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Research Article

Risk assessment of pedestrian red-light violation behavior using surrogate safety measures: Influence of human, road, vehicle, and environmental factors

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ABSTRACT

Pedestrian red-light violation is one of the crucial causes of pedestrian crashes at urban intersections, which cause considerable injuries and casualties to this vulnerable road group of road users. The objective of this study is to evaluate the risk of pedestrian-vehicle collisions by clustering the pedestrians' red-light violations using surrogate safety measures. The present study utilized surveillance camera footage to collect data on pedestrians' red-light violations at two urban intersections in Babol City. Based on critical thresholds of post-encroachment time (PET), Time to Collision (TTC), and Gap Time (GT), three different risk levels of red-light violations were identified through the use of a K-means algorithm. Moreover, structural equation models were developed for each of the risk levels considering variables that are associated with four major components: human, environment, road, and vehicle. Lastly, policy insights into amending pedestrian behavior and promoting traffic safety culture were proposed, with an overarching emphasis on the human factor, due to its identified greater influence on the propensity for red-light violations.

1. Introduction

Pedestrians make up around 23% of all road casualties in the world, of which most occur in urban areas. Most pedestrian collisions occur at urban intersections, where unauthorized crossing by pedestrians (through violations of the red light at traffic signals) constitutes one of the main causation factors [1]. Traffic laws are being enforced on violating pedestrians in many countries of the world, with previous evidence documenting enforcement having a positive effect on the reduction of common violations such as red light violations of pedestrians. Law enforcement agencies in these countries may issue fines or citations for violations of these laws. In Australia, for example, according to section 230 of the Road Rules 2014, jaywalking can cost pedestrians up to $220 [2]. However, in many developing countries (e.g., Iran), despite the high number of pedestrian casualties, law enforcement has been quite passive in dealing with pedestrians' illegal behavior. In most developed countries, laws and regulations are in place to enforce pedestrian safety and prevent violations of pedestrian laws, but this is not the case in many underdeveloped and developing countries. Since these countries may not be able to implement law enforcement regarding pedestrian violations, such as red-light crossings, amending the risky behavior of pedestrians could serve as a first-level intervention with the potential to transform the road use culture and enhance pedestrian safety.

Crossing the intersection during the red light of the pedestrian traffic signal constitutes a major nuance of pedestrian risky behavior, which causes a higher likelihood of pedestrian collisions and therefore casualties. This has been long proved in the literature [1,3–6]. Hence, examining the factors affecting the intentions of pedestrians to cross an intersection despite there being a red traffic light can enlighten the occurrence patterns of this collision-causing violation, and, in turn, expand the evidence basis needed for the development of appropriate

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mitigation measures. The present study, using an active approach, seeks to determine the risk of pedestrian-vehicle collisions occurring at intersections when pedestrians violate the red light. Even though many studies have been carried out on the behavior of pedestrians, focusing primarily on the frequency of violations such as red-light crossing, the risk level of this violation type has not been thoroughly examined via Surrogate Safety Measures (SSMs). As the collision risk is a combination of collision probability and the severity of the aftermath, using measures that could consider both aspects can better quantify the safety hazard brought by red-light violations instead of just measuring the prevalence of these violations. Specifically, through the use of SSMs, the risk of vehicle-pedestrian collisions can be assessed more accurately and comprehensively via different contextual and user elements that potentially affect pedestrians' intention to commit a crossing violation.

The purpose of the study is to present an integrated framework for identifying pedestrian-vehicle collision risk at urban intersections according to several temporal and spatial indices of surrogate safety. In this context, different risk levels of collision associated with red-light violations are identified through a clustering approach based on threshold values of these indices. Moreover, the variables determining the propensity for unauthorized pedestrian crossings on a red light for each risk level are also investigated in this study.

1.1. Previous studies

Table 1 presents the most relevant previous research, which also includes information about the first author, year of publication, study field, sample size (i.e., number of observations/questionnaires used in the analysis), data collection, and analysis method. The studies identified through the literature search have been carried out across the globe, namely in Asia, North America, South America, and Europe. Of the studies, 10 of the 32 had been carried out in North America (the United States or Canada), 9 in China, and the remaining 13 in other countries. The period of research reviewed ranged from 1955 to 2021, but most studies were conducted over the last 10 years. Overall, each study focused on pedestrian crossing behavior at intersections. Nonetheless, each study investigated a specific aspect of pedestrian behavior in a small area or site and used a variety of data collection and analysis methods. Considering this, it could be hard to generalize the results across studies. In the rest of this section, various methods of data collection and analysis will be summarized, as identified from the literature review, and empirical evidence on pedestrian behavior at signalized intersections will be reviewed and presented.

Studies have revealed the effects of personal characteristics (e.g., gender, age), traffic characteristics, and the road environment on the intention of a pedestrian to cross through the estimation of different statistical models [14,21,24,27,29]. Some of these have focused on the effect of personal attributes on individual decision-making, whereas others have stressed the effect of traffic and roadway environmental elements on overall red-light violation rates [20,34,36]. However, examining the role of user-specific and environmental elements in individual decision-making for red-light violations has not been thoroughly examined. Further, interactions between individual-level elements (i.e., pedestrian demographics and pedestrian behavior), traffic conditions, and road environment have not been thoroughly examined, despite their contributing role in the tendency of pedestrians to commit red-light violations. It has been found that individual characteristics, such as gender and age, are significant elements determining the occurrence of pedestrian violations, with gender studied more extensively than age.

If the role of pedestrian demographic characteristics is important for red-light violations, that of specific contextual characteristics becomes even more critical. For instance, the level of pedestrian congestion, i.e., the number of pedestrians waiting to cross together (group size), has been reported to be an important variable influencing pedestrians' propensity toward red-light violations. The higher the number of pedestrians waiting on the roadside, the lower the rate of people crossing during the red light will be. However, some other studies indicated

Table 1
Summary of the literature review on risky and illegal crossing behaviors of pedestrians at intersections.

Authors, year	Study place	Site	Number of observations	Sampling method	Analysis method
[7], 1995	United States of America	Three signalized intersections	2103	Field observation	Statistical tests
[8], 1982	United States of America	One signalized intersection	4011	Field observation	Statistical tests
[9], 2001	United States of America	Two signalized intersections	688	Field observation	Statistical tests
[10], 2011	United States of America	Twelve signalized intersections	1656	Field observation	Statistical tests
[11], 2011	United States of America	Three signalized intersections	2361	Field observation	Statistical tests
[12], 2018	United States of America	Four signalized intersections	3038	Videography	Linear regression
[13], 2018	Canada	Ten signalized intersections	4000	Field observation	Statistical tests
[14], 2018	Canada	Eight signalized intersections	9808	Field observation	Statistical tests
[15], 2018	Canada	Thirteen signalized intersections	2938	Field observation	Logistic regression
[16], 2018	Canada	One hundred and thirty five street	2073	Field observation	Linear regression
[17], 2018	Poland	Eleven signalized intersections	8502	Field observation	Linear regression
[18], 2018	Greece	One signalized intersections	202	Field observation and Questionnaire	Logistic regression
[19], 2018	France	Unknown	2883	Field observation	Logistic regression
[20], 2018	France	Six signalized intersections	442	Field observation and Questionnaire	Logistic regression
[21], 2018	Japan, France	Seven signalized intersections	3666	Supervisor on site	Linear regression
[22], 2015	Australia	Unknown	636	Questionnaire	Linear regression
[23], 2000	Israel	Unknown	203	Questionnaire	Statistical tests
[24], 2018	Qatar	One signalized street	2766	Field observation	Linear regression
[25], 2021	UAE	Ten pedestrian crossings	708	Field observation	Linear regression
[26], 2014	Singapore	Seven pedestrian crossings	3448	Field observation	Logistic regression
[27], 2016	Singapore	One pedestrian crossings	1335	Videography	Fuzzy logit model
[28], 2007	India	Seven signalized intersections	1868	Field observation	Statistical tests
[29], 2020	India	Fifty five signalized intersections	65,500	Field observation and Questionnaire	Negative binomial model
[30], 2011	China	Unknown	1497	Field observation and Questionnaire	Statistical tests
[31], 2011	China	Seven pedestrian crossings	6628	Questionnaire	Statistical tests
[32], 2015	China	Unknown	Unknown	Questionnaire	Statistical tests
[33], 2015	China	Five intersections	1181	Field observation and Questionnaire	Logistic regression
[34], 2016	China	One province	4817	Collision Data	Logistic regression
[35], 2016	China	One city	631	Questionnaire	Logistic regression
[36], 2016	China	One city	260	Questionnaire	Structural equation model
[37], 2017	China	Thirteen intersections	1075	Field observation and Questionnaire	Logistic regression
[38], 2018	China	Four intersections	486	Field observation and Questionnaire	Logistic regression

contradictory findings, arguing that pedestrians who cross in groups tend not to obey traffic signals. The presence of vehicles parked near the crosswalk is another contextual feature that could be associated with pedestrian safety. The scientific literature recognizes that parked vehicles have a substantial impact on pedestrian accidents, especially involving children, as they obstruct drivers' ability to spot pedestrians waiting at the curb. However, there is limited research on how parked vehicles specifically impact pedestrian crossing behavior. Furthermore, it has been observed that adult pedestrians tend to exhibit more cautious crossing behavior when there are no parked vehicles around, but they become more attentive to traffic when parked vehicles are present in the area. However, a very recent study indicated inconsistent findings: the existence of illegally parked vehicles makes adult pedestrians wary and discourages them from crossing the street. Hence, better and more context-specific knowledge of the effects of parked vehicles on pedestrian behaviors before and during the crossing, such as with red-light violations, is required.

The purpose of the study is to fill the gaps in the research relating to pedestrians crossing on a red light in urban intersections through the simultaneous examination of factors associated with driver and pedestrian behavior, road conditions, and traffic on the road; comprehensively controlling for the impact of all these factors on pedestrians' red-light crossing has not been examined up to now. Given the need to pay attention to the prioritization of the importance of the aforementioned elements, an analysis approach based on Structural Equation Modeling (SEM) will be used to identify the observed and hidden (latent) structure of the factors affecting pedestrian red-light violations. Given that the impact of these factors may vary across contexts yielding different levels of collision risk, separate SEM models are estimated for varying risk levels. The latter are derived through a clustering approach using thresholds of several SSMs as defining criteria of collision risk.

2. Method

The risk analyses of pedestrians' red-light violations have been carried out by evaluating the traffic conflicts that occur between vehicles and pedestrians. Firstly, the behavioral state of pedestrians during a red-light violation is examined using surrogate, time-based safety indices. Data has been extracted by viewing surveillance camera footage at the intersection, which makes it possible to examine the impact of potential contributing factors at various time intervals. After calculating the indices, various risk levels of red-light violations were identified on the basis of these indices and with the help of the K-means clustering algorithm. In the last step, the SEM will be determined for each of the identified risk levels according to the variables affecting red-light violations by pedestrians.

2.1. Structural equation model (SEM)

A Structural Equation Model (SEM) is a statistical modeling technique used to examine the relationships between latent and measured variables [39,40]. It is a type of causal modeling that allows for the analysis of both direct and indirect effects of variables on each other. In SEM, a set of equations is developed to represent the relationships among variables. These equations are typically presented in matrix form and are solved using statistical software. The model can be represented by the following equations:

$$\eta = \Lambda\xi + \delta \text{ (Measurement model)}$$

$$\xi = B\xi + \zeta \text{ (Structural model)}$$

In the measurement model, the observed variables are denoted as η, the factor loading matrix is represented by Λ, the latent variables are indicated as ξ, and the measurement errors are symbolized as δ. In the structural model, the latent variables are denoted as ξ, the structural coefficients are represented by B, and the disturbances are indicated as ζ.

2.2. K-means clustering

K-means clustering is a popular unsupervised machine learning technique used to partition a set of observations into a predetermined number of clusters. The algorithm involves randomly selecting k cluster centers, assigning observations to the nearest cluster center, and recalculating the centroid of each cluster until the cluster centers no longer change or a maximum number of iterations is reached [41,42]. K-means clustering is commonly used in applications such as image segmentation, customer segmentation, and document clustering. The algorithm can be represented mathematically using equations that define the distance metric, the calculation of the cluster centroid, and the stopping criteria.

2.3. Surrogate safety measures

2.3.1. Post Encroachment Time (PET)

Post Encroachment Time (PET) is a concept used in traffic safety engineering to measure the amount of time 'needed by a driver' to take an evasive action to avoid a potential collision with another vehicle or obstacle. PET is defined as the time duration between the moment a vehicle encroaches on another vehicle's path and the moment the driver of the encroaching vehicle begins to take evasive action to avoid the potential collision [43,44]. PET is typically measured in seconds and is a critical factor in determining the severity of a potential collision. The longer the PET, the more time the driver has to react and avoid the collision. PET is an important metric used in traffic safety analysis and is often used in accident reconstruction and simulation studies to assess the effectiveness of various safety interventions and countermeasures.

2.3.2. Time to Collision (TTC)

In previous research using traffic conflict techniques, TTC has proven as an effective measure to assess the severity of conflicts. In traffic safety studies, TTC is defined as follows [45,46]: "the time needed for two vehicles to collide if they continue on the same route at their current speed". TTC at the start of braking indicates the available maneuvering space at the moment when the evasive action is starting. The minimum TTC obtained during two vehicles approaching the collision course (TTCmin) is seen as an index of the severity of the collision. The lower the TTCmin, the higher the collision risk will be [47]. Overall, TTC is the best-known time-based safety index. It has proven that TTC is an effective measure to distinguish critical from normal behaviors across different conflict situations among road users.

2.3.3. Gap Time (GT)

This index is equal to the difference in time when the second user reaches the collision point after the first user leaves if both continue at the same speed and on the same paths. This index is the time between the completion of the violation by the moving user and the arrival time of the passing user if they continue at the same speed and route. Despite their seeming similarity, there are some subtle differences of the "GT" relative to the general concept of PET. The concept of "GT" gives an indication of the estimated time to reach the potential point of conflict rather than the actual time difference. This safety index has similarities with the traffic collision concept and relies on a measure of a time point at which an evasive action is first taken. Although this indicates the effect of braking by a secondary vehicle, the nature of the original PET concept is lost as measures of speed and distance resources are needed during the data extraction process.

2.4. Case study

In the present study, two urban signalized intersections - Shahabnia and Amirkabir - in Babol, Mazandaran, Iran were considered (Fig. 1). The specific intersections are in the western belt of Babol, one of the busiest areas in terms of both motorized and non-motorized traffic.

Fig. 1. Red-light crossing during the day by a pedestrian (Left: Amirkabir intersection; Right: Shahabnia intersection).

2.5. Data collection

The surveillance camera recordings from the intersections were carefully analyzed for 11 consecutive days and nights, spanning from June 5th to June 15th, 2022. The primary focus was on studying pedestrians' behavior while crossing the intersections. To identify red-light violations and potential contributing factors, the videos were meticulously reviewed multiple times. A high-speed video camera was used to capture the movement of individuals in the intersection, and advanced image processing software was employed to determine their positions in the pixel space. Subsequently, a calibration process converted these pixel positions into two-dimensional spatial locations, using a predefined network with specific dimensions, enabling measurements in meters.

A team of four expert analysts from the Traffic Research Laboratory of Babol Noshirvani University of Technology manually examined and coded all the relevant videos. Each analyst was given eight events to annotate, and a discussion was held to ensure a consistent understanding of all variables. A random sample of twelve events was initially processed by each analyst to assess the agreement in video annotations. The entire annotation process took two weeks to complete. Pedestrian crossing behavior was then carefully examined, coded, and analyzed based on the video recordings, using the annotation toolbox developed with Microsoft Visual Studio 2019. This toolbox allowed analysts to load selected trips, play, pause, and annotate videos at their preferred speeds. To gauge the agreement between the annotators, two statistical measures were employed: Cohen's Kappa and the intra-class correlation coefficient [48,49]. Cohen's Kappa measures the level of agreement among raters when evaluating or categorizing items on a nominal or ordinal scale, accounting for the agreement that could happen by chance. Higher values indicate stronger agreement beyond chance. The the intra-class correlation coefficient, on the other hand, assesses agreement when multiple independent raters measure a continuous-level outcome. It determines how much of the total variation in the data can be attributed to differences among groups being compared. Using SPSS, the estimated values for Cohen's Kappa and the the intra-class correlation coefficient were calculated. The results indicated a high level of agreement among the annotators, with Cohen's Kappa yielding a value of 0.874 and the intra-class correlation coefficient being 0.935. These robust indicators confirm the strong consensus among the annotators regarding pedestrian crossing behavior.

A preliminary list of different variables that were extracted from the

Table 2
Variables used for further analysis.

Element	Codes	Variables	Aspects	Description
Human (pedestrian)	GRP	Move in a group	Frequency	Passing together
Human (pedestrian)	P.SPD	Speed	m/s	Crossing speed
Human (pedestrian)	P.A	Attention to traffic	Yes: 1, No: 0	He/she looks toward the traffic
Human (pedestrian)	T.C	Style of passing	Runs: 0, walks: 1	
Human (pedestrian)	TRJY	Crossing route	Straight: 1, zigzag or diagonal: 0	
Vehicle	V.TYPE	Vehicle type	Heavy: 1, Light: 0	
Environment	Time	Time	0:12–6, 1: 18–12 2:24–18, 3: 6–24	
Human (pedestrian)	P.G	Gender	Male: 1, female: 0	
Road	P.L	Transit position	Middle: 0, edge: 1	At the moment of encountering the car
Road	R.L	Number of lanes	Three lanes: 0, four lanes: 1, five lanes: 2	
Road	R.O	Limited visibility	Yes: 1, No: 0	Parked vehicle
Human (pedestrian)	P·W	Stopping the pedestrian before starting to move on the path	Yes: 1, No: 0	Before crossing
Human (pedestrian)	P·D	Using mobile phones	Yes: 1, No: 0	
Human (driver)	SPDING	Speeding	Yes: 1, No: 0	That the speed of the driver is more than the legal limit of the route
Vehicle	PIONR	Being a pioneer		Ahead of other vehicles
Human (pedestrian)	P.REQ	Pass request		Request the driver by hand
Vehicle	V. GROUP	Movement of vehicles in groups		Passing together
Human (pedestrian)	RED.L.V	Pedestrian crossing at red-light		Red-light violation

footage analysis is presented in Table 2; these variables were considered as potential factors in the modeling process conducted to identify the impact of human, road, and environmental elements on the level of risk of pedestrian red-light violations. Through the video analysis, a sum of 629 red-light violations from pedestrians were detected in different directions at both intersections during the study time.

3. Results and discussion

3.1. Risk level clustering

The K-means clustering method was used to determine the risk level of violations, and the data were analyzed in MATLAB using the method stated prior. The silhouette method was used to validate the data clustering. The silhouette score falls in the range [1,−1]. A score of 1 means that the clusters are very dense and well-separated. Zero means that the clusters overlap [50]. A score <0 means that the data that belong to the clusters could be correct/incorrect. Using this score, we can identify the best number of clusters (risk levels in our case) for a group of data with the help of intra-data analysis. Values >0.7 show a strong structure, values between 0.5 and 0.7 indicate a reasonable structure, and values below 0.5 indicate a weak clustering structure. In the present study, clustering was carried out into various classes and finally, according to the value of 0.81 for the profile index of the silhouette method, three different and separate classes were determined as optimal, corresponding to three different risk levels. These three risk levels, which are defined on the basis of threshold values for the three surrogate safety measures used for the clustering (i.e., GT, TTC, and PET), are shown in Table 3.

The high level of risk or risky behavior, suggested by the first cluster, introduces time values of <1.55 s for all three indices of GT, TTC, and PET. At this level, because of the short period until the collision between the pedestrian and the vehicle approaching them, examining the videos showed that both road users have to change their current movement. The drivers reacted by changing the direction of movement or by taking actions such as slowing down or stopping. On the other hand, crossing diagonally or zigzag compared to moving directly to cross the street were the changes that the pedestrians made in their behavior.

The medium risk level, indicated by the second cluster, has a lower risk than the first cluster, so in this group, a change in the behavior of at least one of the two users involved during a red-light violation – the pedestrian and the driver – could diminish the probability of a collision. Comparing the critical threshold of indices in the second cluster with the first cluster reveals that the cut-off values increased almost twice, which could suggest an increase in the level of traffic safety, although the risk of collision is still high. Observations of videos show that when a pedestrian violates a red light, evasive maneuvers by either the driver or pedestrian can significantly reduce the likelihood of occurrence. The third cluster, showing a low level of risk of pedestrian violations, provides the safest threshold of indices to prevent pedestrian collisions. The values of all three surrogate safety measures are >2.63 s, providing a lower risk level compared to the first two levels. Examining the videos indicated that changing the behavior of one of the two users could result in safe pedestrian crossing movement, even in the riskiest situation of this category. There is no need for users to change their behavior and there is no danger associated with the safety of pedestrians, especially in cases where the safety indices had larger values.

Table 3
Results of variance analysis for clustering the risk levels of violations according to the safety surrogate indices.

Cluster	Numbers of pedestrian red-light violations (Total:629 cases)	Index	Risk level	Description
1	121	GT ⩽1.09 TTC ⩽1.37 PET ⩽1.55	High	Both the driver and the pedestrian must change their behavior to prevent a collision
2	197	1.09<*GT*≤2.63 1.37<TTC≤2.72 1.55<PET≤2.96	Medium	At least one of them should change their behavior
3	311	GT>2.63 TTC>2.72 PET>2.96	Low	A maximum of one of them should change their behavior
Model	Mean square 0.218		F-test 86.142	Sig 0.001

3.2. Structural equation model (SEM)

In the present study, we used SmartPLS software for SEM analysis. In the first step, the nominal variables were used to reduce the variables examined from the element analysis of data in SmartPLS software. All the variables were divided into dual or binary modes to examine the role of each of the variables with higher accuracy. Accordingly, the number of lanes (R.L) and the time of violation (Time) were divided into 3 and 4 separate variables, respectively, by creating relevant dummy variables. In the next step, modeling was carried out using factor analysis through Varimax rotation on the data, and the results of KMO (0.81) and Bartlett's test (sig = 0.01) showed that the data were suitable for modeling by the factor analysis method. In the next step, factor analysis was carried out for the variables corresponding to the three defined clusters using the K-means algorithm, showing various levels of pedestrian crossing risk. The Varimax rotation technique was used to demarcate the effect (factor loading) of each variable.

Table 4 indicates the findings of the factor analysis according to Varimax rotation for all three risk levels identified by the K-means clustering. Only 13 variables have an effect on the level of the risk of pedestrian red-light violations according to the results of the model, among all the variables examined. The human factor with six variables is the first factor in terms of the number of variables affecting the risk level, the most important of which are: group passing (GRP), paying attention to traffic (PA), passing trajectory (TRJY), passing gender (PG), pedestrian waiting before starting to move on the road (PW), and using the mobile phone (PD). The vehicle factor is the second in order in terms of the number of variables affecting the risk level, where all three risk levels are affected by V.TYPE (vehicle type), PIONR (being a pioneer,) and V.GROUP (movement of vehicles in groups). On the other hand, although the road element consists of five influencing variables, three of them are associated with one main variable (number of lanes). According to Table 4, pedestrian location in the middle (PL), three road lanes on the road (RL*D1), four lanes on the road (RL*D2), five lanes on the road (RL*D3), and the visibility limit (RO) are associated with the vehicle factor. Table 4 shows that red-light violations relating to the road factor are the most effective variables in the risk level. As can be seen in Table 4, the variable time is associated with the risk level in hours during the day and night - Time (6-12), Time (12-18), Time (18-24), and Time (24–06).

- High risk level (GT ⩽1.09; TTC ⩽1.37; PET ⩽1.55)

Fig. 2 presents the structural model of the high-risk level (i.e., the first cluster). Factor loading coefficients and *t*-test coefficients (in parentheses) for each of the variables are given in the figure. Overall, any increase in the value of variables with a positive factor loading leads to an increase in the level of risk for a red-light violation to occur. In other words, there is a direct relationship between these variables and the risk of a red-light violation. On the other hand, variables with a negative factor loading are those with an inverse relationship with the level of risk, and thus any increase in their value or their occurrence leads to a decrease in the risk level of a red-light violation. Given the above, the

Table 4
Results of factor analysis.

Variable	Human factor			Road factor			Vehicle factor			Environmental factor		
	Cluster 1	Cluster 2	Cluster 3	Cluster 1	Cluster 2	Cluster 3	Cluster 1	Cluster 2	Cluster 3	Cluster 1	Cluster 2	Cluster 3
GRP	−0.62	0.37	0.51	–	–	–	–	–	–	–	–	–
P.A	−0.79	0.43	0.54	–	–	–	–	–	–	–	–	–
TRJY (Straight)	−0.41	0.38	0.48	–	–	–	–	–	–	–	–	–
P.G (Male)	−0.49	0.50	0.62	–	–	–	–	–	–	–	–	–
P·W	−0.76	0.42	0.59	–	–	–	–	–	–	–	–	–
P·D	0.83	0.59	−0.37	–	–	–	–	–	–	–	–	–
P.L (Median)	–	–	–	0.52	0.32	−0.39	–	–	–	–	–	–
R.L*D1 (Three lane)	–	–	–	−0.44	−0.36	0.20	–	–	–	–	–	–
R.L*D2 (Four lane)	–	–	–	0.48	0.31	−0.23	–	–	–	–	–	–
R.L*D3 (Five lane)	–	–	–	0.54	0.39	0.24	–	–	–	–	–	–
R.O	–	–	–	0.58	0.38	−0.28	–	–	–	–	–	–
V.TYPE (Heavy)	–	–	–	–	–	–	0.44	0.32	−0.37	–	–	–
PIONR	–	–	–	–	–	–	−0.45	−0.29	0.32	–	–	–
V.GROUP	–	–	–	–	–	–	−0.51	−0.39	0.38	–	–	–
Time*D1 (6–12)	–	–	–	–	–	–	–	–	–	–	–	0.37
Time*D2 (12–18)	–	–	–	–	–	–	–	–	–	–	–	0.35
Time*D3 (18–24)	–	–	–	–	–	–	–	–	–	0.57	0.35	–
Time*D4 (24-6)	–	–	–	–	–	–	–	–	–	0.61	0.44	–

variables with a direct relationship with the level of risk in the first cluster are (ranked in terms of the magnitude of impact as expressed by the factor loadings): using a mobile phone (factor loading: 0.83), time of occurrence between 12 am and 6 am (factor loading: 0.61), visibility restriction (factor loading: 0.58), time of occurrence between 18 and 24 h (factor loading: 0.57), five lanes on the road (factor loading: 0.54), pedestrian position (factor loading: 0.52), four lanes on the road (factor loading: 0.48) and heavy vehicle (factor loading: 0.44). On the other hand, the variables inversely connected to the level of risk, again ranked in order of their magnitude of impact (factor loadings) are: PA (factor loading: -0.79), PW (factor loading: -0.76), GRP (factor loading: -0.62), V.GROUP (factor loading: −0.51), gender (factor loading: -0.49), PIONR (factor loading: −0.45), three lanes on the road (factor loading: −0.44) and direct crossing path (factor loading: −0.41).

- Medium risk level ($1.09 < GT \leq 2.63$; $1.37 < TTC \leq 2.72$; $1.55 < PET \leq 2.96$)

The SEM results at the medium risk level are given in Fig. 3. The key variables that increase the risk level of a red-light violation are (ranked in terms of the magnitude of impact as expressed by the factor loadings): PD (factor loading: 0.59), gender (factor loading: 0.50), time of occurrence between 12 AM and 6 am (factor loading: 0.44), PA (factor loading: 0.43), PW (factor loading: 0.42), RL*D3 (factor loading: 0.39), RO (factor: 0.38), direct passage (factor loading: 0.38), GRP (factor loading: 0.37), time of occurrence between 18 and 24 h (factor loading: 0.35), heavy vehicle (factor loading: 0.32), pedestrian position in the middle (factor loading: 0.32), and RL*D2 (factor loading: 0.31). The variable with negative factor loadings are as follows: V.GROUP (factor loading: -0.39), RL*D1 (factor loading: −0.36), and PIONR (factor loading: −0.29).

- Low risk level ($GT > 2.63$; $TTC > 2.72$; $PET > 2.96$)

Fig. 4 shows the structural model of the low-risk level of violations. The most important variables with a positive factor loading are: gender (factor loading: 0.62), PW (factor loading: 0.59), PA (factor loading: 0.54), GRP (factor loading: 0.51), direct crossing route (factor: 0.48), V. GROUP (factor: 0.38), time of occurrence between 6 and 12 h (factor: 0.37), time of occurrence between 12 and 18 h (factor loading: 0.35), and PIONR (factor loading: 0.32). Likewise, the most important variables with a negative factor loading are: pedestrian location (factor loading: -0.39), PD (factor loading: −0.37), heavy vehicle (factor loading: 0.37), and RO (factor loading: −0.28).

3.2.1. *Evaluation of SEM*

The evaluation of the finals models involved an assessment of both the measurement and structural models, culminating in an overall model evaluation.

3.2.1.1. Evaluation of the measurement model. Convergent validity serves as the assessment criterion for the measurement model, wherein the correlation between each factor and its indicators is examined [51]. The Average Variance Extracted (AVE) represents the mean covariance between each factor and its respective questions. Essentially, AVE indicates the correlation between a factor and its items, with higher values signifying a better fit. In an acceptable model, the AVE should be >0.5 [51,52], implying that the items account for at least 50% of the total variance of their corresponding indicators. Based on Table 5, all variables in the current model exhibit AVE values ≥ 0.5.

3.2.1.2. Evaluation of the structural model. Based on the findings, the variables incorporated into the final model exhibited significant relationships among the latent variables at a 95% confidence level. The R2 values for the dependent factors in the models were positive, with respective values of 0.795 for the High-risk model, 0.813 for the Medium-risk model, and 0.808 for the Low-risk model, thus confirming the appropriateness of the model fit.

The Q2 criterion, which assesses the predictive power of the model, serves as the third index for evaluating the structural model. According

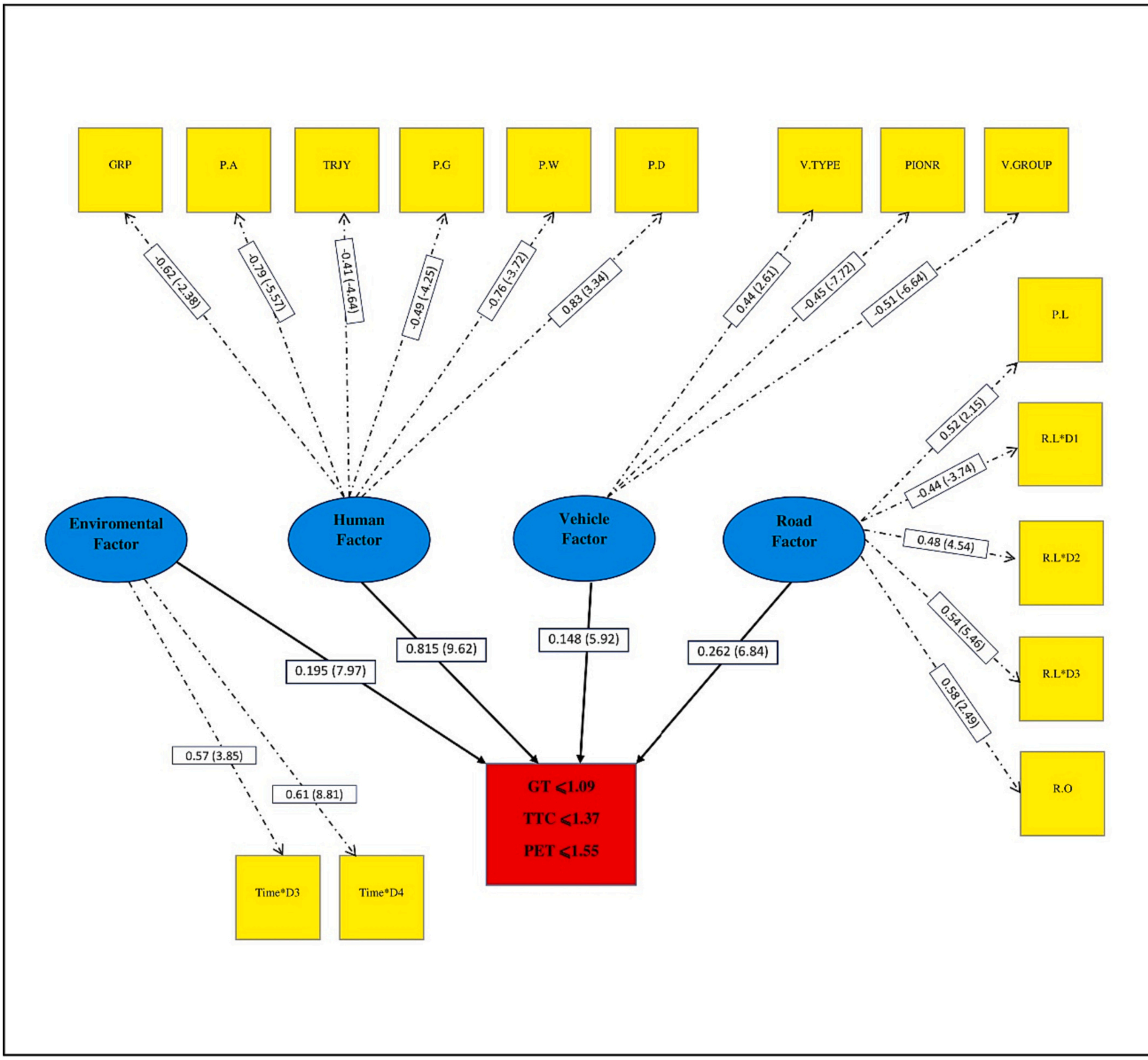

Fig. 2. Structural model of pedestrian red-light violations with the high-risk level.

to some researchers [53], models approved through factor analysis should have the capability to predict latent factors within the model's domain. Put simply, if the relationships among the model's factors are accurately defined, they should sufficiently influence each other. A Q2 value less than or equal to zero indicates that the relationships between the model's other factors and the latent factors may be poorly specified, necessitating model revision.

In our study, the Q2 values for the latent factors were reported as 0.36, 0.43, and 0.40 for the high-risk, medium-risk, and low-risk models, respectively. These values indicate that the measured factors effectively predicted the latent factor, thus supporting the appropriate fit of the structural model.

3.2.1.3. Overall evaluation of the model. The overall adequacy of the Structural Equation Model (SEM) is assessed through two key indices: the Normed Fit Index (NFI) and the Standardized Root Mean Square Residual (SRMR). The NFI serves as an incremental measure of fit, remaining unaffected by the number of model parameters/variables [54]. A value >0.8 indicates a good fit between the model and the data. In contrast, the RMSEA is a significant fit index in structural equation modeling, measuring the difference between the observed and implicit correlation matrix of the model. Generally, values below 0.05 suggest a suitable model fit, although some studies consider values below 0.08 as acceptable. For the high-risk, medium-risk, and low-risk models, the NFI values were 0.823, 0.874, and 0.895, respectively. As for the SRMR, the corresponding values were 0.035, 0.039, and 0.033. These results indicate that the final models exhibit an appropriate fit, providing evidence for their validity.

3.3. Discussion of the findings

Prior to discussing the interpretation, we acknowledge the valuable contributions of previous research in this field. Prior studies have explored several factors, including personal characteristics (e.g., gender, age), traffic conditions, and road environment, which influence pedestrian decision-making and red-light violations [14,21,24,27,29]. Some

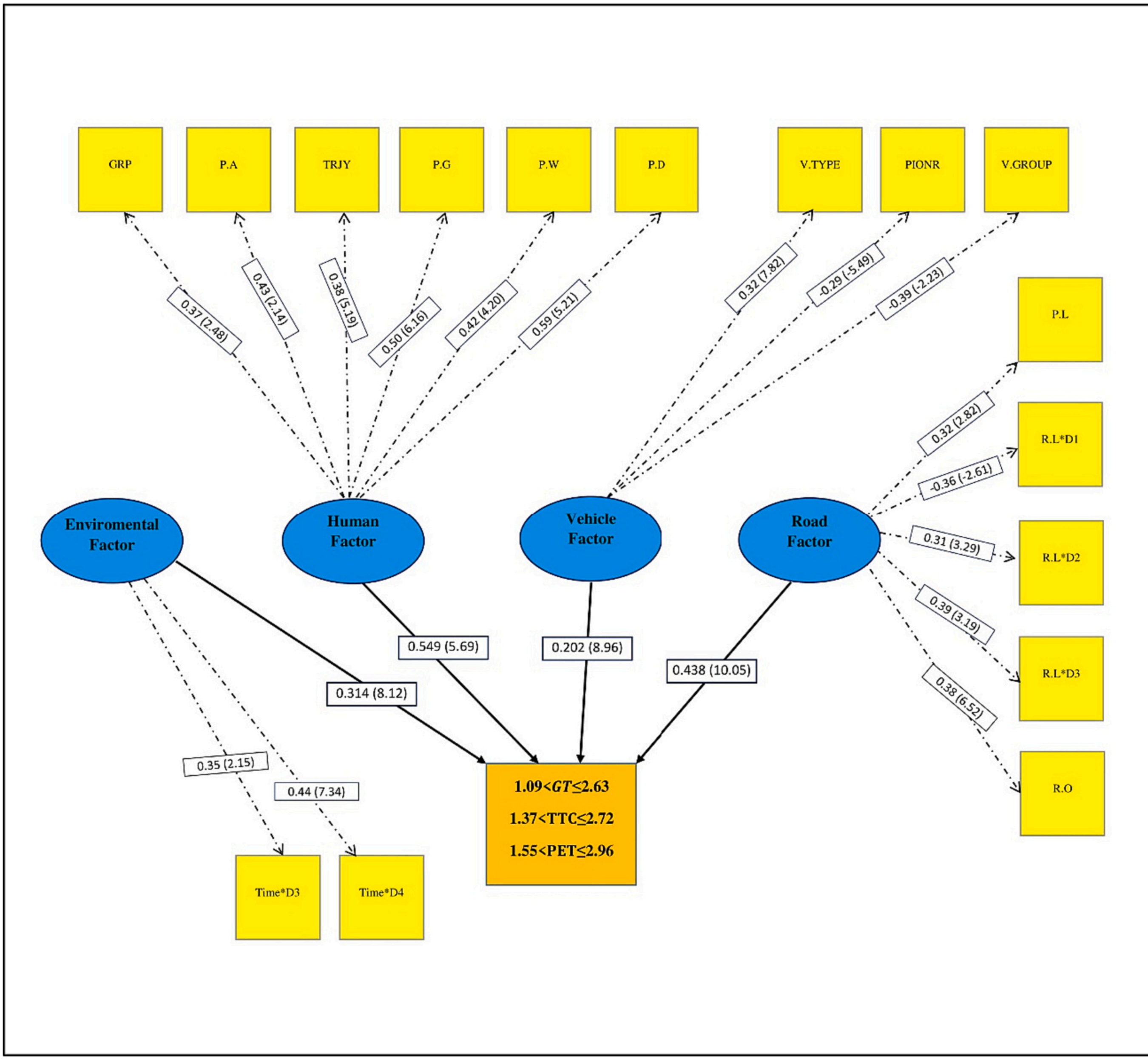

Fig. 3. Structural model of pedestrian red-light violations with a medium-risk level.

studies have focused on personal attributes and decision-making, while others have emphasized the role of traffic and roadway elements in red-light violation rates [20,34,36]. However, there is still a gap in understanding the specific influences of individual decision-making for red-light violations, particularly in the context of the local traffic culture.

In the present research, we conducted a thorough comparison of our research findings with existing studies, taking into account the potential influence of the local traffic culture. We recognize that cultural norms, attitudes, and behaviors related to traffic and pedestrian safety play a significant role in shaping pedestrian conduct at signalized intersections. Therefore, we emphasize the implications of the local traffic culture on the observed patterns of red-light violations in our study area. Our findings revealed interesting connections between pedestrian behavior and the local traffic culture. For instance, we observed that the level of pedestrian congestion (group size) at intersections affects pedestrians' likelihood of committing red-light violations. A higher number of pedestrians waiting on the roadside leads to a reduced rate of people crossing during red lights. However, we acknowledge that some studies have reported contradictory findings, suggesting that pedestrians crossing in groups may not adhere to traffic signals. This discrepancy may be attributed to the specific traffic culture in our study area, warranting further investigation. Furthermore, our study sheds light on the impact of parked vehicles on pedestrian crossing behavior and red-light violations. We acknowledge that the presence of vehicles parked near crosswalks could be related to pedestrian safety, particularly among children, as indicated in previous literature. Our study adds to this knowledge by revealing that adult pedestrians tend to be more cautious when crossing in the absence of parked vehicles, focusing more on traffic. Conversely, the presence of illegally parked vehicles was found to make adult pedestrians wary and discouraged from crossing the street, as suggested by a recent study. These nuanced findings underscore the significance of better and more context-specific understanding of the effects of parked vehicles on pedestrian behaviors during red-light violations, necessitating a deeper exploration of the influence of local traffic culture.

In summary, our research provides vital insights into the

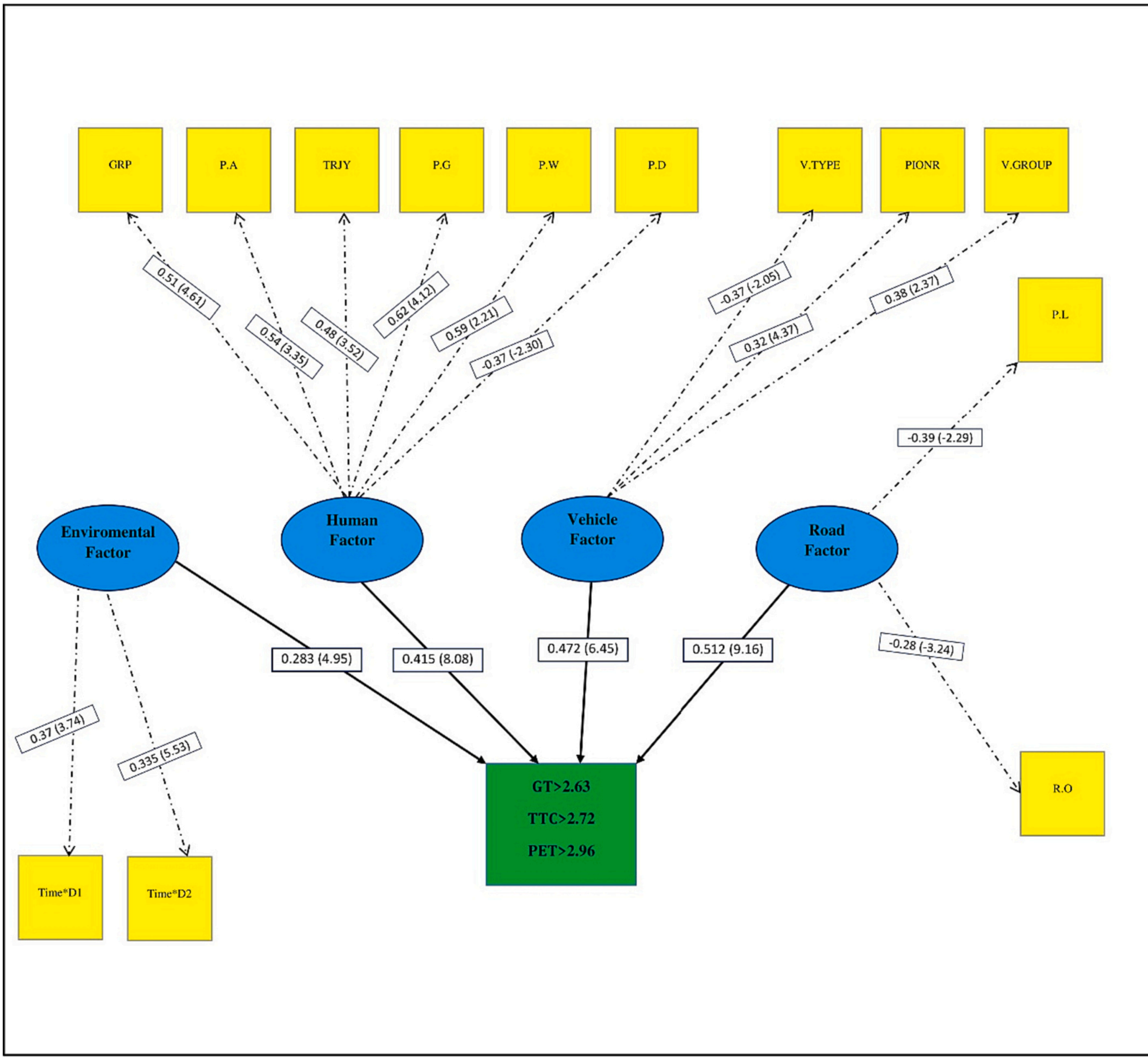

Fig. 4. Structural model of pedestrian red-light violations with a low-risk level.

Table 5
Evaluation of the measurement model.

Latent Variable	Convergent Validity			
	AVE			>0.5
	High-risk	Medium-risk	Low-risk	
Human	0.613	0.574	0.633	✓
Vehicle	0.628	0.602	0.544	✓
Road	0.563	0.621	0.525	✓
Environment	0.627	0.523	0.672	✓

complexities of pedestrian decision-making at signalized intersections within the context of the local traffic culture. We discuss how the human, environmental, road, and vehicle factors identified in our study all play statistically significant roles in determining the risk of pedestrian red-light violations. Moreover, we highlight that the human element may have a more pronounced impact, especially under high-risk conditions, aligning with established literature emphasizing the dominant role of human factors in traffic crashes. Additionally, road and environmental factors were found to be influential in moderate-risk conditions, while the vehicle's influence was comparatively lower but still relevant.

By explicitly examining the role of local traffic culture and comparing our findings with previous studies, we provide a comprehensive understanding of pedestrian behavior at signalized intersections, contributing to the broader field of traffic safety research. Our study underscores the importance of considering the cultural context when designing effective interventions to reduce red-light violations and enhance pedestrian safety.

The results of the effect of variables on the level of risk of violations were given in detail in the previous section. This section attempts to interpret the results to better understand the impact of human, environmental, road, and vehicle factors on red-light violations.

The GRP variable in the present study has an inverse effect on vehicle-pedestrian conflicts with high risk (cluster 1), showing that GRP possibly leads to an increase in traffic safety. In these conditions, examining the videos indicated that the drivers suddenly reduced the speed of the vehicle before reaching the possible place of collision in >50% of the conflicts. Similar to this, variables such as PA to traffic, crossing the road directly, and PW reduce the risk of conflicts. Examining the videos showed that in these conditions, pedestrians start their movement by choosing larger time intervals, although they still tend to cross during the red light. This affects the performance of the drivers of approaching vehicles because those who are farther away from the pedestrian will have more time to take collision-avoidance actions. On the contrary, the variable capturing the use of a mobile phone strongly leads to an increase in traffic risk because distracted pedestrians have generally lower situational awareness, and as such, the probability of collision with passing vehicles may increase. Similarly, the risk of violations increases with the number of lanes. Because of the increase in pedestrian walking distance on roads with multiple lanes and sometimes the short-term cycle of the light, pedestrians are more exposed to passing traffic than on narrow roads, and as a result, more conflicts occur that can result in collisions. Variables such as RO, which are mainly because of vehicles parked on the side of the street, as well as the presence of heavy vehicles on the road, resulting in an increase in the probability of red-light violations by pedestrians. The low speed of heavy vehicles mainly induces the feeling of the pedestrians that they can benefit from a larger time gap relative to the presence of a light vehicle; this perceived gap may prompt the pedestrians to cross the road. However, this variable does not examine the presence of other light vehicles in other lanes, which could also result in pedestrian collisions in lanes far from the edge of the street. On the other hand, variables like the movement of vehicles in a group result in a reduction in the risk of pedestrian violations. There are two main reasons for this; first, under conditions of vehicle group movement, the speed of traffic flow decreases because of the volume of traffic, and a safer gap is provided to pedestrians. Secondly, examining the videos indicated that in some of these cases, the pedestrians show behaviors such as increasing their speed and even running on the road after observing the collective movement of vehicles, and thus they cross the street quite quickly and before the group of vehicles enter the conflict zone. PIONR is another variable that reduces the risk of red-light violations. When a vehicle is ahead of other vehicles, pedestrians will have a greater range of vision than the approaching vehicle that is likely to collide, and as a result, they can make informed behavioral changes to pass more safely during violations. The violation time is another variable that could reduce or increase the risk. According to the results, the risk of violations increases when the volume of vehicle traffic is low, especially under low lighting conditions (e.g., dark conditions). This could be attributed to the increase in the speed of vehicles (because of the decrease in traffic volume) or the decrease in the visibility of the driver and pedestrians (because of the darkness).

Overall, all four factors (i.e., human, environment, road, and vehicle) have statistically significant effects on all risk levels of pedestrian red-light violations at a 95% confidence level, as graphically shown in Fig. 5 below. However, their relative impact varies across the risk levels. Fig. 5 reveals that the human element could affect the level of risk more than other elements, and this effect increases even more under high-risk conditions. This finding is fully in line with long-established literature showing that human factors have contributed to >90% of traffic crashes [55,56]. However, the magnitude of impact of the human factor in the low-risk level is inferior relative to the road and vehicle factors. This result suggests that red-light violations, where the contribution of road- or vehicle-specific characteristics is more dominant, are more likely to result in low-risk situations.

Overall, the road and the environment are two elements that are more influential than the vehicle element in moderate risk conditions and could determine the risk level of violations. The road and environment have been also documented as two factors with a latent impact on pedestrian safety, especially in the context of signalized junctions [57]. Ultimately, the vehicle has the lowest effect in the medium- and high-risk level, compared to all other elements, and the risk level of violations could also be affected, even to a smaller extent, by the conditions associated with it. The relatively weaker impact of the vehicle factor is anticipated given the indirect contribution of the vehicle

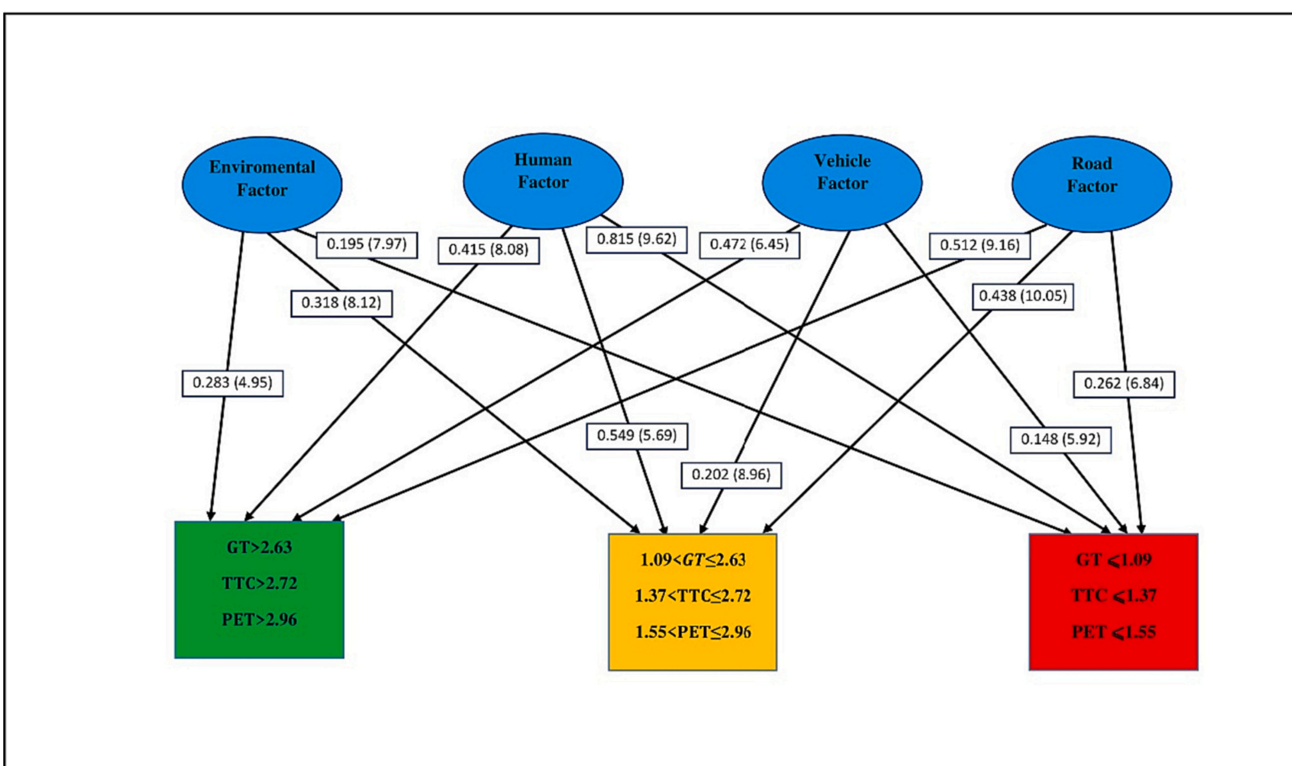

Fig. 5. The relationship between various elements with risk levels of pedestrian red-light violations.

characteristics (e.g., vehicle size, as earlier discussed) on the decision-making underpinning the red-light violations. Fig. 5 shows the regression coefficients of each factor (expressed as factor loading) for each risk level along with the coefficients of the *t*-tests (within the parentheses).

4. Summary, implications and conclusion

This study aimed to shed more light on the main factors determining the propensity of pedestrians to commit red-light violations in signalized urban intersections. The analysis demonstrated the possible effect of each of the various elements considered (i.e., human, environment, road, and vehicle) on the risk level of pedestrian red-light violations using a combination of clustering and SEM approaches. The findings of this study suggest that some variables are more influential than others, although the significance of the impact of all factors included in the models was recognized as significant at a 95% confidence level.

According to the results of the SEM models, the human factor, particularly relating to the pedestrian, has a key role in determining the risk level of violations, as such, any efforts to reduce the risk while crossing signalized intersections should be primarily targeted to pedestrians themselves and to their prevailing behavioral patterns. Focusing on the human element to better evaluate the performance of drivers and pedestrians, and subsequently modifying traffic or crossing behavior, if necessary, could play a major role in enhancing the safety of intersection users, and especially the safety of pedestrians. In this context, the findings of the study can assist policymakers and transport Agencies in implementing appropriate countermeasures in the direction of promoting pedestrian safety in urban intersections.

The use of mobile phones was found to significantly increase the probability of red-light violations in the high- and medium-risk contexts. Similarly, any kind of distraction was observed to favor red-light violation in both low- and medium-risk contexts. While our current research primarily focused on age as a significant factor in distracted pedestrian behavior, it is important to note that other demographic factors, such as gender, can also play a crucial role in understanding these behaviors. Nasar and Troyer's study [58], for instance, not only concluded that young pedestrians who were injured due to mobile phone use were higher in number, but also found gender differences in these trends. To better inform pedestrians about the safety risks stemming from mobile phone use while crossing an intersection, relevant signage can be installed, especially in urban areas, not only for alerting pedestrians but also for informing drivers about the possibility of encountering distracted pedestrians. Similar signs have already been mounted in Sweden and California, USA. Policymakers could also consider a more proactive approach to combating pedestrian distraction by enhancing training and education through targeted pedestrian safety curricula, especially in primary and secondary schools. Exploring the intersection of age and gender in pedestrian safety is an interesting avenue for future research.

The study also found that limited visibility caused by parked vehicles on intersection legs is associated with a higher propensity for pedestrian red-light violations. Situations combining restricted visibility and non-compliant pedestrian movements bear significant hazards given that both drivers and pedestrians have limited visibility, and as a result, any possible conflicts may be quite severe. This finding suggests that restrictions on on-street parking near or on intersections should be enforced ubiquitously by local authorities or any other enforcement entities, whereas supporting measures such as bollards or parking restriction signs can also help safeguard parking restrictions, and in turn, ensure sufficient visibility for both drivers and pedestrians.

Within the environmental factor, the time of the pedestrian movement was found to be crucial in determining the risk of red-light violation, with evening or night movements (mainly occurring under dark conditions) increasing the probability of pedestrian violations. Lower traffic conditions prevailing during these times of the day may lead pedestrians to disregard or violate the traffic signals. In cases of low traffic conditions, the potential delays that may be caused to pedestrians by fixed-cycle signals may prompt some pedestrians to cross the road when they find an acceptable gap regardless of the traffic light. As such, the use of traffic-actuated pedestrian signals, or even flashing lights transferring priority from vehicles to pedestrians, could be considered by traffic authorities as a remedy to boost pedestrian compliance, especially during hours with low vehicular traffic.

Overall, the possible interaction of the human factor, which was identified as the most influential element in the SEM analysis, with all the other factors identified as significant (i.e., environment, road, and vehicle) also highlights the influential role of traffic culture in pedestrian behavior. The findings of this study reiterate the need for effective strategies to address and mitigate the consequences of a potentially unfavorable traffic culture, which constitutes one of the key issues associated with pedestrian behavior [59]. In order to improve road safety, strategies can be implemented to encourage road users to acquire more knowledge and understanding of driving, walking, and other forms of urban transportation. This can be achieved by promoting sociable and helpful behavior, increasing risk awareness, and prioritizing personal safety as well as the safety of others. It should be also acknowledged that examining and figuring out the appropriate nuances of traffic safety culture and strategies that can effectively address high-risk behaviors, such as red-light violations, calls for in-depth knowledge of different behavioral components of both drivers and pedestrians; the latter components are typically dependent on the individual characteristics and living environment of the road user. Future research can explore the reasons behind pedestrians' non-compliant behavior, particularly regarding red-light violations. Such research can delve into the impact of personal characteristics of road users (e.g., age, socio-economic status), contextual and cultural factors, personal and social norms related to them, and personality traits that influence a pedestrian's likelihood to violate traffic laws.

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.

References

[1] D. Zhu, N.N. Sze, L. Bai, Roles of personal and environmental factors in the red light running propensity of pedestrian: case study at the urban crosswalks, Transport. Res. F: Traffic Psychol. Behav. 76 (2021) 47–58, https://doi.org/10.1016/j.trf.2020.11.001.
[2] Road Rules, NSW Legislation, 2014 https://legislation.nsw.gov.au/view/html/inforce/current/sl-2014-0758. Accessed Apr. 26, 2023.
[3] S. Das, S. Ashraf, A. Dutta, L.-N. Tran, Pedestrians under influence (PUI) crashes: patterns from correspondence regression analysis, J. Saf. Res. 75 (2020) 14–23, https://doi.org/10.1016/j.jsr.2020.07.001.
[4] R. Raoniar, A.K. Maurya, Pedestrian red-light violation at signalised intersection crosswalks: influence of social and non-social factors, Saf. Sci. 147 (2022), 105583, https://doi.org/10.1016/j.ssci.2021.105583.
[5] J. Wang, H. Huang, P. Xu, S. Xie, S.C. Wong, Random parameter probit models to analyze pedestrian red-light violations and injury severity in pedestrian–motor vehicle crashes at signalized crossings, J. Transp. Safety Security 12 (6) (2020) 818–837, https://doi.org/10.1080/19439962.2018.1551257.
[6] D. Zhu, N.N. Sze, Propensities of red light running of pedestrians at the two-stage crossings with Split pedestrian signal phases, Accid. Anal. Prev. 151 (2021), 105958, https://doi.org/10.1016/j.aap.2020.105958.
[7] M. Lefkowitz, R.R. Blake, J.S. Mouton, Status factors in pedestrian violation of traffic signals, J. Abnorm. Soc. Psychol. 51 (1955) 704–706, https://doi.org/10.1037/h0042000.
[8] L.A. Jason, R. Liotta, Pedestrian jaywalking under facilitating and nonfacilitating conditions, J. Appl. Behav. Anal. 15 (3) (1982) 469–473, https://doi.org/10.1901/jaba.1982.15-469.
[9] D. Eustace, Pedestrian reaction to crossing signal delay, J. Transp. Res. Forum 40 (1) (2001).
[10] J.F. Cooper, R.J. Schneider, S. Ryan, S. Co, Documenting targeted behaviors associated with pedestrian safety, Transp. Res. Rec. 2299 (1) (2012) 1–10, https://doi.org/10.3141/2299-01.

[11] V. Vasudevan, S.S. Pulugurtha, S.S. Nambisan, M.R. Dangeti, Effectiveness of signal-based countermeasures for pedestrian safety: findings from pilot study, Transp. Res. Rec. 2264 (1) (2011) 44–53, https://doi.org/10.3141/2264-06.
[12] B.J. Russo, E. James, C.Y. Aguilar, E.J. Smaglik, Pedestrian behavior at signalized intersection crosswalks: observational study of factors associated with distracted walking, pedestrian violations, and walking speed, Transp. Res. Rec. 2672 (35) (2018) 1–12, https://doi.org/10.1177/0361198118759949.
[13] B. Cambon de Lavalette, C. Tijus, S. Poitrenaud, C. Leproux, J. Bergeron, J.-P. Thouez, Pedestrian crossing decision-making: a situational and behavioral approach, Saf. Sci. 47 (9) (2009) 1248–1253, https://doi.org/10.1016/j.ssci.2009.03.016.
[14] J. Cinnamon, N. Schuurman, S.M. Hameed, Pedestrian injury and human behaviour: observing road-rule violations at high-incident intersections, PLoS One 6 (6) (2011), e21063, https://doi.org/10.1371/journal.pone.0021063.
[15] M. Brosseau, S. Zangenehpour, N. Saunier, L. Miranda-Moreno, The impact of waiting time and other factors on dangerous pedestrian crossings and violations at signalized intersections: a case study in Montreal, Transport. Res. F: Traffic Psychol. Behav. 21 (2013) 159–172, https://doi.org/10.1016/j.trf.2013.09.010.
[16] U. Lachapelle, M.-S. Cloutier, On the complexity of finishing a crossing on time: elderly pedestrians, timing and cycling infrastructure, Transp. Res. A Policy Pract. 96 (2017) 54–63, https://doi.org/10.1016/j.tra.2016.12.005.
[17] M. Kruszyna, J. Rychlewski, Influence of approaching tram on behaviour of pedestrians in signalised crosswalks in Poland, Accid. Anal. Prev. 55 (2013) 185–191, https://doi.org/10.1016/j.aap.2013.03.015.
[18] E. Paschalidis, I. Politis, S. Basbas, P. Lambrianidou, Pedestrian compliance and cross walking speed adaptation due to countdown timer installations: a self report study, Transport. Res. F: Traffic Psychol. Behav. 42 (2016) 456–467, https://doi.org/10.1016/j.trf.2015.07.010.
[19] N. Guéguen, N. Pichot, The influence of status on Pedestrians' failure to observe a road-safety rule, J. Soc. Psychol. 141 (3) (2001) 413–415, https://doi.org/10.1080/00224540109600562.
[20] A. Dommes, M.-A. Granié, M.-S. Cloutier, C. Coquelet, F. Huguenin-Richard, Red light violations by adult pedestrians and other safety-related behaviors at signalized crosswalks, Accid. Anal. Prev. 80 (2015) 67–75, https://doi.org/10.1016/j.aap.2015.04.002.
[21] M. Pelé, C. Bellut, E. Debergue, C. Gauvin, A. Jeanneret, T. Leclere, L. Nicolas, F. Pontier, D. Zausa, C. Sueur, Cultural influence of social information use in pedestrian road-crossing Behaviours, R. Soc. Open Sci. 4 (2) (2017), 160739, https://doi.org/10.1098/rsos.160739.
[22] J. Freeman, A. Rakotonirainy, Mistakes or deliberate violations? A study into the origins of rule breaking at pedestrian train crossings, Accid. Anal. Prev. 77 (2015) 45–50, https://doi.org/10.1016/j.aap.2015.01.015.
[23] D. Yagil, Beliefs, motives and situational factors related to Pedestrians' self-reported behavior at signal-controlled crossings, Transport. Res. F: Traffic Psychol. Behav. 3 (1) (2000) 1–13, https://doi.org/10.1016/S1369-8478(00)00004-8.
[24] K. Shaaban, D. Muley, A. Mohammed, Analysis of illegal pedestrian crossing behavior on a major divided arterial road, Transport. Res. F: Traffic Psychol. Behav. 54 (2018) 124–137, https://doi.org/10.1016/j.trf.2018.01.012.
[25] S. Bendak, A.M. Alnaqbi, M.Y. Alzarooni, S.M. Aljanaahi, S.J. Alsuwaidi, Factors affecting pedestrian behaviors at signalized crosswalks: an empirical study, J. Saf. Res. 76 (2021) 269–275, https://doi.org/10.1016/j.jsr.2020.12.019.
[26] P.P. Koh, Y.D. Wong, P. Chandrasekar, Safety evaluation of pedestrian behaviour and violations at signalised pedestrian crossings, Saf. Sci. 70 (2014) 143–152, https://doi.org/10.1016/j.ssci.2014.05.010.
[27] C. Chai, X. Shi, Y.D. Wong, M.J. Er, E.T.M. Gwee, Fuzzy logic-based observation and evaluation of Pedestrians' behavioral patterns by age and gender, Transport. Res. F: Traffic Psychol. Behav. 40 (2016) 104–118, https://doi.org/10.1016/j.trf.2016.04.004.
[28] G. Tiwari, S. Bangdiwala, A. Saraswat, S. Gaurav, Survival analysis: pedestrian risk exposure at signalized intersections, Transport. Res. F: Traffic Psychol. Behav. 10 (2) (2007) 77–89, https://doi.org/10.1016/j.trf.2006.06.002.
[29] D. Mukherjee, S. Mitra, A comprehensive study on factors influencing pedestrian signal violation behaviour: experience from Kolkata City, India, Safety Sci. 124 (2020) 104610, https://doi.org/10.1016/j.ssci.2020.104610.
[30] H. Guo, Z. Gao, X. Yang, X. Jiang, Modeling pedestrian violation behavior at signalized crosswalks in China: a hazards-based duration approach, Traffic Inj. Prev. 12 (1) (2011) 96–103, https://doi.org/10.1080/15389588.2010.518652.
[31] G. Ren, Z. Zhou, W. Wang, Y. Zhang, W. Wang, Crossing behaviors of pedestrians at signalized intersections: observational study and survey in China, Transp. Res. Rec. 2264 (1) (2011) 65–73, https://doi.org/10.3141/2264-08.
[32] T. Ding, S. Wang, J. Xi, L. Zheng, Q. Wang, Psychology-based research on unsafe behavior by pedestrians when crossing the street, Adv. Mech. Eng. 7 (1) (2015), 203867, https://doi.org/10.1155/2014/203867.
[33] X. Yang, M. Abdel-Aty, M. Huan, Y. Peng, Z. Gao, An accelerated failure time model for investigating pedestrian crossing behavior and waiting times at signalized intersections, Accid. Anal. Prev. 82 (2015) 154–162, https://doi.org/10.1016/j.aap.2015.04.036.
[34] G. Zhang, Y. Tan, R.-C. Jou, Factors influencing traffic signal violations by car drivers, cyclists, and pedestrians: a case study from Guangdong, China, Transport. Res. F: Traffic Psychol. Behav. 42 (2016) 205–216, https://doi.org/10.1016/j.trf.2016.08.001.
[35] W. Zhang, K. Wang, L. Wang, Z. Feng, Y. Du, Exploring factors affecting Pedestrians' red-light running behaviors at intersections in China, Accid. Anal. Prev. 96 (2016) 71–78, https://doi.org/10.1016/j.aap.2016.07.038.
[36] H. Zhou, S.B. Romero, X. Qin, An extension of the theory of planned behavior to predict pedestrians' violating crossing behavior using structural equation modeling, Accid. Anal. Prev. 95 (2016) 417–424, https://doi.org/10.1016/j.aap.2015.09.009.
[37] S. Chen, J. Xing, Y. Cao, The impact of waiting time on pedestrian violations at signalized intersections, Civil Eng. Urban Plan. 4 (2) (2017) 01–13, https://doi.org/10.5121/civej.2017.4201.
[38] X. Zhuang, C. Wu, S. Ma, Cross or wait? Pedestrian decision making during clearance phase at signalized intersections, Accid. Anal. Prev. 111 (2018) 115–124, https://doi.org/10.1016/j.aap.2017.08.019.
[39] S.A. Useche, A.M. Hezaveh, F.J. Llamazares, C. Cherry, Not gendered… but different from each other? A structural equation model for explaining risky road behaviors of female and male pedestrians, Accid. Anal. Prev. 150 (2021), 105942, https://doi.org/10.1016/j.aap.2020.105942.
[40] D. Yang, K. Xie, K. Ozbay, H. Yang, Fusing crash data and surrogate safety measures for safety assessment: development of a structural equation model with conditional autoregressive spatial effect and random parameters, Accid. Anal. Prev. 152 (2021), 105971, https://doi.org/10.1016/j.aap.2021.105971.
[41] T.K. Anderson, Kernel density estimation and K-means clustering to profile road accident hotspots, Accid. Anal. Prev. 41 (3) (2009) 359–364, https://doi.org/10.1016/j.aap.2008.12.014.
[42] D. Pan, Y. Han, Q. Jin, H. Wu, H. Huang, Study of typical electric two-wheelers pre-crash scenarios using K-Medoids clustering methodology based on video recordings in China, Accid. Anal. Prev. 160 (2021), 106320, https://doi.org/10.1016/j.aap.2021.106320.
[43] M. Paul, I. Ghosh, Post encroachment time threshold identification for right-turn related crashes at unsignalized intersections on intercity highways under mixed traffic, Int. J. Inj. Control Saf. Promot. 27 (2) (2020) 121–135, https://doi.org/10.1080/17457300.2019.1669666.
[44] L.N. Peesapati, M.P. Hunter, M.O. Rodgers, Can post encroachment time substitute intersection characteristics in crash prediction models? J. Saf. Res. 66 (2018) 205–211, https://doi.org/10.1016/j.jsr.2018.05.002.
[45] Y. Li, D. Wu, J. Lee, M. Yang, Y. Shi, Analysis of the transition condition of rear-end collisions using time-to-collision index and vehicle trajectory data, Accid. Anal. Prev. 144 (2020), 105676, https://doi.org/10.1016/j.aap.2020.105676.
[46] K. Vogel, A comparison of headway and time to collision as safety indicators, Accid. Anal. Prev. 35 (3) (2003) 427–433, https://doi.org/10.1016/S0001-4575(02)00022-2.
[47] R. Horst, TIME-TO-COLLISION AS A CUE FOR DECISION-MAKING IN BRAKING. VISION IN VEHICLES–III, 1991.
[48] M.L. McHugh, Interrater reliability: the kappa statistic, Biochem. Med. 22 (3) (2012) 276–282. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3900052/.
[49] T.K. Koo, M.Y. Li, A guideline of selecting and reporting Intraclass correlation coefficients for reliability research, J. Chiropr. Med. 15 (2) (2016) 155–163, https://doi.org/10.1016/j.jcm.2016.02.012.
[50] C. Subbalakshmi, G.R. Krishna, S.K.M. Rao, P.V. Rao, A method to find optimum number of clusters based on fuzzy Silhouette on dynamic data set, Proc. Comp. Sci. 46 (2015) 346–353, https://doi.org/10.1016/j.procs.2015.02.030.
[51] M. Höck, C.M. Ringle, Local strategic networks in the software industry: an empirical analysis of the value continuum (SSRN scholarly paper ID 2383777), Soc. Sci. Res. Netw. (2010). https://papers.ssrn.com/abstract=2383777.
[52] H.-C. Chin, S.-T. Quek, Measurement of traffic conflicts, Saf. Sci. 26 (3) (1997) 169–185, https://doi.org/10.1016/S0925-7535(97)00041-6.
[53] J. Henseler, W.W. Chin, A comparison of approaches for the analysis of interaction effects between latent variables using partial least squares path modeling, Struct. Equ. Model. Multidiscip. J. 17 (1) (2010) 82–109, https://doi.org/10.1080/10705510903439003.
[54] L. Hu, P. Bentler, Fit indices in covariance structure modeling: sensitivity to Underparameterized model misspecification, Psychol. Methods 3 (4) (1998) 424–453. insights.ovid.com.
[55] S. Singh, Critical Reasons for Crashes Investigated in the National Motor Vehicle Crash Causation Survey, Traffic Safety Facts - Crash Stats, 2018.
[56] J.R. Treat, N.S. Tumbas, S.T. McDonald, D. Shinar, R.D. Hume, R.E. Mayer, R. L. Stansifer, N.J. Castellan, Tri-Level Study of the Causes of Traffic Accidents: Final Report. Executive Summary, Indiana University, Bloomington, 1979. Institute for Research in Public Safety.
[57] A. Olowosegun, N. Babajide, A. Akintola, G. Fountas, A. Fonzone, 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 (2022), 106610, https://doi.org/10.1016/j.aap.2022.106610.
[58] J.L. Nasar, D. Troyer, Pedestrian injuries due to Mobile phone use in public places, Accid. Anal. Prev. 57 (2013) 91–95, https://doi.org/10.1016/j.aap.2013.03.021.
[59] T. Nordfjærn, Ö. Şimşekoğlu, The role of cultural factors and attitudes for pedestrian behaviour in an urban Turkish sample, Transport. Res. F: Traffic Psychol. Behav. 21 (2013) 181–193, https://doi.org/10.1016/j.trf.2013.09.015.