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Research Article

Modeling Crossing Conflicts at Unsignalized T-Intersections under Heterogeneous Traffic Conditions

Jaydip Goyani,[1] Ninad Gore,[2] and Shriniwas Arkatkar[1]

[1]*Department of Civil Engineering, Sardar Vallabhbhai National Institute of Technology, Ichchhanath, 395007, Surat, India*
[2]*Department of Civil Engineering, Toronto Metropolitan University (Formely, Ryerson University), Toronto, Canada*

Correspondence should be addressed to Shriniwas Arkatkar; sarkatkar@ced.svnit.ac.in

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The safety of unsignalized intersections is evaluated by correlating the number of crashes with traffic volume and intersection geometry. However, crash-based safety assessment has known drawbacks related to data quality and coverage. Further, the crash-based safety analysis does not account that not all vehicles interact unsafely. Therefore, the present study develops crossing conflict-based safety performance functions (C-SPFs) for eight urban unsignalized T-intersections with varying intersection geometry. Initially, the crossing conflicts were analyzed using post encroachment time (PET); based on that, they are bifurcated into critical and noncritical conflicts. The C-SPFs were modeled as a function of traffic volume and intersection geometry using the generalized estimating equations with the Tweedie distribution (GEE_TD) regression approach. The results revealed the time of the day, intersection geometry, vehicular composition, and traffic volume of both offending and conflicting approaches as significant variables influencing the number of critical and noncritical crossing conflicts. Further, to check the predictive power of the GEE_TD model, the model errors are compared with those obtained using the negative binomial (NB) model. The result revealed that for both critical and noncritical conflicts, the GEE_TD model has better predictivity (lesser error) than the NB model.

1. Background

Traffic safety is an emerging concern in the developing world because it affects a nation's economy and people's welfare. Providing reliable and safe transportation is one of the main goals of federal, state, and local agencies. Meanwhile, traffic safety is evolving as an area of increased attention and concern in many countries, including India; various countermeasures are being practiced/planned worldwide to increase traffic safety. The World Health Organization [1] reported that around 1,350,000 people die annually from traffic crashes. Over the year, researchers have developed models to understand the causal factors influencing safety and implement safety-based countermeasures. In developing countries like India, most intersections along urban arterials are uncontrolled and unsignalized, and they pose significant safety implications in terms of conflicts and interactions. As per the Ministry of Road Transport and Highways [2], 27% of crashes were recorded near the vicinity of road intersections [2]. In the last five calendar years (2014 to 2019), T-intersections added to India's highest percentage of crashes and fatalities [3]. These figures explain the severity of traffic conflicts at uncontrolled intersections, mainly in India. Thus, it is imperative to assess the prevailing level of safety, especially at unsignalized T-intersections.

Traditional traffic safety evaluation methods are based on past crash data where safety is measured using different statistical methods for traffic crashes. This crash data approach is observed as a reactive approach, suggesting that a significant number of crashes must be recorded to assess a particular traffic safety measure. The shortcomings of this approach include (a) low quality and unavailability of crash data in developing countries like India, and (b) the crash-based safety analysis does not explicitly account that all the vehicles in the stream interact unsafely. Hence, the crash-based safety analysis is ethically impartial to countermeasures until the crash occurs. To overcome this drawback, researchers and transportation engineers mostly use proactive traffic safety measures such as traffic conflicts to define critical highways and urban road locations. Traffic conflict is "an observable situation in which two or more road users approach each other in time and space to the extent that there is a risk of collision if their movements remain unchanged" [4]. The traffic conflicts are analyzed using different surrogate safety measures (SSMs). These include post encroachment time (PET), time to collision (TTC), deceleration to avoid a crash (DRAC), the proportion of stopping distance (PSD), and time-integrated TTC (TIT). The SSMs project road user's temporal and spatial closeness to crashes or possible collision points. Researchers and practitioners have applied the SSMs to assess traffic and pedestrian safety at intersections and midblock sections.

The crossing conflicts are the significant conflict movement, and PET is the most suitable proximal safety indicator to evaluate the safety at unsignalized intersections [5–8]. Goyani et al. [6] found that traffic volume, vehicular composition, and intersection geometry significantly affect the probability of critical crossing conflicts (PCCC). 10-15% reduction in PCCC was observed for unsignalized T-intersections with Central Island compared to those without Central Island. Further, they reported an average 10% reduction for intersections with a larger Central Island diameter than intersections with a smaller diameter of Central Island. Zheng and Sayed [9] used two indicators, modified time to collision (MTTC) and PET, to define the traffic conflicts. The result reveals that traffic volume significantly affects PET value as the traffic volume varies and the number of conflicts changes. Ulak et al. [10] found that risk perception significantly affects driving behavior, traffic safety, and performance. Katrakazas et al. [11] indicate that conflicts are significantly higher in congested traffic and fewer during free-flow traffic conditions. Further, they found that the number of conflicts increases as the percentage of heavy vehicles increases.

Trinh et al. [12] developed the conflict-solving model using the two-player game theory to reduce head-on motorcycle conflicts in heterogeneous traffic conditions. The developed model is useful for identifying head-on collisions and taking safety precautions to reduce conflicts at signalized and unsignalized intersections. Muley et al. [13] used a microsimulation to analyze the number of conflicts. They reported that the potential location of conflicts could be identified to assess the impact of geometric improvement in reducing potential conflicts. Qu et al. [14] revealed that the traffic conflicts for congested traffic states are significantly higher, which results in a nonlinear feature for combined traffic states. El-Basyouny and Sayed [15] used the lognormal regression technique-based conflicts model to show that traffic conflicts vary with traffic volume and geometric-related variables. Islam et al. [16] show that hourly-simulated conflicts significantly affected an hourly crash count. The increasing presence of nonmotorized vehicles in the traffic stream contributed to fewer conflicts and crashes. This study is helpful for non-lane-based heterogeneous traffic streams prevalent in urban intersections.

Guo et al. [17] indicated that the traffic conflict rate depends on traffic volume, queue length, shock wave speed, and platoon ratio. The results revealed a higher conflict rate associated with shock-wave characteristics, higher traffic volume, and lower conflict rates related to a higher platoon ratio. Li and Lam [18] generated an algorithm for conflict-free scheduling, which offers possible ways to minimize total delay in the scheduling process. The simulation results verified that the scheduling algorithm efficiently resolves navigational traffic conflicts in seaport situations. Zhang et al. [19] used a negative binomial regression model to identify left-turn conflicts at signalized intersections. They concluded that the effects of conflicting traffic volumes on the number of conflicts vary across different traffic conditions. Guo et al. [20] study a collision-based before-after (BA) analysis using a Poisson-lognormal intervention (PLNI) model and the conflict-based BA analysis by an extreme value theory (EVT). The results revealed a reduction of 56% in actual collisions from the PLNI model and a reduction of 64% in estimated collisions from the EVT model.

Ding et al. [21] developed a crash prediction model for fatal and severe injury crashes using the augmented variational autoencoder technique to resolve the problem related to the imbalance of crash data. The results revealed that road length, traffic flow, intersection density, and the number of lanes positively correlate with fatal and severe injury crashes, whereas lane width and the speed limit negatively correlate with fatal and severe injury crashes. Similarly, Cai et al. [22] used the deep convolutional generative adversarial network (DCGAN) model to capture the effects of traffic on the crash frequency. The results revealed a significant effect of the speed difference between the upstream and downstream locations on crash frequency. Based on these results, highway authorities could plan to implement some traffic management strategies such as variable speed limits and dynamic message signs. Yu et al. [23] used a convolutional neural network (CNN) modeling technique with superior loss functions for real-time crash risk analyses. The authors plotted the distributions of predicted probabilities for balanced and imbalanced data to distinguish the effects of the imbalanced data. The results revealed that the CNN model with focal loss function enhances the model accuracy.

1.1. Study Motivation. Several studies have developed a traffic conflicts model for unsignalized intersections. To the best of the author's knowledge, no studies have tried to model crossing conflicts at unsignalized T-intersections under varying traffic conditions like in India. The traffic situation in developing countries is characterized by a mix of vehicle types that include motorized vehicles such as motorized two-wheelers (2w), auto-rickshaw (3w), cars, trailers, trucks, buses, and nonmotorized vehicles such as bicycles, animal-driven carts, and tricycles [24, 25]. These vehicles have varying physical dimensions, maneuvering abilities, and other static and dynamic properties, resulting in unsynchronised and erratic movement along the road. The sharing of the road by such a heterogeneous mix of vehicles coupled with the absence of proper lane markings and lane discipline (which replicates driver's noncompliance) forms another peculiarity of the mixed traffic conditions, making traffic movement a rather haphazard and complex phenomenon [26]. The mixed traffic flow affects traffic safety because of

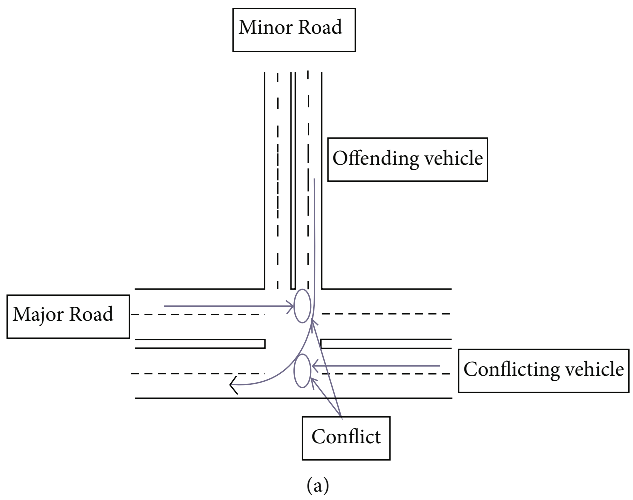


FIGURE 1: Crossing conflicts movement between the offending and conflicting vehicle (a) minor to major (b) major to minor.

complex interactions among various vehicle types. With an indiscriminate mix of vehicles, it is expected that vehicular composition would significantly affect the number of traffic conflicts in conjunction with traffic volume. However, no studies have considered vehicular composition a significant variable for modeling the number of traffic conflicts. Moreover, traffic conditions in India vary significantly compared to those observed in other countries. Therefore, the developed conflicts-based C-SPFs cannot be directly applied to traffic conditions in India to analyze the prevailing level of safety. Observing the variation in the number and type of conflicts is critical to comprehending safety conditions in traffic. With this motivation, the present study aims to develop the crossing conflict models as a function of traffic flow and intersection geometry-related characteristics. The major contribution of the present study is that it explicitly quantifies the effect of heterogeneity in traffic volume on the number of crossing conflicts. The developed conflict models can enable traffic engineers and city planners to identify the critical intersections in terms of crossing conflicts. Therefore, it might help develop strategies to improve safety at unsignalized T-intersections in India.

1.2. Definition. For ease of understanding, the term and their corresponding definition used in the present study are as follow:

(1) Offending vehicle. “Vehicles taking right-turn from the Major road or Minor road and merging into the Minor road or Major road.”

(2) Conflicting vehicle. “Vehicles perform the straight movement on the Major road.”

(3) Post encroachment time (PET). “Two road users is described as the time from the instant when the first road user leaves the conflict area until the second road user reaches it” [27]

(4) Critical conflicts. “The conflicts with PET values between -1 s to 1 s are known as critical conflicts. The threshold of PET value for classifying the critical conflicts is considered based on a past piece of study” [5, 6, 28, 29]

(5) Noncritical conflicts. “The conflicts with PET values other than 1 s (greater than 1 s and less than 6 s or less than -1 s and greater than -6 s) are known as non-critical conflicts.”

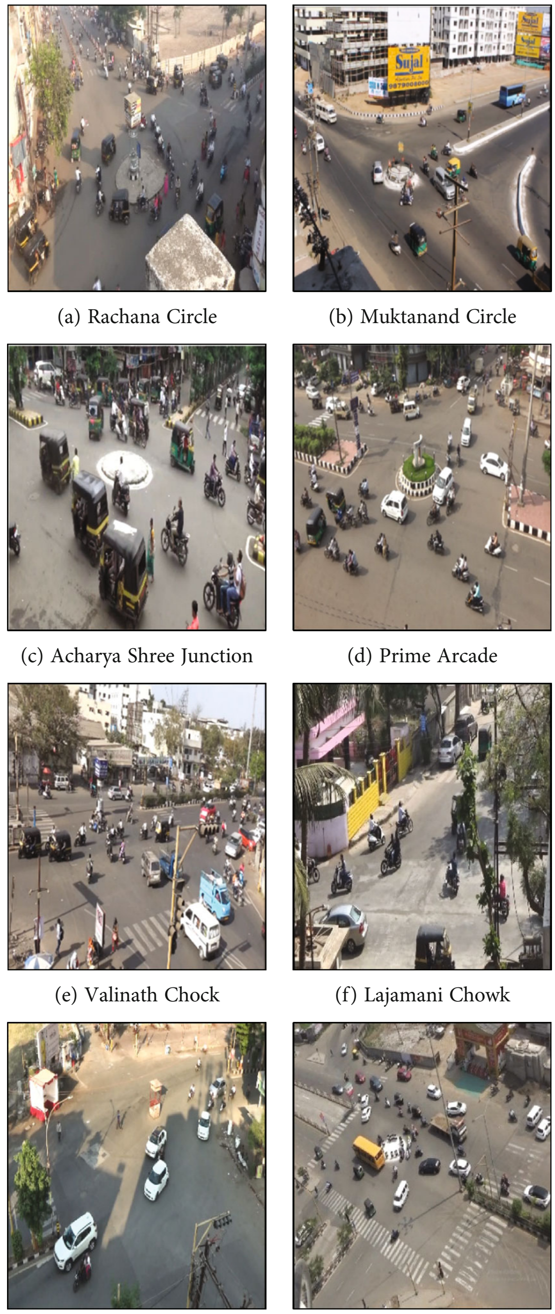
Figure 1 shows a graphical representation of crossing conflict at an unsignalized T-intersection.

2. Study Methodology

2.1. Data Overview. For the present study, eight urban unsignalized T-intersections viz. Rachana Circle (21°12′ 46.59″ N, 72°52′03.61″ E), Muktanand Circle (22°19′ 14.87″ N, 73°11′50.91″ E), Acharya Shree Junction (21°10′ 19.4″ N, 72°50′11.4″ E), Prime Arcade (21°12′08″ N, 72°47′39″ E), Valinath Chock (21°13′26.09″ N, 72°49′ 17.66″ E), Lajamani Chowk (21°14′19.59″ N, 72°53′20.37″ E), Poddar Arcade (21°12′27.44″ N, 72°50′38.03″ E), and Khatushyam Junction (21°08′39.43″ N, 72°47′56.88″ E) having different intersection geometry like, with or without Central Island were selected. The snapshots of the particular selected T-intersection are shown in Figure 2.

The intersection area and the width of each approach leg were measured by conducting field surveys. This was done during free-flow environments with the help of traffic police. The collected road inventory details for the selected study sites are summarized in Table 1. Traffic data from morning 09:00 AM to evening 08:00 PM were collected using the video-graphic technique under ideal/fair weather environments by placing a high-definition (HD) video camera on top of the high-rise building near the vicinity of the particular intersections to serve as a vantage point to capture traffic movement precisely in all traffic directions.

2.2. PET Data Extraction. In the absence of a reliable automatic traffic data extractor, classified vehicle count and



(a) Rachana Circle (b) Muktanand Circle (c) Acharya Shree Junction (d) Prime Arcade (e) Valinath Chock (f) Lajamani Chowk (g) Poddar Arcade (h) Khatushyam Junction

FIGURE 2: Snapshots of the study sections (a) S-1, (b) S-2, (c) S-3, (d) S-4, (e) S-5, (f) S-6, (g) S-7, and (h) S-8.

vehicle-based PET were extracted manually from the recorded video using the AVS data extractor software with an accuracy of 33 milliseconds. To extract the PET data manually, around 80 hours for one intersection (640 hours for all eight intersections) is spent. Further, the data were extracted by one person to minimize human error in extracting the PET data. Using the AutoCAD 2020 software, a grid of 3.5×3.5 m was drawn and overlaid on the particular video file using Corel Video Studio 12 software. The procedure for extracting PET from the video file is shown in Figure 3. The PET is computed using the following:

$$PET = T2 - T1, \tag{1}$$

where $T1 =$ time when the offending road users leave the conflict area; $T2 =$ time when the conflicting road users enter the conflict area.

Due to right-hand driving conditions in India, right-turning (R-T) movements form crossing conflicts and vice versa. The PET value was evaluated only for R-T

Table 1: Road inventory details.

Intersection name	Intersections geometry	Diameter of Central Island (m)	Number of lanes in approaches		Width of the lane (m)		Median width (m)
			Major road	Minor road	Major road	Minor road	
Rachana circle (S-1)	Divided with Central Island	6.7	2	2	3.5	3.5	1.25
Muktanand circle (S-2)		5.4	2	2	3.5	3.5	1
Acharya Shree junction (S-3)	Divided without Central Island	—	2	2	3.5	3.5	1.2
Prime arcade (S-4)		—	2	2	3.5	3.5	1.2
Valinath chock (S-5)	Divided with Central Island	2.25	2	2	3.5	3.5	1
Lajamani chowk (S-6)		2.8	2	2	3.5	3.5	1.4
Poddar arcade (S-7)	Divided without Central Island	—	2	2	3.5	3.5	1
Khatushyam junction (S-8)		—	2	2	3.5	3.5	1.2

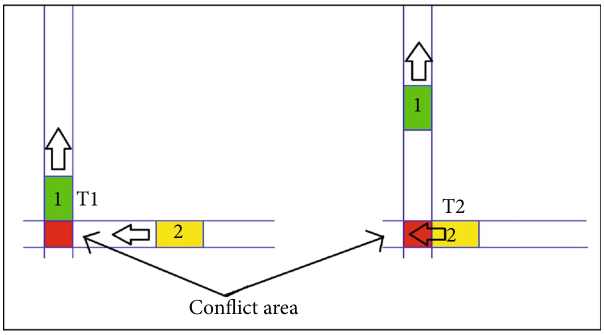


Figure 3: Methodology to extract PET values [T2 – T1 = 0 (Crash), T2 – T1 = >0 (Positive PET), T2 – T1 = <0 (Negative PET)].

movements. Conflicts related to PET values between −6 s and+6 s were selected for the detailed analysis. The threshold for PET values greater than 6 s and lesser than −6 s will be considered because there was less chance of a near-crash, and the driver has enough time to take evasive actions [30]. It was also observed that there might be the possibility to be more than one value of PET (refer to Figure 1) for one observed vehicle. Thus, the minimum PET value is considered for detailed analysis [5, 6, 31]. Further, as shown in Figure 3, positive and negative PET values were observed. A negative PET value implies that the offending vehicle will conflict with the conflicting vehicle's front end. On the other hand, a positive PET value would indicate an offending vehicle conflict with the conflicting vehicle's rear end.

2.3. Modeling Technique. A generalized estimating equation (GEE) models longitudinal or clustered data. It is frequently used when the collected sample is a count data and nonnormal distributed. A GEE is used for estimating the variables of a generalized linear model (GLM) with a probable unknown relationship between results and outcomes. A variables estimation from the GEE is reliable even when the covariance structure is miss specified under mild regularity conditions. Therefore, the present study develops a GEE model for crossing conflicts at unsignalized T-intersections. The GEE procedure is a multinomial analogy of a quasi-likelihood function, extending the GLM. The GLM transforms categorical variables to meet the assumptions of continuity and normality [32, 33]. The GLM can be expressed as:

$$g(u_i) = \beta_i X_i, \tag{2}$$

where $u_i = E(y_i) = g^{-}(\beta_i X_i).g()$ is a link function, which shows the categorical variable by a linear mixture of explanatory variables. $g()$ normally takes an identity, a logit, or a log for continuous, categorical, and count dependent variables.

The present study assumed that Tweedie distribution (TD) is a part of the GLM. The TD plays a major role in GLM since it contains special cases like the normal, Poisson, gamma, and inverse Gaussian. The TD offers an integrated framework to model overdispersed (variance greater than the mean), underdispersed (variance lesser than the mean), zero-inflated (more zeroes than expected), and count data, as well as multiple response variables. The TD is a particular case of an exponential distribution. Therefore, in the present study, the generalized estimation equation with the Tweedie distribution (GEE_TD) regression technique is used for developing a crossing conflict-based C-SPFs as a function of intersection geometry, traffic volume, and vehicular composition.

Let Y_i be the number of crossing conflicts at an intersection for a given time interval and follow the Poisson distribution defined by a single parameter λ_i, as shown in in the following:

$$Y_i \sim \text{Poisson}\,(\lambda_i). \tag{3}$$

Under the Poisson-Tweedie class of model, the Poisson mean parameter follows the Tweedie distribution as shown in the following:

$$Y_i \sim \text{Tw}_p(\mu_i, \phi_i), \tag{4}$$

where $\mu_i > 0$ is the mean parameter, $\phi_i > 0$ is the dispersion parameter, and p indicates the Tweedie power parameter.

The mean and the dispersion parameter can be modeled as a function of covariates. The flexibility of the Tweedie distribution lies in p, which includes positive real number values. The relationship between the mean and variance of the Poisson-Tweedie model is given in the following:

$$\text{Var}(Y_i) = \mu_i + \phi_i * \mu_i^p. \tag{5}$$

The model should not lead to a negative number of crossing conflicts and should predict zero conflict values for zero values of the exposure variable. The commonly used model form consists of an exponential function for including the covariate effect on the dependent variable. In addition, the logarithm link function can be linearized in the model [34]. Statistically, the conflict model is represented as follows:

$$\ln\,(Y_i) = \beta_0 + \beta_1 * X_{i1} + \cdots . + \beta_m * X_{\text{im}}, \tag{6}$$

where $\ln\,(Y_i)$ = predicted number of crossing conflicts; X_{i1}, X_{im} = covariates representing traffic and intersection-related characteristics; $\beta_0, \beta_1, \beta_m$ = model parameters.

The GEE_GLM is estimated by a quasi-likelihood function, as shown in the following:

$$\sum_{i=1}^{N} D_i V_i^{-}(y_i - u_i), \tag{7}$$

where $V_i = \sigma^2[(1-\rho)I + \rho I]$ is a covariates matrix; I is an $N \times N$ identify matrix. J is an $N \times N$ matrix, all of whose elements are 1. ρ is the correlation coefficient between independent and dependent variables.

The present study developed separate models for critical and noncritical conflict. The number of crossing conflicts (critical and noncritical) was computed for 5-minute data aggregation intervals and converted to equivalent hourly

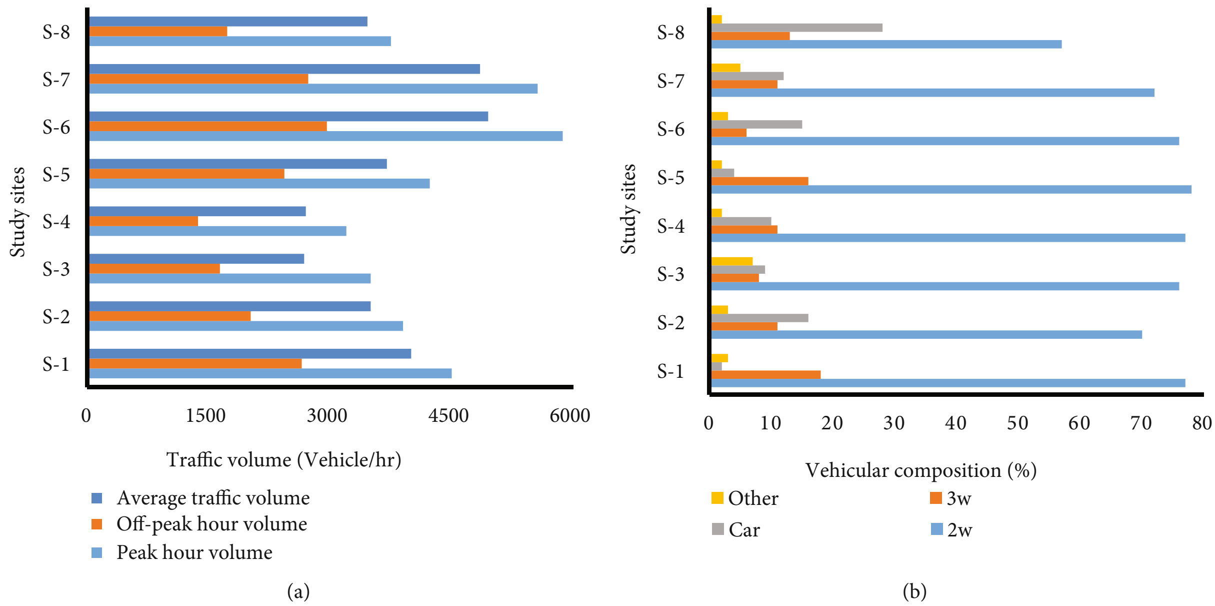


Figure 4: Traffic data overview (a) traffic volume (b) vehicular composition.

conflict rates for developing the conflict model. PET values between (−1 to 0 and 0 to 1) seconds were considered one domain known as critical conflicts. The conflicts with PET values other than 1 s (greater than 1 s and less than 6 s or less than −1 s and greater than −6 s) were termed noncritical conflicts [5, 6, 26].

3. Results and Discussion

3.1. Primary Analysis. A two-hour traffic volume, one hour of off-peak (10:00 to 11:00 AM), and one hour of peak (06:00 to 07:00 PM) were used for the detailed analysis. Majorly four vehicle classes are observed in the study sites, viz., motorized two-wheelers (2w), auto-rickshaw (3w), car, and other (LCV, Bus, and Truck). The traffic volume for an offending and conflicting stream and their vehicular composition were aggregated at a 5-minute data aggregation interval. The traffic volume was also converted to equivalent hourly traffic volume, as shown in Figure 4(a). The total vehicular composition comprising both offending (R-T) vehicles and conflicting (through) vehicles is shown in Figure 4(b).

3.2. Descriptive Statistics of PET Data. The descriptive statistics of the PET dataset for each selected study site by approach leg are summarized in Table 2. A significant variation in the mean and standard deviation of PET values was noted by both approach legs (L1 and L2) for a selected study site. This recommends that risk is different when a major or minor vehicle performs a right-turn to merge into the traffic stream. Further, a significant variation in PET values can be noted between the selected study sites and approach leg, highlighting the combined effect of traffic flow characteristics (traffic volume and composition) and intersection geometry. The higher mean of PET value indicates lesser conflicts and, consequently, lesser risks and vice versa.

4. Model Calibration

For the present study, the crossing conflicts at eight urban unsignalized T-intersections were modeled using the GEE_TD regression approach. The GEE_TD model with a power parameter value of 1.5 and a log-link function was adopted for modeling crossing conflicts. The dispersion or scale parameter was estimated as a function of observed covariates. In the present study, two different models, (a) the critical conflict model and (b) the noncritical conflict model, were developed using a set of independent variables (traffic volume, vehicular composition, and intersection geometry). The descriptive statistics of the dependent and independent variables are summarized in Table 3.

The quasi-likelihood criterion (QIC) was used to measure the goodness-of-fit of the developed model. The different correlation structures were selected for the present study, like independent, exchangeable, and unstructured, for modeling crossing conflicts. Results revealed that the exchangeable matrix has a lower QIC value. Therefore, an exchangeable correlation structure was adopted to develop the GEE_TD model. The model summary and corresponding goodness-of-fit measures are presented in Table 4.

Table 4 shows that the traffic volume of both offending and conflicting streams significantly affects the number of crossing conflicts, either critical or noncritical. With an increase in the traffic volume of the offending stream, the number of critical and noncritical conflicts increases. On the other hand, with an increase in the traffic volume of the conflicting stream, the number of critical crossing conflicts increases, whereas the number of noncritical conflicts decreases. This can be attributed to the fact that the gap in the traffic stream decreases at higher traffic volume. As a result, the drivers of the offending stream roll over smaller gaps, resulting in smaller PET and, thus, a higher number of critical conflicts. At higher traffic volume, the increase in

Table 2: Descriptive statistics of PET data.

Study site	Movement	Mean	Median	Mode	Standard deviation	Standard error
S-1	L1	0.06	-0.30	0.37	1.87	0.04
	L2	0.60	0.43	0.17	2.10	0.06
	Combine	0.28	0.07	0.37	1.99	0.04
S-2	L1	0.60	0.33	-0.53	1.95	0.06
	L2	0.10	0.10	-0.37	2.09	0.07
	Combine	0.39	0.23	-0.37	2.02	0.04
S-3	L1	0.99	0.60	-1.47	2.11	0.07
	L2	1.19	1.33	3.20	2.39	0.11
	Combine	1.05	0.88	3.20	2.26	0.06
S-4	L1	-0.50	-0.64	-0.68	1.84	0.07
	L2	-0.12	-0.28	0.72	1.87	0.11
	Combine	-0.38	-0.52	0.72	1.86	0.06
S-5	L1	0.69	0.44	0.27	1.62	0.07
	L2	0.41	0.16	0.15	1.56	0.06
	Combine	0.53	0.25	0.27	1.59	0.04
S-6	L1	0.12	0.17	-0.50	1.84	0.06
	L2	0.01	-0.12	-0.42	1.78	0.07
	Combine	0.12	0.17	-0.50	1.80	0.06
S-7	L1	-0.56	-0.72	0.13	1.84	0.05
	L2	-0.34	-0.48	0.25	1.80	0.05
	Combine	-0.45	-0.48	0.13	1.83	0.04
S-8	L1	-0.67	-0.54	-2.21	1.90	0.06
	L2	-0.51	-0.21	0.29	1.56	0.07
	Combine	-0.61	-0.37	-2.21	1.79	0.05

Note: L1 = minor road where vehicles are taking right-turn to merge into the major road traffic stream. L2 = major road where vehicles are taking right-turn to merge into the minor road traffic stream.

Table 3: Descriptive statistics of selected variables.

Variable	Type of variable	Levels and coding	Minimum	Maximum	Average	Standard deviation
Critical conflicts (conflicts/hr)	Continuous		96	1284	396	188
Noncritical conflicts (conflicts/hr)			108	1140	454	229
2w C (%)			38	92	72	8
3w C (%)			0	45	13	7
Car C (%)			0	35	12	7
2w O (%)			41	100	70	11
3w O (%)			0	43	11	8
Car O (%)			0	42	14	10
Conflicting volume (vehicle/hr)			960	6588	2914	1188
Offending volume (vehicle/hr)			228	2268	855	393
Intersection geometry	Categorical	0 without Central Island 1 with Central Island		0: 49% of samples 1: 51% of samples		
Time of the day		0-off-peak 1- peak hour		0: 30% samples 1: 70% samples		

Note: Critical and noncritical conflicts per hour, 2w C, 3w C, and Car C = 2w, 3w, and car composition in conflicting approach (%), 2w O, 3w O, and Car O = 2w, 3w, and car composition in offending approach (%).

Table 4: Model summary.

Type of model	Variables	Coefficients	Standard error	p value
Critical conflict model	Intercept	4.738	0.919	≤0.001
	[off-peak]	-0.130	0.013	≤0.001
	[peak]	0^a		
	[with Central Island]	-0.084	0.038	≤0.005
	[without Central Island]	0^a		
	2w C	0.012	0.010	≤0.005
	3w C	0.014	0.008	≤0.010
	Car C	0.017	0.007	≤0.005
	2w O	-0.009	0.006	≤0.010
	3w O	-0.005	0.007	≤0.005
	Car O	-0.009	0.007	≤0.010
	CV	0.000065	0.001	≤0.001
	OV	0.001	0.007	≤0.001
	(scale)	0.802		
	P	1.5		
	QIC		*203.93*	
Noncritical conflict model	Intercept	8.828	0.565	≤0.001
	[off-peak]	-0.081	0.031	≤0.001
	[peak]	0^a		
	[with Central Island]	-0.143	0.020	≤0.001
	[without Central Island]	0^a		
	2w C	-0.043	0.007	≤0.001
	3w C	-0.042	0.007	≤0.001
	Car C	-0.040	0.009	≤0.001
	2w O	0.008	0.003	≤0.001
	3w O	0.004	0.005	≤0.010
	Car O	0.012	0.004	≤0.005
	CV	-0.000085	0.007	≤0.001
	OV	0.001	0.004	≤0.001
	(scale)	0.651		
	P	1.5		
	QIC		*156.13*	

Note: Off-peak/peak = times of the day (hours), with/without Central Island = intersection geometry, CV = conflicting volume (vehicle/hr), OV = offending volume (vehicle/hr), QIC = quasi – ikelihood criterion, and a = Set to zero because this parameter is redundant.

critical conflicts would decrease the number of noncritical conflicts. The effect of traffic volume on crossing conflicts is in line with the observations reported by [15, 35–37].

The number of critical conflicts increases as the proportion of 2w, 3w, and cars increases in the conflicting stream. Lighter vehicles like 2w, 3w, and cars exhibit aggressive driving behavior (maintain lesser relative distance at higher speeds and sudden acceleration/deceleration characteristics). Further, the driver's poor yielding behavior forces drivers of the offending stream to accept and roll over smaller gaps. As a result, the number of critical conflicts increases. On the other hand, if the proportion of 2w, 3w, and cars increases in the offending stream, the number of noncritical conflicts increases. This can be attributed to the fact that the drivers in the offending stream force the drivers in the conflicting stream to decelerate; as a result, the corresponding PET value increases, thereby increasing the number of noncritical conflicts.

Intersection geometry significantly affects the number of critical and noncritical crossing conflicts. The results revealed less critical and noncritical crossing conflicts for urban T-intersections with Central Island than intersections without Central Island. This can be attributed to the presence of Central Island, which causes the drivers to weave through the conflict area. As a result, the number of crossing conflicts (critical and noncritical) decreases. A 25-41% reduction in critical and noncritical conflicts can be observed for similar traffic volumes for intersections with Central Island compared to those without Central Island. Therefore, intersection geometry significantly affects traffic safety and traffic operation. The observation is consistent with those reported by [6, 38]. Time of the day also

Table 5: Model error for the study site.

Study sites	GEE_TD (NB)					
	MAPE		RMSE		MPE	
	Critical conflict	Noncritical conflict	Critical conflict	Noncritical conflict	Critical conflict	Noncritical conflict
S-1	3 (20)	16 (16)	31 (119)	126 (172)	-1 (-19)	15 (-3)
S-2	13 (13)	10 (10)	69 (71)	83 (84)	-4 (-5)	2 (2)
S-3	13 (13)	14 (13)	63 (64)	47 (45)	9 (9)	-12 (-11)
S-4	10 (10)	13 (12)	52 (52)	57 (56)	3 (3)	-2 (-2)
S-5	24 (29)	12 (12)	68 (72)	71 (72)	-26 (-23)	9 (9)
S-6	26 (30)	20 (19)	64 (65)	60 (59)	-19 (-17)	-13 (-11)
S-7	19 (19)	18 (21)	90 (91)	71 (71)	1 (2)	-9 (-8)
S-8	11 (11)	14 (13)	43 (42)	57 (56)	-2 (-2)	-7 (-6)

Note: Parenthesis () indicates the NB model error.

significantly affects the number of critical and noncritical conflicts. Fewer crossing conflicts were observed for off-peak hours than peak hours, which can be attributed to the variation in the traffic volume of both conflicting and offending streams.

4.1. Model Validation. The mean absolute percentage error (MAPE), root mean square error (RMSE), and mean percentage error (MPE) were computed to check the predictability of the developed model. MAPE for critical conflicts and noncritical was observed as 16% and 15%. RMSE and MPE values were 66 and 76, and −4% and −2%, respectively, for critical and noncritical conflicts. The negative value of MPE indicates that the model over-predicts the number of crossing conflicts. However, the overprediction is marginal. Therefore, the developed model can be considered representative and used to predict crossing conflicts at unsignalized T-intersections.

In addition, to check the predictive power of the GEE_TD model, the model errors are compared with those obtained using the negative binomial (NB) model. The MAPE for critical conflicts and noncritical was observed as 18% and 15%. RMSE and MPE values were 76 and 85, and −5% and −4%, respectively, for critical and noncritical conflicts. Moreover, the MAPE, RMSE, and MPE were calculated for all the selected eight urban T-intersections for GEE_TD and NB model, and the results are summarized in Table 5. For both critical and noncritical conflicts, the GEE_TD model performs better (lesser error) than NB. The consistency in the results is observed for all eight urban T-intersections. Therefore, it is concluded that the GEE_TD model is the most suitable modeling technique for predicting critical and noncritical conflicts.

5. Summary and Conclusions

In India, unsignalized T-intersections contribute to a significant number of crashes and fatalities compared to other intersection types. Among all types of conflicts, crossing conflicts are regarded as more severe at unsignalized T-intersections. Therefore, eight urban unsignalized T-intersections with varying roadway geometry and intersection control were selected. The crossing conflicts were identified using post encroachment time (PET). The identified conflicts were bifurcated into critical and noncritical conflicts. The number of crossing conflicts (critical and noncritical) were modeled as a function of traffic volume, vehicular composition, and intersection geometry using the GEE_TD regression approach. Some of the important conclusions drawn from the study are as follows:

(1) critical and noncritical crossing conflicts vary with the traffic volume of the conflicting and offending stream. The number of critical conflicts increases with an increase in the traffic volume of the offending and conflicting stream. On the other hand, with an increase in the traffic volume of the conflicting stream, the number of noncritical crossing conflicts decreases

(2) vehicular composition significantly influences the number of crossing conflicts. Critical conflicts increase with an increase in the proportion of 2w, 3w, and cars in the conflicting stream. With the increase in the proportion of 2w, 3w, and cars in the offending stream, noncritical conflicts increases

(3) traffic conflicts vary by intersection geometry. Fewer traffic conflicts are observed for unsignalized T-intersections with Central Island than intersections without Central Island. At similar volumes, an average reduction of 25-41% in crossing conflicts can be noted at intersections with the Central Island than without Central Island

(4) time of the day (i.e., peak or off-peak hours) significantly affects the number of crossing conflicts. More conflicts can be observed during peak hours than off-peak hours

(5) the developed crossing conflict model is helpful for the city planners and traffic engineers to estimate the number of conflicts with varying geometry characteristics at unsignalized T-intersections. These models can help to identify the critical intersections based on the number of critical crossing conflicts. Therefore, they can facilitate the development of appropriate surrogate safety measures to enhance traffic operations safety

5.1. Future Research Direction. In the present study, eight urban T-intersections were considered for modeling conflicts. The same study can be carried out for urban four-legged, Y-intersection in the future. Crossing conflicts can also be modeled using advanced statistical techniques like Bayesian and hierarchical models to better account for unobserved heterogeneity. The development of safety-based warrants also merits further investigation. The crossing conflicts-based safety performance function incorporating the effects of the other confounding factors like weather conditions, driver perception, gender, age, and drivers' information can be considered as the future scope of the study. In the present study, only crossing conflicts were considered as they are critical compared to other types of conflict. However, in the future, different types of conflicts such as rear-end, sideswipe, angled, and crossing can be analyzed in a unified framework by developing multivariate models.

Data Availability

The data, model, or codes created or used throughout the study are available from the corresponding author by reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

The authors confirm their contribution to the paper as follows: Arkatkar, Gore, and Goyani were responsible for the study conception, design, analysis, interpretation of results, and draft manuscript preparation. Goyani worked on data collection. All authors reviewed the results and approved the final version of the manuscript.

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