Pedestrian safety analysis at urban midblock section under mixed traffic conditions using time to collision as surrogate safety measure

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Pedestrians are the most vulnerable road users, and pedestrian safety has become a major concern among researchers in recent years due to the increasing number of road fatalities. Conflict analysis using surrogate safety measures (SSMs) helps study pedestrian safety, as there are several limitations with collision data. Moreover, it is a cost-effective technique compared to historical crash data analysis. The present study analyses pedestrian safety at urban midblock crosswalks using time-to-collision (TTC) as SSM. The data for the present study were collected from four different midblock pedestrian crossing locations in different cities in the western part of India using the videographic technique. The trajectory of pedestrians and vehicles was extracted for micro-level analysis of pedestrian–vehicle interactions. The trajectory data were further used to calculate TTC at regular time intervals during the interaction of pedestrians and vehicles. Two different types of pedestrian road crossing behaviour, viz. vehicle pass first and pedestrian pass first were identified, and TTC analysis was carried out differently for each scenario. The variation of TTC based on gender and vehicle category was analysed to evaluate the influence of such parameters on pedestrian safety. The generalized linear mixed model approach was used to develop linear regression models for TTC based on empirical data. The threshold values for TTC were used to define various safety levels of pedestrians using a clustering approach.

Keywords: Conflict analysis, mixed traffic condition, pedestrian, safety, time to collision, urban midblock.

A crosswalk is an essential facility that provides a bridge between activities on either side of a road and is frequently used by pedestrians. In developing countries like India, road crossing treatments such as road marking, signboards and signals are mostly absent or disregarded by vehicle users if present. Also, pedestrians show unsafe behaviour while crossing a road compared to walking on a sidewalk at such sections. Such risk-taking behaviour leads to higher accident rates among pedestrians in developing countries. Many studies highlight this scenario and show that the casualty rates of pedestrians are much higher in developing countries compared to developed countries[1–3]. In India, pedestrians cross the road at undesignated midblock sections and are so habituated that they avoid using the grade-separated facility even if it is available. On the other hand, vehicle drivers do not give way to pedestrians even at a marked crosswalk facility. Studies have shown that, urban areas account for 60% of pedestrian fatalities and 85% of these fatalities occur at midblock crosswalks[4]. Pedestrian crossing is fundamentally based on the gap acceptance process. After arriving at the kerb or median, a pedestrian examines the gap and accepts or rejects the vehicular gap based on his perception, speed, approaching vehicle class, behaviour and experience. Mixed traffic conditions are predominant in developing countries, which further complicates the process of road crossing by pedestrians. Any mistake or misjudgement committed by a vehicle driver or pedestrian may result in a collision between them.

Historical crash data are used to evaluate pedestrian safety at crosswalk locations under mixed traffic conditions. However, due to many issues related to the quality and quantity of such data, traffic conflict technique has been introduced and established for vehicle–vehicle conflict analysis. This technique is also used in pedestrian–vehicle conflict analysis[5–7]. The traffic conflict technique can recognize close-miss chances of a conflict. During the traffic operation, some conflicts may result in a collision, causing a fatality or severe to non-severe injury. The traffic conflict technique can identify the severity of a pedestrian–vehicle conflict. Time-to-collision (TTC) is one such a traffic conflict technique to evaluate pedestrian safety[8–10]. TTC is defined as ‘the time required for two entities to collide if they continue at their present speed on the same path’[11,12]. Many researchers have used TTC or TTC-based surrogate safety measures (SSMs) in vehicle–vehicle and pedestrian–vehicle interaction analysis[6]. A decrease in TTC increases pedestrian–vehicle interaction and further increases the probability of conflict with vehicles. The present study aims to evaluate the safety of pedestrians at midblock

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crosswalks under mixed traffic conditions using TTC as an SSM.

Literature review

The studies on pedestrian safety assessment are mainly carried out using crash-based methods such as historical crash data, users' perception surveys or conflict techniques. Researchers have studied the impact of the built environment on pedestrian safety using historical crash data[13–16]. Some researchers focused on identifying the factors affecting pedestrian safety using historical crash data[17–19]. The conflict-based method has been used to study the impact of pedestrian characteristics like age, gender, etc. on the safety of pedestrians during crossing manoeuvres[20–22]. Users' perception-based studies on the effect of pedestrian characteristics like age and gender on their safety have also been conducted[23–25]. Researchers adopted a driving simulator to study pedestrians, safety and behaviour. Wu *et al.*[26] used the driving simulator and designed a full factorial experiment to study pedestrian–vehicle conflict, which includes four different potential risk factors – the time of day, crosswalk marking, roadway type and pedestrian dressing colour. Chrysler *et al.*[27] used a driving simulator to examine the driver's response to a crash-imminent situation involving a pedestrian.

Researchers have emphasized the use of traffic conflict techniques and used different SSMs to analyse pedestrian safety at a midblock crosswalk or intersection due to the qualitative and quantitative issues related to road collision data. Kaparias *et al.*[28] presented a new vehicle–pedestrian conflict analysis technique based on existing vehicle–vehicle techniques for conventional roads and in shared-space environments.

Zhang *et al.*[7] compared 100 pedestrian and vehicle interactions based on vehicle pass first (VPF) and pedestrian pass first (PPF) cases from different safety scenes and introduced a new parameter called time difference to collision (TDTC) related to safety. Zhang *et al.*[29] adopted the TDTC parameter as a variation from TTC and post-encroachment time (PET). The interaction between pedestrians and vehicles was analysed and validated for the TDTC parameter indicating pedestrian safety to correlate the pedestrian-involved potential collisions and conflicts. Zhang *et al.*[30] developed a scene-based pedestrian safety performance evaluation model. Alhajyaseen and Iryo-Asano[31] developed a multinomial logit model to evaluate the probability of a pedestrian suddenly varying his/her speed as a function of one of the various factors affecting the safety of pedestrians at signalized crosswalks. Hagiwara *et al.*[32] studied conflicts between the right-turning vehicles and pedestrians coming from the right (left-turning in the case of USA) on a crosswalk based on time lag. Ismail *et al.*[33] extracted conflict indicators from an automated video analysis system that can calculate four severity conflict indicators in automatically for data collected from Canada. Ismail *et al.*[34] used video data for automated analysis of safety evaluations and demonstrated the feasibility of conducting before–after (BA) scenario safety evaluations. Zheng *et al.*[35] explored pedestrian jaywalking behaviour and corresponding driver yielding behaviour in USA to model vehicle–pedestrian behaviour outside a crosswalk using the micro-simulation approach. Lorion and Persaud[36] proposed a model to predict crash prediction based on two SSMs, namely conflicts and delay, and evaluate their predictively at urban intersections in Canada. Ni *et al.*[37] used trajectories to assess safety by paying more attention to behavioural factors which consider pedestrian–vehicle interactions. They suggested the concept of three interaction patterns using a support vector machine (SVM) in China. Chen *et al.*[38] applied two SSMs of PET and relative time to collision (RTTC), characterizing how spatially and temporally close the pedestrian–vehicle conflict is to a collision using unmanned aerial vehicles (UAVs) in urban intersections in Beijing, China. Paul and Ghosh[39] proposed a new methodology using two proximal safety indicators, PET and conflicting speed of through-moving vehicles on major roads. They found that PET values less than the threshold do not always create critical situations when the speed of the corresponding conflicting vehicle is low and vice versa. Babu and Vedagiri[40] used two surrogate measures of PET and the corresponding speed of the conflicting vehicles to analyse the traffic conflict at an intersection in India. They used the required deceleration rate to categorize the conflicts.

Researchers also focused on the safety of pedestrians during the crossing at the midblock section. Jiang *et al.*[5] estimated the differences between TTC and TTC-related parameters between China and Germany using road user trajectory. Chen and Wang[41] proposed a cellular automata (CA) model to simulate the interaction between vehicle flow and pedestrian crossing. Traffic parameters related to pedestrian and vehicle flow were studied in China. Cafiso *et al.*[6] carried out a BA analysis to assess the safety performance of newly installed traffic-calming devices using the pedestrian risk index (PRI) as SSM at the urban midblock section in Spain. Chandrappa *et al.*[42] examined pedestrian-related safety facets in urban roads in India by assessing PET and the threshold wait time (TWT) for pedestrians during the crossing. Kadali and Vedagiri[43] used pedestrian safety margin (PSM) to examine pedestrian safety at unprotected midblock crosswalks in India. Further, they carried out regression and developed a binary logit model to identify the factors influencing PSM. The developed models can predict the probability of avoiding conflict with an approaching vehicle at unprotected midblock crosswalks. Chen *et al.*[44] applied evolutionary game theory and cumulative prospect theory to consider the decision process of vehicle drivers and pedestrians during an interaction for addressing the crossing decision behaviour under bounded rationality and risk. Rankavat and Tiwari[45] studied the risk perception to identify the potential crash risk for Indian mixed traffic conditions. The results showed that the four-legged intersections below flyovers were the critical locations of risk. Pawar and Patil[46] found that the critical gaps for pedestrian crossings at uncontrolled midblock sections were less than that mentioned in the *Highway Capacity Manual* (*HCM*). Chaudhari *et al.*[47] found that the average value of 6.2 sec as suitable for designing the crossing facility with pedestrian safety. In another study by Chaudhari *et al.*[48], a multilinear regression model was developed for evaluating pedestrian safety margin under Indian traffic conditions for crossing pedestrians. Chen and Fan[49] developed a multinomial logit model of pedestrian–vehicular crash severity and found that the physical condition of the drivers, vehicle categories such as motorcycles and trucks, pedestrian age, etc. are the most significant factors causing crashes. Danaf *et al.*[50] developed a methodology for studying interactions of pedestrians with vehicles under a mixed traffic conditions in the presence of a crosswalk. The results showed that the presence of a crosswalk decreases the pedestrian waiting time and reduces the speed of vehicles in the section before the crosswalks. Golakiya *et al.*[51] suggested a distance-based safety index, namely safe distance (SD) at urban midblock crosswalks under mixed traffic environment and a threshold value for safe crossing. Golakiya and Dhamaniya[52] adopted SSM to evaluate the safety of crossing pedestrians. Safety index threshold value was developed for two separate cases, namely PPF and VPF for different vehicle categories based on vehicle speed as a variable.

The literature review presented above reveals that the safety of pedestrians is a major concern among researchers. They have used different methods to evaluate pedestrian safety such as historical data, user perception, conflict technique and simulation-based method. However, the approach based on the conflict technique is more rational and cost-effective. Researchers have used various surrogate safety parameters to evaluate pedestrian safety. However, majority of the studies have been carried out at intersections. Some studies have also been conducted at the midblock location to examine vehicle–pedestrian interactions. However, a few studies have reported heterogeneous traffic without lane discipline, similar to the Indian condition. Hence, further research in this direction can be useful to focus on pedestrian safety. None of the reported studies has modelled SSM parameters for mixed traffic conditions. The present study has been carried out in this direction to analyse the safety of pedestrians and model TTC at unprotected urban midblock crosswalks under mixed traffic conditions.

Research objectives

A pedestrian crossing in an urban midblock is a common phenomenon observed in developing countries. This pedestrian crossing is a complex phenomenon and has profound safety implications. The prime objective of the present study is to examine the safety aspects of crossing pedestrians using TTC as SSM and to model TTC using the generalized linear model approach. Moreover, it aims to define the threshold value of TTC using a clustering technique to categorize pedestrian risk.

Site selection

To meet the objectives of the present study, four different locations at uncontrolled (no right of way to pedestrian) midblock sections were selected on six-lane urban arterials. These sections were chosen in four different cities (Surat, Vadodara, Ahmedabad and Jaipur) in the western part of India. The criteria for selecting the sections were that they should be free from side frictions other than crossing pedestrians, such as on-street parking, stopped vehicles, hawkers, curb-side bus-stop, etc. The sections should not be under the influence of intersection or grade. Moreover, the sections should have uniform geometry. The selected survey locations had diverse traffic volumes, motor vehicle speeds, pedestrian crossflow and pedestrian behavioural characteristics. At some of the locations, zebra crossing was provided for pedestrian crossing. However, it was observed that vehicle drivers rarely gave way to pedestrians. Hence, the pedestrian road-crossing operation was the same as the undesignated pedestrian crossing section (Figure 1). Data collection was done at the locations without any designated crosswalks and those where crosswalks were present, but the road markings for crosswalks had completely faded and there were no traffic signs and signals informing the vehicular traffic of a crosswalk. This diverseness of pedestrian as well as vehicular characteristics is appropriate for obtaining a wide range of TTC values and is useful for developing the generic model.

Data collection

Data collection was done at the selected midblock sections using a videographic survey with the help of a camera of high resolution and magnification. The data were collected on a dry weather day from 7:00 am to 7:00 pm, which included morning and evening peak hours and off-peak hours to ensure the safety assessment of pedestrians at all possible vehicular and pedestrian flow sceneries. A camera was installed at a 15 m high vantage point to record the simultaneous movement of both vehicles and pedestrians. During the videographic survey, marking was done on the roadway at regular intervals to prepare the grid based on the real dimension (Figure 2 *b*).

Data extraction and trajectory plotting

To study pedestrian safety, it is necessary to study vehicle and pedestrian movement at the micro-level; hence, the trajectory approach was adopted in the present study. The trajectory data ensure an in-depth study of pedestrian–vehicle

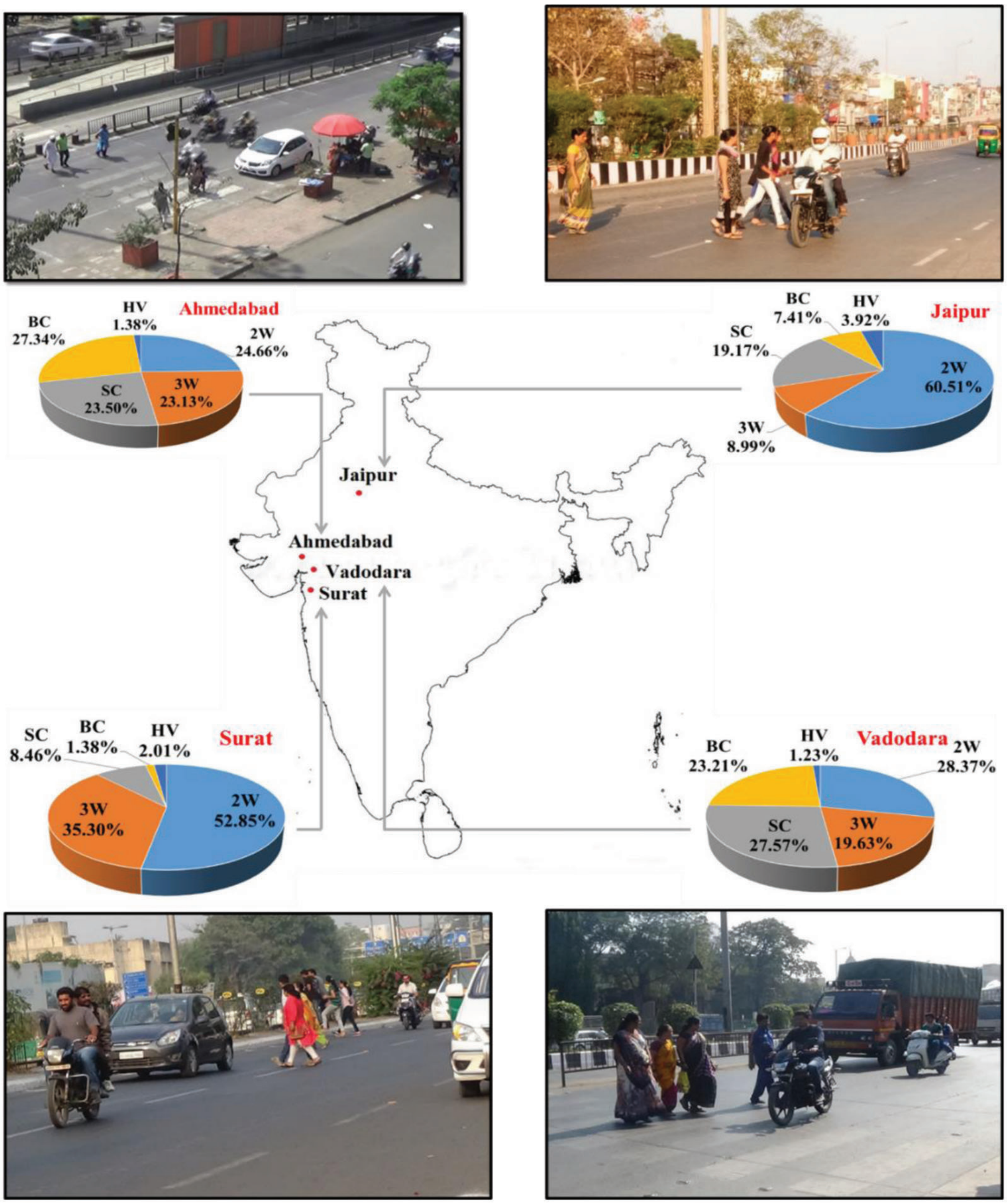

Figure 1. Interruption to vehicles due to crossing of pedestrians.

interactions to examine the safety of pedestrians. The trajectories of the crossing pedestrian(s) and approaching vehicles were plotted using a two-dimensional coordinates system. A grid of size 50 m × 10.5 m was generated using AutoCAD 2016 software by importing the study location image containing the markings done during data collection in the software (Figure 2 *a*). The size of blocks in the grid was kept 1.25 m × 1.25 m. The grid image was overlaid over the captured video using the Ulead Video Studio 11 software, so the grid accurately and exactly fitted over the study location video (Figure 2 *b*). The overlaid video was replayed on a large-screen monitor in the laboratory using AVIDEMUX 2.6. This software can convert every 1 sec of the video into 25 frames, i.e. capture a frame after every 0.040 sec. The exact position of a crossing pedestrian after every 0.48 sec in the grid was observed and recorded manually in an Excel sheet. The position of the interacting vehicles with the crossing pedestrian(s) during the crossing manoeuvre was accurately observed and noted. Utmost care was taken so that the timeline of the crossing pedestrian and vehicle position was kept the same by replaying the video several times for each interacting vehicle.

All the vehicles were classified into five categories (Table 1). There are several models of the same category of cars on Indian roads. Therefore, cars have been divided into two categories: small or standard cars (SC) and big

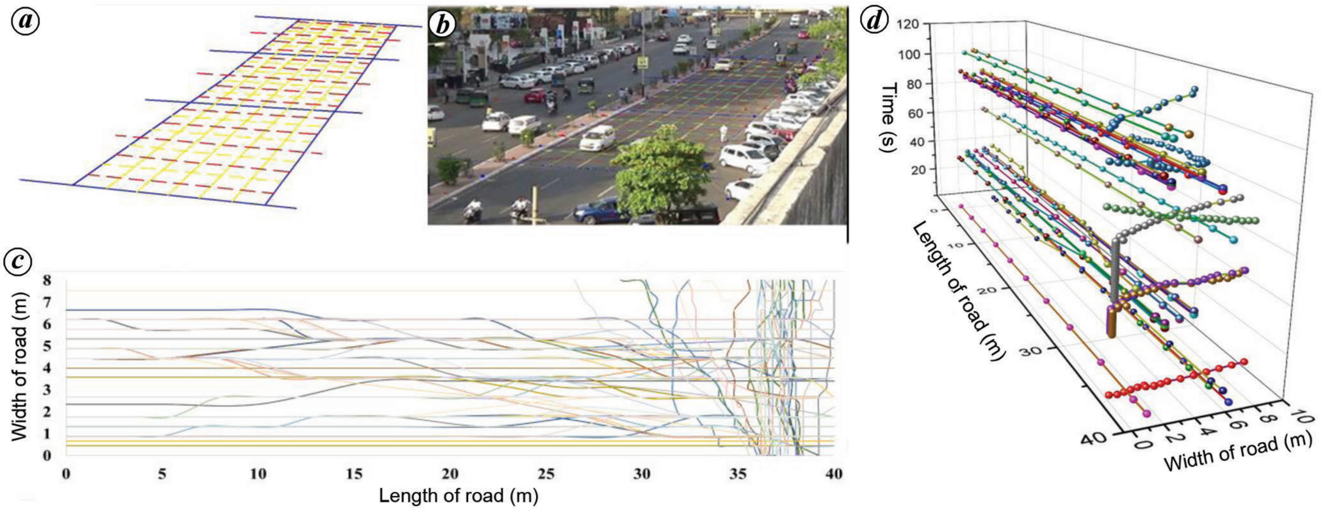

Figure 2. Trajectory and its plotting: (***a***) grid, (***b***) overlaid grid, (***c***) trajectories in the *X–Y* plane and (***d***) trajectories in the *X–Y–Z* plane.

Table 1. Category of vehicles with size

Vehicle type	Vehicles included	Length (m)	Width (m)	Rectangular plan area (m^2)
Two-wheeler (2W)	Scooter, motorcycle	1.87	0.64	1.20
Three-wheeler (3W)	Auto-rickshaw	3.20	1.43	4.48
Small car	Car	3.72	1.44	5.36
Big car	Big utility vehicle	4.58	1.77	8.11
Heavy vehicle (HV)	Standard bus	10.10	2.43	24.54

cars (BC). The classification of car was carried out according to their size and engine power (Table 1). The small car was categorized with engine power up to 1400 cc and the big car with an engine power of more than 1400 cc (Table 1)[53]. The average dimension of the vehicle was taken if more than one type was included in the same category (motorized two-wheelers (2W)).

Trajectory data of various interactions between pedestrian(s) and different vehicle categories were extracted for further analysis. From the extracted data, trajectories for the pedestrian and interacting vehicles were plotted. Figure 2 *c* shows the trajectories of pedestrian and vehicle movements at the section (without time). To plot these trajectories, the length of the grid (50 m) was taken on the *X*-axis and its width (10.5 m) on the *Y*-axis, while time was taken on the *Z*-axis (Figure 2 *d*). Figure 2 *d* shows a sample trajectory plot presenting the interaction of crossing pedestrians with different vehicles. The trajectories along the width of the road are pedestrian trajectories, whereas those along the length of the road are vehicle trajectories. The trajectories are expedient to understand the relative movement of crossing pedestrians and vehicles.

Computation of time to collision

In this study, TTC has been used as an SSM. A higher TTC value indicates a lower probability of conflicts on the contrary, a lower TTC value suggests a high probability of conflict. Thus lower TTC indicates unsafe condition of arising due to the risky or aggressive behaviour of a vehicle driver or pedestrian. To evaluate TTC, two cases were considered – VPF and PPF[7,29]. In the case of VPF, as shown in Figure 3 *a*, the vehicle reaches the theoretical conflict point first, crosses the point and in due course of time, the pedestrian arrives at the conflict point. Figure 3 *a* also indicates the PPF case in which the pedestrian reaches the conflict point before the vehicle.

All kinematic parameters were calculated using the trajectories data, where the conflicting vehicle was traced using a point marking system. However, in terms of collision analysis, vehicle geometry should be considered. At a definite time in the interaction process, the current state of the vehicle and the pedestrian can be defined by the vehicle speed (VS), pedestrian crossing speed (PS), vehicle distance to the conflict point (VDC) and pedestrian distance to the conflict point (PDC). VDC and PDC the distances of the vehicle and pedestrian must travel to reach the conflict point respectively. Initially, the central point of the front bumper of the conflicting vehicle is considered a reference point during the data extraction process. However, during conflict analysis, vehicle dimensions need to be considered. To analyse the effect of the physical dimensions of a vehicle in VPF and PPF cases, VDC and PDC were calculated (Figure 3 *b*).

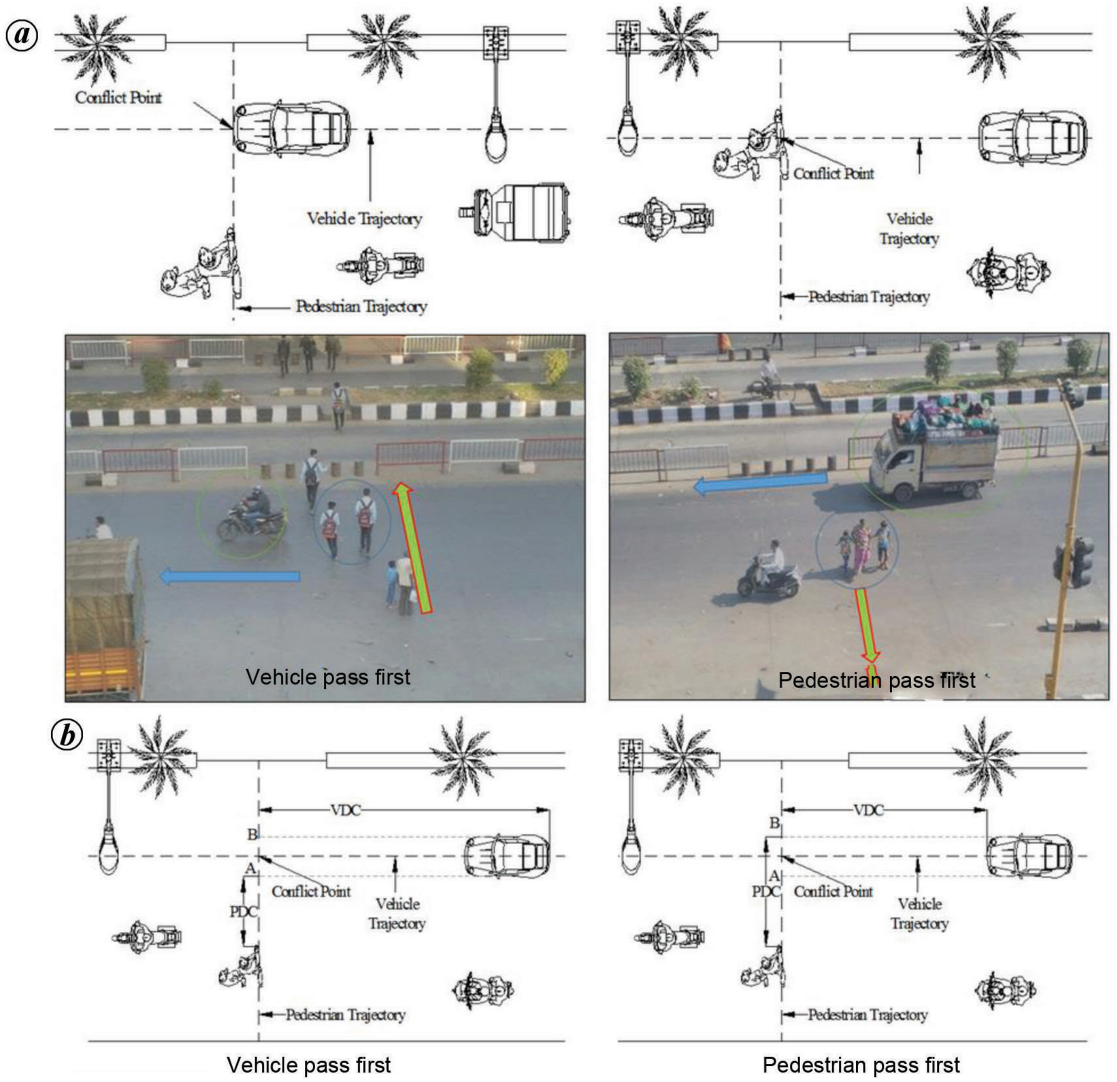

Figure 3. Types of interaction: (***a***) vehicle pass first (VPF) and pedestrian pass first (PPF); (***b***) vehicle distance to the conflict point (VDC) and pedestrian distance to the conflict point (PDC) calculation in VPF and PPF cases.

In the VPF case, conflict may occur before the pedestrian reaches the conflict point (when the pedestrian reaches point *A* in Figure 3 *b*) by the distance equal to the half-width of the conflicting vehicle. In addition, conflict may be possible until the entire length of the vehicle does not cross the conflict point. Hence, in the VPF case, PDC is considered up to point *A* and VDC is calculated by including the length of the vehicle (Figure 3 *b*). In the PPF case, conflict may be possible, even when the pedestrian crosses the conflict point (till the pedestrian does not cross point *B* in Figure 3 *b*). So, in the PPF case, PDC is measured up to point *B*.

TTC_{PED} and TTC_{VEH} are defined as the time required by pedestrian and vehicle respectively, to reach the conflict point if they both continue at the same speed. TTC_{VEP} and TTC_{PED} are estimated using (eqs (1) and (2)).

$$TTC_{VEP} = \frac{VDC}{VS}, \quad (1)$$

$$TTC_{PED} = \frac{PDC}{VS}. \quad (2)$$

TTC is defined as follows.

$$TTC = \{TTCP_{VEH},\ TTC_{VEH} \geq TTCP_{PED}\}, \text{ or}$$

$$TTC = \{TTCP_{PED},\ TTC_{VEH} < TTCP_{PED}\}. \quad (3)$$

For each interaction, TTC is estimated using eq. (3).

Analysis of TTC

In the present study, for analysis, all vehicles have been grouped into different categories. Figure 1 shows the traffic composition observed at the study locations. At most locations, the proportion of 2W is higher, while that of heavy vehicle (HV) is minimum at all locations. Figure 1

Table 2. Vehicle category-wise and gender-wise descriptive statistics of time-to-collision

Particulars	Type of interaction	Mean (sec)	Maximum (sec)	Minimum (sec)	Total	Standard deviation	Percentile values (sec) 15th	50th	85th
2W	VPF	3.41	21.97	0.18	8230	2.45	1.18	2.85	5.62
	PPF	3.08	20.65	0.17	4072	2.22	1.27	2.56	4.74
3W	VPF	3.6	18.36	0.15	4457	2.47	1.4	3.05	5.81
	PPF	3.51	18.200	0.22	2436	2.22	1.55	3.06	5.31
Car	VPF	3.69	20.18	0.12	1634	2.51	1.35	3.14	6.12
	PPF	3.21	17.54	0.27	873	1.91	1.53	2.86	4.91
HV	VPF	4.11	20.03	0.41	563	2.39	1.96	3.62	6.17
	PPF	3.67	19.30	0.52	288	1.99	1.98	3.41	5.08
Male	VPF	3.30	18.83	0.12	5464	2.34	1.15	2.78	5.41
	PPF	3.02	19.31	0.17	3211	2.16	1.21	2.56	4.63
Female	VPF	3.35	20.03	0.18	4078	2.21	1.26	2.95	5.34
	PPF	3.20	20.65	0.22	2230	1.94	1.41	2.82	4.96
Group	VPF	3.87	21.97	0.18	5342	2.73	1.43	3.20	6.51
	PPF	3.63	20.64	0.29	2228	2.41	1.60	3.10	5.44

VPF, Vehicle pass first; PPF, Pedestrian pass first.

also presents the vehicular and pedestrian flow observed in the study sections. As the sample size of BC is less, samples of BC are merged into SC for analysis purposes after the calculation of TTC.

It has been observed that the pedestrian interacts with several vehicles during the crossing manoeuvre. In such instances, he/she may have to wait due to an impending conflict with another vehicle or decide to be cautious and wait for a suitable opportunity. In such cases, it is observed that the pedestrian spends considerable time in the carriageway or at the fringe position. Although he/she ultimately reaches a conflict point shared by another vehicle, can it be called a conflict? The vehicle might have passed long before the arrival of the pedestrian(s). To avoid such instances and measure the risk with higher reliability, only those interactions are considered where the difference between the arrival time of the predecessor and successor in a conflict is less than 2.5 sec. The reason for selecting the limiting time of 2.5 sec is because if a pedestrian travels with an average crossing speed of 1.3 m/s, it will take him/her 2.5 sec to cross a lane of 3.3 m width, after which he/she might be interacting with other vehicles. The total TTC for all interactions has been worked out, fulfiling the above criteria.

The analysis has been carried out based on vehicle category and gender in both VPF and PPF cases. Table 2 shows the vehicle category-wise and gender-wise descriptive statistics of TTC in VPF and PPF. The variation in TTC values for VPF and PPF cases shows that the interaction behaviour between driver and pedestrian is different in both cases. In the VPF case, TTC is higher than PPF, indicating that pedestrians are at higher risk in the PPF-case compared to the VPF case. It can also be noticed from Table 2 that the TTC values are dependent on vehicle category. TTC is the least for 2W and highest for HV. TTC for 3W is higher than that for 2W and lower than that for cars. Thus, TTC increases with vehicle size. Field observations reveal that pedestrians mostly avoid crossing the road when HV is present in the traffic stream. Hence, few samples have been found at all study locations. Minimum TTC value ranges from 0.12 sec for the cars to 0.41 sec for HV in the VPF case, whereas in the PPF case, the minimum TTC value varies from 0.17 sec for 2W to 0.52 sec for HV. The maximum value of TTC ranges from 17.54 sec to 21.97 sec. It can be observed from Table 2 that the mean TTC value for males is least followed by females and the group in both VPF and PPF, which indicates that males take more risk than females. In the group, the TTC value is highest in both VPF and PPF cases, indicating that it is safer to cross the road in a group.

Figure 4 shows the box plot and cumulative frequency of TTC. Figure 4 *a* shows the variation of TTC in VPF and PPF conditions, whereas Figure 4 *b* and *c* shows such variation based on the vehicle class and pedestrian gender respectively. The TTC values are found to be higher in the VPF condition. From Figure 4, it can be confirmed that the TTC value is sensitive to vehicle class and increases with increase in the size of vehicles, as pedestrians perceive higher risk with large-sized approaching vehicles. Moreover, it can also be discerned that in both VPF and PPF cases, TTC is least for males and highest for the group.

Statistical distribution of TTC

TTC was fitted with three types of hypothesized distribution, and Kolmogorov Smirnov (K–S) and Anderson Darling (AD) tests were performed to determine the goodness of fit. General extreme value (GEV) distribution was found to be the best fit TTC in both types of interaction and as a whole dataset. The values of K–S statistics for VPF, PPF and the combined data were 0.0108, 0.0142 and 0.0015 compared to the critical values of 0.0111, 0.0155 and 0.0090 respectively. The K–S statistics values for all three cases were less than the respective critical values, indicating

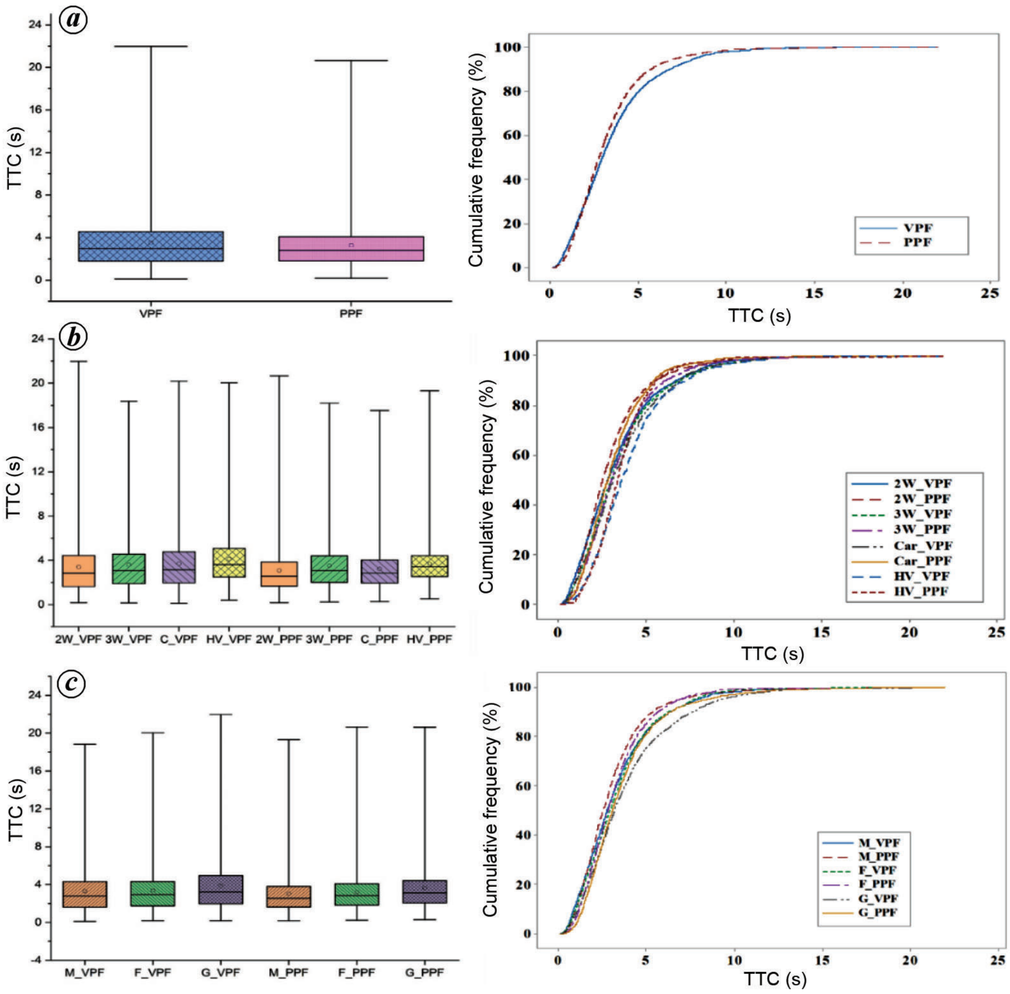

Figure 4. Box plot and cumulative distribution of time-to-collision (TTC) for: (***a***) VPF and PPF, (***b***) vehicle category and (***c***) pedestrian gender.

that TTC follows the GEV distribution. Similarly, the critical value in the AD test for VPF, PPF and overall data was 2.5018, which is higher than the AD statistics value of 1.904, 1.7422 and 1.3717 respectively. Hence, it can be concluded that TTC follows the GEV distribution.

Relationship between TTC, vehicle speed and pedestrian speed

The observed value of TTC was plotted against VS and PS to analyse the relationship among these parameters (Figure 5). The TTC showed a negative relationship with PS. Pedestrians require less time to reach a conflict point if PS increases. A negative logarithmic relationship was observed between TTC and PS. TTC decreased with an increase in VS, thus following a negative logarithmic trend.

Development of generalized linear model for TTC

The extracted trajectory data were used to calculate TTC along with different parameters like VS and PS. The other factors affecting TTC were also identified, such as gender of pedestrian, group of crossing pedestrians, type of interaction, including VPF and PPF, and vehicle category. These were taken as independent variables to develop the GLM model. The TTC value, VS and PS calculated at every 0.48 s (frequency of data extraction) were considered for the model development.

Totally 21,110 valid data were considered for analysis. seventy per cent of the data was used for model formation and the remaining 30% for validation. The GLM model was developed in R software (version 3.5.3). The proposed model for TTC is given in eq. (4).

$$\underset{(28.86)}{\text{TTC} = 0.802 \times \text{GEN}} + \underset{(7.78)}{0.155 \times \text{GRP}} + \underset{(22.81)}{0.543 \times \text{VEH}}$$

$$+ \underset{(30.34)}{1.140 \times \text{CON}} - \underset{(12.56)}{0.462 \times \text{PS}} - \underset{(11.29)}{0.0607 \times \text{VS}}, \quad (4)$$

where GEN is the gender of the pedestrian, which is a discrete variable (1 – male, 2 – female 3 – group), GRP the group size which is a discrete variable (1 – single, 2 – two,

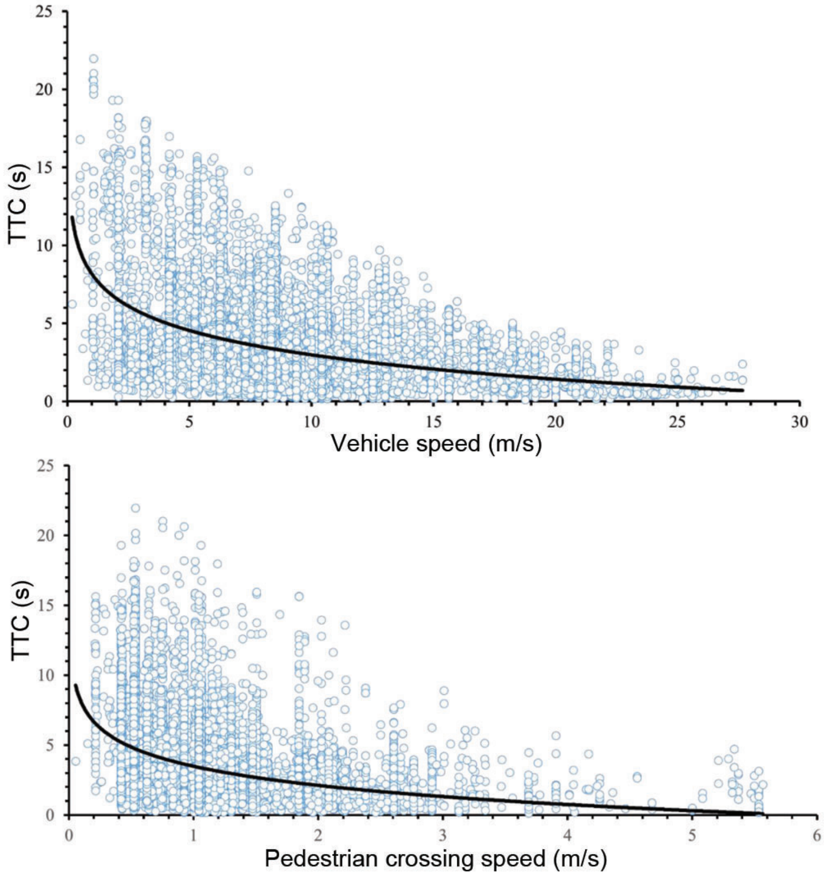

Figure 5. Variation of TTC with vehicle speed and pedestrian crossing speed.

3 – three, 4 – four, 5 – five and more than five), VEH the vehicle class which is a discrete variable (1 – 2W, 2 – 3W, 3 – car, 4 – HV), CON the conflict type which is a discrete variable (1 – VPF, 2 – PPF), PS the pedestrian crossing speed (m/s), which is a continuous variable and VS is the vehicle speed (m/s) which is the continuous variable.

For the developed model, Akaike information criterion (AIC) and Bayesian information criterion (BIC) were obtained as 69,421 and 69,474 respectively. The value of BIC was more than AIC, indicating the best fit of the model. In the developed model, the negative sign of VS and PS reveals that TTC decreases with increasing VS and PS. Similarly, the sign of gender, group, vehicle class and conflict type fits logically. In eq. (4), the t value of all coefficients is more than 1.96, which shows that all coefficients are significant at 95% confidence level.

Model validation

To assess the accuracy of the proposed model, TTC predicted by the model was compared with field-observed values. The data maintained model validation was used for this purpose. The input parameters for the proposed model were observed from the field data. The developed model was used to predict TTC based on input parameters. The predicted TTC values were compared with the TTC values calculated using trajectory data. In order to compare the two datasets, a t-test was carried out at 5% significant level with 6333 degrees of freedom for statistical validation. The test result showed that the t-statistics value (1.11) was less than the t-critical value (1.98) at 5% significant level. Hence, there was no statistically significant difference between the predicted and observed TTC values.

Clustering analysis of TTC

The TTC datasets were classified into different groups to identify the severity of conflict using the k-means clustering technique used by many researchers[54–59]. The clustering analysis was carried out using MATLAB. Classification in the MATLAB tool was conducted for different k-values, which resulted in two-cluster, three-cluster, four-cluster, five-cluster and six-cluster groups. Silhouette analysis was carried out to identify the optimum number of clusters for a given dataset range and variation. The silhouette value was calculated for TTC datasets and used to compare scenarios involving various clusters. Figure 6 shows the average silhouette values and silhouette plots for different clusters.

Based on the average silhouette value, two clusters were found optimum for the TTC dataset. Based on this result, the TTC value was classified into two clusters.

In the present study, TTC value has been estimated based on pedestrian–vehicle interactions with high to moderate risk for pedestrians. During data extraction, only pedestrian–vehicle interactions were considered. The same was verified by silhouette analysis. As the dataset was within the range of high to moderate risk two clusters, cluster-1 identifies pedestrians at high risk and cluster-2 specifies moderate risk of collision with pedestrians.

Based on cluster analysis, the threshold value was estimated, which implies the boundary between high risk to moderate risk of collision. Figure 6 shows that when TTC is less than 3.60 sec, the pedestrian is at high risk of collision.

Conclusion

In the present study, we have evaluated the safety of crossing pedestrians at urban midblock locations under mixed traffic conditions. TTC was taken as SSM for conflict analysis. For TTC measurement at any other location, traffic trajectory data are pivotal. Using traditional methods, trajectory data can be acquired from the field video data following the methodology used in the present study or using other methods[60,61]. Alternatively, an automated video analysis tool can also be used to extract SSMs like TTC more rapidly[10,62]. However, both approaches require analysis of traffic trajectory data for TTC estimation. The method and formula of TTC calculation are the same for both approaches.

The data were collected using a videographic technique from urban midblock sections influenced by crossing pedestrians at six-lane arterials. To assess TTC, the trajectory-based approach was adopted. Two different types of interaction, namely VPF and PPF were considered for analysis. More than 21,000 instances of interactions between pedestrians and vehicles were used. The TTC values are dependent on vehicle category and pedestrian gender. They increase with an increase in the size of vehicles. Moreover, TTC values of 2W were the least among all classes of vehicles, whereas those of HV were the highest. The statistical distribution of TTC showed that it followed a GEV distribution. TTC followed the decreasing logarithmic trend with PS and VS. GLM was proposed to predict TTC under mixed traffic conditions. The *k*-means clustering analysis was carried out to identify the classification of interaction in different categories for risk. The optimum number of clusters was identified using silhouette analysis. It was found that two clusters were optimum based on the silhouette value for the present data. Moreover, the threshold value for pedestrian–vehicle interactions was found to be 3.60 sec.

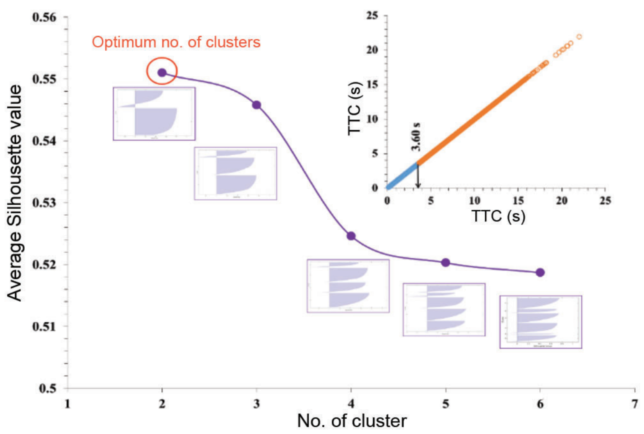

Figure 6. Silhouette analysis for optimum cluster and threshold value for TTC.

Contribution of the present study

The model developed in the present study is based on parameters that can be easily observed and quantified in the field. This reduces the dependability on traffic trajectory data for safety analysis. This study may be used to assess the safety of pedestrians at midblock crosswalks under mixed traffic conditions to improve the planning and design of traffic facilities in order to create a safe environment for vulnerable road users. Using the parameters observed in the field, TTC can be estimated using the model and real-time safety aspects measured. The parameters can be identified using traditional or modern intelligent transport system-based tools, gender of pedestrian, group size, vehicle class, speed of the vehicle, pedestrian speed and the resulting conflict type to measure TTC of the interaction at any other location. Additionally, the effect of different policies and their corresponding changes on the model parameters can be recorded to observe changes in TTC values and risk levels. This also provides robust and practical means to test the effects of different policies on the safety aspects of the traffic infrastructure.

Additionally, the present study assesses the surrogate safety aspects of pedestrian and vehicular interactions at designated and undesignated urban midblock crossings by overcoming the limitations of dependency on underreported crash data using a proactive approach[63,64]. Numerous studies have utilized TTC for the safety assessment of pedestrian and vehicular interactions. However, such studies are limited to the mixed traffic conditions observed in India. The present study helps bridge the literature gaps and provides a methodology for real-time proactive safety assessment.

Limitations and future scope

In the present study, limited trajectory data are used. The study can be evaluated using semi-automated and automated trajectory extraction tools. Further, only TTC as SSM is considered. The different SSMs can be evaluated and compared with the present study results. The models proposed in the present study can be incorporated into the infrastructure and vehicles-to-aid, vehicle-to-vehicle and vehicle-to-infrastructure communications for real-time safety analysis, driver assistance systems and collision avoidance systems. Based on the risk estimated using the model, measures and policies can be tested that support mitigation of risk levels in real time, thus enhancing the safety levels.

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