 2018). Identifying such corner cases is less straightforward in machine-learned algorithms, as their logic is learned from data and incorporated into highly non-linear optimisation functions, making it challenging for researchers to pinpoint the inputs that generate these problematic scenarios (Tian et al., 2018). Therefore, one implication of this thesis is that researchers developing HAV decision-making algorithms could benefit from incorporating the BGT models developed and tested in this thesis (Chapter 3) into their computational framework as they are transparent, interpretable and traceable. Also, the experimental paradigm created in this thesis (Chapter 2) can be used by HAV developers to generate balanced datasets (e.g. children, adults, elderly) to, overall, have transparent decision-making algorithms that are trained by causal data minimising the chances of bias, erroneous predictions and corner-case behaviours.

Additionally, in this thesis, it was shown that by combining the DA model with a conventional payoff structure of a GT model, the simulation of agents' actions from the initiation of interaction (i.e. when they become aware of each other) up to the point where one agent selects a strategy and proceeds with it, is feasible. This concept of time could be utilised in either HAV prediction algorithms to inform the robot about both the intention and final decision of a human road user in time or in their motion planning algorithms to help predict the human road user trajectory in each course of action.

Another aspect of the computational modelling of the thesis is the superior performance of BGT models. This is found while most previous research relied on the Nash equilibrium to explain traffic interactions. It is, therefore, important to not assume that CGT will provide a good account of human behaviour, and to continue to adopt, test, and develop BGT approaches for future HAV-human road user interaction studies.

One more notable implication stemming from the modelling endeavours in Chapter 3 and 4 is the evident significance of employing individualised data for the testing and validation of GT models. This suggests individual differences might have an important role in determining interaction outcomes. This has been overlooked in most past studies concerning AV-human road user interactions most probably because the 'repeated' aspect of interactions cannot be attained by naturalistic data collection tools. Overall, the results in this thesis add to this body of previous research showing that AV expectations differ based on age, gender and personality traits (Zhang et al., 2022) and suggest that more work should be done regarding incorporating pedestrians' age and gender into AVs' motion planning algorithms to enhance pedestrians safety and traffic efficiency (Chen & Zhang, 2021).

5.3.2 Traffic safety and engineering

The current thesis has yielded several findings and observations with broader implications for traffic safety. Chapter 2 presented a notable prevalence of jaywalking behaviour, a trend further supported by the data discussed in Chapter 4. In particular, Section 5.2 highlighted the instances of pedestrians running in front of approaching vehicles. This behaviour was predominantly observed among female pedestrians in Chapter 2 and among children and adolescents in Chapter 4. These findings serve as a critical alert for various stakeholders, including policymakers, educational institutions, traffic engineers, and advocacy groups, shedding light on the pervasive non-compliance tendencies among pedestrians in the UK. Addressing this issue warrants multifaceted approaches. For instance, the introduction of new regulations and policies that treat jaywalking as an unlawful action, similar to the approach in the US, could hold potential for mitigating such conduct. However, alongside regulatory changes, an effort to enhance public awareness and educate pedestrians, especially the younger demographic, about the inherent dangers associated with such behaviours is important (Schmitt, 2020; Yue et al., 2020).

From a traffic engineering and urban planning perspective, these findings underscore the necessity of strategic interventions. Urban environments should ideally feature marked and signalised pedestrian crossings wherever feasible. Moreover, on wider roads, the implementation of staggered crossings could offer a dual benefit—comfort for pedestrians and a reduction in vehicular delays (Chapter 4).

Furthermore, as discussed in Chapter 2 and Section 5.2, some drivers in the DSS accelerated instead of decreasing speed when approaching the pedestrians as they had, overall, high speeds at interaction onset. A feasible policy direction could entail managing vehicle speed through the installation of speed limit signs, indicators, or cameras at suitable positions. Furthermore, employing signs to prompt drivers to slow down at an appropriate distance from intersections could enhance pedestrian crossing decisions.

Finally, SVO holds relevance for various aspects of road traffic beyond its applications in HAVs' decision-making algorithms (as evidenced in Chapter 2), this trait can find application in driver education initiatives, where understanding diverse social orientations may enhance awareness of biases, foster empathy, and encourage safer driving practices. Additionally, customising traffic management strategies based on individuals' SVO could yield benefits in terms of improved traffic flow and safety.

5.4 Future work

This section briefly outlines the possible research directions of the current PhD project.

The focus of the current research was on one-one vehicle-pedestrian interaction to provide a fine-grained understanding of road user behaviour. However, multi-agent interaction in traffic is prevalent and this involves both vehicle-vehicle and vehicle-VRU interactions. Thus, many studies used black-box modelling to simulate and predict multi-agent decision-making in mixed traffic (Camara et al., 2020; Mozaffari et al., 2020). Nonetheless, as previously elucidated, the interpretation of these models' outcomes is complex, and the underlying mechanisms responsible for such results remain obscure. Furthermore, they often necessitate extensive training datasets to exhibit satisfactory performance. Consequently, to achieve a more nuanced grasp of multi-agent interactions and the proficiency to model them, forthcoming research should:

a) Concentrate on amalgamating the glass-box models such as those cultivated in the present thesis with machine-learned models, aiming to strike a balance between the models' interpretability and generalisability. Additionally, exploring methodologies like active inference, which maintains comparable behavioural adaptability to data-driven models while upholding interpretability could be beneficial (Wei et al., 2023).

b) Pave the way for a structured approach to distributed simulation, wherein multiple pedestrians can interact with numerous (automated) vehicles within a VR environment. This could potentially be achieved by interconnecting several HMDs both amongst themselves and with high-fidelity driving simulators via a network. Another viable avenue is the integration of CAVE-based simulators with HMDs for this purpose.

Another notable aspect revealed by the findings is that road infrastructure and the corresponding regulations indeed play a mediating role in shaping road user communication patterns, particularly affecting interaction outcomes. The central focus of this thesis was directed towards unsignalised crossings and pedestrians' jaywalking behaviour. It is important to remember that the behaviour exhibited by both drivers and pedestrians at signalised locations differs substantially, as explained in Section 1.1.2. Furthermore, the scope of the examined scenarios was restricted to instances where the vehicle's orientation was perpendicular to the pedestrian's, a common occurrence in such contexts. However, it is pertinent to acknowledge that numerous other traffic scenarios introduce the second dimension of road user trajectories. Different types of intersections and junctions are examples of this nature. Moreover, as previously deliberated, pedestrians' crossing behaviour changes when interacting with vehicles on two lanes and from two directions. In light of these considerations, it becomes necessary to unravel road user behaviour through the simulation of novel scenarios that account for road infrastructure complexities and an array of environmental factors.

Another crucial consideration involves incorporating additional elements of human factors into the microsimulation models. This encompasses diverse states of road users, particularly drivers, such as drowsiness, intoxication, and distraction, which have been shown to significantly impact human road user behaviour (Zaranka et al., 2021). This endeavour is ambitious, albeit notably demanding. Yet, for the creation of a comprehensive traffic microsimulation model, it is imperative to account for a myriad of potential scenarios. Taking a broader perspective, the microsimulation traffic model should ideally merge with macrosimulation models that encompass the mobility elements on a network level. This holistic integration ensures a more comprehensive understanding of traffic dynamics.

Lastly, a vital point to consider in future distributed simulation studies involves automated-driving scenarios as noted in (Sadraei et al., 2020). This could be integrated as a component of 'catch trials,' wherein both drivers and pedestrians encounter computer-generated yielding/non-yielding pedestrians and HAVs, respectively, every now and then. Furthermore, the utilisation of calibrated avatars (i.e. calculating pedestrians' pose and gait based on motion trackers) could serve to investigate and model various aspects of pedestrians' behaviour, including gait, pose, and even eye contact, along with their impacts on interactive behaviours. Regarding trials involving automated driving, a valuable avenue to explore would be equipping vehicles with diverse types of eHMIs. This exploration could help determine whether the outcomes gleaned from conventional VR studies (mostly with a human pedestrian interacting with HAV) (Lee et al., 2022) persist when two human agents interact in the presence of different eHMI configurations.

5.5 Concluding remarks

To conclude, this thesis has provided a number of novel insights about vehicle-pedestrian communication patterns at unsignalised crossings. The results of all three studies of this thesis showed that the DSS is capable of generating traffic scenarios having a faithful representation of what happens in real traffic and the flexibility of including or excluding different variables to be studied in a safe and controlled nature. This paradigm has effectively established a new benchmark for researchers in HAV development to explore human-robot interactions and for road safety experts and traffic engineers to simulate and study more risky traffic scenarios among human road users that are not possible to investigate in reality. This paradigm also provided a reliable validation tool for GT models developed in this thesis. In particular, the BGT models showed promising results, suggesting that future research efforts in the field of road user behaviour modelling should focus on developing and testing such models to unleash their full potential. The models have potential applications for HAV decision-making and motion planning algorithms as well as traffic safety in general. Extending both the experimental paradigm and the computational models to a multiagent problem is possibly the most important next step for future research.

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