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Deliverable 2.2

Behavioural models explaining and predicting transparent negotiations between AVs and human road users

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Deliverable 2.2 Behavioural models for transparent negotiations between AVs and human road users

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List of Associated Partners

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Note 1: The term Early-Stage Researcher (ESR) is used extensively in this document. The ESRs are PhD candidates funded by the SHAPE-IT project.

Note 2: This document has been submitted to the EC for acceptance as a deliverable in the SHAPE-IT project. If changes are requested by the EC, the document will be updated.

Table of Contents

List of Abbreviations

Acronym	Description
ADE	Average displacement error
AIC	Akaike information criterion
AV	Automated vehicle
BGT	Behavioural game theory
BIC	Bayesian information criterion
CGT	Conventional game theory

Acronym	Description
CNN	Convolutional neural network
CPH	Cox proportional hazard
DA	Dual accumulator
DL	Deep learning
DSS	Distributed simulator study
DTA	Difference in time to arrival
ESR	Early stage researcher
FDE	Final displacement error
FOV	Field of view
GT	Game theory
HDI	Highest posterior density
LR	Linear regression
LSTM	Long short-term memory
MAE	Mean absolute error
ML	Machine learning
MLP	Multi-layer perceptron
NLL	Negative log likelihood
PCAD	Potential collision avoidance difficulty
RF	Random forest
RMSE	Root mean squared error
SMoS	Surrogate measures of safety
SOTA	State of the art
SVM	Support-vector machine
TTA	Time to arrival
TTC	Time to collision
TTLCI	Time to lane change initiation

Executive Summary

One key enabler for the development of automated vehicles that can coexist and negotiate with human road users in a safe, transparent, and human-acceptable manner is the development of mathematical models of human behaviour in the relevant interactive scenarios. Such models are needed as components both in real-time AV algorithms and in simulation tools for virtual AV testing. However, many important questions about how to model human road user interactions remain unanswered, and five of the Early Stage Researchers (ESRs) in the SHAPE-IT project have targeted such research questions. This report provides an overall introduction to the area of human-AV interaction modelling and summarises the ESRs' research and findings in this area, including links to the ESRs' peer-reviewed papers and preprints (providing full details). The SHAPE-IT modelling research by these ESRs has spanned a broad spectrum of modelling approaches and modelling use cases and has generated results such as: More computationally effective and transferable algorithms for real-time prediction of pedestrian movement; novel insights about human driver communication and behaviour during lane changes; a general model of human AV passengers' subjective perception of traffic risk; a demonstration that models of vehicle-pedestrian interactions based on behavioural game theory outperform conventional game theory models; and novel insights about how cyclists' head, eye, and pedalling behaviour predict cyclist-vehicle interactions. The research by these five ESRs has increased our understanding of, and capability to predict and simulate, how humans interact in traffic, with direct relevance for development of safe and human-acceptable AVs.

1 Introduction

Development of automated vehicles (AVs) is very much an engineering challenge, relying heavily on the creation and testing of a wide range of quantitative methods, models, and algorithms (Badue et al., 2021; Gordon & Lidberg, 2015). However, since AVs are meant to coexist with humans, who will ride along in the AVs or share the road with them, there are also very clear human factors challenges to be addressed (Kyriakidis et al., 2019). In order to create AVs which are safe and acceptable to humans, AV engineers therefore need quantitative ways of accounting for the relevant human factors aspects or, to put it differently, they need quantitative models of human-AV interactions (Behbahani et al., 2019; Camara et al., 2020; Markkula & Dogar, 2022). It remains unknown, however, exactly what types of such models are needed, and how best to go about creating them. These questions have been addressed in various ways by several of the Early Stage Researchers (ESRs) in the European Marie Skłodowska-Curie Innovative Training Network SHAPE-IT, and this report provides an overview of their research and findings.

The first section below provides a brief background, outlining the main goals, use cases, and approaches in quantitative modelling in the context of human-AV interaction. Thereafter follows a section where the SHAPE-IT contributions to this research area are presented, with pointers to peer-reviewed papers and preprint manuscripts published by the ESRs, where the interested reader can find further details. Finally, overall conclusions are provided, considering all of the ESR contributions together.

2 Background

2.1 Goals of quantitative human-AV interaction modelling

For what purposes is it useful to develop quantitative models of human-AV interaction? Arguably, the main end goals are the same three as for all types of human factors engineering: human *safety, efficiency, and satisfaction* (Lee et al., 2017). Figure 1 provides a schematic illustration of the idea (Markkula & Dogar, 2022) that achieving human-AV interactions which meet these three goals is effectively the same as constraining the human-AV interaction to those world states and human behaviours which are *preferred* by the involved humans. If the interaction strays from these states and behaviours, dissatisfaction and inefficiencies may arise, and if the interaction requires human behaviours outside of those which are *feasible* for the human, the interaction becomes unsafe. With this perspective in mind, one can suggest that, on a high level, the applied purpose of quantitative human-AV interaction modelling is to *describe what states and behaviours are preferred by and feasible for humans*.

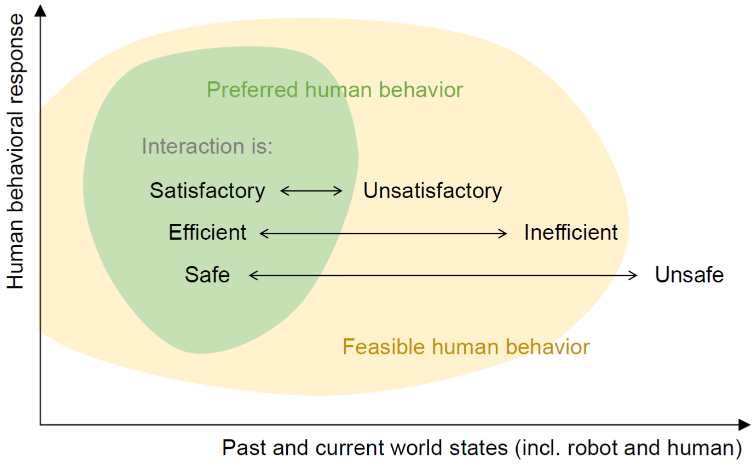

Figure 1 – Schematic illustration of the relationship between the feasible and preferred behaviour and states of a human during interaction with an AV, and the resulting degree of success of the human-AV interaction. © 2022 IEEE. Reprinted, with permission, from IEEE Robotics and Automation Magazine (Markkula & Dogar, 2022).

More specifically, how can mathematical models describing these preferred or feasible human states and behaviours be used to support the development of AVs? A few recurring themes can be discerned in the literature: Models can be used as *components in real-time AV algorithms* to predict likely future behaviour of surrounding human road users (Camara et al., 2020; Mozaffari et al., 2022), as *agent models in simulations for AV testing* (Camara et al., 2020; Feng et al., 2023; Igl et al., 2022), or as a means to better understand human behaviour to *shape and guide the design of AVs* more generally (Markkula et al., 2018; Millard-Ball, 2018;

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Zgonnikov et al., 2023). The SHAPE-IT research described in this report spans all three of these types of use cases for human-AV interaction models.

2.2 Approaches to modelling human-AV interactions

Mathematically modelling the behaviour of even a single human in isolation is highly non-trivial, and the complexity of the task increases further when the behaviour in question involves interactions with other agents. Human interactive behaviour in road traffic involves not only basic perceptual-motor control and collision avoidance, but also reciprocal coordination with other road users, often including different forms of negotiation and communication (Markkula et al., 2020). These behaviours presumably rely on a wide range of underlying cognitive mechanisms, so it is not surprising that there is a large diversity of *mechanistic models* of road user interaction which draw their assumptions about underlying mechanisms from a range of fields including perceptual psychology (Bonneaud & Warren, 2012; Domeyer et al., 2022) and cognitive neuroscience (Pekkanen et al., 2022; Zgonnikov et al., 2022), as well as optimal control and game theory (Hoogendoorn & Bovy, 2003; Schwarting et al., 2019; Wu et al., 2019). The mechanistic modelling approach, if successful, has the benefit of providing an understanding of the modelled behaviour, but it is typically limited by an inability to scale well to real-world scenarios of arbitrary complexity. An alternative approach is to develop *data-driven models*, typically leveraging deep neural networks and large naturalistic datasets to describe behaviour also at complex real-world locations (Igl et al., 2022; Mozaffari et al., 2022). The main limitations of these models are their black box nature and the lack of guarantee that they will capture those aspects of interactions which matter to humans (Siebinga et al., 2022; Srinivasan et al., 2023). In other words, there are currently very clear trade-offs between mechanistic and data-driven models, requiring modellers and model users to choose between interpretability and explainability on the one hand, and generalisability and fidelity on the other. The SHAPE-IT research described in this report spans the entire spectrum between mechanistic and data-driven models, and also provides some contributions aiming to bridge the gap between the two approaches, in order to reduce the mentioned trade-offs.

2.3 SHAPE-IT objectives in quantitative modelling

On a high level, the objectives of the modelling-oriented ESRs in SHAPE-IT can be summarised as follows (note that for some ESRs these are sub-goals of their individual projects):

- ESR3, Chi Zhang: To develop data-driven models for real-time prediction of pedestrian trajectories, with improved consideration of interactions with other road users.
- ESR11, Sarang Jokhio: To develop data-driven, statistical models to identify patterns in turn signal usage in lane changes and lane change initiation, as a prototypical scenario where humans need to cooperate in traffic.
- ESR12, Xiaolin He: To develop computational models of occupants' subjective feeling of risk inside automated vehicles.
- ESR13, Amir Hossein Kalantari: To develop and compare both conventional and behavioural game-theoretic models to understand vehicle-pedestrian interactions at unsignalised crossing locations.
- ESR14, Ali Mohammadi: To develop quantitative models predicting cyclists' behaviour through their kinematics and appearance, to improve automated vehicle interactions with cyclists at intersections.

It should be noted that a general challenge for current human-AV interaction modelling is that AVs are only very recently beginning to be available, leading to a scarcity of data on actual human-AV interactions (see deliverable D2.3 for details about this challenge). Therefore, while all ESRs have developed their models with human-AV interactions in mind, much of the modelling research in SHAPE-IT has in practice focused on human-human interactions, based on the assumption that human-AV interactions will need to leverage much of the same underlying principles.

2.4 Covid-19 impact

Three of the involved ESRs reported that experimental work supporting their research was substantially delayed due to the Covid-19 pandemic; two of them reported that one or more of their planned secondments were delayed.

3 The research

In this chapter, each section describes an ESR's modelling research.

3.1 Modelling Pedestrian Behaviour in Urban Traffic Scenarios Using AI Methods (ESR3)

3.1.1 Related previous work and research gaps

Compared to other road users, pedestrians are more vulnerable, so the need to create safer vehicles to prevent conflicts and collisions with them is great (C. Zhang, 2022). To meet the requirements for reducing fatalities and serious injuries caused by traffic crashes, researchers are developing automated driving (AD) technologies. Predicting pedestrian behaviour is crucial for AD systems (Camara et al., 2020). Incorporating Artificial Intelligence (AI) technologies reduces the operational load of human drivers, lowering the number of deaths brought on by human error while also potentially increasing human productivity and satisfaction.

Existing knowledge-based techniques, such as rule-based and statistics-based models, are not able to forecast pedestrian behaviour accurately or reliably because of the complexity and intricacy of human behaviour (C. Zhang et al., 2021). The rule-based models find it difficult to understand the non-linear behaviour of pedestrians which results from interactions (C. Zhang & Berger, 2023).

Therefore, machine learning and deep learning methods that are more capable of handling complex scenarios should be developed for predicting pedestrians' behaviour, especially when they interact with vehicles/automated vehicles.

3.1.2 Objectives

Our research goal was to model the behaviour of pedestrians interacting with vehicles/automated vehicles using AI methods. It comprises the following objectives:

- Modelling pedestrian trajectories by considering interactions with other road users, including other pedestrians, vehicles, and automated vehicles.
- Modelling pedestrian crossing intentions as interaction outcomes between pedestrians and vehicles.

3.1.3 Methods

The interactions between pedestrians and other road users (e.g., other pedestrians, vehicles, and automated vehicles) are complex. The following factors could impact how people interact in traffic (Rasouli & Tsotsos, 2020; C. Zhang & Berger, 2023).

a) pedestrians' characteristics, such as their posture, direction of travel, age, gender, and even personality traits;

b) vehicle status, such as speed, acceleration, direction, size, etc;

c) environment factors, including the size and number of lanes on the road and traffic signals and signage.

In the field of AI, two other terms are also frequently mentioned: machine learning (ML) and Deep Learning (DL). As described by Sarker (2021), AI is defined as the process of computer systems simulating human intelligence, including learning, reasoning, and self-correction. The subset of AI known as ML enables systems to learn and improve from experience without explicit programming. ML involves using algorithms to analyse data, learn from the data, and make predictions based on the data. In our research (C. Zhang, Kalantari, et al., 2023), we used common ML models including logistic regression, linear regression, support-vector machine (SVM), random forest (RF), and neural networks.

Deep learning (DL) is a subset of ML that utilizes deep neural networks to learn complex patterns from large amounts of data; it is inspired by the structure and function of the brain, and referred to as artificial neural networks (ANN). The activation functions in DL help the model learn the non-linearity that is hard for other knowledge-based models to learn. In our research (C. Zhang et al., 2021; C. Zhang, Ni, et al., 2023; C. Zhang & Berger, 2022a, 2022b), we used multi-layer perceptron (MLP); recurrent neural networks (RNNs), including their variant long short-term memory (LSTM) networks; generative adversarial networks (GANs); convolutional neural networks (CNNs); and transformer (TF) networks.

High-quality datasets are important for ML and DL modelling (C. Zhang & Berger, 2023). We used both naturalistic data and simulator data, such as the Waymo Open Dataset (Sun et al., 2020), released by Google Waymo for trajectory prediction (C. Zhang et al., 2021; C. Zhang, Ni, et al., 2023; C. Zhang & Berger, 2022a, 2022b), and the distributed simulator study data proposed by Kalantari, Yang, et al. (2022) for pedestrian-vehicle interaction modelling (C. Zhang, Kalantari, et al., 2023).

To evaluate the model performance, we used standard metrics from the ML literature. For trajectory prediction, we used the following two measures to report prediction error and evaluate model performance:

- The Average Displacement Error (ADE): the average distance gap between ground truth and predicted trajectories over all predicted time-steps.

$$ADE = \frac{\sum_{i \in n_p} \sum_{t=T_{obs}+1}^{T_{pred}} \left\| Y_t^i - \widehat{Y}_t^i \right\|_2}{n_p \times \left(T_{pred} - T_{obs} \right)}$$

- The Final Displacement Error (FDE): the average distance gap between ground truth and predicted trajectories for the last predicted time-step.

$$FDE = \frac{\sum_{i \in n_p} \left\| Y_t^i - \widehat{Y}_t^i \right\|_2}{n_p}, \ t = T_{pred}$$

To evaluate pedestrian crossing decision prediction during the interaction, the prediction accuracy and F1 score were used:

$$ACC = \frac{TP + TN}{P + N}$$

$$F1 = \frac{2TP}{2TP + FP + FN}$$

where P is the number of positives, N is the number of negatives, TP denotes true positives, TN denotes true negatives, FP denotes false positives, and FN denotes false negatives.

3.1.4 Results

We divided the research into several research topics. We first reviewed a large selection of existing papers on pedestrian behaviour modelling to obtain a comprehensive understanding of deep learning-based approaches for pedestrian behaviour prediction. Then, we built deep learning models to predict pedestrian trajectories, considering both interactions between pedestrians and interactions between pedestrians and vehicles/automated vehicles. Since we want a model trained on one dataset to be transferable to other scenarios, we also investigated the model's transferability and proposed a transferable model. In addition to trajectories, we also investigated the interaction outcomes between pedestrians and vehicles at unsignalised crossings. Below are the results for each topic.

3.1.4.1 Topic 1: Literature Review

We reviewed existing methods for pedestrian behavior prediction that used deep learning (C. Zhang & Berger, 2023). In this study, we analysed, compared, and discussed their performance. We also provided a detailed overview of existing datasets and the evaluation metrics. Finally, we identified research gaps and outlined potential future research directions.

3.1.4.2 Topic 2: Social Interactions Between Pedestrians

We predicted pedestrian trajectories by modelling the social interactions between pedestrians (C. Zhang et al., 2021). We proposed a novel structure, the Social Interaction Extractor, to better and faster capture interactions between pedestrians.

The model structure is shown in Figure 2 and the Social Interaction Extraction in Figure 3.

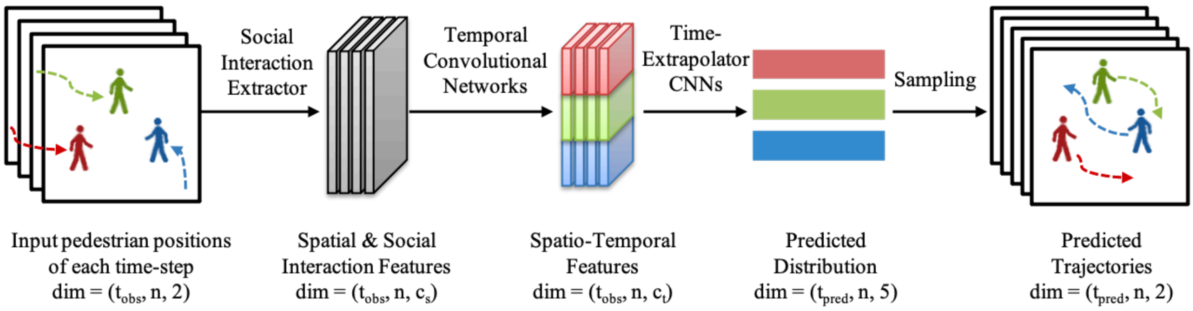


Figure 2. Overall framework of Social-IWSTCNN. Given observed frame sequences, we used the positions in each frame as input to learn the social interaction weights and extract spatial and social interaction features using the Social Interaction Extractor. Following this, we applied TCNs to create spatio-temporal features for each pedestrian. Then we applied Time-Extrapolator CNNs to predict future trajectory distributions. Finally, we sampled to get the predicted trajectories. © 2021 IEEE. Reprinted, with permission, from 2021 IEEE Intelligent Vehicles Symposium (IV) (C. Zhang et al., 2021)

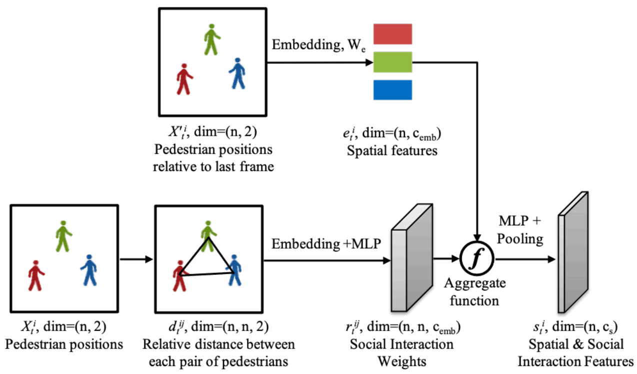


Figure 3. Pedestrian Social Interaction Extractor. The inputs were the positions relative to the last frame and pedestrian positions of each time-step. We used MLP to learn the social interaction weights, and an aggregate function to extract the spatial and social interaction features. © 2021 IEEE. Reprinted, with permission, from 2021 IEEE Intelligent Vehicles Symposium (IV) (C. Zhang et al., 2021)

The total inference speed of our proposed network is 4.7 times faster than the previous SOTA model, Social-STGCNN, while the prediction results are competitive. The models were evaluated on urban traffic scenarios using the Waymo Open Dataset, which contains more urban traffic scenarios and more sequences of pedestrians than the previously commonly used ETH and UCY datasets, to reveal the model performance on real-world traffic tasks.

3.1.4.3 Topic 3: Interactions Between Pedestrians and Vehicles

We predicted pedestrian trajectories by modeling the interactions between pedestrians and vehicles (C. Zhang & Berger, 2022a). In this study, we generalised the pedestrian interaction extractor architecture from a previous work (C. Zhang et al., 2021) to create a pedestrian-vehicle interaction (PVI) extractor to predict pedestrian trajectories.

The proposed PVI extractor performs well on both sequential (LSTM-based) and non-sequential (Conv-based) models, improving ADE and FDE by 1-7% over SOTA benchmarks. Examples of prediction results are shown in Figure 4.

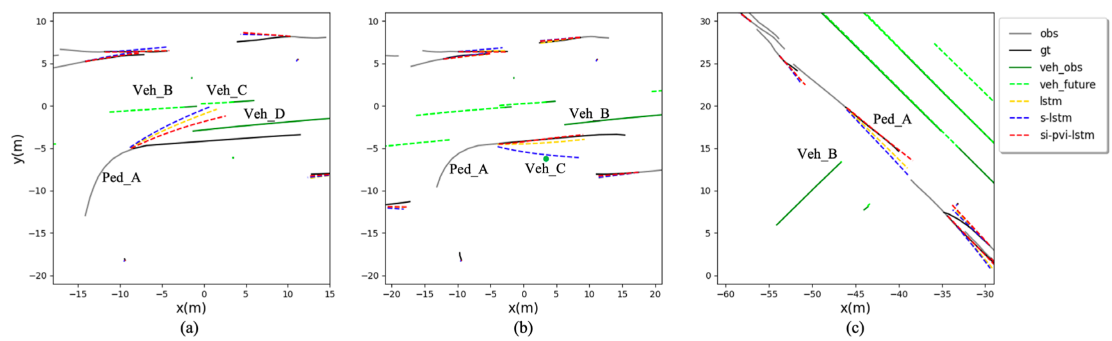


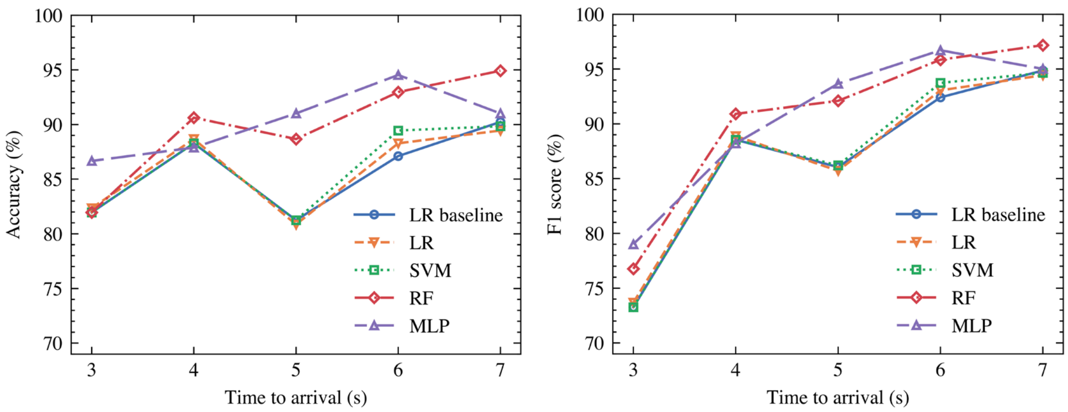
Figure 4. Comparison of trajectories predicted by LSTM, Social-LSTM, and SI-PVI-LSTM in various scenarios. (a) Pedestrian A is turning right, avoiding the moving vehicles B, C, and D. (b) Pedestrian A has turned right and keeps walking straight, avoiding moving vehicle B and parked vehicle C. (c) Pedestrian A is crossing the road, interacting with vehicle B, which is slowing down and waiting. The legends: obs denotes observed paths of pedestrians, gt refers to the ground truth of predicted trajectories of pedestrians, veh obs refers to the observed vehicle trajectories, veh future stands for the future trajectories of vehicles during the prediction time, lstm refers to the LSTM model, s-lstm refers to Social-LSTM, and si-pvi-lstm denotes our proposed Social Interaction and Pedestrian-Vehicle Interaction LSTM model. © 2022 IEEE. Reprinted, with permission, from 2022 8th International Conference on Control, Automation and Robotics (ICCAR) (C. Zhang & Berger, 2022a)

3.1.4.4 Topic 4: Interactions Between Pedestrians and Automated Vehicles

We analysed the interactions between pedestrians and automated vehicles using deep learning methods (C. Zhang & Berger, 2022b). In this study, our results and main contributions are as follows: for the factors that influence the pedestrian behavior, we have investigated interaction factors on both sequential and non-sequential deep learning methods. All these interaction factors can influence the prediction accuracy of pedestrians' future trajectories. Based on the backbone we compared, the prediction accuracy of Conv-based models outperforms the LSTM-based models.

3.1.4.5 Topic 5: Interaction Outcomes

We modelled pedestrian crossing intentions as interaction outcomes between pedestrians and vehicles (C. Zhang, Kalantari, et al., 2023). In this study, we proposed predictive models for the interaction outcome (i.e., whether the pedestrian or the vehicle passes the crossing location first), as well as for the timing of the pedestrian's crossing initiation and the crossing duration, using machine learning-based methods. We obtained substantial improvements over the baseline linear regression models (Kalantari, Yang, et al., 2022). The presence of a zebra crossing, the TTA, and the pedestrian waiting time were found to be important for all models. The prediction accuracy and F1 score versus TTA for the interaction outcome predictions are shown in Figure 5.



(a) (b)

Figure 5. The (a) prediction accuracy and (b) F1 score versus time to arrival of the vehicle at interaction onset, for logistic regression (LR), support-vector machine (SVM), random forest (RF), and multilayer perceptron (MLP) models. © 2023 IEEE. Reprinted, with permission, from 2023 IEEE Intelligent Vehicles Symposium (IV) (C. Zhang, Kalantari, et al., 2023)

3.1.4.6 Topic 6: Model Transferability

We investigated the transferability of pedestrian prediction models (C. Zhang, Ni, et al., 2023). In this study, we proposed a transferable model, namely the spatial-temporal-spectral (STS) LSTM model, which performs well when transferred to target datasets without any prior knowledge, and has a faster inference speed than the state-of-the-art models.

3.1.5 Publications

- Zhang, C., Berger, C., & Dozza, M. (2021). Social-IWSTCNN: A social interaction-weighted spatio-temporal convolutional neural network for pedestrian trajectory prediction in urban traffic scenarios. In *2021 IEEE Intelligent Vehicles Symposium (IV)* (pp. 1515-1522). IEEE. https://doi.org/10.1109/iv48863.2021.9575958
- Zhang, C., & Berger, C. (2022). Learning the pedestrian-vehicle interaction for pedestrian trajectory prediction. In *2022 8th International Conference on Control,*

Automation and Robotics (ICCAR) (pp. 230-236). IEEE. https://doi.org/10.1109/iccar55106.2022.9782673

- Zhang, C., & Berger, C. (2022). Analysing Factors Influencing Pedestrian Behavior in Urban Traffic Scenarios Using Deep Learning. *Accepted in Transport Research Arena (TRA), 2022. Elsevier.*
- Zhang, C. (2022). Predicting Pedestrian Behavior in Urban Traffic Scenarios Using Deep Learning Methods, Doctoral Licentiate Thesis, Chalmers University of Technology.
- Zhang, C., & Berger, C. (2023). Pedestrian Behavior Prediction Using Deep Learning Methods for Urban Scenarios: A Review. *IEEE Transactions on Intelligent Transportation Systems*. https://doi.org/10.1109/tits.2023.3281393
- Zhang, C., Kalantari, A. H., Yang, Y., Ni, Z., Markkula, G., Merat, N., & Berger, C. (2023). Cross or Wait? Predicting Pedestrian Interaction Outcomes at Unsignalized Crossings. *In 2023 IEEE Intelligent Vehicles Symposium (IV). IEEE.* https://doi.org/10.1109/IV55152.2023.10186616
- Zhang, C., Ni, Z., & Berger, C. (2023). Spatial-Temporal-Spectral LSTM: A Transferable Model for Pedestrian Trajectory Prediction. *IEEE Transactions on Intelligent Vehicles*. https://doi.org/10.1109/tiv.2023.3285804

3.1.6 Conclusions and future work

We have proposed deep learning models for predicting the trajectories of pedestrians interacting with other pedestrians and vehicles. We have analysed the influence of pedestrian-automated vehicle interaction on pedestrian trajectory prediction and proposed novel models with predictive accuracy equal to or better than state-of-the-art (SOTA) benchmarks. The new models also reduce computational costs and, importantly, demonstrate improved transferability to new situations. Furthermore, we have also directly modelled the interaction outcomes (i.e., whether the pedestrian will cross or wait when encountering a vehicle), something which has not been previously attempted using ML modelling. One interesting direction for future work is to develop models which can predict both pedestrians' trajectories and their intentions simultaneously.

3.1.7 Highlights

The overall objective of the modelling work by ESR3 was to develop data-driven models for real-time prediction of pedestrian trajectories, with improved consideration of interactions with other road users. Key results include:

- A review of the existing research in the area of pedestrian behaviour prediction was performed, including a proposed framework of the area and an overview of research gaps .
- Pedestrian trajectory prediction methods were proposed which consider social interactions and display improved prediction accuracy, faster prediction speed, and better transferability between datasets.
- Interaction of pedestrians and (automated and non-automated) vehicles was analysed using deep learning models.
- Vehicle-pedestrian interaction outcomes at unsignalised crossings were modelled.

3.2 Cooperative interaction strategies between AVs and mixed motorized traffic (ESR11)

3.2.1 Related previous work and research gaps

Road traffic is a complex social system in which each road user has different goals (Färber, 2016; Wilde, 1976). These goals often extend beyond simply reaching a destination and may encompass timing, safety, and comfort considerations. Conflicts may arise when the individual goals of different road users interact with each other. These conflicts, if not resolved, could result in collisions. Lane changing, when a driver moves laterally to an adjacent lane which may already be occupied, is one of the common manoeuvres in everyday driving which could result in a conflict.

Autonomous vehicles (AVs) have the potential to reduce some of the complexity of road traffic by replacing human drivers. However, the full potential of this technology can only be achieved when a significant number of vehicles on the road are AVs. There will be a long period of mixed traffic in which the AVs share the road space with human-driven vehicles. Throughout this period, certain negative consequences of AVs could be observed, such as adversely affected traffic flow (Al-Turki et al., 2021; Calvert et al., 2017) and traffic safety (Garg & Bouroche, 2023; M. M. Morando et al., 2018; Ye & Yamamoto, 2019).

To evaluate the AVs' influence on the existing traffic system and vice versa, researchers often use traffic simulations in the absence of real-world interaction data (Beza et al., 2022; Garg & Bouroche, 2023). By adjusting the parameters and conditions within these simulations, we can anticipate potential challenges AVs might encounter and formulate effective strategies for integrating them into the existing traffic ecosystem. However, traffic simulation relies heavily on driver-behaviour models to represent different traffic participants, such as when studying lane changing behaviour (Zheng, 2014). While lane-changing models have improved, they are far from replicating human behavior.

One of the ways to improve the existing models is to improve our understanding of the overall lane change process. So far, most research has primarily focused on understanding gap acceptance behaviour and the duration of lane changes (Y. Li et al., 2021; Yang et al., 2019). We currently lack a full understanding of how drivers communicate their intention (e.g., use their turn signal) during lane change. Studies, mainly from the United States and China, have shown that drivers often do not use turn signals, which are a direct form of communication (Dang, Ruina et al., 2013; Lin & Bao, 2019; Ponziani, 2012; Wang et al., 2019). Additionally, we also lack an understanding of drivers' pre-lane change behaviour, in particular how long they wait after signalling before changing lanes. Integrating actions that a driver performs prior to changing lanes into the lane-changing models will make them more realistic.

3.2.2 Objectives

This work aims to gain better insight into the lane-changing process by analysing and modelling real-world driving data using various statistical models. The overarching goal is to support the development of realistic lane change behavioural models, as well as develop guidelines for autonomous vehicles' interactions in mixed traffic. The objective of the first study is to identify turn signal usage patterns during lane changing and the factors impacting it. The objective of the second study is to get deeper insights into pre-lane change behaviour by analysing how long drivers typically wait between using the turn indicator and starting a lane change.

3.2.3 Methods

The data used here were part of a larger real-world data collection effort during the L3Pilot European project (Hiller, 2019). The specific dataset used in this study was collected by Volvo Car Corporation in Gothenburg, Sweden (Penttinen et al., 2019). The data include both lane-changing vehicles' information (e.g., turn signal usage, longitudinal and lateral position and velocity) and surrounding vehicles' information (e.g., speed and position).

A rule-based algorithm based on lateral velocity and lateral position was developed to determine the initiation and end of a lane change. In total 1791 lane-change cases were extracted (Jokhio et al., 2023). Subsequently, turn signal usage was calculated by comparing the time of the turn signal activation to the time of the lane change initiation. To gain a better understanding, we divided turn signal usage into three categories: used before initiating a lane change, used after initiating a lane change, and not used at all.

Real-world driving data are frequently extensive, noisy, sparsely populated, and imbalanced (A. Morando et al., 2019). Moreover, they often exhibit a hierarchical or multilevel structure, with observations grouped under individual participants. As a result, we implemented statistical models best suited to handle this type of data. The subsequent sections provide a more detailed discussion of each of these approaches.

3.2.3.1 Bayesian hierarchical model to explore turn signal usage

The first study used real-world data to examine patterns in turn signal usage among human drivers, to identify potential influencing factors (Jokhio et al., 2023). As previously mentioned, real-world data are often imbalanced and structured hierarchically, since they originate from a variety of participants. These challenges can be tackled by using a Bayesian approach, which allows a more intuitive interpretation of results by using probabilities, rather than relying on p-values (as in traditional methods). The Bayesian methodology can manage more complex, non-linear relationships and data that are not normally distributed (Kruschke & Liddell, 2018).

The Bayesian approach employs Bayes' theorem to revise previous beliefs or knowledge by incorporating observed data and drawing conclusions about unknown parameters (Van De Schoot et al., 2021). It is used extensively in many fields, including transportation, social and behaviour sciences and artificial intelligence (Daziano et al., 2013; Russo, 2020; Van De Schoot et al., 2021).

As mentioned earlier, the outcome variable has three possibilities: turn signal use before initiating a lane change ('before'), turn signal use after initiating a lane change ('after'), and no turn signal use ('no'). The probability of observing each level of the outcome variable is given by the following equations:

$$logit\left(\frac{P(signal = after)}{P(signal = before)}\right) = \alpha_{after} + \beta_{after} * X + b_{oj,after}$$

$$logit\left(\frac{P(signal = no)}{P(signal = before)}\right) = \alpha_{no} + \beta_{no} * X + b_{oj,no}$$

Here, X represents the vector of predictor variables and α_{after} and α_{no} are the intercepts for the "after" and "no" categories, respectively. β_{after} and β_{no} represent the fixed effect coefficients for the "after" and "no" categories, respectively, corresponding to the vector X of predictor variables (fixed effects). The fixed effects are speed, direction, rear veh, rear gap, lag veh, lag gap, traffic density, and driver type. $b_{0j,after}$ and $b_{0j,no}$ represent the random intercepts for each driver ID.

In our study, we used non-informative priors with normal distribution $N(0, 1 \times 10^4)$ for the fixed effects and half-normal $Half - normal(0, 1 \times 10^4)$ distribution for the random effects (Gelman, 2006).

3.2.3.2 Survival analysis of time-to-lane-change-initiation

The purpose of a turn signal extends beyond merely communicating a driver's intention to change lanes; it also serves to alert surrounding drivers, enabling them to adjust their behaviour accordingly. The existing research has shown that lag vehicle drivers (i.e., drivers in the target lane, behind the lane-changing vehicle) appreciate an early warning from the lane-changing driver (Kauffmann et al., 2018). Furthermore, three seconds of delay between turn indicator use and lane change increased the lag vehicle driver's perception of cooperativeness (Kauffmann et al., 2018). However, whether or not drivers actually wait after using the turn signal before initiating a lane change is currently unknown. We refer to this duration as time-to-lane-change-initiation (TTLCI). This study is aimed at understanding TTLCI and the factors that might have an impact on it. In this study we only considered the 1073 lane-change cases in which a turn signal was used before initiating a lane change.

We analysed the impact of different factors on TTLCI using survival analysis, which is a collection of statistical techniques suitable for outcome variables having a time-to-event nature. These techniques are widely used in medical science where the outcome variable is often time to death after exposure to a disease (Clark et al., 2003).

To get an overview of the typical TTLCI found in the real-world driving scenarios, we employed the Kaplan-Meier (K-M) method, a widely used technique for calculating the likelihood of a specific event occurring across a time span. The survival function in the K-M method is given by

$$S_t = S_{t-1} * \frac{N_t - E_t}{N_t}$$

In the context of our study, N_t represents the total number of lane changes at specific time t, while E_t is the number of instances (in this case, lane-change initiations) that occur at that exact time t.

To determine which factors impact the TTLCI, we used a popular regression technique with survival analysis known as the Cox proportional hazard (CPH) model (Cox, 1972). To account for the variability (due to different drivers), we used a mixed effects CPH model (Wienke, 2010). The mixed-effect extension of the CPH model incorporates both fixed effects and random effects. The model is given by

$$h_i(t) = h_0(t) * exp(\Sigma(\beta_n X_n i) + u_i)$$

In this context, $h_i(t)$ denotes the hazard function for the *i-th* subject at time *t*, while h_o(t) represents the baseline hazard function. The β_n corresponds to the coefficients associated with the fixed effects (covariates) X_ni, and u_i represents the random effects for the *i-th* subject.

3.2.4 Results

3.2.4.1 Study 1: Turn signal usage

The descriptive analysis showed that in almost 60% of cases, a turn signal was used before initiating a lane change (identified using the rule-based method mentioned in Section 3.2.3). It was used after initiating a lane change in almost 33% of instances; in about 7% of cases, no turn signal was used at all.

Table 1 shows estimates for the fixed effects in the “after” and “no” response levels compared to the “before” level for the response (turn signal usage) variable. The “l-95%” HDI and “u-95% HDI” columns show lower and upper bounds of the highest posterior density interval (HDI), respectively. It is the range within which we can be 95% confident that the true parameter value lies: thus a broader HDI suggests increased uncertainty (Kruschke & Liddell, 2018). When the HDI encompasses zero, it implies that, based on the data and model, the actual parameter value might be indistinguishable from zero (Kruschke & Liddell, 2018).

Table 1. BHM fixed effect results.

Predictors	**Estimate**	**Est. Error**	**l-95% HDI**	**u-95% HDI**
Level: After				
Intercept	-1.67	0.51	-2.68	-0.7
Speed	0.02	0.01	0.01	0.04
Direction (right)	-0.81	0.11	-1.03	-0.59
Rear vehicle (yes)	-0.37	0.18	-0.74	-0.02

Rear gap	0.19	0.09	0.02	0.37
Lag vehicle (yes)	-0.23	0.18	-0.59	0.13
Lag gap	0.07	0.09	-0.12	0.24
Traffic density	-0.02	0.01	-0.04	0
Driver type (pro)	0.3	0.18	-0.04	0.65
Level: No				
Intercept	-5.92	1.34	-8.6	-3.41
Speed	0.01	0.01	-0.01	0.03
Direction (right)	0.02	0.22	-0.4	0.47
Rear vehicle (yes)	-0.44	0.38	-1.16	0.32
Rear gap	0.26	0.18	-0.1	0.6
Lag vehicle (yes)	-1.1	0.35	-1.83	-0.46
Lag gap	0.48	0.14	0.2	0.75
Traffic density	-0.07	0.03	-0.12	-0.02
Driver type (pro)	2.87	1.19	0.69	5.34

Table 2. BHM random effects

Estimates	**Est.Error**	**l-95% HDI**	**u-95% HDI**	**Rhat**
Standard deviation (Level: After)				
0.36	0.11	0.13	0.57	1
Standard deviation (Level: No)				
2.69	0.55	1.58	4.19	1

Overall, the results show that different variables impact turn signal usage with varying levels of uncertainty. For example, speed is positively associated with an entirely positive HDI range. This result indicates that as speed increases, drivers are less likely to use the turn signal before starting a lane change.

The standard deviation of the random intercept in Table 2 for both levels indicates variation in the logits among various drivers. This finding means that, when accounting for the average influence of all other aspects, the probability that a driver will use the turn signal after initiating a lane change or not use it at all differs from one driver to another.

3.2.4.2 Study 2: Time-to-lane-change-initiation

The results of the K-M method are shown in Figure 6. The step-like line represents the survival function and the shaded area around it represents the confidence interval. The graph illustrates a sharp decrease in the survival function in the initial two seconds, indicating that the majority of lane changes (about 90%) were initiated within two seconds of the activation of the turn signal.

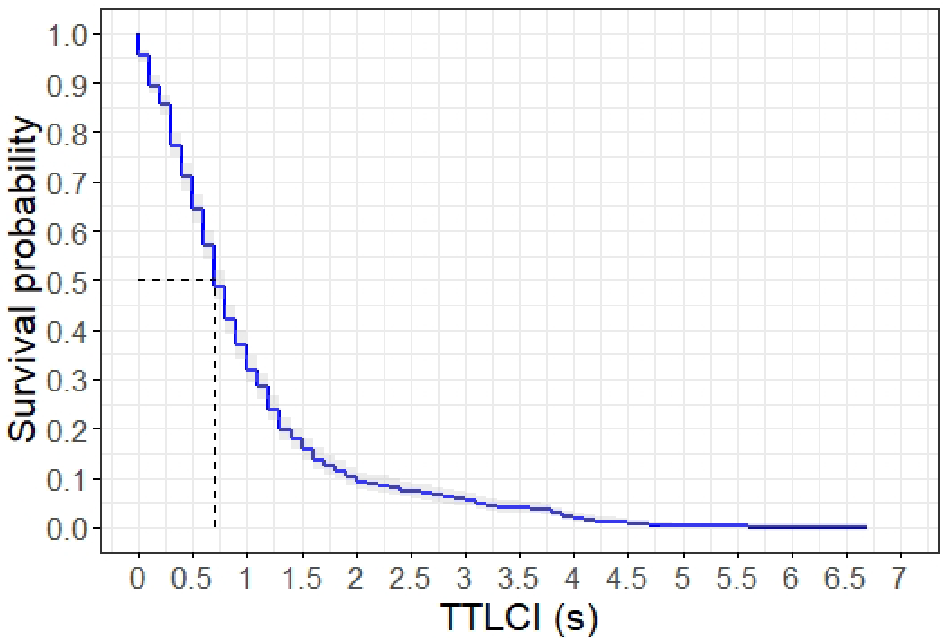


Figure 6. K-M survival curve of TTLCI.

The results of the mixed effect CPH analysis are provided in Tables 3 and 4. The fixed effects represent the average effects of each predictor on the response variable across all the subjects (drivers). The direction and magnitude of the effect of each predictor is represented by the sign of 'Coeff' and the magnitude of 'Exp(Coeff)'. The 'Exp(Coeff)' is the hazard ratio, which, for a categorical predictor, gives the relative probability of an event happening for a specific category compared to another category. For continuous predictors, it shows the multiplicative change in the probability of the event occurring for every one-unit increment in that predictor. In other words, a hazard ratio higher than one implies an increased probability of the event occurring, while a hazard ratio lower than one implies a decreased probability of the event occurring. The significance of each predictor is represented by the *p*-value. Overall, these results show that TTCLI is impacted by various factors, such as the direction of lane change and the presence of surrounding vehicles.

Table 3. Mixed effect CPH model results (fixed effects)

Predictor	**Coeff**	**Exp(Coeff)**	**Std. Error**	**p-value**
Speed	0.025	1.025	0.004	<0.001
LC Direction (right)	-0.15	0.86	0.072	0.039
LC Type (SLC)	0.388	1.474	0.136	0.005
Rear Vehicle (yes)	0.148	1.16	0.117	0.21
Rear Gap	-0.063	0.939	0.0591	0.28
Lag Veh (yes)	-0.298	0.742	0.106	0.005
Lag Gap	0.139	1.15	0.045	0.002
Traffic Density	0.001	1.001	0.007	0.87
Lead Vehicle (Yes)	-0.199	0.819	0.067	0.003
Driver Type (Pro)	-0.16	0.852	0.146	0.27

The random effects are grouped by Driver ID, reflecting individual differences in driving behaviour that are not captured by the fixed effects in the model. The variable considered for the random effect is the Intercept, representing the baseline hazard function. The standard deviation of 0.374 translates to a relative increase in the likelihood of the event taking place, as indicated by exp(0.374) = 1.45. For a driver who is one standard deviation above the mean, the probability of the event (in this case, initiating a lane change) happening is increased by nearly 45% in comparison to the mean probability for all drivers.

Table 4. Mixed effect CPH model results (random effects)

Group	Variable	Standard deviation
Driver ID	Intercept	0.374

3.2.5 Conclusion and future work

The studies outlined above focus primarily on the driver's behaviour before initiating a lane change. Synthesising the knowledge from current research demonstrates that the use of turn signals not only influences surrounding traffic but is also affected by it. For example, the probability of using a turn signal decreases with an increase in the gap between the vehicle changing lanes and the lag vehicle. Additionally, the findings suggest that drivers might use turn signals more to comply with legal requirements than to alert other drivers. The second study reveals that when a turn signal is activated, a lane change is initiated within two seconds 90% of the time. This particular aspect of lane-changing is something that existing models have overlooked. While further exploration is needed to enhance our comprehension of driver behaviour prior to a lane change, the data supplied by these two investigations serve to improve the existing lane-changing models. Understanding how human drivers initiate lane changes, including the timing and the factors influencing this decision, is also essential for developing AV algorithms that can interact safely and efficiently with human-driven vehicles on the road.

3.2.6 Publications

- Jokhio, S., Olleja, P., Bärgman, J., Yan, F., & Baumann, M. (2023). Exploring Turn Signal Usage Patterns in Lane Changes: A Bayesian Hierarchical Modelling Analysis of Realistic Driving Data. *arXiv preprint arXiv:2305.16401*. https://doi.org/10.48550/arXiv.2305.16401

- Jokhio, S., Olleja, P., Bärgman, J., Yan, F., & Baumann, M. (in press). Analysis of Time-to-Lane-Change-Initiation Using Realistic Driving Data. *IEEE Transactions on Intelligent Transportation Systems*. https://doi.org/10.1109/TITS.2023.3329690

3.2.7 Highlights

The overall objective of ESR11's modelling work was to develop data-driven, statistical models to identify patterns in turn signal usage in lane changes and lane change initiation, as a prototypical scenario where humans need to cooperate in traffic. Key results include:

- There are clear differences in real-world turn signal usage between drivers and this behaviour is also affected by factors such as direction of lane change, speed of lane changing vehicle, and the presence and position of surrounding vehicles.
- Drivers typically take less than two seconds after turn signal activation to change lanes, but again this delay is also context-dependent.
- The results of these studies are crucial for improving existing lane-changing models, for example by including considerations of waiting time duration.
- The results can also help improve current AV algorithms by allowing them to better understand human drivers, for example by predicting time-to-lane-change-initiation.

3.3 Computational perceived risk modelling for automated vehicles based on potential collision avoidance difficulty (ESR12)

3.3.1 Previous related work and research gaps

Perceived (or subjective) risk, which is different from actual risk, plays a pivotal role in influencing drivers' behaviour and their acceptance of automated driving systems. When perceived risk is low, drivers tend to feel safe and relaxed, but when it is high, they exhibit cautious behaviour. Misinterpretations of risk during automated driving at levels of automation requiring human monitoring can lead to either unnecessary interventions or failure to intervene when required (Xu et al., 2018). The failure of vehicles at higher levels of automation to properly consider the risk perceived by human passengers (or surrounding road users) can lead to low automation acceptance. Therefore, understanding and quantifying drivers' perceived risk is essential for designing driving automation that is not only technically safe but also perceived as safe. However, an accurate computational model to quantify drivers' perceived risk is still lacking.

Several previous attempts have been made to develop computational perceived risk models. These models fall into two categories: empirical models based on data, and mechanistic models based on first principles. Empirical models, such as those developed by Kolekar et al. (2020a), Ping et al (2018) and He et al. (2022) use drivers' subjective risk ratings, steering responses, surrounding information, and the corresponding kinetic data to model perceived risk in various driving scenarios.

Mechanistic models, on the other hand, typically use surrogate measures of safety (SMoS) like time to collision (TTC) and time headway (THW). Models using TTC and THW capture one-dimensional interactions and are mainly validated for car-following situations (Kiefer et al., 2005). Some models, like the probabilistic driving risk field model (PDRF), consider motion probability distributions of other road users and the collision severity to estimate the collision risk (Mullakkal-Babu et al., 2020).

However, both types of models have limitations. Empirical models often lack extensive validation and interpretability; mechanistic models struggle to accurately map actual collision risk to perceived risk and lack empirically supported thresholds for SMoS (Kondoh et al., 2008, 2014). Therefore, there is a need for a computational model of perceived risk that is explainable, validated across diverse scenarios, and effectively bridges the gap between actual and perceived risk. This model would contribute significantly to the design of safer automated driving systems that can effectively interpret and respond to real-world driving situations.

3.3.2 Objectives

This study has two main objectives:

Objective 1 is to formulate an explainable computational perceived risk model grounded in the human drivers' risk perception mechanism and applicable to general 2D movements. The objective can be divided into several sub-objectives:

1. to understand the underlying principles of human drivers' risk perception.
2. to apply these principles in formulating the computational perceived risk model.

Objective 2 is to analyse our new model both theoretically and empirically. Our sub-objectives are:

1. to perform a theoretical examination of the new model.
2. to empirically evaluate the model using real-world data, specifically those involving 2D movements, including drivers' reported perceived risk during specific events.

The new model in this study, validated using event-based self-reported perceived risk, describes perceived risk per event in the continuous time domain. The model is developed for the general driver population instead of being personalised, but we can capture individual differences by tuning model parameters.

3.3.3 Methods

Firstly, we did a simulator experiment to investigate how perceived risk works in common driving scenarios when the AV reacts to merging and hard-braking events. Eighteen merging events with different merging distances and braking intensities on a two-lane highway were simulated. The participants were asked to monitor the scenario as fall-back-ready drivers for an SAE Level 2 AV. After each event, the participants were asked to give a verbal perceived risk rating from 0-10 regarding the previous event. The corresponding kinematic data (e.g., position, speed, and acceleration of the subject vehicle and neighbouring vehicles) were collected in the meantime.

An event-based perceived risk model was developed using regression which can predict human drivers' perceived risk ratings ranging from 0-10 regarding merging events based on the kinetic data, as shown in Equation x:

$$Perceivedrisk = 2.699 + 8.484 \cdot 1/TTC_{min} - 0.161 \cdot BI_{max}$$

where *perceived risk* is the event-based perceived risk (from 0-10), TTC_{min} is the minimum time to collision to the leading vehicle during an event, and BI_{max} denotes the maximum braking intensity of the leading vehicle.

This regression model of perceived risk demonstrates that smaller gap, smaller minimum TTC, and stronger brake lead to higher perceived risk. Also, the inverse TTC represents the relative visual expansion of the obstacle, commonly referred to as looming, which means perceived risk is highly correlated with the looming rate of other road users.

The regression model can predict perceived risk in the longitudinal direction (1D). To quantify perceived risk in both longitudinal and lateral directions (2D), we developed the "potential collision avoidance difficulty model" (PCAD), grounded in looming theory (Tian et al., 2022; Ward et al., 2015; Xue et al., 2018) and risk allostasis theory (Fuller, 2011). The model is based on the concept of potential collision avoidance difficulty, which quantifies the velocity gap to the safe velocity region. This region accounts for vehicles' kinematics, including uncertainty, as well as collision severity. The model describes perceived risk per event in continuous time. Figure 7 shows the safe velocity region and the velocity gap, which is the defined perceived risk in this study. The model considers all motion information, including position, velocity, and acceleration, highlighting the importance of these factors in risk perception. The model also considers the uncertainties in the motion of the subject vehicle and other road users, which can contribute to perceived risk. Specifically, at each moment, the model calculates a safe velocity region (the light blue area in the velocity space in Figure 7) for the subject vehicle based on its current position, velocity, and acceleration as well as on the uncertainties of both the subject and neighbouring vehicles. The minimum distance from the subject velocity (the yellow arrow v_s' in Figure 7) to the safe velocity region (the light blue area in Figure 7) is the perceived risk (the red arrow v_g in Figure 7) for the current moment.

The 2-D model describes the perceived risk per event in continuous time and was validated using event-based reported perceived risk.

This project has received funding from the European Community's
Horizon 2020 Framework Programme under grant agreement 860410

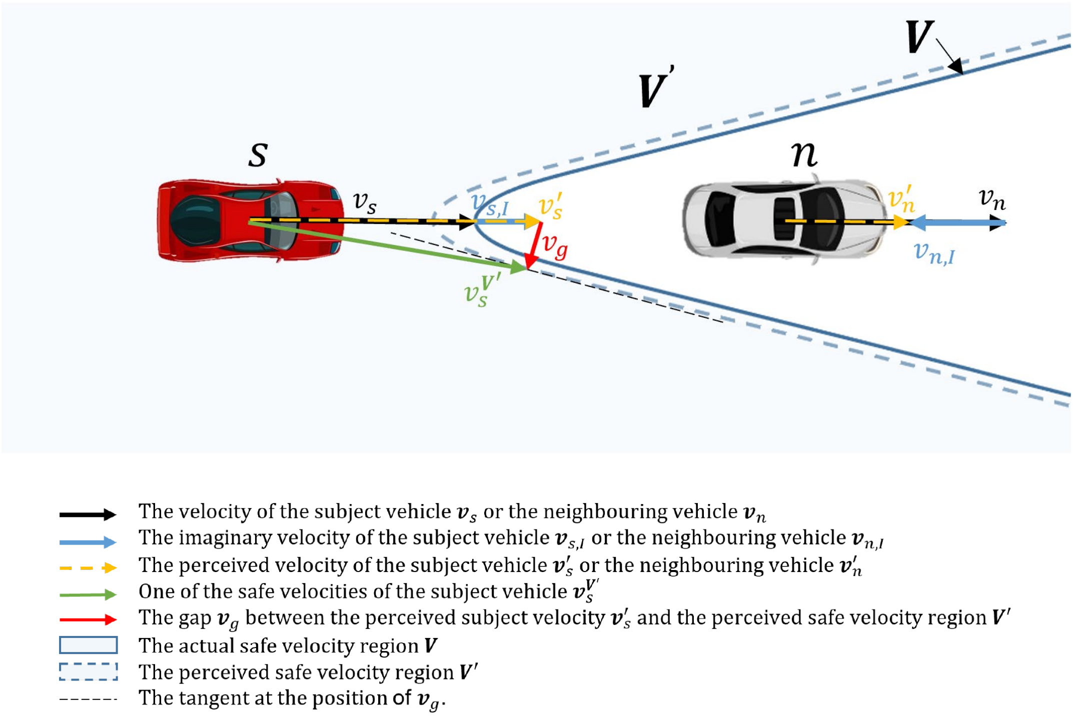


*Figure 7. The safe velocity regions **V** and **V'** (with and without uncertainties) and the velocity gap $\mathbf{v}_g$, which is the defined perceived risk in this study. This figure is from a preprint on arXiv (He et al., 2023).*

3.3.4 Results

The PCAD considers factors such as distance, relative motion, acceleration, and subject speed. The model shows that perceived risk increases as a vehicle approaches an object faster, and that subject velocity significantly influences perceived risk. Compared to other models, PCAD can output different perceived risk values for different driving conditions (See Figure 8).

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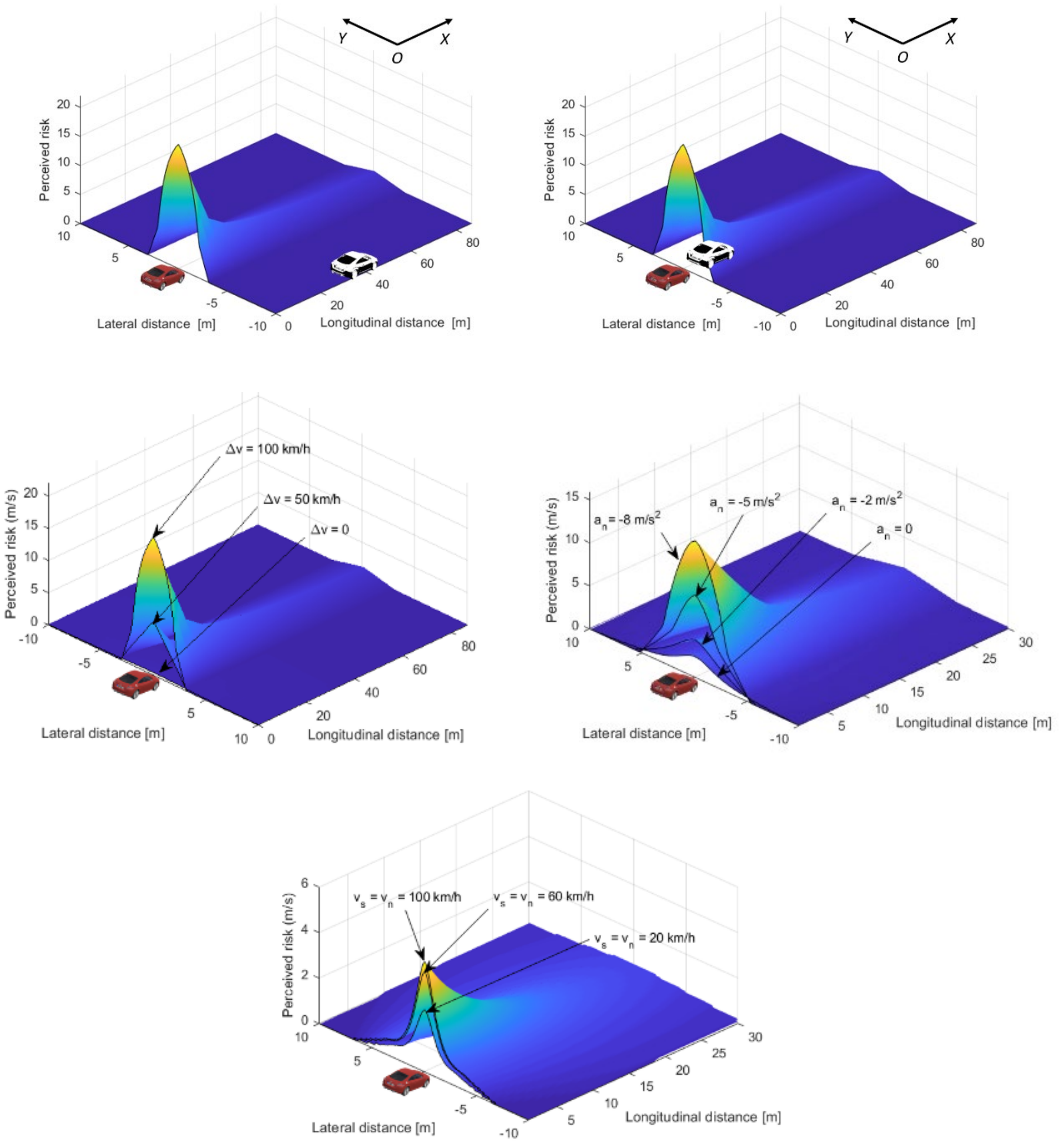

(a) Effect of relative speed, deceleration, and own vehicle speed.

Figure 8. (a) An illustration of the PCAD model, in two example situations where another vehicle is in a region of high perceived risk (left) versus low perceived risk (right). (b) The effects of relative speed, deceleration, and own vehicle speed on the perceived risk function.

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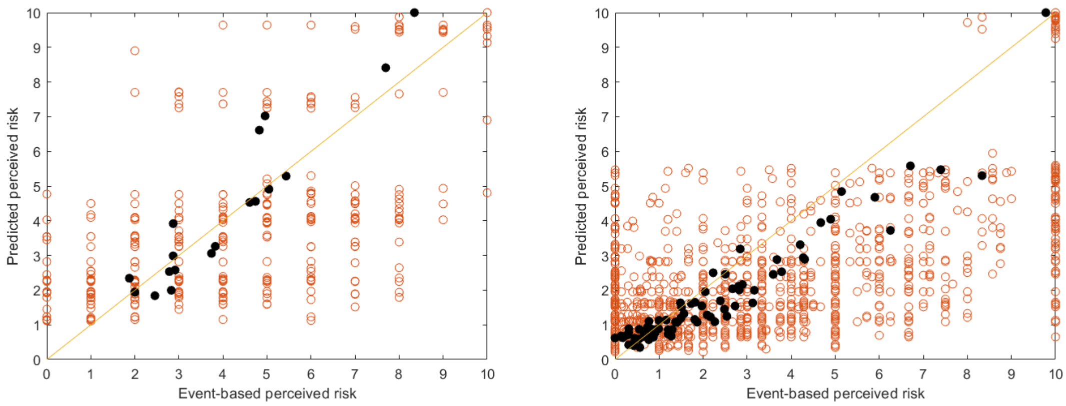
The model calibration and evaluation process used two datasets: "Dataset Merging" from a simulator experiment with automated vehicles reacting to merging and hard-braking events (He et al., 2022), and "Dataset Obstacle Avoidance" involving drivers facing sudden obstacles (Kolekar et al., 2020b). Both datasets contain event-based perceived risk ratings from participants and the corresponding kinematic data. The goal of model calibration was to minimise the prediction error, measured by Root Mean Squared Error (RMSE). Figure 9 shows the prediction results for the two datasets. The performance indicators detection rate and computation cost were used to evaluate the model. The model performed well, achieving a high detection rate and acceptable computation cost, indicating its potential for real-time risk assessment in automated vehicles (see Figure 10).



(a) Dataset Merging. Adjusted R^2 =0.90 (b) Dataset Obstacle Avoidance. Adjusted R^2 =0.90

Figure 9. Predicted and measured event-based perceived risk for Dataset Merging and Dataset Obstacle Avoidance. '○' indicates raw event-based perceived risk and '●' indicates the averaged event-based perceived risk across the same event type.

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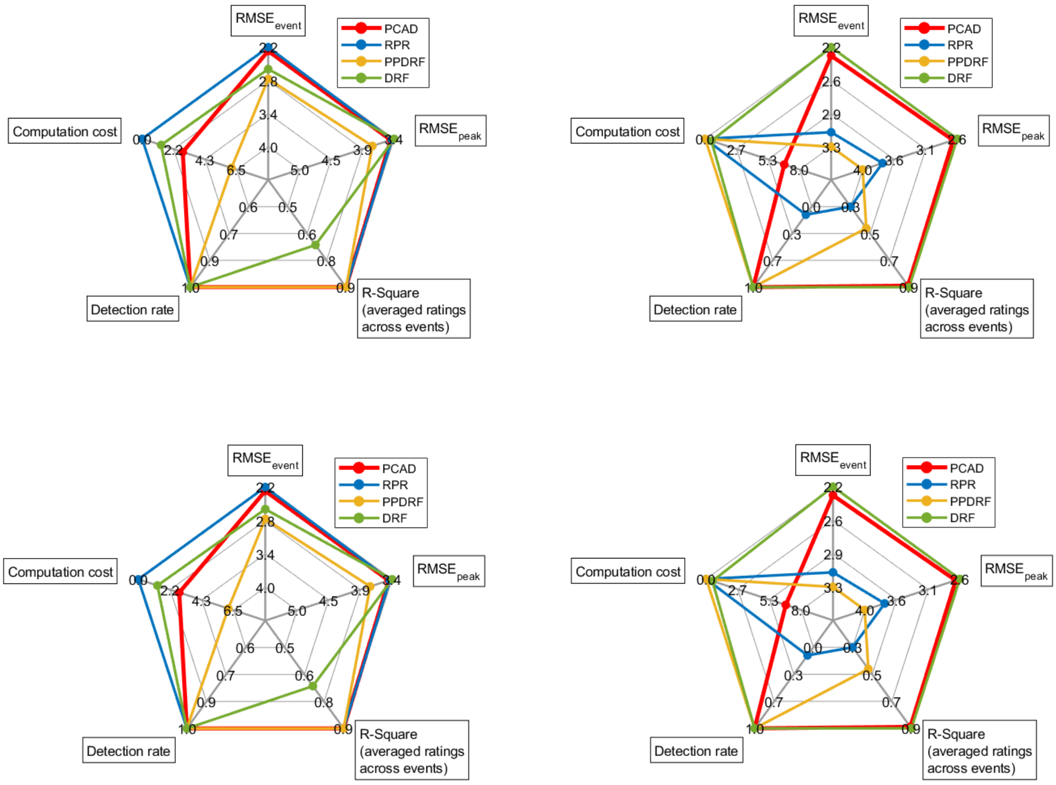

(a) Dataset Merging (b) Dataset Obstacle Avoidance

Figure 10. Radar charts of performance indicators comparing the PCAD model with three existing models for two datasets: the farther from the centre, the better the performance.

The results of the model evaluation show that PCAD demonstrates strong performance in terms of overall error, R-square, and detection rate. The model had a small RMSE, meaning that it can describe the tendency of human drivers' risk perception well in both datasets. Additionally, the model achieved a perfect detection rate (100% in both datasets), indicating that it could recognize all events that were marked as dangerous by human drivers in the experiment. Overall, across all metrics, none of the other models performed as consistently highly as the PCAD model. The primary drawback of PCAD is its high computation cost, which results from its complexity. However, this cost is within acceptable limits, in the sense that the computation of perceived risk could be completed in real time in an automated vehicle.

In summary, PCAD demonstrated a strong performance in the evaluation, showing its potential for effective use in automated vehicles to assess perceived risk based on the difficulty of avoiding potential collisions.

3.3.5 Conclusions and future work

We have formulated, calibrated, and evaluated a novel computational perceived risk model and compared its performance with three well-established models across two different datasets. This model not only contributes to addressing the challenge of perceived risk computation for SAE Level 2 driving automation, but also illustrates the mechanisms underlying human drivers' risk perception.

The demonstrated superior performance of our PCAD model unveils new insights into perceived risk. Firstly, PCAD considers all motion information, highlighting the importance of position, velocity, and acceleration for risk perception. Secondly, the model can capture lateral risk, leading to a higher detection rate, which indicates that perceived risk is 2-D: human drivers perceive the risk from all directions in a 2-D plane when driving. Thirdly, motion uncertainties of the subject vehicle and other road users cause extra perceived risk, an insight which is supported by Kolekar et al (2020b). Lastly, perceived risk in driving scenarios is a dynamic concept which varies with changing traffic conditions. This observation motivates the need for models which, like the proposed PCAD model, can adjust to varying driving scenarios even without recalibration.

To further advance perceived risk modelling, we recommend collecting more perceived risk data in various scenarios through video-based online surveys, simulator experiments and on-road observation. In the meantime, the model’s potential for estimating perceived risk while driving along a curve and during multi-object interactions at different driving automation levels will be studied. Moreover, internal HMIs reduce human drivers' perceived risk; thus perceived risk modelling will be further improved if we consider internal HMI conditions (Kim et al., 2023). Most importantly, our PCAD model can be used as a cost function, a constraint, or a reference of perceived risk in driving automation path planning, decision-making, or controller design (L. Li et al., 2020), enhancing trust (Hu & Wang, 2021) and acceptance of automated vehicles.

3.3.6 Publications

Lu, C., He, X., van Lint, H., Tu, H., Happee, R., & Wang, M. (2021). Performance evaluation of surrogate measures of safety with naturalistic driving data. *Accident Analysis & Prevention*, 162, 106403. https://doi.org/10.1016/j.aap.2021.106403

He, X., Stapel, J., Wang, M., & Happee, R. (2022). Modelling perceived risk and trust in driving automation reacting to merging and braking vehicles. *Transportation Research Part F: Traffic Psychology and Behaviour*, 86, 178-195. https://doi.org/10.1016/j.trf.2022.02.016

He, X., Happee, R., & Wang, M. (2023). A new computational perceived risk model for automated vehicles based on potential collision avoidance difficulty (PCAD). *arXiv preprint arXiv:2306.08458*. https://doi.org/10.48550/arXiv.2306.08458

3.3.7 Highlights

The overall objective of ESR12’s modelling work was to develop computational models of occupants’ subjective feeling of risk inside automated vehicles. Key results include:

- A comprehensive understanding of Autonomous Vehicle (AV) occupants' perception of safety in relation to AV behaviours was developed, contributing to the broader field of human-machine interaction in automated driving.
- A new computational model was created, the potential collision avoidance difficulty (PCAD) model, which outperforms existing models in accurately capturing human drivers' perceived risk. The PCAD model can adapt to various traffic conditions with minimal recalibration, demonstrating its robustness and practical applicability.
- The project's findings have significant implications for the design of user interfaces and safety measures in AVs, potentially enhancing user trust and perceived safety.

3.4 Computational models of vehicle-pedestrian interaction (ESR13)

3.4.1 Related previous work and research gaps

Vehicle-pedestrian interactions at unsignalised locations are an important yet understudied phenomenon. On one hand, pedestrians constitute a great proportion of road users, and their interaction with others at locations without clear regulations has a great impact on traffic safety and efficiency; on the other hand, recent developments such as highly automated vehicles (Koopman & Wagner, 2018) require understanding human-AV interactions via different tools including mathematical models (for simulation testing of AVs for example).

Previous studies of road user interactions have employed computational models such as logit models (Zhao et al., 2019), agent-based models (ABMs) (Rad et al., 2020), evidence accumulation models (EAMs) (Pekkanen et al., 2022), and game theory (GT). Each has its strengths and weaknesses. Among these, GT has been found to be successful in explaining road user interactions (Kalantari, Markkula, et al., 2022; Y. Zhang et al., 2022) by considering interdependencies, unlike logit models and ABMs (Bonabeau, 2002), and multi-agent decision-making, unlike EAMs (Evans & Wagenmakers, 2020). However, empirical findings from behavioural economics suggest that people do not play the Nash equilibrium, which is the core idea in conventional GT (CGT; Wright & Leyton-Brown, 2017). Is this also the case in road traffic interactions? Some studies have employed behavioural game theory (BGT) models in the road traffic context, such as the logit quantal response equilibrium in vehicle-pedestrian interactions (Y. Zhang & Fricker, 2021) and both 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. However, none of these (or similar) studies discussed the distinction between CGT and BGT, so that it is not clear whether the BGT approach is really warranted. In other words, there is a lack of comparison between CGT and BGT in vehicle-pedestrian interactions; it is currently unclear whether CGT models are sufficient for vehicle-pedestrian interactions, or whether the higher complexity provided by BGT is needed. There is also a lack of comparison between game-theoretic models and logit models in general, which this PhD project seeks to address.

Another important research gap relates to the data used to develop and validate GT models. The abovementioned GT studies have all used naturalistic data, which has its strengths—but also clear weaknesses, in terms of not permitting distinctions between correlation and causation and not permitting repeated observations of individual road users. Controlled studies, e.g., virtual reality simulations, do not have these weaknesses, but it has not been explored whether controlled studies can be meaningfully used for GT models of road user interactions.

3.4.2 Objectives

The main objective of this project is to employ and compare both conventional and behavioural (GT) models to see how pedestrians interact with vehicles in different crossing scenarios. To achieve this objective, the following sub-objectives were defined:

- Identifying the proper modelling candidates for a computational model.
- Planning, designing, and conducting controlled studies using human-in-the-loop simulated environments to provide validation tools for GT models.
- Planning and conducting naturalistic studies.
- Comparing the computational model(s) performance using both controlled and naturalistic data.

3.4.3 Methods

3.1.3.1. Experimental study

A novel distributed simulator study (DSS) was designed, developed, and conducted to address the second objective. This work was made possible by connecting the University of Leeds Driving Simulator (UoLDS) to the HIKER (Highly Immersive Kinematic Experimental Research) pedestrian lab, so that both participants could see virtual representations of each other and interact dynamically; see Figure 11. In this study, 64 participants (32 drivers [Age: M = 31.53, R = 21–50, SD = 1.72] and 32 pedestrians [Age: M = 25.09, R = 19–34, SD = 0.87]) were placed in interacting driver-pedestrian pairs. They experienced different traffic scenarios based on different crossing types (zebra and non-zebra crossings) and five different vehicle time-to-arrival conditions (TTA, i.e., the temporal distance of the vehicle to the centre of the crossing, 3 – 7 s), resulting in ten conditions that were repeated twice in each experimental block. There were two blocks, resulting in 40 randomised trials per participant pair. The pedestrian was instructed to stand at a point on the HIKER's floor and step to a second point (the kerb of the virtual road) after hearing an auditory tone. At that point the driver could see the pedestrian and the interaction started. For full details, see the work by Kalantari, Yang, Pedro, et al. (2023).

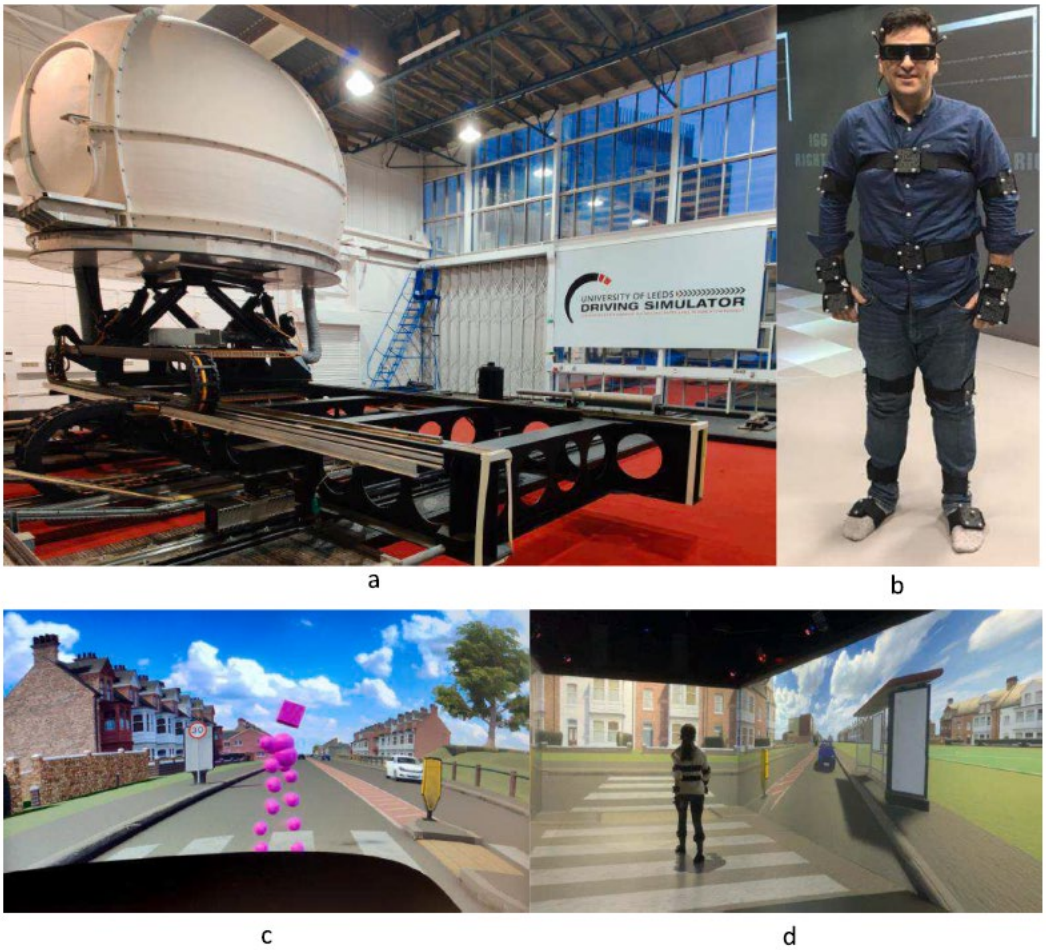

Figure 11. (a) The high-fidelity driving simulator. (b) The motion trackers. (c) The driver's view of the pedestrian: the driver is stationary on the road, and the pedestrian is the pink bubbles. (d)The pedestrian's view of the vehicle in the CAVE-based pedestrian lab: the pedestrian is crossing the road and the vehicle is to the right. (Figure and caption text from Kalantari, Yang, Pedro, et al., 2023, under a CC-BY license.)

3.1.3.2. Naturalistic study

Real-time traffic data were collected by surveying two marked crossings in the city of Leeds, England. The selection of these crossings was based on safety concerns and the high frequency of one-to-one interactions between vehicles and pedestrians, as observed during roadside assessments and consultations with Leeds City Council regarding crash history. The chosen locations were 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). Data collection was conducted over 14 days, with each location monitored for seven days. Two [Viscando](https://www.viscando.com) camera sensors, known as OTUS3D, were employed for data collection. These sensors can distinguish among various road users, such as light vehicles, heavy vehicles, cyclists, and pedestrians, and track their trajectory and speed at discrete time intervals. Figure 12 shows the trajectory maps of road users for both locations.

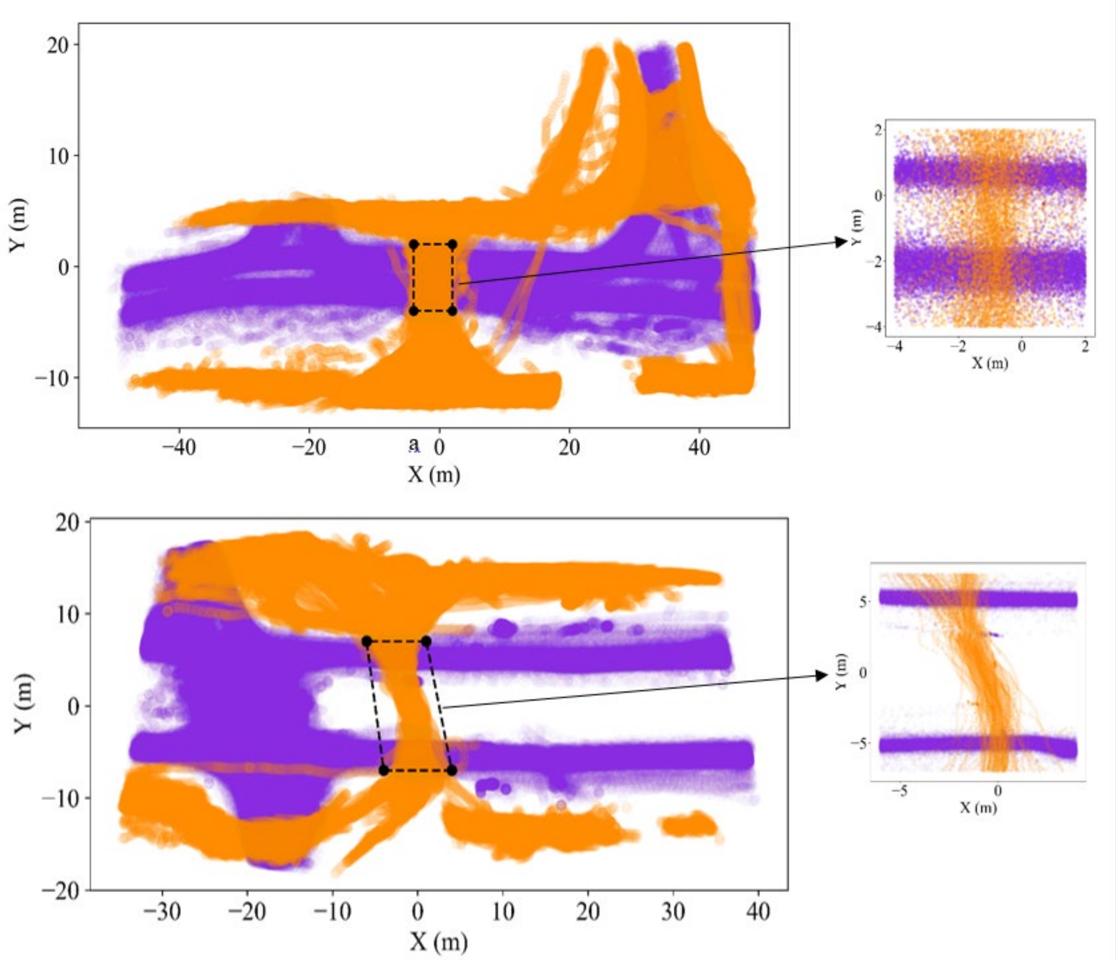

Figure 12. Trajectory map of (top) Queensway Road and (bottom) Belle Isle Road; the orange and violet dots show pedestrians and cars, respectively. The insets show the potential conflict zones (from kerb to kerb plus one meter from each side) for each location.

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3.1.3.3. Modelling

Five computational models were considered:

a) A logit (aka Logit) model with different intercepts for each crossing type (zebra/non-zebra crossing), defined as a linear function of TTA and waiting time of the pedestrians.

b) An original CGT (aka OCGT) model from the literature (Wu et al., 2019), with the payoff formulation shown in Table 5.

Table 5. Wu et al. payoff matrix (the vehicle is the row player and the pedestrian is the column player)

	Pedestrian pass	Pedestrian wait
Vehicle pass	$-\mathrm{k} - \mathrm{act_v}, \; -\mathrm{k} - \mathrm{act_p}$	$k + \mathrm{at_v}, \; \mathrm{k} - \mathrm{at_p}$
Vehicle wait	$\mathrm{k} - \mathrm{at_v}, \; \mathrm{k} + \mathrm{at_p}$	$\mathrm{k} - \mathrm{at_v}, \; \mathrm{k} - \mathrm{at_p}$

Payoffs in the model are calculated as sums of utilities relating to (I) the feeling of being on a collision course with another road user (modelled as k = 1/TTA), and (II) the loss of time as a result of yielding to another agent (equal to the time taken by that agent to pass the crossing, defined by $\mathrm{t_i}$). Both of these utility values are assumed to exist in all outcomes, with a negative sign when they have a negative influence on a road user, and a positive sign otherwise. In addition, a multiplier (c) was incorporated to account for the extra waiting time required when both agents try to cross simultaneously and thus need to avoid collisions, e.g., by braking suddenly (Wu et al., 2019). The model was solved by a mixed-strategy Nash equilibrium.

c) The payoff formulation of the OCGT model was revised to adjust some of the model's assumptions that were believed to hinder the model from fully capturing road user behaviour (see Kalantari, Yang, Merat, et al., 2023 for a complete explanation).

   The revised payoff formulation of the model is shown in Table 6.

Table 6. Alternative payoff formulation

	Pedestrian pass	Pedestrian wait
Vehicle pass	$-\mathrm{k}(\mathrm{nR}_p+\mathrm{R}_v)$ – act_v, $-\mathrm{k}\,(\mathrm{nR}_v+\mathrm{R}_p)$– act_p	$k(nR_p-2nR_p+R_v)+at_v, -a(t_v+t_p)$
Vehicle wait	$-\mathrm{a}(t_v+t_p)$, $\mathrm{k}(\mathrm{nR}_v-2\mathrm{nR}_v+\mathrm{R}_p)+\ \mathrm{at}_\mathrm{v}$	$-amt_d,\ -amt_p$

The revised model, named the alternative conventional game-theoretic (ACGT) model, was solved by a mixed-strategy Nash equilibrium.

d) Models ***b*** and ***c*** were solved using the dual accumulator (DA) model (Golman et al., 2020) from the BGT domain, resulting in two new model variants: OBGT (original solved by behavioural game theory) and ABGT (alternative solved by behavioural game theory) models.

All models were fitted to the DSS (Kalantari, Yang, Merat, et al., 2023) and naturalistic dataset using maximum likelihood estimation.

3.4.4 Results

Figure 13 shows the average of all 32 crossing probabilities, corresponding to the 32 participant pairs in the DSS, over time gaps for both crossing types. The dashed lines show the empirical data, indicating a clear effect of both initial time gap and crossing type on the interaction outcome. The figure also shows the fits for all models. Table 3 shows the model comparison, including the information loss criteria (AIC, BIC) and error indices (MAE, RMSE). From both the figure and table, it is evident that the ABGT model exhibited a strong overall performance, and the combination of the Wu et al. model and the DA model (OBGT) outperformed the original model (OCGT) for both types of crossings. Overall, moving from the OCGT model towards the ABGT model in the table, the improvements in all criteria, including negative log-likelihood, are observable—which confirms the observations of Figure 3 to a greater extent.

An added benefit of the DA model is that it also provides an account of the decision-making process over time for each agent. Therefore, a possible association between the ABGT model's estimated decision time (the time to convergence of the DA solution) and crossing initiation time of the pedestrian (the time when the pedestrian started crossing the road) in the DSS was examined using Spearman's' correlation. The results showed there was a significant positive correlation between these two measures: $r(821) = .213$, $p = .000$.

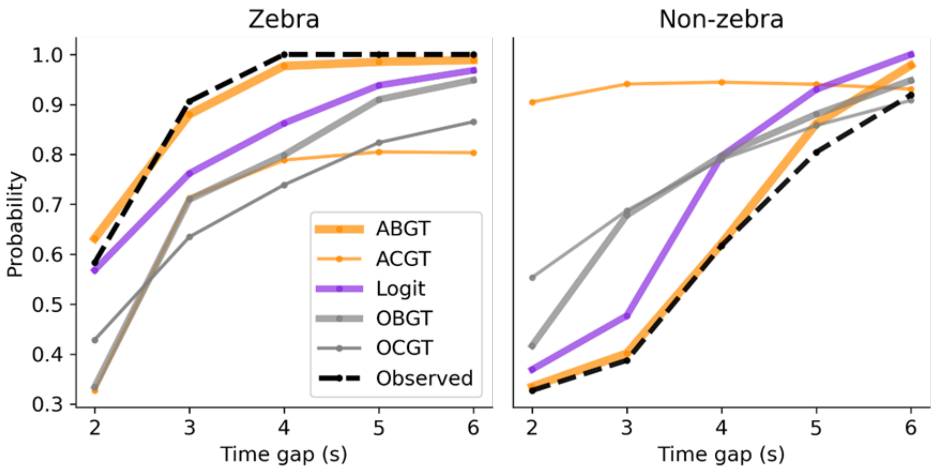

Figure 13. Average probability that the pedestrian crosses first graphed against the time gap for the DSS empirical data for each model.

Table 7. Model comparisons for the controlled experiment data (DSS).

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

Figure 14 shows the results for the naturalistic dataset, with the probability that the pedestrian will cross first graphed against the time gaps at the normal zebra crossing (left), the staggered zebra crossing (middle), and the total dataset (right) for all computational models. Table 8 presents the information loss criteria (AIC, BIC) and error indices (MAE, RMSE) for all models and datasets. denoted by "S" for staggered, "N" for normal zebra, and "T" for total data. Both the figure and the table indicate that, except for ACGT, all the models performed about equally well. However, the behavioural game-theoretic models stood out as the best performers for the normal zebra crossing, with OBGT performing best. The situation is more complex for the staggered crossing: the Logit and OCGT models excelled in terms of model parsimony, but once again, the behavioural game-theoretic models outperformed them for prediction accuracy. Finally, for the total dataset, the ABGT model performed best, reaffirming our earlier findings from the DSS, albeit by a smaller margin. Overall, it is noteworthy that while there were significant performance differences among the models when they used the DSS data, this was not the case when they used the naturalistic data.

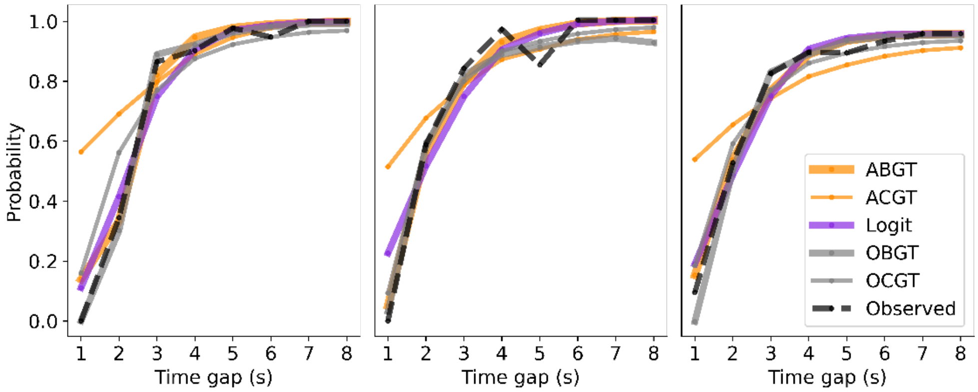

Figure 14. Probability that the pedestrian passes first graphed against the time gap fitted to the naturalistic data for each model.

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Table 8. Model comparisons for the naturalistic data.

Model		**ABGT**			**ACGT**			**Logit**			**OBGT**			**OCGT**		
Crossing type		N	S	T	N	S	T	N	S	T	N	S	T	N	S	
MAE	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	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		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		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		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		3			3			4			2			2		

3.4.5 Publications

- Kalantari, A. H., Markkula, G., Uzondu, C., Lyu, W., Garcia de Pedro, J., Madigan, R., ... & Merat, N. (2022). Vehicle-Pedestrian Interactions at Uncontrolled Locations: Leveraging Distributed Simulation to Support Game-Theoretic Modeling. In *Proceedings of the TRB Annual Meeting*, Paper No. TRBAM-22-0187. https://eprints.whiterose.ac.uk/188434/
- Kalantari, A. H., Yang, Y., Pedro, J. G. de, Lee, Y. M., Horrobin, A., Solernou, A., Holmes, C., Merat, N., & Markkula, G. (2023). Who goes first? A distributed simulator study of vehicle–pedestrian interaction. *Accident Analysis & Prevention*, 186, 107050. https://doi.org/10.1016/j.aap.2023.107050
- Kalantari, A. H., Yang, Y., Merat, N., Lee, Y.M., & Markkula, G. (2023). Driver-Pedestrian Interactions at Unsignalized Crossings Are Not in Line With the Nash Equilibrium. IEEE Access, 11, 110707-110723 https://doi.org/10.1109/ACCESS.2023.3322959
- Kalantari, A. H., Lin, Y. S., Mohammadi, A., Merat, N., & Markkula, G. (2023, in review). Investigating vehicle-pedestrian interactions at marked crossings: A comparison of two methodologies. *PsyArXiv preprint*. https://doi.org/10.31234/osf.io/gk9af

3.4.6 Conclusions and future work

The DSS provides an experimental paradigm that generates traffic scenarios where traffic agents dynamically interact with each other, showing behavioural patterns similar to those observed in naturalistic studies of vehicle-pedestrian interactions. Hence, distributed simulation can be considered as a promising tool for studying repeated road-user interactions in a controlled manner, and provides a strong validation tool for computational models of road user interaction.

The results of the modelling, especially regarding the DSS dataset, suggest that, besides the inevitable role of the payoff formulation in GT modelling, the way that the game is solved is also a determinant factor in the extent to which the model can predict the interaction outcomes.

This finding confirms the hypothesis that people do not always make optimal choices or act purely rationally (as is assumed in CGT); rather they may choose suboptimal options under some circumstances. In these cases the 'bounded rationality' is a better model than the Nash equilibrium (Camerer & Fehr, 2006; Wright & Leyton-Brown, 2017), an observation which has recently been made for pedestrian-cyclist interactions as well (Alsaleh & Sayed, 2022). However, the differences in performance among the models were much smaller in the real traffic data compared to the simulation data, perhaps because the models were fitted to the average population for the naturalistic study, whereas in the DSS each model was fitted to the repeated observations per participant pair. This finding suggests that inter-individual differences may be quite important and should be considered in the virtual testing of AVs to avoid underestimating human behaviour complexity.

Another key finding of the proposed ABGT model was the correlation between the model's predicted time of decision (accumulation convergence) and the observed pedestrian crossing initiation times in the DSS, which suggests that the model is reasonably emulating the deliberation and negotiation process of the two road users. Our current model's account of this process is, however, relatively limited; a more complete account should also include a consideration of how the road users might adjust their behaviour multiple times during an interaction.

Furthermore, it is essential to develop a methodology that examines situations where multiple pedestrians interact with multiple vehicles. This consideration is especially important, as there is more to BGT than bounded rationality; some of its features, such as those related to collective behaviour, have not been investigated within the context of traffic. Doing so could provide valuable insights into road user interactions.

3.4.7 Highlights

The overall objective of ESR13's modelling work was to develop and compare both conventional and behavioural game-theoretic models to understand vehicle-pedestrian interactions at unsignalised crossing locations. Key results include:

- An experimental paradigm was introduced in which two or more road users can interact with each other in a safe and controlled environment.
- Five computational models were introduced and tested against both naturalistic and lab data.
- The BGT models showed an overall better performance for both datasets in almost all cases.
- Besides predicting interaction outcomes, the proposed BGT models can predict which interaction will take the longest time to resolve, something that traditional models such as logit and CGT cannot do.

3.5 Computational interaction models between automated vehicles and cyclists (ESR14)

3.5.1 Related previous work and research gaps

Most cyclists' crashes with vehicles occur at intersections where the two road users share the right of way and must agree on who should cross the intersection first (Isaksson-Hellman & Werneke, 2017, Bjorklund, 2005). At the same time, with the advancement in automated vehicles, there is a crucial need to define a safe and comfortable way of interacting with vulnerable road users in such conflict scenarios.

So far, very few studies have tried to model and analyse cyclist-vehicle interactions in crossing scenarios. In one such study, Silvano et al. (2016) constructed a logistic model aimed at predicting cyclists' yielding behaviour utilising kinematic data, such as speed and distance. Their study revealed that the time it took for a cyclist to reach the intersection and the speed of the approaching vehicle significantly influenced the cyclist's decision whether to yield. It is worth noting that their investigation centred on a roundabout rather than an unsignalised intersection, and their dataset did not have complete trajectory information. Instead, they relied on discrete data points indicating the presence of bicycles and cars at various locations within the intersection.

In a separate study, Bella and Silvestri (2018) employed a driving simulator to examine how different infrastructure designs impact drivers' responses. They evaluated the effectiveness of various safety measures, such as pavement colour and raised islands, in reducing drivers' speed when interacting with cyclists at intersections.

Nuñez and colleagues (2021) also investigated cyclist-vehicle interactions. In their experiment, they presented cyclist participants with videos through virtual reality (VR) headsets. These videos depicted cyclists approaching unsignalised intersections, requiring them to make decisions on whether to proceed or yield. The researchers observed the factors influencing cyclists' decisions in this context; the distance to the car and the cyclist's right-of-way status were the primary determinants of their choices at the intersection.

In the course of our research, the objective was to address the shortcomings found in prior studies of cyclist-vehicle interactions at uncontrolled intersections by gathering real-world data and exploring the influence of supplementary visual information. An in-depth understanding of the interaction process will help develop robust behavioural models to predict cyclist behaviour at intersections. In the context of this scholarly research endeavour, our primary aim is to formulate quantitative models with the purpose of predicting cyclists' behaviour. These models are intended to leverage kinematic data alongside discernible behavioural cues exhibited by cyclists.

3.5.2 Objectives

This research project addresses the following research questions: 1. How do cyclists communicate their intent while interacting with vehicles? and 2. What visual cues do cyclists use to communicate their intent? In addressing these research questions, we pursued the following research objectives. First, to develop quantitative models to predict cyclists' behaviour through their kinematic and visual information. Secondly, to propose behavioural models for use by automated vehicles to enable them to interact safely and comfortably with cyclists at intersections.

3.5.3 Methods

3.5.3.1 Experimental study

A cycling simulator experiment was conducted to evaluate cyclists' response process as they interacted with an approaching vehicle at an unsignalised intersection. Cycling simulators have gained popularity for observing cyclists' behaviour in recent years due to their controllability and safety (Farah et al., 2019, Calvi et al., 2022). A real intersection was simulated in which the participants encountered an automated vehicle. Twenty-seven participants were tested in the experiment. Two independent parameters were varied across trials: the difference in time to arrival between vehicle and cyclist at the intersection and visibility distance (field of view; FOV). Subjective and objective data were analysed to answer the research questions.

Figure 15. Cycling simulator.

3.5.3.2 Naturalistic field data

A field dataset was collected from an unsignalised intersection in Gothenburg, Sweden. A camera-based sensor categorised the road users as vehicles, heavy vehicles, cyclists, or pedestrians and recorded their trajectories. The collected dataset consists of fourteen days of data. Interaction events between vehicles and cyclists were extracted from the dataset. Further information about the cyclists' actions, like pedalling and head movement, was added to the extracted dataset by manual annotation of the recorded video (Mohammadi et al., 2023).

Figure 16. Camera based sensor's view over the intersection.

3.5.3.3 Modelling framework

In this research, we mainly used generalised linear regression models to describe the datasets. A logistic model was developed to predict the cyclists' crossing decision based on the naturalistic dataset. The significant variables affecting the cyclists' yielding decision consist of the difference in time to arrival at the intersection (DTA), cyclist's speed, vehicle's speed, head turn, and pedalling. A leave-one-out cross-validation method was used to evaluate the accuracy of the model.

A linear mixed effect model was developed to investigate the significant parameters affecting the cyclists' yielding decisions based on the simulator experiment. The random effect in this model accounts for the repeated measurements of each participant. In addition, an arctan equation with four coefficients was used to model the cyclists' speed profiles as they approached the intersection, in order to compare the cyclists' speed profiles in each trial (Mohammadi et al., 2023).

3.5.4 Results

Table 9 shows the output of the logistic regression predicting the cyclist's crossing decision: specifically, the statistically significant variables affecting the cyclists' crossing decision and their trends.

Table 9. Summary of model estimation results.

Variables	Coefficients	std err	Z score	P-value	lower bound (0.025)	Upper bound (0.975)
Intercept	-4.3523	1.474	-2.953	0.003	-7.241	-1.464
Bike speed	-4.7794	2.041	-2.342	0.019	-8.779	-0.780
Vehicle speed	9.4198	1.910	4.932	$2*10^{-4}$	5.676	13.163
DTA	5.5818	1.194	4.675	$4*10^{-5}$	3.242	7.922
Pedaling or not	1.1403	0.551	2.068	0.039	0.060	2.221
Looking or not	-1.4132	0.689	-2.050	0.040	-2.765	-0.062

Results from the mixed effect model showed that of the independent variables defined in the simulator experiment, only DTA affected the cyclists' yielding decision. This result is consistent with the previous modelling output. Visibility distance affected the cyclists' speed profiles; as

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cyclists' visibility at the intersection increased, we recorded smoother interactions with the vehicle. The figures below compare average speed profiles in different trials.

A. Comparing average speeds across FOV

B. Comparing average speeds across DTA

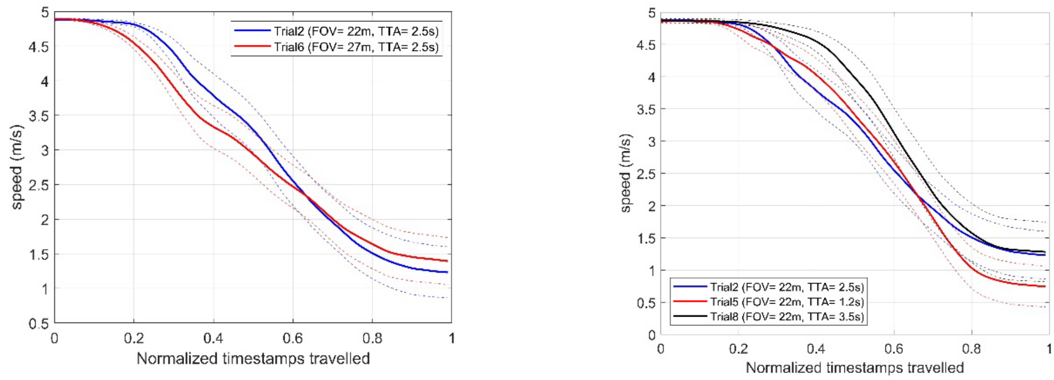

Figure 17. Average speed profiles and confidence intervals: (A) a comparison between trials that have the same DTA and different FOV values and (B) a comparison between trials that have the same FOV and different DTA values.

3.5.5 Conclusions and future work

Our naturalistic study showed that both kinematics (speed and position) and cyclists' actions (head turn and pedalling) are significant predictors for the cyclists' crossing decision. Thus cyclists' behavioural cues can be useful in predicting their decision. Our simulator experiment showed that DTA significantly affected the cyclists' yielding decision. Increasing FOVs resulted in smoother interactions with the vehicle (lower deceleration rates).

Future work within this project compares professional drivers (truck and taxi drivers) and passenger car drivers in terms of their interactions with cyclists. In addition, we aim to compare different modelling approaches to achieve better prediction accuracy.

3.5.6 Publications

Mohammadi, A., Piccinini, G. B., & Dozza, M. (2023). How do cyclists interact with motorized vehicles at unsignalized intersections? Modeling cyclists' yielding behavior using naturalistic data. *Accident Analysis & Prevention*, 190, 107156.
https://doi.org/10.1016/j.aap.2023.107156

3.5.7 Highlights

The overall objective of ESR14's modelling work was to develop quantitative models predicting cyclists' behaviour through their kinematics and appearance, to improve automated vehicle interactions with cyclists at intersections. Key results include:

- Communication and eye contact between cyclists and drivers play an important role in decision making.
- Not only kinematics but also cyclists' head movements and pedalling action are important parameters for predicting cyclists' behaviour.
- Providing more visibility at intersections will result in having less severe encounters between cyclists and vehicles.

4 Conclusions

Looking across the five ESR research projects presented in this report, we can note that they span the spectrum of modelling approaches mentioned in Section 2, and also include some efforts toward increased cross-fertilisation between approaches. ESR3 had a clear data-driven ML focus in their pedestrian prediction models, but with some mechanistic elements in terms of their more detailed representation of interactions and various features affecting them. ESRs 12 and 13 had a clearly mechanistic focus in their modelling of perceived safety and game-theoretic interactions. ESRs 11 and 14 took an intermediate approach based on statistical data-driven modelling with handcrafted features based on assumptions about mechanisms, in their modelling of drivers' lane changing and cyclist-car interactions, respectively. The ESRs also provided good coverage of the mentioned different use cases for modelling: ESRs 3, 12 and 14 emphasised the use of models in real-time AV algorithms, whereas ESRs 13 and 11 emphasised simulated testing of AVs and the use of models to guide AV design, respectively.

A common denominator across all ESR projects described here is that they have provided substantial contributions to our scientific understanding of how humans interact in traffic, and consequently also to our understanding of how to design safe, transparent, and human-acceptable vehicle automation. This increased understanding concerns both aspects of fundamental collision avoidance and risk minimisation (especially ESRs 3, 12, and 13) as well as aspects of reciprocal coordination and communication (especially ESRs 11, 13, and 14).

At the same time, it is clear from the ESRs' future work statements that the problem of road user interaction modelling will need continued efforts, to cover a more complete range of modelling use cases (ESR3), modelled scenarios (ESRs 12, 13), human behaviours (ESR11), and types of road users (ESR14).

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