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Evasive actions to prevent pedestrian collisions in varying space/time contexts in diverse urban and non-urban areas

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ABSTRACT

This study aims to identify driver-safe evasive actions associated with pedestrian crash risk in diverse urban and non-urban areas. The research focuses on the integration of quantitative methods and granular naturalistic data to examine the impacts of different driving contexts on transportation system performance, safety, and reliability. The data is derived from real-life driving encounters between pedestrians and drivers in various settings, including urban areas (UAs), suburban areas (SUAs), marked crossing areas (MCAs), and unmarked crossing areas (UMCAs). By determining critical thresholds of spatial/temporal proximity-based safety surrogate techniques, vehicle–pedestrian conflicts are clustered through a K-means algorithm into different risk levels based on drivers' evasive actions in different areas. The results of the data analysis indicate that changing lanes is the key evasive action employed by drivers to avoid pedestrian crashes in SUAs and UMCAs, while in UAs and MCAs, drivers rely on soft evasive actions, such as deceleration. Moreover, critical thresholds for several Safety Surrogate Measures (SSMs) reveal similar conflict patterns between SUAs and UMCAs, as well as between UAs and MCAs. Furthermore, this study develops and delivers a pseudo-code algorithm that utilizes the critical thresholds of SSMs to provide tangible guidance on the appropriate evasive actions for drivers in different space/time contexts, aiming to prevent collisions with pedestrians. The developed research methodology as well as the outputs of this study could be potentially useful for the development of a driver support and assistance system in the future.

1. Introduction

According to the World Health Organization (WHO), pedestrian crashes accounted for 23% of all road traffic crashes, resulting in 300,000 deaths in 2018 (WHO, 2018). In addition, the characteristics of pedestrian crashes and fatalities differ across road types. For instance, WHO identifies star roads as among the most dangerous areas for pedestrians to cross. Star roads refer to roads without any sidewalk or safe crossing infrastructure, while the minimum speed of vehicles is 60 km per hour. This type of road may exist in urban areas (UAs) or suburban areas (SUAs); pedestrians commuting on these roads are generally not protected from motorized traffic.

The relationship between unprotected crossing facilities and pedestrian safety is quite pronounced in developing countries (Kadali and Vedagiri, 2016). For example, in Iran, there were over 4000 pedestrian deaths in 2020, of which 46% occurred on SUAs (Iranian Legal Medicine Organization, 2022). More than 66% of fatal crashes occurred in unmarked crossing areas (UMCAs). There are no designated crossing facilities in these areas, so pedestrians cannot cross the road safely.

Apart from the presence of protected or unprotected crossing facilities, there is a wide range of factors that can also determine the level of pedestrian safety, including the overall road design and environment, pedestrian and motorized traffic as well as pedestrians' and motorists' behavior (Campos Ferreira et al., 2022). The impact of all these factors may vary between urban and suburban areas (Sheykhfard et al., 2020). As such, the prevalence of pedestrian crashes and casualties may vary between urban and suburban roads (Olowosegun et al., 2022). The pattern pf varying crash frequencies is observed in several parts of the world, and not only in developing countries, with pedestrian crashes being more frequent in some area types than others. Interestingly, the International Traffic Safety Data and Analysis Group (IRTAD) showed that most road fatalities occur in SUAs; these areas account for more

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than 60% of road fatalities in Sweden, Australia, and France (Forum, 2020). Focusing on pedestrian casualties, according to data from the National Highway Traffic Safety Administration (NHTSA) in the US, most pedestrian traffic deaths in 2020 occurred on urban roads (80%), while the rest occurred on non-urban roads (National Safety Council, 2020). In Iran, nearly 40% of pedestrian crashes in 2020 occurred on non-urban roads (Iranian Legal Medicine Organization, 2022). This discrepancy in safety statistics between urban and non-urban areas may be attributed to the driver decisions and pedestrian behavior while crossing these roads. Even though a number of research studies have recently shed light on the crash-prone interactions between pedestrians and drivers (Bella and Nobili, 2020; Kathuria and Vedagiri, 2020; Obeid et al., 2017; Sheykhfard et al., 2022; Sheykhfard and Haghighi, 2018), there is always a need for more empirical evidence relating to the different nuances of pedestrian crossing risk, especially between urban and non-urban roads, which will help assess how pedestrians and drivers interact reciprocally in such roads.

In the context of pedestrian safety assessment, human factors relating to both pedestrians and drivers have been long recognized as major determinants of pedestrian crashes (Akanbi et al., 2009; Laux, 2019; Sagberg et al., 2015). Therefore, examining the behavior of drivers when confronting pedestrians may provide insight into their evasive actions based on the risk level of crossing pedestrians. The behavior of both drivers and pedestrians in circumstances of interactions between them is naturally subject to human error and its pronounced impact on users' actions; this is also acknowledged by the Safe System Approach (SSA), which focuses on the design of effective safety systems considering that human mistakes will unavoidably occur, and the system should accommodate these mistakes and prevent serious injuries or fatalities (USDOT, 2022). The SSA incorporates the following principles: 1) Death and serious injuries are unacceptable, 2) Humans make mistakes, 3) Humans are vulnerable, 4) Responsibility is shared, 5) Safety is proactive, and 6) Redundancy is critical. The SSA is based on five core pillars, which are 'Safe Road Users,' 'Safe Road,' 'Safe Speeds,' 'Safe Vehicles,' and 'Post-Crash Care.

To identify the major factors affecting driver-pedestrian interactions, many pedestrian crossing safety studies have been conducted both in real-world settings (Sheykhfard and Haghighi, 2019, 2020; Sun et al., 2015) in simulation (Cavallo et al., 2019; Feldstein et al., 2016; Mollu et al., 2018; Tapiro et al., 2016) or naturalistic environments (Pantangi et al., 2021; Sarwar et al., 2017). Several studies have also examined drivers' behavior when encountering pedestrians under specific conditions (Ābele et al., 2018; AlKheder et al., 2020; Bella and Silvestri, 2016; Kathuria and Vedagiri, 2020). Moreover, these studies are usually confined to specific areas, such as UAs or Marked Crossing Areas (MCAs) (Cheng et al., 2018; Havard and Willis, 2012; Sheykhfard et al., 2021; Zhuang and Wu, 2011).

Although extensive research has been conducted on driver behavior, the literature still lacks a comprehensive analysis of drivers' evasive actions, which could assist in determining the different risk levels associated with pedestrian crossing behavior in various urban and non-urban areas. Between urban and non-urban areas, there may be significant differences in the prevalence and extent of factors that can determine pedestrian crash risk, such as the actual vehicle speed, the speed variations of motorized users, or the magnitude of roadside activities (Kraidi and Evdorides, 2020; Quddus, 2013). Such differences may not be aligned with the expectations of both drivers and pedestrians, thus resulting in evasive maneuvers from both users (Finch et al., 1994), the characteristics of which may vary depending on the level of risk emerged in the vehicle–pedestrian interaction. Similar variations in evasive maneuvers and the observed level of crash risk may be also present between marked and unmarked crossing areas; for example, in marked crosswalks, vehicle approaching speeds may be relatively lower compared to unmarked crosswalks (Zeeger et al., 2001; Pantangi et al., 2021), or motorists may be more likely to yield for pedestrians. However, in marked crossing areas, some pedestrians may feel that the drivers will adjust their behavior to protect them, and as such, incidents of non-compliant pedestrian behavior may be more frequent, especially when compared to unmarked crosswalks where pedestrians are more likely to be alerted about speeding or non-yielding behaviors of drivers.

We have previously examined pedestrian crossing behavior on UAs and SUAs, focusing on interactions between vehicles and pedestrians (Sheykhfard and Haghighi, 2020). The present study investigates drivers' behaviors, and especially their evasive actions, in order to determine pedestrian crash risk using a series of Surrogate Safety Measures (SSMs). By leveraging real-life driving data, the present study, therefore, examines the drivers' evasive actions and the reciprocal behavior of pedestrians in UAs and SUAs, as well as in MCAs and UMCs. The objective is to identify driver-safe evasive actions that are associated with the different levels of pedestrian crash risk in various types of urban and non-urban areas. The hypothesis of this study is based on the assumption that the choice of evasive action by drivers depends on the critical threshold of SSMs in different areas. In light of the analysis of the drivers' evasive actions, a pseudo-code algorithm is also developed using as input the estimated critical thresholds of SSMs across different areas. Such an algorithm can provide tangible guidance as to the appropriate evasive actions that need to be undertaken by drivers in different space/time contexts in order to avoid collisions with pedestrians.

The study consists of four sections. Data collection and study sites are discussed in the second section. Additionally, the paper introduces the evasive action-based traffic conflict technique, as well as the temporal and spatial proximity-based technique, along with the overall research framework. In the third section, the results of the study are presented, including critical thresholds of indicators, pedestrian crossing risks based on different clusters, and evasive actions by drivers and pedestrians, as well as a comparison of the results with those from previous studies. The conclusion comprises the last section, and it summarizes the research findings. Moreover, some suggestions are made for future research taking also into account the limitations of the current study."

2. Literature review

As the development of Advanced Driver Assistance Systems (ADAS) and autonomous driving features progresses, ensuring pedestrian safety has become increasingly crucial. While Autonomous Vehicles (AVs) have the potential to enhance pedestrian safety, adapting them to effectively interact with pedestrians remains uncertain. Unlike human drivers, AVs cannot always yield to pedestrians due to the impracticality of a simple yielding strategy. Consequently, conflicts in pedestrian-AV interactions are inevitable and need to be resolved. Therefore, AVs must engage in negotiation with pedestrians to establish priorities and reach satisfactory or acceptable resolutions during interactions (Hulse, 2023). For AVs to be effective in this regard, they need to be capable of identifying pedestrian behavior, evaluating the likelihood of such behavior in a given situation, and assessing the associated collision risk. Therefore, insights from research on pedestrian behavior in interactions with human-operated vehicles can inform the initial programming of AVs.

Driver-safe evasive actions are of paramount importance when drivers encounter pedestrians on the road (Happee et al., 2017). In this situation, it is crucial for them to prioritize taking appropriate evasive actions to ensure safety. By being prepared, attentive, and responsive, drivers can minimize the chances of accidents, protect pedestrians' well-being, and fulfill their role as responsible participants in the transportation system (Happee et al., 2017; Lubbe, 2017; Shah and Lee, 2021). An evasive action refers to the ability of drivers to promptly and effectively respond to unforeseen situations on the road, particularly when pedestrians are involved (Jurecki and Stańczyk, 2014; Scanlon et al., 2015). The need for safe evasive actions arises primarily from the vulnerability of pedestrians as road users. Unlike drivers who are shielded by their vehicles, pedestrians are more exposed and have limited means of protection. Consequently, any collision between a vehicle and a pedestrian can have severe and even fatal consequences. Therefore, it is the responsibility of drivers to take all possible measures to prevent such accidents. Another reason for the significance of safe evasive action is the unpredictability of pedestrian behavior. Pedestrians may suddenly cross the road without warning, disregard designated crosswalks, or be distracted by electronic devices. In such situations, drivers must be prepared to react swiftly and take evasive action to avoid a collision. This involves maintaining awareness of the surroundings, scanning the road ahead, and being ready to apply brakes or maneuver the vehicle as necessary. Safe evasive actions are particularly important when drivers encounter pedestrians who may be impaired, such as individuals under the influence of alcohol or those with physical disabilities (Salamati et al., 2013). In such cases, drivers must exercise additional caution and adjust their driving behavior accordingly. Evasive maneuvers may be required to navigate around pedestrians who are unable to follow typical walking patterns or who might inadvertently step into the path of oncoming traffic (Happee et al., 2017; Lubbe, 2017; Shah and Lee, 2021). Furthermore, the significance of safe evasive action extends beyond legal and moral obligations. Accidents involving pedestrians can have significant legal ramifications for the driver, including financial liabilities and potential criminal charges. By taking evasive actions, drivers demonstrate their commitment to road safety and minimize the risk of harm to themselves and others, including pedestrians. To ensure safe evasive action, drivers should adhere to responsible driving practices, such as obeying speed limits, maintaining a safe following distance, and avoiding distractions while driving. Additionally, drivers should be knowledgeable about and comply with traffic laws and regulations, which often prioritize pedestrian safety.

Over the past several decades, studies have extensively evolved and focused on several aspects regarding driver's evasive actions, such as interrelationship between driving speed and pedestrian safety (Bella and Silvestri, 2015; Kröyer et al., 2014; Rosén et al., 2011), drivers' yielding behaviour to pedestrian (Fisher and Garay-Vega, 2012; Gómez et al., 2011), driver performance to some pedestrian facilities (Salamati et al., 2013; Schroeder and Rouphail, 2011), and turning time and acceptable gaps for drivers under various situations (Alhajyaseen et al., 2013). A study by (Jiang et al., 2017) showed the majority of drivers tend to display more aggressive reactions, resulting in shorter braking distances and higher maximum average deceleration rates during yielding situations. Additionally, the study observed that the maximum average deceleration rate increases as the volume of traffic rises. During the acceleration phase, drivers compete for the right-of-way by accelerating. Jiang et al., (2019) analyzed the relationship between deceleration rate and vehicle speed and analyzed how time and distance-related measures influenced the choice of deceleration rate. The study proposed the concept of an effective decelerating zone for drivers, considering both longitudinal and lateral conflict behavior. The researchers calculated the minimum distance for vehicle–pedestrian conflicts and suggested a 2 m threshold for collision discrimination. In a study by (Shah and Lee, 2021), the relationship between the duration of a driver's evasive action and the risk of rear-end collisions were considered. The researchers used surrogate safety measures based on vehicle trajectories to estimate collision risk but acknowledge their limitations in capturing the timing of evasive actions. Through observations using a driving simulator, they analyzed the effects of the evasive action time on collision risk for fifty drivers in two different traffic scenarios. The study found that a longer evasive action time reduces crash risk, and driver characteristics, such as gender and experience, influence effective evasive actions.

Although extensive research has been conducted on driver behavior, the literature still lacks a comprehensive analysis of drivers' evasive actions, which can assist in determining the different risk levels associated with pedestrian crossing behavior in various urban and non-urban areas. Between urban and non-urban areas, there may be significant differences in the prevalence and extent of factors that can determine pedestrian crash risk, such as the actual vehicle speed, the speed variations of motorized users, or the magnitude of roadside activities (Kraidi and Evdorides, 2020; Quddus, 2013). Such differences may not be aligned with the expectations of both drivers and pedestrians, thus resulting in evasive maneuvers from both users (Finch et al., 1994), the characteristics of which may vary depending on the level of risk emerged in the vehicle–pedestrian interaction. Similar variations in evasive maneuvers and the observed level of crash risk may be also present between marked and unmarked crossing areas; for example, in marked crosswalks, vehicle approaching speeds may be relatively lower compared to unmarked crosswalks (Zeeger et al., 2001; Pantangi et al., 2021), or motorists may be more likely to yield for pedestrians. However, in marked crossing areas, some pedestrians may feel that the drivers will adjust their behavior to protect them, and as such, incidents of non-compliant pedestrian behavior may be more frequent, especially when compared to unmarked crosswalks where pedestrians are more likely to be alerted about speeding or non-yielding behaviors of drivers.

To sum up, by employing an approach based on real-life driving data, the current research seeks to demonstrate the safe actions that drivers can take to reduce the likelihood of vehicle–pedestrian collisions and prevent pedestrian crashes. Consequently, these research findings can establish a proactive framework based on drivers' actions and benchmarked against critical thresholds of Safe Surrogate Measures (SSM), with the aim of minimizing pedestrian crashes. Such an initial framework could be potentially implemented in future driver assistance systems within the automotive industry.

3. Materials and methods

3.1. Study sites

An integrated methodological framework was developed and applied to conduct this research. At first, naturalistic data was collected through the use of instrumented vehicles in order to identify drivers' evasive actions as well as the reciprocal behavior of pedestrians across different area contexts. The study received ethical approval upon review of its experimental design. Two approaches of surrogate safety analysis (evasive action-based traffic conflict technique and spatial and temporal proximity-based traffic conflict technique) were then identified and applied on the collected data. Finally, a pseudocode algorithm was proposed using temporal and spatial indicators to predict drivers' evasive actions.

The naturalistic data was collected from the Mazandaran Province (population: 3,283,577), located in the north of Iran. In that area, there are significant road safety issues, as it constitutes one of the three provinces with the highest crash rates in the country. The Iranian Legal Medicine Organization estimates that over 500 people died in road crashes in this province in 2021, while more than 13 thousand were injured (Iranian Legal Medicine Organization, 2022). Most of these fatalities and injuries occurred in the Babol county (population 540.571; 119 dead, 3117 injured), which is the most hazardous area for pedestrians in the Mazandaran province, with half of the casualties involving pedestrians (Iranian Legal Medicine Organization, 2022). In this context, various urban and suburban areas from Babol County were studied.

3.2. Ethics approval

Research on human subjects was approved by the Babol Noshirvani University of Technology's ethics committee, ensuring participants' safety. The data of all participants was kept confidential and anonymous. Participants were recruited by the Traffic Research Laboratory of Babol Noshirvani University of Technology, following the launch of a call for participation in the research. Social media and newspapers were used for the dissemination of the call.

3.3. Data collection and analytical strategy

Following the dissemination of the call for participation, 44 people expressed interest to join the study. Before the onset of the study, the participants signed a consent form that also includes a confidentiality clause warranting that the collected information will only be used for research purposes. The participants were briefed to ensure that they have sufficient information about the overall concept and operational characteristics of the instrumented vehicles. The current research objectives were not presented to them to avoid any possible influence of prior knowledge on their behavior and performance.

A total of 41 people (21 men and 20 women, aged between 18 and 65) participated in the study, since three people finally refused to participate. Table 2 shows an overview of the demographic characteristics of participants. Based on Table 2, an approximately equal number of male and female drivers took part in this study, and this balance is consistent across different age groups. Around 55% of participants reported having less than 10 years of driving experience, while the remaining majority had more than a decade of experience. On average, these experienced drivers cover over 6,000 km annually, and a significant proportion (over 80%) of them have been involved in traffic accidents at least once. For additional details, please refer to the comprehensive information presented in Table 2.

For the NDS studies, video cameras were placed in participants' vehicles for seven consecutive days. In the call for participation, it was stipulated that participants should have access to a Peugeot in order to join the study. Therefore, all the participants drove the same vehicle model, which subsequently enabled us to control for the influence of vehicle features on driving behavior. A camera (CARPA-120 Dual Dashcam) mounted on the participant's vehicle recorded the inside and outside aspects of the vehicle (Fig. 1). The playback resolution was 640 × 480 DVD quality, and the camera also recorded interior audio. The naturalistic data was collected between June 2019 and March 2020. In addition to video data collected from the vehicle-mounted camera, GPS map data (i.e., a pinpoint of the participant's exact location) and vehicle's acceleration rates (in G's) were also obtained from the camera. Three expert analysts from the Traffic Research Laboratory of the Babol Noshirvani University of Technology manually coded and inspected all videos with events. Analysts received instructions on the first day of training. Each analyst was assigned six events to annotate, and then a discussion was held to ensure that all variables were understood. A random sample of ten events was processed by each analyst in order to initially evaluate the consistency of analysts' video annotations. Overall, it took four weeks to complete the annotation process. The behavior of drivers and pedestrians in UA, SUA, MCA, and UMCA was then examined by viewing, coding, and analyzing video recordings. The annotation toolbox was developed using Microsoft Visual Studio 2019. By using the toolbox, the analysts loaded the selected trips, paused, played, and annotated the videos at their desired speeds (Table 3).

To assess the agreement between annotators, we employed two statistical measures, namely Cohen's Kappa and the intra-class correlation coefficient (ICC). Cohen's Kappa is a statistical measure used to assess the level of agreement between two or more raters when they are evaluating or categorizing items on a nominal or ordinal scale, taking into account the agreement that could occur by chance and provides a measure of agreement beyond chance alone (McHugh, 2012). It is calculated by comparing the observed agreement between raters to the expected agreement based on chance. A value between 0 and 1 represents varying levels of agreement beyond chance, with higher values indicating stronger agreement. Also, the Intraclass correlation correlation (ICC) is used to assess agreement when there are two or more independent raters and the outcome is measured at a continuous level (Koo and Li, 2016). Raters should be independent, but should also be trained in the operational definition and identification of the construct. The ICC evaluates the proportion of the total variance in the data that can be attributed to the between-group variability (differences among groups) relative to the within-group variability (variations within each group). In other words, it assesses how much of the total variation can be explained by the differences between the groups being compared. The ICC can range from 0 to 1. A value of 0 indicates no agreement or similarity among the observations within the group, while a value of 1 indicates perfect agreement or similarity (Koo and Li, 2016). Based on the estimated values obtained from SPSS, the results indicate a high level of agreement between the annotators. Specifically, Cohen's Kappa yielded a value of 0.829, while the intra-class correlation coefficient was

Table 1
Geometric and traffic characteristics of the studied roads.

Feature	Suburban areas (SUA)	Urban areas (UA)	Marked crosswalk areas (MCA)	Unmarked crosswalk areas (UMCA)
Pedestrian crossing	Uncontrolled	Controlled	Controlled	Uncontrolled
Speed limit	95 km/hr	30 km/hr	40 km/hr	40 km/hr
Total of lanes	3	2	2	3
Lane width	3.75 m	3.75 m	3.75 m	3.75 m
Direction of traffic	Two-way	Two-way	Two-way	Two-way

Table 2
Demographic data of research participants.

Variable		*(N = 41) (%)*
Gender	*Male*	*21 (51.21)*
	Female	*20 (48.79)*
Age Group (years)	*18–25*	*8 (19.51)*
	25–35	*10 (24.39)*
	35–45	*9 (21.95)*
	45–55	*8 (19.51)*
	55–65	*6 (14.64)*
Number of years with a driving license (years)	*<5*	*10 (24.39)*
	5–10	*13 (31.70)*
	10–15	*7 (17.07)*
	15–20	*6 (14.64)*
	> 20	*5 (12.20)*
Daily average kilometers driven (km)	*< 15*	*12 (29.27)*
	15–30	*10 (24.39)*
	'30–45	*12 (29.27)*
	>60	*7 (17.07)*
Number of crash experiences in lifetime	*0*	*8 (19.51)*
	1	*16 (39.02)*
	2	*11 (26.84)*
	3–5	*3 (7.31)*
	5–8	*1 (2.44)*
	>8	*2 (4.88)*

Fig. 1. Driving behavior situations in the present study.

Table 3
Descriptive statistics of driver evasive action.

				Variable	UAs	SUAs	MCAs	UMCAs
	Count	Proportion	Count	Proportion	Count	Proportion	Count	Proportion
Deceleration	368	39.69	60	16.71	274	52.89	154	20.06
Acceleration	108	11.65	107	29.80	19	3.67	196	25.52
Braking	276	29.77	27	7.52	189	36.49	94	12.24
Changing lane	175	18.89	165	45.97	36	6.95	324	42.18

found equal to 0.903. These indicators serve as robust measures in evaluating the level of agreement, reinforcing the conclusion that there exists a strong consensus among the annotators.

Using the video data, an analysis of participant behavior in urban (UA), suburban (SUA), marked crosswalks (MCAs) and unmarked (UMCA) crosswalks was conducted, with the focus of the analysis being on conflicts involving pedestrians. It should be noted that a traffic conflict is defined as "an observable event that will result in a crash unless one of the involved parties slows down, changes lanes, or accelerates in order to avoid collision" (Amundson and Hyden, 1977; Allen and Shin, 1978). As a result of a traffic conflict occurrence, drivers perform evasive maneuvers such as accelerating, decelerating, changing the movement path, or stopping their vehicles in order to avoid colliding. Video recordings of pedestrian crossing and driver behavior were reviewed, coded, and analyzed. The vehicle-mounted camera also recorded GPS map data, including the exact location of the participant as well as the vehicle's speed and acceleration rate. The video recordings showed that 2,443 interactions occurred between vehicles and pedestrians in UAs, out of which 1686 cases required evasive maneuvers from road users. In other words, 69% of all interactions were identified as conflicts. In SUAs, 2579 interactions were recorded, out of which conflicts were observed in 48% (1236) of cases. Therefore, the likelihood of an interaction to result in a conflict was 1.43 times higher ($\frac{69\%}{48\%}$) in UAs than in SUAs. The conflict data were then used for further statistical analysis. A total of 70% of the dataset (2046 samples) was used to estimate the models, and the rest 30% of the dataset (876 samples) was used for validation of the models.

3.4. Methods

Various surrogate safety measures (SSMs) are applied to identify traffic conflicts and evaluate their severity levels through naturalistic driving data. Specifically, the data are analyzed using: a) An evasive action-based traffic conflict technique and b) A spatial and temporal proximity-based traffic conflict technique.

For the identification of traffic conflicts, we used the Swedish Traffic Conflict Technique (Swedish TCT) (Hyden, 1987). The latter technique uses continuous indices to monitor the evasive actions of road users before a possible collision, and in particular, the Time to crash (TA) and conflict speed (CS) indicators. The temporal proximity-based technique assesses collision probability and severity, irrespective of the evasive reactions of the users, through time-based indicators, such as Time to collision (TTC) and Gap Time (GT). In the context of the spatial proximity-based technique, the Proportion of Stopping Distance (PSD) and Deceleration of Safety Time (DST) are used to analyze the spatial distance and acceleration of the vehicle. For all considered approaches, conflict indicators and the severity of conflicts are estimated. Furthermore, critical thresholds are determined for each level of severity. Based on these critical thresholds, pedestrian crossing risks and evasive driving actions are identified.

3.4.1. Evasive action-based traffic conflict technique

The evasive action-based traffic conflict refers to an event in which one user causes another user to make an evasive action to avoid a collision (Parker and Zegeer, 1989). Under this definition, conflicts and crashes share a similar nature, except that evasive action is successfully implemented in conflicts. The Swedish Traffic Conflict Technique (Swedish TCT) is a traffic conflict technique based on evasive actions, which applies time and space criteria between the approaching road users for estimating crash risks. In this method, two indicators, namely the conflicting speed and the time to crash, are used to detect conflict severity.

- Conflicting Speed (CS): Speed of the user when an evasive action is taken.
- Time to Crash (TA): The time that remains from when the evasive action is taken until when the collision would have occurred, if the road users had continued their movement without changing their speeds and directions. The TA value can be calculated based on distances (d) and speed (v) estimates, as shown by the following Equation:

$$TA = \left(\frac{d_i}{v_i}\right) \quad (1)$$

Where, d_i is the distance of the road user to the possible point of collision, and v_i is the road user speed.

3.4.2. Temporal and spatial proximity-based traffic conflict technique

The likelihood of a collision increases when vehicles are closer, either in space or time. According to Amundson and Hyden (1977), proximity-based traffic conflicts occur when one or more vehicles are in imminent danger of colliding if their movements remain unchanged (Amundson and Hyden, 1977). This definition has the advantage that collisions always precede conflicts. Additionally, this method can be quantified, making it more objective. As such, an interpretable quantitative measure of collision closeness can be derived, which is relatively objective. In addition, proximity can also be defined in terms of space or time. In this context, the following surrogate measures are estimated:

- Time to Collision (TTC), is defined as the time until two road users collide if they continue at their present speed and along the same paths (Hayward, 1971). Specifically, the TTC is quantified as:

$$\text{If a pedestrian passes first, } TTC(i) = max\left(\frac{d_p(i) + w}{v_p(i)}, \frac{d_c(i)}{v_c(i)}\right) \quad (2)$$

$$\text{If a vehicle passes first, } TTC(i) = max\left(\frac{d_p(i)}{v_p(i)}, \frac{d_c(i)}{v_c(i)}\right. \quad (3)$$

$$\mathrm{TTCmin} = \min(\mathrm{TTC}(\mathrm{i}))$$

where, $\mathrm{d_p}$ is the distance of the pedestrian to the possible point of collision, $\mathrm{d_c}$ is the distance of the vehicle to the possible point of collision, $\mathrm{v_p}$ denotes the pedestrian speed, $\mathrm{v_c}$ represents the vehicle speed, l is the vehicle length, and w represents the vehicle width.

- Gap Time (GT), i.e., the time difference between the moment when the second user arrives at the conflict point after the first user leaves it when both continue at the same speed and along the same paths (Vogel, 2002), is also recognized as a predicted post encroachment time (PET). PET represents the time difference between a road user leaving the area of encroachment and a conflicting other road user entering the same area (Sheykhfard et al., 2022)

$$GT(i) = \left|\frac{d_p(i) + w}{v_p(i)} - \frac{d_c(i)}{v_c(i)}\right| \tag{4}$$

$$GT(i) = \left|\frac{d_p(i)}{v_p(i)} - \frac{d_c(i) + l}{v_c(i)}\right| \tag{5}$$

$$\mathrm{GTmin} = \min(\mathrm{GT(i)})$$

where all notations are as previously defined.

- Deceleration-to-Safety Time (DST) is defined as the necessary deceleration to reach a non-negative PET value if the movements of the conflicting road users remain unchanged. DST was selected since it captures greater details of the traffic event (Hupfer, 1997).

$$DST = \frac{2(S_{jk} - V_{ij}t_{ijk})}{t_{ijk}{}^{*}t_{ijk}} \tag{6}$$

where, S_{jk} is the distance between point j and k, V_{ij} is the second road user's speed at point j, and t_{ijk} denotes the travel time of the second road user from point j to k.

- The proportion of Stopping Distance (PSD) is the ratio of the distance available for an action to that of the necessary braking distance to a projected collision point (Allen and Shin, 1978).

$$PSD = \frac{RD}{MSD}, MSD = \frac{V^*V}{2MADR} \tag{7}$$

Where, RD is the remaining distance to the point of collision, MSD is the minimum acceptable stopping distance, v is the vehicle speed, and MAD denotes the maximum acceptable deceleration rate (3.4 m/s^2).

3.4.3. K-means clustering

K-means clustering is a popular unsupervised machine learning algorithm used to partition a given dataset into distinct groups or clusters. It aims to minimize the intra-cluster variance, which means that the data points within each cluster should be as similar to each other as possible. The algorithm works by iteratively assigning data points to the nearest cluster centroid and then updating the centroids based on the newly formed clusters. This process continues until the centroids stabilize or a predefined number of iterations is reached (Anderson, 2009; Pan et al., 2021). K-means clustering is chosen for its simplicity, efficiency, and effectiveness in a wide range of applications. It is particularly appropriate when the number of clusters is known or can be estimated, and when the dataset has a clear separation between clusters. Furthermore, k-means scales well with large datasets and can handle both numerical and categorical data, making it a versatile choice for clustering tasks.

4. Result and discussion

4.1. Descriptive statistics

The analysis of the video recordings revealed 2046 conflicts between vehicles and pedestrians, 1248 of which occurred in UAs and 798 in SUAs. The conflict rate was 60.9% in UAs and 39.1% in SUAs. The yielding behavior was associated with 927 conflicts (74%) among 1248 observed in UAs. Study results showed that 44% of drivers in SUAs were willing to yield to pedestrians (359 out of 798). Over 589 conflicts were identified in the MCAs, with 88% (518 cases) involving driver-yielding behavior. There were only 36% of conflicts in UMCAs with driver-yielding behavior (524 cases).

Upon the observation of the recordings, it became evident that drivers took an evasive action after deciding to yield to pedestrians crossing the street. The frequency and percentage of pedestrian evasive actions by drivers are shown in Table 1, showing four different evasive actions. In UAs, drivers who take evasive actions tend to slow down (decelerate) and brake to stop their vehicles. Around 40% of conflicts involved drivers decelerating, while 30% involved braking. 19% of yielding behaviors in UAs were observed with drivers changing the direction of vehicle movement. In SUAs, 30 percent of conflict situations involved drivers increasing their speed or changing lanes to yield to pedestrians. 17% and 8% of conflicts in SUAs involved evasive actions such as speed reduction and braking. Across all MCAs, 53% and 37% of drivers responded by slowing down or stopping when they saw pedestrians. A total of 4% and 7% yielding behaviors in MCAs included drivers speeding up and changing lanes. The results indicate that drivers in UMCAs are more likely to speed up and change lanes than in MCAs. Two-thirds of evasive actions in UMCAs involved speeding up or changing lanes. Furthermore, only 21% and 13% of evasive behaviors, such as slowing down and braking, were observed across UMCAs.

4.2. Swedish TCT (evasive action-based technique)

4.2.1. Conflict severity

Conflicts were identified and evaluated using time to crash (TA) and conflicting speed (CS) in SUAs and UAs, as well as MCAs and UMCAs. Fig. 2 illustrates scatter plots of conflicting speed and time to crash for conflicts identified through the Swedish TCT. Conflicts appear at different levels on the plot, which consists of 30 levels. These points indicate conflicts where at least one of the two road users (driver or pedestrian) has taken an evasive action to prevent a collision.

Table 4 provides the number and percentage of conflicts at each level and for each area type, and Fig. 3 graphically illustrates the conflict through scatter plots. The analysis of the evasive action indicators revealed four different categories of conflict severity:

- **Serious level**: evasive action was taken by both road users to avoid the collision. In this level, the driver reacted through performing a harsh action (e.g., changing lanes, braking), and the pedestrians reacted to the possibility of collision with the vehicle by undertaking a hard action (aggressive crossing behavior in the form of running or zigzag movement).
- **Slight level**: an evasive action was performed by both users. However, a harsh action was observed only by one of the two users. Slowing down and increasing speed was among the soft action of drivers and crossing the road through walking by pedestrians.
- **Potential level**: any harsh evasive action by users was not observed. At this level, one of the two road users performed at least one soft evasive action.
- **Normal level**: At most, one user performed a soft evasive action to avoid a collision.

In general, it can be concluded that the conflicts pattern in the SUAs are similar to the conflicts pattern in the UMCAs. Additionally, MCAs and UAs have also similar conflict patterns. Moreover, it is evident from the results of the data analysis that the probability of conflicts of the same severity differs between MCAs and UAs, as well as between UMCAs and SUAs. A total of 53% of conflict resolutions in the UAs required both road users to take evasive actions, at least one of which was harsh. This issue applies only to 38% of the conflicts in MCAs. It appears that road users on MCAs behave more conservatively than road users on UAs. Analyses of data showed that there is no similar pattern in evasive action between MCAs and UMCAs. Furthermore, about 50% of all conflicts involved serious and slight levels of road users reacting in UMCAs. About 15% of conflicts detected in MCAs were classified as serious (levels 26 to 30 in the graph of the Swedish TCT). Additionally, 23% of the identified conflicts with slight severity were placed between levels 20 and 26.

Approximately 19% of the total conflicts in MCAs were detected between levels 10 and 20. A total of 43% of conflicts in MCAs fell into the group of normal conflicts, ranked in the levels ranging from 0 to 10 on the Swedish TCT graph. Overall, the comparison between MCAs and

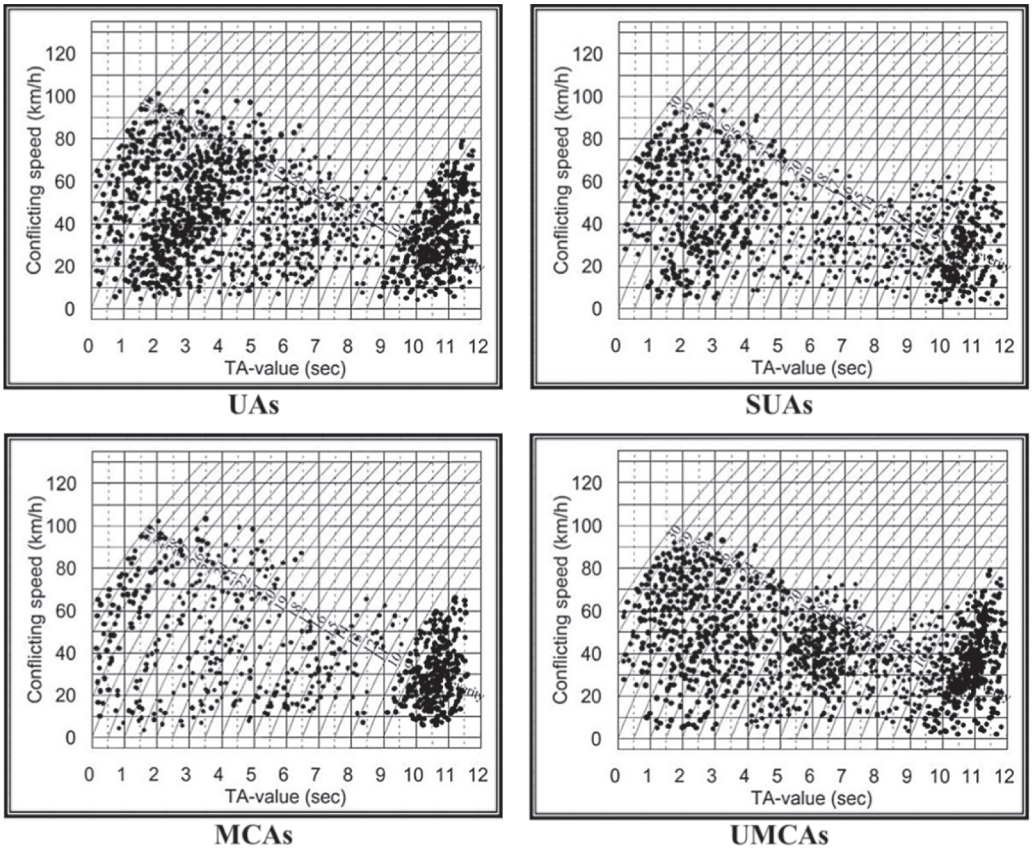

Fig. 2. Swedish TCT graph of conflicts in different areas.

Table 4
Conflict severity level in different areas.

Risk level of conflict	Count				Proportion				Level on the graph			
	UAs	SUAs	UMCAs	MCAs	UAs	SUAs	UMCAs	MCAs	UAs	SUAs	UMCAs	MCAs
Serious	251	191	407	88	20	24	28	15	26–30	20–30	20–30	26–30
Slight	411	194	320	135	33	24	22	23	20–26	14–20	14–20	20–26
Potential	262	115	145	111	21	15	10	19	10–20	9–14	9–14	10–20
Normal	324	298	585	255	26	37	40	43	0–10	0–9	0–9	0–10

UMCAs showed that conflicts with high-risk levels are more likely to occur in UMCAs. As such, both involved users must perform evasive actions in these areas to avoid collisions. In terms of severity, 28%, 22%, 10%, and 40% of conflicts detected in the UMCAs were classified as of serious, slight, potential, and normal severity, respectively.

4.2.2. Critical thresholds

K-means clustering was implemented in MATLAB software to evaluate the conflicts identified in different study areas. Different clustering patterns were demonstrated for the distance to accident (DA) variable based on TA and CSs. A total of three clusters ($k = 3$) were found to be the optimal cluster structure on the basis of the silhouette criterion (Subbalakshmi et al., 2015). The cohesion and resolution of clusters play a role in determining this criterion. For each observation of the sample, the degree of proximity to the neighboring cluster is estimated based on its silhouette value. The silhoutette value is placed in the range of (-1,1). A value close to + 1 indicates a distance between the sample and neighboring clusters. A value of 0 indicates that the observation is on the boundary of two neighboring clusters or very close to it, while a negative value indicates that the observation may be assigned to the wrong cluster. An overall silhouette with a lower value indicates weak clustering, and an overall silhouette with a higher value suggests robust clustering. Generally, a high-quality clustering structure has silhouette value between 0.71 and 1. A value within the range of 0.51 and 0.70 indicates a reasonable structure, a value within 0.26 and 0.50) shows a weak structure, and a value less than 0.25 suggests no structure (Subbalakshmi et al., 2015). In the present study, the silhouette values of the cluster analysis were within 0.59 and 1, thus indicating a satisfactory fit of the selected clusters.

Table 5 shows the critical thresholds for these three clusters along with the results of an Analysis of Variance (ANOVA) that was conducted on the basis of the clustering variable (i.e., the DA). There are statistically significant differences between the DA values across the three clusters (the p-value is less than 0.05) at a 95% confidence level, so this clustering pattern is deemed appropriate for the data.

Table 5 shows that the critical DAs for each cluster differ across the study areas. Conflicts are divided into three clusters based on the type of performance of drivers in each category. According to the clustering of conflicts, the pattern of DAs may share similarities across all areas, but the possible hard and soft evasive actions by drivers differ at the same distance. As shown in the first cluster, there are several high-risk conflicts in which drivers take a hard evasive action, as they may feel unsure whether a collision is about to occur. More than 80% of drivers' hard actions, including lane changes and braking, fall into the first cluster.

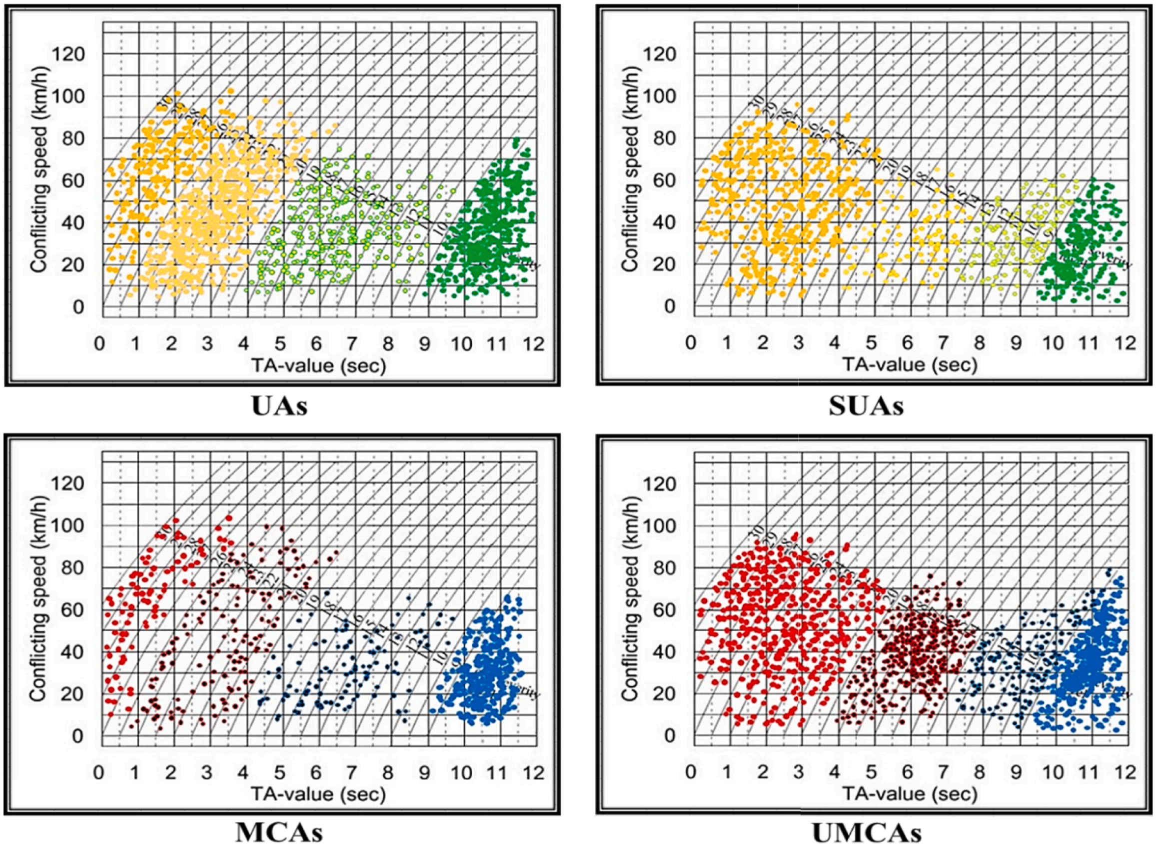

Fig. 3. Distribution of vehicle–pedestrian conflicts in different areas.

Table 5
Results of the clustering analysis based on DA.

Cluster	Distance to crash (DA), meter SUAs Frequency	Index	UAs Frequency	Index	MCAs Frequency	Index	UMCAs Frequency	Index
1	254	DA ⩽34.55	334	DA ⩽26.22	109	DA ⩽30.05	515	DA ⩽37.74
2	201	34.55<DA ≤ 59.68	498	26.22<DA ≤ 47.15	154	30.05<DA ≤ 51.42	279	37.74<DA ≤ 57.36
3	343	DA > 59.68	416	DA > 47.15	326	DA > 51.42	663	DA > 57.36
Mean square	0.064		0.072		0.315		0.106	
F-test	94.216		78.512		111.154		102.498	
P-value	0.021		0.031		0.005		0.009	

More than half of the conflicts in this category involve the possibility of a harsh action. The second cluster is more likely to involve hard actions rather than soft ones, even though the process of making decisions is different for hard and soft ones. The second cluster revealed that, in such cases, drivers tended to make harsh and soft evasive actions. However, the probability of making harsh actions was 1.5 times higher than the probability of making soft ones. At the third cluster, there are conflict, however the likelihood of a crash is lower than in the first and second clusters, so the decision of drivers to take a soft action can reduce collisions with pedestrians. More than 75% of the conflicts in the third cluster relate to soft evasive actions taken by the drivers, such as reducing or increasing their speed to yield to pedestrians.

4.3. *Temporal proximity-based technique*

Conflicts are evaluated using TTC and GT in this section. To identify the risk potential of conflicts before drivers take any evasive actions, all conflicts must be considered regardless of whether the driver performs an evasive action.

4.3.1. *Critical thresholds of temporal indicators*

Conflicts were clustered based on two temporal indicators using K-means clustering in MATLAB software. Three classes were found to provide the optimal clustering structure based on the Silhouette criterion and the results of the Analysis of Variance (ANOVA). Silhouette criteria varied between 0.69 and 0.83, which indicates that the clustering structure is generally of high quality (Subbalakshmi et al., 2015). Table 6 presents the thresholds of each cluster according to the values of

Table 6
Results of clustering analysis based on temporal indicators.

Cluster		Temporal indicators SUAs	UAs	MCAs	UMCAs
1		$GT \leqslant 0.74$	$GT \leqslant 1.19$	$GT \leqslant 1.28$	$GT \leqslant 0.67$
		$TTC \leqslant 1.08$	$TTC \leqslant 1.28$	$TTC \leqslant 1.54$	$TTC \leqslant 1.34$
2		$0.74 < GT \leq 2.35$	$1.19 < GT \leq 2.94$	$1.28 < GT \leq 3.12$	$0.67 < GT \leq 2.42$
		$1.08 < TTC \leq 3.26$	$1.28 < TTC \leq 2.97$	$1.54 < TTC \leq 3.84$	$1.34 < TTC \leq 3.57$
3		$GT > 2.35$	$GT > 2.94$	$GT > 3.12$	$GT > 2.42$
		$TTC > 3.26$	$TTC > 2.97$	$TTC > 3.84$	$TTC > 3.57$
Mean square	GT	0.068	0.014	0.078	0.096
	TTC	0.120	0.215	0.167	0.362
F-test	GT	86.26	96.62	93.32	94.55
	TTC	89.41	102.24	90.06	76.16
P-value	GT	0.005	0.011	0.014	0.023
	TTC	0.016	0.032	0.004	0.003

two temporal indicators. Three different severity levels of conflict are defined by the three clusters: high risk, medium risk, and low risk. It has been shown that drivers do not take evasive action towards pedestrians in some cases with a high TTC value. Considering the vehicle's current speed and trajectory, drivers would believe that pedestrians could cross over the collision point before the vehicle reaches it. There is a higher critical threshold of TTC in the UAs and MCAs than in the UMCAs and SUAs in each cluster. The GT threshold values show that SUAs and UMCAs have higher values than other areas, and this trend differs between the two areas. Drivers may be more likely to yield in these areas than in other areas (e.g., UAs). Therefore, drivers on UMCAs and SUAs are forced to perform evasive actions due to the higher likelihood of collision than MCAs and UAs. Table 6 shows the results of the ANOVA analysis for the clusters defined based on the temporal indicators. At a 95% confidence level, the differences of the temporal indicators are statistically significant, according to the p-values. Furthermore, the F-test values indicate the proportionality of the temporal indices across the clusters. The next section analyzes the pedestrian crossing risk probability based on critical thresholds for two temporal indicators.

4.3.2. *Pedestrian crossing risk based on critical thresholds*

In this section, the pedestrian crossing risk is evaluated for each cluster within different areas. Based on the evasive actions taken by drivers and pedestrians, three crossing patterns with different risk levels were identified:

- **Low-risk crossing**: Pedestrians cross the possible collision point while walking, so the driver is not required to take an evasive action.
- **Medium-risk crossing**: Pedestrian collisions must be avoided by the driver. The pedestrian does not change their walking position. As a result of this evasive action, a pedestrian passes through a possible collision point while walking before a vehicle reaches it.
- **High-risk crossing**: A pedestrian must change their walking mode to avoid colliding with an approaching vehicle, even if the driver takes

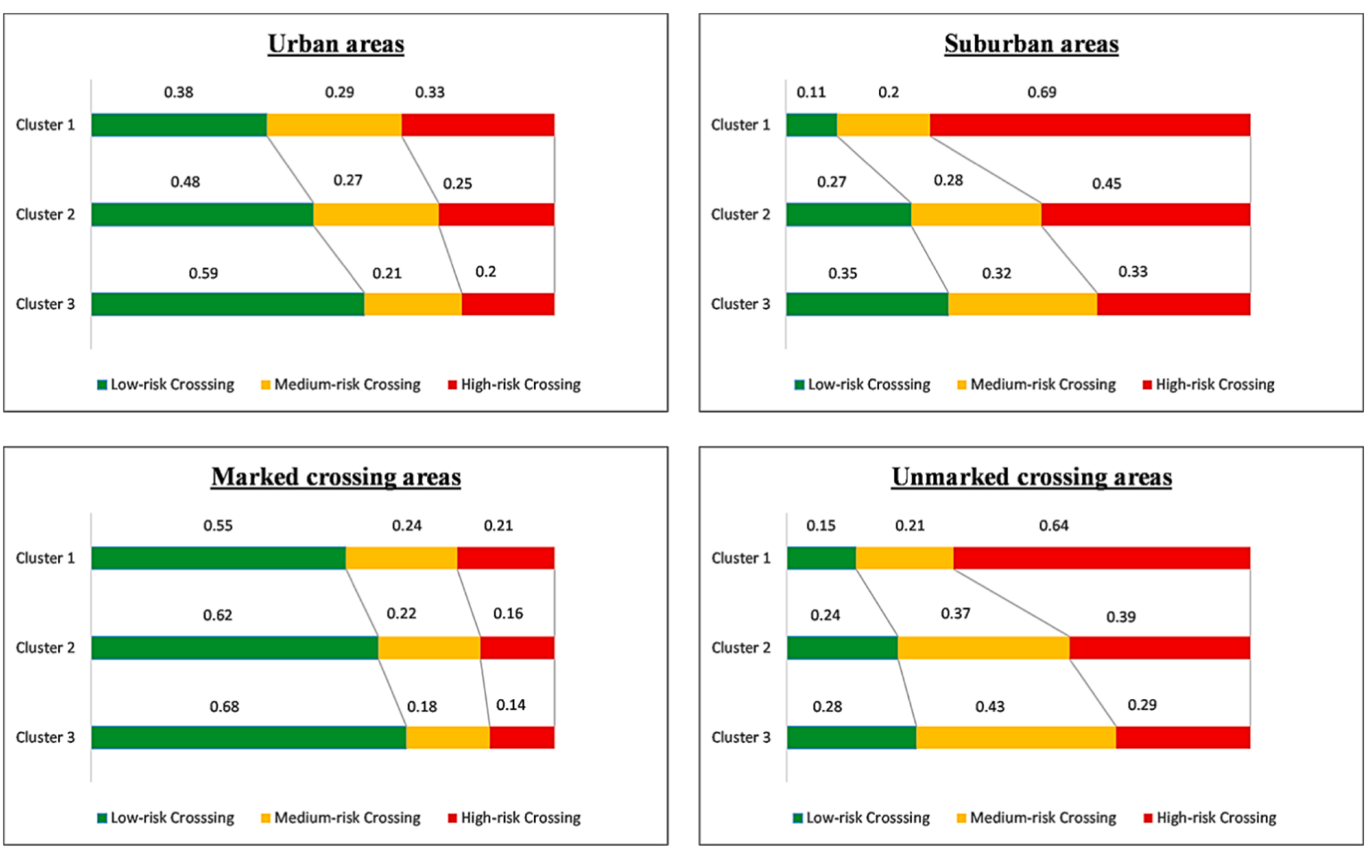

Fig. 4. The risk level of pedestrian crossing in different clusters based on temporal indicators.

an evasive action. Running and zigzag crossing were the most evident pedestrian crossing styles in this situation.

Fig. 4 shows the pedestrian crossing risk, as derived from the critical thresholds of the three clusters. Overall, the Figure shows a similar pattern of pedestrian crossing risk in UAs and MCAs. There is a slight difference in the behavior of drivers and pedestrians in these two areas, but the difference is not significant. SUAs and UMCAs also exhibit a similar pattern. High-risk pedestrians crossing was found to occur in each cluster, but with stark differences across the clusters in terms of prevalence. Over 62% of the pedestrian crossing maneuvers in the first cluster of UAs have a medium or high-risk level, while this problem can be observed in about 71% of the crossing in the first cluster in SUAs. Meanwhile, 45% and 65% of the crossings in the first cluster of MCAs and UMCAs have a medium and a high-risk level, respectively. Based on the data analysis, most of the evasive actions of drivers in the first cluster were hard actions. There is a high likelihood of conflict turning into a collision, during which both the driver and pedestrian are forced to take harsh actions. In SUAs and UMCAs, pedestrian low-risk crossing has increased by 24% and 13%, respectively, with increased values for the temporal indicators. Over 60% of all conflicts in these areas occur during high-risk crossing maneuvers. High-risk crossings in these two areas have been reduced by 36% and 35%, resulting from the critical thresholds of time indicators in the third cluster. Based on the data analysis, it was observed that in high-risk situations, evasive actions were taken by drivers only when the probability of collision was high. In pedestrian crossing of medium risk, the likelihood of soft evasive action was reported to be higher (more than twice) than the probability of harsh evasive action.

4.4. Spatial proximity-based technique

4.4.1. Critical threshold of spatial indicators

The identified conflicts were clustered through two measures, PSD and DST, using the mean chi-square method. Finally, the analysis of different clusters by the Silhouette criterion as well as the results of the Analysis of Variance (ANOVA) suggested a three-cluster structure as optimal. The overall Silhouette criterion of the clusters varied between 0.71 and 0.83, which indicates that the selection of three classes provides a high-quality structure. Table 7 presents the thresholds of each cluster concerning the values of the two measures. Additionally, Table 7 shows the key statistics of the analysis of variance showing statistically significant results at a 95% level of confidence. Also, the F-test provides the relative weight of the measure to conclude whether the measure is significantly proportional to its clusters. F values for both measures at a significance level of 95% are statistically significant, and then appropriate clusters are assigned to both measures. According to the average maximum deceleration rates (3.4 m/s^2) recommended by the American Association of State Highway and Transportation Officials (A Policy on Geometric Design of Highways and Streets, 2011 - American Association of State Highway and Transportation Officials - Google Books, n.d.), DST provides the basis for braking behavior during conflict. PSD is the ratio between the route and the remaining distance between the driver and the collision point.

Table 7
Critical thresholds of spatial indicators.

Cluster		Temporal indicators			
		SUAs	UAs	MCAs	UMCAs
1		PSD ⩽0.49 DST > 3.41	PSD ⩽0.63 DST > 2.51	PSD ⩽0.68 DST > 1.92	PSD ⩽0.44 DST > 3.86
2		0.49 < PSD ≤ 2.35 1.48 < DST ≤ 3.26	0.63 < PSD ≤ 0.97 1.12 < DST ≤ 2.51	0.68 < PSD ≤ 1.01 0.95 < DST ≤ 1.92	0.44 < PSD ≤ 0.81 1.94 < DST ≤ 3.86
3		PSD > 0.86 DST ⩽1.48	PSD > 0.97 DST ⩽1.12	PSD > 1.01 DST ⩽0.95	PSD > 0.81 DST ⩽1.94
Mean square	PSD	1.025	0.086	0.869	0.628
	DST	0.039	0.429	0.064	0.325
F-test	PSD	67.642	89.215	94.448	82.416
	DST	72.452	60.768	79.285	59.493
P-value	PSD	0.022	0.018	0.000	0.005
	DST	0.025	0.038	0.032	0.002

The results of the clustering analysis show different patterns among clusters in similar areas. Table 7 shows that the PSD in SUAs and UMCAs is less than 0.5, showing that drivers have less than 50% of the stopping distance required to reduce the speed to 3.4 m/s^2 (braking behavior). In the first cluster, driver actions, such as lane changes, and reciprocal evasive actions by pedestrians have prevented collisions. It was found that in the second cluster, the braking behavior of drivers did not enable them to stop completely before they reached a possible collision point with pedestrians. However, the existing vehicle–pedestrian distance caused a more significant reduction in the vehicle speed than in the first cluster.

A significant share of the drivers' evasive actions in the second cluster was accomplished through lane changes. There are more drivers in the third cluster taking soft evasive actions than harsh evasive actions, as the available distance allows them to reduce their speed before a possible collision. Also, PSD thresholds in MCAs and UAs are higher than in UMCAs and SUAs. Still, there are conflicts in both areas' first and second clusters, where drivers do not have enough time to stop before colliding. The lane changing behavior and the possibility of pedestrians taking evasive action is less prevalent in the second cluster of UMCAs and SUAs. The PSD available for UAs and MCAs in the third cluster significantly improves the driver's ability to stop the vehicle entirely before hitting a pedestrian. As a result of this issue, the drivers decelerated more (released the gas pedal), so, in some cases, braking behavior was not observed. In such a context, the pedestrian had the opportunity to cross before the vehicle reached the possible point of collision. PSD thresholds in UAs and MCAs are higher than those in other areas. As a result of choosing lower speeds in these areas, the PSD threshold was found to be higher compared to other areas.

The DST value indicates that the driver must decelerate to allow pedestrians to cross before the vehicle reaches a possible collision area. According to Table 6, in SUAs and UAs, drivers should brake to ensure the safety of pedestrian crossings (low-risk crossing, first cluster). In UAs and MCAs, the conflict analysis of the first cluster indicates that there is no urgent need for braking. In UAs and MCAs, the speed reduction required for this indicator is lower than in SUAs and UMCAs. Lower driving speed is one of the most important reasons for this result. In the third defined cluster, the required speed reduction in the MCAs and UAs is less than 1.5 m/s^2, which indicates a low-risk conflict in the area. While UMCAs and SUAs have higher critical thresholds than other areas, their minimum threshold (less than 2 m/s) indicates conflicts of medium risk.

4.4.2. Evasive actions by drivers and pedestrians in different clusters

As shown in Fig. 5, evasive behavior among drivers and pedestrians depends on the critical thresholds of PSD and DST in different areas. In the UAs, the results of the data analysis show that more than 77% of the evasive actions taken by drivers in the first cluster were harsh, with a probability of changing lanes being 1.5 times greater than the likelihood of braking. Understanding that the distance available is insufficient, drivers in this area are more likely to change lanes. Meanwhile, pedestrians were forced to perform harsh evasive actions in 74% of these conflicts. The most common evasive behaviors were running, and zigzag crossings; running behaviors were estimated to be three times more likely than other crossing styles. The braking behaviors were chosen by drivers more than twice as frequently as lane-changing behaviors in the second cluster of UAs. Drivers chose the hard actions for avoiding collisions in this area. Meanwhile, pedestrians were less likely to engage in risky crossing behaviors than in the first cluster, but they were still involved in more than half of the conflicts. A higher threshold of the

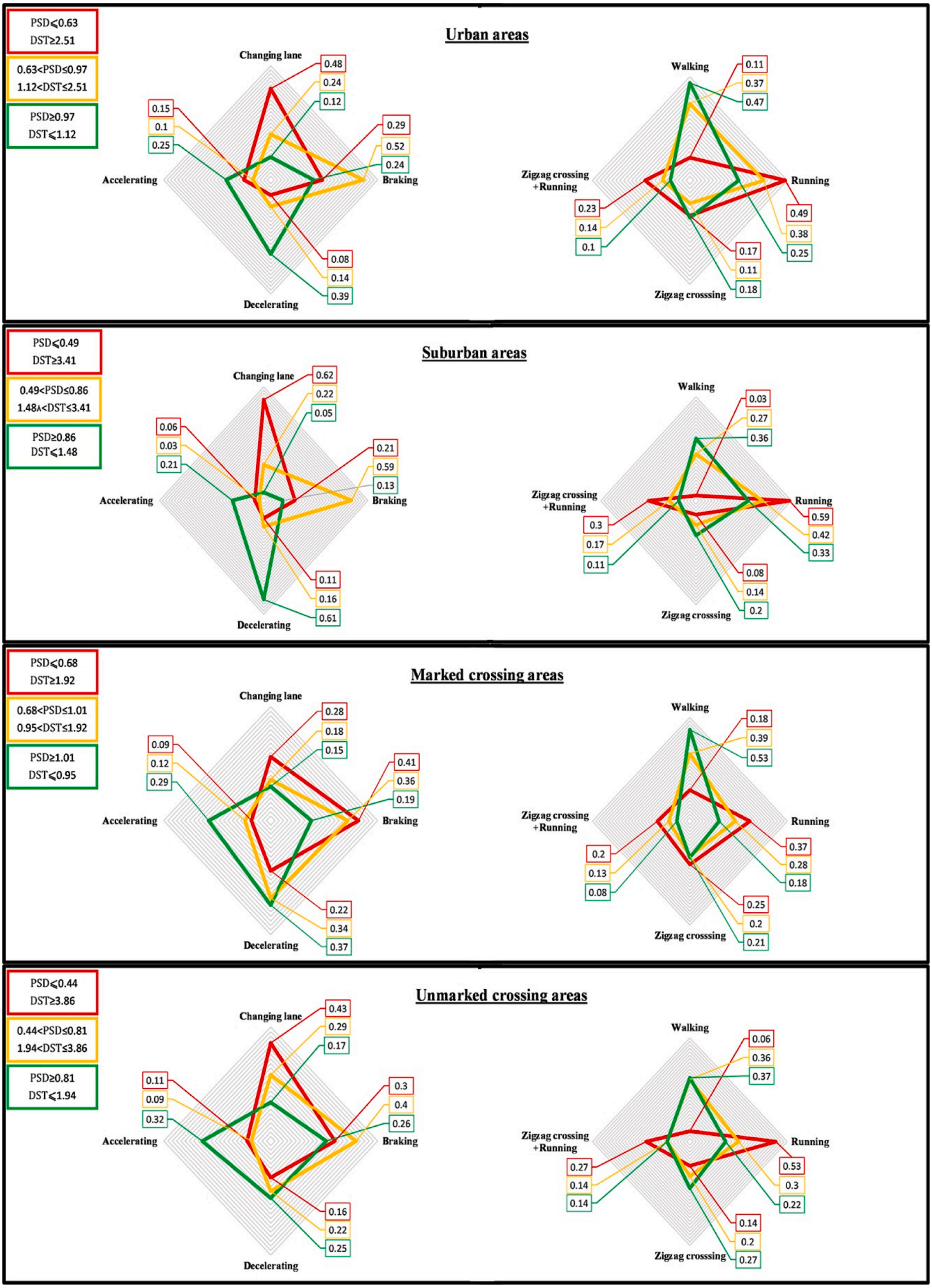

Fig. 5. Evasive actions by drivers and pedestrians in different clusters based on spatial indicators.

spatial indicators of the third cluster allowed drivers to perform evasive actions when encountering pedestrians. In more than half of the conflicts, the behavior of reducing speed was observed. Half of the pedestrians could cross the road using their normal walking behavior. SUAs and UAs exhibit similar patterns of reciprocal evasive behavior between pedestrians and drivers, although their probabilities are not the same. Accordingly, drivers are generally compelled to make a harsh evasive action at high-risk crossings in the first and second clusters. At lower PSD thresholds, lane-changing behavior was more likely to occur than braking behavior. Additionally, drivers are more likely to change lanes instead of braking when the required amount of DSD increases. Furthermore, pedestrians in this situation are forced to take risky evasive actions to avoid collisions. The probability of pedestrians crossing at low risk increases with an increase in the PSD threshold and a decrease in DST (third cluster). In addition, the driver performs soft evasive actions in such circumstances. Fig. 5 depicts the reciprocal evasive behavior of pedestrians and drivers based on PSD and DST thresholds in MCAs. To avoid collisions, drivers prioritize harsh evasive behaviors in the first and second clusters. In addition, MCAs showed a greater tendency to engage in braking behaviors, while UMCAs exhibited a greater tendency to change lanes. Compared to UMCAs, MCAs provided drivers with more opportunities to react to braking. Furthermore, pedestrian behaviors in UMCAs were more risky than in MCAs. Both areas, however, showed a similar pattern of high-risk crossing behavior compared to low-risk crossing behavior. In the third cluster, the soft evasive behavior by drivers increased, and pedestrians under these conditions had a safer margin to cross the road walking.

4.5. Thresholds for driver support system

In the present study, a pseudocode algorithm has been developed in light of the results of the conflict analysis to predict drivers' evasive actions. As a result of the findings of this study, three different levels of severity have been defined according to the critical thresholds of the spatial and temporal indicators. These thresholds provide information about what actions the driver must take to avoid colliding with a pedestrian. Table 8 presents the pseudocode and its coding and structure. Furthermore, the flowchart in Fig. 6 illustrates how the algorithm can be applied. The presented algorithm was validated using a 30% of the sample that was collected in the current study. This portion of the dataset was not used for the model calibration process. Data were analyzed using both temporal and spatial indicators in different study areas. The indicators were calculated separately for each conflict. The presented algorithm determines the evasive actions that should be taken by the driver on the basis of the calculated indicators. Table 8 provides the frequency and proportion of evasive actions that are predicted by the algorithm in this study. Comparing the drivers' real-life evasive behavior with the algorithm-predicted evasive actions can provide insights into the algorithm's prediction accuracy. As can be seen in Table 9, the prediction accuracy of the algorithm is quite satisfactory, as such, it could be potentially used for the identification of an appropriate evasive action to be taken by the driver to avoid a collision with a pedestrian. The process of determining and applying such algorithms can be considered in future automotive industry studies in an effort to tailor the use of the driver assistant devices to the specific driving conditions of each user. For example, the developed algorithm of this study can be used to determine the appropriate evasive response to be taken in situations where the driver is unable to react, as, for example, in cases of

Table 8
Algorithm for estimating drivers' evasive action.

Pseudocode of the algorithm	Thresholds of indicators
`while (detecting_system()==True){` `measure sv;` `measure D;` `Calculate DST;` `Calculate GT;` `if(TTC=<TTC_class1)`	TTC TTC ≤ 1.08 in SUAs TTC ≤ 1.28 in UAs TTC ≤ 1.54 in MCAs TTC ≤ 1.34 in UCMAs
`if(DST>=DST_class1 && DST <1)` `if(GT<GT_class1)` `ChangeLane();` `else` `Brake();`	PSD PSD ≤ 0.49 in SUAs PSD ≤ 0.63 in UAs PSD ≤ 0.68 in MCAs PSD ≤ 0.44 in UCMAs
`if(DST_class2<DST<DST_class1 && PSD<1)` `if(GT<GT_class1)` `Brake();` `else` `Decelerate();`	DST DST ≥ 3.41 in SUAs DST ≥ 2.51 in UAs DST ≥ 1.92 in MCAs DST ≥ 3.86 in UCMAs
`if(GT_class1<GT<GT_class2)` `Decelerate();` `else` `AlertToDriver();`	GT GT ≤ 0.74 in SUAs GT ≤ 1.19 in UAs GT ≤ 1.28 in MCAs GT ≤ 0.67 in UCMAs
`if(DST_class2<DST<DST_class1) && PSD<1)` `if(GT_class1<GT<GT_class2)` `Breaking();` `else` `Decelerate();` `else` `AlertToDriver();` `}`	

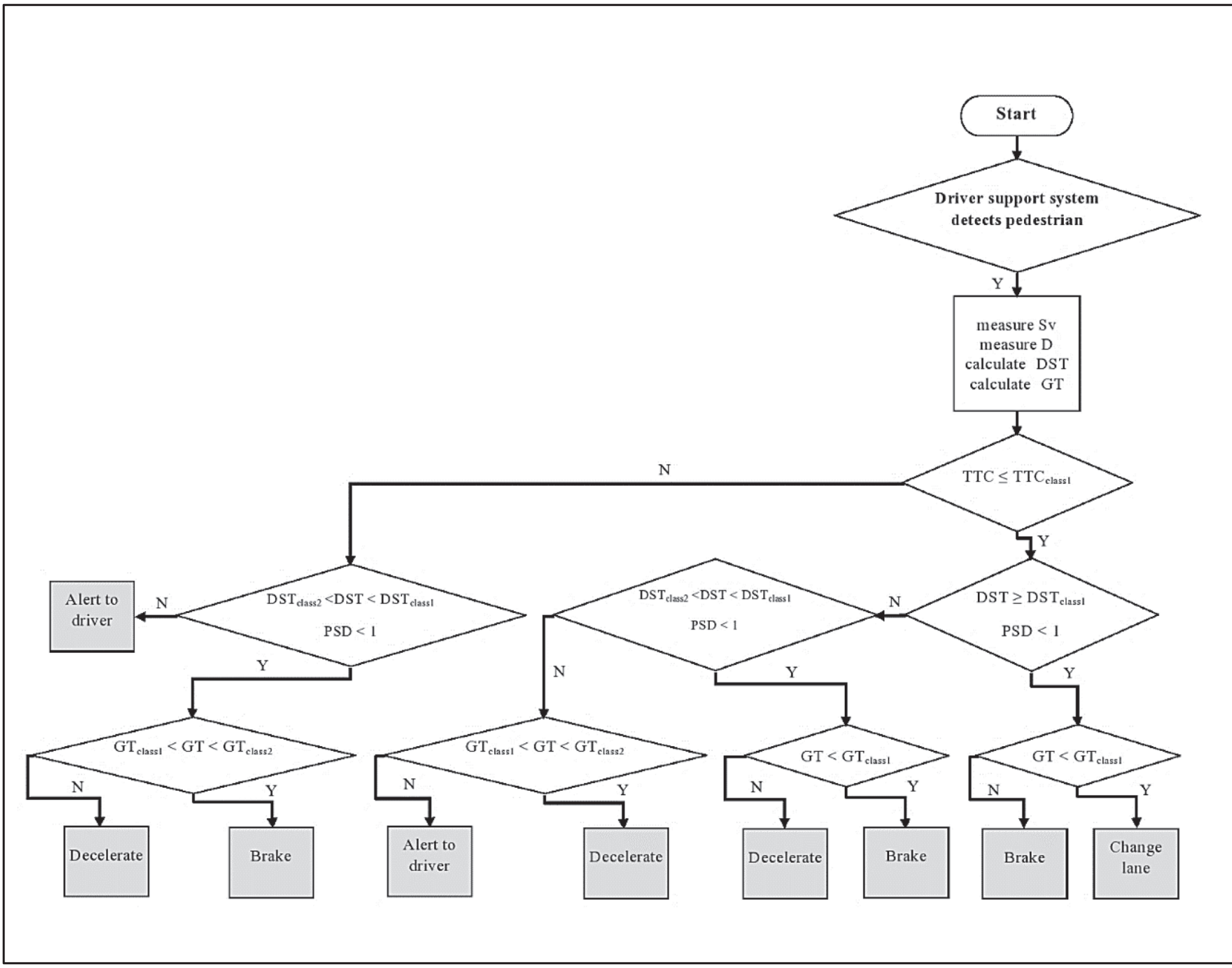

Fig. 6. Purposed flow chart of driver evasive action.

Table 9
Algorithm validation.

Area	Observed	Predicted Braking	Decelerating	Changing lane	Percentage
SUAs	Braking	89	7	2	90.81
	Decelerating	5	26	2	78.78
	Changing lane	12	3	118	88.72
	Total percentage	–	–	–	86.10
UAs	Braking	136	3	14	88.88
	Decelerating	12	205	4	92.76
	Changing lane	8	3	97	89.81
	Total percentage	–	–	–	90.48
MCAs	Braking	107	3	7	91.45
	Decelerating	7	74	1	90.24
	Changing lane	4	2	36	85.71
	Total percentage				89.13
UMCAs	Braking	68	2	7	88.31
	Decelerating	8	70	5	84.33
	Changing lane	21	14	304	89.67
	Total percentage	–	–	–	87.43

driver distraction by external factors.

4.6. *Discussion*

The findings of this study can provide useful insights into the patterns of vehicle–pedestrian conflicts and driver evasive actions across different area types and crossing infrastructure types.

4.6.1. *Driver evasive actions*

Drivers' evasive actions were identified to vary as a function of two factors: vehicle speed and pedestrian distance. Furthermore, UAs showed almost identical patterns of evasive actions with MCAs. Moreover, similar patterns of drivers' actions were observed for both SUAs and UMCAs.

The study results showed that there is a similarity in the relationship between the aforementioned factors (i.e., vehicle speed and pedestrian distance) with the probability of drivers yielding across different areas (i.e., negative correlation with speed, positive correlation with distance). However, drivers in SUAs and UMCAs drive at higher speeds, leading to in shorter distances between the driver and pedestrians, which reduce the available reaction and decision-making time of the driver. Drivers in SUAs and UMCAs were less likely to take an evasive action than drivers in UAs and MCAs.

Behavioral patterns among drivers and pedestrians are quite similar when evasive maneuvers are measured at different levels of severity. In areas with low severity levels of conflict, pedestrians are often the key users in preventing collisions from occurring. A number of drivers in these situations attempted to prevent collisions with pedestrians by leveraging soft maneuvers such as increasing or decreasing the speed of the vehicle, which resulted in safer crossing of pedestrians in several casesbraking to stop. Additionally, drivers in UAs and MCAs are less likely to make a hard maneuver when encountering pedestrians than drivers in SUAs and UMCAs, especially at high levels of conflict severity. In addition to lowering speed, drivers provided sufficient time to pedestrians, so the latter could be identified from a longer distance. As a result, drivers were more able to maintain control over their driving style and avoid systematic harsh maneuvers.

Previous studies have also found relationships between driver behavior and vehicle speed and/or distance to pedestrians that are consistent with the present results. The speed of the vehicle (Chung and Chang, 2015; Mohamed and Bromfield, 2017) and the distance between the vehicle and the pedestrian (Alferova et al., 2017; Ni et al., 2016) have been found to influence driver behavior in previous studies. Furthermore, the findings of this study support some previous research stating that drivers behave similarly in urban areas (Cheng et al., 2018; Jiang et al., 2019; Kumar Abhinav et al., 2019). Even though many underlying factors could play an influential role, the speed limit might be an important factor in affecting driver behavior. However, further research on potential factors related to road design and operational characteristics is needed in order to get more reliable insights.

4.6.2. Conflict patterns based on SSMs

4.6.2.1. Conflict analysis based on the Swedish TCT. According to the conflict speed/time to accident graph, the conflict patterns in SUAs are similar to those observed in UMCAs based on the varying levels of conflict severity. Similar patterns of conflicts were also observed in UAs and MCAs as well. There is consistent evidence to support this finding in several previous studies, despite different factors being identified as key factors.

The present study showed that about 53% of conflicts in UAs require both driver and pedestrian to take evasive action, and at least one of these actions is a hard reaction. Comparatively, conflicts in MCAs require evasive actions from both users in 38% of cases. Moreover, conflict severity levels indicate a more conservative behaviour among road users in MCAs. About 50% of all conflicts in UMCAs were either or slight or serious severity, with both road users being forced to react. Overall, UAs and MCAs exhibited almost identical conflict patterns. Additionally, SUAs and UMCAs had generally similar conflict patterns.

4.6.2.2. Temporal and spatial proximity-based technique. The results showed that drivers' decisions are influenced by the risk of encountering pedestrians. In UAs and MCAs, conflicts were lower than in SUAs and UMCAs, indicating reluctance on the part of drivers to make evasive maneuvers. In these areas, PET critical threshold values indicate that there are conflicts with a low collision risk that do not trigger driver reactions. Additionally, the analysis of the TTC critical threshold for different levels of conflict severity indicates that drivers may not take action if pedestrians pass the point of a collision sooner than anticipated. This usually results in a TTC value of over 3.5 s. As an alternative, GT and PET values differ substantially in various areas, suggesting that SUAs and UMCAs have higher values than other indicators. Overall, an association between the type of drivers' evasive actions and the SSM thresholds was identified in these areas.

The PSD values in SUAs and UMCAs were also less than 0.5, which indicates that the available stopping distance for drivers is less than 50% of what is required to reduce the speed at 3.4 m/s^2 (behavior braking). In this situation, lane changes by the driver and reciprocal behavior by pedestrians have prevented a collision along with the driver's braking. There is a similar pattern of reciprocal avoidance reactions between pedestrians and drivers in SUAs and UAs, however the probability of these behaviors is not the same. Conflicts in the first and second clusters force drivers to make hard evasive maneuvers. Lane changing behavior is more likely to occur at lower PSD time thresholds than braking behavior. Furthermore, as DSD requirements increase, drivers are more likely to choose lane-changing behavior over braking behavior. Pedestrians, however, are forced to perform risky evasive reactions in order to avoid a collision in this situation. By lowering the DST and raising the PSD threshold, pedestrian crossings are more likely. As a result of this issue regarding the evasive behavior of drivers, soft actions are selected by the driver since evasive actions do not have to be harsh.

In the present study, the critical threshold of TTC for serious conflict is less than 1.08 s in SUAs and less than 1.28 s in UAs. MCAs and UCMAs also had critical thresholds below 1.54 s and 1.34 s, respectively. In a previous study focusing on conflicts in intersections in Mumbai, India, Kathuria and Vedagiri (2020) suggested that TTC values smaller than 1.2 s correspond to medium-risk conflicts and values greater than 2.5 s to critical-severity conflicts. A TTC of less than 1.5 s has been found by Haus et al. (2018) to be a hazardous level of conflict in UAs (Haus et al., 2018). In another study (Cheng et al., 2018), 1.5 s was also used to distinguish between serious and non-serious conflicts. Furthermore, Jiang et al. (2019) recommended TTC values greater than 2 s as serious conflicts using data from Germany and China. The present study also revealed the values of GT for serious level of conflict in SUAs, UAs, MCAs, and UCMAs; these values were less than 0.74 s, 1.19 s, 1.28, and 0.67 s, respectively.

The results showed that the critical thresholds of DST for SUAs, UAs, MCAs, and UCMAs are 3.41 s, 2.51 s, 1.92 s, and 3.86 s, respectively. Guido et al. (2011) cite that DST values of 3.92 m/s^2 indicate serious conflicts (Guido et al., 2011) in their research in urban roads. Also, a study by Kumar Abhinav et al. (2019) showed that DST values of 1.24 m/s^2 indicate serious conflict (Kumar Abhinav et al., 2019) in signalized intersections. In our study, the critical thresholds of PSD values in SUAs, UAs, MCAs, and UCMAs were calculated less than 0.49 s, 0.63 s, 0.68 s, and 0.44 s, respectively. According to Wu et al., (2010), PSD values below 0.5 indicate serious conflicts, whereas PSD values between 0.5 and 1 indicate low-risk conflicts. A PSD value of less than one was recommended by Guido et al. (2011) as indicative of a serious conflict. A study by Kuang and Qu (2015) found a value of 0.5 to be an acceptable PSD threshold for serious conflicts, which has also been corroborated by previous other studies (Guido et al., 2011; Wu et al., 2020).

5. Conclusion and further research

This study provides a comprehensive identification and analysis of driver-safe evasive actions considering varying levels of pedestrian crash risk across different area types (i.e., urban and suburban areas) and different types of crossing infrastructure. To that end, real-life driving data were collected and analyzed in UAs, SUAs, MCAs, and UMCAs. Vehicle and pedestrian conflicts were identified through evasive action-based techniques and temporal and spatial proximity-based techniques. Using a clustering approach, three severity levels of conflicts were defined corresponding to varying degrees of pedestrian crossing risk. The thresholds of the different levels of conflict severity for each area were identified, demonstrating the difference in thresholds for each indicator across different areas. Furthermore, the evasive actions diagrams for all areas showed the probability of drivers taking different evasive actions. As a result of the data analysis, it was determined that evasive actions of drivers could be classified into two categories: hard actions (such as, lane changing and braking behaviors) and soft actions (such as, slowing down through releasing the gas pedal, and increasing speed). Drivers in SUAs and UMCAs were found not to have sufficient time to perform soft evasive actions for various reasons, including driving speed, so changing lanes was their key evasive action to avoid pedestrian collisions.

Analyses based on evasive action techniques revealed that conflicts in SUAs are similar to those in UMCAs. MCAs and UAs also have similar conflict patterns. Furthermore, the data analysis shows that the likelihood of conflicts with the same severity varies between SUAs, UMCAs, and UAs and MCAs. It is evident from the assessment of conflict severity levels between MCAs and UAs that road users in MCAs have a more risk-averse behavior. There was no identified similarity between the types of evasive actions that were performed in UMCAs and MCAs. Approximately half of all conflicts included serious and slight levels of conflict; in UMCAs both road users were identified to take an evasive action in most of these cases. The spatial and temporal proximity-based technique shows that in some cases, drivers do not yield to pedestrians because there is little risk of a collision occurrence. Based on vehicle speed and trajectory, drivers believed pedestrians could cross the intersection before the vehicle reached the possible collision point.

Based on the analysis of conflicts with GT, vehicle–pedestrian collisions were more likely to occur in UMCAs and SUAs, thus requiring drivers to take necessary evasive actions to avoid a collision. For SUAs and UMCAs, PSD was consistently found less than 0.5, which means the available stopping distance is less than 50% of the amount needed to reduce the speed at 3.4 m/s2 (braking behavior). Therefore, in this case, behaviors such as lane changing by the driver and reciprocal actions by pedestrians prevented a collision. The pattern of reciprocal evasive actions in SUAs was similar to that in UAs, although the likelihood of occurrence of these behaviors is different. Generally, drivers were found more likely to take a hard evasive action in the first and second clusters of crossing risk. At lower PSD thresholds, lane changing was found more likely than braking. Drivers are more likely to choose changing lanes over braking when the amount of required DSD increases. In this situation, pedestrians must perform risky evasive actions to avoid collisions. As PSD thresholds increase and DSTs decrease, pedestrians were identified more likely to cross at low risk. Drivers' evasive behavior also leads to the selection of soft actions since they are not forced to perform hard evasive actions.

Finally, the unique contribution of this study is to develop and deliver an algorithm for preventing pedestrian crashes based on the critical thresholds of various SSMs. The algorithm was also tested for its prediction accuracy based on real-life collected data. Based on the critical thresholds of SSMs, this algorithm can suggest safe driver evasive actions in different time/space intervals, especially in cases when the driver is distracted and unable to comprehend the imminent risk of a pedestrian crash.

To improve drivers' yielding patterns, it is important to install effective countermeasure on locations prone to vehicle–pedestrian crashes. Rectangular rapid flashing beacon (RRFB) is one of the safety devices that has resulted in significant improvements in improving driver yielding behavior to crossing pedestrians. Some of the other countermeasures are making non-motorists as visible as possible and lowering the posted speed limit (FHWA, 2020). To further safeguard the safety of non-motorists on the roadways, it is anticipated that the results of this study can be used to devise valuable policies and develop more effective in-vehicle warning technologies. In addition, the findings can be used in informing policy development based on the principles of the Safe System Approach (SSA), which can further improve driver attention and reduce non-motorist collisions.

Several limitations need to be noted regarding the present study. First, bicycles and motorcycles were not considered in this research. All road users contribute to the overall safety performance of the road through their interactions. To obtain more comprehensive insights, future studies should explore the simultaneous effects of different road users involved in the conflict. Second, the current research did not establish a driving simulator system. Simulators can be used to probe the algorithm's effectiveness for driver support systems by implementing the study results in an experimental phase considering drivers with disparate behavioral characteristics. Third, we faced some limitations with regard to the sample size that was available for conducting this study, so future research should assess the driving behavior from a larger sample from the study's target population. Several variables, such as age groups and driving experience, can be evaluated more precisely in this context. Furthermore, one notable limitation of our research was the challenge posed by limited visibility and compromised video quality during nighttime driving data collection. As the natural light decreased during evening hours, the in-vehicle camera's ability to capture clear and detailed imagery was hindered, leading to darker and shadowy video recordings. Consequently, this limitation affected the precision and accuracy of identifying critical events, such as pedestrian-driver interactions near crosswalks and traffic conflicts. Additionally, artificial lighting sources and adverse weather conditions further contributed to glare, reflections, and distortion in the recorded footage, making it difficult to analyze driving behaviors with certainty during nighttime. To address the limitation of compromised data collection during nighttime driving, future research endeavors should explore and implement technological advancements in in-vehicle camera systems. Advancements in camera sensor technology and low-light image processing algorithms can significantly enhance video quality during low-light conditions, enabling clearer and more detailed recordings. Additionally, the integration of infrared or night vision capabilities in the camera system could provide improved visibility during nighttime data collection, thereby mitigating challenges related to limited lighting. Conducting systematic comparisons between different camera technologies and configurations would help identify the most suitable and reliable setup for nighttime data collection. Furthermore, future studies may consider conducting data collection across multiple seasons and weather conditions to account for varying lighting and environmental factors. By leveraging emerging technologies and considering diverse data collection scenarios, future research can yield more comprehensive and reliable insights into driving behaviors throughout different times of the day and under varying illumination conditions. Moreover, to enhance future research endeavors, researchers should consider expanding data collection efforts, utilizing weather-resistant cameras, and adopting advanced image processing techniques to enhance video quality. Addressing these limitations will provide valuable insights into pedestrian safety under adverse weather scenarios. Further work can be also devoted to the integration of behavioral and demographic characteristics of drivers and pedestrians with naturalistic data, which will allow the development of even more granular behavioral models and the identification of relationships between key evasive actions and road user profiles.

Despite its limitations, the study certainly adds to the current state of understanding concerning the evasive actions of drivers in potential interactions with pedestrians. The use of real-life driving data provides a satisfactory level of credibility on the study findings and inferences. The proposed analysis framework can be used both for safety studies based on traffic conflicts as well as for a more general quantification and visualization of road user behavior.

6. Author statement

The authors confirm contribution to the paper as follows: study conception and design: Abbas Sheykhfard; acquisition of data: Abbas Sheykhfard; analysis and interpretation of results: Abbas Sheykhfard, Farshidreza Haghighi, Subasish Das, and Grigorios Fountas; draft manuscript preparation: Abbas Sheykhfard, Farshidreza Haghighi, Subasish Das, and Grigorios Fountas. All authors reviewed the results and approved the final version of the manuscript.

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

References

Ābele, L., Haustein, S., Møller, M., 2018. Young drivers' perception of adult and child pedestrians in potential street-crossing situations. Accid. Anal. Prev. 118, 263–268. https://doi.org/10.1016/j.aap.2018.03.027.

Abhinav, K., Madhumita, P., Indrajit, G., 2019. Analysis of Pedestrian Conflict with Right-Turning Vehicles at Signalized Intersections in India. J. Transp. Eng. Part A: Syst. 145 (6), 04019018. https://doi.org/10.1061/JTEPBS.0000239.

Akanbi, O.G., Charles-Owaba, O.E., Oluleye, A.E., 2009. Human factors in traffic accidents in Lagos, Nigeria. Disaster Prev. Manage. Int. J. 18 (4), 397–409. https://doi.org/10.1108/09653560910984456.

Alferova, I., Polyatsko, V., Gorodokin, V., 2017. Method of Hazard Occurrence Moment Definition in the Event of Pedestrian Knockdown Accident (Pedestrian Crossing the Road out of Walkway). Transp. Res.Procedia 20, 14–20. https://doi.org/10.1016/j.trpro.2017.01.004.

Alhajyaseen, W.K.M., Asano, M., Nakamura, H., 2013. Left-turn gap acceptance models considering pedestrian movement characteristics. Accid. Anal. Prev. 50, 175–185. https://doi.org/10.1016/j.aap.2012.04.006.

AlKheder, S., Al-Rukaibi, F., Al-Faresi, A., 2020. Driver behavior at Kuwait roundabouts and its performance evaluation. IATSS Res. 44 (4), 272–284.

Anderson, T.K., 2009. Kernel density estimation and K-means clustering to profile road accident hotspots. Accid. Anal. Prev. 41 (3), 359–364. https://doi.org/10.1016/j.aap.2008.12.014.

Bella, F., & Silvestri, M. (2016). Driver's Braking Behavior Approaching Pedestrian Crossings: A Parametric Duration Model of the Speed Reduction Times. https://doi.org/10.1002/atr.1366.

Bella, F., Nobili, F., 2020. Driver-pedestrian interaction under legal and illegal pedestrian crossings. Transp. Res. Procedia 45, 451–458. https://doi.org/10.1016/j.trpro.2020.03.038.

Bella, F., Silvestri, M., 2015. Effects of safety measures on driver's speed behavior at pedestrian crossings. Accid. Anal. Prev. 83, 111–124. https://doi.org/10.1016/j.aap.2015.07.016.

Campos Ferreira, M., Dias Costa, P., Abrantes, D., Hora, J., Felício, S., Coimbra, M., Galvão Dias, T., 2022. Identifying the determinants and understanding their effect on the perception of safety, security, and comfort by pedestrians and cyclists: A systematic review. Transport. Res. F: Traffic Psychol. Behav. 91, 136–163. https://doi.org/10.1016/j.trf.2022.10.004.

Cheng, Q., Wang, L., Li, C., Jiang, X., Wang, W., 2018. A Research on Traffic Conflicts Between Vehicle and Pedestrian on Urban Typical Road Section. In: Wang, W., Bengler, K., Jiang, X. (Eds.), Green Intelligent Transportation Systems. Springer, pp. 187–195. https://doi.org/10.1007/978-981-10-3551-7_14.

Chung, Y., Chang, I., 2015. How accurate is accident data in road safety research? An application of vehicle black box data regarding pedestrian-to-taxi accidents in Korea. Accid. Anal. Prev. 84, 1–8. https://doi.org/10.1016/j.aap.2015.08.001.

Finch, D. J., Kompfner, P., Lockwood, C. R., & Maycock, G. (1994). SPEED, SPEED LIMITS AND ACCIDENTS. TRL PROJECT REPORT, PR 58. https://trid.trb.org/view.aspx?id=409371.

Fisher, D., Garay-Vega, L., 2012. Advance yield markings and drivers' performance in response to multiple-threat scenarios at mid-block crosswalks. Accid. Anal. Prev. 44 (1), 35–41. https://doi.org/10.1016/j.aap.2010.11.030.

Forum, I. T. (2020). Road Safety Annual Report 2020. https://www.oecd-ilibrary.org/content/publication/f3e48023-en.

Gómez, R.A., Samuel, S., Gerardino, L.R., Romoser, M.R.E., Collura, J., Knodler, M., Fisher, D.L., 2011. Do Advance Yield Markings Increase Safe Driver Behaviors at Unsignalized, Marked Midblock Crosswalks?: Driving Simulator Study. Transp. Res. Rec. 2264 (1), 27–33. https://doi.org/10.3141/2264-04.

Happee, R., Gold, C., Radlmayr, J., Hergeth, S., Bengler, K., 2017. Take-over performance in evasive manoeuvres. Accid. Anal. Prev. 106, 211–222. https://doi.org/10.1016/j.aap.2017.04.017.

Havard, C., Willis, A., 2012. Effects of installing a marked crosswalk on road crossing behaviour and perceptions of the environment. Transport. Res. F: Traffic Psychol. Behav. 15 (3), 249–260. https://doi.org/10.1016/j.trf.2011.12.007.

Hyden, C. (1987). The development of a method for traffic safety evaluation: the Swedish traffic conflicts technique. Bulletin Lund Institute of Technology, Department, 70. https://trid.trb.org/view.aspx?id=239059.

Jiang, X., Wang, W., Bengler, K., Guo, H., Li, C., 2017. Analysis of drivers' performance in response to potential collision with pedestrians at urban crosswalks. IET Intel. Transport Syst. 11 (9), 546–552. https://doi.org/10.1049/iet-its.2016.0344.

Jiang, X., Wang, W., Guo, H., Cheng, Q., Bengler, K., 2019. Drivers' effective decelerating zone in an urban Vehicle-Pedestrian conflict situation: Observational studies and analyses. Transp. Res. Part D: Transp. Environ. 66, 76–84. https://doi.org/10.1016/j.trd.2018.05.004.

Jurecki, R.S., Stańczyk, T.L., 2014. Driver reaction time to lateral entering pedestrian in a simulated crash traffic situation. Transport. Res. F: Traffic Psychol. Behav. 27, 22–36. https://doi.org/10.1016/j.trf.2014.08.006.

Kadali, B.R., Vedagiri, P., 2016. Proactive pedestrian safety evaluation at unprotected mid-block crosswalk locations under mixed traffic conditions. Saf. Sci. 89, 94–105. https://doi.org/10.1016/j.ssci.2016.05.014.

Kathuria, A., Vedagiri, P., 2020. Evaluating pedestrian vehicle interaction dynamics at un-signalized intersections: A proactive approach for safety analysis. Accid. Anal. Prev. 134, 105316 https://doi.org/10.1016/j.aap.2019.105316.

Koo, T.K., Li, M.Y., 2016. A Guideline of Selecting and Reporting Intraclass Correlation Coefficients for Reliability Research. J. Chiropr. Med. 15 (2), 155–163. https://doi.org/10.1016/j.jcm.2016.02.012.

Kraidi, R., Evdorides, H., 2020. Pedestrian safety models for urban environments with high roadside activities. Saf. Sci. 130, 104847 https://doi.org/10.1016/j.ssci.2020.104847.

Kröyer, H.R.G., Jonsson, T., Várhelyi, A., 2014. Relative fatality risk curve to describe the effect of change in the impact speed on fatality risk of pedestrians struck by a motor vehicle. Accid. Anal. Prev. 62, 143–152. https://doi.org/10.1016/j.aap.2013.09.007.

Laux, L., 2019. Chapter 24—Human Factors in Accident Analysis. In: McLay, R.W., Anderson, R.N. (Eds.), Engineering Standards for Forensic Application. Academic Press, pp. 433–449. https://doi.org/10.1016/B978-0-12-813240-1.00024-8.

Lubbe, N., 2017. Brake reactions of distracted drivers to pedestrian Forward Collision Warning systems. J. Saf. Res. 61, 23–32. https://doi.org/10.1016/j.jsr.2017.02.002.

McHugh, M.L., 2012. Interrater reliability: The kappa statistic. Biochemia Medica 22 (3), 276–282. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3900052/.

Mohamed, M., Bromfield, N.F., 2017. Attitudes, driving behavior, and accident involvement among young male drivers in Saudi Arabia. Transport. Res. F: Traffic Psychol. Behav. 47, 59–71. https://doi.org/10.1016/j.trf.2017.04.009.

Ni, Y., Wang, M., Sun, J., Li, K., 2016. Evaluation of pedestrian safety at intersections: A theoretical framework based on pedestrian-vehicle interaction patterns. Accid. Anal. Prev. 96, 118–129. https://doi.org/10.1016/j.aap.2016.07.030.

Obeid, H., Abkarian, H., Abou-Zeid, M., Kaysi, I., 2017. Analyzing driver-pedestrian interaction in a mixed-street environment using a driving simulator. Accid. Anal. Prev. 108, 56–65. https://doi.org/10.1016/j.aap.2017.08.005.

Olowosegun, A., Babajide, N., Akintola, A., Fountas, G., Fonzone, A., 2022. Analysis of pedestrian accident injury-severities at road junctions and crossings using an advanced random parameter modelling framework: The case of Scotland. Accid. Anal. Prev. 169, 106610 https://doi.org/10.1016/j.aap.2022.106610.

Iranian Legal Medicine Organization. (2022). Iranian Legal Medicine Organization. http://www.lmo.ir/web_directory/53999-%D8%AA%D8%B5%D8%A7%D8%AF%D9%81%D8%A7%D8%AA.html.

Pan, D., Han, Y., Jin, Q., Wu, H., Huang, H., 2021. Study of typical electric two-wheelers pre-crash scenarios using K-medoids clustering methodology based on video recordings in China. Accid. Anal. Prev. 160, 106320 https://doi.org/10.1016/j.aap.2021.106320.

Pantangi, S.S., Ahmed, S.S., Fountas, G., Majka, K., Anastasopoulos, P.C., 2021. Do high visibility crosswalks improve pedestrian safety? A correlated grouped random parameters approach using naturalistic driving study data. Anal. Methods Accid. Res. 30, 100155 https://doi.org/10.1016/j.amar.2020.100155.

A Policy on Geometric Design of Highways and Streets, 2011—American Association of State Highway and Transportation Officials—Google Books. (n.d.). Retrieved August 26, 2022, from https://books.google.com/books/about/A_Policy_on_Geometric_Design_of_Highways.html?id=puLERKfS0RcC.

Quddus, M., 2013. Exploring the Relationship Between Average Speed, Speed Variation, and Accident Rates Using Spatial Statistical Models and GIS. J. Transp. Saf. Security 5 (1), 27–45. https://doi.org/10.1080/19439962.2012.705232.

Rosén, E., Stigson, H., Sander, U., 2011. Literature review of pedestrian fatality risk as a function of car impact speed. Accid. Anal. Prev. 43 (1), 25–33. https://doi.org/10.1016/j.aap.2010.04.003.

Sagberg, F., Selpi, B.P., G. F., & Engström, J., 2015. A Review of Research on Driving Styles and Road Safety. Hum. Factors 57 (7), 1248–1275. https://doi.org/10.1177/0018720815591313.

Salamati, K., Schroeder, B.J., Geruschat, D.R., Rouphail, N.M., 2013. Event-Based Modeling of Driver Yielding Behavior to Pedestrians at Two-Lane Roundabout Approaches. Transp. Res. Rec. 2389 (1), 1–11. https://doi.org/10.3141/2389-01.

Sarwar, M.T., Fountas, G., Bentley, C., Anastasopoulos, P.C., Blatt, A., Pierowicz, J., Majka, K., Limoges, R., 2017. Preliminary Investigation of the Effectiveness of High-Visibility Crosswalks on Pedestrian Safety Using Crash Surrogates. Transp. Res. Rec. 2659 (1), 182–191. https://doi.org/10.3141/2659-20.

Scanlon, J.M., Kusano, K.D., Gabler, H.C., 2015. Analysis of Driver Evasive Maneuvering Prior to Intersection Crashes Using Event Data Recorders. Traffic Inj. Prev. 16 (sup2), S182–S189.

Schroeder, B.J., Rouphail, N.M., 2011. Event-Based Modeling of Driver Yielding Behavior at Unsignalized Crosswalks. J. Transp. Eng./Am. Soc. Civil Eng. 137 (7), 455–465. https://doi.org/10.1061/(ASCE)TE.1943-5436.0000225.

Shah, D., Lee, C., 2021. Analysis of effects of driver's evasive action time on rear-end collision risk using a driving simulator. J. Saf. Res. 78, 242–250. https://doi.org/10.1016/j.jsr.2021.06.001.

Sheykhfard, A., Haghighi, F., 2018. Behavioral analysis of vehicle-pedestrian interactions in Iran. Sci. Iranica 25 (4), 1968–1976. https://doi.org/10.24200/sci.2017.4201.

Sheykhfard, A., Haghighi, F., Papadimitriou, E., Van Gelder, P., 2021. Analysis of the occurrence and severity of vehicle-pedestrian conflicts in marked and unmarked crosswalks through naturalistic driving study. Transport. Res. F: Traffic Psychol. Behav. 76, 178–192. https://doi.org/10.1016/j.trf.2020.11.008.

Sheykhfard, A., Haghighi, F., Bakhtiari, S., Pariota, L., 2022. Safety Margin Evaluation of Pedestrian Crossing through Critical Thresholds of Surrogate Measures of Safety: Area with Zebra Crossing versus Area without Zebra Crossing. Transp. Res. Rec. 2677 (1), 396–408.

Subbalakshmi, C., Krishna, G.R., Rao, S.K.M., Rao, P.V., 2015. A Method to Find Optimum Number of Clusters Based on Fuzzy Silhouette on Dynamic Data Set. Procedia Comput. Sci. 46, 346–353. https://doi.org/10.1016/j.procs.2015.02.030.

WHO | Global status report on road safety 2018. (n.d.). WHO. Retrieved December 19, 2019, from http://www.who.int/violence_injury_prevention/road_safety_status/2018/en/.

Zhuang, X., Wu, C., 2011. Pedestrians' crossing behaviors and safety at unmarked roadway in China. Accid. Anal. Prev. 43 (6), 1927–1936. https://doi.org/10.1016/j.aap.2011.05.005.