Journal of Traffic and Transportation Engineering (English Edition) 2024; 11 (5): 853–866

Available online at www.sciencedirect.com

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journal homepage: www.keaipublishing.com/jtte

Original Research Paper

Assessing the risk of pedestrian crossing behavior on suburban roads using structural equation model

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HIGHLIGHTS

- Use post encroachment time to identify high, medium, and low risk levels for pedestrians during crossing movements.
- Human, road, and vehicle factors impact pedestrian risk, with human factors having a dominant influence.
- The findings emphasize the need to address road users' performance, compliance, alertness, and interaction for pedestrian safety.

ARTICLE INFO

Article history:
Received 7 June 2023
Received in revised form
29 November 2023
Accepted 11 December 2023
Available online 3 October 2024

Keywords:
Pedestrian
Crossing safety
Suburban roads
Speed
Structural equation model

ABSTRACT

While pedestrian crashes on suburban roads have received more attention over recent years, the role of pedestrian crossing risk in areas adjacent to pedestrian crossing facilities, such as pedestrian overpasses, has been neglected. Most pedestrians in suburban areas tend to avoid pedestrian overpasses, exhibiting crossing behaviors that increase the likelihood of pedestrian-involving crashes. As a result of the presence of overpasses, drivers may think that there are no pedestrians in the surroundings, so they choose a speed based only on the prevailing traffic and road environment without accounting for potential interactions with pedestrians. Consequently, crashes will occur, with pedestrians typically being the most seriously affected casualties. In this study, using video recordings from a suburban road in Amol-Babol, Iran, the risk of pedestrian crossing behavior in areas near pedestrian overpasses is investigated. The speed selection behavior of drivers in these areas has also been examined using speedometer cameras. To quantify the level of risk for pedestrians when interacting with approaching vehicles during the crossing movements, the post encroachment time (PET) was used as a surrogate safety measure. Based on critical thresholds of PET, three different risk levels were identified using a *K*-means algorithm: high, medium, and low risk. To identify the elements affecting the risk of pedestrian crossing behavior, structural equation models were estimated for all three risk levels. The results showed that human factors, relating to both drivers and pedestrians, have a dominant impact on pedestrian safety, especially in high and medium risk contexts. Road and vehicle factors were also found to have statistically observable effects on

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Peer review under responsibility of Periodical Offices of Chang'an University.
https://doi.org/10.1016/j.jtte.2023.12.001

pedestrian safety, but to a milder extent compared to human factors. The findings of this study highlight the need for intervening in several aspects of vehicle-pedestrian interactions with critical importance for pedestrian safety, including road users' performance and compliance, state of alertness, and interaction with road infrastructure.

1. Introduction

Nowadays, traffic crashes lead to major human losses around the world, with more than one million people passing away because of traffic crashes every year. Among them, a large share of injuries and deaths (more than 40 %) are attributed to crashes associated with pedestrians (Sheykhfard et al., 2022; Wang et al., 2022; Yang et al., 2023). As such, pedestrians are widely considered as one of the most vulnerable groups of road users.

Pedestrian crossing behavior is crucial for pedestrian safety (Day et al., 2023; Jain et al., 2014; Pantangi et al., 2021; Sheykhfard et al., 2023c), especially on suburban roads with higher traffic speeds. Hence, the purpose of the study is to analyze the elements that affect the risk of pedestrian crossing on these roads. Examining the elements composing the risk of pedestrian crossing movements can help understand not only the causes of pedestrian-involving crashes but also the measures that need to be implemented to mitigate such crashes (Ackaah et al., 2020; Arhin et al., 2022; Mahmoud et al., 2021; Song et al., 2021). In suburban areas, vehicle speeds may be higher than those in urban areas, not only because of lower traffic patterns but also due to the surrounding land uses, which may be perceived by drivers as generators of low pedestrian traffic. However, due to the presence of residential areas in the vicinity of major suburban arterials or other commercial or leisure developments that can induce substantial pedestrian traffic, there is a consistent demand for pedestrian crossing movements on suburban roads. However, this pedestrian demand may not be taken into account by all drivers, who may select speeds acceptable for the road environment but severely hazardous in cases of interactions with pedestrians; such unsafe vehicle speeds can result in collisions with pedestrians attempting to cross the road. The level of pedestrian safety is further exacerbated by specific behavioral patterns of pedestrians relating either to (non) use of dedicated crossing infrastructure, the acceptance of unsafe gaps for crossing the road, the risky interactions with approaching vehicles, or their cognitive state while performing the crossing movement. Thus, the study attempts to comprehensively identify, observe, and examine the elements affecting the risk of pedestrian crossing maneuvers on suburban roads by simultaneously investigating three major aspects of pedestrian safety: (i) the human element, which includes not only the behavior of pedestrians or drivers when crossing/traversing the road, but also their personal characteristics (such as age, gender, and so on); (ii) the environment/road element; (iii) the vehicle element.

To quantify the relationships of these elements with the pedestrian safety level in cases of pedestrian crossing movement, a staggered analytical approach is followed based on a safety surrogate measure, i.e., the post encroachment time (PET). Upon observing and analyzing video-recorded pedestrian behavior on suburban roads, *K*-means clustering was implemented to identify different levels of pedestrian risk. To understand the disaggregate and aggregate impacts of human, road, and vehicle elements on pedestrian crossing risk and to identify how these impacts vary across different risk contexts, structural equation models (SEMs) were developed. The findings of this analysis, and particularly the identification of the elements with the most critical impact on pedestrian safety, can pave the way for prioritization of actions that will make pedestrian crossing movements safer for all road users involved in these.

2. Previous studies

Over the last decades, despite the growing interest in the safety level of vulnerable road users in general, research on pedestrian safety in suburban areas still faces limitations, especially in low- and middle-income countries. Several factors make it necessary to put greater emphasis on pedestrian safety in suburban areas and expand research differently. The first challenge arises from the lack of data on traffic and land use in suburban areas, as well as some smaller urban areas, which serves as a barrier to analyzing traffic operation and safety in these areas (Jamali and Wang, 2017). As a second point, suburban areas have different road characteristics as compared to urban areas, such as shoulders instead of sidewalks and a higher speed limit (Yan et al., 2012). In addition, pedestrian accidents in suburban areas are relatively rare and sporadic in comparison to those in urban areas, inducing additional challenges as to the estimation of accident frequency, injury severity, and hotspot identification (Sheykhfard et al., 2023b; Zajac and Ivan, 2003). Lastly, pedestrian exposure to vehicular traffic in suburban areas may differ from that in urban centers (Millward and Spinney, 2011).

Numerous studies have examined the factors contributing to pedestrian crashes and injury severity in urban areas, including researches by Abay (2013), Dai and Jaworski (2016), Kim et al. (2008), Moudon et al. (2011), Sheykhfard et al. (2023a), and Oshanreh et al. (2023). It has been demonstrated that pedestrian safety is an important concern in urban areas. Specifically, these studies examined pedestrian behavior at signalized and unsignalized intersections (Brosseau et al., 2013; Liu et al., 2017), as well as unmarked midblock roads (Shaaban et al., 2018; Zhuang and Wu, 2011). In intersections with traffic lights, pedestrians can cross the street safely when they are alerted that approaching motorists should slow down. As a result, pedestrians have the right of way during the green-light phase, and most drivers are likely to give way to pedestrians to minimize the risk of accidents (Shaaban et al., 2018). However, for pedestrians who jaywalk, drivers are unable to predict their movements, resulting in longer reaction times for drivers (Patil and Pawar, 2016). In comparison with pedestrians who use crosswalks and intersections, jaywalkers are more likely to cause traffic congestion and accidents.

Few studies are focusing on pedestrian safety in suburban and small urban areas. There is a critical gap in the current understanding of what causes pedestrian crashes and how to enhance pedestrian safety in suburban and small urban areas. Jaywalking by pedestrians in suburban areas poses a serious health and safety risk. There are fewer pedestrian-friendly features such as sidewalks and crosswalks in these areas due to their wider roads and higher speed limits. As a result of the road design of suburban roads, pedestrians may be forced to jaywalk in the street or on the shoulder due to the lack of sidewalks or the presence of narrow sidewalks. Consequently, conducting in-depth research on jaywalkers in suburban areas is particularly important. Recent studies have focused on pedestrians crossing the road illegally (Malenje et al., 2018). Several studies have addressed some factors that may influence jaywalking, as well as the characteristics of such behavior (Demiroz et al., 2015; Papadimitriou et al., 2016; Xu et al., 2013). As part of their observation experiments around the University of Florida campus, some researchers examined the characteristics of pedestrian-vehicle interaction when jaywalking, and developed a model for a driver's response to jaywalkers by detecting vehicle equipment. It has been shown that the road environment has a significant influence on pedestrians' jaywalking behavior.

Jaywalking events are inversely proportional to traffic volume and directly proportional to the road width, pedestrian number, and crosswalk distance. In Qatar's Doha metropolis, Shaaban et al. (2018) examined the pedestrian crossing behavior on a high-speed six-lane arterial road through a densely populated urban area. As pedestrians enter roads, they must anticipate and handle traffic conditions on multiple lanes. Moreover, high-speed driving will restrict the behavior of vehicles and pedestrians. Using the principles of waiting time, running behaviors, and looking behaviors, Zhuang and Wu (2011) studied pedestrian crossing behavior and safety on unmarked roadways. As a result of the study, unsignalized, unmarked, low-speed crossings are found to be the safest (Scholl et al., 2019).

Overall, although some studies have reported the lack of facilities as one of the most important reasons for pedestrian crashes on the roads, in some other studies, pedestrians' unwillingness to use some of these facilities has been cited as an equally important reason for a lower level of pedestrian safety. What has not been extensively factored in past studies is the evaluation of the risk level of pedestrian crossing movements near an overpass in suburban routes; the presence of the overpass could make the drivers expect that the crossing movements will be performed via the overpass, and not through the road on the ground. As such, the presence of pedestrians on the road could confuse the drivers, potentially leading to errors and risky behavioral reactions.

Given the high number of pedestrian casualties on the suburban routes in Iran, and especially in Mazandaran, and the presence of pedestrian overpasses in that area, the examination of various variables associated with human elements, environment/road, and vehicles could bring about a clearer picture of the effect of each of these elements. Hence, in this study, the behavior of pedestrians on suburban routes near the overpass was conducted through videography of the routes in the present study. Further, the SEM approach was used to determine the effect of human, environment/road, and vehicle elements and to identify significant variables on the risk level of pedestrian crossing movements.

3. Method

3.1. *Overview*

The methodology employed in this study encompasses several key components aimed at comprehensively evaluating pedestrian crossing risk. The process begins with data collection through extensive video recording of the study area. This involved the installation of a high-speed Canon camera positioned strategically on an overpass, capturing crucial information over the course of four days. The subsequent analysis involved meticulous viewing and processing of recorded videos, enabling the extraction of pertinent details regarding pedestrian and vehicle behavior. Furthermore, this study has proactively considered past research findings and environmental conditions that have demonstrated influence on pedestrian safety. A preliminary set of variables was carefully curated from the video recordings, forming the basis for an in-depth statistical analysis. In addition to data collection, this study employs advanced statistical modeling techniques such as SEM to explore relationships between latent and observed variables. The adoption of *K*-means clustering offers a powerful tool for dividing observations into distinct clusters, contributing to a more nuanced understanding of the data. This unsupervised machine-learning technique employs a series of iterations to assign observations to clusters based on their proximity to cluster centers. Next, the incorporation of surrogate safety measures provides a critical step towards evaluating collision potential and assessing the efficacy of safety interventions through the use of widely acknowledged metrics. The conclusive phase of this section pertains to the presentation and delineation of the designated case study regions. This pivotal step serves to provide a comprehensive contextual framework for the ensuing analysis and examination.

3.2. *Structural equation model*

Structural equation model (SEM) is one of the most commonly used statistical modeling techniques for examining the relationship between latent and measured variables (Sheykhfard et al., 2023d; Useche et al., 2021; Yang et al., 2021; Sheykhfard et al., 2022).

Models of causality that involve both direct and indirect effects allow the statistical analysis of both direct and indirect effects. SEM involves the development of equations describing the relationships between variables. The equations are typically presented as matrices and solved using statistical software. The measurement model reflects the indicator-to-construct relationships, i.e., it represents the relationships between the latent variable (construct) and its observed indicators. Each observed variable is regressed on its corresponding latent variable. The structural model captures the relationships between latent variables themselves (i.e., how they are connected to each other). In other words, it represents the relationships between the latent variables in the model. The equations that represent the model are expressed as follows.

Measurement model

$$x_i=\lambda_i X+\epsilon_i \tag{1}$$

where x_i is the observed variable (i-th), λ_i is the factor loading (loading of the i-th indicator on the latent variable), X is the latent variable, ϵ_i is the error term for the i-th indicator.

Structural model

$$Y=\beta X+\zeta \tag{2}$$

where β is the path coefficient (regression coefficient), Y is the outcome latent variable, ζ is the error term for the outcome latent variable.

The varimax rotation technique will be used to determine the effect (factor loading) of each variable. Varimax rotation is a statistical technique used at one level of element analysis to clarify the relationship between elements. Overall, the process involves adjusting the coordinates of the data resulting from the principal component analysis. Adjustment or rotation is to maximize the shared variance between items. By maximizing the common variance, the findings more discretely show how the data correlates with each principal component. Variance maximization generally means increasing the squared correlation of items on one factor, while decreasing the correlation on any other factor. In other words, varimax rotation simplifies item loadings by removing the median and specifically identifying the element on which the data is loaded.

3.3. *K-means clustering*

K-means clustering divides a set of observations into a predetermined number of clusters using an unsupervised machine-learning technique. In the algorithm, *K* cluster centers are randomly selected, observations are assigned to the nearest cluster center, and the centroid of each cluster is recalculated until the cluster centers no longer change or the maximum number of iterations is reached (Anderson, 2009; Pan et al., 2021). To represent the algorithm mathematically, it is necessary to create equations defining the distance metric, the calculation of the centroid of the cluster, and the stopping criteria.

3.4. *Surrogate safety measures*

Post encroachment time (PET) is a concept used in traffic safety engineering to measure the amount of time a driver has to take an evasive action to prevent a potential collision with another vehicle or obstacle. PET is defined as the time between encroaching on another vehicle's path and evasive action being taken by the encroaching vehicle's driver to avoid colliding (Paul and Ghosh, 2020; Peesapati et al., 2013). PET measures the potential severity of a collision and is usually measured in seconds. When PET is longer, more time is given to the driver to react and avoid a collision. PET is a metric used in traffic safety analysis and for assessing the effectiveness of various safety interventions and countermeasures in accident reconstructions and simulation studies.

3.5. *The study area*

The first site was located on the 11th kilometer of the Amol-Babol Road, which crosses the villages of Noabad, Arabakhil, Qalyan Kola, Diyeh, Kashi Mahalle, and Musa Mahalle. This area is part of the Amol and Dasht Sar district. Fig. 1 is an image recorded by the video camera installed on the overpass in this area. Fig. 2 displays an aerial view of the study area. According to the census, the population of Noabad village is 131 (33 households), Arabkhil village 329

Fig. 1 – A snapshot of pedestrians crossing the road captured by a fixed video camera installed on the overpass (blue point) at the first location.

Fig. 2 – A snapshot of pedestrians crossing the path by a fixed video camera installed on the overpass (blue point) in the second location.

(79 households), Ghoyan Kola village 243 (67 households), Diyeh village 170 (50 households), Kashi Mahalle village 213 (55 households), and for the village of Musa Mahalle the population is estimated at 225 (57 households).

The second study site was located on the 14th kilometer of the Amol-Babol Road and crosses the villages of Ali Abad (population 455, 116 households), Shariat Kola village (population 604, 179 households), and Motahar village (population 506, 163 households).

3.6. *Data collection*

The video recording process spanned across four operational days in May 2022, resulting in a compilation of 12 hours' worth of footage. Filming was executed from elevated positions on overpasses, situated approximately 6 m above ground level, affording a comprehensive view of the road (Figs. 1 and 2). These recordings were conducted at various intervals throughout the day, consistently wrapping up prior to sunset, and in conditions of abundant sunlight with dry road surfaces.

The video capture of the designated study area was accomplished through the installation of a Canon camera equipped with the capacity to record at a rate of 30 frames per second. The subsequent videos underwent meticulous scrutiny and processing on multiple occasions, with the aim of extracting pertinent data regarding the conduct of both pedestrians and vehicles.

A team of four proficient analysts, affiliated with the Traffic Research Laboratory at Babol Noshirvani University of Technology, undertook the manual coding and examination of videos pertaining to the observed events. The initial day of this endeavor was dedicated to training the analysts. They were tasked with annotating eight events, followed by a collective deliberation to ensure a comprehensive understanding of all relevant variables. To gauge their concurrence, each analyst evaluated a randomized set of ten events. The remaining events were then distributed to each analyst by chance. This annotation process consumed a month to reach completion.

Considering the recording conditions and capabilities as well as the factors that were reported in past studies as influential for pedestrian safety, a preliminary list of variables to be retrieved from the video recordings was prepared. Table 1 presents the variables that were retrieved from the recordings and are further examined for statistical analysis. It is evident that these variables can capture several aspects of the relationship between human, road, and environmental elements with the risk level of pedestrian crossing behavior in the examined locations. Examining the videos revealed that 773 pedestrian crossing movements were made during the study period; this set of crossing movements was further analyzed through statistical modeling.

4. Results and discussion

4.1. *Risk level clustering*

Table 2 shows that the minimum recorded PET is 0.69 s, representing the shortest duration observed in the dataset. Conversely, the maximum PET is 3.46 s, signifying the longest duration recorded. The mean post encroachment time is approximately 1.3542 s, serving as a central measure of the dataset. Furthermore, the standard error of the mean is equal to 0.01791 s, indicating the precision of the sample mean as an estimate of the population mean. Additionally, the standard deviation of the PET is approximately 0.49808 s, revealing the extent of variability or dispersion around the mean. This standard deviation value suggests a moderate level of variability in post encroachment times within the dataset.

The silhouette method, which is an exploratory method for cluster validation, was used to validate the clusters (Mohamed et al., 2013; Subbalakshmi et al., 2015). This indicator determines the optimal number of clusters for a set of data through intra-data checks. A smaller overall silhouette value shows weak clustering and a higher value indicates a strong structure. According to the study of Spector (2011), the value of this indicator for high-quality clustering should be in the range of 0.71–1.00. A value in the range of 0.51–0.70 shows a reasonable structure, a value in the range of 0.26–0.50 shows a weak structure, and a value less than 0.25 indicates the

Table 1 – Variables used in data analysis.

Element	Variable	Variable description	Unit	Details on the variable description
Human (pedestrian)	GROUP	Move in a group	Frequency	Passing together
Human (pedestrian)	P.SPEED	Speed	m/s	Crossing speed
Human (pedestrian)	P.ATT	Attention to traffic	Yes: 1, No: 0	He/she looks toward the traffic
Human (pedestrian)	T.CROSSING	Style of passing	Runs: 0, walks: 1	
Human (pedestrian)	TRAJECTORY	Crossing route	Straight: 1, zigzag or diagonal: 0	
Vehicle	V.TYPE	Vehicle type	Heavy: 1, light: 0	
Human (pedestrian)	P.GENDER	Gender	Male: 1, female: 0	
Road	P.LOC	Where pedestrian stands	Middle: 0, edge: 1	At the moment of encountering the car
Road	R.LANE	Number of lanes	Two lanes: 1, three lanes: 0	
Road	R.OBS	Limited visibility	Yes: 1, No: 0	Parked vehicle
Human (pedestrian)	P.WAIT	The pedestrian stops before starting to move on the path	Yes: 1, No: 0	Before traveling
Human (pedestrian)	P.DIST	Using mobile phones	Yes: 1, No: 0	
Human (driver)	SPEEDING	Speeding	Yes: 1, No: 0	The speed of the vehicle exceeding the posted speed limit
Vehicle	PIONEER	Being a leading vehicle	Yes: 1, No: 0	Ahead of other vehicles
Human (pedestrian)	P.REQ	Pass request	Yes: 1, No: 0	Request the driver by hand
Vehicle	V.GROUP	Movement of vehicles in groups	Yes: 1, No: 0	Passing together
Human (driver)	D.YIELD	Does the driver yield?	Yes: 1, No: 0	Before reaching the possible point of collision with a pedestrian

Table 2 – Descriptive statistics for PET (unit: s).

N	Minimum	Maximum	Mean		Std. deviation
			Statistic	Std. error	
773	0.69	3.46	1.3542	0.01791	0.49808

absence of a significant structure (Spector, 2011). In our study, the value of the overall indicator was 0.74, 0.63, and 0.54, considering 3, 4, and 5 clusters (corresponding to risk levels), respectively. From these values, it is clear that three clusters should be selected, as that structure delivers the highest silhouette value. As such, three levels of pedestrian crossing risk were identified and defined based on PET values.

Table 3 provides the three risk levels as well as their defining criteria, as derived from the cluster analysis. The first cluster indicates a group of pedestrian crossing maneuvers bearing a high conflict risk; the PET value is lower than 1.25 s, which suggests a high probability of conflicts, and as such, high collision risk. Under the conditions of this high risk context, both users must perform an evasive maneuver to avoid a collision between the vehicle and the pedestrian. Examining the videos indicated that pedestrians move away from the possible point of collision with the vehicle through behavioral reactions, such as running or crossing in a diagonal or zigzag way. On the other hand, increasing or decreasing speed as well as changing the lane of movement are among the key evasive maneuvers employed by the drivers. The obtained PET threshold value for this high risk cluster is close to the findings of Chen et al. (2017), where the PET threshold was less than 2.00 s.

The second cluster indicates a medium level of crossing risk with the PET value ranging between 1.15 and 3.25 s. At this level of risk, a pedestrian crossing is secured through the evasive maneuver taken by one of the two parties involved in the interaction (either the pedestrian or the driver of the vehicle approaching the pedestrian). In other words, the act of performing an evasive maneuver by one of the two road users (not both) could result in creating a safe distance between the pedestrian and the vehicle. In this case, most of the maneuvers were carried out by the drivers, and speed reduction was the most widely observed behavior. Moreover, increasing the speed of their movement was another action that the pedestrians exhibited to cross safely before the vehicle reached the possible point of collision.

The lowest level of pedestrian crossing risk in the present study is when the PET indicator takes values greater than

Table 3 – The results of the clustering analysis based on the PET indicator.

Cluster	Index	Risk level	Description
1	PET $\leq$1.15 s	High	Both the driver and the pedestrian must change their behavior to prevent a collision.
2	1.15 s < PET $\leq$ 3.25 s	Medium	At least one of the users (pedestrian, driver) should change his/her behavior.
3	PET > 3.25 s	Low	A maximum of one of the users (pedestrian, driver) should change his/her behavior.
Model	Mean square: 0.314	F-test: 65.51	Sig.: 0.008.

3.25 s. Under these conditions, it is not always mandatory to carry out an evasive maneuver, and in a critical situation, an evasive maneuver, at most, will guarantee the safety of the pedestrian crossing maneuver. Previous research considered a crossing maneuver as safe when in a pedestrian-vehicle interaction, the PET value was greater than 3 s. Likewise, Ni et al. (2016) considered 3 s, while Almodfer et al. (2016) used 5 s as the upper threshold limit of PET (Almodfer et al., 2016; Chen et al., 2017; Ni et al., 2016).

4.2. *Structural equation model (SEM)*

The SmartPLS software was used in the study for carrying out the SEM analysis. In the first step, nominal variables were converted into binary variables to evaluate the effect of various categories on the dependent variable. In the next step, all the variables were analyzed by conducting an exploratory factor analysis (EFA) through varimax rotation. The findings of KMO (0.78) and Bartlett's test (Sig. = 0.01) revealed that the data is suitable for the SEM analysis. In the next step, EFA was carried out for the three clusters, which indicate various levels of pedestrian crossing risk and were identified using the K-means algorithm.

Table 4 indicates the findings of the EFA using varimax rotation across the three levels of pedestrian crossing risk. Table 4 indicates that only 12 variables affect pedestrian crossing safety out of all the variables examined in the current study. The effect of each of these variables on various crossing risk levels is different. The main outcome from the EFA is that all three considered elements, i.e., human, road, and vehicle play a role in pedestrian crossing safety. The key variables associated with the human element are speeding (SPEEDING), pedestrian crossing request from the driver (P.REQ), pedestrian distraction caused by mobile phone (P.DIST), pedestrian stopping to find the safety crossing distance (P.WAIT), the gender of the pedestrian (P.GENDER) and the look of the pedestrian towards the vehicles approaching them before moving on the path (P.ATT).

In our study, the role of the road element was found to be influential on the level of pedestrian crossing risk through variables such as the location where the pedestrian encounters the vehicle (P.LOC), the number of lanes (R. LANE), and the visibility restriction (R.OBS). The loading factors of these variables are different between them and across the clusters, as shown in Table 4. Also, elements such as the type of vehicle (V. TYPE), the leading vehicle in the path of movement (PIONEER), and the group of vehicles in the path of movement (V.GROUP) were the key variables affecting the risk level of pedestrian crossing, which are attributed to the vehicle factor. Two indices, the normal fit indicator (NFI) and the Standardized Root Mean Square Residual (SRMSR) were used to assess the overall fit of the SEM model. NFI standard values for the present models were 0.929, 0.868, and 0.834, respectively, for low, medium, and high risk levels. Further, values equal to 0.035, 0.042, and 0.029 were obtained for the SRMSR indicator, showing the proper fit of the SEM model.

4.2.1. *High risk level (PET $\leq$ 1.15 s)*

Fig. 3 is the diagram presenting the SEM results for the high risk level of pedestrian crossing (cluster 1). The positive and negative signs of factor loadings show the type of direct or reverse relationship between each variable and the level of risk. Given that the dependent variable of the model is subject to the PET threshold of the studied risk level, a positive factor loading of a variable implies an increase in the likelihood of PET to be less or equal to 1.15; in other words, the impact of this variable is associated with increased crossing risk. For instance, the illegal speed variable, which is characterized by a positive factor loading, has a direct relationship with the level of crossing risk. In other words, this variable suggests an increase in the risk level of pedestrian crossing with an increase in illegal speed. On the other hand, a variable with a negative factor loading (e.g., pedestrian crossing request) reduces the level of pedestrian crossing risk. Although at a high risk level, all three elements of human, vehicle, and road affect crossing risk, the findings reveal that their relationships with the target variable (risk level) are not aligned. Among the human factor elements, variables such as illegal speed (factor loading: 0.76) and pedestrian distraction (factor loading: 0.65) have a direct relationship with the level of risk, with the relationship between illegal speed being stronger. On the other hand, there is an inverse relationship between the crossing request (factor loading: −0.49), P.WAIT (factor loading: −0.44), and P.ATT (factor loading: −0.45) with the

Table 4 – Varimax rotation factor analysis results.

Variable	Human factor			Road factor			Vehicle factor		
	Cluster 1	Cluster 2	Cluster 3	Cluster 1	Cluster 2	Cluster 3	Cluster 1	Cluster 2	Cluster 3
SPEEDING	0.76	0.51	−0.36	–	–	–	–	–	–
P.REQ	−0.49	0.12	0.63	–	–	–	–	–	–
P.DIST	0.65	0.35	−0.39	–	–	–	–	–	–
P.WAIT	−0.44	0.22	0.62	–	–	–	–	–	–
P.GENDER	−0.34	0.37	0.45	–	–	–	–	–	–
P.ATT	−0.45	0.41	0.68	–	–	–	–	–	–
V.TYPE	–	–	–	–	–	–	−0.22	0.21	0.39
PIONEER	–	–	–	–	–	–	0.35	0.30	−0.27
V.GROUP	–	–	–	–	–	–	−0.14	0.19	0.23
P.LOC	–	–	–	0.33	0.25	−0.42	–	–	–
R.LANE	–	–	–	0.53	0.22	−0.37	–	–	–
R.OBS	–	–	–	0.40	0.29	−0.17	–	–	–

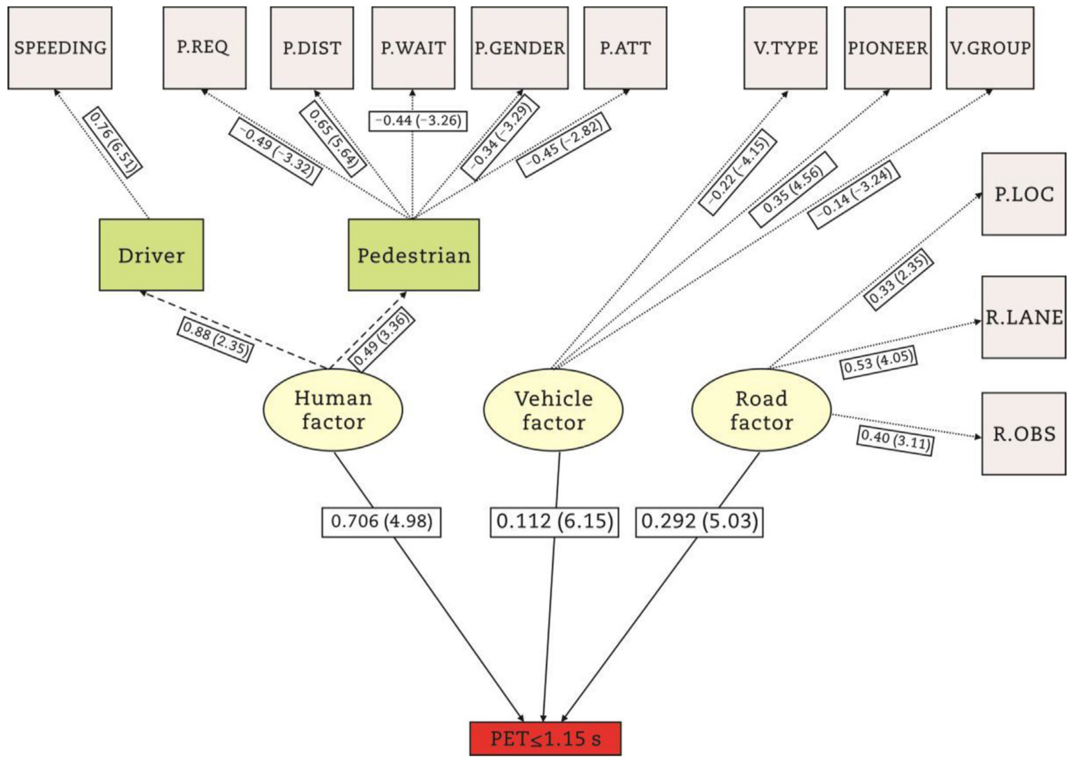

Fig. 3 – SEM results for the high risk level of pedestrian crossing.

level of risk, which shows, that under circumstances where the pedestrians wait before starting to cross the road and show attention to traffic, they are more likely to cross the road with a reduced level of risk. The negative coefficient of the gender element (factor loading: −0.34) shows that women are more exposed to high risk crossing than men, and the key reasons for this could potentially be their walking speed patterns and possible inattention to the road before moving on the path. Here, the crossing request element (if this behavior is indeed exhibited by the pedestrian) could create a safer crossing context because of its higher factor loading than other variables, although this difference is not significant.

The vehicle factor, similar to the human factor, includes variables that affect the level of crossing risk either with positive or negative impacts. The vehicle type (factor loading: −0.22) and the movement of vehicles in the group (factor loading: −0.14) have an inverse relationship with crossing risk. Hence, the interactions of pedestrians with heavy vehicles are associated with a safer margin of crossing (in terms of PET values) compared to interaction with light vehicles. The lower speeds of heavy vehicles, as well as the possibility of being noticed at longer distances by pedestrians due to their size or the topography of the road, may create a safer pedestrian crossing environment, especially when compared with lighter vehicles. Moreover, the lack of groups of vehicles leads to more freedom of action for drivers, and this is one of the reasons for the adoption of higher speeds by vehicles that are moving individually on the road. Another effect arises from the leading vehicle in the group that is crossing the road. The factor loading for this variable is positive, thus indicating that in arrangements where there is a distinct vehicle leading the way and the other vehicles on the road are following, the risk of pedestrian crossing movement increases.

The road factor indicates a different pattern of effects, compared to the other two factors, on the risk level of pedestrian crossing movements. According to the findings, all three components of the factor, i.e., pedestrian position on the road (factor loading: 0.33), number of lanes (factor loading: 0.53), and visibility restriction (factor loading: 0.40) have a positive relationship with the risk level. The risk of pedestrian crossing increases with an increase in the number of lanes, more restrictions on visibility, and with pedestrians being on the edge of the road at the start of the crossing maneuver. Based on the factor loading values, the effect of the number of lanes, under high risk conditions, is more pronounced than the other two components.

4.2.2. *Medium risk level (1.15 s < PET ≤ 3.25 s)*

Fig. 4 illustrates the results of the SEM of pedestrian crossing risk at a medium level (cluster 2). Among the human elements, the speeding indicator (factor loading: 0.51) and the pedestrian's attention to the road (factor loading: 0.41) have the most pronounced effects on the level of pedestrian safety, however, both elements increase the crossing risk. On the other hand, the effect of elements such as the pedestrian's request to pass (factor loading: 0.12) and the pedestrian's behavior to stop before moving (factor loading: 0.22) had lower impacts on the safety level. Nonetheless, a significant observation stems from the inverse relationship between these two elements with the level of crossing safety compared to the high risk context. In that case (first cluster), these pedestrian behaviors were found to lead to an overall improvement in crossing safety, the most important causes

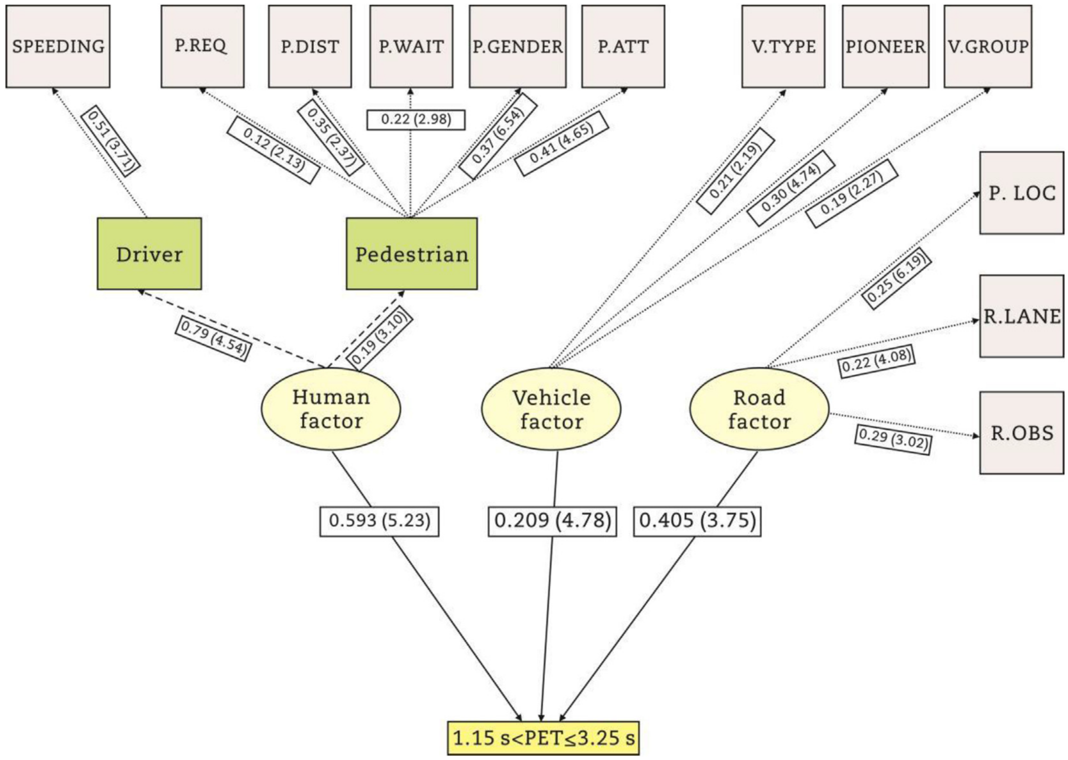

Fig. 4 – SEM for the medium risk level of pedestrian crossing.

of which were the change in the direction of drivers and the limited speed reduction of vehicles. Pedestrians may be less inclined to perform these behaviors at the medium risk level, because of other, more favorable circumstances, such as the sufficient distance of the vehicle to reach them; thus, the effect of these variables could be less evident than other elements, such as the speeding behavior of approaching drivers. Male pedestrians exhibit a higher degree of crossing risk than women at the medium risk level (factor loading: 0.37). In addition, pedestrians who are more prone to distractions and use their mobile phones are also associated with higher crossing risk (factor loading: 0.35).

The positive coefficients of the three variables representing a pedestrian position on the road (factor loading: 0.25), number of lanes (factor loading: 0.22), and RO (factor loading: 0.29) indicate the direct relationship between these elements and the level of crossing risk; these findings are similar to those of first model corresponding to the high risk level. Here, this relationship has become weaker, but it is still influential for the crossing risk level. Among the elements stated, the effect of visibility restriction seems to be stronger than other components of the road factor, although this difference is insignificant.

4.2.3. *Low risk level (3.25 s < PET)*

The SEM results for the low risk level of crossing risk (cluster 3) are illustrated in Fig. 5. The latter demonstrates a set of elements that have a key role in creating a safe crossing margin for pedestrians within a low risk context. Given the PET threshold that has been defined for the low risk level (PET > 3.25 s), a positive factor loading in this case implies an increase in the PET value, i.e., a reduction in the pedestrian crossing risk, whereas the opposite is applicable for negative factor loadings. Behavioral elements such as the pedestrian's request to cross the road, the pedestrian's waiting before crossing the road, and the pedestrian's attention to the road are among the most important elements that reduce the level of crossing risk. However, behaviors such as pedestrian distraction because of the use of mobile phones and speeding seem to compromise this level of safety.

In the low risk context, the number of lanes, and the position of the pedestrian have an inverse relationship with the risk level of the pedestrian crossing movement. Specifically, the level of risk on two-lane roads is found to be higher than on three-lane roads. Moreover, when the visibility is restricted, the crossing risk further increases. On the other hand, the level of crossing risk for pedestrians who are on the edge of the road is higher than for those standing in the middle of the road when facing vehicles. Various causes, including smaller distances for pedestrians to cross as well as better and more versatile visibility, could be the key reasons for this effect.

The findings of the SEM indicate that situations where the vehicle is on the lead has an inverse relationship with the level of pedestrian risk, showing the negative impact of this situation on the safety level of pedestrian crossing. On the other hand, the grouping of vehicles could create a better safety margin for pedestrian crossing movements.

4.3. *Evaluation of SEM*

The final models were assessed by considering both the measurement and structural models, resulting in a comprehensive evaluation of the overall model.

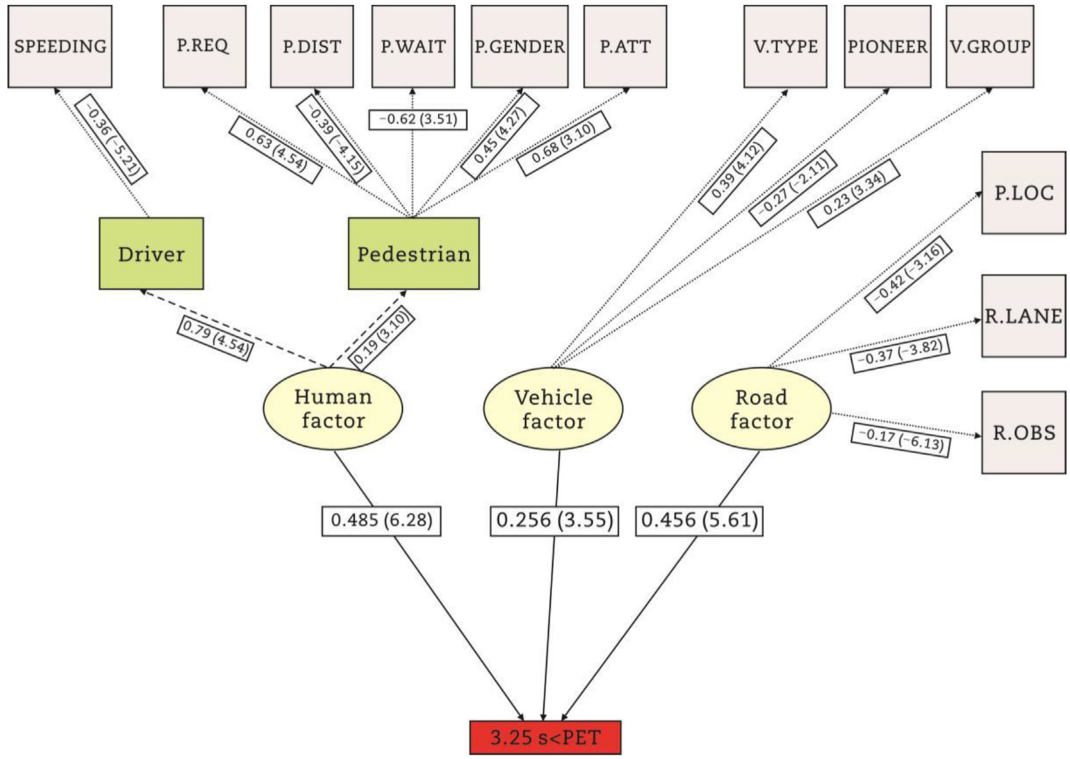

Fig. 5 – SEM for the low risk level of pedestrian crossing.

- Evaluation of the measurement model

Convergent validity acts as the criterion for evaluating the measurement model, wherein the correlation between each factor and its indicators is scrutinized (Höck and Ringle, 2010). The average variance extracted (AVE) denotes the average covariance between each factor and its associated questions. Essentially, AVE reflects the correlation between a factor and its items, with higher values indicating a better fit. In a satisfactory model, the AVE is expected to exceed 0.5 (Chin and Quek, 1997; Höck and Ringle, 2010), suggesting that the items explain at least 50% of the total variance of their respective indicators. According to Table 5, all variables in the present model demonstrate AVE values ≥ 0.5.

- Evaluation of the structural model

Based on the results, the variables integrated into the final model demonstrated statistically significant relationships among the latent variables at a 95% confidence level. The R^2 coefficients for the dependent factors in the models were positive, registering values of 0.821 for the high risk model, 0.751 for the medium risk model, and 0.782 for the low risk model. This affirms the suitability of the model's fit.

The Q2 metric, which evaluates the predictive capacity of the model, constitutes the third indicator for assessing the structural model. As per some researchers (Henseler and Chin, 2010), models endorsed through factor analysis should possess the ability to forecast latent factors within the model's domain. In simpler terms, if the relationships among the model's factors are accurately defined, they should exert a substantial influence on one another. A Q2 value less than or equal to zero implies that the connections between the model's various factors and the latent factors might be poorly specified, necessitating a revision of the model. In our investigation, the Q2 values for the latent factors were recorded as 0.45, 0.39, and 0.42 for the high risk, medium risk, and low risk models, respectively. These figures indicate that the observed factors effectively anticipated the latent factor, thereby providing further support for the fittingness of the structural model.

Table 5 – Evaluation of the measurement model.

Latent variable	Convergent validity			
	AVE			>0.5
	High risk level	Medium risk level	Low risk level	
Human	0.549	0.632	0.613	√
Vehicle	0.563	0.528	0.594	√
Road	0.571	0.602	0.634	√

- Overall evaluation of the model

The overall appropriateness of the SEM is evaluated using two primary indices: the NFI and SRMSR. The NFI acts as an incremental measure of fit, unaffected by the number of model parameters or variables (Henseler and Chin, 2010). A value exceeding 0.8 signifies a strong fit between the model and the data. Conversely, the RMSEA is a significant fit index in structural equation model, quantifying the disparity between the observed and implied correlation matrix of the model. Generally, values below 0.05 indicate a favorable model fit, although some studies consider values below 0.08 as acceptable. In the case of the high risk, medium risk, and low risk models, the NFI values were 0.862, 0.832, and 0.819, respectively. As for the SRMR, the corresponding values were 0.034, 0.031, and 0.036. These outcomes suggest that the ultimate models demonstrate appropriate statistical fit, which further substantiates their validity.

4.4. Discussion about the findings

Through this study, the impact of human, road, and vehicle factors elements on pedestrian crossing safety was assessed. Fig. 6 indicates the overall factor loadings of these three factors (as obtained from the SEM results) for the three risk levels examined in the study. According to the *t*-test coefficients (in parentheses), one can conclude that all relationships between these factors and all three risk levels are statistically significant at a greater than 99% level of confidence. Nevertheless, the magnitude of the impact of these factors on pedestrian crossing risk varies across the different risk contexts. The comparison of factor loading coefficients reveals that the role of the human element is more pronounced in determining the level of pedestrian crossing risk. That is naturally in line with previous research, which has established the major role of human factors in the decision-making process of pedestrians when crossing the road (Guo et al., 2011, 2014). The road is identified as the second factor with an observable impact on the level of pedestrian crossing safety, whereas the vehicle factor has the most modest effect on pedestrian crossing safety. The milder relationships between the road and vehicle factors and pedestrian crossing risk are anticipated, given that human factors and the external environment have been long established as key determinants of pedestrian crossing behavior (Guo et al., 2011, 2014). In our study, we have also identified statistically significant elements that capture interactions between human factors and the external environment, such as the attention to traffic and the pedestrian's request to the driver to safely cross the road.

Focusing on the human factor, the comparison of the factor loading coefficients across the three risk levels reveals that the riskier in the context of the pedestrian-vehicle interaction, the more pronounced is the role of the human factor. Interestingly, the factor loading corresponding to the human element increases by about 20% when comparing a less risky with a more risky context (i.e., when the PET values are lower). On the other hand, despite the documented impact of road and vehicle elements on pedestrian safety, the magnitude of their impact decreases with an increase in the risk level. According to the findings, one can see that the factor loadings corresponding to road and vehicle elements decrease by 36% and 56%, respectively, with an increase in the risk level of the studied context. However, such reductions in the factor loadings for contexts of higher risk are also accompanied by increases in the factor loadings of the human factor, which confirms, once again, the dominant role of the latter for the safety of pedestrian crossing movements (Guo et al., 2012; Olowosegun et al., 2022).

The variation of impacts of the three considered factors across different risk situations clearly shows that the human element has the greatest effect on pedestrian safety. This highlights the need to prioritize behavioral interventions that can address those nuances of driving and pedestrian behavior that make pedestrian crossing movements unsafe. The importance of behavioral elements, identified as significant in this study, such as the level of attention to traffic, pedestrian's request to the driver to cross the road, and pedestrian distraction while crossing, as well as speeding for drivers give rise to issues relating to the established road safety culture in the area of the case study. For example, the lack of willingness to use the crossing infrastructure (which may not be adequately provided) or the lack of enforcement may prompt the pedestrians either to indulge in unsafe behaviors (e.g., accepting unsafe gaps for crossing the road) or, at least, establish an informal communication with the approaching drivers to ensure a minimum level of safety for their crossing movement. Similarly, drivers may continue to exert speeding behaviors despite the occasional presence of pedestrians in the surroundings of the road. Interestingly, speeding behavior constitutes an aspect of road safety culture with a prevalent impact on pedestrian crossing risk in this study, given that it consistently delivered the largest (in magnitude) factor loading across all components of the human element for both medium and high risk contexts. User training via long-term educational programs and safety awareness campaigns with

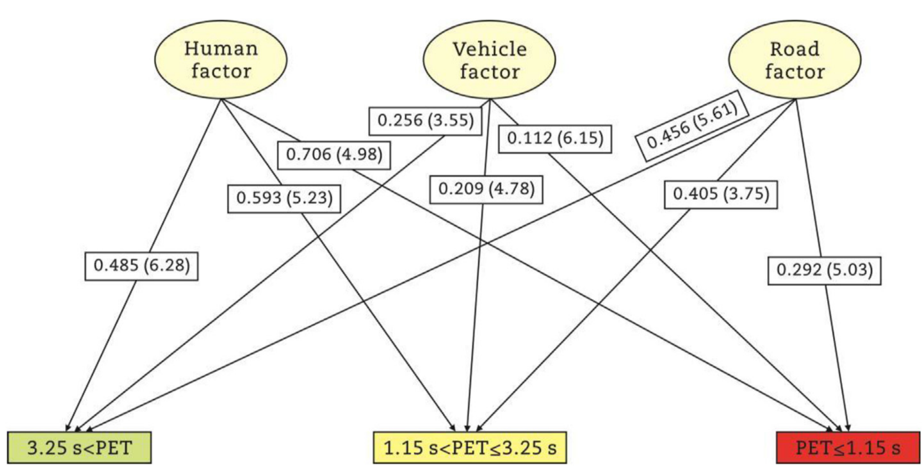

Fig. 6 – The relationship between various elements with the risk levels of pedestrian crossing.

an aim to improve the safety culture of both pedestrians and drivers located in suburban areas can have a positive effect on pedestrian safety; such training can contribute towards mitigating behaviors that can result in driving errors and traffic regulation violations, and in turn, collisions.

5. Conclusions and future work

The SEM analysis elucidates that a comprehensive understanding of pedestrian crossing risk hinges upon a nuanced examination of the behavioral attributes of road users and their interactions with the road and vehicle characteristics. The established associations among these three pivotal factors underscore that the dynamics of vehicle-pedestrian encounters substantially shape the causal patterns underlying collision risks. Thus, delineating these patterns represents a crucial stride toward formulating robust models for identifying high-potential vehicle-pedestrian conflicts.

In light of our findings, it is imperative to augment the effectiveness of safety improvement strategies, specifically long-term educational programs and safety awareness campaigns. These strategies necessitate supplementary support to bolster their efficacy. To this end, the following measures can be considered.

(1) Performance enhancement of road users: recognizing the undeniable impact of driving errors on pedestrian accidents, the implementation of driver assistance systems emerges as a pressing imperative. This innovation holds the potential to significantly elevate driver performance, thereby enhancing pedestrian safety and diminishing collision risks. Concurrently, targeted pedestrian safety campaigns, especially in high risk zones, stand as a crucial avenue for instigating behavioral shifts among pedestrians.

(2) Optimizing user-infrastructure interaction: a prompt recourse lies in the adoption of a road safety audit at the examined locations. Notably, our study underscores the influential role of lane configurations in pedestrian safety. Modernizing pedestrian bridges with amenities like escalators, strategic lighting, security provisions, and vigilant surveillance can markedly elevate pedestrian compliance with crossing protocols and overall safety. In instances where infrastructure alterations are impracticable, the judicious application of cost-effective traffic calming measures, both perceptual and physical, can temper vehicle speeds and bolster pedestrian adherence to traffic regulations.

(3) Enhancing driver alertness to pedestrian presence: this facet of driving behavior assumes paramount importance in locales where pedestrians may not be anticipated due to the built environment. Fostering heightened driver vigilance can be achieved not only through in-vehicle assistance systems but also through uncomplicated infrastructure interventions. High-visibility crosswalks, particularly in mid-block zones, warning signage, and pedestrian refuge islands offer tangible means to streamline the pedestrian crossing experience while augmenting overall safety.

While our study provides valuable insights, it is essential to acknowledge its limitations. The study's constrained budget and resource pool may restrict the scope of its generalizability. Furthermore, the research was geographically confined, potentially limiting the extrapolation of findings to diverse driver populations. The relatively modest sample size necessitates prudent interpretation of statistical outcomes. Additionally, the time-bound data collection may not comprehensively capture nocturnal or diverse weather-related driving and crossing behaviors. Future investigations could adopt a driver-centric approach, employing methods such as naturalistic driving studies in similar contexts. Such endeavors hold promise for advancing our comprehension of the intricate interplay between driver conduct and pedestrian safety.

Conflict of interest

The authors do not have any conflict of interest with other entities or researchers.

Acknowledgments

The authors extend their gratitude to all individuals who took part in the current study.

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