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An Interaction Game for Prediction of Road Users' Conflict Resolution Strategies in Uncontrolled Traffic Environments

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To my family

*for their unparalleled love, unfailing support,
and continuous encouragement.*

Abstract

Slowly but surely, automated driving systems (ADS) will become prevalent on public roads. With the integration of automated vehicles into the public realm as a new road user, the conventional form of traffic interactions experiences a considerable change. ADS will need to deal with various road user types and the established communication methods to execute safe and efficient driving manoeuvres. In the current stage of advancement in automated technologies, automated systems face challenges in interaction with pedestrians —as one of the most vulnerable user groups with specific decision-making systems. For instance, in complex urban scenarios (e.g., uncontrolled crossing settings, shared spaces), ADS are not yet able to dynamically interact with pedestrians and adequately react to their traffic behaviour.

Although there are various technological solutions to compensate for the loss of human drivers in fully ADS and maintain pedestrian safety in uncertain traffic situations, a proper interaction concept has not been formulated. By reviewing the results of several studies, it is concluded that pedestrians and ADS need to comprehend and predict the actions of one another for a safe and efficacious interaction process. An overview of the literature on topics of traditional traffic interactions, pedestrian decision-making process, and future of traffic interactions and user behaviour in the presence of ADS, provides the basis for the following study that explicitly focuses on the modelling of pedestrian-ADS interactions in uncontrolled traffic environments.

In this dissertation, a game-theoretic approach is employed to model pedestrian interactions with ADS and predict the conflict resolution strategies taken by users to avoid a conflict on the road. A comprehensive literature review is performed to identify the most influential decision factors for pedestrian road crossing and provide the basis for the model framework. The interaction game developed within this dissertation incorporates a broad aspect of user behaviour to reflect their decision-making process better. The proposed interaction game is formulated in three layers: (1) the safety layer to evaluate the safety level of user decisions, (2) the travel layer to cover the energy loss imposed on users by performing different evasive manoeuvres, and (3) the social layer to include the impact of traffic environment on user decisions.

The proposed modelling framework can facilitate pedestrian-ADS interactions and assist ADS in making more informed decisions during traffic interactions. This Dissertation provides a suitable framework for modelling pedestrian-ADS interactions, and recommendations for further development, besides adding to the present knowledge and general discussion on the literature related to the ADS interactions with pedestrians.

Zusammenfassung

Langsam aber sicher werden sich automatisierte Fahrsysteme (ADS) im öffentlichen Straßenverkehr durchsetzen. Mit der Integration automatisierter Fahrzeuge in den öffentlichen Raum als neue Verkehrsteilnehmer erfährt die herkömmliche Form der Verkehrsinteraktion eine erhebliche Veränderung. ADS werden mit verschiedenen Verkehrsteilnehmern und den etablierten Kommunikationsmethoden umgehen müssen, um sichere und effiziente Fahrmanöver durchzuführen. In der gegenwärtigen Phase des Fortschritts bei automatisierten Technologien stehen automatisierte Systeme vor Herausforderungen bei der Interaktion mit Fußgängern —als eine der am meisten gefährdeten Nutzergruppen mit spezifischen Entscheidungssystemen. In komplexen städtischen Szenarien (z. B. unkontrollierte Kreuzungen, gemeinsam genutzte Flächen) sind ADS beispielsweise noch nicht in der Lage, dynamisch mit Fußgängern zu interagieren und angemessen auf deren Verkehrsverhalten zu reagieren.

Obwohl es verschiedene technologische Lösungen gibt, um den Verlust menschlicher Fahrer in ADS zu kompensieren und die Sicherheit von Fußgängern in unsicheren Verkehrs-situationen aufrechtzuerhalten, wurde bisher kein geeignetes Interaktionskonzept formuliert. Die Ergebnisse mehrerer Studien lassen den Schluss zu, dass Fußgänger und ADS die Handlungen des jeweils anderen verstehen und vorhersagen müssen, um einen sicheren und effizienten Interaktionsprozess zu gewährleisten. Ein Überblick über die Literatur zu den Themen traditionelle Verkehrsinteraktionen, Entscheidungsprozesse von Fußgängern und die Zukunft von Verkehrsinteraktionen und Nutzerverhalten in Anwesenheit von ADS bildet die Grundlage für die folgende Studie, die sich explizit mit der Modellierung von Fußgänger-ADS-Interaktionen in unkontrollierten Verkehrsumgebungen beschäftigt.

In dieser Dissertation wird ein spieltheoretischer Ansatz verwendet, um die Interaktion von Fußgängern mit ADS zu modellieren und die Konfliktlösungsstrategien vorherzusagen, die von den Nutzern angewandt werden, um einen Konflikt auf der Straße zu vermeiden. Eine umfassende Literaturrecherche wurde durchgeführt, um die einflussreichsten Entscheidungsfaktoren für Fußgänger beim Überqueren von Straßen zu ermitteln und die Grundlage für den Modellrahmen zu schaffen. Das in dieser Dissertation entwickelte Interaktionsspiel bezieht einen breiten Aspekt des Nutzerverhaltens ein, um den Entscheidungsprozess der Nutzer besser widerzuspiegeln. Das vorgeschlagene Interaktionsspiel ist in drei Ebenen formuliert: (1) die Sicherheitsebene, um das Sicherheitsniveau der Nutzerentscheidungen zu bewerten, (2) die Reiseebene, um den Energieverlust zu erfassen, der den Nutzern durch verschiedene Ausweichmanöver entsteht, und (3) die soziale Ebene, um die Auswirkungen der Verkehrsumgebung auf die Nutzerentscheidungen zu berücksichtigen.

Der vorgeschlagene Modellierungsrahmen kann die Interaktion zwischen Fußgängern und ADS erleichtern und ADS dabei unterstützen, fundiertere Entscheidungen während der Interaktion mit dem Verkehr zu treffen. Diese Dissertation bietet einen geeigneten Rahmen für die Modellierung von Fußgänger-ADS-Interaktionen und Empfehlungen für die weitere Entwicklung, neben der Ergänzung des derzeitigen Wissens und der allgemeinen Diskussion über die Literatur in Bezug auf die ADS-Interaktionen mit Fußgängern.

Contents

List of Figures

List of Tables

1 Introduction

1.1 Motivation

Traffic safety has become a paramount global issue for decades because of its significant impact on nations' economies and victims' welfare. Every year approximately 1.3 million people lose their lives as a result of road traffic crashes, and between 20-50 million people suffer non-fatal injuries [7]. Among all, vulnerable road users (VRUs), such as pedestrians, motorcyclists, and cyclists, account for more than half of all road traffic fatalities [7]. As one of the most VRU groups, pedestrians have no protection of an outer shield, safety belts, or helmets to safeguard them when a traffic collision occurs. Hence, these road users are exposed to an increased risk of severe injuries and fatalities in car-dominant road space. Statistically, the majority of traffic crashes involving pedestrians occur in urban areas and while pedestrians cross the roadway either at pedestrian crossing facilities or outside of designated crosswalks [8]. Uncontrolled traffic settings —as a form of pedestrian crossing facilities— can create increased traffic hazards for pedestrians, due to the intricate nature of such environments. At uncontrolled traffic settings, there are no traffic management and control systems to conduct the movements of road users, regulate the traffic, and determine the road space priority. Therefore, traffic movements in such environments majorly rely on priority negotiation and interactions among road users. Pedestrians need to frequently negotiate priority with motorised vehicles and assess the traffic situation for a safe road crossing. On the other hand, vehicle drivers need to monitor the road ahead and adjust their driving behaviour according to the traffic situation in the crossing area. As a result, a more frequent and complex interaction process is required to ensure traffic safety and efficiency in uncontrolled traffic settings.

A traffic conflict or collision will occur if road users fail to form successful traffic interactions. Traffic collisions and conflicts result in adverse impacts —sometimes irrevocable consequences— on traffic safety and efficiency, besides the negative effect on the user's travel experience. While the outcomes of traffic collisions and conflicts are well understood [9, 10, 11], the knowledge and understanding of users' decision-making process during traffic interactions is still relatively obscure. Despite the substantial number of studies in this field, there are many uncertainties regarding influential factors in users' decisions, possible interconnections among these factors, how and to which extent these factors impact the traffic decisions of road users, and whether these factors can alter crossing/driving manoeuvres performed by road users in a conflict scenario. For instance, in a pedestrian-vehicle interaction scenario, a pedestrian deviates from its forward trajectory to cross in front of a vehicle —and the driver yields instead of continuing its path. In this hypothetical interaction scenario, we need to know which dynamic, environmental-, or individual-associated factors influenced users' traffic decisions, and whether traffic communication cues were utilised to facilitate the interaction. Such knowledge of the user decision-making process is essential for developing suitable behavioural models and designing collision avoidance systems to prevent a traffic collision or mitigate its severity.

In the user behaviour and traffic interaction domain, research has been mainly focusing on a limited number of factors influencing pedestrian-driver interactions, without taking into account the decision-making process of road users collectively and investigating the factors that may influence the process [12]. Besides, most collision prediction models assume that the trajectory and speed of users would remain unchanged and evaluate the traffic safety accordingly [5]. The latter assumption ignores the variability of evasive manoeuvres that users can execute during a traffic conflict and thus, limits the model capability to evaluate the safety level of various traffic outcomes [5].

In the future of mobility and with the advent of automated driving systems (ADS), the conventional role of drivers will gradually be replaced with a broad range of technologies taking control of the driving tasks. In the absence of a human driver —for the case of fully automated vehicles— and partial engagement of drivers —for the case of partially automated vehicles— the traditional form of traffic interaction is subject to a significant change. Traffic interaction may become even more challenging during the transition phase, when ADS are integrated to the current traffic patterns and the road infrastructure is not fully ready for serving such vehicles as a new road user. In such traffic systems, ADS have to understand the behaviour of their interaction users, predict their movement intentions, and perform suitable driving manoeuvres [12, 13]. However, similar to conventional traffic interactions, understanding and predicting user behaviour is complicated.

The emergence of automated vehicles, as new road users, into the public road can impact the behaviour of other traffic participants. For example, pedestrians may expect ADS to drive perfectly safely and always yield to other participants, leading to risk-taking behaviours that jeopardise traffic safety and efficiency. Besides, the existing automated driving technologies have difficulties managing complex traffic situations, due to the incomplete understanding of user behaviour and decision-making process. Therefore, there are several ongoing questions with respect to the pedestrian-ADS interactions; which decision factors influence pedestrian behaviour in interaction with ADS, how to incorporate these factors in behavioural models and the manoeuvres' planning module of ADS, and how ADS can efficiently collect and prioritise relevant information while interacting with a pedestrian.

The investigation of pedestrian-ADS interactions in general, and user behaviour in particular, is one of the most challenging topics in ADS-related research. Although several data collection methods are used to unfold different aspects of traffic interactions in the presence of ADS, users' behaviour changes with the widespread deployment of automated vehicles in the future —or possibly over prolonged use— are undisclosed. More research is required to focus on the most relevant influential decision factors that provide insights into user behaviour and take into account the expectations and requirements of users interacting with ADS. These are necessary inputs for developing a suitable interaction method that can ensure the safety of pedestrians interacting with ADS and ensure the efficiency of these systems on the road.

1.2 Problem Definition and Dissertation Objectives

In order to improve the safety and efficiency of ADS in interaction with pedestrians, ADS need to play the role of an active road user by predicting the intentions of other parties on the road and performing suitable driving manoeuvres [13, 14]. In this direction, one of the main issues identified within this research concerning the modelling of pedestrian-ADS interactions is the rather restrictive framework (in terms of, for instance, defined conflict resolution strategies of users, methods used, and decision factors included in the modelling approaches) in which relevant research revolves. Researchers, in most cases, focus on either collision avoidance-based factors or limited/selective number of environmental and/or user-associated factors to model pedestrian-ADS interactions, and thus, partially reflect users' decision-making process to avoid a conflict on the road. Although these efforts aim at developing a simplified pedestrian-ADS interaction concept and their limitations can be attributed to the challenges that the absence of large-scale fleets of automated vehicles and complexity of user behaviour impose, this could negatively impact the efficiency of ADS on the road and lead to confusion and frustration among pedestrians interacting with ADS [14, 15].

In this context, this dissertation focuses on developing a modelling framework for the interaction of ADS with pedestrians by employing the most relevant factors in users' decision-making process. The proposed modelling framework is built upon user-specific goals/utilities on the road and aims to predict different conflict resolution strategies of users during traffic interactions. The main research question is:

How to develop a modelling framework for the interaction of ADS with pedestrians that (i) reflects the user's decision-making process and behaviour during traffic interactions in uncontrolled environments and (ii) accommodates a safe and efficient interaction process?

The principal research question evokes a set of objectives that guide the required work:

- Investigate the conventional traffic interactions among road users and the future of interactions when ADS operate on the road.
- Identify and review pertinent research on user behaviour and decision-making during traffic interactions.
- Derive the most influential factors in user behaviour and traffic decision, and specify requirements and specifications for a safe and efficient traffic interaction process.
- Design a modelling framework to predict conflict resolution strategies of users in interaction.
- Evaluate and validate the performance of the proposed model, and discuss its applicability.

1.3 Dissertation Contributions

This doctoral dissertation compounds, summarises, and documents the author's studies, [16, 12, 5, 6] in particular, and developments towards understanding and modelling the interaction of pedestrians with different vehicle types in uncontrolled traffic environments. Thus, this doctoral research makes the following contributions in theoretical, methodological and practical levels:

- **Synthesis on Traffic Interactions Research (Ezzati Amini et al. [16]):** A thorough investigation on VRUs, particularly pedestrians, interactions with manual-driven vehicles, factors influencing their behaviour, and the utilised communication methods.
- **Advance the Understanding of Pedestrian-ADS Interactions (Ezzati Amini et al. [12]):** A comprehensive literature review and discussion to explore pedestrian interactions with ADS, the challenges that ADS face concerning traffic interactions, the complexity of understanding and predicting pedestrian behaviour, and the transformation of the traffic interactions and communication methods in the near future.
- **Evaluation of Pedestrian Behaviour (Ezzati Amini et al. [16] & Ezzati Amini et al. [12]):** Exploring and evaluating factors influencing the decision-making process of pedestrians in interaction with different user types, i.e., manual-driven vehicles and ADS, how pedestrian behaviour, requirements, and expectations would change when ADS join the transport systems.
- **Traffic Interaction Data Analysis Approach (Ezzati Amini et al. [5] & Ezzati Amini et al. [6]):** The use of simplified data analysis technique to evaluate the behaviour of interacting users and determine their conflict resolution strategies.
- **Development of a Conflict Risk Evaluation Model (Ezzati Amini et al. [5]):** A model to assess pedestrian safety in interaction with other road users. The model evaluates the conflict risk of different evasive manoeuvres —available for different user types— and their combinations.
- **Development of a Game-theory-based Model (Ezzati Amini et al. [6]):** Developing a game-theoretic approach to predict conflict resolution strategies of users performed to avoid a conflict on the road.

1.4 Dissertation Structure

With regards to the objectives mentioned above, this dissertation contains four studies that cover various aspects of road users interactions and the details of the proposed methodology to model user behaviour in uncontrolled traffic environments.

- Ezzati Amini et al. [16] (see Appendix A).
- Ezzati Amini et al. [12] (see Appendix B).
- Ezzati Amini et al. [5] (see Appendix C).
- Ezzati Amini et al. [6] (see Appendix D).

This remainder of this dissertation is structure as follows (Fig. 1.1):

Chapter 2. Background: This chapter overviews the research background, provides general information about the research topic, establishes the research context, and explains why this topic is significant to understanding the principal aspects of the research.

Chapter 3. Traditional Traffic Interactions of Pedestrians with Vehicles: This chapter presents an overview of the related work, including a description of the conventional pedestrian-vehicle interaction concepts, data collection methods, and the exploration of the traffic communication methods. Particular focus is given to the factors influencing users' decision-making process during an interactive process, where the literature review is performed, followed by a targeted presentation of topics pertinent to this dissertation.

Chapter 4. Interaction of Pedestrians with Automated Driving Systems: This chapter includes a comprehensive literature review and discussion of the aspects to be considered for a safe and efficient interaction process among pedestrians with ADS. Different aspects of automated driving are investigated with respect to the current advancement of the technologies as well as the future of the interaction concepts when automated vehicles operate on public roads. Furthermore, the modelling approaches to predict user behaviour in interaction with ADS and the most significant factors in their decision-making process are evaluated. Besides, this chapter overviews the new forms of communication developed to assist traffic interactions in the presence of ADS.

Chapter 5. Modelling Framework - Conflict Risk Evaluation: A model to assess the safety level of users in interaction is proposed in this chapter. The developed conflict risk evaluation model relies on surrogate safety measures to evaluate the crash risk and severity of a conflict event, and separate the potential conflict/crash from the normal/safe traffic situations. Besides, the chapter entails the extensive detail of data analysis, conflict detection procedure, and determination of conflict resolution strategies.

Chapter 6. Modelling Framework - Game of Interaction: This chapter focuses on developing a game-theoretic approach for predicting the conflict resolution strategies of users in conflict. Further, the framework of the interaction game, model application, estimation, validation, and performance are studied.

Chapter 7. Discussion, Limitations & Directions for Future Research: This chapter provides an overview of the modelling approach developed within this dissertation. Potential future research directions and limitations are outlined in general and for specific parts of applied model, for which the implementation raised additional questions.

Chapter 8. Conclusions: The last chapter of this dissertation elaborates on the conclusions of this dissertation.

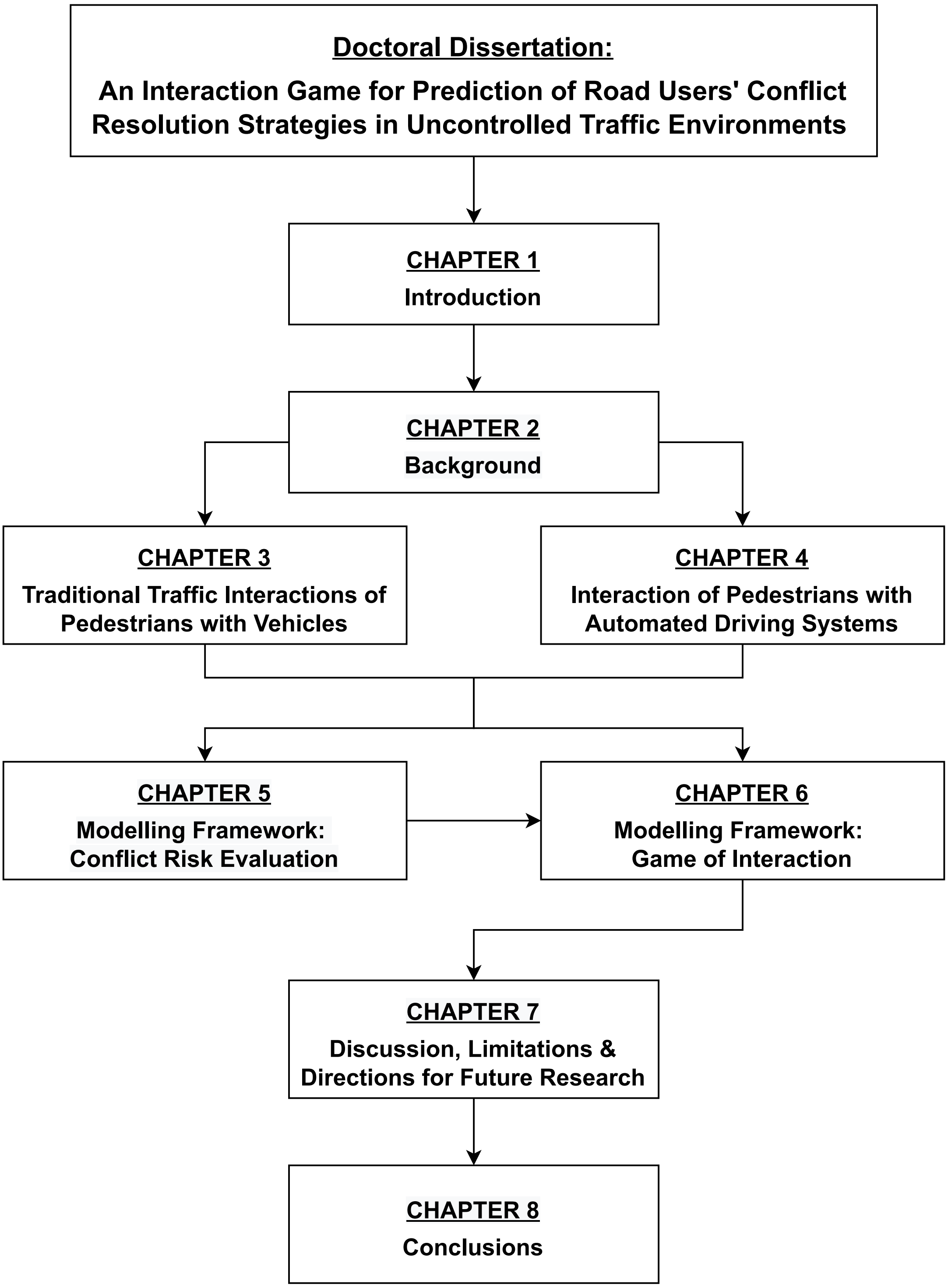


Figure 1.1: Dissertation Structure

2 Background

2.1 Traffic Interactions

Participating in traffic demands a constant interaction among road users [17]. During the transport time, traffic participants deal with a significant amount of information that requires users to process it and react to it efficiently [17, 18]. Thus, it is indispensable for road users to manage their movements while taking account of other traffic participants' presence on the road [17]. Furthermore, the traffic interaction process involves unremitting monitoring and communicating of users' positioning regarding one another, along with appropriate reactions to the features associated with the surrounding traffic and environmental context [19, 20, 21]. As a result, traffic safety in urban settings majorly depends on successful interactions among road users [13]. Figure 2.1 depicts an example of a traffic interactions among a passenger car and pedestrians, where the right of way in the shared road space is negotiated.

It must be noted that in the context of this research, traffic interactions are referred to a bilateral process among involved road users, when road users are capable of communicating their movements/intentions with the interacting party. Therefore, behaviour of road users with impaired performance, such as distraction engagement, and alcohol impairment are out of this research interest.

2.1.1 Traffic Conflicts

Traffic Conflict refers to a traffic event involving the interaction of road users and in which an evasive manoeuvre must be taken by at least one of the interacting users to avoid a

Figure 2.1: An example of traffic interaction and priority negotiation between pedestrians and vehicles in a shared space area. Extracted from: [1]

collision [22]. During the traffic conflict, interacting road users intend to dominate the road space they are moving towards by executing various crossing/evasive manoeuvres. A collision will occur if evasive manoeuvres performed by users, for instance, swerving or changes of speed, fail to prevent physical contact with the interacting users. Nevertheless, traffic collisions are relatively rare events, and the majority of critical situations usually lead to traffic conflicts [23]. Madigan et al. [11] argued that the majority of road users interact with no serious conflict or collision and are not of interest from the traffic safety standpoint, but yet crucial in terms of road user experience and traffic efficiency.

In uncontrolled traffic environments, a higher level of traffic interaction is required to guarantee the safety of road users. In the absence of strict enforcement (e.g., traffic signal or stop signs), drivers may disregard the VRUs' right of way [24]. In a similar manner, in the absence of crossing facilities, pedestrians may adapt jaywalking to avoid detour and shorten the travel time [24, 25]. Such unpredictable crossing behaviour of pedestrians can potentially lead to critical conflict with approaching vehicles, as well as interrupting the normal traffic flow [26]. In addition, an appropriate understanding of the users' intentions is essential for the safe movement of users in uncontrolled traffic settings, since there is no standard agreement for users to indicate their movement decisions in advance. Occurrence of the aforementioned scenarios signifies the necessity for utilising some additional techniques by road users to communicate their movement intentions to avoid conflict and solve ambiguity regarding the right of way in such traffic settings.

2.1.2 Traffic Communication Methods

Road users utilise different communication means to negotiate their intended movements and solve ambiguous traffic situations [27, 28]. For an efficient traffic communication, the interacting users need to understand/predict the intentions of one another, as well as the situation in which the communication occurs [29]. Although, anticipations and expectations of behaviours of interacting users is challenging due to the stochastic nature of human behaviour [30], i.e., traffic participants may behave in contradiction of formal and informal traffic rules. Besides, the brief process of traffic interactions limits the communication opportunities, and oftentimes leads to misunderstanding and misinterpretations among users [31]. According to the pertinent literature, the communication methods employed by road users to convey their movement intentions can be classified as:

- **Implicit Communication Methods:** through using non-regulated cues to negotiate the user's intention, or to help with anticipating their future actions, e.g., deceleration to encourage the interacting user to cross [32, 33].

- **Explicit Communication Methods:** through using defined/regulated communication cues (e.g., light and sound signals) to transfer intentions directly to the interacting users [33]. In traffic context, nonverbal communication methods are used to send explicit messages [34]. Driver's hand gestures to signal pedestrians that they can cross in front of the car safely is examples of explicit cues in traffic interactions.

Pedestrians mainly communicate with other road users by employing nonverbal signals (i.e., explicit communication methods). However, in some circumstances, the message transferred via nonverbal cues is missed, ignored, or incorrectly interpreted by the interacting users [35]. Further, traffic participants may behave differently in various traffic settings [36]. For instance, pedestrians are more likely to cross in controlled traffic settings without looking at the oncoming traffic since they expect drivers to comply with the traffic regulations. Whereas, in uncontrolled traffic environments, pedestrians frequently monitor the approaching traffic to assess the environment and the other road users' intentions [36, 37].

2.2 Crossing Behaviour of Traffic Participants

Traffic participants can display various behaviours on approaching a crossing site. Vehicle drivers have different strategy choices in an interaction scene to decide whether or not to give way to their interacting users. These strategy choices are subject to several factors, such as the vehicle approaching speed and its gap distance to the conflict zone with the interacting users [16]. Further, driver behaviour can be influenced by social environment factors that includes other traffic participants, social norms, and formal traffic regulations [38]. Also, drivers commonly coordinate their intentions through their movements, e.g., decelerating in advance of a pedestrian crossing to indicate their intention to yield priority [39].

On the other hand, it is vital to understand factors influencing the crossing-decision strategies of pedestrians. Pedestrian crossing decisions can vary based on factors, such as the speed of oncoming vehicles, pedestrian group size, demographics, available time and distance gaps, and number of lanes. For instance, the gap distance available between the pedestrian and their interacting user can influence pedestrian expectations regarding the behaviour of other traffic participants. Further, communication cues oftentimes accompany pedestrian crossing behaviour to indicate their crossing intentions to the approaching vehicle, such as stepping into the road, leaning forward, and scrutinising the oncoming vehicle [16]. Figure 2.2 overviews significant decision factors and communication methods identified in pedestrian-vehicle interactions research.

Concerning the pedestrians' strategy choices, some studies classified their crossing behaviour into three phases: (I) approaching with no change of the walking speed, (II) appraising with deceleration based on the speed and distance of approaching vehicles, and (III) crossing with the acceleration of the walking speed [40]. However, pedestrians with a high level of movement freedom are capable of sudden changes in their movement direction and speed on the road and hence, can perform various crossing strategies during a conflict event, e.g., deviating from the forward trajectory to cross the road behind or in front of the interacting vehicle. Figure 2.3 illustrates some of the conflict resolution strategies of pedestrians in interaction with vehicles, where various trajectories and crossing speed are employed. Besides the common conflict strategy choices, the agile characteristics of pedestrians can lead to unexpected/irrational crossing behaviour on the road. For example, a pedestrian can step backward or run to evade collision with vehicles

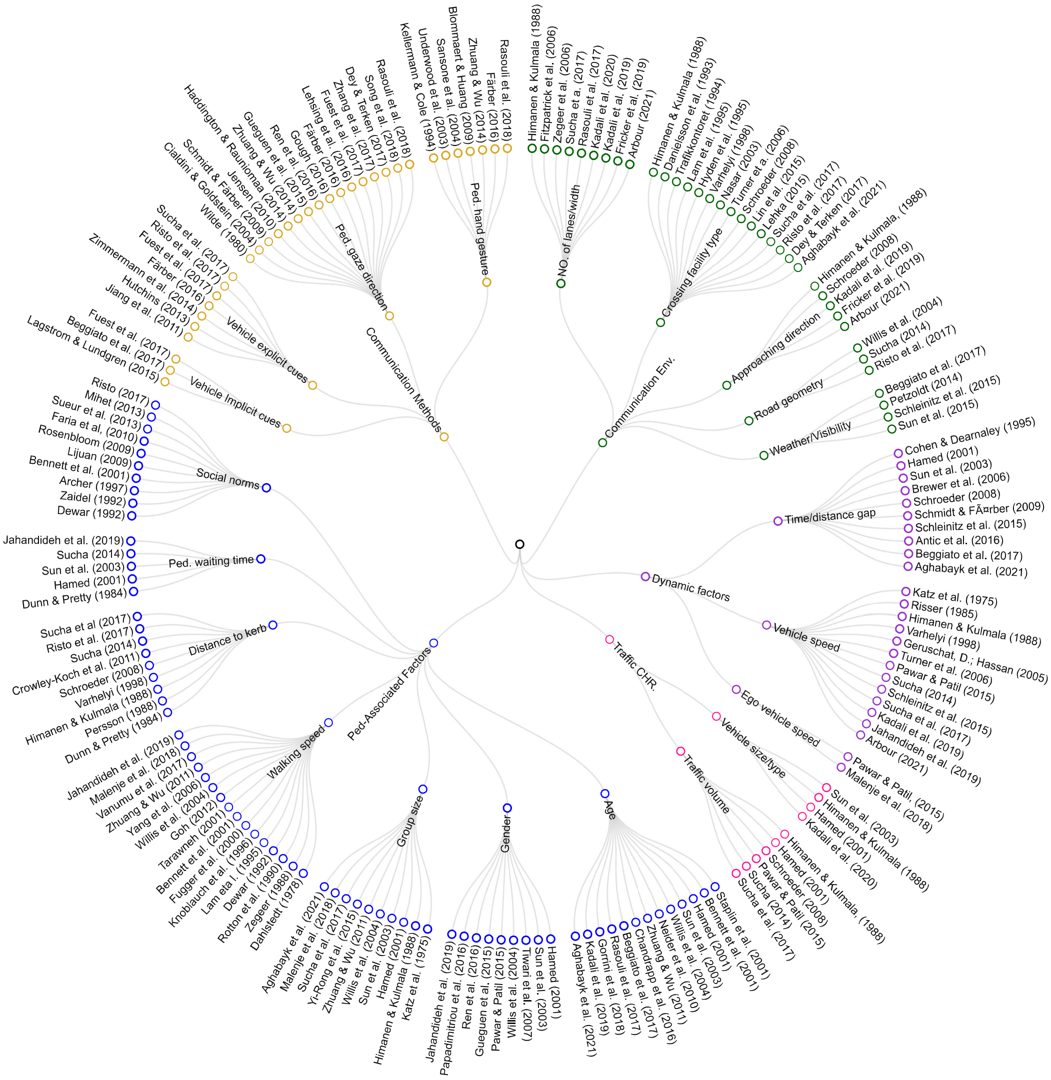


Figure 2.2: Overview of the decision factors and communication cues identified in studies on pedestrian-vehicle interactions. Source: authors elaboration, based on the reviewed references in this research.

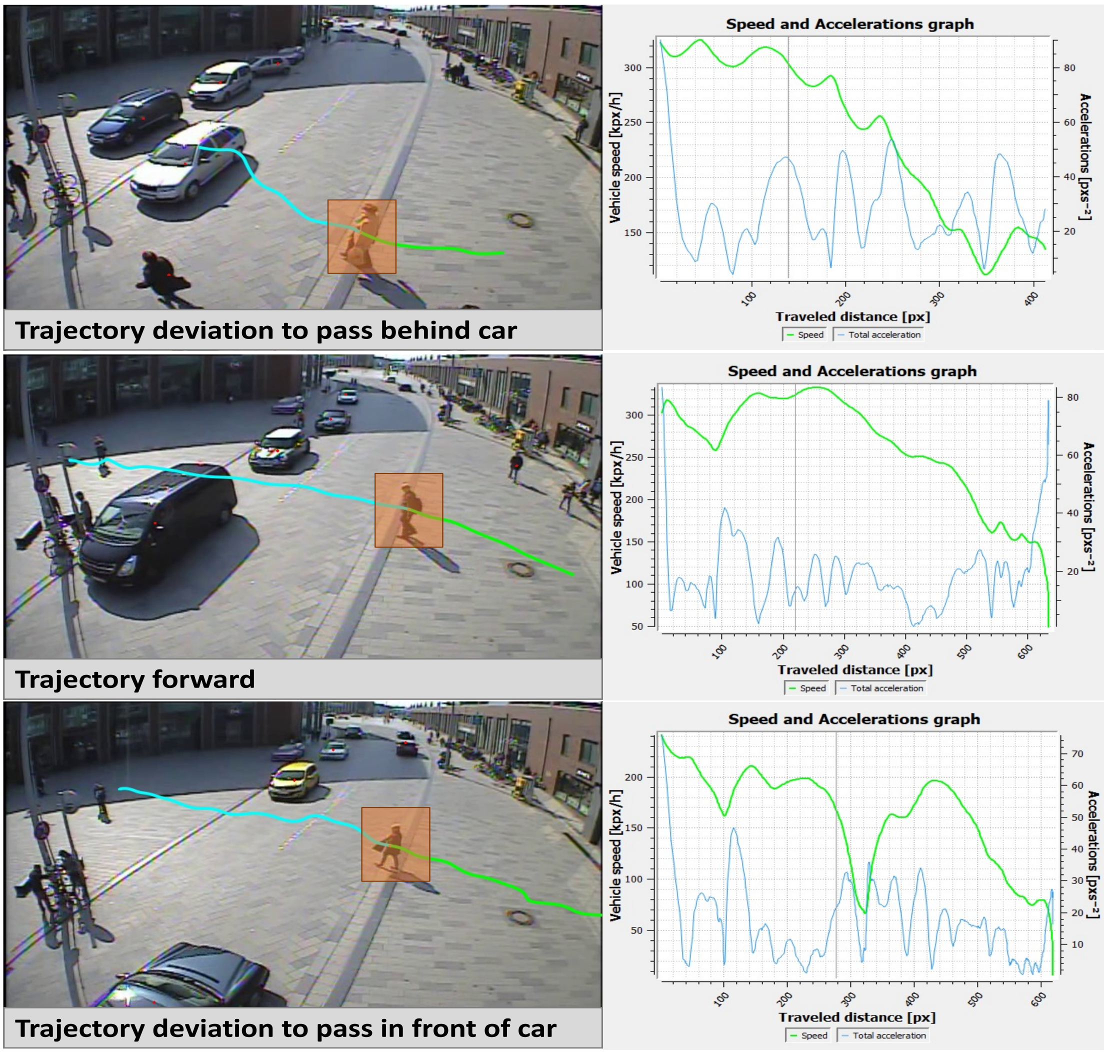


Figure 2.3: Examples of the pedestrian conflict resolution strategies in interaction with vehicles, where various trajectories and crossing speed are employed. Extracted from: [1] by using Data From Sky.

when the gap is not long enough to complete the crossing [41]. Yet, Sucha et al. [30] discussed that most pedestrians wait until the vehicles come to a complete stop rather than relying on their perception of whether it is safe to cross.

As such, investigating conventional traffic interactions and user behaviour provides more detailed insights into the user's decision-making process, and can assist with the formulation of pedestrian-ADS interaction concept before ADS –either in the near or far future– be in vast operation.

2.3 Emergence of Automated Driving Systems

The continuing advancement of ADS aims to minimise driver intervention in controlling the vehicle and handling the driving task. The traffic safety can be improved through minimising the drive role, and thus, eliminating crashes caused by human error. Although the integration of automated vehicles into the public realm, where a variety of road user types interact, can still raise traffic safety challenges [12]. Currently, various aspects of driving can be performed automatically with the assistance of ADS and advanced technologies, such as radar, LIDAR (light detection and ranging) systems, and ultrasonic and ultrasound sensors. The interaction of such systems with different algorithms and tools can enable vehicles to monitor the driving environment, make informed decisions, and navigate to their destinations. During the traffic interaction, ADS supply additional solutions to enhance the safety of VRUs [42]. Collision avoidance systems are an example of such driver-assistance systems, which aim to prevent collisions with other road users in critical traffic conditions [43]. Furthermore, in traffic scenarios when a collision is unavoidable, the pedestrian protection system (PPS) can apply automatic brake or inflate pedestrian airbags to mitigate injury [44]. An additional communication channel is also provided via external human machine interfaces (eHMIs) to handle information communication with human road users and compensate for the driver loss (Fig. 2.4).

Figure 2.4: Examples of visual eHMI types proposed to accommodate the pedestrian-ADS interaction process: crossing projection [2], light-strips [3], and text-based signal [4].

2.3.1 Future of Traffic Interactions

Automated vehicles will be integrated into the existing transport system, and thus, ADS will have to deal with the existing traffic regulations and a variety of different road user types (e.g., other automated vehicles, human-driven vehicles, pedestrians, cyclists). In a transport system of this kind, the notable amount of interaction strategies elaborated among traffic participants delivers a significant challenge for ADS. With fully ADS, a human driver is not available for an active interaction and communication with other road users. The absence of an active driver becomes crucial particularly in uncontrolled environments, such as unmarked pedestrian crossings, and shared spaces, where the right of way is not clearly predetermined by traffic regulations and users require to negotiate priority [45]. Similar interaction challenges would arise when there is no dedicated infrastructure to serve automated vehicles and ADS have to communicate their movement intentions with other traffic participants [46]. Previous studies revealed that the vehicle's precise control of the driving tasks and its knowledge of the traffic environments are insufficient for performing safe automated driving manoeuvres in urban settings [13]. Instead, an appropriate interaction concept is required to guarantee the safety of road users interacting with ADS via coordinating with the traffic rules and satisfying the expectations of engaged road users [13]. For a safe and efficient interaction, ADS have to simulate the behaviour of human drivers and have a detailed analysis of the pedestrian-driver interaction process. These are essential inputs for designing decision-making systems of automated driving, as road users may not behave as ADS expect them to [47].

2.3.2 ADS Challenges in Interaction with Pedestrians

While various automated technologies, such as collision avoidance systems, assist with traffic interaction safety, it is still essential to apprehend the pedestrian decision-making procedure for a smooth interaction process [12]. With the current advancement of automated technologies, the estimation of pedestrian intentions is a crucial task for the ADS scenario understanding [47, 16]. This is due to the complexity of pedestrian behaviour and their decision-making systems which the ADS must consider during interactions to predict their behaviour and respond suitably [45]. Further, pedestrians, and VRUs in general, need to have a particular comprehension vis-à-vis the ADS' intentions in traffic situations, such as vehicle's intention to slow down or change movement direction [48, 49]. However, the existing knowledge of pedestrian-ADS interactions is insufficient, especially from the pedestrian standpoint in real-world traffic environments [12]. The deployment of fully automated vehicles on the public road as a new user type and the absence of a human driver may cause stress and conservative crossing behaviour among pedestrians [14]. Besides, the possible ADS errors/failure in unexpected traffic circumstances and transmitting insufficient information about their movement intentions may lead to pedestrian concern during traffic interactions [12]. Although, ADS are programmed to pursue the safest approach for interacting with users on the road. Nevertheless, it is not always viable to determine the safest behaviour sequence due to the conditional essence of traffic interactions [50]. Eccentric driving manoeuvres by ADS and sometimes their incorrect prediction of road user behaviour may cause minor collisions, even though ADS follow the traffic regulations and are not at fault [50].

2.3.3 Pedestrians' Attitudes in Interactions with ADS

A significant aspect of the future of road user interactions —when automated vehicles operate on the road— is the reaction of pedestrians to ADS in the absence of a human driver [12]. An experimental study on pedestrian-ADS interactions showed that pedestrians managed to interact with ADS, besides the events when the car misbehaved by not yielding to the pedestrians who had already initiated crossing [50]. Factors such as pedestrian characteristics, risk-taking behaviour, a tendency to violate traffic rules, and trust in ADS may significantly affect pedestrian crossing decisions [51]. An analysis of naturalistic data collected from an automated pods trial demonstrated the occurrence of one "near-miss" incident in every three hours of autonomous driving —where users closely dodged a collision [11]. Besides, the observation showed that pedestrians purposely intercepted the vehicle path once every 4.8 hours. This may become problematic since road users may constantly attempt to gain priority, assuming that the ADS safety systems are programmed to stop in case of any obstacle in their path [52, 53]. This situation, known as the "Freezing Robot Problem", can also lead to shorter and possibly more unsafe time/distance gaps accepted by pedestrians crossing the road in front of fully automated vehicles [14].

During the live demonstrations of automated pods in European cities, users who interacted with the ADS underlined that a confirmation signal on their detection as necessary information they would like to receive [54, 55]. This is a critical information input for pedestrians as it lets them make sure that they are detected or/and that their crossing intentions are identified by the ADS [12]. On the other hand, implementing implicit signals in ADS is essential to notify pedestrians of the vehicle's intention and encourage them to cross, or wait for the vehicle to pass first [50, 55]. In conventional pedestrian-driver interactions, drivers employ more anticipatory behaviour and brake notably earlier when approaching the crosswalk at higher speeds [12]. Accordingly, ADS should have the same timing response to a pedestrian intending to cross [13, 32]. Further, ADS must have a similar understanding and interpretation of communication cues utilised by traffic participants [56]. For example, understanding the meaning of pedestrian hand gestures in different traffic circumstances: whether the pedestrian requests the car to yield, proceed or pull over. Consequently, eHMIs as an additional coordination channel are designed to supplement conventional forms of communication with the purposes of:

- Providing advisory messages on the subsequent actions of interacting traffic participants;
- Transmitting information to VRUs regarding the movement intentions of ADS on approaching a crossing site;
- Informing VRUs about the vehicle functioning in automated mode;

- Informing VRUs on their detection by ADS.

The design of eHMIs contains adding externally installed visual cues that can be either positioned on the car's exterior or projected on the roadway. In addition, speaker systems are included in some experiments to broadcast audible messages.

2.4 Modelling Approaches

In partially automated driving, advanced driver assistance systems (ADAS) in vehicle use automated technologies to adapt, and enhance vehicle technology for safe driving manoeuvres. Through ADAS, safety features are developed to avoid collisions by offering technologies that warn the driver in hazardous situations, implementing safeguards, and gaining vehicle control if required. To prevent a traffic collision, real-time crash prediction models are utilised to assess traffic safety levels based on real-time traffic data and separate the potential conflict/crash from the normal/safe traffic conditions [5]. If a critical condition or collision is predicted, proactive traffic safety management systems will trigger interventions to prevent collisions and change hazardous conditions to safe ones. Such collision avoidance systems are designed to detect an imminent collision on a vehicle's forward path and prevent a collision or lessen its severity in the few moments before it occurs. Hence, the user speed and future positioning are the essential components of utilised models in such systems, and factors associated with the traffic environment and user behaviour are often neglected (for instance, in [57, 58]). Some researchers embedded additional traffic and user-associated variables in conjunction with the SSMs in developing proactive safety systems. For example, Formosa et al. [59] developed a deep learning approach to predict critical traffic conflicts using dis-aggregated traffic data, in-vehicle sensors data, traffic variables and surrogate safety measures (SSMs). To evaluate the collision risk with pedestrians, a Monte Carlo simulation method was employed by relying on the scenario type and pedestrian behaviour [60]. Agarwal [61] applied time to collision (TTC) measure to develop a pedestrian conflict model at controlled and uncontrolled intersections and roundabouts, incorporating variables, such as the number of conflicts, and the number of lanes that pedestrians are interacting with vehicles.

In fully automated driving and through the application of various methods, dynamic objects (e.g., vehicles, pedestrians, cyclists) are tracked to predict their trajectories and future positions. Then, the prediction system hypothesises multiple possible predictions of the future movement of objects in motions, and ADS execute the safest automated driving manoeuvre [12]. In the presence of fully automated vehicles on the road, a robust modelling approach is crucial to guarantee the safety of road users interacting with such systems. For this reason, several models are proposed to simulate the interaction of VRUs with ADS and deliver a more accurate prediction of the future behaviour of interacting users [62, 63, 64]. Feng et al. [65] developed a Cellular Automaton model to simulate pedestrian-ADS interactions at unsignalised mid-block crossings by considering different factors, such as the existence of a vehicle approaching the crosswalk, the number of lanes, the crossing's length and width, walking speed, vehicle speed, the pedestrian's lane/direction, and the post-encroachment time (PET). Rehder et al. [66] proposed an

Artificial Neural Network approach for pedestrian intention recognition and planning-based prediction. The proposed approach receives pedestrian destinations from images and positions as inputs and applies trajectory planning towards these destinations. As output, the network predicts possible destinations in the form of a probability distribution map, and the final model prediction is obtained by using Markov Decision Processes and the Forward–Backward algorithm. Jayaraman, et al. [67] proposed a hybrid system model for long-term pedestrian trajectory prediction by using pedestrian gap acceptance behaviour and user speeds describing the pedestrian's states as: approaching crosswalk, waiting, crossing, and walking away. Parameters such as pedestrian distance to the crosswalk and kerb, waiting time, vehicle distance to pedestrian, and gaze ratio were considered in designing the model. Fox et al. [52] proposed a game-theoretic approach for modelling the priority negotiation between an automated vehicle and another vehicle at unsignalised intersections, or with a pedestrian (jaywalker) at an unsignalised crossing. The model assumes that the agents' optimal behaviours include a non-zero probability of collision occurrence. The model's assumption validates the intuition mentioned before that ADS will make little or no progress if users consider them completely safe and always yield to the interacting users. In this model, the yielding probability gradually increases as the distance gap decreases between users. The model then prompts their yield or non-yield strategy from this probability.

Yet despite the significance of pedestrian-ADS interactions and various behavioural models developed in this field, the concept has not been adequately formulated in the design of automated driving technology [12]. Therefore, it is essential to explore the research and recommendations in this field, inspect how such issues are examined while fully automated vehicles are not yet on the road, and develop a model that handles the complexity of traffic interactions.

3 Traditional Traffic Interactions of Pedestrians with Vehicles

R. Ezzati Amini, C. Katrakazas, and C. Antoniou. Negotiation and decision-making for a pedestrian roadway crossing: A literature review. Sustainability, 11(23): 6713, 2019.

Summary

This study provides an overview of previous research on user negotiation and decision-making in roadway crossing scenarios. One hundred five studies were reviewed to identify the prominent behaviours of drivers and pedestrians in such scenarios, investigate the traffic interactions and synergies between such users, and the influencing factors in their decision-making process. The studies were evaluated using three questions:

What communication methods do users employ during a traffic interaction? Road users utilise a broad range of implicit and explicit communication techniques to co-ordinate their actions with interaction partners in ambiguous traffic situations. The communication signals are primarily transferred to acknowledge that interacting users are seen, confirm their movement intentions, or influence each other's yield/not-yield decision strategies.

How does user communication affect traffic behaviour? According to previous studies, traffic communications have a vital role in forming a smooth and efficient traffic flow and improving safety. However, most informal traffic rules and communication methods are developed based on other participants' behaviour expectations, primarily when formal traffic rules do not correspond with the road design or when expected user behaviour is contravened.

Which factors influence the decision-making process of road users in traffic interactions? The reviewed literature revealed that road users adopt their crossing strategies by considering a wide range of factors knowingly (e.g., estimation of time and distance gap) or unknowingly (e.g., the impact of age or gender), while they employ different communication techniques to ease the interaction when needed. This shows the complexity of the pedestrian-vehicle interactions, in which solely consideration of some factors or communication methods may not provide a consummate understanding of the process.

To conclude, a holistic interaction approach is proposed for pedestrian-vehicle interaction. The holistic interaction approach aims to streamline the complex decision-making procedure of pedestrians by considering the most significant factors and communication techniques influencing the process.

4 Interaction of Pedestrians with Automated Driving Systems

R. Ezzati Amini, C. Katrakazas, A. Riener, and C. Antoniou. Interaction of automated driving systems with pedestrians: challenges, current solutions, and recommendations for eHMIs. Transport Reviews, 41(6): 788–813, 2021.

Summary

This study reviews existing literature on the ADS interactions with pedestrians, current challenges, various data collection and modelling approaches, the limitations and drawbacks emerging from ADS implementation in the current traffic patterns, and technological solutions to replicate pedestrian-driver communications.

In complex urban scenarios and with the current development of ADS, automated technologies cannot support an active interaction and efficient priority negotiation with pedestrians. Pedestrians' agility, unexpected behaviour, and reliance on nonverbal communication cues deliver significant challenges to ADS capabilities in handling possible conflicts. Previous studies showed that a suitable interaction concept is necessary for executing safe automated driving manoeuvres in urban settings besides the vehicle's precise control of the driving tasks and its knowledge of the traffic environments. Such interaction concepts can be attained by ADS compliance with traffic regulations, as well as fulfilling the expectations of interacting road users. However, pedestrian behaviour and expectations may change when large-scale fleets of automated vehicles appear on the road and infrastructure for ADS has been implemented. Hence, more research should be performed to understand how the emerging automated technology will alter the requirements/expectations of users compared to conventional pedestrian-vehicle interactions.

The relevant research findings reveal several different factors that may influence pedestrian behaviour in interaction with ADS. Therefore, ADS must have an in-depth knowledge of the pedestrian decision-making process, the most pertinent factors affecting their decisions, and their expectations regarding the movement intentions of ADS. This underlines the complexity of pedestrian-ADS interactions, in which predicting pedestrian intentions and strategies requires considering a combination of contributory factors.

Finally, the studies reviewed suggest that implicit and explicit communication methods should be incorporated in ADS design to facilitate pedestrian-ADS communications. ADS need to combine suitable external communication cues (eHMIs) with appropriate driving manoeuvres deriving from an accurate interpretation of pedestrian behaviour and requirements in the traffic scene for dynamic and safe interactions.

5 Modelling Framework: Conflict Risk Evaluation

R. Ezzati Amini, K. Yang, and C. Antoniou. Development of a conflict risk evaluation model to assess pedestrian safety in interaction with vehicles. Accident Analysis & Prevention, 175:106773, 2022.

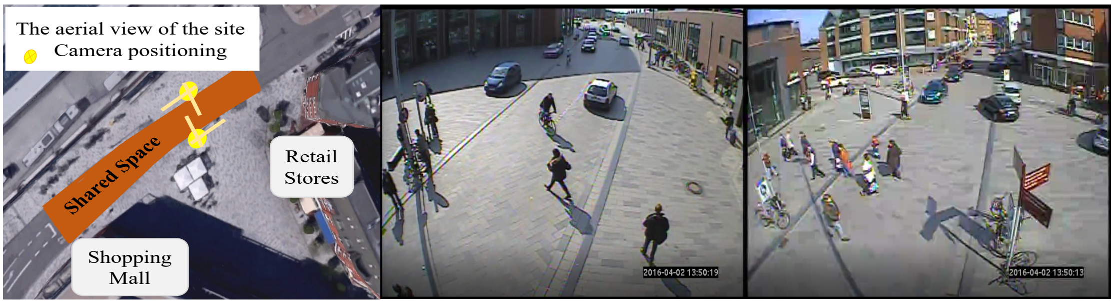
Summary

This paper describes the development of conflict risk evaluation models to assess the safety level of pedestrian conflict with other road users and identify the hazardous traffic conditions between them. The models allow the conflict risk evaluation of different users' strategy combinations and can be implemented in the ADAS to improve pedestrian safety in interaction with different vehicle types, particularly in uncontrolled traffic settings.

Methodology

As discussed in Section 2.1.1, traffic conflicts are defined as events where interacting users (or at least one of them) need to take an evasive manoeuvre to avoid a collision [22]. However, the likelihood of turning a serious conflict into a collision may depend on different factors, such as time/space margin between interacting users, user types, and type of users' evasive manoeuvres [23]. Based on this knowledge, the research methodology is built in three steps for developing the conflict risk evaluation model:

Step 1. Model Formulation: A logit model is used to formulate the conflict risk evaluation model, in which the discrete choices of conflict and non-conflict are examined. A set of SSMs are employed as predictor variables to suitably address the outcome of performing different evasive manoeuvres and by considering the possible reaction of the interacting user. The selected safety measures estimate the users' time and distance proximity after performing various combinations of evasive manoeuvres on the road —based on user types. The minimum relative distance (MD) measure is proposed to replace the traditional theoretical collision point and compensate for the collision point's absence while users deviate from their forward trajectories. The time-based indicator of relative time to the minimum distance (TMD) is used to estimate the arrival of the users at the collision zone (i.e., the MD). Additionally, the speed-based indicator of conflicting speed (CS) is utilised to account for users' rolling over behaviour in pedestrian-vehicle interactions.



(a) Shared space area [1]

(b) Mid-block crossing area [68]

Figure 5.1: The street view from camera/-s (right), and the aerial view of the sites (left).

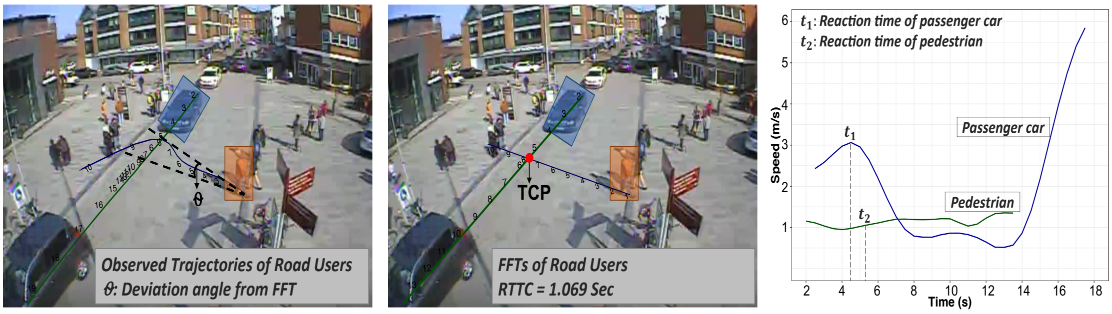
Step 2. Threshold selection methods: Four threshold determination methods (i.e., intersection point, p-tile, maximum between-class variance, and minimum cross-entropy method) are selected in this study to identify the cut-off point beyond which the outcome of the conflict prediction model would vary. The conflict risk evaluation model provides the probability of the conflict occurrence and classifies the traffic event as conflict (critical traffic condition) or non-conflict (normal traffic condition) based on the threshold.

Step 3. Threshold evaluation criteria: The F-score is frequently used in statistical analysis of binary classification, reflecting the accuracy of a test and used in this study to select the optimal threshold given by applied threshold determination methods.

Data Collection and Analysis

The safety analysis in this study was performed by using two video graphic surveys:

- **Shared Space Interactions:** This includes the interaction data for a 63-meter shared space zone in the district of Bergedorf (Weidebaumsweg), Hamburg city, Germany [1] (Fig. 5.1.a). The extracted data contains the trajectory, velocity, and acceleration data of passenger cars, pedestrians, and cyclists; however, the cyclists are out of this research interest and neglected in the analysis.



(a) (b)

Figure 5.2: a) An example of conflict detection procedure application on a pedestrian-passenger car conflict. The numbers labelled on trajectories shows the time in second. **b)** Speed profiles of road users in the conflict event. Source: [5]

- **Mid-block Crossing Interactions:** This includes the interaction data of various road users in two lanes of a road in a mid-block crossing area in Surat city, Gujarat, India [68] (Fig. 5.1.b). The extracted data includes the trajectory, velocity, and acceleration of passenger cars, heavy and large goods vehicles, two-wheel vehicles, three-wheel vehicles, and pedestrians.

The data analysis preliminary relies on users' trajectories extracted from the video data and a set of explanatory variables acquired through mining the data sets. In this study, a conflict detection procedure identifies potential conflicts among road users and determines conflict resolution strategies. Initially, street boundaries are specified in the data sets to only keep the trajectories of users in the studied zone. Then, users' free flow trajectories (FFT) are plotted, providing the shortest path from their origin to their destination. In the next step, a theoretical collision point (TCP) is defined to identify the users' intersected trajectories if they would have taken the FFTs to reach their destinations. A buffer zone is considered for all user types to reflect the real-world collision events where vehicles hit the pedestrians at the buffer than/before the TCPs. Finally, a minimum relative time-to-collision (RTTC) of 3 seconds [69] is used to capture the simultaneous arrival of the interacting users at the TCP and buffer zone (near- or far-buffer, depending on the direction of approach). Figure 5.2.a illustrates an identified conflict event between a pedestrian and a passenger car in the shared space by applying the conflict detection method. In this example, users' FFTs are plotted to identify the TCP, and the RTTC is computed. The users' speed changes in Figure 5.2.b shows that the passenger car decelerates in reaction to the pedestrian, while the pedestrian crosses the road with nearly constant speed (Fig. 5.2.b) and by deviating from its FFT —with the deviation angle of θ. Hence, the conflict resolution strategies in this example are determined as deceleration for the passenger car and deviation for the pedestrian.

The application of the conflict detection procedure resulted in identifying 120 conflict events between road users in the shared space data set and 158 conflict events in the mid-block crossing data set, where one/both of them employ evasive manoeuvres to avoid the potential collisions (see Table 5.1 for the summary of events). Accordingly, the evasive actions of users to avoid a conflict are specified as:

- **Continuing Strategy**, by moving along the FFT with preferred/current speed. This strategy is applicable for all user types.
- **Deceleration Strategy**, by moving along the FFT with reduced speed. This strategy is applicable for all user types.
- **Deviation Strategy**, by deviating from the FFT —and thus TCP— to the left or right, with current/preferred speed. This strategy is only applicable for lighter road users (i.e., pedestrians, two- and three-wheel vehicles).

The proposed SSMs (i.e., MD, TMD, CS) are estimated for all possible combinations of evasive manoeuvres (i.e., all combinations of strategies classified in this study for each user type) that interacting users could perform to escape a conflict, including the actually taken strategies in the data set. A critical conflict is assumed to occur when TMD is below $1.5sec$ [23], the MD between interacting users is below the vehicle type plus pedestrian half body, and the CS exceeds $1m/s$. Finally, the events' outcomes were labelled as conflict and non-conflict to apply the logit model.

Analysis and Results

The analysed conflict data are used to develop and validate conflict risk evaluation models for the interaction of pedestrians with passenger cars and light vehicles (two- and three-wheel vehicles) separately. Tables 5.2 & 5.3 summarise the parameter estimates for pedestrian-passenger car conflict events in the shared space and pedestrian-light vehicle events in the mid-block crossing. All SSMs are statistically significant in predicting conflict outcomes in both models, with no evidence of poor fit for models. As expected, the MD and TMD indicators have negative coefficients indicating that smaller values would increase the risk of critical traffic conditions. In contrast, the CS is positive, meaning a higher speed would increase the conflict severity level.

The predicted conflict is determined by applying selected methods (i.e., intersection point, p-tile, maximum between-class variance, and minimum cross-entropy) and on the basis of conflict cases in the data sets. The precision of predictive conflict and non-conflict of various thresholds is evaluated using the F-score method to select the optimal threshold. For pedestrian-passenger car cases, the optimal threshold is determined as **0.425** through the p-tile method with the highest F-score (0.890), and for pedestrian-light vehicle cases as **0.512** through the p-tile method with the highest F-score (0.905). It is worth noting that F-score values are between 0 to 1, in which higher scores (or closer to 1) indicate a better predictive model performance.

The optimal thresholds will label the outcome of the model predictions as critical conflict (when it exceeds the thresholds) or normal traffic condition (when below the thresholds). In the case of ADAS implementation, the system triggers a warning for predictions labelled as critical conflict.

Table 5.1: Summary of the identified conflict events with pedestrians in the studied areas [5]. 2W: two-wheel vehicle, 3W: three-wheel vehicle, HGV: heavy goods vehicle, LGV: large goods vehicle

Location	Passenger Car	2W	3W	HGV/LGV	Total
Shared space area	120	NA	NA	NA	120
Mid-block crossing	11	92	51	4	158

Table 5.2: Logit model estimation for pedestrian-passenger car conflict events. Source: [5]

Parameter	Estimate	Std. Error	Z-Value	Pr(> |z|)
Intercept	4.327	0.578	7.48	$< 7e^{-14}***$
MD	-2.898	0.256	-11.31	$< 2e^{-16}***$
TMD	-3.067	0.304	-10.08	$< 2e^{-16}***$
CS	0.376	0.079	4.73	$2.2e^{-06}***$
Iteration			9	
AUC			0.97	
Accuracy (0.50 cut-point)			92.4%	

Table 5.3: Logit model estimation for pedestrian-light vehicle conflict events. Source: [5]

Parameter	Estimate	Std. Error	Z-Value	Pr(> |z|)
Intercept	4.490	0.373	12.03	$< 2e^{-16}***$
MD	-2.813	0.168	-16.69	$< 2e^{-16}***$
TMD	-2.365	0.184	-12.80	$< 2e^{-16}***$
CS.	0.263	0.040	6.24	$3.5e^{-11}***$
Iteration			10	
AUC			0.98	
Accuracy (0.50 cut-point)			92.7%	

6 Modelling Framework: Interaction Game

R. Ezzati Amini, M. Abouelela, A. Dhamaniya, B. Friedrich, and C. Antoniou. A game-theoretic approach for modelling pedestrian-vehicle conflict resolutions in uncontrolled traffic environments. Manuscript under review, 2022.

Summary

In this paper, a game-theoretic model is developed to predict the conflict resolution strategies of pedestrians interacting with different vehicle types in uncontrolled traffic settings. The proposed models employ the most influencing factors in the user's decision and choice of strategy to predict the movements and conflict resolution strategies of traffic participants in the interaction and have the potential to be used as a behavioural model for ADS.

Methodology

In a traffic interaction, the users' competition over the road space results in conflicting interests. Given the conflicting interests among users, a strategic game of Stackelberg leadership competition is formulated in this study to model pedestrian-vehicle interactions. The two-player Stackelberg game assumes one of the players (referring to the interacting road users) is the leader and the other is the follower, in which the leader plays a strategy first, and the follower reacts to the leader's announced strategy. Based on the game's assumptions, users select a conflict resolution strategy that maximises their utilities and is based on the possible reaction of the interacting user. This approach highlights the very fact of most traffic interactions in which users' decisions are made in the form of action and reaction. Besides, the player's strategy set in the game is defined based on combinations of the trajectory and speed changes that users can employ to avoid a conflict (as classified in section 5 - Data Collection and Analysis): the game leader (L) role with its available strategy choice $(s_1^L, \ldots, s_n^L) \in S^L$ and the follower (F) with $(s_1^F, \ldots, s_m^F) \in S^F$ as its strategy set.
The mixed strategy approach is utilised to find the optimal game solution: the probability vectors of $P^L(s^L)$ and $P^F(s^F|s^L)$ reflect the likelihood of performing a strategy by the game leader and the follower given the leader's strategy, respectively [70]. Hence, one mixed strategy Nash Equilibrium exists in a game given the outcomes of:

$$P(s^L, s^F) = P^L(s^L) * P^F(s^F|s^L) \tag{6.1}$$

The game utilities are formulated in three layers of safety, travel, and social to cover all aspects of user behaviour and decision-making process in a traffic conflict:

- *Safety Layer:* In the safety layer (SL), previously developed conflict risk evaluation models [5] are utilised to assess the safety of interacting users after performing each strategy pair. Based on the estimated surrogate safety indicators and predetermined thresholds, the model identifies the hazardous traffic conditions between pedestrians and vehicles and returns a dis-utility if applicable.
- *Travel Layer*: The comfort level of different strategies is quantified in the travel layer for the detour (DT), and deceleration (DC) imposed by users' speed/trajectory changes. The users receive dis-utilities for the corresponding energy loss of each conflict resolution strategy available for users in the game.
- *Social Layer*: The third utility layer covers three of the most significant environmental factors influencing the user's choice of strategy: pedestrian group size (PL), pedestrian approaching lane (LN), and the right of way (RW). For pedestrian group size and approaching lane utilities, the strategies are evaluated with respect to the interacting user's strategy, and users receive utility/dis-utility based on the aggressiveness level: aggressive, neutral, and courteous. Regarding the right of way, the players' utilities are assigned to the users who get priority first. The social layer signifies the importance of social norms in improving safety in uncontrolled traffic environments.

Data Collection and Analysis

Two video graphic surveys are used in this study for conflict analysis and model application, i.e., a shared space in Hamburg, Germany [1], and amid-block crossing area in Surat, India [68]. The conflict analysis and determination of conflict resolution strategies are explained in Section 5 - Data Collection and Analysis. Further, the preferred speed, deceleration rates, and deviation angles specified for strategies per user type are estimated based on the interaction data. In the shared space, the pedestrians' preferred speed for road crossing is extracted from the non-conflict pedestrians data —who are not involved in any conflicts/interactions. Based on pedestrians' non-conflict trajectories, the crossing is divided into three movement phases: (1) pedestrian decelerates on approaching the crossing/road kerb, (2) pedestrian accelerates to reach the crossing speed, and (3) pedestrian crosses the road with nearly constant speed. Accordingly, a k-mean clustering approach is applied, and the mean pedestrian walking speed that corresponds to the third movement phase of crossing is selected as the preferred crossing speed of pedestrians for continuing and deviation strategies in the shared space. Regarding the mid-block crossing, the 85^{th} percentile of the speed is assumed as the preferred crossing speed of pedestrians, given the small number of the user free flow crossing in the data set. The 85^{th} percentile of the speed for the vehicle type in both data sets are considered as the preferred speed for the continuing strategy of all vehicle types. A similar approach is employed to assume the preferred speed of light vehicles in deviation strategies.

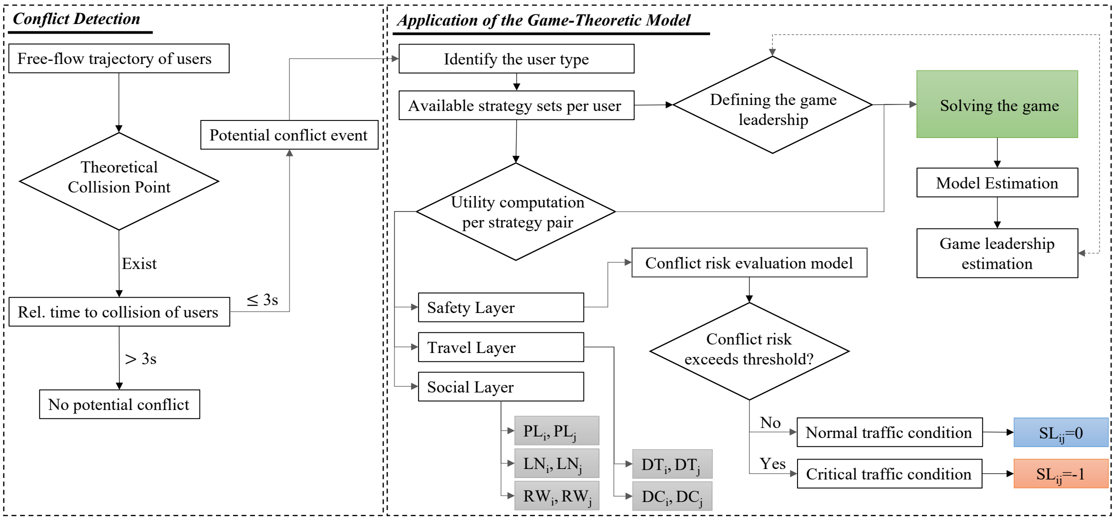


Figure 6.1: A general framework of the game-theoretic model application. Source: [6]

Deceleration rate determination of user types for the deceleration strategy is not straightforward since it depends on several factors, e.g., the user's initial speed or available gap. Consequently, the average deceleration rate of user types in both data sets is used to predict the deceleration strategy in the model. The average deviation angle of users deviated from their forward trajectories —and consequently from the TCP— is regarded as the deviation angle of user type for the deviation strategy.

For every conflict event, users' utilities are computed for all combinations of conflict resolution strategies —based on user types and available choice of strategies. Then, the probability of performing a strategy by a user in conflict is calculated based on the user role (i.e., leader or follower), and the probability of the outcomes is determined through the equation 6.1 for each strategy combination in the game. Therefore, the highest probability returns the game solution and the user's choice of actions to solve the conflict. In the model application, all users in conflict are assumed to be the leader and once the game follower. Figure 6.1 illustrates a general framework of the game-theoretic model application in this study.

Analysis and Results

A log-likelihood approach and the numerical optimisation algorithm for a quasi-Newton method of Broyden Fletcher Goldfarb Shanno (BFGS) are employed to estimate the parameter values of the Stackelberg game. A hold-out method is applied by splitting the conflict events into 70% for training and 30% for testing purposes in both data sets. The proposed model is estimated separately for pedestrian interactions with passenger cars and light vehicles (i.e., two-wheel and three-wheel vehicles) and by using training samples in the shared space and the mid-block crossing, respectively. Besides, different parameters' combinations are examined to obtain the optimal training results, revealing that the combination of all proposed parameters has the best results in both models and is thus, utilised in the models estimation. The statistical tests on the model estimation show that all the employed parameters are significant for predicting game outcomes in the models.

In the next step, different approaches are evaluated to determine the game leadership in the model:

- *Time to TCP:* The user closer to the TCP is the game leader.
- *User Type:* The type of user (heavy user vs. light user) defines the game leadership.
- *Reaction Time:* The user reacting first during the conflict is the game leader.

A log-likelihood approach is employed to select the best method, showing that reaction time is the best fit to define the game leadership in the pedestrian-passenger car model and user type in the pedestrian-light vehicle model.

Finally, the testing data sets are used to assess the overall performance of the developed models. For this reason, confusion matrices are created for categories of game choice (as "success") and non-choice (as "failure"), and the accuracy, sensitivity, and specificity across all classes are then evaluated in both models (see Table 6.1 for summaries of results). A pedestrian-light vehicle conflict example is selected from the mid-block crossing data set to explain the model performance and characteristics, and the game-theoretic method is applied. Figure 6.2 visualises the probability of various strategy choices in the time frames prior/following the actual reaction time of the interacting users in the game. The preferred strategy of the light vehicle (two-wheel vehicle in this example), as the game leader, is to continue its path where the highest utility is received. The game outcomes probability shows that the pedestrian selects the left deviation strategy to cross the roadway behind the two-wheel vehicle rather than waiting until the conflict zone is clear. Eventually, the strategy pair of continuing-deviation left returns the highest probability at the actual reaction time of users (time frame = 0) as the final game outcome, in which game leader receives its highest utility from its strategy choices. The final game outcome ($P(s^L, s^F)$) is similar to the performed strategies of users in the real-world conflict scenario.

The overall results indicate that the developed interaction game models have satisfactory performances on both data sets —verifying the model transferability— and have the potential to be used as a behavioural model for the ADS to improve pedestrian safety, particularly in uncontrolled traffic settings.

Table 6.1: Summary of the results obtained from the confusion matrices to evaluate the models' performance.

Location	Model	Accuracy	Sensitivity	Specificity
Shared space area	pedestrian-passenger car	95.8%	83.3%	97.6%
Mid-block crossing	pedestrian-light vehicle	95.7%	65.8%	97.7%

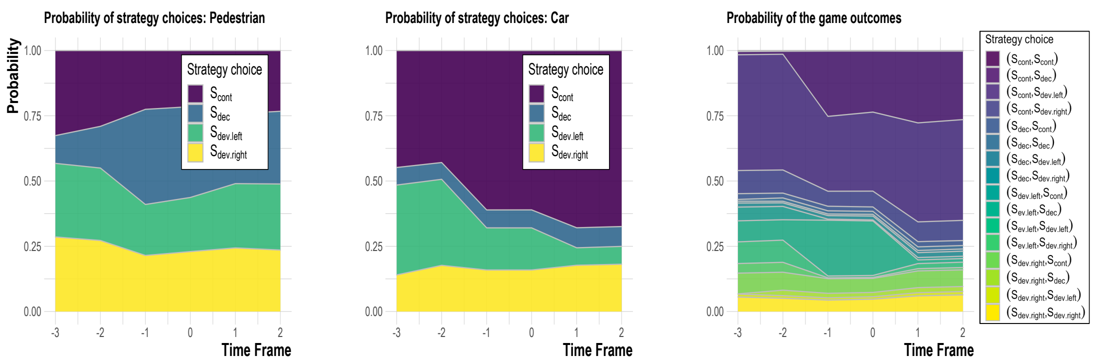


Figure 6.2: Probabilities of strategy choices in a pedestrian-light vehicle conflict. From left: probability of strategy choices for pedestrian as the follower, for two-wheel vehicle as the game leader, and the probability of game outcomes for strategy combinations $(P(s^L, s^F))$. S_{cont} stands for the continuing strategy, S_{dec} stands for the deceleration strategy, $S_{dev.left}$ stands for the left deviation strategy, and $S_{dev.right}$ stands for the right deviation strategy. Source: [6]

7 Discussion, Limitations & Directions for Future Research

The major traffic safety threat to pedestrians comes from the high level of interactions on the road, particularly in uncontrolled traffic settings. Pedestrians are frequently required to negotiate priority while avoiding conflicts with other traffic participants. Such traffic interactions will become even more complex with the integration of automated vehicles into the public road. The elimination of human role in fully automated driving systems and accordingly human errors aims to improve traffic safety; however, the complexity of human behaviour and the absence of fully automated vehicles in the public realm still raise substantial challenges for ADS, especially in unexpected traffic circumstances.

This dissertation analyses the conventional form of interactions among pedestrians and motorised vehicles, as well as factors influencing the decision-making process of users, particularly pedestrians, during traffic interactions (Chapter 3). It also investigates the future of traffic interactions, in which ADS will operate on the road, and evaluate the user behaviour, requirements and expectations in the presence of such vehicles (Chapter 4). A conflict risk evaluation model is proposed to assess the safety level of users in interaction, and separate the safe/normal traffic conditions with critical/hazardous traffic conditions (Chapter 5). The model is, then, extended to a game-theoretic approach to cover a wider range of factors (i.e., safety aspect, comfort level of travel, and factors associated with the traffic environment) that affect the decision of interacting users during a conflict on the road (Chapter 6).

This chapter will provide a general discussion of the results and limitations of the studies performed, as well as recommendations for future research. The aim of this dissertation was to provide an in-depth understanding of interaction process among pedestrians and vehicles, with respect to the existing traffic pattern and the future of the mobility. The game-theoretic approach developed within this research enables the prediction of users' conflict resolution strategies in interaction with different vehicles types in uncontrolled traffic environments. Such behavioural models can improve pedestrian trust in automated driving technologies, assist ADS to perform safe driving manoeuvres, and consequently enhance traffic safety and efficiency on the road.

7.1 Discussion

7.1.1 Pedestrian Decision-making Process

Pedestrians display different behaviours at road crossings that do not always follow a consistent pattern and may vary from one situation to another [16]. However, the state-of-the-art negotiation and decision-making for pedestrian road crossings have achieved substantial progress in understanding road users' behaviour in interactions, factors influencing their decisions, and traffic communication methods.

Based on the reviewed literature in Chapter 3, pedestrian-vehicle interactions can be divided into five distinct phases to simplify the decision-making process [16]. Before forming any interaction, traffic participants superficially assess the road characteristics while approaching a conflict zone. In the pre-interaction phase, pedestrians choose a crossing point. At the same time, drivers constantly monitor the road ahead and ideally adjust their behaviour by the road/traffic requirements. Pedestrians, then, demonstrate their crossing intentions to the drivers approaching the conflict zone, commonly via presence at or walking towards the curb. When interacting road users detect one another, the interaction starts. At this point, interacting road users have their initial assessment of the traffic environment and available information and select their conflict resolution strategies accordingly. In ambiguous traffic conditions, interacting users employ communication methods to indicate their intentions and facilitate traffic interaction. The interaction process ends when at least one of the interacting users leaves the conflict zone. Although, road users can engage in multiple interactions or execute more than one conflict resolution strategy while negotiating priority and vacating a conflict zone. Such circumstances usually require users to re-assess the traffic environment and communicate their new movement intentions with one another.

On the other hand, previous studies identified a broad number of factors that influence the crossing-decision strategies of pedestrians during interactions with vehicles. Therefore, a systematic literature review is performed to derive pertinent parameters and facilitate the development of a suitable interaction model. Factors with the most impact on the decision-making process of users in interactions (i.e., based on the number of times the influencing factors found to be relevant in the reviewed studies) are selected as the potential parameters of the proposed interaction game-theoretic model:

- *Road Characteristics:* The impact of road characteristics, such as the number of lanes, and type of crossing facilities, on the user's safety perception and anticipation of traffic behaviour, was highlighted in the reviewed literature [71, 72, 73]. For instance, previous research showed substantial differences in the driver's yielding rates amongst various pedestrian crossing facilities with varying control levels [74, 75, 76, 77].

- *Temporal & Spatial Gap Acceptance:* From a pedestrian perspective, the time and distance gap with the oncoming vehicle must be long enough for a safe road crossing [72, 78]. Sun et al. [79] argued that pedestrians and drivers could manifest various gap acceptance behaviour due to the higher speed of vehicles compared to the pedestrians. Further, factors such as group size and approaching lane can decline the likelihood of accepting shorter gaps among pedestrians [32, 79, 80]. However, estimating the critical gap in which no pedestrians commence crossing can be tricky since it varies among users depending on several factors (e.g., road geometry and pedestrian characteristics) [32, 81].

- *Speed of Road Users:* The speed of users (i.e., approaching vehicles and pedestrians) can significantly affect the driver's yielding behaviour, and crossing-decision of pedestrians [30, 77, 82]. Although, the estimation of the vehicle speed can be a difficult task for pedestrians. Regarding the walking speed, it can alter with factors, such as pedestrian age, gender, group size, crossing facility type, and weather conditions [78, 83].

- *Pedestrian Characteristics:* From pedestrian-associated factors, age and gender are two of the most influencing factors of pedestrian behaviour identified in the reviewed literature. People of different ages and gender can have various attitudes, traffic experiences and judgements, risk perception, and physical and cognitive abilities, thus behaving differently in a road crossing scenario [41, 84, 85, 86].

- *Pedestrian Group Size:* The reviewed research revealed that the size of pedestrian platoons is associated with both pedestrian crossing behaviour and driver yielding behaviour [26, 30, 79]. The driver's yielding likelihood increases by increasing the size of pedestrian groups, whereas pedestrians in groups may tolerate a lower waiting time at crosswalks [80, 87].

As such, the framework (Chapter 3) deliberately investigates the conventional traffic interactions and decision-making process of road users in a qualitative manner, and it serves to frame the discussion of results within the relevant literature.

7.1.2 Pedestrian-ADS Interactions

ADS will have to deal with a variety of well-established traffic communications methods among human road users and respond to their expectations and requirements while ensuring traffic safety and efficiency.

The comprehensive literature review in Chapter 4 showed that the human factors research involved in real-world traffic environments is not yet well developed, mainly due to the absence of fully automated vehicles in the public realm [52]. Hence, there are many unresolved questions in the automation technology domain, including determining the most influential factors of the pedestrian decision-making process and their impact on pedestrian behaviour, implementing these factors in ADS, and whether user behaviour will change with the integration of ADS as new road users. The latter is a particularly significant subject in the future of mobility, where vehicles of different automation levels and human-driven vehicles —possibly for decades before the complete transition to ADS— coexist [56], since the factors influencing the pedestrian decision-making process in conventional interactions may not be relevant to their interactions with ADS [12].

The reviewed research in Chapter 4 revealed that similar to conventional pedestrian-vehicle interactions, dynamic factors such as temporal/spatial gap and vehicle speed are considered most important by pedestrians while assessing the safety level of different crossing strategies and deciding whether to cross the roadway or yield priority [14, 64, 65]. Road characteristics, such as crossing facility, and road types also found to have great impact on pedestrian crossing decisions [11, 39, 51]. The existing ADS technology does not support active interaction and efficient priority negotiation with pedestrians and is thus, problematic in environments with less advanced traffic control systems and lower levels of segregation, where an increased level of interaction is required. With respect to the pedestrian-associated factors (e.g., gender, and personal characteristics), it is hard to impossible for the current stage of ADS development to process such information. Although, these factors are found significant in the traditional pedestrian-vehicle interaction studies and can affect pedestrian behaviour. Concerning the pedestrian age, it may be feasible for ADS (or, at least, future technologies) to differentiate age groups —for instance, children, adults, disabled/elderly (with mobility aids)— and to take relevant features (e.g., walking speeds) into account for each group [12]. The studies reviewed suggest that pedestrian walking speed should not be considered in isolation, as it can be affected by group size, pedestrian physical abilities, waiting time, and approaching lane.

Where explicit communication signals are concerned, various technological solutions are proposed to accommodate pedestrian-ADS communications; however, the ultimate form of eHMIs is still an issue. How to develop a uniform and universally understandable eHMI concept, which information eHMI cues should communicate, and when eHMI cues should be used are questions on which research has not yet reached a consensus.

In essence, Chapter 4 explores the pedestrian-ADS interactions, the possible requirements for developing a safe and efficient interaction concept, the capabilities of automated driving technologies in interaction with pedestrians, and the current challenges and limitations. The results of this chapter assist in preparing a conceptual framework for developing the interaction game based on the user requirements and behavioural changes in the future of traffic interactions.

7.1.3 Conflict Risk Evaluation Model

During traffic interactions, the most crucial component of the user decision-making process is to ensure safety. Although a broad range of influential decision factors is identified in the literature for pedestrians deciding to cross a roadway, users' principal objective is to avoid critical traffic conditions. With a similar goal, different collision avoidance systems are designed to perform safe driving manoeuvre and prevent a collision with pedestrians.

Chapter 5 reports the development of conflict risk evaluation models to assess the safety of pedestrians interacting with vehicles and identify the hazardous traffic conditions between them. The conflict risk evaluation model is formulated by using a logit model. Interaction data collected from a shared space in Hamburg, Germany, and a mid-block crossing area in Surat, India, are used to develop and validate the model. The interaction of pedestrians with vehicles (passenger cars) and light vehicles (two- and three-wheel vehicles) are formulated separately in two models to better reflect the traffic layouts and user behaviour in the surveyed sites. After developing the models, the thresholds are specified by applying various methods (i.e., intersection point, p-tile, maximum between-class variance, and minimum cross-entropy method) to separate potential critical conflicts and normal traffic conditions. Then, the optimal thresholds are

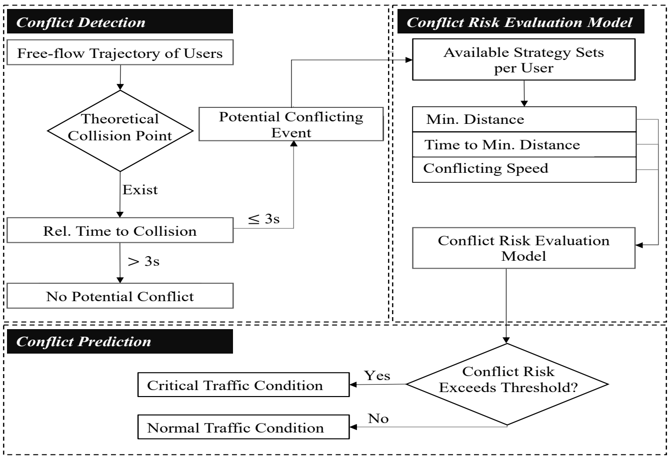


Figure 7.1: A real-time implementation of the conflict risk evaluation models. Source: [5]

selected by applying an F-score method. The cut-off point of 0.425 is chosen for the pedestrian-passenger car model, and 0.512 for the threshold of the pedestrian-light vehicle model through the p-tile method. By applying the evaluation criteria, both model thresholds showed a high predictive performance (0.890 for pedestrian-passenger cars and 0.905 for pedestrian-light vehicle models).

In the developed models, a set of SSMs are employed to address the outcome of performing different evasive manoeuvres appropriately. Due to the agile characteristics of pedestrians and in general light road users (e.g., two- or three-wheel vehicles), the prediction of their next action and associated risk is challenging. With a high degree of movement freedom, such traffic participants have a broader range of available evasive manoeuvres to solve conflict situations. From the reviewed literature in Chapter 5, it is evident that most of the previously proposed models extensively rely on measures based on the initial speed and trajectory of users to evaluate the safety level of a traffic conflict. For instance, some frequently applied safety measures, such as TTC and time advantage (TAdv) estimate the time proximity of users to a collision, assuming that the speed and movement direction remain unchanged [88]. However, this may become impractical: (1) when users deviate from their forward trajectory to avoid a conflict with the interacting user, and (2) when users decelerate to create a long time gap in arrival at the collision point. To overcome these limitations, the conflict risk evaluation models proposed in Chapter 5 utilise safety measures that would allow estimation of the users' time (TMD) and distance (MD) proximity after performing different combinations of evasive manoeuvres and explain the speed changes (CS) of users in reaction to a conflict.

The conflict risk evaluation models developed in Chapter 5 describe the collision avoidance mechanism of pedestrians interacting with different vehicle types and have the potential to be implemented in the ADAS (Fig. 7.1). In a possible real-time implementation of the conflict risk evaluation models, the outcome of the models will be estimated upon detection of a potential conflict event. Then, the determined threshold will label the model outcome as a critical conflict (when it exceeds the thresholds) or a normal traffic condition (when below the thresholds). The ADAS alert drivers for predictions labelled as critical.

7.1.4 Interaction Game

As discussed in chapter 3 & 4, the decision-making process of users in interaction depends on a broad range of factors. For this purpose, the conflict risk evaluation models developed in Chapter 5 are expanded to a game-theoretic model by including significant decision factors in the user's selection of conflict resolution strategies.

In traffic interactions —as bilateral events among involved road users— the collective strategies of interacting users determine the outcome; whether the interaction users pass the conflict zone safety or a collision/critical conflict would occur. Further, in most traffic interactions, the decisions of road users are not made concurrently but more in the form of action and reaction. These traffic interactions' properties support the logic behind the Stackelberg leadership game, where the game leader plays a strategy first, and the follower reacts to the leader's announced strategy. Both players (interacting road users) of the game intend to maximise their utilities, and the game outcome would be determined according to the strategy pair that they select.

The game utilities are formulated in three layers of safety, travel and social to cover a broad range of factors influencing the user's decision in a traffic conflict. For the safety layer, the conflict risk evaluation models developed in Chapter 5 is embedded in the game to assess the safety of conflict resolution strategy pairs employed by users. The gap acceptance behaviour of users, previously identified as a significant factor in user decisions and as a measure to determine how safe pedestrians feel about crossing [89] is reflected in the conflict risk evaluation models. However, since the user perception may not always be correct, a comparison between two temporal and spatial indicators is commonly required to quantify the safety level of a traffic decision [32, 71, 81, 36]. Besides, the initial speed of interacting road users —as another crucial factor in user' decision— as well as possible changes after performing evasive strategies are incorporated in the computation of SSMs used in formulating the conflict risk evaluation models. In the travel layer, the energy loss of different strategies is quantified in terms of the detour and deceleration associated with users' trajectory and speed changes [72, 52]. This layer assists with the better distinction between user choice of strategies during a traffic conflict, e.g., understanding how users prefer strategies such as deviation from forward trajectory to deceleration, while both strategies return similar safety outcomes. The third utility layer entails the pedestrian group size and approaching lane as two of the identified influential decision factors in traffic interactions. Besides, the priority negotiation process among the interacting users is reflected in the social level.

Similar to the conflict risk evaluation model, the proposed game-theoretic approach is estimated separately for pedestrian interactions with passenger cars and light vehicles (two- and three-wheel vehicles). A hold-out method is used for model estimation and validation. The model estimations are applied to the training samples, and various combinations of parameters are examined to obtain the optimal training results. The combination of all proposed parameters returns the best performance in both pedestrian-passenger car and pedestrian-light vehicle models, and consequently, all are utilised in the models' estimation.

The pedestrian-passenger car model with a misclassification rate of 16.7% shows a good performance reflecting the user decision-making process in the shared space (with respect to the performance of previously proposed predictive modelling approaches for road user behaviour in the literature, such as [90], [91], and [92]). Concerning the mid-block crossing model, the misclassification rate is 34.2% for the pedestrian-light vehicle model. This performance considers satisfactory given the user behaviour in the studied location and the wide range of factors impacting the user decisions, such as high traffic volume, road design, traffic behaviour, size of vehicles, and driving culture. Furthermore, the methodology used shows that the models can be applied in different traffic setups (e.g., mid-block crossing, shared spaces), traffic patterns (e.g., different user types), and traffic behaviour (i.e., user traffic behaviour in different countries).

As such, Chapter 6 describes the development of a game-theoretic approach to predict the conflict resolution strategies of users in interaction. The proposed approach has the potential to be used as a behavioural model for ADS and improve pedestrian safety, particularly at uncontrolled traffic settings.

7.2 Limitations & Directions for Future Research

This section is classified into two groups: (I) limitations of traffic interaction research and modelling, and (II) recommendations and directions for future work. While the former focuses on strengthening the methodological framework, the latter provides ideas for developing a more suitable and realistic traffic interaction concept for the future of mobility.

7.2.1 Limitations

Modelling pedestrians interaction with ADS faces significant challenges. The following describes the major limitations in the development of pedestrian-ADS interactions model in this dissertation.

In this dissertation, the models are developed using the pedestrian-vehicle interaction data collected at different uncontrolled crossing areas (i.e., a shared space and mid-block crossing area). Although a significant number of conflict events are analysed for model development purposes, the data includes the conventional form of traffic interaction among users. As discussed earlier in Section 7.1.2, the user behaviour may change with the appearance of large-scale fleets of automated vehicles on the road, or possibly over the long use. Furthermore, adjusting infrastructure to the new modes of transport (i.e., vehicles of different automation levels) may lead to a new form of traffic interactions in which currently identified influential factors of the pedestrian's decision-making process may no longer be relevant. These unresolved issues create a knowledge gap in the existing pedestrian-ADS interaction research and inevitably restrain a precise prediction of the user behavioural changes in the future of mobility.

Further, the models developed within this dissertation consider a set of available conflict resolution strategies per user type:

- Continuing along the free-flow trajectory with constant preferred/current speed. This strategy is applicable for all user types.
- Deceleration by reducing the current speed and by moving along the free-flow trajectory. This strategy is applicable for all user types.
- Deviation from the free-flow trajectory with constant preferred/current speed. This strategy is only applicable for lighter road users (i.e., pedestrians, two- and three-wheel vehicles).

However, in real-world traffic interactions, road users can perform a broader range of evasive manoeuvres to avoid a conflict on the road. For instance, pedestrians may run into the roadway, execute unexpected changes in their movement directions, or suddenly stop at any point of crossroads. Such unpredictable behaviours per se can be hard to impossible to incorporate in the behavioural modelling approaches. Therefore, the conflict resolution strategies of road users are limited to the above-mentioned categories in the model developed within this dissertation. In addition, the deviation strategy of users is considered with no speed changes. This assumption is sometimes in contradiction with the user behaviour in real-life traffic interactions, in which they deviate from the forward trajectory with reduced/increased speed (in comparison with the current speed). Yet, the assumption is made in the model development to simplify the interaction model and avoid generating a computationally expensive algorithm. This research suggests future studies to focus on solutions to tackle computational problems while incorporating a broader range of conflict resolution strategies available per user type.

Finally, the Stackelberg game, utilised for modelling pedestrian-ADS interactions, assumes that game players (i.e., interacting road users) are rational and try to maximise their payoffs; however, this may not always be the case in traffic interactions. As mentioned in the previous paragraph, road users may behave irrationally or make unsafe traffic decisions in interaction with vehicles. Unexpected running into the roadway while the available time/distance gap with the approaching vehicle is not sufficient in an example of such behaviours. Besides, some external factors, such as distraction or alcohol/drugs impairment, can cause users to perform irrational behaviour. In such cases, users are no longer active players in the interaction process. Therefore, in future works, the model can be improved by adding an element of randomness that can explain some phenomena where players do not behave in line with the rationality assumptions of the game theory.

7.2.2 Recommendations and Future Work

Eventually, additional work is necessary to further improve the design of the framework for modelling pedestrians interaction with ADS. Therefore, this section provides recommendations for follow-up studies besides the suggestions to overcome the above-stated limitations that restricted the development of the interaction model in this dissertation (see Section 7.2.1).

Further Research on Pedestrian Behaviour in Interaction with ADS: There is still no established methodology to explain and identify all aspects of pedestrian behaviour on the road. Several studies have investigated the behaviour patterns of pedestrians in interaction with partially/fully automated vehicles by using different data collection approaches, e.g., real-life exposure of automated bus shuttles, simulator-based, Wizard-of-Oz, and survey-based techniques. However, most of the reviewed research (Chapter 3 & 4) focus on limited aspects of pedestrian behaviour, perform with relatively small sample size, or potentially produce culture-specific outcomes. To overcome this limitation, the current study employed the most dominant decision factors identified in the literature. Yet, the following recommendations can be considered for further model development:

- Further studies are required to investigate how the vast existence of automated vehicles in the public realm can alter pedestrian behaviour and thoroughly understand the influencing factors applicable within the ADS conceptual framework.
- Some of the influential decision factors are hard for the current stage of ADS development to process and neglected in the model development. For instance, pedestrian age and gender. Nonetheless, if still applicable in the pedestrian-ADS interactions, such pedestrian-associated information can be incorporated in future models.
- Some decision factors, such as personal characteristics, culture, and traffic experiences, may not be possible to embed even in the future advancement of automated technologies. However, if still relevant in the pedestrian-ADS interactions, traffic education and road safety awareness programs can be provided to improve the user's knowledge and attitudes for safe traffic interactions with ADS.

Extensive Data on Traffic Interactions: The models developed within this dissertation demonstrated good performance on two different types of crossing facilities with substantial differences in user behaviour, verifying the transferability of the proposed models. Yet, an extensive data analysis of various traffic settings in different locations is required to build a more suitable and realistic model. Utilising diverse interaction data can assist researchers in developing a behavioural model that precisely reflects user behaviour in uncontrolled traffic environments and is widely functional.

Further Model Testing and Validating: The interaction model in this research and its capability in various traffic contexts can be tested by using the multiple participant simulator (MPS) technique [21]. The MPS utilises two or more separate —but physically connected— simulators and provides the same virtual environment for simultaneous interactions among participants [27]. The MPS techniques provide a safe and controlled synthetic environment for testing the capability of the developed models in various traffic contexts —which was not feasible within the scope of this dissertation.

This research suggests future works to focus on further model testing and validation since it is essential for improving the model performance.

Expansion of the Modelling Framework: The final recommendation is regarding the implementation of external communication cues to facilitate the pedestrian-ADS interaction process. According to the reviewed literature in Chapter 4, automation technologies should be adjusted to the elaborated communication methods road users employ to avoid confusion and frustration. One significant aspect of the eHMI implementation is the question of when eHMI cues should be used. This question has received the least attention in the literature since most studies focus on the efficiency of various eHMI cues without addressing the issue of how the pedestrian-ADS modelling approaches are used in combination with eHMIs. This requires further research to investigate how a combined eHMI and modelling approach can manage the pedestrian-ADS interaction process. The combined eHMIs with the ADS behavioural models can assist with handling ambiguous traffic circumstances in which interacting human road users behave unexpectedly/irrationally, such as standing still to block the vehicle's path. In such traffic situations and when user behaviour prediction fails, additional information can be provided for the interacting users through the eHMI channels to manage unexpected behaviours. The combined behavioural model with eHMIs can lead to a fully developed interaction concept, in which ADS understand the intentions of their interaction road users, perform suitable automated driving manoeuvres, handle users' irrational/unexpected traffic behaviour, and consequently fulfil the role of safe and efficient traffic participants in the future of mobility.

8 Conclusions

This doctoral dissertation consolidates the research by Ezzati Amini et al. [16] (Appendix A), Ezzati Amini et al. [12] (Appendix B), Ezzati Amini et al. [5] (Appendix C), and Ezzati Amini et al. [6] (Appendix D), focusing on pedestrian interactions with ADS at uncontrolled traffic environments.

Within the context of the presented research, traffic interactions are understood as situations in which traffic participants compete over the same road space and adapt their behaviour according to one another while analysing the environmental context and surrounding traffic. The research, as mentioned above, explored the conventional form of pedestrian interactions with vehicles [16], identified influential decision factors of road users and communication methods employed to accommodate the interaction process [16], investigated the future of the traffic interactions when automated vehicles operate on the road [12], and provided outlines for modelling pedestrian-ADS interactions [16, 12]. Said research showed that a fully developed concept of interaction is required to resolve possible ambiguities and conflicts in pedestrian-ADS interactions. This is particularly crucial for the wide diffusion of ADS, in which different user types will have to coordinate their movements for an efficient and safe interaction.

High expectations have been placed on ADS for substantially improving safety and efficiency on the road, through elimination of human errors. On the basis of existing literature; however, ADS are not yet able to match the high level of elaborated interaction strategies among road users in complex traffic scenarios. This drawback may lead to erratic behaviours of ADS towards pedestrians, generating hazardous traffic situations/conflicts, confusion among pedestrians interacting with ADS, and negative impact on the efficiency of ADS and the traffic flow.

In this dissertation, a game-theoretic approach is proposed to model pedestrian-ADS interactions and predict their conflict resolution strategies in uncontrolled traffic settings. The proposed models [6] employ a variety of factors influencing the decision-making process of users in three layers: (1) the *safety layer* to assess the safety level of conflict events after performing various conflict resolution strategy pairs by road users, and by developing conflict risk evaluation models to identify the hazardous traffic conditions between pedestrians and vehicles [5], (2) the *travel layer* to reflect the comfort level of executing various evasive manoeuvres on the road, and (3) the *social layer* to cover environmental factors influencing the conflict resolution decisions of users in conflict. The models are developed and estimated separately for interactions of pedestrians with passenger cars and light vehicles using data of shared space and mid-block crossing areas. The developed models indicate satisfactory performance and can potentially be used as a behavioural model for the ADS. The proposed modelling framework can enable the ADS to make more informed decisions during traffic interactions, have dynamic interactions with pedestrians, and react adequately to their actions when required. The dissertation is, thus, hoped that the presented modelling framework facilitates and encourages further studies.

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A Ezzati Amini et al. (2019). Negotiation and Decision-Making for a Pedestrian Roadway Crossing: A Literature Review

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Review

Negotiation and Decision-Making for a Pedestrian Roadway Crossing: A Literature Review

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Abstract: The interaction among pedestrians and human drivers is a complicated process, in which road users have to communicate their intentions, as well as understand and anticipate the actions of users in their vicinity. However, road users still ought to have a proper interpretation of each others' behaviors, when approaching and crossing the road. Pedestrians, as one of the interactive agents, demonstrate different behaviors at road crossings, which do not follow a consistent pattern and may vary from one situation to another. The presented inconsistency and unpredictability of pedestrian road crossing behaviors may thus become a challenge for the design of emerging technologies in the near future, such as automated driving system (ADS). As a result, the current paper aims at understanding the effectual communication techniques, as well as the factors influencing pedestrian negotiation and decision-making process. After reviewing the state-of-the-art and identifying research gaps with regards to vehicle–pedestrian crossing encounters, a holistic approach for road crossing interaction modeling is presented and discussed. It is envisioned that the presented holistic approach will result in enhanced safety, sustainability, and effectiveness of pedestrian road crossings.

Keywords: pedestrian behavior; vehicle–pedestrian interactions; road crossing; decision-making process

1. Introduction

Participating in traffic requires road users to continuously interact with one another [1]. During the time spent for transport, traffic participants have to face a great amount of information and react efficiently to it [1–3]. In such a system, it is essential for road participants to manage their own moves, while taking into account the presence of other users, as all of the participants usually share a pre-defined space [1]. These mobile encounters entail a continual monitoring and communicating of users' positions with regards to one another, along with suitable reactions to the features associated with the surroundings [4]. Furthermore, traffic safety in urban settings heavily depends on successful interactions among traffic participants [5]. For this reason, fundamental traffic rules have been established to manage traffic, especially in vehicle–pedestrian encounters. The traffic management and control systems can diminish the conflicts and uncertainty by specifying the right of way for different road users (e.g., traffic rules imposed by different phases of traffic signals at signalized intersections). Road traffic, however, involves many circumstances for which it may not be possible to specify explicit rules [6], such as a sudden change of direction by pedestrian, while crossing the road. Hence, traffic participants and particularly pedestrians extensively rely on communication methods, elaborated over the course of time amongst them, to avoid conflict and solve ambiguous traffic situations [7]. For instance, hand gestures by drivers to convey the message "it is safe to cross" to pedestrians, while there is no traffic control systems on the road segment. The role of these communication cues is dominant in situations in which the right of way is not clearly defined [8], or road users expose unexpected traffic behaviors [9]. In these circumstances, road users employ explicit and implicit signals to communicate their intention regarding either gaining or giving the priority in the crossing scenarios. However, sometimes pedestrians are engaged in multi-tasking (such as mobile-phone conversation, texting, listening to music, reading), and are therefore not able to communicate their movements/intentions with the interacting party. Such behaviors have not been captured in this paper, as the focus is on traffic interactions as a bilateral process among involved road users. In addition to communicating intended movements, traffic interactions require road users to properly interpret and predict the actions of their interactive party. However, this may become problematic in some situations since traffic participants demonstrate different behaviors on approaching the crossing sites. Previous studies have investigated a broad range of factors that may affect the behaviors of road users, namely drivers and pedestrians, on approaching the crossing sites, such as pedestrian walking speed and characteristics, speed of approaching vehicle, road characteristics, etc. [10–14].

Moreover, mobility technologies have been constantly changing in the recent years, as more and more vehicles will have automation functions in the imminent future [15]. The changes of transportation means have inevitably led to an adjustment of road designs, and a new set of rules and social norms emerging to manage the mobility of traffic participants [16]. Since fully automated vehicles will be integrated into the existing transportation system, the interaction with pedestrians becomes challenging in cooperative situations (e.g., when road users require sharing their intentions to communicate the right of way, or to coordinate their reactions) [5,17–21]. This is primarily related to the absence of a human driver in vehicles and thereby an absence of driver cues in vehicle–pedestrian communications, which may decline the trust and confidence of pedestrians [22–25]. To overcome these limitations, the intentions of such vehicles need to be clearly transmitted to other traffic participants [24]. In addition, ADS must have a proper understanding of pedestrians' behaviors and their decision-making strategies to execute appropriate driving maneuvers [8]. The complexity of crossing strategies performed by pedestrians, and difficulty to thoroughly analyze their decision-making process, have also engendered challenges in designing ADS [5,8], insomuch that human road users may act differently from the system's presumptions [16].

The main focus of this paper, therefore, is to review the previous findings of crossing behavior studies in order to investigate how pedestrians negotiate the road crossing with motorized vehicles and make decisions at crossing sites, in which the right of way is not determined by formal traffic rules or road designs. A proper understanding of these matters can provide useful recommendations for designing the ADS, and ensuring a safe, smooth, and efficacious interaction process amongst pedestrians and vehicles [5]. The paper is intended to provide in-depth insights into the following issues:

1. The efficiency of different communication techniques and their impact on behavior of road users have been investigated thoroughly in this paper by reviewing previous studies. How road users react to various communication signals, how a signal is interpreted by receiver, which methods road users choose to communicate their intentions, and how they send the signal are substantial components of traffic communications. An in-depth examination of these elements can assist ADS in forming efficient communication methods with pedestrians.
2. Factors influencing crossing behaviors of pedestrians have been reviewed in order to understand why pedestrians behave differently from one situation to another while crossing the roadway. Since understanding of pedestrians' behaviors is not intuitive [7], a comprehensive analysis of decision-making procedure and factors influencing them is required for the design of ADS [17].
3. The vehicle–pedestrian interaction process includes movements/intentions communications, as well as decision-making processes of interactive parties which are reflected in their crossing behaviors. A vast number of studies have been performed to assess different aspects of vehicle–pedestrian interactions; however, the focus on the entire process has been mostly disregarded due to the complexity of the subject. This is crucial as ADS requires an appropriate

interaction concept for driving safely in urban environments [5]. Therefore, formulating the whole interaction process in the existing traffic context, by considering the role of different communication methods and users' crossing strategies, is vital for designing efficient ADS and external human–machine interfaces (eHMIs).

The paper is structured as follows: Section 2 includes the fundamental definitions, while Section 3 provides an overview of the potential conflict points of pedestrians with vehicular traffic. The interactive parties in various crossing scenarios, presently only human road users, interact with one another by a variety of verbal and nonverbal communication means. These traffic communication methods used by road users on approaching the crossing sites are reviewed in Section 4. The employment of different cues and their impact on the yielding behaviors were also investigated in this section. In what follows, previous studies of crossing behaviors at unmarked/unsignalized crossing sites are reviewed. For this purpose, the behavior of drivers and pedestrians on approaching different uncontrolled pedestrian crossing facilities has been explored in Section 5, to identify factors influencing their crossing-decision strategies.

2. Definitions

Traffic Conflict is defined as an event between traffic participants, in which an evasive maneuver needs to be taken by one of them to avoid a collision [26].

Jaywalking is a term used to describe the action of crossing a road with no regard to the pedestrians' traffic regulations [27].

Traffic Interaction is defined as situations in which the traffic participants adapt their behaviors according to one another [28], as well as interpreting the environmental context, surrounding traffic, and responses to one's own behavior [29,30].

Pedestrian Gap Acceptance (GA) refers to the time or space gap between vehicle and pedestrians [31], and can be determined based on the speed of oncoming vehicles, as well as its distance from the pedestrian crossing [11].

Post-Encroachment-Time (PET) value can be used to describe the time gap, from the moment that one of the interacting road users leaves the potential collision point to the moment another user arrives at it [32].

Time-To-Collision (TTC) value is the time between approaching road users and the potential collision point [33], and can be used to describe the severity of conflict events [32].

Time-To-Arrival (TTA) estimation can be used to evaluate the time gap perception between approaching vehicles and the own position/a person/specific place [10,34].

Time Advantage (TAdv) as an indicator describes the expected PET value for each moment, considering an unchanged speed and paths of road users [35].

3. Vehicle-Pedestrian Safety Considerations

Most vehicle–pedestrian collisions occur when pedestrians cross the roadway illegally at locations out of crosswalks, or at pedestrian crossing facilities particularly with lower protection [36–39]. Traffic participants may not comply with formal traffic laws for reasons, such as lack of sufficient knowledge about the rules in specific situations or the ambiguity of rules, which may be understood differently by users [40,41]. Some of the traffic rules may also not perfectly correspond to the road design or the natural human behavior patterns [40]. Dey and Terken [42] claimed that the lack of strict enforcement like traffic lights at uncontrolled pedestrian crossings may result in disregarding users' right of way by drivers. In a similar manner, in the absence of crossing facilities in a road segment, pedestrians may adapt mid-block crossing and jaywalking, in order to avoid detour and shorten the travel time (instead of walking an additional distance to a crosswalk) [42–45]. Such unpredictable crossing behaviors by pedestrians create a potential critical conflict with approaching vehicles, as well as interrupting the normal traffic flow [46]. However, the majority of road users interact without any serious conflict and are therefore of little/no interest from a traffic safety point of view [16]. The interactions may be important from the user experience perspective, which may result in unpleasant interaction experience, and therefore encouraging/discouraging specific behaviors or road designs [16]. In addition, pedestrians are notified of the spots to cross the road by marked crosswalks and signs, but there is still no standard agreement for them to indicate their crossing decision intention in advance of drivers, besides standing in/at the crosswalk [47]. However, pedestrians stepping into the roadway, or signs and markings may induce drivers to give way to pedestrians at crossings, but there is still no effectual and certain prompt that a pedestrian, who has commenced crossing, can use to enhance the possibility of a driver yielding [47–49], since there are still some situations in which drivers do not give way to pedestrians who stepped into the street. For instance, an observation study on zebra crossings showed that about 30% of pedestrians continued walking when the vehicle was approaching, and the vehicle took the evasive action to avoid collision [13], whereas, in 4% of the situations, the pedestrians either retreated or ran from the path of the vehicle to avoid collision [13]. Occurrence of the aforementioned scenarios signifies the necessity for utilizing some additional techniques by road users to communicate their movement intentions in advance of the interacting party. Therefore, a variety of communication methods, which are mostly based on the human communication principles, have been developed between human road users in order to avoid conflict and resolve ambiguity regarding the right of way.

4. Communication between Traffic Participants

Communication is an essential element of traffic interactions, as it assists human users with resolving ambiguous circumstances on the road [50]. Traffic participants communicate a range of actions regarding their intended movement, such as going straight, stopping, and going ahead of someone [51]. For an efficient communication, the interacting parties need to understand the intentions of one another, as well as the situation in which the communication is occurring [52]. Since it varies from one situation to another and it always depends on the circumstances [21], this also requires communicators to anticipate each other's future actions [7,21,52]. However, anticipations and expectations concerning the other's behavior may not always be correct [53]. The situation may also become problematic when traffic participants behave according to contradictory formal and informal traffic rules, in which the traffic participant's ability to rightly anticipate another user's behavior declines [53,54]. Traffic interactions are also relatively short, which limits the opportunities to communicate among traffic participants [37]. This may oftentimes lead to misunderstanding and misinterpretations and thus annoyance amongst participants [37]. Furthermore, the need for social interaction among drivers, cyclists, and pedestrians is more substantial in urban traffic [50], and mostly occurs in the front and the side of the car [25]. The actions employed by interactive parties to convey their movement intentions can be classified as different communication methods, as discussed in the following subsections.

4.1. Anticipatory Behaviors of Traffic Participants

Anticipatory behaviors are minor activities performed by road users that make others able to predict their intentions [6]. Examples of such behaviors include changes in walking speed or placing a foot on the road, which in general helps drivers to anticipate a potential crossing intention for a pedestrian [6,10]. These behaviors are classified as one of the informal and non-regulated communication methods among road users to anticipate what action another user may possibly do [10]. Another anticipation of traffic participant's behavior is associated with the physical characteristics of communicators. This communication signal is the same as what is named "schema formation" by Merten [55] in grouping different communication choices. For instance, the physical traits of pedestrians can give drivers clues about their age and their mobility behaviors, while elderly pedestrians may walk slower than younger ones [6], or children may have more unpredictable behaviors than adults. Pedestrians can also utilize the same available information on the road about the vehicle's model/category, e.g., the driver of an ambulance may behave differently from a van driver [6].

4.2. Human Driver Communication Methods in Interaction with Pedestrians

Drivers anticipate the intentions of other road users by interpreting various nonverbal communication cues. This is mostly presented among drivers and pedestrians, while negotiating right of way [20]. Although the decisions of drivers are affected by the traffic regulations on the road, there is still some uncertainty in circumstances, where the traffic laws are not sufficient [56]. These situations can occur at uncontrolled intersections, transition of traffic signals, merging/changing lane, multi-lane roundabouts, etc. [56]. From the vehicle's point of view, communication style can be classified as implicit and explicit [12,21]. These terms are defined below:

- ***Implicit Communication*** (also referred as informal communication): In general, when the content of a message is indirectly included in that instead of clearly being stated, then the message is conveyed implicitly [21]. In terms of traffic, implicit communication refers to using non-regulated communication cues to negotiate the driver's intention, or to help communicators to anticipate future actions of them, e.g., deceleration to encourage the pedestrian to cross [10,21,57].
- ***Explicit Communication*** (also referred as formal communication): A message is transmitted explicitly, if the sender transfers intention directly to the receiver by using clear cues [21]. In traffic situations, explicit communication usually refers to using light and sound signals to communicate the intention of vehicles [21]. Explicit communication includes defined/regulated communication means. Horn, turn indicator, emergency lights, warning lights, brake lights, and even labelling a car (as an ambulance, automated vehicle, police, etc.) are examples of this type of communication [6,21,53]. Nonverbal behaviors are usually used to transfer implicit messages; however, in traffic, nonverbal communication methods are used for sending explicit messages [58,59]. Hand gestures executed by drivers to signal pedestrians that they can cross in front of the car safely, or expression of gratitude to a fellow driver by waving a hand are examples of explicit cues performed by drivers in traffic encounter [6].

4.3. Pedestrians Communication Methods in Interaction with Drivers

Pedestrians mainly interact with other road users by using nonverbal communication signals. However, in some situations, the message transferred via nonverbal cues is missed, ignored, or not correctly comprehended by the interacting party [60]. The main nonverbal communication signals used by pedestrians are:

- ***Gaze Direction***: The most significant message that is essential to be transferred to pedestrians is whether they have been seen [6]. Therefore, in the crossing scenes, they mostly establish eye contact with drivers or wait to receive an explicit cue from them to confirm that they have been detected, and the driver will yield if they start crossing [6,61,62]. If the driver who receives the signal returns the eye contact, then pedestrians presume that they have been seen [63]. Moreover, head orientation, which occurs with the purpose of looking or glancing at the approaching traffic, can be a robust sign of crossing intentions by pedestrians [64]. However, traffic participants behave differently in the various traffic settings [64]. For example, pedestrians intending to cross a road are more likely to cross without looking at the oncoming traffic in the presence of traffic signals and stop signs, since they expect drivers to obey the traffic rules [64], whereas, in the absence of traffic regulations, they frequently monitor the approaching traffic and mostly establish eye contact with the driver to assess the environment and whether the driver may give way [64,65].
- ***Hand Gesturing***: Gestures are described as efficient nonverbal signals amongst road users, which are mostly interpretable and explicit [6,66]. However, the concept of the message transferred by using this kind of signals can vary from situation to situation. For example, hand gesturing

can show thankfulness, giving priority, or requesting the right of way, while the responses are in the form of changes in pedestrian behavior like deceleration, acceleration, or stop [64,67,68]. According to previous studies of driver's interaction with the environment, three fundamental dimensions have been defined to evaluate a signal: visibility, clarity, and motive power [66,69]. From the visibility point of view, gesturing a dynamic signal is found to stand out more than traffic signs and road markings, since driver's attention is more easily caught by moving rather than static objects [70]. Clarity, on the other hand, varies across gestures, as some are more effective than others. Finally, driver compliance may vary according to the concept of the gestures, i.e., whether they are commanding or polite [66]. This can reflect compliance obtaining strategies through "assertion" and "direct request" [66,71].

4.4. The Impact of Communication between Road Users on Traffic Behaviors

Road users communicate with each other through various unregulated methods, which include their movements and positioning, as well as establishing eye contact. According to previous studies, these interactions have a vital role in forming a smooth and efficient traffic flow, as well as improving safety [7,21,25,50,72,73]. Road traffic is fundamentally directed by a range of official regulations, which define the right of way for traffic participants in various road designs and facilitate social interaction [37]. Furthermore, in many countries, drivers give way to pedestrians to protect them at pedestrian crossings or unregulated crosswalks [66]. However, drivers may be more likely to conform with the official traffic control regulations rather than gesturing or gazing cues displayed by pedestrians [74]. Road users, particularly drivers, may also receive informal communication signals from authorized traffic directors, which is mostly by means of hand gesturing [75]. On the other hand, pedestrians may employ nonverbal communication indicators only when an expected driving behavior of an oncoming vehicle has been contravened [42]. In these situations, pedestrians are looking for a confirmation of intent from the drivers before carrying out their crossing decisions [42], while most drivers give way to pedestrians who have already stepped into the street, but there are still some drivers who ignore the pedestrian's right of way, and speed up or swerve to pass them at crossings sites [76]. For example, an observation on Columbus, Ohio showed that the majority of drivers never came to a complete stop, and 43% of them did not stop with pedestrians walking in the crosswalk [76]. Another study revealed that more than a third of drivers (36%) failed to yield to pedestrians at uncontrolled marked crossings [53].

In the process of negotiating priority in driver–pedestrian interactions, either pedestrian or driver has to give way. Pedestrians give way to drivers by making the roadway clear for them to cross by, for example, waiting at the curb or stepping out of the road. On the other hand, a driver yields by; (1) a reasonable complete stop (hard yield), (2) delaying vehicle arrival at the crosswalk enough to create a crossing opportunity for the pedestrian (rolling/soft yield), and (3) slowing down and eventually stopping for an extended duration before restarting movement (hard yield and stop) [46,48]. In hard-yield conditions, the driver is usually too close to the crosswalk during a crossing activity and must stop momentarily, while soft-yield is a condition based on the driver's observations and anticipations of pedestrian action [46]. On the other hand, pedestrians cross the roadway first in three circumstances: (1) before the arrival of the vehicle and without influencing its speed, (2) when the oncoming car is motivated to stop by a pedestrian who does not stop before crossing, and (3) when the approaching vehicle brakes on the driver's own initiative to yield to pedestrian (ideal situations) [32]. Such [37] classified eye contact as a means of communication for both drivers and pedestrians at crosswalks considered by pedestrians when deciding to wait/go, and by drivers as a way to force pedestrians to stop. A study to assess the influence of pedestrian's gaze on driver's yielding behavior at pedestrian crosswalk showed that gazing increased the number of drivers who gave way to pedestrians [77,78]. In contrast, another research paper indicated that nonverbal communication signals, such as eye contact and gestures, do not play a significant role in crossing negotiation [42]. Another experimental study criticized the possibility of performing mutual eye contact between pedestrians and drivers [79]. The results showed that over 90% of the participants cannot determine the gaze of the driver at 15 m and see the driver at all at 30 m. The authors then argued that, considering the speed limit of 25 mph in urban settings, more than 99% of pedestrians would have begun crossing, before being able to see either the driver or the driver's gaze. An experimental study performed in Beijing, China evaluated the impact of various pedestrian hand gesturing on driver yielding rate at non-signalized crossings, which showed a slight increase in the overall yielding rate among drivers when pedestrians performed hand gestures [66]. The same study in the US also showed greater yielding rates at uncontrolled marked crossings when pedestrians displayed hand gestures, compared with not using hand movements [47]. Most of these informal traffic rules and communication methods are developed through traffic participants' interactions, and based on expectations about other participants' behavior, mostly when formal traffic rules do not correspond with the road design [40]. The expectation about the behaviors of other interacting agents can be formed due to the chosen strategies or transferred communication signals. However, the interaction strategies executed by road users may be influenced by various factors, such as interaction environment or road users' characteristics, and need to be correctly interpreted.

5. Crossing Behaviors of Traffic Participants

Traffic participants manifest varied behaviors on approaching a crossing site. Drivers, as a party in the interaction with pedestrians, have several strategies to decide whether or not to give way to pedestrians. These strategies are subject to several factors, such as speed of the vehicle on approach, or its distance to the common spatial zone with pedestrians. Zaidel [80] discussed that every driver is influenced by social environment factors, including other traffic participants, general social norms, and formal traffic rules. Every traffic participant is also a part of other participants' social environments [80]. Social environment can influence drivers in four different ways: (1) communication with other participants, (2) behaviors of other participants as a source of information, (3) other participants as a reference group, and (4) emulation of others. Another common strategy utilized by drivers to coordinate their behavior is "movement pattern", showing how road users communicate their intentions through their movements [81]. For example, on approaching crosswalks, drivers stop before where they legally must, signaling their intent to wait for others to take the right of way. Then, they move forward slowly to indicate that they will take the right of way next [81]. In addition, the meaning of road users' actions can only be comprehended in the context of their occurrence [81,82]. Therefore, the meaning of the actions of a single road user cannot be understood by looking at the actions alone, and must be interpreted by considering the whole road system, containing road users, road geometry, etc. [81,82].

On the other hand, it is important to understand under which circumstances pedestrians feel safe to cross, and which factors influence their crossing-decision strategies. Pedestrian crossing behaviors are oftentimes accompanied by some sort of signals and information to indicate their crossing intentions to the approaching vehicle, such as forward movement, stepping into the road, leaning forward, putting one foot on the road, looking at oncoming vehicle, informal signals, etc. [81]. Distance between agents, as a result of movement, also influences pedestrians' expectations regarding the other traffic participants' behavior [83]. In addition, pedestrians cross the roadway in different ways, based on the speed of oncoming vehicles, available gaps, and number of lanes: (1) single stage, (2) two stage, (3) and rolling [43]. Pedestrian crossing behavior can also be classified into three phases: (1) approaching (without changing the walking speed), (2) appraising (decelerating due to the speed and distance of approaching vehicles), (3) and crossing (acceleration) [84]. It is also possible for a pedestrian to step backwards or run to avoid collision with vehicles, when the gap is not long enough to complete the crossing [36]. However, the majority of pedestrians waits before crossing, until the vehicles come to a complete stop, instead of relying on their own perception of whether it is safe to cross [53]. The factors, identified in the literature, influencing the crossing behaviors of users are presented next:

5.1. Pedestrian-Associated Factors Influencing Crossing Behaviors

5.1.1. Pedestrian Characteristics

Age is one of the factors influencing pedestrian behavior, meaning that people of different age groups may have various crossing behaviors. Road crossing is a challenging cognitive task, which makes safe traffic judgements difficult for children younger than 9 years old. It may even take until the age of 11 or 12 for children to fully develop all required abilities and gain an adequate understanding of the concept of traffic rules [85,86]. In addition, the lack of experience among young children in crossing roads can make them incapable of making safe decisions, and therefore is a concern for roadway designers. This is along with unpredictable behaviors, inattentiveness, and problematic risk perception, which have been found to be the leading reasons for child pedestrian accidents [85–87]. On the other hand, older pedestrians demonstrate more conservative behaviors in comparison with younger people [10]. For example, the percentage of pedestrians 65 years and older crossing on red phase is notably lower than the percentage of younger pedestrians [88]. However, physical conditions of elderly pedestrians restrict their abilities to precisely judge the traffic situation and speed of approaching vehicles, and lead to difficulty negotiating curbs, and excessive start–up time before leaving the curb [86,89]. Bennett et al. [90] observed different average of start time loss of 2.68 s and 1.3 s for all groups of pedestrians at signalized intersections and controlled mid–block crossing sites, respectively. The start–up time to initiate the crossing is also higher among distracted pedestrians than non-distracted pedestrians [91]. On the other hand, middle-aged adults are found to be more aware of the traffic environment by looking at oncoming traffic more frequently before crossing the road, having a larger safety margin, and better perspective skills [36]. Alcohol impaired pedestrians (in the 1980s, around 44% of killed/injured pedestrians had BACs (Blood Alcohol Concentration) of 10% or greater) and pedestrians with physical disabilities also have different behaviors due to the mobility impairment [92].

Pedestrians' behaviors can be also different because of their gender. For example, females seem to wait longer during the red phase of signalized crossings before attempting illegal crossing than males [93]. Female pedestrians may also demonstrate less risk-taking behaviors at crossings, compared with males [13,94]. In contrast, another observation of pedestrian behavior at crosswalks exposed no difference between female and male risk-taking behaviors while crossing [95].

5.1.2. Pedestrian Walking Speed

One of the most fundamental elements of human movement behavior in urban spaces is walking speed, as it is a dominant parameter of most microscopic simulation models, and which can be affected by individual pedestrian behavior and habit [14,96]. Walking rates vary among different studies [14,86,92,97]. In accordance with Manual on Uniform Traffic Control Devices (MUTCD), the average walking speed for typical groups of pedestrians is 1.22 m/s, suggested as a basis to evaluate the sufficiency of the pedestrian clearance interval at traffic signals with the possibility to extend the phase for slower pedestrians by pressing a push-button [92,96,98]. The recommendation for the design of traffic signal timing without an actuator is lower—0.91 to 0.99 m/s [99]. However, pedestrian crossing speed may also vary for different countries, for instance a study showed 1.53 m/s for the average of crossing speed at intersections and mid-block crossings in Melbourne, Australia [90], the average of 1.34 m/s in Jordan [100], 1.39 m/s at non-signalized crosswalk in Malaysia [101], and 1.4 m/s as the design speed by the Turkish Standards Institution [102].

Walking speed declines by increasing age, as a study showed an average walking speed 1.53 m/s for pedestrians younger than 16 years old, while 1.16 m/s for those older than 64 years old [14,103]. In addition, the elderly, pedestrians with disabilities, and those pushing baby prams or walking along with younger children tend to walk at slower speeds [14]. Different walking speed can be also related to the gender, as some studies showed that, on average, males walk faster than females [96,104]. The group size can be another factor influencing the walking speed, since people in a group of two or more walk slower than individuals and take longer to complete the crossing process [14,46,104,105]. It is also found that environmental factors, such as weather, time of day (slightly higher during the morning and evening peak period), type of facility, and the overall function of pedestrian area (e.g., shopping, school, business) also affect the walking speed of pedestrians [14,106]. For example, pedestrians walk faster at signalized intersections than the mid-block locations [90], when crossing roadways than walking in a footpath [14,107], or when the traffic volume is high [104,108]. This might even turn to running in some circumstances: at signalized crosswalks to use the limited green-light phase left to traverse the roadway, or at uncontrolled unmarked crossings or illegal sites to traverse the road from the start of the lane to its end before arrival of approaching vehicles [36,109]. The latter one may cause a new independent crossing task for pedestrians at each lane requiring a new evaluation of the traffic situation and possibly adjustment of the crossing manner, which may again change their walking speed.

5.1.3. Pedestrian Group Size

The size of pedestrian platoons is associated with both pedestrian crossing behavior and driver yielding behaviors. As the number of pedestrians waiting at crosswalks increases, the likelihood of drivers' yield increases. The probability of yielding is two times greater, when the number of pedestrians waiting increases from three to six persons, since a big group captures more attention of drivers for yielding than smaller groups [11,53,110]. It has also been found that the possibility of a group of four pedestrians continuing to traverse crosswalk is 70% higher than individual pedestrian [13]. This also enhances safety of pedestrians, as pedestrians in groups are more detectable [36]. Due to the frequency of crossing, smaller pedestrians' platoons cause more traffic interruptions and higher cumulative delay, and consequently driver inconvenience compared to bigger platoons, which cross at once [46]. Analyzing the impact of pedestrian platoons on yielding rate at illegal mid-block crossings also revealed that the rate of "hard-yield and stop" increases significantly by increasing the size of groups. This shows that pedestrians in groups require longer crossing time, which might not be provided by rolling/soft yield. Hence, drivers have to stop approaching the crossing points, which may trigger a traffic wave and last until pedestrians cross. As a result, drivers may slow down proactively on approaching a crossing point in anticipation of a pedestrian crossing maneuvers, particularly if there is a pedestrian platoon waiting by the roadside [46,111]. Moreover, it is observed that the waiting time of pedestrians at zebra crossings reduces by increasing the number of pedestrians at crosswalks [94].

5.1.4. Pedestrian Presence at the Curb

The only possible way for pedestrians to indicate their crossing intention is to stand at the curb side [47]. However, studies showed that the presence of pedestrians at the curb side does not necessarily lead to changes of driver behavior in terms of sufficiently adapting the speed on approaching the zebra crossings [32]. Pedestrians waiting at curb sides, without any attempt to cross, may even increase driver tendency to not give way to pedestrians [37]. An observation at a zebra crossing showed that almost none of the drivers yield to pedestrians who were waiting at the curb and looking at the oncoming traffic/drivers [112]. However, pedestrian distance to the curb is found to be one of the most significant explanatory variables influencing the behavior of drivers, and is utilized to model the probability of a driver braking [13,48]. A study on users' behaviors at crosswalks showed that drivers are less likely to yield if a pedestrian was waiting more than half a meter away from the curb [53]. Furthermore, when the pedestrian is already on the crossing, the probability of driver reaction increases as the pedestrian's distance from the curb/refuge increases [13]. At uncontrolled mid-block crossing, higher risk-taking behaviors of pedestrians at central refuge islands is found to be associated with longer waiting time at the first curb (30 s waiting time or more [113]) as pedestrians become impatient to cross the roadway [94].

5.2. Environmental and Dynamic Factors Influencing Crossing Behaviors

5.2.1. Gap Acceptance

From pedestrian perspective, time, or distance gap with the closest oncoming vehicle must be long enough for safely crossing the road [48,114]. The required time for pedestrians to cross can be described as "critical safe gap", and it is computed based on the crossing length and pedestrian crossing speed [115]. Sun et al. [11] stated that there is a remarkable difference between the pedestrian GA behavior and driver GA, due to the higher speed of motorized vehicles compared to the pedestrian's speed. Pedestrians need larger gaps for a safe crossing maneuvers, which may result in longer waiting time and thus increased risk-taking behavior to accept shorter gaps [11]. The likelihood of pedestrians accepting shorter gaps also declines, when they are in a group than individual pedestrians. Moreover, the minimum gap accepted by younger pedestrians is smaller than the minimum gap accepted by elderly pedestrians [10,11]. It is also observed that pedestrians accept a shorter gap, while waiting on central refuge islands, compared to the curb side [94], or in narrow streets rather than wide environments [63,115]. A study in the UK showed that all pedestrians accepted 10.5 s gaps between approaching vehicle, while no one accepted gaps less than 1.5 s [116]. Accordingly, "pedestrian critical gap" reflects the minimum time interval, in which no pedestrian commences crossing [96]. Estimation of critical gap is based on the greatest and smallest accepted gap for a given intersection [96], and can vary among road users depending on road geometry, vehicle features, and pedestrian characteristics [10,11,48,63]. For instance, heavy vehicles accept larger gaps and have greater courtesy towards pedestrians to compare with passenger cars [11,96]. Pedestrians also accept available shorter and riskier gaps, when they wait too long for the critical gap [117]. A study at unsignalized crossings found that pedestrians sought rolling gaps in high traffic volume, meaning that pedestrians do not wait for all lanes to be clear; instead, they predict where a gap will be available in the next lane [118].

5.2.2. Speed of Approaching Vehicle

The speed of a vehicle approaching a pedestrian crossing is one of the most important factors that pedestrians consider, when making the crossing decision [12,37]. However, pedestrians may have some difficulties in estimating the speed of approaching vehicles [13]. Vehicle speed is also identified as a factor influencing yielding behavior [114,119], where lower speeds are associated with increased yielding behavior [13,53,120]. A study in Helsinki, Finland, found that the reacting probability of drivers traveling at the speed of 50 km/h is nearly zero, when individual pedestrians are just waiting at the curb, without stepping on the street [13]. Driver's acceleration strategy (or no deceleration) on approaching pedestrian crossings is interpreted as an implicit signal to show their tendency to maintain priority, and not giving way to the pedestrians (see Section 4.2) [37]. However, speed adaptation prior to reaching pedestrian crossings is a significant factor to ensure pedestrian safety [121]. For this reason, a sufficient distance between oncoming vehicle and crosswalk is required for drivers to react submissively to an unexpected emerging pedestrian [32]. Drivers may also be forced to slow down (anticipatory avoidance response) or stop (delayed avoidance response) in some risky circumstances [32]. For example, when pedestrians who commence crossing: do not look at the oncoming traffic, are distracted and running/stepping into the roadway, show sudden/unexpected pedestrian's movement, or are jaywalkers [37,110].

5.2.3. Road Characteristics

Road environmental factors, such as road width to be crossed by the pedestrian, total road width, number of lanes, and various pedestrian engineering and crossing treatments, may influence the pedestrian–driver interactions in terms of the perceived safety of crossing and the road users' anticipation of different types of behaviors [12,48,122]. For example, a study by Turner et al. [119] showed that the number of lanes crossed was a significant predictor of motorized vehicles yielding rates. The drivers' yielding rate may also vary among different types of pedestrian crossing facilities with various levels of control. Previous studies showed noteworthy difference in the number of drivers who adhere to the traffic rules by yielding to pedestrians at different crossings: 4–45% at marked unsignalized crossings [123–126] vs. 17–94% at marking crossings with one type of traffic management and treatment, or written social assistance [48,76,119]. The yielding rate also varies at marked uncontrolled crossings at entry (higher) and exit (lower) legs of roundabouts [48]. On the other hand, pedestrians may feel safer, when the width of the crossing is shorter [53,127,128]. Pedestrian refuge islands and high visibility markings can also produce better compliance rates on roads with lower speed limit [119]. However, Himanen and Kulmala [13] found that road width and the existence of refuge had no significant effects in modeling the driver and pedestrian behaviors at pedestrian crossings.

5.2.4. Size of Approaching Vehicle

The size of vehicles can influence the behavior of both pedestrian and driver, and is an important factor for modeling of road users' behaviors [11]. For instance, the possibility of pedestrians continuing to walk is lower by 20%, when the oncoming vehicle is a lorry or bus instead of a passenger car. The number of attempts by pedestrians to cross also declines if the oncoming vehicle is a heavy vehicle, like a bus or a coach [94]. The probability of drivers reacting is also 30% lower amongst heavy vehicle drivers than car drivers [13].

5.2.5. Traffic Volume

Traffic density is a factor that pedestrians consider, when making the crossing decision; high traffic density is considered as a risky situation [12,37]. Pedestrians also make more attempts to cross the roadway in heavy traffic volume and may be more likely to accept shorter gaps from individual vehicles than platoons [48,94]. On the other hand, the driver's tendency to give priority to pedestrians declines in high traffic volume [13,48,53,129]. Moreover, the possibility of the lead driver reacting decreases by increasing number of approaching vehicles. In a group of five vehicles, the probability of reacting can decrease by almost 40% more than with only one vehicle [13].

5.2.6. Traffic Behaviors and Situations

Traffic behaviors and situations like the presence of a downstream queue after the crossing [48], yielding event in the opposite direction or adjacent travel lane [48], the gap between the car in front and the one following behind it [12,46], distance of the oncoming vehicle [12,46], or driver's direction of approach towards the pedestrian [13], may have some impact on the amount of risk perceived by road users, and thus their crossing-decision strategies.

5.3. Other Contributing Factors

In addition to the aforementioned factors, there are some other elements and circumstances surrounding the interaction, which may influence the decision-making process at crosswalks. Such factors include:

- User familiarity of the place (frequent use of a particular crossing point) can be linked with the higher risk taking behaviors of pedestrians and lower waiting time at crossing [37,94]. It also affects drivers' behaviors on approaching a road segment with no pedestrian facilities. For example, drivers who are familiar with a road segment are likely to drive cautiously in anticipation of pedestrians' unexpected crossing attempt [111], whilst the pedestrian behavior may be surprising for those who are not familiar and can lead to conflict [46].
- Size of the city [13].
- Cultural differences, which can influence the crossing behaviors and the interpretation of informal traffic rules [81,130]. Social norms, cultures, and faith in different countries may influence the

risk perception of users in crossing scenarios, and therefore their crossing behaviors [131,132]. As Western cultures are found to be more risk-prone in road crossing than Asian cultures [132–135]. Pedestrian crossing speed, and gap acceptance are also some of the factors that might be effected by road users' cultures [90,99]. Communication signals employed by road users and their implications may also being interpreted differently in varied cultures [136]. For instance, the meaning of hand gestures, or honking a horn in India may differ with the translation of such behaviors in Germany.
- Visibility, light and weather conditions [10,114,137,138].

5.4. The Correlation of Crossing Behaviors with Surrogate Safety Measures

Surrogate safety measures, as the name implies, are proposed as alternative or complementary methods to identify safety issues [139]. The studies reviewed in this paper have shown some correlations between these indicators and various pedestrian crossing behaviors and factors influencing them:

- The probability of pedestrians crossing the road increases by higher TTC values [63]. A study by Schroeder [48] showed that the TTC threshold is satisfied, if the TTA at the crosswalk is less than 3 s (similar finding as [63]), and everyone crossed the road, when TTC was above 7 s. He, then, analyzed the effect of different treatments at uncontrolled mid-block crossings on yielding behavior. According to this study, TTC declined after treatments' installation. It is also necessary to mention that the expected value of TTC is correlated with the dependent variable yield, in which TTC is lower at non-yielding events compared with yielding ones [48].
- With respect to TTA indicator, an acceptable gap to execute a safe crossing maneuvers may be determined by factors like the level of users' risk acceptance, or pedestrian's perception of how long the gap is [43,137]. However, the perception may not be always correct and might be much longer/shorter than the person's perception [10]. Hence, a pedestrian is required to make a comparison between two microscopic parameters to decide whether it is safe to cross or not [10,12].
- Road users with larger TAdv are most likely to be the first ones who pass the common zone. However, if the TAdv is small, the second user may accelerate with the aim of passing first instead. This is mainly observed when one of the users is "stronger" than the other e.g., private car vs. pedestrian [32,35].

6. Synthesis

Walking is the most widely used mode of transportation and is subject to a considerable risk of injury or fatality on the road, which is mainly caused by motorized vehicles. The majority of these traffic fatalities and injuries occur at pedestrian road crossing scenarios in urban settings at either pedestrian crossings or illegal locations out of crosswalks. However, many road users interact with one another without any serious conflict and are not of interest from a traffic safety perspective, but vital in terms of road users' experience. Traffic interaction, therefore, has been expanded to involve less critical conflicts. Drivers may neglect the pedestrians' right of way at some pedestrian crossing facilities with less strict traffic enforcement, and pedestrians may attempt mid-block crossing or jaywalking in the absence of crossing facilities or just to shorten the travel time. In such situations and more ambiguous circumstances, human road users are required to communicate their movement intentions with another interacting party to resolve the ambiguity regarding the right of way. For an efficacious vehicle–pedestrian interaction process, users ought to indicate their own intentions, understand the other's intentions, and anticipate their next actions.

This cooperative procedure complies with the human interaction fundamentals in which the interacting agents form a mutual behavioral compliance, while responding to each others actions. Furthermore, the situation in which the communication is happening needs to be correctly understood by traffic communicators. Finally, with respect to all prerequisite input information in such traffic scenes, road users utilize a broad range of implicit and explicit communication methods to coordinate their actions with interaction partners. These signals are mostly transferred to acknowledge that interacting parties are seen by another one, confirm their intents, or to influence each other's yield/not-yield decision strategies. A significant number of the reviewed studies in this paper (approximately 29%) found that pedestrians use some form of nonverbal cues such as hand gesture, gaze, or head movement to indicate their crossing intentions to the oncoming vehicles (see Figure 1). In addition, 25% of the reviewed papers revealed that drivers utilize various explicit signals, such as light indicators, horn, or hand gesture, to communicate with pedestrians on approaching crossing sites. In addition, the majority of reviewed studies (39.3%) emphasize the importance of eye contact establishment between drivers and pedestrians, while communicating their movement at conflict points. However, pedestrians may not always receive a response from drivers by returning eye contact, and instead may receive signals, such as hand gesture or light indicators. A smaller number of reviewed studies (7%) indicated that using communication signals among traffic participants has no impact on yielding and traffic behaviors of users.

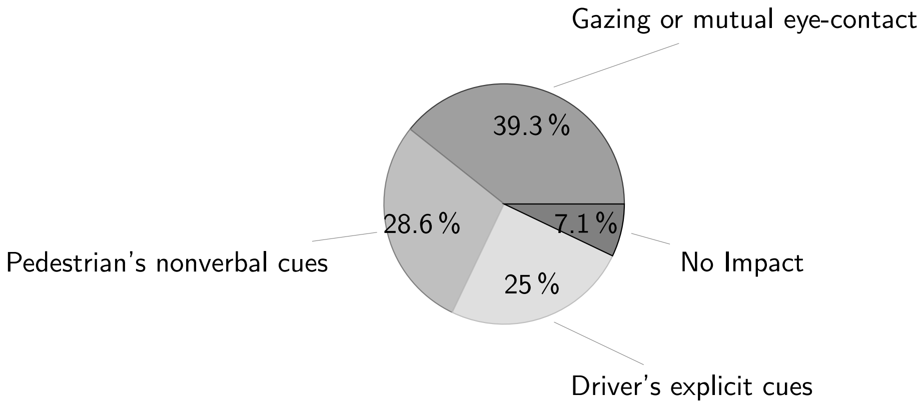
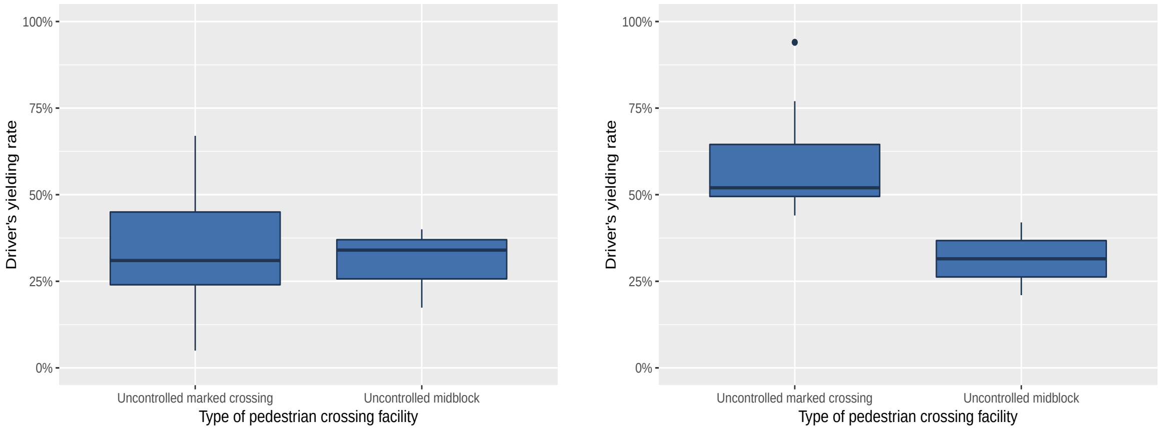


Figure 1. Share of reviewed literature emphasizing the impact of nonverbal cues on traffic behaviors. Source: own elaboration, based on the reviewed references in this research.

On the other hand, the driver's willingness to yield to pedestrians varies among different studies. Figure 2 illustrates the driver's yielding rate at various uncontrolled crossing facilities reviewed in this paper. In Figure 2a, the crossing facilities have no treatment interventions, while Figure 2b shows the rate at crossing sites with at least one treatment implementation, such as warning signs, or pedestrian actuator signals. It is necessary to mention that, in Figure 2b, uncontrolled marked crossing category includes some mid-block crossings' rates, which were considered as uncontrolled marked for the ease of use (e.g., the average of yielding rate for each treatment is representing all type of studied crossings in the study performed by Turner et al. [119]).

In addition, in the priority negotiation process, drivers have some strategies to decide whether or not to give way to pedestrians. A number of factors also influence the crossing-decision strategies of pedestrians at crosswalks to decide whether or not cross the roadway. Figure 3 indicates a summary of all influencing factors in the decision-making process of road users identified in the reviewed literature. The figure illustrates how many times the influencing factors are found to be relevant in the reviewed studies in relation to the total number of reviewed studies. As demonstrated in the figure, the impact of road characteristics, pedestrian age, walking speed, group size, and the speed of oncoming vehicle on behavior of traffic interacting parties have been highlighted in previous studies reviewed in this paper, while the environmental and dynamic factors have presented a higher effect. Some of these factors also influence one another in the crossing scenarios, meaning that the presence or the quantity of one can affect another. Figure 4 illustrates the interrelationship between factors according to the reviewed literature.



(**a**) (**b**)

Figure 2. Driver's yielding rate at uncontrolled crossings in the reviewed literature: (**a**) with no treatment interventions; (**b**) with treatment interventions. Source: own elaboration, based on [13,32,48,53,76,112,119,123–127,140].

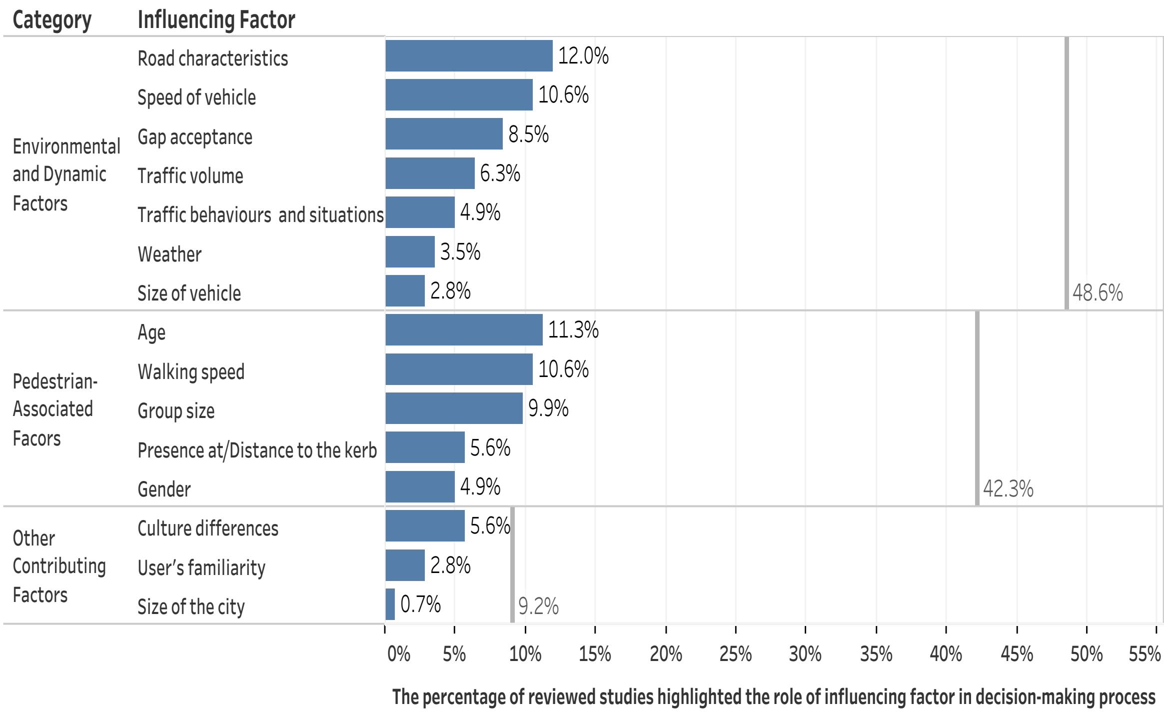


Figure 3. Influencing factors in decision-making process of road users at crosswalks, and the percentage of studies highlighted their impacts with respect to the total number of reviewed studies. Source: own elaboration, based on the reviewed references in this research.

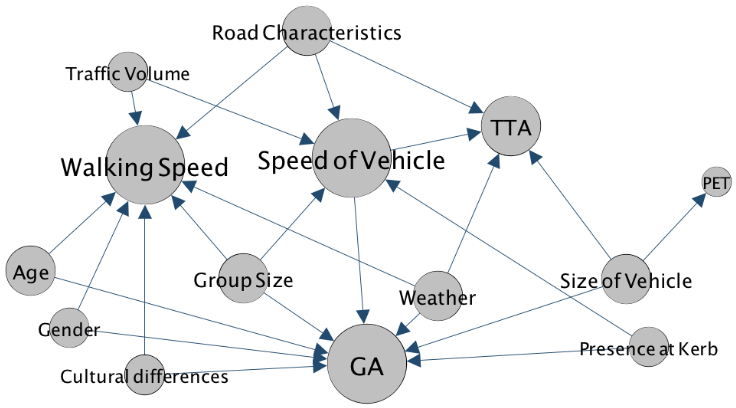


Figure 4. Interrelationship between factors influencing crossing-decision strategies of pedestrians. The direction of arrows shows influence direction from one factor to another. The size of the circles changes based on the number of factors influencing them or being influenced by them. Source: own elaboration, based on the reviewed references in this research.

7. Discussion

The state-of-the-art in negotiation and decision-making for pedestrian road crossings has achieved significant progress on identifying the prominent behaviors of vehicles and pedestrians, the interactions between such traffic users and the factors that influence the most, synergies between pedestrians and motorized vehicles. It is evident from the reviewed literature that studies are so far mostly focused on a limited number of factors influencing driver–pedestrian interactions (e.g., speed of vehicle, road geometry) and investigate their impact on behaviors and decision-making processes of both pedestrians and drivers. Furthermore, the effect of communication methods and intention propagation are usually studied by focusing on specific strategies (yielding behaviors or non-yielding behaviors) without taking into account the decision-making process of road users and investigating the factors that may influence the process. However, the reviewed literature showed that road users adopt their crossing strategies by considering a broad range of factors knowingly (such as estimation of time and distance gap) or unknowingly (such as influence of age or gender), while they employ different communication techniques to ease the interaction when it is needed. This shows the complexity of the vehicle–pedestrian interaction, in which solely consideration of some factors or communication methods may not provide a consummate understanding of the process. This becomes crucial for the design of emerging technologies such as ADS, requiring an accurate comprehension of human road users' behaviors in a traffic interaction to correctly predict their reactions and fulfill their expectations. With the purpose of advances in vehicle–pedestrian safety, the consideration of those interactions from ADS and the enhancement of existing infrastructure, a holistic approach is oddly yet to be considered by researchers with regards to modeling interactions of pedestrians with vehicles. However, for example, the authors in [141] have introduced a novel data-set to analyze the pedestrian behavior in interaction with vehicles by taking into account a wide range of behavioral, contextual, and dynamic factors, as from the authors' point of view sole consideration of dynamic variables (such as speed or trajectory) is not sufficient enough for prediction of pedestrians behaviors. Such an approach emphasizes even more the necessity of a vehicle–pedestrian interaction framework for a better perception of users' behaviors. Based on the findings of the reviewed literature, Figure 5 presents an example of how a holistic approach for vehicle–pedestrian interactions could be shaped.

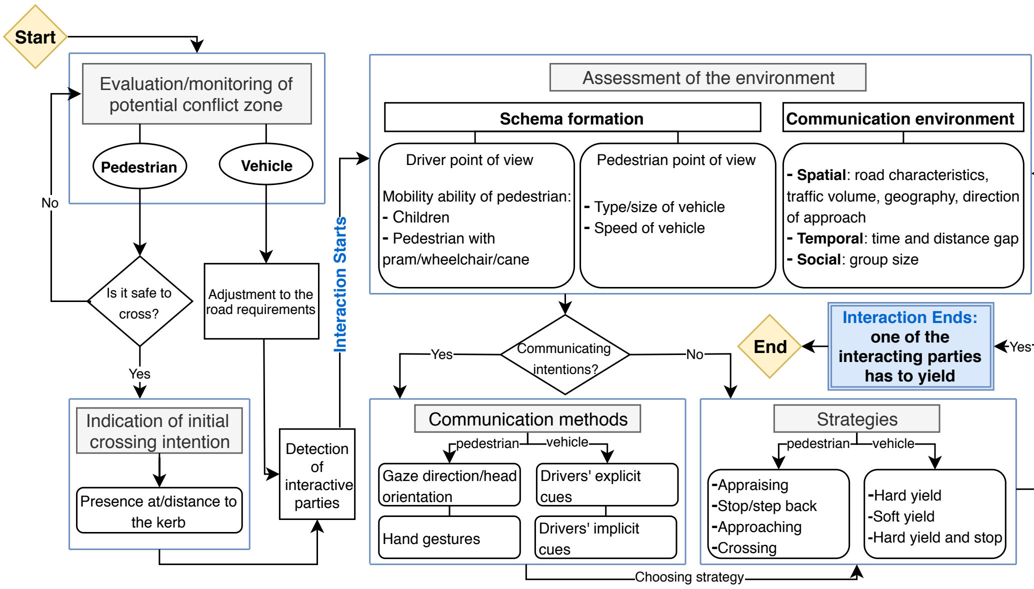


Figure 5. The simplified vehicle–pedestrian interaction process for the road crossing scenarios. Source: own elaboration, based on the reviewed references in this research.

According to Figure 5, the vehicle–pedestrian interaction can be divided into five different phases in order to simplify their decision-making process. Before forming any interaction among road users, interacting parties superficially evaluate the road characteristics on approaching the potential conflict zone. In this pre-interaction phase, a pedestrian selects the crossing point, while the drivers, on the other hand, continuously monitor the road and ideally adjust their behaviors in accordance with the road/traffic requirements. This phase is not directly involved in the vehicle–pedestrian interactions; rather, it can prepare the vehicle for an anticipatory avoidance response, rather than a delayed one on approaching a potential encountering zone. Pedestrians, then, indicate their initial crossing intentions to the users approaching the common zone, which is generally achieved through presence at or walking towards the curb. When interaction starts (the moment interacting parties detect each other), involved road users have their very first assessment about the communication environment, where they can select their strategies according to the received information and their assessment. Traffic participants can utilize communication cues to indicate their intentions or directly perform their selected crossing strategies. The interaction ends when at least one of the agents leaves the conflict zone, and can be repeated with a replaced approaching road user for the one who has not obtained the right of way. However, during the interaction, interactive agents can change their strategies or execute more than one strategy, while negotiating the right of way. Such situations generally require agents to reassess the communication environment, and communicate their new movement intentions with one another.

This holistic interaction process can provide recommendations for designing the decision-making systems of automated driving technology in confronting pedestrians. It aims at simplifying the complex decision-making procedure of pedestrians by considering the most significant factors and communication methods influencing the process. Furthermore, it could become part of the maneuvers' planning module of ADS ensuring safe maneuvering among populated spaces [142]. Finally, according to such a holistic approach, effective communication protocols and devices could be designed for faster, more comprehensive and efficient negotiations of road crossings. For example, smart-phone notifications [143], sound and optical signals [62,144], or illuminating signs [25] could provide significant help in the future for pedestrians and their corresponding actions, while on the road. Understanding the sequence of events in the vehicle–pedestrian interactions may help ADS to perform more effective communication strategies than always coming to a complete stop for pedestrians detected in their path [145]. The communication cues employed by ADS can also vary based on the environment evaluation, such as indicating visually designed eHMI instead of audible one, when the pedestrian's head is oriented towards the vehicle, or utilizing messages with the command concept rather than requesting when the pedestrian hesitates to cross.

In the present state-of-the-art, various methods have been employed to investigate the pedestrian crossing behaviors and their interaction with ADS, such as virtual reality (VR)-based simulations [146,147], the Wizard-of-Oz technique, in which the driver is hidden in the driver seat [148,149], and using the real-life exposure of automated bus shuttles [150,151]. Keferböck and Riener [152] evaluated various signs and gestures of pedestrians to explore the importance of vehicle–pedestrian interaction, and the necessity for implementation of them in the communication systems of ADS. Other studies raised relevant questions concerning the design of external communication cues, the content of communication, and the impact of different environmental factors on crossing behaviors [141,146,149,150]. Future research can potentially address pedestrian crossing behaviors and their decision-making process with respect to ADS, as a new interacting party on the road. A thorough insight into the possible changes of pedestrians' crossing-decisions while interacting with fully automated vehicles, the communication signals that pedestrians expect to receive, and the applicability of the current communication methods can be crucial for the design of ADS and thus successful deployment of such technologies. Moreover, the ubiquity of smart devices like mobile-phone, and their prevailing role in today's life of people may alter the traffic interaction concept. As distracted pedestrians are no longer an active party in the interaction process, and vehicles have to first detect such users and then react appropriately to avoid conflict. Such imperfect traffic interactions could be investigated in the future work.

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Abbreviations

The following abbreviations are used in this manuscript:

GA	Gap Acceptance
PET	Post-Encroachment-Time
TTC	Time-To-Collision
TTA	Time-To-Arrival
TAdv	Time Advantage
ADS	Automated Driving System
MUTCD	Manual on Uniform Traffic Control Devices
eHMI	External Human–Machine Interface
VR	Virtual Reality

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Interaction of automated driving systems with pedestrians: challenges, current solutions, and recommendations for eHMIs

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ABSTRACT

The conventional form of traffic interaction undergoes a notable change with the integration of automated driving systems as a new road user, into the public roads. This may be more challenging during the transition phase, while manual-driven vehicles are still on the road, and the road infrastructure is not fully ready for merging such vehicles into the traffic patterns. Therefore, developing a robust interaction method is crucial to ensure the safety of those users interacting with automated driving systems and to ensure the efficiency of these systems on the road. For this purpose, the interaction of automated driving systems with pedestrians, as one of the most vulnerable road user groups, is investigated in this paper. Previous studies have shown the necessity for a comprehensive understanding of pedestrian behaviours and intentions, their responses to different stimuli on the road, the factors influencing their decisions during the interaction, and various external communication techniques among road users. As a result, a wide range of factors related to the communication environment, pedestrian characteristics, and existing communication methods have been found to be significant in the decision-making process of pedestrians.

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1. Introduction

Automated driving technology has come a long way since the earliest efforts of researchers and car manufacturers in the 1920s to make driving a vehicle safer and easier. The continuing advancement of automated driving systems (ADS) aims to minimise driver intervention in controlling the vehicle and to develop a technology that can ultimately handle the whole task of driving. Although ADS may improve safety on the road by eliminating crashes caused by human error, the integration of automated vehicles into the public realm, where a variety of road user types actively interact, can still raise safety challenges.

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Currently, different aspects of driving can be performed automatically with the assistance of ADS and advanced technologies, such as radar, LIDAR (light detection and ranging) systems, and ultrasonic and ultrasound sensors. The interaction of such systems with different algorithms and tools can enable vehicles to monitor the driving environment, make informed decisions, and navigate to their destinations. Where ADS interact with other road users, these systems provide additional solutions to improve the safety of vulnerable road users (VRUs), such as pedestrians, and motor/pedal cyclists (Katrakazas, Quddus, Chen, & Deka, 2015). These road users are more endangered in traffic, as they have no protection to safeguard them when collisions occur (Constant & Lagarde, 2010). An example of such driver-assistance systems is collision avoidance systems, which can avoid VRUs in critical encounters (Llorca et al., 2011). In traffic scenarios in which a collision is inevitable, the pedestrian protection system (PPS) can automatically brake or use pedestrian airbags to mitigate damage (Deb, Rahman, Strawderman, & Garrison, 2018). An additional coordination channel is also provided via an External Human Machine Interface (eHMI) to manage the communication of information with human road users and compensate for the absence of a driver.

While the collision avoidance systems may ensure the safety of pedestrians in traffic interactions most of the time, there is still a need to obtain a clear understanding of the pedestrian decision-making process in order to execute safe and efficient automated driving manoeuvres, and consequently a smooth interaction process. However, the current state of knowledge about ADS-pedestrian interactions is incomplete, particularly from the pedestrian perspective in real-world traffic environments. The deployment of fully automated vehicles as an unprecedented transportation mode on the public road, as well as the absence of a human driver and the consequent loss of communication cues, may result in elevated stress and conservative crossing behaviour among pedestrians (Palmeiro et al., 2018). In addition to this, ADS errors in unexpected traffic circumstances and in situations where insufficient information is available on what the vehicle's response will be is a matter of concern for pedestrians. Consequently, the focus of this paper is on investigating the challenges and limitations that ADS may face in interaction with pedestrians, as well as summarising the existing research into ameliorating such interactions. A fully developed concept of interaction is required for the resolution of possible ambiguities and conflicts in ADS-pedestrian interactions. This is vital for the future diffusion of fully automated vehicles, in which different traffic participants will have to not only coexist but coordinate their movements for an efficient and safe interaction.

This paper is organised as follows: The current challenges in the study of ADS-pedestrian interaction and various data collection approaches are reviewed in section 2 and 3, respectively. Section 4 gives an overview of the previous research and recommendations for resolving the possible conflicts. Section 5 documents the modelling approaches. The limitations and drawbacks emerging from the implementation of ADS in the current traffic patterns and also from technological solutions to the problem of replicating driver-pedestrian communications, identified in the literature reviewed, are discussed in section 6. Section 7 includes a synthesis and discussion of the literature, and section 8 provides conclusions from reviewing previous studies and research in this field.

2. Automated driving challenges in interaction with pedestrians

Because automated vehicles will be incorporated into the existing transport system, ADS will have to deal with the existing traffic regulations and a variety of different road users (e.g. other automated vehicles, human-driven vehicles, pedestrians, cyclists). In a transport system of this kind, the notable amount of interaction strategies elaborated among traffic participants delivers a significant challenge for ADS. The challenges that ADS face in relation to traffic interactions, as well as the complexity of understanding and predicting pedestrian behaviours, are discussed in this section.

2.1. Interaction concept

With fully automated driving systems, a human driver is not available for interaction and communication with road users. This plays a central role especially in environments, in which: (1) the right of way is not clearly predetermined by traffic rules (e.g. unmarked crossings, shared spaces) and traffic participants have to negotiate vehicle priority (Camara, Giles, et al., 2018); (2) there is no dedicated infrastructure and users have to communicate their intentions/movements to resolve a conflict on the road (Löcken, Golling, & Riener, 2019). Schneemann and Gohl (2016) argue that executing safe autonomous driving manoeuvres in urban settings is not only subject to the vehicle's precise control of the driving tasks and its knowledge of the traffic environments, but that a suitable interaction concept is also required. Such an interaction concept for ADS can be achieved by ensuring that ADS conform to the traffic regulations, as well as fulfilling the expectations of involved road users (Schneemann & Gohl, 2016). To attain the latter, the system has to simulate the behaviours of human drivers and requires a thorough analysis of the driver-pedestrian interaction process. These are crucial inputs for the design of decision-making systems of automated driving, as road users may not behave in the way ADS expect them to behave (Šikudová et al., 2019).

2.2. Complexity of pedestrian behaviours

Pedestrians are capable of sudden changes in their movement direction and speed. For this reason, the estimation of pedestrian intentions becomes a crucial task for scenario understanding in ADS (Šikudová et al., 2019). In addition, understanding pedestrian behaviours is particularly challenging, since they are influenced by a broad range of factors, such as environmental conditions and traffic dynamics (Ezzati Amini, Katrakazas, & Antoniou, 2019; Rasouli & Tsotsos, 2019). Camara, Giles, et al. (2018) describe pedestrians as complicated agents with specific decision-making systems, which must be taken into account while interacting with them in order to predict their behaviours and respond appropriately. The prediction of a pedestrian's next action is a complex problem and includes both understanding and predicting surroundings, and the pedestrians' understanding and prediction of the ADS' current and future actions (Fox et al., 2018). Pedestrians, and VRUs in general, also need to have a certain comprehension vis-à-vis the ADS' next action in traffic situations, such as slowing down and changes of direction (Dziennus, Schieben, Ilgen, & Käthner, 2016; Zhang, Vinkhuyzen, & Cefkin, 2017).

2.3. ADS failure

ADS follow the safest procedure for interacting with agents on the road. However, the conditional nature of road interactions means it is not always possible to determine what the safest behaviour sequence is. Eccentric driving manoeuvres by ADS may cause minor accidents, even though they follow the traffic regulations and are not at fault (Rothenbücher, Li, Sirkin, Mok, & Ju, 2016). A report showed that in a trial of Google's fleet of fully automated vehicles they experienced five minor accidents while driving 200,000 miles (Harris, 2015). 90% of the failures occurred in busy streets and 10% of these were related to the incorrect prediction of road user behaviours.

Yet despite the significance of ADS-pedestrian interaction, the concept has not been adequately formulated in the design of automated driving technology. Therefore, it is essential to investigate the research and recommendations in this field, and to review how such issues are examined while fully automated vehicles are not yet on the road.

3. Data collection approaches to research into ADS-pedestrian interactions

To date, several studies have investigated the behaviour patterns of pedestrians in interaction with partly/fully automated vehicles. These studies vary in their data collection methods and research questions. This section includes some examples of different data collection approaches to research into ADS-pedestrian interactions.

3.1. Survey-based studies

Survey-based studies in the form of face-to-face interviews or online/written questionnaires are widely used to address the impact of the implementation of automated driving technology in the future (Blau, 2015; Fridman et al., 2017). Deb, Rahman, et al. (2018), in a review of pedestrian acceptance of automated vehicles, suggest that pedestrian behaviour questionnaires ought to be validated and developed in relation to automated driving technologies. This is necessary particularly for understanding pedestrian intentions in road crossing interactions. The absence of automated vehicles in public roads limits the validity of survey-based studies investigating the acceptance of and the expected interactions with ADS, since the technology may be under/over-estimated (Diels & Thompson, 2017; Vilimek & Keinath, 2018).

3.2. Simulator-based studies

Different simulator-based methods and virtual environment (VE) tools are used to investigate the ADS-pedestrian communication possibilities (Aparow et al., 2019; Feldstein, Dietrich, Milinkovic, & Bengler, 2016). One innovative approach investigates road user behaviours in selected environments by using the Multiple Participant Simulator (MPS) (Lehsing & Feldstein, 2018). The MPS utilises two or more separate – but physically connected – simulators and provides the same virtual environment for participants to interact simultaneously (Lehsing, Fleischer, & Bengler, 2016) (Figure 1). The capability of ADS in various traffic contexts can be tested by using the MPS technique in a safe and controlled

Figure 1 .#Possible constellation of connected simulators (MPS). Source: Lehsing and Feldstein (2018).

synthetic environment, where two or more traffic participants interact one with another in the same traffic scenario.

A similar technique is applied in Virtual Reality (VR)-based simulators, which make it possible to observe pedestrian behaviours under different circumstances (Burns, Oliveira, Hung, Thomas, & Birrell, 2019; Mahadevan, Sanoubari, Somanath, Young, & Sharlin, 2019). Most of these devices, often referred to as pedestrian simulators, can be categorised as Cave Automatic Virtual Environment (CAVE) setups, which employ projector screens to create a simulation environment (Cavallo, Dommès, Dang, & Vienne, 2019), and Head-Mounted Display (HMD) setups (Deb, Strawderman, & Carruth, 2018). Another system of this type is the VR-based pedestrian simulator developed by Doric et al. (2016) to study pedestrian behaviours in different traffic scenarios. The simulator uses an HMD combined with a dynamic driving simulation and a wearable human motion capture system to create visual feedback for human subjects. The VR technology is also used to examine how the exterior design of an automated vehicle and eHMI can affect the pedestrian crossing intention (Löcken, Golling, et al., 2019; Velasco, Farah, van Arem, & Hagenzieker, 2019).

3.3. Wizard-of-Oz technique

The Wizard-of-Oz (WoZ) technique is used to analyse how pedestrians may interact with fully automated vehicles, by using a fake driver-less car in a real-world traffic setting (Clamann, Aubert, & Cummings, 2017; Lagstrom & Lundgren, 2015; Lundgren et al., 2017). In this technique, either a trained driver is hidden in a specially constructed car seat to mimic an automated system, or the car is driven by an unseen controller in the vehicle (Figure 2). The WoZ technique is also used to investigate: (1) how vehicles

Figure 2 .#Examples of the WoZ technique. (a) Dummy steering wheel with no function for the driver (Habibovic et al., 2016), (b) Seat cover used to hide the driver (Fuest et al., 2018), (c) In-vehicle controller with an inactive driver (Palmeiro et al., 2018).

communicate their intended movements and (2) how the absence of the driver affects pedestrian behaviours (Fuest, Michalowski, Träris, Bellem, & Bengler, 2018).

3.4. Road trial

The road trial, as the most realistic test environment, is another approach employed to collect ADS-pedestrian interaction data. In this method, the relevant data are collected via the instrumented automated pods currently in place on the roads (Boersma, Van Arem, & Rieck, 2018; Löcken, Wintersberger, Frison, & Riener, 2019; Madigan et al., 2019). A video-data stream is provided using this method by positioning cameras outside the vehicles and recording the road scene (Figure 3). Automated pods travel at low speed (up to 25 mph in urban settings), for a short distance, in less complex traffic environments, and have similar functional features to level-4 ADS (Cregger et al., 2018). Other examples of the deployment of automated pods in the form of public transport are EasyMile EZ10 shuttles (EasyMile, 2015), Google driver-less pods (Google, 2016), and the automated pods developed by NAVYA (NAVYA, 2015).

Table 1 summarises the advantages and limitations of the data collection methods and their usefulness for different types of studies in relation to ADS-pedestrian interactions. Road trials – which have undeniable advantages over the other methods – can provide naturalistic data on user behaviours and requirements in interaction with ADS; however, the existing automated pods are not fully representative of the automated technologies due to their low speed and limited functionality. Alternatively, WoZ is used to investigate user behaviours interacting with simulated ADS in different traffic settings. An added advantage of the WoZ technique is that pedestrian behaviour data is collected in a naturalistic setting, where pedestrians believe that the vehicle is operating automatically. In contrast, simulator-based studies are suitable for assessing both user behaviours and ADS functionality in a controlled environment, with the possibility of testing risky events and complex scenarios. Survey-based studies seem to be an efficient way to collect large-scale data on user expectations of ADS, particularly if the survey is intended to reach a specific target group.

4. ADS-pedestrian interactions research

A variety of studies have been conducted to provide an in-depth understanding of ADS-pedestrian interactions and to address the possible drawbacks of the current automated

Figure 3 .#Example of data collection in a road trial of CityMobil2 shuttles. (a) The positioning and area covered by three 3DV cameras, (b) Example of a road scene displayed by three 3DV cameras. Source: (Madigan et al., 2019).

Table 1. A summary of pros and cons of different data collection techniques for studying ADS-pedestrian interactions.

Method	Advantages	Disadvantages
Survey-based	• High response rate with relatively low effort • Can be combined with other data collection methods • Inexpensive • Allows collecting data on road user expectations/requirements in the absence of ADS • Ease of data collection • Easy to reach various target groups	• In interviews: the interviewer can bias responses • Target group can be biased • Validity issues and possibility of invalid/unrealistic research outcomes
Simulator-based	• Ease of data collection • Controllability of the testing environment • Possibility of repeating the experiments • Possibility of testing risky driving conditions in a safe environment • Possibility of investigating complex driving tasks, variety of traffic situations, etc.	• Possibility of invalid/unrealistic research outcomes in low-fidelity simulators • Simulator sickness and discomfort may arise • Validity issues due to the lack of risk in the trials • It requires participants to become familiar with the techniques, which can be time-consuming • Expensive • Learning effects – participants' performance may be affected by repetition of the events
WoZ	• Possibility of testing full automation functionality in the absence of automated vehicles on the road • Allows collecting data on user behaviours interacting with the simulated ADS • A variety of eHMI designs, crossing facilities, road types or a combination of them can be tested by WoZ	• Relatively expensive • Difficult to reproduce experiments, as the vehicle is controlled by a human • Ethical issues may arise, since interacting users are deceived into thinking that the vehicle is operating automatically. • The wizard requires a significant amount of training to control the vehicle
Road trial	• Allows collection of large-scale data over longer periods • Allows collecting a variety of variables, e.g. road layouts, environment factors • Natural traffic behaviours and interactions are collected on real ADS-pedestrian interactions. • Easy to set up	• No control over the scenario, environment, etc. • Uncontrollable variables • Confounding variables • Instruments may need recalibration during the trial • Data collected by instrumented automated pods may not fully/precisely represent the ADS-pedestrian interaction.

driving technologies in confronting pedestrians. These studies investigate ADS-pedestrian interactions by considering both the capabilities of automated driving technologies and factors influencing the decision-making process of road users.

4.1. Attitudes of pedestrians in interactions with ADS

An important aspect of road user interactions in the future – when automated vehicles operate on the road – is the response of pedestrians to ADS in the absence of a human driver. In an experimental study carried out by Rothenbücher et al. (2016), pedestrians stated that they managed to interact with the vehicle in the absence of a driver, excluding the occasion when the car misbehaved by not yielding to the pedestrians who already commenced crossing. A simulation experiment by Rad, de

Almeida Correia, and Hagenzieker (2020) indicated that individual-specific characteristics like risk-taking behaviours, a tendency to violate traffic rules, and trust in ADS may have significant in pedestrian crossing decisions. An analysis of naturalistic data collected from an automated pods trial by Madigan et al. (2019) showed one "near-miss" incident, where users closely avoided an accident, in every three hours of autonomous driving. The observation also revealed that pedestrians deliberately blocked the vehicle path once every 4.8 hours. This may become a concern, since road users may always try to take priority, presuming that the ADS safety systems are programmed to stop if any obstacle is in their path (Connor, 2016; Fox et al., 2018). This problem, known as "Freezing Robot Problem", can also lead to shorter and possibly more hazardous gaps being accepted by pedestrians in crossing in front of fully automated vehicles (Palmeiro et al., 2018).

4.2. Factors influencing pedestrian behaviours in interactions with ADS

During the live demonstrations of automated pods in European cities, a questionnaire-based study was used to collect feedback from participants in different age groups (Merat, Louw, Madigan, Wilbrink, & Schieben, 2018). The study analyses the safety perception of VRUs interacting with automated pods in shared spaces, as well as the type of information participants considered important to be displayed externally by automated pods. Results indicated that pedestrians found designated lanes safer than shared space (similar findings as Blau [2015]). The great majority of pedestrians also believed that they had priority over automated pods in unsegregated infrastructures. They also emphasised that confirmation by the vehicle that they had been detected was the most essential information they would like to receive during the interaction (similar results to those obtained in Löcken et al. [2019]). The latter is a particularly valuable information input for pedestrians because it allows them to make sure that they have been seen or that their intention to cross the road has been recognised by the vehicle.

4.3. Implicit signals

The implementation of implicit signals in ADS is found to be essential, particularly in the form of a deceleration cue to inform pedestrians of the vehicle's intention and to encourage them to cross (Löcken, Wintersberger, et al., 2019; Rothenbücher et al., 2016). Beggiato, Witzlack, and Krems (2017) argue that an estimation of pedestrians' expectation from the time of braking needs to be considered in order to carry out a "natural-looking" automated deceleration. Their experimental video-based study indicates that an identical Time-to-Arrival (TTA) value for all speeds should not determine the brake initiation for ADS, since the accepted time gap by pedestrians may vary at different speeds and depending on their age-group or the vehicle size. Therefore, the study recommends that ADS braking initiation should be adjusted, according to the speed-dependent time gap acceptance, for different age-groups and vehicle size. In addition, to ensure that pedestrians are given sufficient time for crossing, the study recommends that their age should be considered in the estimation of braking timing, although the study accepts that it might be hard for sensors to evaluate the age. In traditional driver-pedestrian communication, drivers employ more anticipatory behaviours and brake notably earlier at higher speeds on approaching the crosswalk. Accordingly, ADS should also have the same timing response to a pedestrian intending to cross (Schneemann & Gohl, 2016). Driver movement patterns are also found to be a well-established interaction method among human road users, based on a mutual understanding of the meaning of movement patterns (Risto, Emmenegger, Vinkhuyzen, Cefkin, & Hollan, 2017), which allows pedestrians to interpret the driver's intentions. Hence, developers should recognise movement patterns as a way of communicating vehicle intentions and avoiding confusion amongst road users, even if it may not be possible to implement this in the system (Hoffman & Ju, 2014; Risto et al., 2017). This is important since the execution of a particular movement pattern by ADS may generate unexpected/hazardous responses from VRUs in the vicinity (Risto et al., 2017).

The literature studying pedestrian interactions with fully automated vehicles is summarised in Figure 4. As shown in the figure, the road trial method is typically employed to study the expectations and requirements of pedestrians while interacting with ADS, with a focus on shared spaces in view of the fact that automated pods are currently operating in these traffic settings. In contrast, pedestrian crossing behaviours and various communication techniques are evaluated in more controlled environments and by using simulator-based and WoZ methods, combined in most cases with prior/post-experiment questionnaires.

4.4. Nonverbal communications

Nonverbal signals are a well-established means of communication used by road users in existing driver-pedestrian interactions, and thus ADS must have a similar understanding and interpretation of these communication cues (Keferböck & Riener, 2015). For instance, understanding the meaning of pedestrian hand gestures in different situations: whether the pedestrian requests the car to yield, proceed or pull over. For this reason, an additional coordination channel has been developed through eHMIs to supplement conventional forms of communication. The purposes of implementing such cues are summarised as:

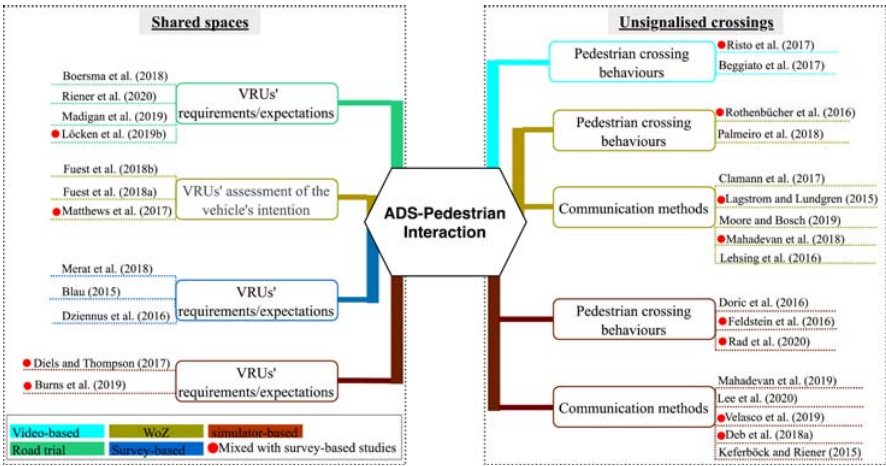

Figure 4 .#Summary of the studies reviewed investigating ADS-pedestrian interactions by employing various data collection methods.

- Advise other traffic participants regarding their next action
- Convey information to VRUs regarding the vehicle's movement intention when approaching a crosswalk
- Inform VRUs whether the vehicle is functioning in automated mode
- Inform VRUs when they are detected by ADS

The design of eHMIs includes adding externally installed visual cues, which can be either placed on the car's exterior or projected on the roadway. In some experiments, speaker systems are included to broadcast audible messages. Some of the eHMI designs proposed to handle the communication of information with VRUs are discussed below.

4.5. Text-based and animated signals

Different text-based message and sign interfaces have been developed to deliver information about yielding to pedestrians. Text-based messages can be in the form of advisory (e.g. "safe to cross") (Fridman et al., 2017; Urmson, Mahon, Dolgov, & Zhu, 2015), affirmative (e.g. "OK" meaning that the system is ready to yield to the pedestrian), command-giving (e.g. "GO" to instruct pedestrians that intend to cross) (Song, Lehsing, Fuest, & Bengler, 2018), or informative (e.g. vehicle speed information, countdown timer) messages.

4.6. Lighting signals

Research has been conducted into the use of static and animated lighting signals to indicate vehicle intentions. The colour of light signals can play a vital role in conveying messages from vehicles. A study by Zhang et al. (2017) shows that respondents associate the intention indicator as a communication about the vehicle's internal state rather than as a response to other road users. This is completely in contradiction with the initial design of the display option, which was meant to communicate to other road users in a way similar to traffic lights (a green signal allows pedestrians to cross, and a red signal means stop). Dey, Martens, Wang, Ros, and Terken (2018) introduce new interface concepts to overcome the current limitations of eHMI. They suggest using the blue light strip as a neutral colour, which is not in use with existing traffic lights and is less confusing for VRUs.

Some examples of eHMI lighting and animated signals are shown in Figure 5.

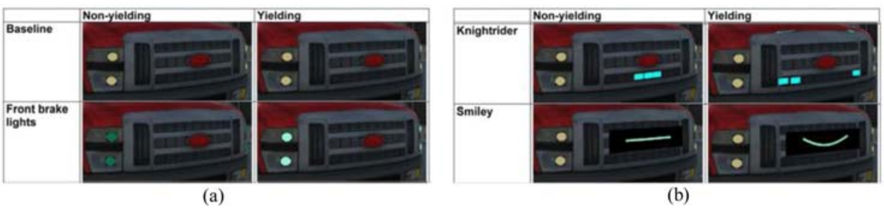

Figure 5. Example of eHMI signals to indicate a vehicle's intended movements (de Clercq, Dietrich, Núñez Velasco, de Winter, & Happee, 2019). (a) The baseline without eHMI and a lighting signal in the form of front brake lights, (b) animated signals in the form of the knightrider and smiley symbols.

4.7. Smart infrastructure

Another form of the visual cue is the so-called "smart infrastructure". In this concept, the communication is through the infrastructure, e.g. illumination of red signals on the road in the form of a zebra crossing when it is not safe to cross the street, and green signals which indicate that it is safe to cross. In some studies, pedestrians recognised this eHMI concept more readily than they recognised displays (Ackermann, Beggiato, Schubert, & Krems, 2019), and perceived as safer and more effective than light signals placed on the vehicle (Löcken, Golling, et al., 2019).

4.8. Bilateral communication via eHMI

In comparison with the above-mentioned eHMI designs, in which ADS unilaterally signal pedestrians, the Imperial College of London and the Royal College of Art have developed a new concept, called Blink (Peters, 2017). The design allows for two-way communication between ADS and pedestrians. Blink detects pedestrians on the road and acknowledges them by displaying a pedestrian silhouette on the vehicle's external display. Pedestrians can hold up their hands when they want to cross in which case the car will stop in response (if it can safely brake in time) and display a green walk signal on the windshield and rear window. If pedestrians do not want to cross, they can wave the vehicle ahead, and it will signal back that it understands and continue on its way (see Figure 6).

4.9. Cross-device applications of eHMI

Along with the proposed external visual and auditory cues, one study has suggested the use of mobile-phone vibration for explicitly communicating ADS awareness and intentions to pedestrians (Mahadevan, Somanath, & Sharlin, 2018). In this study, pedestrians received direct feedback about the vehicle's next action via their mobile-phone vibration. This interface proposed a combination of visual cues through an animated face and a physical cue through haptic feedback. However, participants preferred the animated face to the phone vibration, due to the subtlety of the communication and the possibility of confusion with other phone functionality (e.g. receiving a text message). The study suggests that additional information can support pedestrian crossing decisions, while information overload may arise if pedestrians are provided with too many cues. This highlights the previous findings about receiving too much information, indicating that

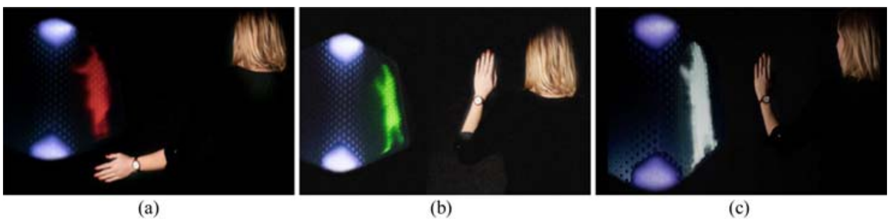

Figure 6. Blink Concept: (a) pedestrian detection confirmation, (b) pedestrian claiming the right of way, (c) pedestrian yielding to the car. Source: (Peters, 2017).

individual decision-making performance rapidly declines after a certain threshold (Matthews, Chowdhary, & Kieson, 2017).

Figure 7 shows a summary of eHMI concepts proposed in the studies reviewed.

5. ADS-pedestrians interactions – modelling approaches

With the assistance of ADS and through the application of a variety of methods, objects in motion such as other vehicles, pedestrians, and cyclists can be tracked to predict their trajectories and future positions. Typically, the prediction system generates multiple possible predictions as hypotheses for the future movement of dynamic objects. Several models have been proposed to simulate the ADS-VRUs interaction and to provide a more precise prediction of the future behaviours of interacting users (Chen, Liu, Liu, Miller, & How, 2016; Møgelmose, Trivedi, & Moeslund, 2015; Schneemann & Heinemann, 2016). A summary of the recent approaches is discussed in this section.

Figure 7 .#eHMI concepts proposed in different studies. The use of multiple cues in some studies is shown via additional circles in which their colour reflects the type of signal. Source: authors elaboration, based on the reviewed references.

5.1. Cellular automaton model

Feng, Cunbao, and Bin (2019) develop a Cellular Automaton model to simulate ADS-pedestrian interaction at unsignalised mid-block crossings. In this model, ADS judge the pedestrian behaviours by considering different factors, such as the existence of a vehicle approaching the crosswalk, the number of lanes, the crossing's length and width, walking speed, vehicle speed, speed limit, the pedestrian's lane/direction, and the Post-Encroachment-Time (Feng et al., 2019). The model takes into account a wide range of factors influencing user crossing behaviours, and it is based on the yielding norms and regulations in China.

5.2. Data-driven approach

Völz, Mielenz, Gilitschenski, Siegwart, and Nieto (2019) show that the correct prediction of pedestrian intentions at crossings is vital to prevent slowing down traffic unnecessarily. An example would be the case of an automated vehicle stopping for a pedestrian who does not intend to cross the roadway. To address this problem, they propose a hierarchical system to (1) identify the intention of pedestrians, (2) provide qualitative measures such as Time-to-Collision, for those pedestrian intentions classified as a crossing. The study uses prediction of significant events rather than solely predicting the trajectories. The model considers the dynamic distance measures, with respect to both pedestrian and vehicle motion on approaching the crossing site, including the longitudinal, lateral and minimal orthogonal distance of the pedestrian to the kerb, as well as the vehicles' distance to the crossing and the pedestrian. The model can improve the previous approach of the Standardised Euro NCAP Tests (NCAP, 2017), in which the focus was on the speed of pedestrian movements, and on the assumption of linear and orthogonal crossings. Another significant aspect of the model is to track the history of the features (as defined by a "feature set") since the machine learning algorithm is capable of learning from time sequences.

5.3. Deep learning-based approach

Currently, ADS are commonly constructed around a "pipeline of individual components", which connects sensor inputs to the system outputs (Figure 8), and by implementing different tools, such as deep learning methods (McAllister et al., 2017). In such a configuration, the inputs from the sensors/cameras provide an understanding of the objects in motion, and the physical context of the traffic scene. From this information, the trajectory of the detected objects can be predicted accordingly and used to select the ADS strategy (McAllister et al., 2017). The MIT AgeLab is building and analysing new deep learning-based perception and motion planning technologies for ADS (Adams, 2017). The micro-movements of pedestrians are automatically detected at a busy intersection, while they are crossing. The system, applying deep learning and computer vision methods, employs video data to estimate the body position of pedestrians, including head, arm, feet, and full-body motions, and, thus, to develop an understanding of human behaviour in the driving context. Rehder, Wirth, Lauer, and Stiller (2018) propose an Artificial Neural Network approach for pedestrian intention

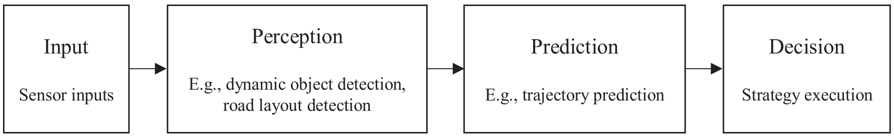

Figure 8. An end-to-end Bayesian deep learning framework – as an example of a machine learning module – indicating the pipeline of ADS individual components. Adapted from McAllister et al. (2017).

recognition and planning-based prediction. This approach determines pedestrian destinations from images and positions (as inputs) and applies trajectory planning towards these destinations for prediction. As output, the network predicts possible destinations in the form of a probability distribution map. The final prediction of the model is obtained by using Markov Decision Processes and the Forward–Backward algorithm. Wang and Papanikolopoulos (2020) employ a neural network classifier to distinguish three pedestrian movement states: crossing, not-crossing, and walking along the direction of vehicle movement. The proposed state estimation method is based on a single body pose and showed an average of 81.23% accuracy.

5.4. Social force model

Zhang, Chen, Yang, Jin, and Zhu (2020) investigate the pedestrian path prediction by using a waiting/crossing decision model and modifying the social force model. The waiting/crossing decision model is employed to judge pedestrian waiting/crossing intentions when a vehicle travelling in a straight direction is approaching and makes use of traffic states and pedestrian characteristics (age and gender). The model takes into account the collision avoidance strategy of pedestrians, reaction to crosswalk boundary, desired speed and relaxation time. Yang, Redmill, and Ozguner (2020) develop a multi-state social force based pedestrian motion model to describe the microscopic motion of the pedestrian crossing behaviour. The pedestrian model considers interaction factors such as gap acceptance attitudes, desired speed, and the vehicle's effect on the pedestrian while the pedestrian is crossing the road. The longitudinal motion control – obstacle avoidance and model predictive control – is applied to model vehicle driving strategies.

5.5. Hybrid automaton model

Jayaraman, Tilbury, Yang, Pradhan, and Robert (2020) have developed a hybrid system model for long-term pedestrian trajectory prediction by using pedestrian gap acceptance behaviour and agent speeds. The model describes the pedestrian's states by using four discrete categories: approach crosswalk, wait, cross, and walk away. Parameters such as pedestrian distance to the crosswalk and kerb, waiting time, vehicle distance to pedestrian, agent speed, and gaze ratio were considered in designing the model. However, the application of gaze ratio did not improve the gap acceptance predictions in the model. The authors explain that a rational pedestrian intending to cross always looks for approaching vehicles, regardless of her decision to cross or not.

5.6. Game theoretic approach

Fox et al. (2018) recently proposed a game-theoretic model for the priority negotiation between an automated vehicle and another vehicle at unsignalised intersections, or with a pedestrian (jaywalker) at an unsignalised crossing. The model is developed under several assumptions, including no lateral movement, communication through agent positioning on the road, and discrete space and time. The model indicates that the agents' optimal behaviours must include a non-zero probability of collision occurrence. The model's assumptions validate the intuition mentioned before, that ADS will make little or no progress if they are known to be perfectly safe and always yield to the interacting agents. In this model, the yielding probability gradually increases as agents get closer. The model then elicits their yield or non-yield strategy from this probability (Fox et al., 2018).

6. Limitations and drawbacks

6.1. Limitations and drawbacks in modelling ADS-pedestrian interactions

The complexity of traffic interactions among road users presents considerable challenges for the design of ADS, while studies of the human factors involved in real-life environments are not yet well developed (Fox et al., 2018). Song et al. (2018) emphasise the point that pedestrians have to learn and adapt their behaviours in relation to automated vehicles as new road users. A further consideration is that automation technologies should be adjusted to the elaborated communication methods road users employ to avoid confusion and frustration. The major drawbacks and limitations of the ADS-pedestrian interactions identified in the literature are discussed below:

(1) **The absence of fully automated vehicles in the public realm**: Fully automated vehicles are not yet widely available and may take decades to become the norm. This gives rise to the question of what level of automated traffic can alter user behaviours. We can also ask whether the coexistence of human-driven vehicles with vehicles of different automation levels will lead to significant changes in user behaviours. Besides, it may take decades before the transition to full automation and the disappearance of human-driven vehicles from the road is completed (Keferböck & Riener, 2015). Consequently, the infrastructure will be gradually adjusted to the new modes of transport. This is an important point, since the factors influencing the pedestrian decision-making process in conventional interactions may not be relevant to their interactions with ADS.
(2) **Complexity of human behaviours**: There is still no established methodology to explain and identify all aspects of pedestrian behaviours on the road. There are many unresolved questions in the automation technology domain, including identifying the most influential factors of pedestrian behaviour, how these factors have an impact on pedestrian behaviours, what the possible interconnection between these factors is, and how to implement these factors in ADS.
(3) **Bullying behaviours of VRUs towards ADS**: Since automated pods currently travel with no active human driver engaged in driving tasks, they may be subject to so-called "bullying behaviour" by other traffic participants (Färber, 2016). For instance,

pedestrians may step in front of the vehicles to force them to change their route, thus delaying the vehicles, or interrupt their operation altogether (Madigan et al., 2019; Riener et al., 2020). Such behaviours may reduce safety by increasing the risk-taking behaviour of other traffic participants. Camara, Romano, et al. (2018) maintain that human drivers manage all such threats by understanding and predicting the VRUs' behaviours. For example, drivers may exhibit dominant behaviours (e.g. speeding up to encourage pedestrians to clear their path), or polite behaviours (e.g. backing off and giving way to pedestrians to cross).

(4) **Lack of appropriate ADS-pedestrian communication methods**: Previous studies suggest that an insufficiency of social understanding can result in traffic accidents (Anthony, 2016), erratic behaviours towards pedestrians (Richtel & Dougherty, 2015), and negative impact on traffic flow. Several studies demonstrate a form of "standstill" between automated pods and VRUs, particularly pedestrians. The standstill forms due to the lack of effective external communication by automated pods (Merat et al., 2018; Riener et al., 2020) when the vehicle path is blocked. In such situations, either the VRU has to change position to unblock the path, or a human operator has to intervene to provide an escape from this conflict. Such behaviours can adversely affect the efficiency of ADS and the traffic flow by causing unnecessary vehicle stoppages on the road, and they may also generate hazardous situations (Jin, Qu, Xu, & Wang, 2013).

6.2. Limitations and drawbacks in the design and implementation of eHMI concepts

Different external interfaces designed for transferring information to the VRUs still face problems concerning, for example, preferable positioning, and preferable type of signals. It has even been suggested that implementing external communication cues may not be necessary for ADS-pedestrian interactions and they are instead just "nice-to-have" (Löcken, Golling, et al., 2019). For this reason, the development and implementation of fully-functioning communication systems could take decades. Various elements and considerations must also be taken into account in developing the eHMI concepts of ADS, since research has not yet reached a consensus on their ultimate form (Dey et al., 2020). They include:

(1) **Understandability of eHMI cues**: The type and concept of external cues need to be universally understandable and learnable for all road users (e.g. using a specific language must be avoided in designing the visual cues). The ADS messages should be clear enough for pedestrians of all age groups and with different physical abilities (e.g. visual or hearing problems, colour vision deficiency). It is noted that the special needs of such road users are mostly unmet in the existing design proposals (Colley, Walch, Gugenheimer, & Rukzio, 2019). In addition, multi-modal communication channels may be required to assist mobility-restricted users, since a single eHMI solution will not meet all users' needs. However, it may still take some years for road users to gain a proper understanding of the new communication systems (which will have a similar function to traffic signals in the way they manage and control users' movements).

(2) **Cultural discrepancies**: Cultural discrepancies among traffic participants should be considered in designing physical or audible interfaces, since signals may be interpreted differently from one country to another (Lee et al., 2019).
(3) **Visibility of eHMI cues**: The visibility of signals seems to be problematic in dense traffic situations, specific weather conditions (e.g. sunlight, rain) (Risto et al., 2017), or when signals are displayed on the outside of the vehicle. The latter is particularly significant in shared space settings, where pedestrians may approach from different directions.
(4) **Practicality of eHMI cues**: Most of the external cues designed to display ADS intentions are practical in one-to-one situations, where a single vehicle communicates with a single VRU, and are not suitable for traffic scenarios with many participants (Risto et al., 2017). This may lead to confusion among users concurrently communicating with the ADS, who may in this situation receive a signal from the vehicle that is not meant to be directed at them.
(5) **Clarity of displayed intention**: Pedestrians also found some types of messages displayed by ADS confusing, in terms of whether the ADS are indicating their intentions or instructing other road users (Zhang et al., 2017). For this reason, training may be required to help VRUs to have a better understanding of the meaning and purpose of the external interfaces displayed by ADS (Habibovic, Andersson, Nilsson, Lundgren, & Nilsson, 2016).
(6) **Triggering time and duration of eHMI cues**: The type and amount of information displayed by the ADS, and the triggering time and duration of displaying the signals in the interaction phase are also crucial in enhancing the efficiency of such communication methods.

7. Discussion

With the advent of ADS, the conventional role of the driver will gradually be replaced with a broad range of automated technologies. In the absence of a human driver, the existing forms of communication among road users will lose their functionality, since one of the interacting agents is no longer available to interact with the other road users. However, there are various technological solutions to compensate for the loss of human drivers and to maintain pedestrian safety in uncertain or conflicting situations, such as uncontrolled crossings or shared spaces. Such automated technologies can detect pedestrians from an adequate distance, track dynamic objects to obtain their movement trajectories, apply the brake or take evasive actions to avoid collision with detected objects/users, and minimise the damage by using PPS when collisions are unavoidable. Receiving real-time infrastructure information, like speed limits or stop signs or lights, as well as the ability to comply with formal traffic rules, are among the other advanced technological aspects of ADS.

In complex urban scenarios, where road users need to negotiate priority, ADS are not yet able to match the high level of elaborated interaction strategies among road users. Several studies have investigated the capabilities and limitations of automation technologies in interaction with pedestrians and have accordingly provided various recommendations and solutions for the design of ADS in scenarios of this kind. A summary of the main findings and unresolved issues discussed in the literature is provided below.

7.1. ADS-pedestrian interactions studies

In the papers reviewed, various data collection approaches are employed to study ADS-pedestrian interactions. The absence of fully automated vehicles on the road is the major issue concerning the ADS-pedestrian interactions studies and data collection approaches. Most of the research reviewed focuses on limited aspects of pedestrian behaviours; for instance, how pedestrians respond to a communication cue, or how the vehicle speed on approaching a crossing site can affect pedestrian crossing decision. A few studies have investigated the overall requirements and expectations of pedestrians in interaction with ADS but using a relatively small sample size. Instead, road trials are used to collect larger scale data over a longer period, although the outcomes may be culture-specific, given that automated pods are not yet operating widely. This points to the need for a larger number of studies with larger sample sizes in order to fully understand pedestrian behaviours in interaction with ADS, and to understand how the emerging automated technology will alter the requirements/expectations of users in comparison with conventional vehicle-pedestrian interactions.

7.2. Influencing factors in ADS-pedestrian interactions

The literature reviewed reveals a wide range of factors influencing pedestrian behaviours in interaction with ADS. Figure 9 summarises the factors influencing crossing behaviours of pedestrians and the essential communicative signals currently identified in the literature that may facilitate the ADS-pedestrian priority negotiation process.

Among all the factors investigated in previous studies, the dynamic factors of the communication environment have the greatest impact on the pedestrian decision-process while interacting with automated vehicles. In the same way as with conventional vehicle-pedestrian interactions, dynamic factors such as the time/distance gap and vehicle speed are the ones considered most important by pedestrians when evaluating the safety level of different crossing strategies and deciding whether to cross the road or yield to the vehicle.

Road users' segregation levels in different traffic settings and related physical contexts of the road also affect user crossing decisions. Environments with less advanced traffic control systems and lower levels of user separation require an increased level of interaction amongst users to avoid a conflict. The current stage of ADS development does not support active interaction and efficient priority negotiation between pedestrians and automated vehicles, and thus pedestrians may behave differently in different traffic settings. However, pedestrian experience with ADS will change when large-scale fleets of automated vehicles appear on the road and an infrastructure for ADS has been implemented, and thus more research should be carried out to reassess the impact of different road contexts on pedestrian crossing decision.

In the current stage of ADS development, it is hard or impossible for the systems to process information about pedestrian-associated factors such as gender, personal characteristics and culture, though these factors can affect pedestrian behaviours. Where a pedestrian's age is concerned, it may be possible for ADS (or, at least, future automated technologies) to distinguish different age groups – for example, children, adults, disabled/elderly people (with mobility aids) – and to take relevant features (e.g. walking speeds) into account for each group. Moreover, factors like pedestrian walking speed

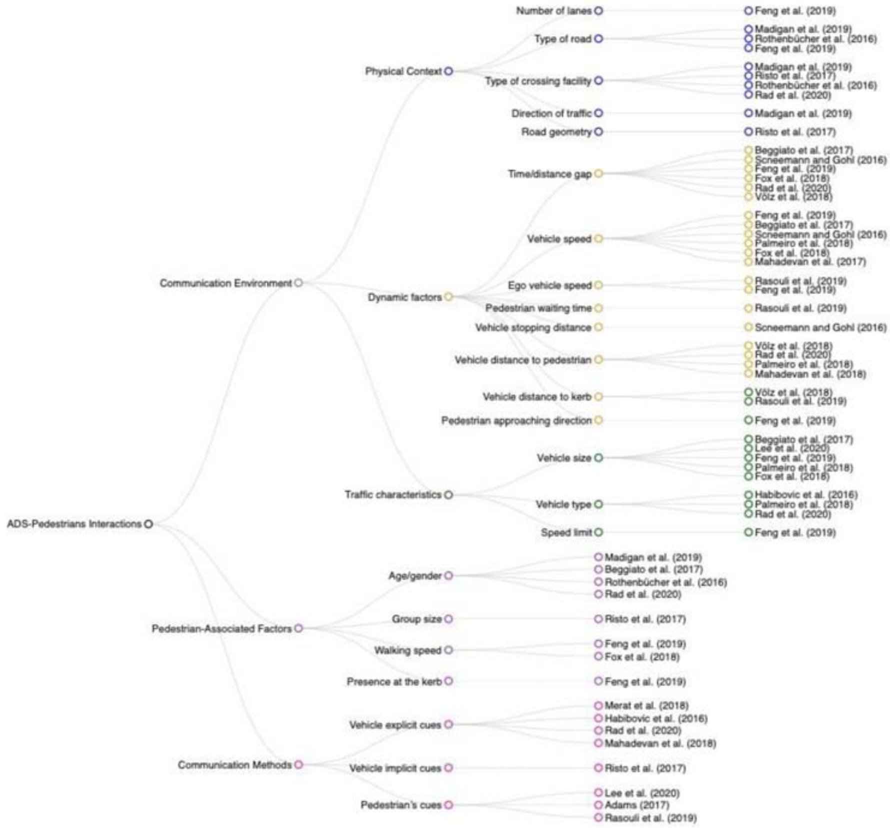

Figure 9. Overview of the factors and communication cues recommended in studies on ADS-pedestrian interactions. Source: authors elaboration, based on the reviewed references in this research.

should not be considered in isolation, as they can be influenced by other factors such as group size, pedestrian physical abilities, waiting time, approaching lane.

Studies on traditional vehicle-pedestrian interactions have discovered a wider range of factors affecting user behaviours than research in the ADS area. For instance, impairment related to alcohol, drugs/medicine, and fatigue can affect the cognitive and physical abilities of pedestrians, and, as a result, may lead to different crossing behaviours. Pedestrian behaviour may be also affected by changes in the weather and visibility conditions. Moreover, there is an interrelationship between most of the factors influencing pedestrian crossing-decision strategies. Consequently, further studies are required to investigate whether influencing factors in conventional interactions are still relevant within the ADS conceptual framework.

7.3. Communication methods

The studies reviewed suggest that both implicit and explicit communication methods should be included in the design of ADS. For implicit signals, a variable TTA should be developed for ADS brake initiation. However, cultural discrepancies and differences in the way users comprehend vehicle movements in different countries make the task of implementing implicit signals like vehicle movement patterns more demanding.

Where explicit (nonverbal) communication cues are concerned, a variety of interfaces have been proposed to accommodate ADS-pedestrian communications and compensate for the loss of the human driver; but the ultimate form of eHMIs is still an ongoing problem. Three major issues on which there is currently no agreement among researchers are: how to develop a uniform eHMI concept that is universally understandable and meets all user requirements; the question of which information should be communicated via eHMI cues; and the question of when eHMI cues should be used. The latter question has received the least attention in the literature. For instance, many studies focus on the efficiency of various eHMI cues, without addressing the issue of how the ADS-pedestrian modelling approaches are used in combination with eHMIs. This requires further research to evaluate how a combined eHMI and modelling approach can manage the ADS-pedestrian interaction process.

7.4. Necessary information inputs in ADS-pedestrian interactions

In uncontrolled environments, both ADS and pedestrians need to receive information about each other's intentions in order to have a smooth and safe interaction process. Some of the most significant information inputs are:

for pedestrians

- whether vehicles are functioning in automated mode
- whether pedestrians are detected by ADS
- what is the movement intention of the ADS?

for ADS

- what are the valuable informative features to be collected on approaching the interaction scene?
- whether pedestrians are going to cross
- what is the pedestrian crossing strategy (regarding the speed and trajectory)?

7.5. Prioritisation of information inputs

Another significant issue for ADS, which may have received insufficient attention in the modelling of crossing behaviours, is the sequence of actions they should follow during interactions with pedestrians. This is also relevant to the sequence of information that ADS may receive while interacting with a pedestrian. For instance, the ADS receive information about the road first, followed in sequence by information on pedestrian position, and pedestrian motions (Camara, Giles, et al., 2018). Throughout the time ADS are processing the information inputs, they may decide either to act (e.g. stop or signal to the pedestrian) or to defer action until more information has been collected. However, the ADS need to act at the right time, since a long waiting time for gathering information may lead to hitting/passing the pedestrian they are interacting with before they have come to a decision on how to act; while in case of an early reaction, the ADS may fail to gather useful information which could improve its selected strategy (Camara, Giles, et al., 2018). Prioritisation of information inputs is required for efficient real-time ADS-pedestrian interaction on the road and should be considered in future research.

8. Conclusions

This paper comprises an overview of ADS-pedestrian interactions, the possible requirements for developing a safe and efficient interaction concept, the capabilities of automated driving technologies in confronting pedestrians, and the current challenges and limitations. The high level of movement freedom of pedestrians on the road, the possibility of performing unexpected behaviours, and the reliance of pedestrians on nonverbal communication cues present substantial challenges to ADS capabilities in handling the possible conflicts. Therefore, ADS must have an in-depth knowledge of the pedestrian decision-making process, the most relevant factors influencing their decisions, and their expectations concerning the action/reaction of the automated vehicles. This highlights the complexity of ADS interaction with pedestrians, in which predicting their intentions and strategies requires taking into account a complex mix of contributory factors. In addition, ADS must be able to interact with pedestrians dynamically and react adequately to their actions when needed. To achieve this, they need to combine appropriate external communication cues (in the form of eHMIs) with suitable driving manoeuvres arising from an accurate understanding of pedestrian behaviours and requirements in the traffic scene.

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Development of a conflict risk evaluation model to assess pedestrian safety in interaction with vehicles

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ABSTRACT

Interactions of motorised vehicles with pedestrians have always been a concern in traffic safety. The major threat to pedestrians comes from the high level of interactions imposed in uncontrolled traffic environments, where road users have to compete over the right of way. The interactions become more complex with the variety of user types and their available conflict resolution strategies. In this research, a conflict risk evaluation model is developed to assess the safety level of pedestrian conflict with other road users. Surrogate safety indicators are employed to measure road users' temporal and spatial proximity during a conflict. The thresholds are determined through the application of various methods (i.e., intersection point, p-tile, maximum between-class variance, and minimum cross-entropy method) to separate potential critical conflicts against normal traffic conditions, on the basis of the conflict risk evaluation model. An F-score method is used to select the optimal threshold given by various applied methods. Two data sets of shared space and mid-block were used to develop and validate conflict risk evaluation models for the interaction of pedestrians with vehicles (passenger cars) and light vehicles (two- or three-wheel vehicles) separately. The proposed model can potentially be used as a real-time conflict risk evaluation model to improve traffic safety.

1. Introduction

Pedestrians, as one of the most vulnerable user groups, are usually exposed to a high risk of severe injuries and a lower chance of surviving road collisions. In 2018, more than 11 million pedestrians were injured, and pedestrian fatalities accounted for approximately 23% of the total road crashes (World Health Organisation). The growing number of severe injuries and moralities on the road signifies the need to implement appropriate techniques to analyse traffic safety and develop collision avoidance systems. Traditionally, crash statistics have been the leading source for pedestrian safety analyses. However, the crash statistic approaches rely solely on reported crash data and neglect the traffic conflicts – where interacting users avoid a collision through evasive manoeuvres (Parker Jr. and Zegeer, 1989). This vitiates the efficiency of crash statistic approaches since collisions are relatively rare events and the majority of critical situations usually lead to traffic conflicts (Hydén, 1987).

Surrogate safety measures (SSMs), if properly applied, are suitable tools to address the constraints of crash statistics-based methods. Surrogate measurement techniques can predict a traffic crash by using measurable or observable non-crash events (Tarko et al., 2009) and characterising safe/normal traffic encounters and critical situations, including traffic collisions (Laureshyn et al., 2010). In most conflict prediction models, a condition is evaluated as a traffic conflict when selected SSMs are below the predetermined thresholds. Besides, SSMs describe the correlation between user behaviour and associated risk. The latter property is substantial for assessing evasive manoeuvres undertaken by road users to avoid a collision and understand the collision avoidance mechanism. If users' evasive actions, such as swerving or sudden speed changes, fail to prevent physical contact with the interacting user/users, a collision will occur (Tageldin et al., 2017).

With respect to pedestrian safety, the major threat comes from the high level of interactions imposed in uncontrolled traffic environments, where users have to compete over the right of way. Such competition over the road space is more complicated when heterogeneous users interact with one another. Furthermore, pedestrians and, in general, lighter road users (e.g., two- or three-wheel vehicles) have a higher degree of movement freedom compared with heavier users (e.g., passenger cars, light/heavy goods vehicles), and thus, capable of changing their movement trajectories on the road. Therefore, predicting the user's next action and associated risk becomes complex with the variety of user types and their available evasive manoeuvres to avoid conflict situations.

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Research contribution

The main objective of this paper is to develop a conflict risk evaluation model to assess the safety level of pedestrian interactions with vehicles. From the reviewed literature in the next section (Section 2), it is evident that most of the proposed models rely extensively on users' speed and trajectory before they take any evasive manoeuvres. This would ignore the traffic situations in which users deviate or decelerate to escape a conflict. The conflict risk evaluation model proposed in this study considers various combinations of the evasive manoeuvres of users to avoid a conflict. Time and distance proximity measures are employed to describe the collision avoidance mechanism of interacting users, and a speed-based indicator explains the speed changes of users in reaction to a conflict. The model can potentially be used as a real-time conflict risk evaluation model to warn drivers in hazardous traffic situations.

The remainder of this paper is organised as follows: Section 2 reviews the relevant studies and different modelling approaches. The proposed methodology for developing the conflict risk evaluation model for pedestrian–vehicle interactions is explained in Section 3. Description of the studied areas, conflict detection, and analysis approach are explained in Section 4. Section 5 presents the application of the conflict risk evaluation models on the analysed data and the selection of thresholds. Discussion of the results and model performance are included in Section 6. Finally, Section 7 presents the paper's conclusions.

2. Literature review

2.1. Surrogate safety measures

Most crash prediction and conflict analysis methods rely on SSMs – as an alternative or complementary method – to identify safety issues and evaluate the crash risk and severity of a conflict event. Surrogate safety indicators mostly rely on the users' temporal and spatial proximity to predict a possible conflict and estimate its safety level. The standard approach utilised to present the concept of SSMs is based on the Svensson (1998) classification of the factors influencing the crash risk: (1) time proximity, (2) spatial proximity, and (3) speeds of involving road users. However, Davis et al. (2011) proposed a different method to represent the probability of traffic crashes and conflict risk through the relation between initial conditions and evasive actions of involved road users. In this approach, the initial conditions of involved road users are assessed to identify critical events and by employing measures, such as time and distance proximity. Similarly, metrics such as braking, deceleration, and acceleration rate are used to identify critical events when road users take evasive actions. Eventually, the said method estimates the collision risk by evaluating the initial conditions and effectiveness of potential evasive actions. The latter consideration is crucial to accurately reflect the safety level of traffic events when pedestrians and, in general, vulnerable road users (VRUs) interact with vehicles. Johnsson et al. (2018) reasoned that an ideal indicator to study VRUs' safety should be able to: (1) estimate the closeness (in terms of time and distance) of road users, (2) evaluate the traffic outcomes based on the potential evasive actions of involved road users, and (3) reflect the fragile nature of the VRUs.

In the following, some of the most significant indicators to study critical traffic events – when pedestrians are involved – are reviewed.

2.1.1. Time-based indicators

Time to collision (TTC) is one of the most frequently applied SSMs in traffic conflict techniques to measure the time proximity of road users. TTC indicator refers to the remaining time between two users before they collide (Chen et al., 2017). In some situations, the minimum TTC (TTCmin) value during a conflict event or the relative TTC (RTTC), as the time difference between the arrival of road users at the potential conflicting location, are estimated as replacements of the TTC (Liu et al., 2017). Although, TTC neglects the users' evasive actions to avoid a conflict and assumes that users continue on the same trajectories with their present speeds. Therefore, it would become impractical in pedestrian–vehicle interactions when pedestrians deviate from their forward trajectories or decelerate to avoid a conflict (Ezzati Amini et al., 2021a). In such cases, the potential collision points would change or not exist to estimate the arrival time of users. As an extension of the TTC and to take users' reactions into account, the time to accident (TA) indicator was developed within the Swedish conflict technique measuring TTC from the moment users take evasive actions (Hydén, 1987). The TA indicator can appropriately assess the conflict proximity when interacting users change speed to avoid a collision. However, deviation strategies – as common evasive actions of pedestrians – are neglected in the estimation of the TA indicator. Another frequently applied SSM is post-encroachment time (PET), defined as the time gap between a user leaving the potential conflict point until the interacting one reaches there (Allen et al., 1978). In the pedestrian–vehicle context, PET may not always be a precise measure to reflect the conflict severity (Ezzati Amini et al., 2021a). For instance, users – involved in multiple conflicts – may pass the potential collision zone long after the interacting user with priority cleared the zone. This delay creates a higher PET value that does not necessarily indicate the safety level of the conflict. The time advantage (TAdv) measure – introduced by Laureshyn et al. (2010) – can predict the PET value by assuming that speeds and trajectories remain unchanged. TAdv can compensate the false PET values for the delay in passing the collision zone but ignores the evasive actions taken by users to avoid a conflict.

2.1.2. Distance-based indicators

Few indicators have been developed to identify critical events by measuring the physical distance among involved road users. For instance, a safe distance (SD) indicator was developed by Golakiya et al. (2020) as the user's distance from the conflict point (the potential point where users may collide if their movement states remain unchanged) when the interacting user reaches there. Olszewski et al. (2020) utilised the passing distance (PD) indicator as to the spatial proximity between interacting road users at the moment the front of the vehicle passes the pedestrian. A lower value in both indicators shows a higher risk of a critical traffic situation. Pascucci (2020) employed the minimum future relative distance (MD) between road users to identify the collision risk. The proposed indicator considers the users' evasive actions (e.g., deceleration and deviation) and estimates their future distance proximity. The authors combined this distance-based indicator with the time proximity to estimate the users' arrival time to the minimum distance (TMD). A similar approach (combination of predicted MD and TMD) is used by Polychronopoulos et al. (2004) to evaluate the safety level of traffic events.

2.1.3. Speed-based indicators

Several speed-based indicators have been proposed to assess the severity level of traffic events. Traditionally, deceleration rate (DR) is used to detect critical traffic situations (Van der Horst, 1991). Shelby et al. (2011) introduced the Delta-V indicator to measure the users' change of velocity in reaction to a conflicting situation and based on the mass of involved road users and the approaching angle among them. The Delta-V indicator can reflect the severity of a traffic conflict between road users with different vulnerability levels (e.g., pedestrians vs. passenger cars). Deceleration to safety time (DST) is another measure to determine safety level in pedestrian–vehicle interactions. The DST indicator is applied in traffic conflict techniques to estimate the required deceleration for a user to escape a conflict (i.e., to reach a non-negative PET) (Hupfer, 1997). Finally, the speed-based indicator of conflicting speed (CS), developed within the Swedish conflict technique, is commonly used to assess the conflict severity by referring to the road users' speeds at the moment just before the start of the evasive action (Hydén, 1987). However, all said indicators ignore the

Table 1
Summary of SSMs, validation studies, and indicators' basis in estimating collision/conflict risk. The VRU column shows whether VRUs are included in the indicators' validation/development. Abbreviations: Initial conditions ('Int. Cond.') & deviation ('Dev.').

Category	Reference	Indicator	Threshold[a]	VRU	Collision/Conflict Risk		
					Int. Cond.	Evasive Actions	
						Speed changes	Dev.
Time-based	El-Basyouny and Sayed (2013)	*TTC*	<1.5 s	✓	✓	–	–
	Sacchi and Sayed (2016)		<1.5 s	✓	✓	–	–
	Sacchi et al. (2013)		<3 s	–	✓	–	–
	Hydén (1987)	*TA*	<1.5 s	✓	✓	✓	–
	Lord (1996)		<1.5 s	✓	✓	✓	–
	Lord (1996)	*PET*	<3 s	✓	–	✓	✓
	Peesapati et al. (2013)		<1 s	–	–	✓	✓
	Laureshyn et al. (2010)	*TAdv*	<2 s	✓	✓	–	–
	Hansson (1975)		<2 s	–	✓	–	–
Distance-based	Golakiya et al. (2020)	*SD*	Varied[b]	✓	–	✓	✓
	Olszewski et al. (2020)	*PD*	<1.7 m	✓	–	✓	✓
	Pascucci (2020)	*MD*	<1.5 m	✓	–	✓	✓
	Polychronopoulos et al. (2004)		<3 m	–	–	✓	✓
Speed-based	Van der Horst (1991)	*DR*	>3 m/s^2	✓	–	✓	–
	Bonsall et al. (1992)		>3 m/s^2	✓	–	✓	–
	Malkhamah et al. (2005)		>4.5 m/s^2	✓	–	✓	–
	Hupfer (1997)	*DST*	>1 m/s^2	–	–	✓	–
	Ismail et al. (2009)		>1.5 m/s^2	✓	–	✓	–
	Tageldin et al. (2015)	*Yaw rate*	>0.08 rad/s^2	✓	–	✓	✓
	Tageldin et al. (2015)	*Jerking*	>1 m/s^3	✓	–	✓	–
	Svensson (1998)	*CS*	>35 km/h when *TA*≥1.5 s	✓	✓	✓	–

[a]The majority of the thresholds are exercised in combination with other safety indicators.
[b]Based on the user and event type.

users' deviation strategies to avoid collisions. Tageldin et al. (2015) suggested studying jerk profile (acceleration/deceleration rate changes per unit of time) and yaw rate (the angular velocity of the road user's rotation) to consider evasive actions performed by lighter users (e.g., motorcyclists).

Table 1 shows an overview of the previously validated safety indicators and a summary of indicators' basis in estimating collision/conflict risk. As presented in the Table, some safety indicators, such as TTC, merely rely on the initial conditions of involved road users to identify hazardous traffic situations. PET measure considers the users' evasive manoeuvres to identify critical events; however, the focus is on the traffic events' outcomes rather than the effectiveness of the performed evasive actions. Further, most distance- and speed-based indicators estimate a traffic event's collision/conflict risk based on the users' evasive actions. Johnsson et al. (2018) argued that relying solely on evasive actions can be problematic in some traffic situations. For instance, road users can create a severe condition when performing no evasive action. No evasive action commonly refers to the situations when users pass/cross the conflict zone without changing their speed or direction of movement. Therefore, a set of SSMs are required to appropriately reflect all possible manoeuvres (including evasive and non-evasive) that interacting users might perform to avoid a conflict on the road. Further, researchers commonly utilise a combination of SSMs to develop traffic conflict techniques and real-time crash prediction models since it provides a more accurate estimation of the collision/conflict risk and severity levels of different traffic events.

The following sections review some traffic conflict techniques and real-time crash prediction models to analyse pedestrian–vehicle conflicts.

2.2. Traffic conflict techniques

The existing traffic conflict techniques commonly employ SSMs to quantify the severity of traffic conflicts (Sayed et al., 2013a,b; Ni et al., 2016). Bagdadi (2013) defined the conflict severity as a combination of Delta-V, TA, and the maximum average deceleration indicators, in which the two latter indicators estimate the effectiveness of deceleration as an evasive manoeuvre. Tageldin and Sayed (2016) investigated the applicability of time proximity indicators, such as PET and TTC, to evaluate pedestrian safety in less-organised traffic environments with heterogeneous traffic complexities. The authors recommended evasive action-based indicators representing variations in the spatiotemporal gait parameters (i.e., step length and frequency) as complementary measures to evaluate pedestrian traffic conflict severity (similar to Medina et al., 2008). However, the mentioned methods classify users' evasive actions based on speed profiles and ignore swerving.

In a pattern-based approach, Zhang et al. (2011) compared pedestrian–vehicle interaction cases based on two outcome categories (vehicle passing first cases and pedestrian passing first cases) to evaluate various indicators and their relation to safety. The comparison showed that distance and speed values varied with outcomes, and the time difference to collision (TDTC) indicator could suitably describe the safety level of traffic events. Golakiya et al. (2020) employed a distance-based measure to describe the safety level of pedestrian–vehicle interaction instances and by considering two separate crossing scenarios similar to Zhang et al. (2011). Later, the authors developed the safety index threshold value for different vehicle types based on vehicle speed as a variable. This study suggests that a distance-based indicator can be more perceivable than time-based safety indicators for the detection of dangerous traffic conditions; however, the proposed safety index majorly relies on the outcome of a traffic event, i.e., the safety evaluation alters based on the user type who gains the right of way and passes first. In another work, Kathuria and Vedagiri (2020) classified pedestrian interactions with vehicles into responsive and non-responsive behaviour based on SSMs, such as speed, TTC, and gap time profiles of users. The variable analysis revealed the importance of the TTC indicator for responsive and TTC and PET for non-responsive behaviour patterns. Besides, from the patterns' severity levels, the authors observed that events involving non-evasive behaviour could also lead to critical interaction. Similarly, Chen et al. (2017) utilised RTTC and PET indicators to represent the spatial and temporal closeness of interacting road users and analyse the safety level of traffic events among them. Although a study by Paul and Ghosh (2017) showed that PET values less than the threshold do not necessarily create critical situations, an additional speed-based indicator is required to appropriately determine critical conflicts and collisions' severity. For this reason, the authors used the CS measure to detect critical conditions based on the speed of the conflicting vehicle when PET values are below the defined threshold (to separate safe and normal traffic conditions).

Saunier and Sayed (2008) suggested a probabilistic framework, which leans on the safety hierarchy concept, implying the highest risk in a collision at the top of the hierarchy, safe interactions or undisturbed passages at the bottom, and traffic conflicts between the two. In addition, the proposed framework provides severity measures and a method to identify traffic conflicts by inspecting all traffic interactions and their link to safety. With a similar assumption, Saunier et al. (2010) utilised a refined probabilistic framework to analyse road user interactions. The authors introduced a probabilistic TTC parameter to estimate the collision probabilities and, thus, understand the mechanisms that may lead to collisions. The core concept of the probabilistic framework is the collision course, and that various chains of events may lead road users to collide; hence it predicts road users' positions and evaluates their probability of collision. Likewise, Laureshyn et al. (2010) designed a framework to organise various traffic encounters into a severity hierarchy and classify their severity concerning the entire interaction process. The authors utilised time-based indicators (e.g., TTC, TAdv, and time gap) and speed profiles to describe the encounter process and severity level.

2.3. Real-time crash prediction

The development and application of real-time crash prediction models have gained momentum due to the recent implementation of advanced driver assistance systems (ADAS) technologies in vehicles. Real-time crash prediction models are a novel approach to evaluate traffic safety levels based on real-time traffic data and employed to separate the potential conflict/crash from the normal/safe traffic situations. The distinction between normal and hazardous traffic conditions typically occurs through a predefined threshold computed by investigating the algorithm to select the optimal cut-off point of the posterior probability (i.e., crash/conflict risk) (Abdel-Aty et al., 2006). Accordingly, proactive traffic safety management systems trigger interventions to prevent collisions and change hazardous conditions to safe ones.

The real-time crash risk analyses are proposed to establish a relationship between crash occurrence probability and pre-crash traffic operational conditions (Hossain and Muromachi, 2012). Most existing crash risk analysis studies develop a functional relationship between traffic-related variables and crash outcomes (crash vs. non-crash) (Roshandel et al., 2015). For example, Abdel-Aty et al. (2004) framed logistic regression models to measure the relationship between traffic flow variables (e.g., speed variation, geometry, and occupancy at the crash site) and crash occurrence in real-time. Yu et al. (2020) argued that the rare event feature of crash occurrence and thus outnumbered non-crash samples within the empirical data (as explained by Abdel-Aty et al., 2004) could lead to the imbalanced data classification issue of crash risk analysis. Therefore, the authors utilised a convolutional neural network (CNN) modelling approach with refined loss functions for real-time crash risk analyses. The proposed approach aimed at (1) employing the tensor-based data structure to examine the multi-dimensional, temporal–spatial correlated pre-crash operational features and (2) optimising the loss functions to overcome the low classification accuracy problem conveyed by the imbalanced data. However, in both studies by Yu et al. (2020) and Abdel-Aty et al. (2004), the models were developed and validated based on empirical data from an urban expressway system and freeways, respectively, with no crashes involving pedestrians. In another approach, Zheng and Sayed (2020) proposed a combination of a generalised extreme value (GEV) model and a Bayesian hierarchical structure to predict real-time crash risk at signalised intersections at the signal cycle level. This approach extracted traffic conflicts as an intermediate for crash prediction and developed GEV models based on conflict extremes. The Bayesian hierarchical structure was developed for the GEV model to combine conflict extremes of different intersections. Further, modified time to collision and three cycle-level traffic parameters (traffic volume, shock wave area, and platoon ratio) were used to detect traffic conflicts, and two safety indices, risk of a crash (RC) and return level of a cycle (RLC), were derived from the GEV model to measure the safety cycle-by-cycle. However, the proposed modelling approach was formulated and validated based on conflicts in signalised intersections without including user behaviour in uncontrolled traffic settings.

Hamidun et al. (2013) introduced Petri Nets as an alternative method to the classical statistical approach to producing a pedestrian crossing risk index. In this method, the risk assessment is viewed holistically as an interacting system of subsequent events in a crash process and based on analysis of the critical signalised crossing and crash history data. Karim et al. (2021) utilised a scene analysis system to assist automated driving systems in identifying crash risks from the surrounding traffic. The Multi-Net of the system includes two multi-task neural networks that perform scene classification to label each scene. The system combines the DeepLab v3 (instance segmentator) and YOLO v3 (object detector) to detect and locate risky pedestrians and the nearest vehicles. Using vehicular onboard devices, Zeng et al. (2015) developed a logical framework for crash risk identification and warning system. First, wireless communication devices connecting the subject vehicle to roadside equipment (V2I) and other vehicles (V2V) are applied to comprehensively track the motion status of the different road targets (approaching vehicles, obstacles, and pedestrians). Then, the motion state of detected road users and obstacles is predicted using the Kalman filter (KF). Furthermore, vehicular distance is predicted and compared with the estimated safe threshold to evaluate the traffic crash risk. In a recent study, Yue et al. (2020) proposed an augmentation function to current active pedestrian safety systems expected to be practical for pedestrian crashes caused by pedestrians' unexpected behaviour. The augmentation function estimates the crash risk using a Monte Carlo process based on the vehicle and pedestrian kinematic features (time–space–distance relationship). The estimated crash risk denotes the probability of colliding with a pedestrian, given all possible future random trajectories of the pedestrian. The function activates evasive actions once the crash risk exceeds a tolerance threshold.

Few studies focused on predicting critical traffic conflicts – as more frequent events – rather than collisions on the road among all developed models. For instance, De Nicolao et al. (2007) developed a model based on extensive offline Monte Carlo simulations to suitably assess the collision risk with pedestrians and avoid generating false interventions. Therefore, the model relies on pedestrian behaviour and three scenario types: (1) pedestrians crossing in front of vehicles, (2) pedestrians walking in the same or the opposite direction as vehicles, and (3) pedestrians traversing a curved path in front of vehicles. With a similar purpose, Agarwal (2011) formulated a linear regression model and applied TTC measure to develop conflict models at controlled and uncontrolled intersections and roundabouts. The model can predict the total number of conflicts for the entire intersection area or per intersection approach. Variables, such as the number of conflicts, and lanes, were significant for safety level prediction of a conflict. However, the applicability of the models in intersections with varying characteristics and speed limits was not studied. Another study by Formosa et al. (2020) employed a deep learning methodology to predict traffic conflicts. Highly dis-aggregated traffic data and in-vehicle sensors data from an instrumented vehicle were integrated with traffic variables and SSMs. Although the developed models focused on the crash prediction among vehicular traffic without including pedestrian–vehicle interactions. Noh et al. (2022) combined the field and the centralised processes

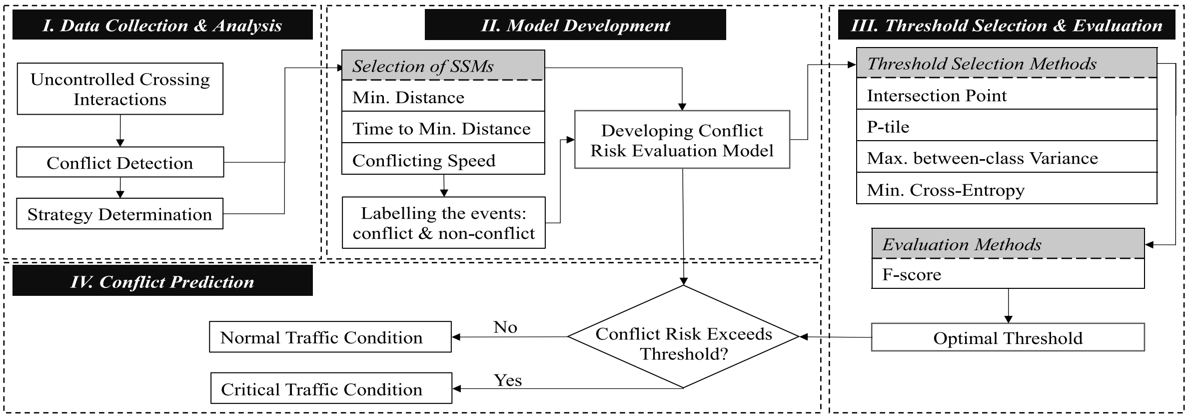

Fig. 1. The methodology flowchart for developing the conflict risk evaluation model.

to develop an analytical framework for a crosswalk safety assessment (in severity levels of relatively safe, caution, warning, and danger) with various behaviours of vehicles/pedestrians and environmental features (e.g., relative distance, speed, deceleration). The proposed framework analyses these behaviours by constructing a data cube structure that combines the long short-term memory (LSTM)-based predictive collision risk (PCR) estimation model and the online analytical processing operations. The analysis is conducted based on two scenarios: the movement patterns of vehicles and pedestrians by road environment and the relationships between risk levels and vehicle speeds. In the proposed PCR model, the separation of various risk levels is solely based on the relative time of arrival at a potential collision point; however, this could cause triggering false warnings, mainly because the majority of detected risky situations (at warning and danger levels) were scenes with low vehicle speed (<10 km/h). Thus, combining these safety measures (time- and speed-based) would be necessary to correctly identify all dangerous traffic situations between vehicles and pedestrians.

The following section explains the proposed methodology for developing the conflict risk evaluation model for pedestrian–vehicle interactions in this study.

3. Methodology

Traffic conflicts are defined as events where interacting users (at least one of them) need to take an evasive manoeuvre to avoid a collision (Parker Jr. and Zegeer, 1989). Hydén (1987) argued that the likelihood of turning a severe conflict into a collision depends on various factors, such as time/space margin between the interacting users, type of road users, and type of evasive actions undertaken by users to avoid a conflict/collision. Based on this knowledge, the methodology introduced by Yang et al. (2018) is adopted in this paper for the development of a conflict risk evaluation model for pedestrian–vehicle interactions. The methodology is built in three steps: (I) formulating the conflict risk evaluation model, (II) threshold selection methods, and (III) threshold evaluation criteria. Fig. 1 depicts the methodology flowchart for developing the conflict risk evaluation model in this study.

3.1. Model development

The conflict risk evaluation model is formulated using a logit model, in which the discrete choices of conflict and non-conflict are examined. The logit model assumes a linear relationship between the predictor variables (e.g., $x_1, x_2, \ldots, x_i$) and the logit of the event (i.e., the binary response variable Y). The linear relationship can be formed as Eq. (1), where ℓ is the logit, b is the logarithm base, and θ_i are model parameters.

$$\ell = \log_b \frac{p}{1-p} = \Sigma\theta_i x_i \tag{1}$$

Hence, the probability that the response variable $Y = 1$ is:

$$p = \frac{1}{1 + b^{-(\Sigma\theta_i x_i)}} = S_b(\Sigma\theta_i x_i) \tag{2}$$

where S_b is the sigmoid function with base b. Once, the predictor variables of θ_i are estimated, the logit/probability that $Y = 1$ can be computed for a given observation. The predictor variables influencing the conflict risk outcome should appropriately reflect the traffic safety level of the events. In this study, the proposed model evaluates the outcome of traffic events for various evasive manoeuvres (i.e., deceleration, deviation from the forward trajectory, and no evasive actions) and the combinations of these strategies performed by interacting users to avoid a conflict in the road. Thus, the evasive manoeuvres are the predicted future motion states of involved road users that the algorithm assumes to evaluate the associated conflict risk. Accordingly, the time and distance proximity of interacting users should be estimated to assess the conflict risk; however, as Laureshyn et al. (2010) proved, time-based and distance-based indicators are not sufficient to describe the severity of a conflict, and an additional speed-based indicator is required to suitably address the outcome of a traffic event. Therefore, based on the reviewed literature in Section 2.1, three safety indicators are selected to estimate the spatial proximity, time proximity, and speed of users after performing various evasive manoeuvres:

I. Minimum Future Relative Distance (MD): Minimum distance indicator evaluates how close the users would get – in terms of distance – by applying a strategy pair (Pascucci, 2020; Polychronopoulos et al., 2004). Most SSMs predict the collision risk by assuming that road users collide if the condition remains unchanged. However, the assumption is irrelevant for deceleration and deviation strategies since users' speed, and movement direction would change. Further, for deviation strategies, the theoretical collision point (TCP) will change (deviating to cross in front of the interacting user) or no longer exist (deviating to cross behind the interacting user). As a solution, the MD indicator identifies the new collision points and/or computes the distance proximity of interacting users.

II. Time to Minimum Distance (TMD): The TMD is employed as a complementary measure to describe the available time gap for users to arrive at the MD after the first user cleared the zone (Polychronopoulos et al., 2004; Pascucci, 2020; Ezzati Amini et al., 2021a). This SSM is added to the conflict analysis since a distance-based measure cannot correctly describe the severity of a conflict. For instance, the MD of 0.2 m between users reflects a critical conflict while the second user might arrive at the MD long after the first user passed the point, thus, a safe traffic condition. Besides, the TMD measure reflects the user's speed change in the deceleration strategy. The latter property would be practical to account for the speed reduction of users to avoid conflicts and compute the arrival time to the MD/TCP accordingly.

III. Conflicting Speed (CS): This speed-based measure – inspired by Hydén (1987) and Svensson (1998) – is included in the analysis by referring to the speed of the heavier interacting road user (i.e., vehicular traffic) when evasive actions are taken and at the moment of minimum distance. In most traffic conflicts, user speed changes are considered an evasive action. While most of the employed SSMs largely ignore the varied speed profiles of users under the assumption that a collision would occur if the trajectory and speed remain unchanged (e.g., TTC). The CS would compensate for the absence of a proper speed-based indicator to predict the severity of a conflict by considering various evasive manoeuvres. This is particularly important for the deceleration strategies of users. For instance, conflict events with the MD and TMD values below the thresholds are considered safe if users' speed is close to zero. This reflects the traffic situations, where users (i.e., vehicular traffic) either come to a complete stop before/while reaching the MD threshold, or they are rolling over a small gap, and thus, still a safe traffic condition.

The proposed model focuses on predicting critical traffic conflicts rather than merely collisions, in which conflict and non-conflict traffic situations are separated based on the collective effect of selected safety indicators. The threshold determination approach employed to separate normal and hazardous traffic conditions is explained in the following.

3.2. Threshold determination

Threshold defines a cut-off point beyond which the outcome of the prediction model would vary. Similar to the threshold determination in real-time crash prediction (Yang et al., 2018), in this conflict risk evaluation model, there is a dilemma since a high threshold may fail in detecting many potential conflict conditions on the road, while a low threshold will lead to triggering false warnings. The latter issue can negatively affect drivers' reliance on the ADAS and consequently road safety by ignoring correct warnings. Therefore, four practical methods (i.e., intersection point, p-tile, maximum between-class variance, and minimum cross-entropy method) are selected in this study to identify the conflict risk threshold. The conflict risk evaluation model will provide the probability of the conflict occurrence, and the event will be classified as conflict (critical traffic condition) or non-conflict (normal traffic condition) based on the determined threshold:

$$Predicted\ Conflict = \begin{cases} 1, & if\ conflict\ risk \geqslant threshold \\ 0, & if\ conflict\ risk < threshold \end{cases} \tag{3}$$

where conflict risk is the predicted probability value returned by the conflict risk evaluation model, i.e., the logit model developed in Section 3.1.

3.2.1. Intersection point method

The intersection point method applied in different fields (e.g., motion planning, collision detection) computes the cut-off point where two curves take the same values. This method determines the threshold by using the intersected point of the cumulative predictive conflict and non-conflict events.

3.2.2. P-tile method

The p-tile method – as a threshold determination method – is based on the grey level histogram, assuming that objects in an image are brighter than the background (Gen-yuan et al., 2009). In image segmentation techniques, the detected objects occupy a fixed percentage of the image area (P%). Concerning conflict and non-conflict events, P% corresponds to the proportion of conflict events. Therefore, the threshold is selected when the overall proportion of the conflict events is equal to P% (Yang et al., 2018).

3.2.3. Maximum between-class variance method

Maximum between-class variance is a threshold determination method, initially proposed by Otsu (1979). The algorithm uses maximum between-class variance to measure the difference and select an optimal threshold. When the classes are characterised as conflict and non-conflict events, the between-class variance (σ_b^2) separated by threshold T is formed as:

$$\begin{aligned} \sigma_b^2 &= \sigma^2 - \sigma_w^2 = \omega_0(\mu_0 - \mu)^2 + \omega_1(\mu_1 - \mu)^2 \\ &= \omega_0\omega_1\left(\mu_0 - \mu_1\right)^2 \end{aligned} \tag{4}$$

where μ_0 is the mean of conflict events with level between T_0 and T_{t-1}, and μ_1 mean of non-conflict events with level between T_t and T_{l-1}. μ represents the conflict risk means between levels T_0 and T_{l-1}. ω_0 denotes the probability of conflict events $\omega_0 = \sum_{i=0}^{t-1} p(i)$, and ω_1 denotes the probability of non-conflict events $\omega_1 = \sum_{i=t}^{l-1} p(i)$.

The optimal threshold is taken, when the σ_b^2 is maximised.

3.2.4. Minimum cross-entropy method

The minimum cross-entropy method estimates the probability of rare events and the optimum threshold value. As proposed by Li and Lee (1993), the optimal threshold can be found by minimising the cross-entropy between the foreground and the background in image segmentation techniques. In the conflict risk evaluation application, the optimal threshold (T) can be obtained by minimising the cross-entropy between the conflict and non-conflict data and the threshold data set:

$$T^* = \boldsymbol{argmin}\left[\sum_{i=0}^{t-1} T_i P_i \log\left(\frac{t_i}{\mu_0}\right) + \sum_{i=t}^{l-1} T_i P_i \log\left(\frac{t_i}{\mu_0}\right)\right] \tag{5}$$

where μ_0 represents a similar metric as Eq. (4).

3.3. Threshold evaluation criteria

The F-score is frequently used in the statistical analysis of binary classification, reflecting the accuracy of a test. The measure is calculated based on the precision and recall of the test:

$$\text{F-score} = \frac{2}{precision^{-1} + recall^{-1}} \tag{6}$$

where precision is the number of conflicts correctly predicted as conflicts divided by the number of all predicted events as conflict (including false predictions). The recall denotes the proportion of non-conflict events correctly predicted as non-conflict (i.e., correct non-conflict predictions divided by the number of all samples that should have been identified as non-conflict). The F-score returns a value between 0 and 1, in which the highest value indicates better method performance.

4. Data collection and analysis

The safety analysis in this study was performed by using two video graphic surveys. The safety analysis preliminary relies on the trajectories of users extracted from the video data and a set of explanatory variables achieved through mining the data sets. A conflict detection procedure was applied in the second stage to classify road users' interactions and identify conflict resolution strategies. Later, the selected SSMs (see Section 3.1) were estimated for all possible combinations of evasive manoeuvres that interacting users could perform to escape a conflict, including the taken strategies in the data sets.

4.1. Video graphic surveys and data extraction

In this study, two previously developed video graphic surveys were examined: (1) a mid-block crossing area in Surat city, Gujarat, India (Golakiya and Dhamaniya, 2018), and (2) a shared space zone in Hamburg city, Germany (Pascucci et al., 2021). The conflict data of two different sites were analysed to develop a more comprehensive and holistic modelling approach capable of evaluating the traffic conflict

Fig. 2. The mid-block crossing from cameras view (Golakiya and Dhamaniya, 2018).

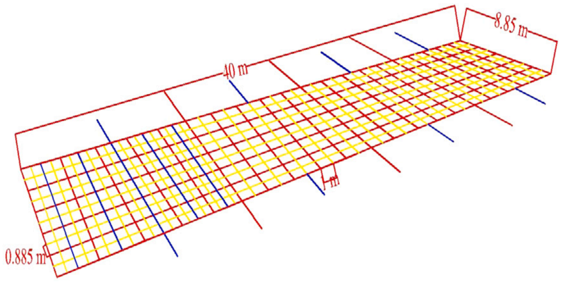

Fig. 3. Grid details to track the location of road users in the mid-block crossing area (Golakiya and Dhamaniya, 2018).

Fig. 4. Grid overlaid over the captured video data of the mid-block crossing area (Golakiya and Dhamaniya, 2018).

risk, regardless of the differences in layouts and traffic behaviour. Areas with high traffic volumes are selected to investigate road user behaviour when exposed to a high number of traffic interactions since there are less significant safety concerns in areas with low traffic volumes. Besides, study locations are chosen in the road layouts with longitudinal movement of vehicular traffic where pedestrians cross the road from one side to the other. The number of lanes and width of the roadways are also considered in selecting the study locations. Another significant criterion was the type of traffic participants since this study concentrates on developing a modelling approach to detect critical pedestrian conflicts with passenger cars and light vehicles (e.g., two-wheel and three-wheel vehicles). For this reason, the case studies should accommodate a high number of the said road user types while the participation of other user types is negligible, i.e., the number of passenger cars and light vehicles is dominant in the shared space and mid-block crossing area, respectively. Consequently, there is less interference in the interaction dynamic among road users and in the traffic performances (Pascucci, 2020).

Case study 1: Mid-block crossing interactions

Two lanes of a road in a mid-block crossing area in Surat city, Gujarat, India, are selected for the video observation and data analysis (Golakiya and Dhamaniya, 2018). The crossing is on a six-lane arterial urban road with an additional bus rapid transit (BRT) lane, where traffic drives on the left. Diverse traffic participants pass through the road, leading to more complex traffic interactions in the mid-block crossing area. The video survey was performed by placing a high-resolution camera at a 15-meter elevation of a building (Fig. 2). The duration of the recorded video is 30 min, and recorded on January 3rd, 2017, on a typical weekday. The road users' trajectories were plotted in the AutoCAD 2016 software using a grid of size 40×8.85 m^2 as per actual dimensions taken in the field, and the same could be overlaid on the captured camera view (Golakiya and Dhamaniya, 2018). The grid was plotted with block size 1.0×0.44 m^2 for the first 30 m, and 0.40×0.44 m^2 for the last 10 m to track the exact location of the vehicular traffic and pedestrians in both longitudinal and lateral directions (X–Y coordinates), respectively (Fig. 3). Then, the grid was overlaid over the captured video using the Ulead VideoStudio 11 software (Fig. 4). The Avidemux 2.6.8 software converting one second into 25 frames was utilised to replay the overlaid video on a large screen monitor. The road users' positioning was tracked and recorded every 0.48 s time step (12 video frames) using a two-dimensional coordinates system. The size of different vehicles was measured in the field – measuring the maximum length and width – and vehicles in the stream were divided into different categories based on their type (Golakiya and Dhamaniya, 2018). The extracted data includes the trajectory data of passenger cars, heavy and large goods vehicles (HGVs, LGVs), two-wheel vehicles (2W), three-wheel vehicles (3W), and pedestrians. Based on the coordinates of users, the velocity and acceleration rate were computed. The pedestrian flow was 304 ped/h at the study location, 2W flow was 2393 veh/h, and 3W flow was 1350 veh/h.

Case study 2: Shared space interactions

The subject data set was collected through video recording for a shared space zone in the district of Bergedorf (Weidebaumsweg), Hamburg city, Germany (Pascucci et al., 2021). The area is 63 meters long and is in the vicinity of a shopping mall and retail stores. Various road user types share the road in this area, where vehicles with a 20 km/h speed limit have priority, and pedestrians should cross the road when the given/available gap is long enough to traverse the roadway. The video survey was performed by placing two cameras of 640×480-pixel resolution and 30 frames per second at an elevation of about 7 meters and towards opposite directions of traffic (Fig. 5). The video was recorded on Saturday, April 2, 2016 (2:00 p.m.–4:00 p.m.), and 30 min of the recorded data were selected for analysis. The position of road users was tracked at discrete time steps of 0.5 s using the software Tracker and through the projection of the body barycentre (for pedestrians) and the observable extreme of the passenger cars (front or rear) on the ground (Douglas, 2017; Pascucci et al., 2021). Later, the tracked vehicles' points were moved along the symmetrical axis of the vehicle to shift the position to the barycentre. Then, all tracked positions from both cameras were imported in the same 2D coordinate system to cover the entire area. Finally, to obtain continuous and stable trajectory data for road users, tracked points were smoothed in X and Y over time by a smoothing spline with 4 degrees of freedom. The level of inaccuracy was estimated to be at a maximum of 25 cm for pedestrians and 40 cm for vehicles (Pascucci, 2020). The extracted data contains the trajectory data in terms of coordinates every 0.5 s, velocity, and acceleration for 331 passenger vehicles, 1115 pedestrians, and 29 cyclists; however, the cyclists are out of this research interest and neglected in the analysis. The vehicle flow rate was 600 veh/h and pedestrian flow rate 2200 ped/h within an extension of about 60 meters in the shared area, meaning that eight pedestrians were present on average at every time step against approximately four vehicles in the 63-meters-long circulation zone (Pascucci, 2020).

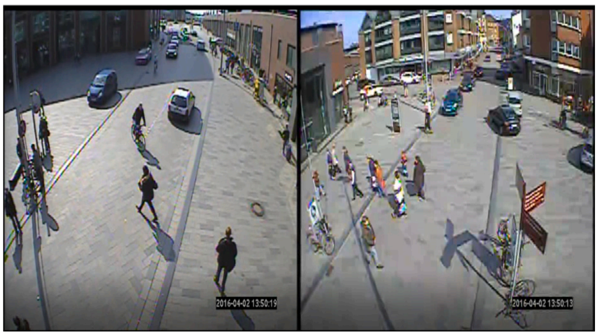

Fig. 5. The shared space site from cameras view (Pascucci et al., 2021).

4.2. Conflict detection procedure

Mid-block crossings and shared spaces, as uncontrolled traffic environments, require constant interaction among road users to ensure safety. In this research, a conflict detection procedure was designed to classify the safety level of users interacting on the road, based on the Parker Jr. and Zegeer (1989) definition of traffic conflicts as events, where interacting users (at least one of them) require taking an evasive manoeuvre to avoid a collision. In order to transfer this definition from the traffic conflict technique field into the designed conflict detection method, the interacting users are detected, and two points are specified on each user's trajectory: (1) the point in which users initialise an evasive manoeuvre (e.g., change of speed or movement direction), and (2) the estimated point of traffic conflict between users. The entire conflict detection procedure is programmed using Rstudio programming language and consists of the steps below:

Step 1. Specifying Street Boundaries: Street boundaries are specified in both data sets to only keep the trajectories of traffic participants in the studied zone. As a result, the trajectories of pedestrians walked along the road (without crossing the roadway), and vehicular traffic exited the road before reaching the crossing area – in the mid-block crossing – and parked the vehicle along the road – in both study locations – are removed from the conflict analysis.

Step 2. Plotting Free Flow Trajectories (FFTs): The FFTs of road users are plotted, providing the shortest path from their origin to destination. In the absence of a traffic conflict, road users tend to take the shortest path to reach their destinations and avoid performing any evasive manoeuvres (Schönauer, 2017). Hence, the FFTs are employed to hypothesise the spatial proximity of users and, consequently, the traffic outcome if road users would have continued the shortest path to reach their destinations.

Step 3. Identifying Intersection Points: A Theoretical Collision Point (TCP) identifies the users' intersected trajectories if they would have traversed the FFTs to reach their destinations. Algorithm 1 explains the applied method to identify the intersected trajectories of users. A buffer zone is considered for all user types at TCPs to improve the accuracy of the collision points. This assumption aims to reflect the real-world collision events where vehicles hit the pedestrians at the buffer than/before the TCPs and are reflected in the users' arrival time (see next step).

Step 4. Defining a Minimum Time to collision (TTC): For interacting pairs with identified TCPs, a minimum RTTC of 3 s (Sayed and Zein, 1999) is considered to capture the simultaneous arrival of the interacting users (i.e., vehicular traffic vs. pedestrians) and at the TCP and users' buffers (near- or far-buffer, depending on the direction of approach). The RTTC is estimated based on the individual average speed and computed as:

$$|TTC_{vehicle} - TTC_{pedestrian}| \leqslant 3 \text{ s} \tag{7}$$

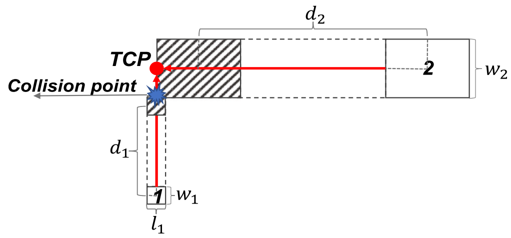

Fig. 6. An example of TTC Calculation for perpendicular trajectories.

Algorithm 1: Identifying the intersection points of road users' FFTs in the shared space area*.

Input: *FFTs-List* is the list of road users FFTs labelled with users' IDs and types (*user ID* & *user type*) and includes a set of coordinates for users' positioning, if the FFTs were traversed.
Output: *Intersection-List*: the list of intersected points of road users' FFTs.

```
for i ← 1: length (FFTs-List) do
    Temporary-List <- FFTs-List [[i]];
    Car-Users <- Temporary-List %>%
    filter (user type == "car") %>%
    distinct (user ID) %>% pull (user ID);
    Ped-Users <- Temporary-List %>%
    filter (user type == "pedestrian") %>%
    distinct (user ID) %>% pull (user ID);
    Combined-List <- expand.grid (Car-Users, Ped-Users);
    x <- Temporary-List$Frame [1];
    Combined-List$Frame <- x;
    names (Combined-List) <- c ("Car-ID", "Ped-ID", "Frame");
    for j ← 1: nrow (Combined-List) do
        Car-Points <- Car-FFT %>%
        filter (user ID == Combined-List [j, "Car-ID"]) %>%
        filter (Frame == Combined-List [j, "Frame"]);
        Ped-Points <- Ped-FFT %>%
        filter (user ID == Combined-List [j, "Ped-ID"]) %>%
        filter (Frame == Combined-List [j, "Frame"]);
        Intersected-Points <- st-intersection (Car-Points, Ped-Points);
        Small-List [[j]] <- Intersected-Points;
    end
    Intersection-List [[i]] <- Small-List;
    Small-List <- list ()
end
```

*Some lines of the code are excluded for simplification.

An example of the TTC calculation in perpendicular trajectories is depicted in Fig. 6, in which the TTC of users is estimated as (similar to Van der Horst, 1991):

$$\begin{cases} TTC_{vehicle} = \dfrac{d_2 - (l_1/2)}{\bar{v}_2} \\ TTC_{pedestrian} = \dfrac{d_1}{\bar{v}_1} \end{cases} \tag{8}$$

where d_1 and d_2 are distances from the centres (body barycentre) of road users 1 (pedestrian) and 2 (vehicle), respectively, to the intersection area; l_1, l_2 and w_1, w_2 are the lengths and widths of users 1 and 2, respectively; and $\bar{v}_1$ and $\bar{v}_2$ are the users' average speed.

The application of the conflict detection procedure led to the identification of 120 conflict events between road users in the shared space data set and 165 conflict events in the mid-block crossing data set, in which one/both took evasive actions to escape the potential collisions. However, seven conflict events were detected in the mid-block crossing

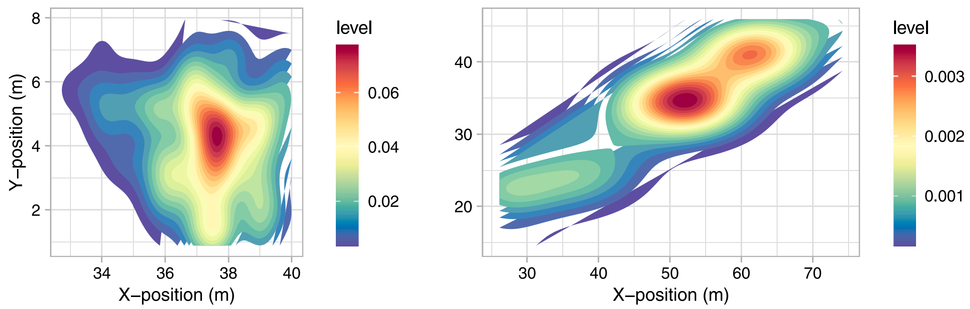

Fig. 7. Conflict density based on the TCPs of pairs in the mid-block crossing (left) and the shared space area (right).

Table 2
Summary of the identified conflict events with pedestrians in the studied areas.

Location	Car	2W	3W	HGV/LGV	Total
Shared space area	120	NA	NA	NA	120
Mid-block crossing	11	92	51	4	158

Table 3
Variables considered to analyse the theoretical conflict events.

Variable	Unit	Description
$\bar{v}_{ped}$	m/s	Pedestrian's average speed
$\bar{v}_{car}$	m/s	Vehicle's average speed
$\bar{a}_{ped}$	m/s^2	Average acceleration of pedestrian users
$\bar{a}_{car}$	m/s^2	Average acceleration of vehicle users
d_{ped}	m	Pedestrian's free-flow distance to the CP
d_{car}	m	Vehicle's free-flow distance to the CP
dev_{ped}	m	Pedestrian's deviation from CP
dev_{car}	m	Vehicle's deviation from CP
TTC_{ped}	s	Pedestrian's TTC
TTC_{car}	s	Vehicle's TTC
t_{ped}	s	The start time of pedestrian's trajectory
t_{car}	s	The start time of vehicle's trajectory

CP refers to the collision point as explained in Section 4.2.

where road users showed erratic behaviour (e.g., pedestrians stepping backwards or running to avoid collision with vehicles) and thus, removed from the analysis. Table 2 summarises the final conflict events after applying the conflict detection procedure on both data sets, and Fig. 7 shows the conflict density based on the TCPs detected during the analysis of the studied areas. Eventually, a set of explanatory variables listed in Table 3 was computed during the analysis for every identified conflict instance.

4.3. Determination of evasive strategies

The detected conflicting pairs are analysed separately to evaluate their behaviour and classify the users' evasive strategies. Initially, the relevant variables listed in Table 3 are utilised to compare the FFTs of users with their observed trajectories, and deviation angles (from FFTs) are determined accordingly. In the next step, the speed profiles of users in every conflict event are analysed. For this reason, two different 'decision points' are defined to detect the acceleration changes of road users between every two consecutive points in their trajectories:

- The speed changes of the interacting users if the user switches from deceleration to acceleration and vice versa. This decision point labels speed changes of users during the conflict.
- The acceleration changes of the interacting users if the change is more than half of the average acceleration per user type. This decision point determines users' change of speed strategy, i.e., whether users employ a deceleration/acceleration strategy in reaction to a conflict on the road.

Subsequently, the point (i.e., user positioning) and time when users initialise an evasive manoeuvre (either change of speed or movement

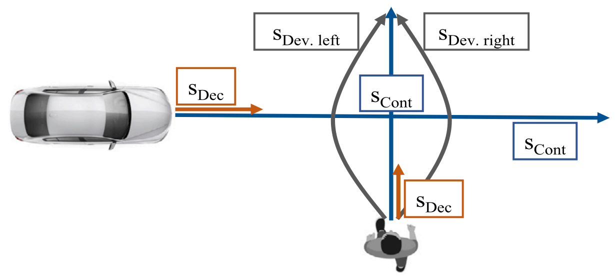

Fig. 8. An example of possible evasive manoeuvres in pedestrian–vehicle interactions. Dec stands for deceleration, Dev for deviation, and Cont for continuing strategies.

direction) are recorded. In the final step, the evasive actions taken by users were classified manually by using the collected information on their movements during the conflict. Furthermore, for each time interval, a Graphics Interchange Format (GIF) video file was generated to scrutinise the interaction process and verify the identified strategies by showing the decision points of users and their animated movements. Fig. 9 illustrates an identified conflict event between a pedestrian and a passenger car in the shared space by applying the conflict detection method. In this example, the users' FFTs are plotted – based on their origin and destination coordinates – to identify the TCP among them, and the RTTC to reach the TCP is computed (1.069 s). The users' speed changes over the interaction time show that the passenger car decelerates in reaction to the pedestrian while the pedestrian crosses the road at a nearly constant speed (Fig. 10). Besides, as shown in Fig. 9 (left figure), the pedestrian deviates from its FFT – with the deviation angle of θ – to cross the roadway behind the car. Hence, in this example, the users' conflict resolution strategies are determined as deceleration for the passenger car and deviation for the pedestrian. After analysis of user behaviour in all detected conflict events, their evasive actions to avoid a conflict are classified as:

- **Continuing** (applicable for all user types): Moving along the FFT with preferred/current speed.
- **Deceleration** (applicable for all user types): Moving along the FFT with reduced speed.
- **Deviation** (applicable for pedestrians, 2Ws & 3Ws): Deviating from the FFT – and thus TCP – to the left or right, with current/preferred speed.

Fig. 8 illustrates a schematic overview of the users' simplified trajectories corresponding to the strategies identified in the analysis. It is worth noting that this approach may not capture all traffic conflicts or evasive manoeuvres of users on the road, and the simplified trajectories may not perfectly correspond to the real-world trajectories of users.

4.4. Estimation of surrogate safety indicators

In this study and as explained in Section 3.1, a set of indicators (i.e., MD, TMD, and CS indicator) is proposed to address the safety

Fig. 9. An example of conflict detection procedure application on pedestrian–passenger car conflict in the shared space. The numbers labelled on trajectories shows the time in second.

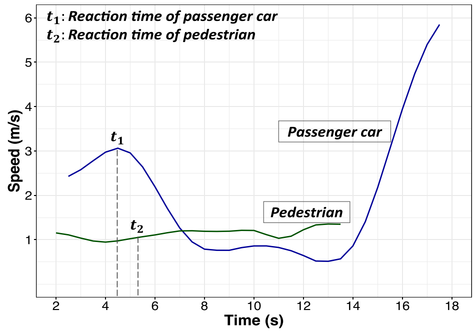

Fig. 10. Speed profiles of road users in the conflict event depicted in Fig. 9.

level of pedestrian–vehicle interactions and overcome the insufficiency of previously applied SSMs. The proposed time-, distance- and speed-based safety parameters estimate the safety level of the conflict events and are computed for all possible strategy pairs that users can perform to avoid a conflict (i.e., all combinations of strategies available for user types in the interaction and classified in this study, including the taken strategies). Fig. 13 illustrates the schematic overview of the MD estimation among road users for two different strategy combinations in which, based on that, the TMD and CS are also measured.

According to Hydén (1987), conflicts are considered dangerous through computing a speed-dependent TTC or when TTC is below 1.5 s. The latter assumption is used in this study to identify critical conflicts. A critical conflict is assumed to occur when TMD is below 1.5 s, i.e., time to the existing/new theoretical collision point is below the defined threshold. The MD is considered a collision when the minimum distance between interacting users is below the vehicle type plus pedestrian half body (similar to Pascucci, 2020). The width of vehicle types is used for deviation strategies to compute the MD parameter. The users' speed profiles – as described in Section 3.1 – is taken into account for classifying the critical conditions, where the CS below 1 m/s reflects a non-critical rolling stop situation (Schmidt et al., 2019). This assumption is based on the small stopping distance (~0.07 m) of the vehicular traffic from the braking point until the complete stop when the speed is 1 m/s (Jones et al., 1992). Since drivers are already rolling over the small gap, the perception–reaction distance is not considered. Based on these hypotheses, a critical conflict can arise if the CS exceeds 1 m/s and the MD and TMD are below the determined thresholds.

The SSMs' profiles of a conflict event from the shared space data are depicted in Figs. 11 and 12. In Fig. 11, the selected SSMs are shown for the strategy pair of deceleration-continuing taken by a pedestrian and a passenger car during an interaction on the road. In real-world data, the pedestrian decelerates to avoid a conflict with the car, and the car continues with the desired speed to pass the conflict zone first. The speed profiles of the interacting users are extracted from the data set, and the arrival time of the users to the TCP is computed accordingly. As shown in Fig. 11: Distance to TCP, the MD between interacting users is greater than the defined threshold, and thus, no collision would occur between users after performing the strategy pair of deceleration-continuing. The evaluation of the SSMs and the event's outcome reveals that users could safely avoid the conflict. However, the interacting users in the conflict event example have other strategy choices. As an example in Fig. 12, the SSMs are estimated for the same users if they would have taken the right deviation–deceleration strategy pair to avoid the conflict. Although the deviation strategy changes the TCP, the MD still estimates the distance proximity of the users after taking the evasive strategies. In this example, the arrival time of users at a colliding MD would be below the safe threshold and with a CS greater than 1 m/s. Therefore, the event is labelled as a crash/conflict for performing the right deviation–deceleration strategy.

The estimation of the SSMs is programmed using Rstudio programming language and computed for all combinations of strategies per conflict event. Then, the outcomes of the events are labelled as conflict and non-conflict. Finally, the conflict data are prepared to apply the logit models and develop the conflict risk evaluation models. The results of the logit model applications and threshold determinations are presented in the following section.

5. Analysis and results

5.1. Conflict risk evaluation model

Due to the different vehicle sizes, conflict resolution strategy types, and also the small number of cars in the mid-block crossing data set, two conflict risk evaluation models are developed separately for pedestrian conflict with vehicles (i.e., passenger cars) and light vehicles (i.e., 2W and 3W). The logit models shown in Eq. (2) were developed based on the selected SSMs and for each combination (defined within this study) of strategy pairs of users. Table 4 summarises the parameter estimates for pedestrian–vehicle conflict events. Table 5 shows model estimation results for conflicts between pedestrians and light vehicles at the mid-block crossing. In both models, all SSMs are statistically significant for predicting conflict outcomes. In addition, the standard errors of all parameters in both models are statistically significant, indicating that the parameter effect varies over the conflict samples. Finally, the AUC-ROC curve is used to evaluate the performance of the logit models. The ROC is a probability curve, and AUC represents the degree or measure of separability. The results show the AUC of 0.97 and cut-point accuracy of 92.4% for the car's model and the AUC of 0.98 and cut-point accuracy of 92.7% for the light vehicle's model, and

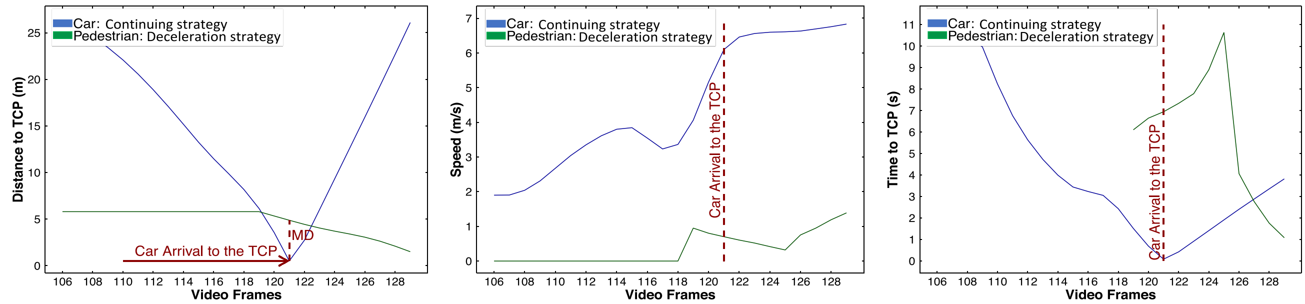

Fig. 11. Example of SSMs' profiles for a pedestrian–passenger car conflict in deceleration-continuing strategy taken by users on the real-world scenario.

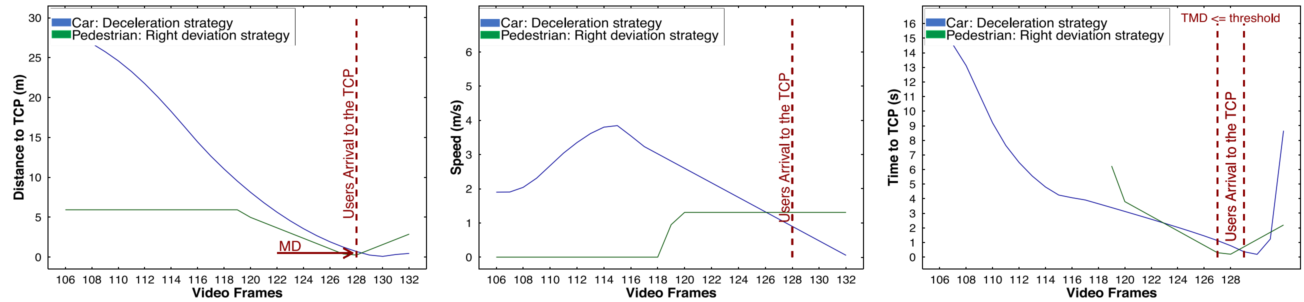

Fig. 12. Example of SSMs' profiles for a pedestrian–passenger car conflict in right deviation–deceleration strategy computed based on the proposed methodology.

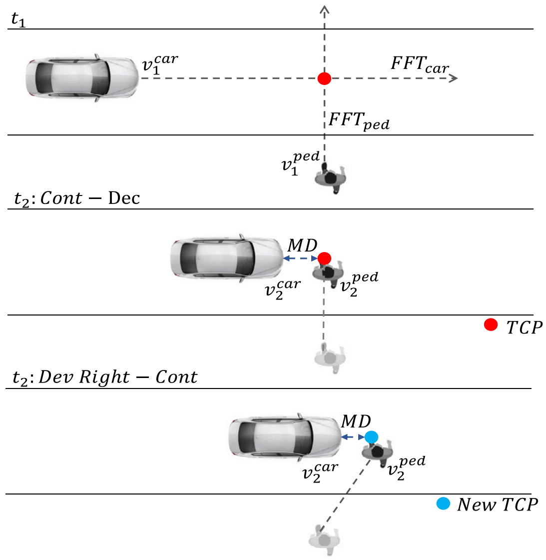

Fig. 13. The MD for continuing-deceleration and right deviation-continuing strategy pairs taken by a pedestrian and a car. The users' speed (v) at the first and last moment of the strategy performance (t) is shown. The MD is shown without the users' body size and for two alternative strategy combinations of interacting users to avoid a conflict.

indicating no evidence of poor fit for models. The MD and TMD indicators are returned with negative coefficients indicating that smaller MD and TMD would increase the risk of critical traffic conditions and collisions. In contrast, the CS is positive, meaning that a higher speed of users would increase the severity level of a conflict/crash.

5.2. Threshold selection

After the development of logit models, the methods proposed in Section 3.2 (i.e., intersection point, p-tile, maximum between-class variance, and minimum cross-entropy method) are employed to determine the predicted conflict thresholds on the basis of conflict cases in the data set. Fig. 14 illustrates the thresholds determined by various methods for pedestrian conflict events with passenger cars. The intersected point of the conflict and non-conflict rate – where two curves take the same values – for the cumulative proportion of 90.1% is 0.238 in the intersection point method (Fig. 14a). The threshold determined by the P-tile method is 0.425 when the cumulative proportion curve (CPC) of conflict risk (i.e., the overall proportion of the conflict events) equates to 76.8% (Fig. 14b). The threshold returned by the maximum between-class variance method is 0.451, where the σ_b^2 is maximised (Fig. 14c). The threshold is selected as 0.184 for the minimum cross-entropy method by minimising the cross-entropy between the conflict and non-conflict data (Fig. 14d).

Fig. 15 shows the selected thresholds for conflict events between pedestrians and light vehicles. Similarly, the intersection point method

Table 4
Parameter estimates of the logit model for pedestrian conflict events with passenger cars.

Parameter	Estimate	Std. Error	Z-value	Pr(>|z|)
Intercept	4.327	0.578	7.48	$<7e^{-14}$***
MD	−2.898	0.256	−11.31	$<2e^{-16}$***
TMD	−3.067	0.304	−10.08	$<2e^{-16}$***
CS	0.376	0.079	4.73	$2.2e^{-06}$***
Iteration			9	
AUC			0.97	
Accuracy (0.50 cut-point)			92.4%	

Table 5
Parameter estimates of the logit model for pedestrian conflict events with light vehicles (2W and 3W users).

Parameter	Estimate	Std. Error	Z-value	Pr(>|z|)
Intercept	4.490	0.373	12.03	$<2e^{-16}$***
MD	−2.813	0.168	−16.69	$<2e^{-16}$***
TMD	−2.365	0.184	−12.80	$<2e^{-16}$***
CS	0.263	0.040	6.24	$3.5e^{-11}$***
Iteration			10	
AUC			0.98	
Accuracy (0.50 cut-point)			92.7%	

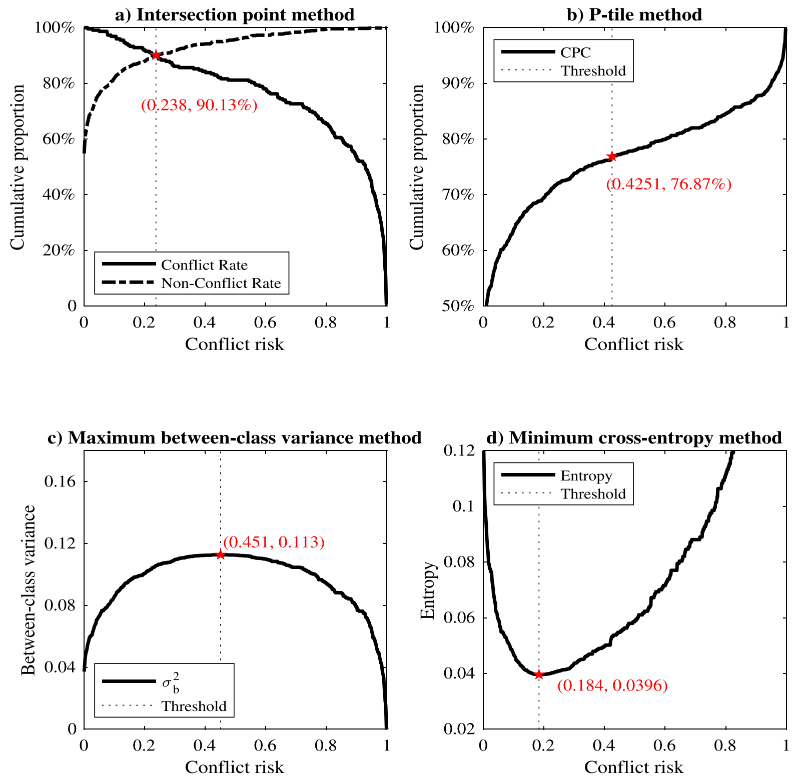

Fig. 14. Threshold selection of pedestrian conflict events with all passenger cars.

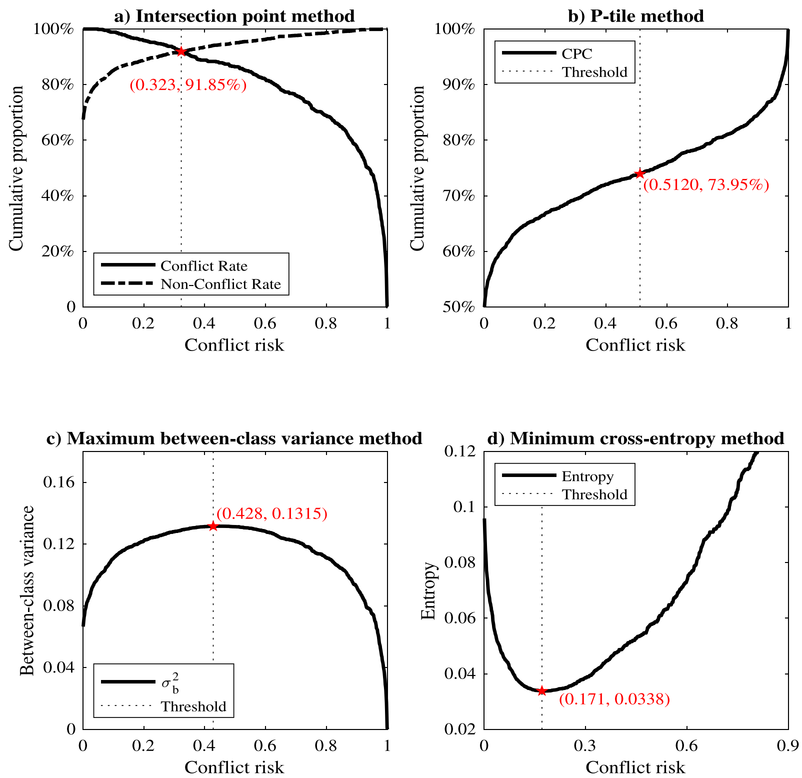

Fig. 15. Threshold selection of pedestrian conflict events with light vehicles (2W & 3W users).

application returns the threshold of 0.323 for the conflict and non-conflict cumulative proportion of 91.8% (Fig. 15a). From the CPC, the cut-off point of conflict risk for the P-tile method is 0.512 when the proportion is 73.9% (Fig. 15b). In addition, the threshold is 0.428 by the maximum between-class variance when the σ_b^2 is maximum (Fig. 15c), and 0.171 by the minimum cross-entropy method when the cross-entropy between the conflict and non-conflict data is minimised (Fig. 15d).

Table 6
Predictive performance by evaluation criteria.

Method	F-Score		Thresholds	
	Cars	2W/3W	Cars	2W/3W
Intersection point	0.810	0.854	0.238	0.323
P-tile	**0.890**	**0.905**	**0.425**	**0.512**
Max. between-class var.	0.889	0.888	0.451	0.428
Min. cross-entropy	0.774	0.804	0.184	0.171

The entire threshold determination procedure is programmed using MATLAB.

5.3. Threshold evaluation

The F-score method is used to evaluate the precision of predictive conflict and non-conflict of various thresholds. The scores are summarised in Table 6 for pedestrian conflicts with passenger cars and light vehicles. As expected, the values are between 0 to 1, in which higher scores (or closer to 1) indicate a better predictive performance of the model. For pedestrian–passenger car cases, the threshold is determined as **0.425** through the p-tile method with the highest F-score (0.890). The threshold determined through the p-tile method as **0.512** receives the highest score (0.905) for the pedestrian–light vehicle model.

6. Discussion

As discussed earlier, several variables have been proposed in the literature as SSMs for the safety evaluation of pedestrian–vehicle interactions. However, there is no suitable measure to describe the risk associated with all types of evasive manoeuvres that road users may take to avoid a conflict. Some safety indicators (e.g., TTC and TAdv) estimate the time proximity of users to a collision, assuming that the speed and movement direction would remain unchanged. This would become impractical when: (1) users with higher movement freedom deviate to escape a conflict with the interacting user, and thus, their movement direction changes, and (2) users decelerate to create a larger time gap in arrival at the collision point. In this study, a set of SSMs are employed to appropriately address the outcome of performing different evasive manoeuvres and by considering the possible reaction of the interacting user. The selected safety measures would allow estimation of the users' time and distance proximity after performing various pairs of evasive actions – based on user types – on the road. The minimum relative distance indicator is replaced with the traditional theoretical collision point to compensate for the absence of the collision point while users (or one of the users) deviate from its forward trajectory. Accordingly, the time to the minimum distance between users is measured to estimate the arrival of the users at the collision zone (i.e., new collision point). When the collision point no longer exists (i.e., one of the interacting users deviates to pass behind the other one), the MD still estimates the distance proximity of the users and evaluates the safety level of the evasive manoeuvre with respect to the performed strategy of the other user in the interaction. Additionally, the speed-based indicator of conflicting speed is used to particularly account for rolling over behaviour – in deceleration manoeuvre – that might occur in pedestrian–vehicle interactions. The latter measure would prevent the false labelling of an event as unsafe, while one of the road users is rolling a small gap to escape a conflict. After computing the SSMs and based on the literature, various criteria are used to identify the critical traffic conflicts. Finally, the conflict data were analysed from two different sites to develop a modelling approach capable of evaluating the traffic conflict risk regardless of the differences in layouts and traffic behaviour.

6.1. Impact factors

The conflict risk evaluation model is formulated by using a logit model. Since the two sites surveyed have different traffic layouts and participants, two separate conflict risk evaluation models are developed. Fig. 18 illustrates the interaction between the TMD and MD variables. As expected, the probability of a critical conflict declines by increasing the minimum distance between the users and the time gap to pass this zone. When the minimum distance and time gap exceed the defined criteria, the critical conflict changes to normal conditions. To better evaluate the models, the partial residuals and the confidence bands are superimposed in Figs. 16 and 17 for the pedestrian–passenger car and pedestrian–light vehicle models, respectively. The confidence intervals in the figures are Wald confidence intervals based on standard errors of the model predictions, and the partial residuals are computed based on the default residuals (Breheny and Burchett, 2017). The plots describe how the response (i.e., conflict occurrence) is expected to vary with respect to an explanatory variable (e.g., TMD, MD, CS) while the other variables in the model are held constant. In both models, the TMD and MD variables reveal a fairly precise model fit, particularly for smaller values which are more frequent in the data set. For the CS variable, there are potential departures from the model assumptions, specifically in the pedestrian–light vehicle models. This can be related to (1) the model assumption regarding the speed greater/smaller than $1\ \mathrm{m/s}$ to distinct the conflict severity and (2) different speed limits for 2Ws and 3Ws on the mid-block crossing, which shows higher deviations in the CS plot in Fig. 17.

6.2. Conflict risk evaluation models

The conflict risk evaluation models in this study are developed to identify the hazardous traffic conditions between pedestrians and vehicles. For this purpose, different methods are employed to determine the thresholds of the models. The cut-off point of 0.425 is selected for the pedestrian–passenger car model, and the threshold of 0.512 for the pedestrian–light vehicle model is returned by the p-tile method. Both thresholds showed a high predictive performance (0.890 and 0.905, respectively) by applying the evaluation criteria. In addition, two metrics are used to assess the overall performance of the models: (I) model accuracy, which reflects the percentage of correct predictions (i.e., normal, and critical traffic conditions), and (II) model sensitivity which shows the percentage of the events correctly labelled as critical traffic conditions. The pedestrian–passenger car model shows an average accuracy of 92.4% and a sensitivity of 83.4%. The pedestrian–light vehicle model returns 92.9% and 86.2% for the model accuracy and sensitivity, respectively.

The conflict risk evaluation models have the potential to be implemented in the ADAS to improve pedestrian safety in interaction with vehicles, particularly in uncontrolled traffic settings. Fig. 19 demonstrates a possible real-time implementation of the conflict risk evaluation models. Upon detection of a potential conflict event, the model variables and, thus, the outcome of the prediction models will be estimated. The thresholds, then, will be used to label the outcome of the model predictions as critical conflict (when it exceeds the thresholds) or normal traffic condition (when below the thresholds). The ADAS triggers a warning for predictions labelled as critical conflict. The development of the conflict risk evaluation models is based on the flexible surrogate measures covering a wide range of users' strategy choices. This is particularly practical for situations in which interacting users change their trajectory or speed to escape a conflict instead of a complete stop. In such cases, the model can evaluate the conflict risk associated with the evasive actions performed by users and trigger a warning if needed. A similar approach applies to defensive manoeuvres like deceleration. If a driver rolls over a small gap, the warning system would correctly label the traffic condition as normal.

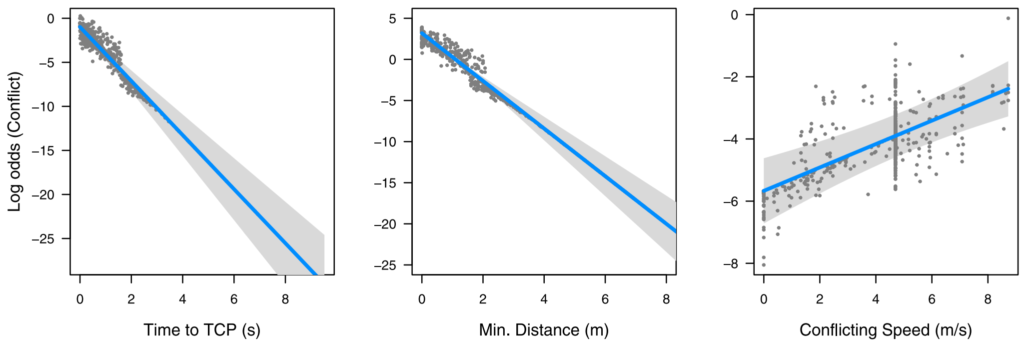

Fig. 16. Visualisation of the logit model of pedestrian–passenger car conflicts in Log odds scale.

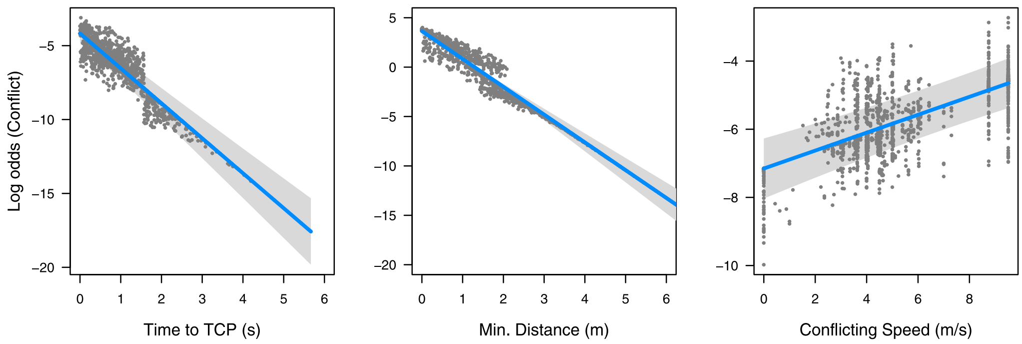

Fig. 17. Visualisation of the logit model of pedestrian–light vehicle conflicts in Log odds scale.

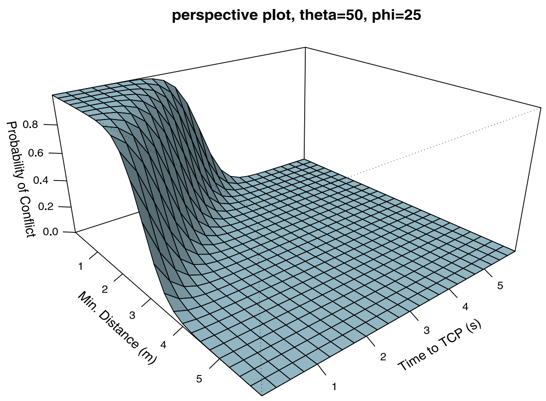

Fig. 18. Interactive perspective plot of the TMD and MD variables in the pedestrian–passenger car model.

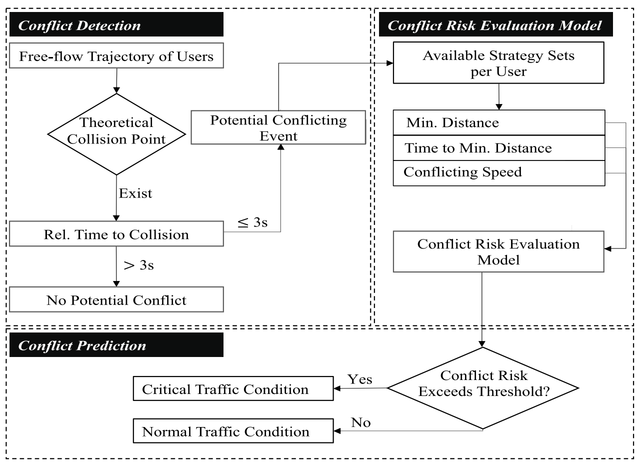

Fig. 19. A real-time implementation of the conflict risk evaluation models.

6.3. Limitations and further research

In this study, the conflict risk evaluation models and their thresholds are developed based on interaction data collected in a shared space in Hamburg, Germany, and a mid-block crossing in Surat, India. This study utilises conflict data of these two locations with substantial differences in user behaviour and infrastructure designs, which can assist in developing conflict risk evaluation models that reflect user behaviour in uncontrolled traffic environments and are widely functional. The latter property is crucial for developing a modelling framework that is not culture-specific and can evaluate the safety level of traffic conflicts despite the user type and traffic behaviour. Although a large number of conflict data is analysed in this work, further research is still required with an extensive data analysis of various traffic settings in different locations to avoid transferability issues of the model estimations and threshold values and build a more robust and realistic model.

Further, the models developed within this study consider a set of available conflict resolution strategies per user type (i.e., deceleration, deviation, and no evasive as moving along the FFT with preferred/current speed). However, a broader range of evasive manoeuvres is available for different user types in real-world traffic interactions to avoid conflict. For instance, pedestrians may run into the roadway, perform unexpected changes in their movement directions, or suddenly stop at any point of crossroads. Such unpredictable behaviour can be hard to insert into the modelling approaches. Therefore, the evasive manoeuvres of road users are limited to the categories mentioned above in the developed models. In addition, the focus of this study is purely on developing conflict risk evaluation models to assess the safety level of pedestrian conflict with other road users. With this objective, the safety outcome of users' decisions is evaluated without investigating their decision-making processes that may lead to performing various evasive manoeuvres to avoid conflict. Therefore, the interaction process among road users and pedestrian-, vehicle-, and traffic environment-related factors (e.g., pedestrian groups and approaching lane) that can affect the user behaviour are ignored in this study (Ezzati Amini et al., 2019). Hence, the model expansion will be the focus of future works.

Finally, the proposed conflict risk evaluation model, its capability in various traffic contexts, and its application to ADAS (e.g., defining fixed-timing warnings based on the algorithm's running time) can be tested and further validated through a simulated driving environment. The driving simulator provides a safe and controlled environment for testing the capability of the developed models in various traffic contexts – which was not feasible within the scope of this study. This research suggests future works to focus on further model testing and validation since it is essential for improving the model performance.

7. Conclusions

The prediction of pedestrian behaviour in interaction with vehicles is a substantial component of efforts to prevent road traffic injuries and fatalities. However, the complexity of pedestrian behaviour and their agility on the road make their behaviour harder to predict and, therefore, a critical issue for ADAS and the future of automated driving systems. Besides, developing a robust interaction method is crucial to ensure the efficiency of such systems on the road (Ezzati Amini et al., 2021b). Previous studies showed that pedestrians may always try to take priority, presuming that the safety systems of automated driving are programmed to stop if any obstacle is in their path (Connor, 2016; Fox et al., 2018; Madigan et al., 2019).

This paper aims to develop a conflict risk evaluation model for pedestrian–vehicle interactions with an emphasis on how performing various evasive manoeuvres affects the safety of users. In traffic conflict events, evasive actions can be in the form of deceleration or deviation. However, swerving is a more common strategy among road users with a higher level of movement freedom (e.g., pedestrians, motorcyclists). To better study the conflict avoidance strategies of road users, a set of relevant SSMs is employed to formulate conflict risk evaluation models for pedestrian interactions with passenger cars and light vehicles separately. First, the proposed SSMs are computed for all possible combinations of evasive manoeuvres in the analysed data sets. Then, the outcome of performing different strategy pairs is classified as critical traffic condition (i.e., TMD is below 1.5 s when the MD is labelled as collision and CS is greater than 1 m/s) or normal traffic conditions (when the mentioned criteria are not met). Next, a logit model is used to develop the conflict risk evaluation model, and thresholds are determined by applying different threshold selection methods. Later, the F-score method is employed to evaluate the performance of different thresholds: F-scores of 0.890 for pedestrian–passenger cars and 0.905 for pedestrian–light vehicle models representing a good classification of each conflict event (i.e., normal traffic conditions vs. critical traffic conditions). Besides, the developed conflict risk evaluation models show a good performance, with a miss-classification rate of 16.6% for pedestrian events with passenger cars and 13.8% for pedestrian conflict events with light vehicles. Finally, the proposed models allow the conflict risk evaluation of various action–reaction strategies of users in traffic interactions and, therefore, can be used to predict the outcome of a conflict event between pedestrians and vehicles in uncontrolled traffic settings.

CRediT authorship contribution statement

Roja Ezzati Amini: Conceptualization, Methodology, Software, Visualization, Validation, Formal analysis, Writing – original draft. **Kui Yang:** Methodology, Software, Supervision, Writing – review & editing. **Constantinos Antoniou:** Supervision, Writing – review & editing.

Declaration of competing interest

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

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D Ezzati Amini et al. (2022). A game-theoretic approach for modelling pedestrian-vehicle conflict resolutions in uncontrolled traffic environments

A game-theoretic approach for modelling pedestrian–vehicle conflict resolutions in uncontrolled traffic environments

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ABSTRACT

The interactions of motorised vehicles with pedestrians have always been a concern in traffic safety. The major threat to pedestrians comes from the high level of interactions imposed in uncontrolled traffic environments, where road users have to compete over the right of way. In the absence of traffic management and control systems in such traffic environments, road users have to negotiate the right of way while avoiding conflict. Furthermore, the high level of movement freedom and agility of pedestrians, as one of the interactive parties, can lead to exposing unpredictable behaviour on the road. Traffic interactions in uncontrolled mixed traffic environments will become more challenging by fully/partially automated driving systems deployment where the intentions and decisions of interacting agents must be predicted/detected to avoid conflict and improve traffic safety and efficiency. This study aims to formulate a game-theoretic approach to model pedestrian interactions with passenger cars and light vehicles (two-wheel and three-wheel vehicles) in uncontrolled traffic settings. The proposed models employ the most influencing factors in the road user's decision and choice of strategy to predict their movements and conflict resolution strategies in traffic interactions. The models are applied to two data sets of video recordings collected in a shared space in Hamburg and a mid-block crossing area in Surat, India, including the interactions of pedestrians with passenger cars and light vehicles, respectively. The models are calibrated using the identified conflicts between users and their conflict resolution strategies in the data sets. The proposed models indicate satisfactory performances considering the stochastic behaviour of road users —particularly in the mid-block crossing area in India— and have the potential to be used as a behavioural model for automated driving systems.

1. Introduction

Every year approximately 1.3 million people lose their lives as a result of a road traffic crash, and between 20-50 million people suffer non-fatal injuries (World Health Organisation, 2019). Among all, vulnerable road users (VRUs) such as pedestrians, motorcyclists, and cyclists account for more than half of all road traffic fatalities (World Health Organisation, 2019). Crashes involving pedestrians occur most often in urban areas and while pedestrians cross the roadway at either illegal locations out of crosswalks or pedestrian crossing facilities (NSC-Injury Facts, 2019). Amongst pedestrian crossing facilities, uncontrolled traffic environments can create a potential hazard for pedestrians since there are no traffic management and control systems to conduct the traffic. Hence, traffic movements implicate a more frequent and complex interaction process among road users. During a traffic conflict —a traffic event involving the interaction of users (Parker Jr and Zegeer, 1989)— traffic participants intend to dominate the road space they are moving towards while avoiding a collision. To fulfil these goals, road users perform various crossing/evasive manoeuvres. A collision occurs if the performed manoeuvres fail to prevent physical contact between the interacting users. However, the majority of road users interact with no serious conflict or collision and are not of interest from the traffic safety point of view, but still crucial in terms of road user experience and traffic efficiency (Madigan et al., 2019).

A safe and efficient traffic interaction requires road users to correctly interpret and predict the strategies of their interactive party (Ezzati Amini et al., 2019). The interpretation and prediction of the interacting parties' subsequent actions may become problematic when heterogeneous traffic participants interact on a crossing site. The characteristics discrepancy of different user types may lead to exposing various behaviour in the interaction scene. Pedestrians can make a sudden change of direction or speed and, thus, are prone to perform more unpredictable behaviour on the road. Further, heterogeneity of users (vehicles vs. pedestrians) may cause different decision-making processes and users to react differently during the interaction process. For instance, a driver approaching a crossing may decelerate and let the pedestrian cross the road first, while the pedestrian deviates to create a bigger gap with the car and, thus, escape a potential conflict. Previous studies have investigated a broad range of factors that may influence user behaviour on the road, such as pedestrian characteristics and walking speed, vehicle's approaching speed, and road characteristics (Beggiato et al., 2017; Sun et al., 2003; Pawar and Patil, 2015). Ezzati Amini et al. (2019) argued that road users adopt a conflict resolution strategy by considering a wide range of

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factors knowingly (e.g., the time/distance gap estimation) and/or unknowingly (e.g., user age or gender) while they employ different communication methods to ease the interaction when needed. Besides, various strategies that users can perform to avoid a potential conflict on the road may result in different granted/expected utilities, e.g., gaining priority, saving time and shortening the traversed distance. Therefore, a thorough understanding of user behaviour is vital for building a suitable model to predict the trajectory and movement of traffic participants during a traffic conflict and consequently enhance safety on the road. Further, developing a safe and efficient interaction concept is crucial for emerging technologies design, such as advanced driver assistance systems (ADAS) and automated driving systems (ADS). Such systems would require an accurate comprehension of human road users' behaviour in a traffic interaction to predict user behaviour and react aptly (Schneemann and Gohl, 2016).

Several studies investigate user behaviour and model pedestrian–vehicle interactions in unregulated settings at a microscopic level. Himanen and Kulmala (1988) applied a multinomial logit model to investigate pedestrian–vehicle interactions on approaching unsignalised crossings. The model considers the pedestrian distance to the kerb, pedestrian and vehicle group size, vehicle speed, and city size as the most influencing variables in the user's choice of strategy. Pascucci et al. (2018) formulated a discrete choice model to identify the conflict resolution strategies of users interacting on the road. The authors defined a set of explanatory variables to build the model, i.e., the movement-specific parameters (e.g., relative position, speed, acceleration), collision-specific parameters (e.g., time to collision, the existence of leading car), and the number of simultaneous conflicts of users. In another approach, Pascucci et al. (2015) utilised the future position of the interacting users and the time of leaving the conflict zone as indicators to determine the crossing priority. A logistic regression application on microscopic data by Schroeder (2008) showed that dynamic features of vehicles, pedestrian characteristics, and simultaneous occurrence of other events at crossings could impact the driver's yielding behaviour and pedestrian crossing strategies. Schönauer (2017) used a Stackelberg competition game to model road user behaviour in conflicting situations, in which the probability of collision, agents' position and distance, and rule-based and social-based behaviour of users determine their conflict resolving strategies. Johora and Müller (2020) combined the social force model with the Stackelberg competition approach to model the road user interactions. In this approach, the interactions are classified into simple and complex. The model covers the pedestrian–pedestrian, multiple pedestrian-vehicle, and vehicle–vehicle interactions.

With respect to the ADS, and through the application of various methods, objects in motion (e.g., vehicles, pedestrians, cyclists) are tracked to predict their trajectories and future positions. The prediction system, then, hypothesises multiple possible predictions of the future movement of dynamic objects. Several studies investigated the interaction of pedestrians with automated vehicles and proposed modelling approaches to simulate the ADS interactions with VRUs (Schneemann and Heinemann, 2016; Chen et al., 2016; Møgelmose et al., 2015). Feng et al. (2019) used Cellular Automata to model interactions at mid-block crossings by considering a broad range of factors, such as the lane width and length, number of lanes, speed limit, vehicle size, and speed. The model employs the yielding regulations at crossings in China and evaluates the lane-based post-encroachment time between a vehicle and pedestrian as a safety index. Völz et al. (2018) combined motion tracking algorithms with data-driven methods to predict the crossing intention of pedestrians. The authors argued that the correct prediction of pedestrian intentions at a crossing is essential to prevent unnecessarily slowing down traffic. For instance, when an automated vehicle stops for a pedestrian with no intentions to cross the roadway. The proposed model considers the dynamic distance measures of pedestrian and vehicle motion on approaching the crossing site to predict the next action. Rehder et al. (2018) proposed an Artificial Neural Network approach for pedestrian intention recognition and planning-based prediction. As inputs, this method determines pedestrian destinations from images and positions and applies trajectory planning toward these destinations. As an output, the possible destinations are predicted in the form of a probability distribution map using Markov decision processes and the forward-backward algorithm. Jayaraman et al. (2020) developed a hybrid system model for pedestrian trajectory prediction using pedestrian gap acceptance behaviour and interacting user speeds. The model describes the pedestrian states as approaching a crosswalk, waiting, crossing, and walking away. Fox et al. (2018) formulated a game-theoretic model for the priority negotiation between an automated vehicle and another user (e.g., a vehicle or pedestrian) in unsignalised intersections/crossings. The model assumes that the agents' optimal behaviour includes a non-zero probability of collision occurrence. The yielding probability in the model gradually increases as interacting users get closer. The model assumption of the non-zero probability of collision occurrence validates the previous findings that ADS will make little or no progress if they are known to be perfectly safe and always yield to the interacting users (Fox et al., 2018).

Research contributions

The main objective of this research is to model pedestrian interactions with motorised vehicles in uncontrolled traffic environments. It is evident from the reviewed literature that the applicability of the previously proposed models is mostly restricted to specific types of road users (i.e., passenger cars and pedestrians). This would ignore the variety of strategy choices available for user types based on their speed limit and degree of movement freedom (e.g., deviation and deceleration strategy), and thus a less efficient prediction of their behaviour. Therefore, game-theoretic models are developed in this study for pedestrian interactions with passenger cars and light vehicles in different road designs.

To better reflect the user decision-making process, the utility functions of the proposed game are formulated based upon three principle layers; (1) safety level to estimate the severity level and the collision probability of a conflict event, (2) travel level associated with the detour, and deceleration imposed to interacting users by changing their speed and movement direction to escape a conflict and (3) social layer to describe the traffic environment conditions influencing the user's choice of strategy. The proposed interaction model predicts the conflict resolution strategies of users in interaction and has the potential application as a behavioural model of the ADS.
The remainder of this paper is organised as follows: The detailed formulation of the game-theoretic model is described in Section 2. Section 3 includes the description of the study areas, as well as conflict detection and analysis strategies. Section 4 documents the application of the game-theoretic approach to the analysed data. Section 5 presents the model evaluation and estimation using the analysed data. Finally, Sections 6 and 7 present the discussions and conclusions, respectively.

2. Conflict resolution model

Understanding and predicting road user behaviour is a complex modelling problem since it includes understanding and predicting of surroundings, and interacting users' current and future actions (Fox et al., 2018). The latter issue may lead to paradox and incomputability issues as described in Gödel theorem and Halting problem (Velupillai, 2009). Game theory provides a cooperative and competitive paradigm to manage the self-referential decisions of players (i.e., road users in the game) and describe pairwise traffic interactions (Fox et al., 2018). For this reason, a game-theoretic approach is applied in this research to determine the user decisions interacting in uncontrolled traffic settings and predict the conflict resolution strategies. Depending on the user type, each player in the game (referring to the interacting users in a conflict) has specific degrees of permitted movements that define their trajectories in the game. For instance, a large goods vehicle commonly moves straight without deviating from its forward trajectory (in a safe driving situation): while lighter user types, such as pedestrian, two-wheel (2W) and three-wheel (3W) vehicles, can swerve right or left due to their agile characteristics. Further, users may apply speed changes/adjustments to avoid conflicts. A combination of the trajectory and speed changes that users can employ to avoid a conflict is defined as the player's strategy set in the game and clustered as:

- **Continuing strategy** (S_{Cont}): applicable for all user types and by moving along the free-flow trajectory (FFT) with preferred/current speed,
- **Deceleration strategy** (S_{Dec}): applicable for all user types, and by moving along the FFT with reduced speed,

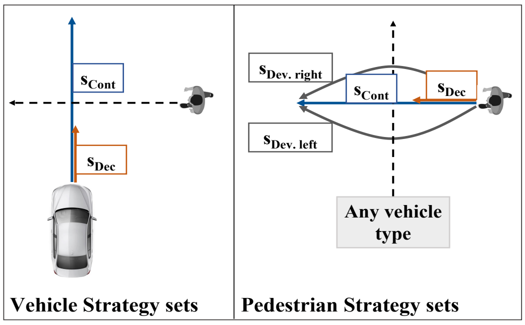

Figure 1: Conflict resolution strategies of passenger cars (left) and pedestrians (right) in an interaction. 2W and 3W users have similar strategy sets as pedestrians.

- **Deviation strategy** (S_{Dev}): applicable only for light users (i.e., pedestrians, 2W and 3W), and by deviating to the left ($S_{Dev.left}$) or right ($S_{Dev.right}$) from the FFT or collision point with preferred/current speed.

Figure 1 demonstrates a schematic overview of the users' trajectories corresponding to the various available strategy choices defined per user type.

2.1. General structure of the Stackelberg game

In a traffic interaction, the competition of road users over the right of way results in conflicting interests among them. Given the conflicting interests among users, a strategic game of Stackelberg leadership competition is formulated to model pedestrian-vehicle interactions in uncontrolled traffic settings (Ezzati Amini et al., 2021a). The two-player Stackelberg game assumes that one of the players is the leader of the game and the other is the follower. In the game, the leader plays a strategy first, and then the follower reacts to the leader's announced strategy. This approach highlights that in most traffic interactions, the decisions of road users are not made concurrently but more in the form of action and reaction. Besides, the users employ a conflict resolution strategy with respect to the strategy of their interacting users, i.e., the gain/expected utility of the users depends on the interacting user's reaction. Figure 2 illustrates a two-player Stackelberg game tree and payoffs for taking each strategy pair in the game. One player performs the game leader (L) role with its available strategy choice $(s_1^L, \ldots, s_n^L) \in S^L$ and another player is the follower (F) with $(s_1^F, \ldots, s_m^F) \in S^F$ as its strategy set. Specifying one strategy s_n^L for the leader and one strategy s_m^F for the follower yields an outcome represented as a payoffs pair of $(U^L(s_n^L, s_m^F), U^F(s_m^F|s_n^L))$, where U^L is the utility that leader receives and U^F is the utility of the follower. In this paper, payoff and utility terms are used interchangeably.

2.2. Stackelberg game solution

The game solution is determined by finding the subgame perfect Nash equilibrium (SPNE). One prevalent method to find the SPNE is backward induction, i.e., the best

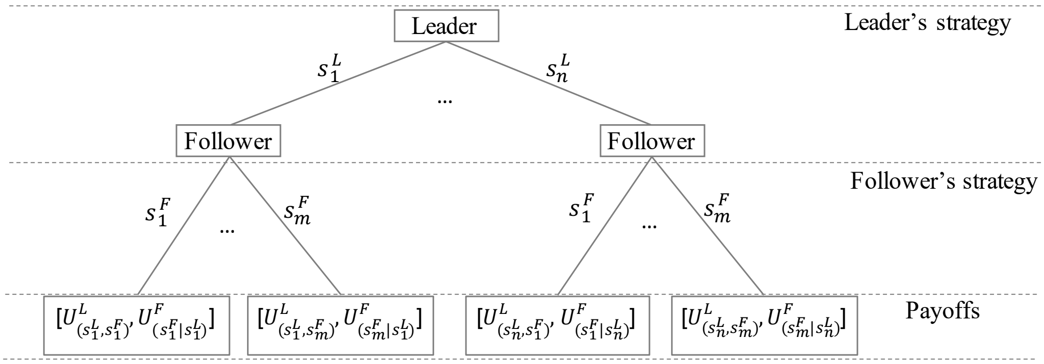

Figure 2: Stackelberg game tree and sub-games. The payoffs of playing each strategy pair are shown in the terminal nodes.

responses of the follower (B_{follower}) must be computed first to allow the leader to maximise its payoff:

$$B_{\text{follower}} = max_{(s^F \in S^F)} U^F(s^F|s^L) \tag{1}$$

$$\text{SPNE} = \boldsymbol{argmax}_{s^L \in S^L} U^L(s^L, B_{\text{follower}}) \tag{2}$$

Where U^L yields the leader's maximum utility for selecting the best strategy from its choice of actions (S^L, $s^L \in S^L$). In the proposed game-theoretic approach, agents may receive different payoffs by playing the same strategies, as conflicting users are heterogeneous (vehicle vs. pedestrian) with distinct characteristics and objectives on the road. Further, road users' payoffs/strategies may vary depending on the strategy choice of their interacting user. Therefore, Equations 1 & 2 can be transformed into the mixed strategy approach to finding the optimal game solution. In this approach, the probability vectors of $P^L(s^L)$ and $P^F(s^F|s^L)$ reflect the likelihood of performing a strategy by the game leader and a strategy by the follower given the leader's strategy, respectively. As proved by Nash (1951), one mixed strategy Nash Equilibrium exists in a game given the outcomes of:

$$P(s^L, s^F) = P^L(s^L) * P^F(s^F|s^L) \tag{3}$$

2.3. Formulation of utility functions

The Stackelberg game assumes that players are rational, and the choice of strategy correlates with utility maximisation in the game. Regarding the application of the Stackelberg game in the traffic conflict, players achieve the maximum utilities by performing a strategy that minimises the collision risk and energy loss and maximises the driving/crossing comfort. The formulation of the utility function is based upon three layers; safety layer, travel layer, and social layer, and explained in the following sub-sections.

2.3.1. Safety layer

The safety layer is defined to estimate the severity level and the collision probability of conflict events regarding the performed conflict resolution strategies. For instance, how safe a conflict outcome would be if a car continues its path and a pedestrian (as its interacting user) deviates right to cross in front of the car. Whether the time/distance gap would be long enough for the pedestrian to cross the road safely or a critical condition/collision would occur. The conflict risk evaluation model for pedestrian–vehicle interactions, developed by Amini et al. (2022), is embedded in the game to assess the severity of traffic conflict. The model emphasises how performing various evasive manoeuvres affects the users' safety. The conflict risk evaluation models are formulated using logit models and three surrogate safety measures where the discrete choices of conflict and non-conflict are examined. In a logit model, the probability of the response variable $Y = 1$ (i.e., critical conflict) with the predictor variables (i.e., x_i) is:

$$p = \frac{1}{1 + b^{-(\Sigma\theta_i x_i)}} = S_b(\Sigma\theta_i x_i) \tag{4}$$

Where S_b is the sigmoid function with base b, and θ_i are model parameters. The selected surrogate safety indicators employed in the model are as follow:

I. Minimum future relative distance (MD) indicator evaluates the distance proximity of users after applying different strategy pairs. The MD compensates for the limitations of previously implemented measures for collision risk prediction, assuming that users would collide if the condition remains unchanged. The MD indicator identifies new collision points or estimates the distance proximity of users when the theoretical collision point changes or no longer exists (e.g., in deviation strategies).

II. Time to minimum distance (TMD) indicator estimates the available time gap between the arrival of the users to the MD or theoretical collision point, if any. This time-based indicator is added to the conflict analysis to capture the simultaneous arrival of the users to the MD, i.e., the distance and time proximity of the users after performing conflict resolution strategies. The TMD estimation is based on the speed of the users defined per strategy.

Table 1
Utility functions to compute payoffs of strategy pairs for player i as the game leader, and j as the follower. d^{str} refers to the traversed distance in each game strategy, and d^{FFT} to the distance of traversing the FFT (see Section 3.2, Step 2).

Category	Metrics	Utility	Formula	Specification
Safety Layer	MD (m) TMD (s) CS (m/s)	SL_{ij}	predicted conflict of the estimated models in Tab. 2 for user type conflicts.	Model thresholds: pedestrian-car = 0.425 pedestrian-light vehicle = 0.512
Travel Layer	Detour (d_i, d_j) Deceleration rate (dc_i, dc_j)	DT_i, DT_j DC_i, DC_j	$\exp(d_i^{FFT} - d_i^{Str}) - 1$ $\exp(dc_i) - 1$	$d_i^{Str} > d_i^{FFT}$
Social Layer	Pedestrian group size Pedestrian approaching lane Right of way	PL_i, PL_j LN_i, LN_j RW_i, RW_j	$\{-1, 0, 1\}$ $\{-1, 0, 1\}$ $\{0, 1\}$	Group size> 2 The middle lane or kerbside Who gets priority?
Utility of playing strategy pair (S^L, S^F)		Leader: $U_L(S^L, S^F) = \sum Utilities$ Follower: $U_F(S^F \mid S^L) = \sum Utilities$		

III. Conflicting speed (CS) refers to the speed of heavier interacting road users when evasive manoeuvres are taken and at the moment of minimum distance. The CS reflects the severity level of the conflict by taking into account the speed changes of users during an evasive action (e.g., deceleration strategy). This is particularly important in traffic situations where users (usually motorised vehicles) either come to a complete stop before/while reaching the MD threshold or roll over a small gap. Although the MD and TMD are below the thresholds in such cases, the traffic condition is still considered safe.
The model estimates these three safety measures for all possible combinations of strategies available for user types to avoid a conflict and evaluates the safety of the outcomes. The model thresholds are determined by applying various methods (i.e., intersection point, maximum between-class variance, p-tile, and minimum cross-entropy method) to separate potential critical conflicts against normal traffic conditions. Then, the F-score method is used to select the optimal thresholds with the best performance (van Rijsbergen, 1979). Finally, similar data sets as this study are used to develop and validate conflict risk evaluation models for the interaction of pedestrians with vehicles (passenger cars) and light vehicles (2Ws and 3Ws) separately. Table 2 summarises the parameter estimates for pedestrian–vehicle and pedestrian–light vehicle conflict risk evaluation models. The threshold of 0.425 is determined for the pedestrian–vehicle model, and 0.512 for the pedestrian–light vehicle model through the p-tile method with the best performance. In the concept of game theory, if the conflict risk exceeds the determined thresholds, the event is labelled as a critical conflict, and players receive (-1) as a penalty for playing the strategy pair. Conversely, for taking strategies with conflict risk lower than the thresholds, users receive (0) for the safety layer utility:

$$Safety\ utility = \begin{cases} \text{-1}, conflict\ risk \geqslant threshold \\ 0, conflict\ risk < threshold \end{cases} \quad (5)$$

2.3.2. *Travel layer*

This layer is associated with the detour (DT) and deceleration (DC) imposed on interacting users by changing their speed and movement direction to escape a conflict. This class aims to quantify the comfort level of different strategies. Road users tend to reach their destinations by taking the shortest path (i.e., the FFT) while maintaining their speed. Therefore, the extra traversed distance by players to reach their destination return a detour dis-utility for users. A similar approach is applied for users decelerating due to a conflict on the road. The exponential functions scale the utility values between (-1) and (0) in the travel layer.

2.3.3. *Social layer*

This layer describes the traffic environment conditions that influence the user's choice of action. This class includes the influencing factors of pedestrian group size (PL), approaching lane (LN), and the right of way (RW). For pedestrian group size and approaching lane, the strategies are evaluated with respect to the interacting user's strategy, and based on the aggressiveness level: aggressive, neutral, and courteous. Players receive (-1) as a penalty for performing aggressive strategies, (0) for neutral strategies, and $(+1)$ as an incentive for taking courteous manoeuvres. For instance,

Table 2
Parameter estimates of the logit models for pedestrian conflict events with passenger cars and light vehicles (Amini et al., 2022).

Parameter	Estimate	Std. Err.	Z-value	Pr(>|z|)
Pedestrian–passenger car model				
Intercept	4.327	0.578	7.48	$< 7e^{-14}$***
MD	-2.898	0.256	-11.31	$< 2e^{-16}$***
TMD	-3.067	0.304	-10.08	$< 2e^{-16}$***
CS	0.376	0.079	4.73	$2.2e^{-06}$***
Pedestrian–light vehicle model				
Intercept	4.490	0.373	12.03	$< 2e^{-16}$***
MD	-2.813	0.168	-16.69	$< 2e^{-16}$***
TMD	-2.365	0.184	-12.80	$< 2e^{-16}$***
CS	0.263	0.040	6.24	$3.5e^{-11}$***

Figure 3: The street view of the mid-block crossing area from where the camera is placed (right) (Golakiya and Dhamaniya, 2018), and the aerial view of the site (left).

a car receives dis-utility of (-1) if it continues its path and does not yield to the interacting pedestrians who cross in a group greater than two persons. In the same scenario, the car gets $(+1)$ as a utility if it decelerates, and pedestrians continuing to cross the road would receive (0). Similarly, users receive (-1), (0), or $(+1)$ for pedestrians approaching from the kerbside or the middle lane of the road based on the performed manoeuvres. Factors of pedestrian group size and approaching lane are added to the game utilities to reflect the importance of the social norms in traffic conflicts, i.e., whether or not social norms support a conflict resolution strategy. These factors aid in weighting the high utility of saving energy in taking aggressive manoeuvres (e.g., continuing strategy with high detour, and deceleration utilities) and the energy loss in taking courteous strategies in the presence of risky conditions (e.g., deceleration strategy with low detour, and deceleration utilities). In the absence of the social norm utility, interacting users intend to maximise their utilities through minimising energy loss. Consequently, users invariably prefer to take strategies that return such utilities, and strategies such as continuing always become dominant in the game, which contrasts with the real-world decision-making process of users in interactions. Regarding the right of way, the player who gets priority by taking a strategy receives utility $(+1)$ and (0) otherwise.

Table 1 summarises the utility computations in all layers of the game.

2.3.4. Utility function

All attributes influencing the agents' preferences to deliver the supra objects integrate into one utility function (multi-attribute utility function), representing the overall agent's utility. The final formulation of utilities for the leader strategy choice is calculated in the following way by considering a set of weights θ for the parameters:

$$U_L(s^L, s^F) = \theta_{sl} SL_{ij} + \theta_{dt} DT_i + \theta_{dc} DC_i + \theta_{pl} PL_i + \theta_{ln} LN_i + \theta_{rw} RW_i \tag{6}$$

A similar approach is applied to compute the utility of the follower $U_F(s^F|s^L)$.

3. Data collection and conflict analysis

Two video graphic surveys are used for conflict analysis and model application in this research. The data analysis relies on the users' trajectories and a set of explanatory variables extracted from the data sets. A conflict detection procedure is applied to identify the potential conflicts among road users and determine the conflict resolution strategies of interacting users. For each conflict event, the utilities of interacting users are computed for all possible combinations of strategies (with respect to the user type) that players could perform in the game, including the real-world strategies in the data sets.

3.1. Video surveys

3.1.1. Mid-block crossing interactions

The first video graphic survey is collected in a mid-block crossing area in Surat city, Gujarat, India, where traffic drive on the left (Golakiya and Dhamaniya, 2018). The crossing is located on a six-lane arterial urban road with an additional Bus Rapid Transit lane and in the vicinity of businesses, stores, and hospitals. Two lanes of the road in the mid-block crossing area are selected for the video observation and data analysis (Fig. 3). The video survey is performed by placing a camera on a building at an elevation of 15 meters. The duration of the recorded video is 30 minutes and was recorded on January 3rd, 2017, on a typical weekday. The data is pre-processed by overlaying a grid of size $40 \times 8.85m^2$ over the captured video using the Ulead VideoStudio 11 software (Golakiya and Dhamaniya, 2018). The Avidemux 2.6 software is used for tracking the video by 0.48 seconds time steps (12 video frames). A variety of traffic modes pass through the road leading to more complex traffic interactions in the mid-block crossing area. The extracted data contains the trajectory of passenger cars, heavy goods vehicles (HGVs), large goods vehicles (LGVs), 2Ws, 3Ws, and pedestrians.

3.1.2. Shared space interactions

The second video graphic survey is collected through video recording for a shared space zone in the district of Bergedorf (Weidebaumsweg), Hamburg city, Germany (Pascucci et al., 2021). The length of the shared space area

Figure 4: The street view of the shared space area from where the cameras are placed (right) (Pascucci et al., 2021), and the aerial view of the site (left).

is 63 meters and is in the proximity of a shopping mall and retail stores. Two cameras were placed at an elevation of approximately 7 meters and in opposite directions of traffic to perform the video survey (Fig. 4). The video was recorded on Saturday, April 2, 2016, from 14:00 to 16:00. A 30-minute of the recorded data is selected for analysis. The software Tracker is used to pre-process the data (Douglas, 2017; Pascucci, 2020). The extracted data includes the trajectory data in terms of coordinates every 0.5 seconds, velocity, and acceleration for passenger cars, pedestrians, and cyclists. However, cyclists are out of this research interest and neglected in the analysis. In the shared space, vehicles have priority over other road users, and pedestrians should use the given/available gap when it is long enough to traverse the crossing.

It is worth noting that there is no real-world collision between traffic participants in the studied data; however, a conflict detection procedure was applied to identify traffic conflicts and evasive actions of interacting road users.

3.2. Conflict detection strategies

Uncontrolled traffic environments entail a constant interaction among road users. In such traffic events, at least one of the interacting users would need to take an evasive manoeuvre to avoid the conflict; otherwise, a collision would occur. For this reason, a four-step conflict detection procedure is designed to identify the users in conflict:

Step 1. Data simplification: A street boundary is specified to keep the trajectories of pedestrians who cross the roadway and remove the rest walking along the road. Then, data are divided into 60-second time intervals to reduce the number of events and simplify the analysis.

Step 2. Free flow trajectories (FFTs): The FFTs of road users are plotted by connecting the shortest path from their origin to their destination. The FFTs are employed since traffic participants tend to take the shortest path to reach their destination without a traffic event and evasive manoeuvre.

Step 3. Intersection points: A theoretical collision point (TCP) is defined to identify the intersected trajectories of users if they would have taken the FFTs to reach their destinations (Fig. 5). In addition, a buffer zone is considered for all vehicle types to improve the accuracy of the collision points. The buffer zone assumption implies the real-world collision events in which vehicles hit the pedestrians at the buffer than/before the TCPs.

Step 4. Time to collision (TTC): For identified TCPs, a minimum relative TTC of 3 seconds (Sayed and Zein, 1999) is assumed to capture the simultaneous arrival of the vehicle and pedestrian at the TCP and users' buffers (near- or far-buffer, depending on the approaching direction). TTC is calculated based on the average speed for each user. The Minimum TTC was computed as:

$$|TTC_{vehicle} - TTC_{pedestrian}| \leqslant 3sec \tag{7}$$

The position of interacting users and their direction of movement/approach concerning the other involved user are taken into account during the procedure. The application of the conflict detection procedure to the collected data led to identifying 120 conflict events between pairs in the shared space data set and 158 events in the mid-block crossing, where evasive manoeuvres were performed by one/both interacting users to escape the potential collisions (Tab. 3). Some users had more than one theoretical conflict (i.e., involved in multiple conflicts) and were analysed independently. In the shared space area, the group of pedestrians

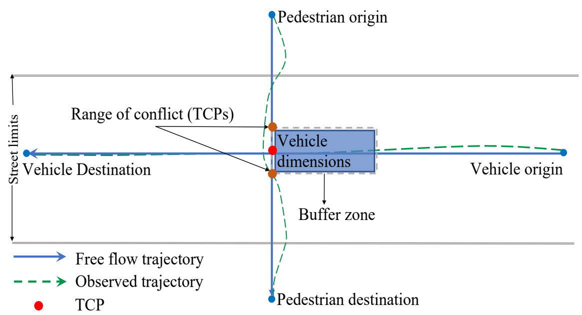

Figure 5: A simplified example of the conflict detection procedure in a pedestrian–passenger car interaction.

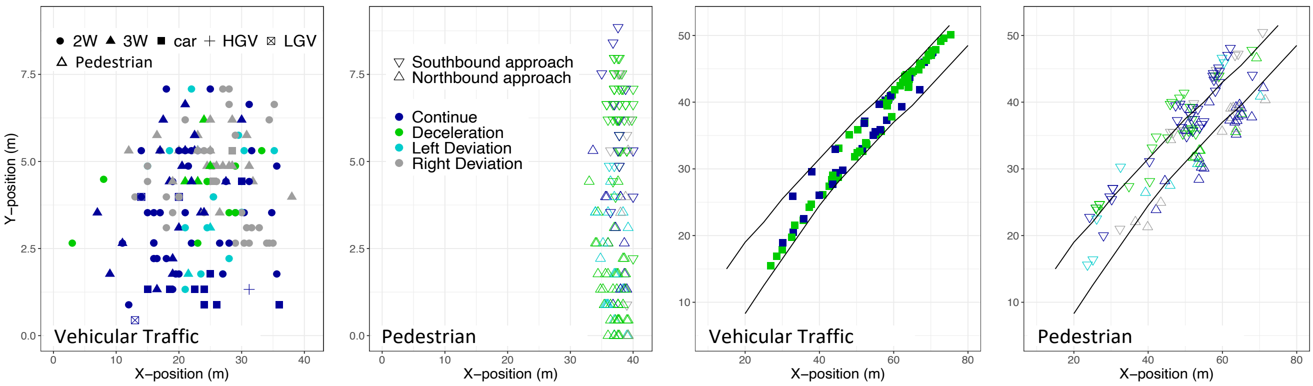

Figure 6: Conflict resolution strategy of users plotted by their position at the reaction time. From left to right: the first two figures show the vehicular traffic and pedestrians' strategies on approaching the mid-block crossing area, the second two figures show the vehicular traffic and pedestrians' strategies in the shared space.

at the crossing —interacted with the same vehicles— were analysed separately. The presence of other road users in the interaction scene, regardless of playing their independent games, is reflected in pay-off functions, such as pedestrians walking in a group or approaching from the opposite lane. However, the collected data in the mid-block crossing did not allow the independent analysis of the pedestrians crossing in a group, and they were analysed as a group.

Table 3
Summary of the identified conflict events with pedestrians in the studied areas (Amini et al., 2022).

Location	Car	2W	3W	HGV/LGV	Total
Shared space area	120	NA	NA	NA	120
Mid-block crossing	11	92	51	4	158

3.3. Conflict resolution determination

The conflict resolution strategies of users are determined manually and according to their FFTs, observed trajectories and speed profile during the interaction process. Additionally, the graphics interchange format (GIF) files were generated to verify the identified strategies by displaying the decision points of users (i.e., to spot where/when users change their speed) and their animated movements. For simplification, the combination of the strategies and performing multiple strategies were neglected in the analysis, and the last actions were considered the users' conflict resolution strategies. The identified strategies are clustered as described in section 2 for each user type. Figure 6 shows the strategy of users in conflict determined through the conflict resolution determination procedure for both data sets.
The following sub-sections explain the preferred speed, deceleration rates, and deviation angles specified for strategies per user type.

3.3.1. Determination of the preferred speed

For continuation and deviation strategies, the users' preferred speed for crossing the road is extracted from the data sets for each user type. Since there are significant differences regarding user behaviour and infrastructure designs in the studied locations, the preferred speed of user types is estimated separately.
A k-mean clustering approach is used to compute the preferred crossing speed of pedestrians in the shared space data set. Initially, non-conflict pedestrians —who are not involved in any conflicts/interactions— are grouped based on the approaching direction. Then, different crossing phases are defined for pedestrians on approaching a crosswalk (Gorrini et al., 2016), or while avoiding a conflict on the road (Pascucci, 2020). Based on non-conflict trajectories of pedestrians in the shared space data, the crossing is divided into three movement phases: (I) pedestrian decelerates on approaching the crossing/road kerb while evaluating the available gap to cross the road, (II) after accepting the gap, pedestrian accelerates to reach the crossing speed, and (III) pedestrian crosses the road with roughly constant speed, which is assumed to be the preferred crossing speed. These stages are displayed in Figure 7, where the acceleration changes of pedestrians reflect the movement phases. It is worth noting that few samples with constant crossing speeds greater than 2.5 m/s are removed from the analysis. Finally, a k-means algorithm is applied on variables walking speed, acceleration, and corresponding crossing time (i.e., speed and acceleration at each time step of crossing) of pedestrians as below (Lloyd, 1982):

- Determination of the number of clusters (k): The Elbow method is used to determine the optimal number of clusters (k=3).
- Centroid initialisation: The traditional random points method is used to initialise centroids for clustering.
- Assigning points to the closest cluster centroid: Based on the distance from the centroid, data points are assigned to different clusters.
- Re-computation of centroids: The process is repeated

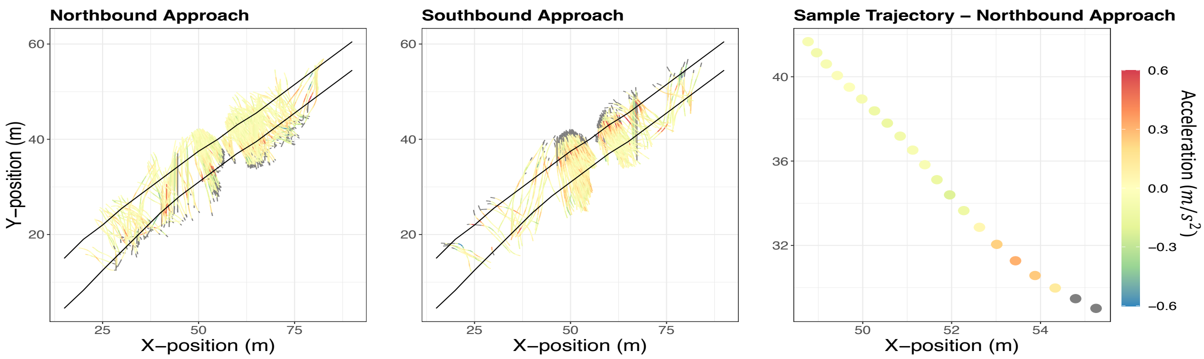

Figure 7: Non-conflict trajectories of pedestrians in crossing the road in the shared space data set.

until the centroids of clusters remain unchanged (100 iteration).

Table 4 summarises the details of the K-means clustering application, as well as the Silhouette coefficients for validation of consistency within data clusters. The mean pedestrian walking speed in cluster 3 (1.31 m/s) —corresponding to the third movement phase of crossing— is selected as the preferred crossing speed of pedestrians for continuing and deviation strategies in the shared space.

In preference to the speed limit, the 85th percentile of the speed for the vehicle type in the data set is considered as the preferred speed (Tab. 5). Vehicles commonly tend to drive at or near the same speed as traffic around regardless of the speed limit. This is in accordance with the Vienna Convention speed adjustment rules, where drivers need to pay constant regard to the circumstances, such as the state of the road, the weather conditions, and the density of traffic, to be able to stop the vehicle timely if needed (Vienna convention on Road Traffic, 1968). Although India is not a signatory of the Vienna Convention, driver behaviour to adjust the speed assumes to be similar. The preferred speed is applied in the continuing strategy of all vehicle types, and deviation strategy of light vehicles. The 85th percentile of the speed is also assumed to determine the preferred crossing speed of pedestrians at the mid-block crossing, given that a small number of the user free flow crossing is available from the data set (Tab. 5). This is due to the high level of interactions and the traffic density at the mid-block crossing, where pedestrians predominantly cross the roadway after escaping a conflict with the vehicles (based on the applied conflict detection procedure in this study).

For all user types, when the user speed at the reaction moment is higher than the preferred speed, the current speed is considered the strategy speed (in continuing and deviation strategies).

Table 4
K-Means clustering results of preferred crossing speed of pedestrians in the shared space.

Cluster	Variables			Size	Silhouette width
	Speed	Acceleration	Time		
1	1.184	-0.009	3.49	4023	0.65
2	1.270	0.039	9.91	4294	0.52
3	**1.312**	0.006	17.84	3971	0.52
$Between_S S / total_S S = 86.6\%$					

3.3.2. Determination of deceleration rate

Determination of the deceleration rate of user types for the corresponding strategy (i.e., deceleration strategy) is not straightforward. The reason is that the deceleration rate depends on several factors, e.g., the user's initial speed, available time/distance gap to clear the conflict zone, and the presence of other road users. As a consequence, it is difficult to estimate an explicit deceleration rate that reflects the general behaviour of users decelerating in reaction to a conflict on the road. Nevertheless, the average deceleration rate of user types in both data sets is used to predict the deceleration strategy in the model.

3.3.3. Determination of deviation angle

The average deviation angle of users deviated from their forward trajectories —and consequently from the TCP— is regarded as the deviation angle of user type for the associated strategies (i.e., deviation right and deviation left strategies). As the degree of movement freedom can vary from one road design to another, the deviation angles of users are estimated independently for the shared space and mid-block crossing. In the shared space, the average deviation angle of pedestrians is 22.28 degrees with a standard deviation of 9.15°. For simplification reasons, the deviation angle of the pedestrians is assumed as 22 degrees in the model. In the

Table 5
The preferred speed of vehicle types in the studied areas.

Vehicle type	Speed limit	Mean speed	Std. dev.	85th percentile
Vehicles in the shared space				
Passenger car	5.5	2.64	1.91	**4.7**
Vehicles in the mid-block crossing				
Passenger car	16	7.83	2.43	**10.41**
2W	14	8.76	4.27	**9.51**
3W	10	7.61	2.32	**8.75**
LGV&HGV	11	8.43	1.67	**10.41**
Pedestrian	-	0.81	0.66	**1.04**

Speed unit: m/s

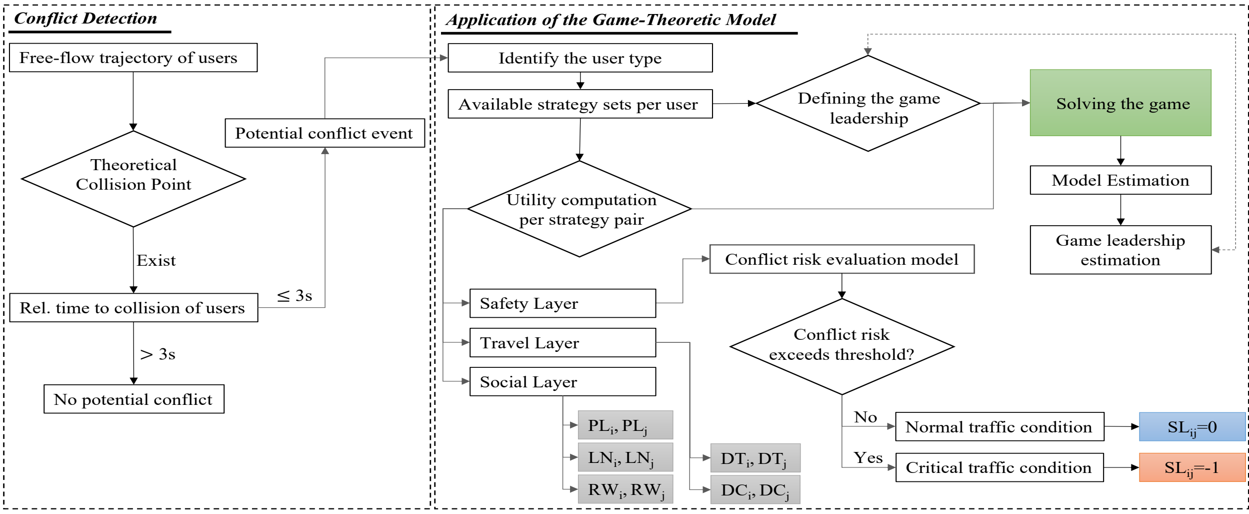

Figure 8: A general framework of the game-theoretic model application.

mid-block crossing, pedestrians and light vehicles (2Ws and 3Ws) deviate with the average angle of 26.5° (rounded as 26° in the model) with a standard deviation of 9.35°, and 11.11° (rounded as 11° in the model) with a standard deviation of 6.85°, respectively. Other vehicle types in the data sets have no deviation strategy in their choice of actions.

4. Application of the Stackelberg game

This section discusses the application of the developed game-theoretic model to conflict events. A general framework of the game-theoretic model application is depicted in Figure 8. As shown in the figure, the initial step to apply the model is detecting a conflict. In this work, a conflict detection procedure is applied to the collected data to identify the users in conflict (see Section 3.2 for details). However, for the general application of the model, the perpendicular users' trajectories would be replaced with the proposed FFTs to identify the theoretical collision point and the conflict event, if any. After identifying the conflict events, the interacting users' position and speed at the moment of conflict detection, and the TCP coordinates are used to compute the game utilities. Users receive utility for each strategy combination in the game, i.e., the leader and follower strategy combination determined from their available choice of actions. The game outcome, then, is determined through the backward induction method as discussed in Section 2.2.
The Rstudio (R Core Team, 2020) programming language is used for detecting conflict events, the utility computation, and finding the game solution. Algorithm 1 (see Appendix A) presents the employed approach for probability computation of performing a strategy by a user in conflict. The computation is based on the user role (leader or follower) and the interacting user choice of action. The probability of the outcomes is, then, determined through the equation 3 for each strategy combination in the game. The highest probability returns the game solution and, therefore, the user's choice of actions to avoid the conflict. In the model application, all users in conflict are assumed to once be the leader and once the follower of the game.

5. Model results

5.1. Estimating the game-theoretic models

A likelihood approach is employed to estimate the parameter values (θ_i) of the Stackelberg game. The utility of strategy choice ($s \in S$) for players in the game is computed based on equation 6 for the game leader and a similar approach for the follower. The probability of strategy choice for players can be obtained through the sub-game probability for the follower and choice probability for the leader of the game, providing the overall probability of the strategy pairs as:

$$P(s^L, s^F) = P_L(s^L) * P_F(s^F | s^L) \tag{8}$$

Therefore, the log-likelihood function is applied for the model estimation:

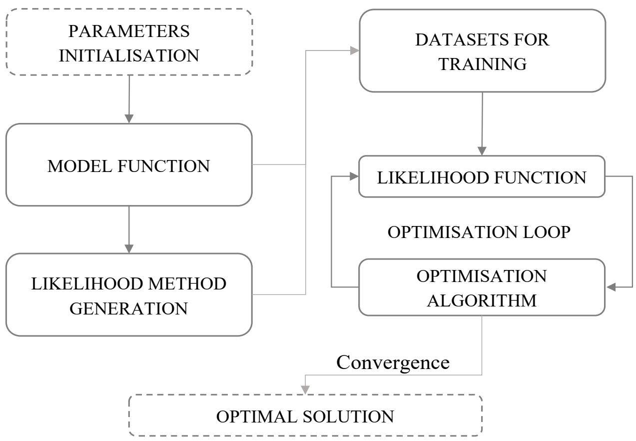

Figure 9: Flowchart of the optimisation process

Table 6
Parameter values and their standard deviation for model estimations in the shared space and mid-block crossing data sets. LB and UB: Lower and upper bound of confidence intervals. $Alpha = 0.05$

Parameter	Shared space						Mid-block crossing					
	μ	$\sigma_{\bar{\imath}}$	LB	UB	t-value	p-value	μ	$\sigma_{\bar{\imath}}$	LB	UB	t-value	p-value
θ_{sl}	1.42	0.20	1.02	1.81	6.97	<.0001	1.77	0.16	1.45	2.09	10.98	<.0001
θ_{dt}	1.99	0.28	1.45	2.54	7.20	<.0001	1.48	0.12	1.25	1.71	12.49	<.0001
θ_{dc}	1.13	0.54	0.07	2.18	2.09	<.01	3.36	0.26	2.85	3.87	12.89	<.0001
θ_{pl}	1.17	0.14	0.88	1.45	8.13	<.0001	1.29	0.20	0.89	1.69	6.37	<.0001
θ_{ln}	1.05	0.11	0.84	1.26	9.79	<.0001	0.80	0.10	0.61	1.00	8.05	<.0001
θ_{rw}	0.88	0.13	0.62	1.14	6.54	<.0001	0.80	0.11	0.59	1.01	7.44	<.0001

$$LL(\theta|y_{in}) = \sum_i \sum_j y_{in} \log\left(P(s^L, s^F)\right) \tag{9}$$

where y_{in} is 1 when the strategy pair is selected by the players in the game, and otherwise 0. Then, the negative log-likelihood is minimised using the numerical optimisation algorithm for a quasi-Newton method of Broyden Fletcher Goldfarb Shanno (BFGS) (Coppola et al., 2014) in Rstudio programming language. Figure 9 depicts the optimisation flowchart employed for the estimation of parameter values in the model. Since data sets have substantial differences in terms of user behaviour and infrastructure design, the model estimations are applied separately to the shared space for pedestrian–passenger car conflicts and the mid-block crossing for the pedestrian–light vehicle conflicts. Few passenger cars, HGVs, and LGVs in the mid-block crossing are not considered in the estimation to improve the model's accuracy involving light vehicles. This is mainly to develop a model that predicts the conflict resolution strategies of users with respect to their type. In order to have different data sets for model estimation and validation, a hold-out method is applied to split the conflict events on both data sets into 70% for training and 30% for testing purposes. The model estimations are applied to the training samples, and different parameters' combinations are examined to obtain the optimal training results (i.e., highest sensitivity, specificity, and accuracy). In both models, the combination of all proposed parameters provides the highest performance, and thus all utilised in the models estimation. Table 6 summarises the estimated parameters (θ_i) in both models using the calibration data acquired at the shared space and mid-blocking data sets. The mean values (μ) are returned by the maximum likelihood method, and the standard error of the mean ($\sigma_{\bar{\imath}}$) and confidence intervals for parameter estimates are computed through the observed Fisher information. The t-statistic and the p-value are used to assess the significance of the estimated parameters. As summarised in Table 6 all the employed parameters are statistically significant for the prediction of game outcomes in the models.

5.2. Game leadership estimation

As mentioned earlier in section 4, the models are applied by switching the leadership role among the users in conflict. To better determine the game leadership in the model, different approaches are evaluated:

- **Time to TCP:** The player closer to the TCP (in terms of time) is the game leader, while the other interacting player is the follower.
- **User type:** The type of users interacting on the road defines the leadership; motorised versus non-motorised road users. In case of pedestrian interaction with motorised vehicles, pedestrian is the follower and motorised vehicle is the game leader.
- **Reaction time:** The user who reacts first to a stimulus (i.e., conflict) on the road is considered the game leader, and its interacting user is the follower. In this research, users' reaction time is recorded based on their speed and trajectory changes during the conflict resolution determination procedure and utilises to determine the game leader.

A likelihood approach is employed to select the best leadership determination method (similar to the utilised method by Schönauer (2017)), and the results are shown in Table 7. The likelihood results in the pedestrian–passenger car model and the shared space data set reveal that reaction time is a better method for leadership determination. This supports the logic behind the Stackelberg leadership game, where the leader of the game plays a strategy first, and the follower reacts to the leader's strategy. Regarding the pedestrian–light vehicle model in the mid-block crossing, the likelihood method yields slightly similar results for the time to TCP and reaction time methods; however, as expected, the user type is the best fit to define the game leadership.

5.3. Model performance and validation

The testing data sets are used to assess the overall performance of the developed models. For this reason, confusion tables are created for categories: game choice (as "success") and non-choice (as "failure"), denoting the counts by true positive (TP), false positive (FP), true negative (TN), and

Table 7
Leadership determination methods for the pedestrian–passenger car and the pedestrian–light vehicle models.

Selection criteria	Negative log-likelihood	
	Shared space	Mid-block crossing
Time to TCP	976.4	1335.0
User type	985.8	**1280.2**
Reaction time	**826.6**	1352.2

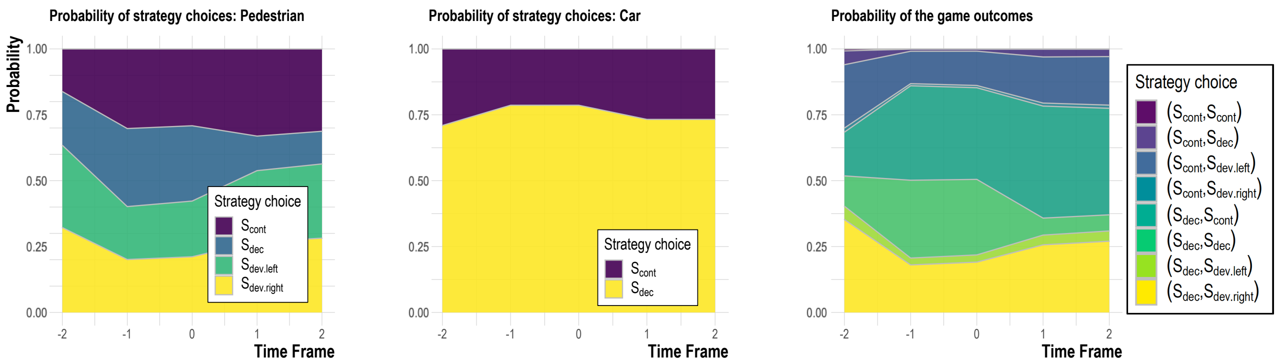

Figure 10: Probabilities of strategy choices in a pedestrian–passenger car conflict. From left: probability of strategy choices for pedestrian as the game leader, for car as the follower, and the probability of game outcomes for strategy combinations ($P(s^L, s^F)$).

false negative (FN). The accuracy, sensitivity, and specificity across all classes are computed for both models. The results are summarised in Tables 8 & 9. The model sensitivity and specificity are used as metrics to evaluate the model's ability to predict TPs and TNs of each conflict event, respectively. The pedestrian–passenger car model in the shared data set shows an average accuracy of 95.8%, a sensitivity of 83.3%, and specificity of 97.6% (see Tab. 8). The accuracy of the pedestrian–light vehicle model is 95.7%, with a sensitivity of 65.8% and specificity of 97.7% (see Tab. 9). The pedestrian–passenger car model with a misclassification rate of 16.7% shows a good performance reflecting the user decision-making process in the shared space. Regarding the mid-block crossing model, the misclassification rate amounts to 34.2% for the pedestrian–light vehicle model. This performance considers satisfactory given the user behaviour in the studied location and the wide range of factors influencing the user decisions, such as high traffic volume, road design, traffic behaviour, vehicle size, and driving culture. The methodology used shows that the models can be applied in different traffic setups (e.g., mid-block crossing, shared spaces), traffic patterns (e.g., various user types), and traffic behaviour (i.e., user behaviour in different countries).

Two specific examples are selected from data sets to further explain the model performance and characteristics. The results are visualised in Figure 10 & 11. The model is applied to conflict events in the time frames prior/following the actual reaction time of the interacting users in the game. The application of time frames aims to demonstrate the model performance concerning the variation in the game. The first example is a pedestrian–passenger car conflict in the shared space where the pedestrian is the game leader, and the passenger car is the follower (Fig. 10). In the real-world scenario, the pedestrian continues its path, and the passenger car decelerates to let the pedestrian pass first. The probability of strategy choice in Figure 10 shows that the deviation strategy to cross behind the passenger car initially returns a higher utility (time frame $= -2$); however, the probability of the continuing strategy increases over the time and remains the preferred strategy of the leader. The strategy choice probability for the passenger car in Figure 10 demonstrates the highest utility in taking the deceleration strategy during the illustrated period. The high utility of the deceleration strategy is mainly due to the pedestrian group size (> 2) in the conflict example. The probability of the game outcomes ($P(s^L, s^F)$) shows that the strategy deceleration-continuing returns a higher probability at the reaction time (time frame $= 0$), where both players receive the highest utility from their strategy choices.
The second example is a pedestrian-2W conflict from the mid-block crossing data set (Fig. 11). The preferred strategy of the 2W, as the game leader, is to continue its path where the highest utility is gained. The pedestrian selects the left deviation strategy to cross the roadway behind the 2W rather than waiting until the conflict zone is clear. The strategy pair of continuing-deviation left returns the highest probability at the actual reaction time of users (time frame $= 0$) as the final game outcome, in which game leader receives its highest utility from its strategy choices. The final game outcome ($P(s^L, s^F)$) is similar to the taken strategies of users in the real-world conflict scenario.

Table 8
Confusion table for pedestrian-passenger car model.

	True value		Total
	Choice	non-choice	
predicted: choice	60	12	72
predicted: non-choice	12	492	504
***ACC* = 0.958**			

Table 9
Confusion table for pedestrian-light vehicle model.

	True value		Total
	choice	non-choice	
predicted: choice	54	28	82
predicted: non-choice	28	1202	1230
***ACC* = 0.957**			

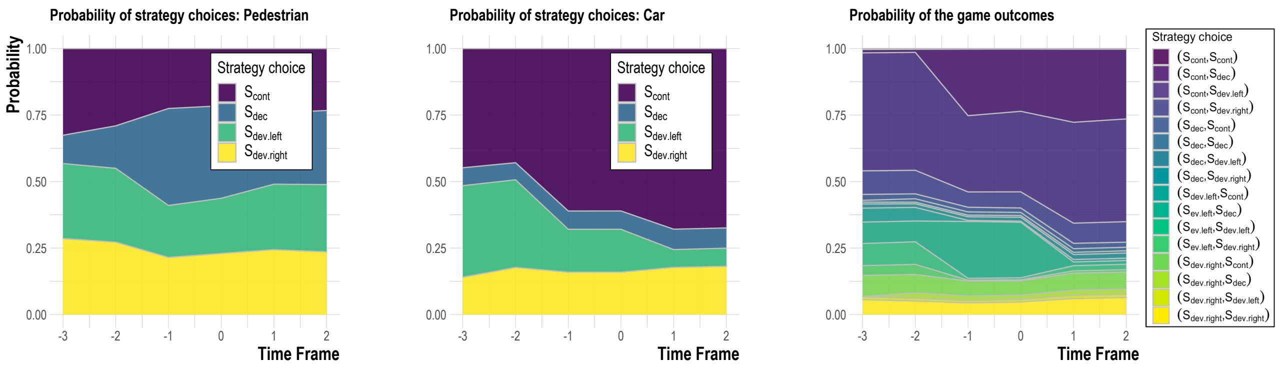

Figure 11: Probabilities of strategy choices in a pedestrian-2W conflict. From left: probability of strategy choices for 2W as the game leader, for pedestrian as the follower, and the probability of game outcomes for strategy combinations ($P(s^L, s^F)$).

6. Discussion

In this research, a game-theoretic model is applied to predict the conflict resolution strategies of pedestrians interacting with motorised vehicles. The model assumes that users select a strategy that maximises their utilities. Further, the user's choice of strategy in the proposed Stackelberg game is based on the possible reaction of the interacting user to avoid a conflict. The latter property is substantial for a safe traffic interaction —as a bilateral event— where the collective strategies of interacting users determine the outcome. The game utilities are formulated in three layers of safety, travel, and social to cover a broad range of factors influencing the user's decision in a traffic conflict. In the safety layer, previously developed conflict risk evaluation models by Amini et al. (2022), are utilised to assess the safety of interacting users after performing each strategy pair. The safety layer estimates the future minimum distance between interacting users, the relative time of users' arrival at the collision zone (i.e., new collision point or MD), and conflicting speed. Then, based on the estimated surrogate safety indicators and model thresholds, the model identifies the hazardous traffic conditions between pedestrians and vehicles and returns a dis-utility when applicable. The comfort level of different strategies is quantified in the travel layer for the detour, and deceleration imposed by users' speed/trajectory changes. The users receive dis-utilities for the corresponding energy loss of each conflict resolution strategy available for users in the game. The third utility layer covers three of the most significant environmental factors influencing the user's choice of strategy; pedestrian group size, pedestrian approaching lane, and the right of way. The social layer signifies the importance of social norms in improving safety in uncontrolled traffic environments. Finally, the outcome of the proposed strategic game of the Stackelberg leadership competition is determined through the backward induction method. The proposed game-theoretic approach is estimated separately for pedestrian interactions with passenger cars and light vehicles (i.e., 2Ws and 3Ws).

6.1. Impact factors

To better evaluate the model variables, a Probability Density Function (PDF) (sampling distribution of the sample mean) is used to visualise the relation between the shared space and mid-block crossing for each parameter value (θ_i) returned after the model estimations (see Fig. 12):

$$f(\theta_i|\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \tag{10}$$

where μ is the mean value and σ is the standard error computed by the maximum likelihood method per θ.

Safety layer ($\boldsymbol{\theta_{sl}}$): As expected, in both shared space and mid-block crossing data sets, safety layer plays a significant role ($\theta_{sl} > 2\sigma_{\bar{sl}}$). This is because road users maximise their safety by employing conflict resolution strategies that minimise the critical conflict and/or collision risk on the road. In the mid-block crossing model, the collision avoidance is crucial in strategy choice of users; however the analysed data indicates that pedestrians primarily take courteous strategies during the interactions.

Travel layer ($\boldsymbol{\theta_{dt}}$, $\boldsymbol{\theta_{dc}}$): In both models (i.e., data sets), the parameter value of detour is substantial in user's choice of strategy ($\theta_{dt} > 2\sigma_{\bar{dt}}$); however, it is stronger in the pedestrian-passenger car model with deviation strategy choices available only for pedestrians. The effect of deceleration variable is strong in both models ($\theta_{dc} > 2\sigma_{\bar{dc}}$); however, deceleration is clearly dominant in the decision-making process of users in the mid-block crossing. This supports the user behaviour in the studied location, in which there is less tendency to slow down to give the right of way in traffic interactions. The overall driver yielding rate for pedestrians during the conflict scenarios in the mid-block crossing is approximately 12%, and motorised vehicles often deviate to pass the conflict zone. Therefore, the strategies with no speed changes are preferred by users in the game.

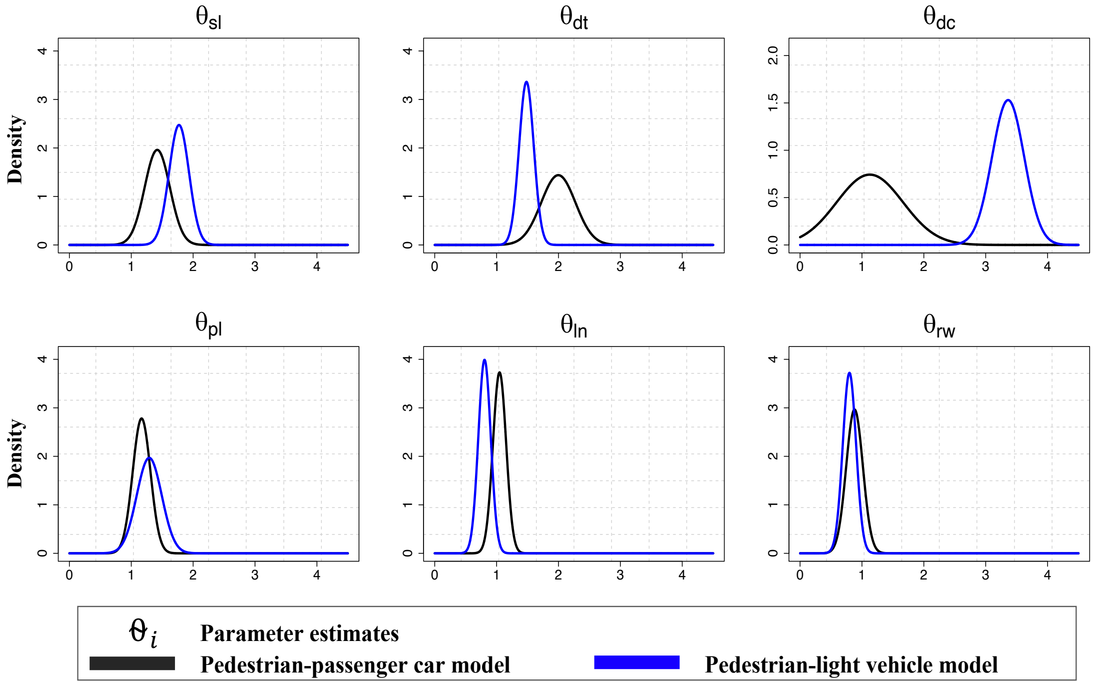

Figure 12: Comparison of the parameter estimates in developed models using the shared space and mid-block crossing data sets.

Social layer (θ_{pl}, θ_{ln}, θ_{rw}): This layer of the game utility incorporates the pedestrian group size, approaching lane, and the right of way. All three variables have significant impact on user's strategy choice in the shared space model ($\theta_{pl} > 2\sigma_{\bar{pl}}$ & $\theta_{ln} > 2\sigma_{\bar{ln}}$ & $\theta_{rw} > 2\sigma_{\bar{rw}}$) reflecting the importance of social norms in safe movements of different user types in such urban designs. The social layer has slightly different influence on the pedestrian–light vehicle model due to the user behaviour in the studied location. While the pedestrian group size is relevant for the decision-making process of users in conflict in the mid-block crossing, approaching lane seems to be less strong.

It is worth noting that previous studies found a wider range of factors influencing pedestrian behaviour during interactions, such as pedestrian age and gender, personal characteristics, culture, and waiting time. However, it is hard for the current stage of ADS development to process such pedestrian-associated information (Ezzati Amini et al., 2021b). Therefore, this research only employs the most significant factors —identified in the literature— currently feasible to process by the ADS.

6.2. Stackelberg game model applicability

The complexity of pedestrian interactions with motorised vehicles presents considerable challenges for users' behavioural modelling and prediction. The characteristics discrepancy of different road user types and, thus, their granted/expected utilities, lead to exposing different behaviour on the interaction scene, where users employ various strategies to escape a conflict. In the automation technology domain, there are many uncertainties regarding the most influential factors of pedestrian behaviour, the possible impact of these factors on pedestrian behaviour, and the implementation of these factors in ADS (Ezzati Amini et al., 2021b). However, there are several technological advancements to maintain pedestrian safety in the absence of a human driver in uncertain/conflicting traffic situations, such as pedestrian/object detection, tracking objects in motion, automated braking systems in case of hazardous conditions, and pedestrian protection systems to minimise the damage when a collision is unavoidable. Yet, in complex urban scenarios with a high level of elaborated interaction strategies among road users, ADS are not fully capable of handling an efficient priority negotiation with traffic participants (Fox et al., 2018). Therefore, a suitable interaction method is required to ensure the efficiency of ADS on the road and the safety of road users interacting with such vehicles. The proposed game-theoretic approach predicts the conflict resolution strategies of users in interaction by taking into account the safety outcome of various strategies in a conflict event and the impact of travel and environmental factors on user decisions. The game-theoretic approach has the potential to be used as a behavioural model for ADS and improve pedestrian safety, particularly in uncontrolled traffic settings. The proposed model enables the ADS to make more informed decisions during a traffic interaction, have a dynamic interaction with pedestrians, and react adequately to their actions when required. Such interaction concept can prevent the "bullying behaviour" by other traffic participants to block the automated vehicle path or/and occurring so-called "freezing robot problem" that they may be subject to (Madigan et al., 2019; Färber, 2016).

6.3. Limitations and further research

In this research, the game-theoretic models are developed based on interaction data in a shared space in Hamburg, Germany, and a mid-block crossing in Surat, India. Despite the differences in crossing facility types and user behaviour in the studied locations, the models demonstrated good performance, verifying the transferability of the proposed models. Yet, an extensive data analysis of various traffic settings in different locations is required to build a more suitable and realistic model. Further, the Stackelberg game assumes that players (i.e., interacting road users) within the game are rational and will try to maximise their payoffs; however, this may not always be the case. Therefore, the model requires adding an element of randomness that can explain several phenomena where players do not behave in line with the rationality assumptions of the game theory. Besides, road users can perform a broader range of evasive manoeuvres to avoid conflict in real-world traffic interactions. For instance, pedestrians may execute unexpected changes in their movement directions or suddenly stop at any crossroads point. However, it can be hard to incorporate such unpredictable behaviour into the behavioural modelling approaches. In addition, the deviation strategy of users in the model is considered with no speed changes to simplify the interaction model and avoid generating a computationally expensive algorithm. Finally, the independent parameters of the proposed model are mostly based on the findings of the studies on traditional pedestrian-vehicle interactions and the current stage of ADS development. This research suggests further studies to investigate how the vast existence of automated vehicles in the public realm can alter pedestrian behaviour, and which influencing factors in traditional interactions are applicable within the ADS conceptual framework.

7. Conclusions

Pedestrians with a high level of movement freedom on the road can perform unexpected behaviour leading to more complex traffic interactions. Traffic participants intend to dominate the road space during the interaction process while their safety is assured. Such competitions over the road space are more complicated in uncontrolled mixed environments where users have to negotiate the right of way. Furthermore, the pedestrian interactions with other road users may become more challenging with the integration of ADS as a new road user into the traffic and when the road infrastructure is not fully ready for merging such vehicles. In this case, the ADS require a suitable interaction method to predict the intentions/decisions of interacting users and consequently avoid conflict and improve traffic efficiency.

In this research, a game-theoretic approach is proposed to predict the conflict resolution strategies of pedestrians interacting with passenger cars and light vehicles (two-wheel and three-wheel vehicles) in uncontrolled traffic settings. The models employ a variety of factors influencing the decision-making process of users during a traffic conflict and are calibrated using interaction data of shared space and mid-block crossing areas. The models indicate good performance given the stochastic behaviour of road users —particularly in the mid-block crossing area in India—f and can potentially be used as a behavioural model for the ADS.

Declaration of competing interest

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

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A. Appendix

Algorithm 1: The strategy performance probability with respect to the interacting user strategy in a pedestrian-passenger car conflict.

Input: U is the player exponential utility for each strategy (combination), i is the user in conflict events n. s is the user strategy, and S is strategy combinations always in order of $(s_{car}, s_{pedestrian})$:
$cc = (s_{cont}, s_{cont})$; $cd = (s_{cont}, s_{dec})$
$cl = (s_{cont}, s_{dev.left})$; $cr = (s_{cont}, s_{dev.right})$
$dc = (s_{dec}, s_{cont})$; $dd = (s_{dec}, s_{dec})$
$dl = (s_{dec}, s_{dev.left})$; $dr = (s_{dec}, s_{dev.right})$
Output: P: the strategy performance probability
for $i \leftarrow 1$ ***to*** n **do**
  if $leader = car$ & $player = car$ **then**
    $P_i^L(s_i) = U_{s_i}^L / \sum U_{s \in ALL}^L$
  else if $leader = car$ & $player = pedestrian$ & $s_i \in S_1 : \{cc, cd, cl, cr\}$ **then**
    $P_i^F(s_i|s_{cont}) = U_{s_i}^F / \sum U_{s \in S_1}^F$
  else if $leader = car$ & $player = pedestrian$ & $s_i \in S_2 : \{dc, dd, dl, dr\}$ **then**
    $P_i^F(s_i|s_{dec}) = U_{s_i}^F / \sum U_{s \in S_2}^F$
  else if $leader = pedestrian$ & $player = pedestrian$ **then**
    $P_i^L(s_i) = U_{s_i}^L / \sum U_{s \in All}^L$
  else if $leader = pedestrian$ & $player = car$ & $s_i \in S_3 : \{cc, dc\}$ **then**
    $P_i^F(s_i|s_{cont}) = U_{s_i}^F / \sum U_{s \in S_2}^F$
  else if $leader = pedestrian$ & $player = car$ & $s_i \in S_4 : \{cd, dd\}$ **then**
    $P_i^F(s_i|s_{dec}) = U_{s_i}^F / \sum U_{s \in S_4}^F$
  else if $leader = pedestrian$ & $player = car$ & $s_i \in S_5 : \{cl, cl\}$ **then**
    $P^F(s_i|s_{dev.left}) = U_{s_i}^F / \sum U_{s \in S_4}^F$
  else
    $P_i^F(s_i|s_{dev.right}) = U_{s_i}^F / \sum U_{s \in S_5}^F$; $s_i \in S_5 : \{cr, cr\}$
  end
end

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