Modeling of Pedestrian Safety in School Zones Based on Behavioural Risk

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ABSTRACT

Pedestrians, especially school children, are vulnerable in road traffic incidents near school zones. This study addresses pedestrian safety issues by examining the behavioral risks of school children in school zones. Data was collected from different school zones, covering road inventory, crash incidents, and pedestrian road risk behavior. Emphasis was placed on user behavior at pedestrian crossings and sidewalks, with data collected from video recordings by observing pedestrians. The collected data was analyzed to estimate Post Encroachment Time to identify crash-prone locations. A pedestrian crash prediction model was developed using negative binomial crash modeling. The model effectively identified critical risk factors, paving the way for targeted interventions to enhance safety for schoolchildren. The study identified crash-causing factors, recognizing significant risks near school zones. Safety performance functions developed, incorporating road infrastructure, land use planning, pedestrian behavior, and traffic volume will aid for comparing safety measures in future road planning and development.

Keywords: Crash prediction model, Negative binomial Regression model, Safety performance functions (SPFs).

INTRODUCTION

Road safety in school zones is a paramount concern in traffic safety, mainly due to the vulnerability of pedestrians, among the most at-risk road user categories. Unlike passengers inside vehicles, pedestrians are directly exposed to injury in motor vehicle crashes, making them susceptible to more severe consequences (*1*). Pedestrian road-crossing decisions become even more critical in countries experiencing rapid population aging. Moreover, uncontrolled midblock sections pose significant risks to pedestrians, as drivers often prioritize yielding pedestrians the least, increasing the likelihood of accidents in countries like India. According to the Ministry of Road Transport and Highways (*2*), pedestrians were killed in 8.7% of total traffic accidents in the country.

Globally, pedestrians account for 22% of all road deaths, with proportions rising as high as two-thirds in certain countries. This can be found in the World Health Organization (*3*) Global Status Report on Road Safety 2018. This report provides comprehensive data on road traffic injuries and fatalities worldwide. Pedestrian behavior is frequently assessed in terms of compliance with road safety regulations, and it has been observed that students tend to exhibit more unsafe behavior, leading to an increased incidence of crashes. Road Safety Manual For Schools (*4*), specifies speed limits in school zones, design solutions for school entry/exit gates, parking, and pick-up/drop-off zones, etc. for Indian traffic conditions. However, such policy regulations are often being violated in many of the school zones. Hence, there is a pressing need for a study focused on pedestrian safety analysis in school zones to ensure the safety of school students. This study aims to address the critical issue of pedestrian safety in school zones, focusing on understanding behavioral risks that school children face. By developing pedestrian crash prediction models, identifying contributing factors to crashes, and proposing safety measures, the project aims to enhance the safety of school students in Thiruvananthapuram City of, Kerala, India.

LITERATURE REVIEW

This literature review focuses on pedestrian safety, particularly understanding behavioral characteristics and crash prediction models. The studies reviewed were crucial in formulating the study's objectives and subsequent steps to improve pedestrian safety in school zones. A study conducted by (*5*) analyzed pedestrian safety in Colombo school zones based on behavioral risk. They found consistent vulnerability values for not using pedestrian crossings and sidewalks across selected zones, indicating that pedestrian safety was relatively secure under current traffic conditions. (*6*) identified that a combination of an overhead speed sign with alternating flashing beacons and pavement marking would help reduce mean speed near school zones to manage pedestrian flows effectively.

Video-graphic survey was conducted by (*7*) at four urban midblock crossings in different parts of India. They concluded that vehicle speed, pedestrian speed, and vehicle gap were the variables that influence pedestrian safety the most. In contrast, pedestrian age and platoon size had the slightest effect. The effectiveness of four countermeasures for school zone speeding was analyzed by (*8*) using a driving simulator. The countermeasures being evaluated were Two-Step Reduction (TSR) signs, overhead signs, forward-reduction speed ahead (RSA) signs, and Speed Monitoring Displays (SMD). The study identified the effectiveness of TSR in reducing speed in a school zone, indicating that it is effective in roadway segments where the difference between the posted speed limit and the speed of the school zone is more than ten mph.

The unsafe pedestrian road-crossing behaviors was explained by (*9*) using a psychophysics-based gap acceptance model, which effectively analyzed gap-acceptance data collected in simulated pedestrian-driver environments. Additionally, Safety Performance

Functions were utilized in several ranking methods by Thomas et al., 2017 to aid in prioritization of locations that require safety improvement.

The factors affecting pedestrians' risk-taking behavior while crossing intersections in urban streets was evaluated by (*10*). The binary logit model was applied to identify factors affecting pedestrians' risk-taking behavior. The results showed that the average time to collision (TTC) chosen by pedestrians was about 6·6 s at signalized intersections and about 5·8 s at un-signalized intersections. It was also indicated that factors including individual characteristics (e.g., gender, age, dressing type, pedestrian speed, etc.), environmental conditions (e.g., other violating pedestrians, curb parking, waiting time, etc.), and traffic conditions (e.g., speed of approaching vehicles, TTC, etc.) could significantly affect pedestrians' risk-taking behavior. A study conducted by (*11*) assessed the safety effects of different roadway countermeasures in school zone areas by employing the Surrogate Safety measures (SSMs) in a before-and-after study using microsimulation, thereby providing valuable insights for transportation and safety planners.

Based on the literature review, it can be observed that most studies highlight the significance of crash prediction models in assessing safety performance and identifying hazardous locations in school zones. These models are instrumental in evaluating the effectiveness of interventions to improve pedestrian safety. However, limited studies have been carried out to evaluate the pedestrian risk near school zones, under mixed traffic conditions where there are varying vehicle classes ranging from slow-moving three-wheelers to fast-moving cars occupying the entire width of the road without any lane discipline. This study aims to develop a crash prediction model focusing on school zones and to identify the factors causing crashes under mixed traffic conditions. Further, the study also developed Safety Performance Functions (SPF) to identify the significant factors causing pedestrian crashes near school zones, ranging from road infrastructure to land use, planning, pedestrian behavior, traffic volume, etc. The following section discusses the study methodology, data collection, data analysis, and model development, followed by results and discussion.

STUDY METHODOLOGY

This section presents the methodology adopted in this study to enhance pedestrian safety in school zones. The study locations were selected in Thiruvananthapuram, Kerala, India. Thirty high-risk locations near school zones were identified based on crash data provided by the District Crime Records Bureau (DCRB) and Kerala Road Safety Authority (KRSA) reports. Data collection involved three classifications: (i) Road inventory data, including traffic control measures and geometric details; (ii) Filtered Crash data to screen out child-related crashes at selected locations; and (iii) Data on pedestrian road risk behavior to identify crash-prone locations. The collected data was analyzed using linear regression, Poisson, and negative binomial model, considering over-dispersion issues to develop crash prediction models. Safety Performance Functions (SPFs) were developed to assess the risk of pedestrian crashes based on factors such as road infrastructure, traffic volume, and pedestrian behavior. The study methodology adopted for improving pedestrian safety in school zones involved data-driven analysis and crash prediction modeling. **Figure 1** shows the study methodology.

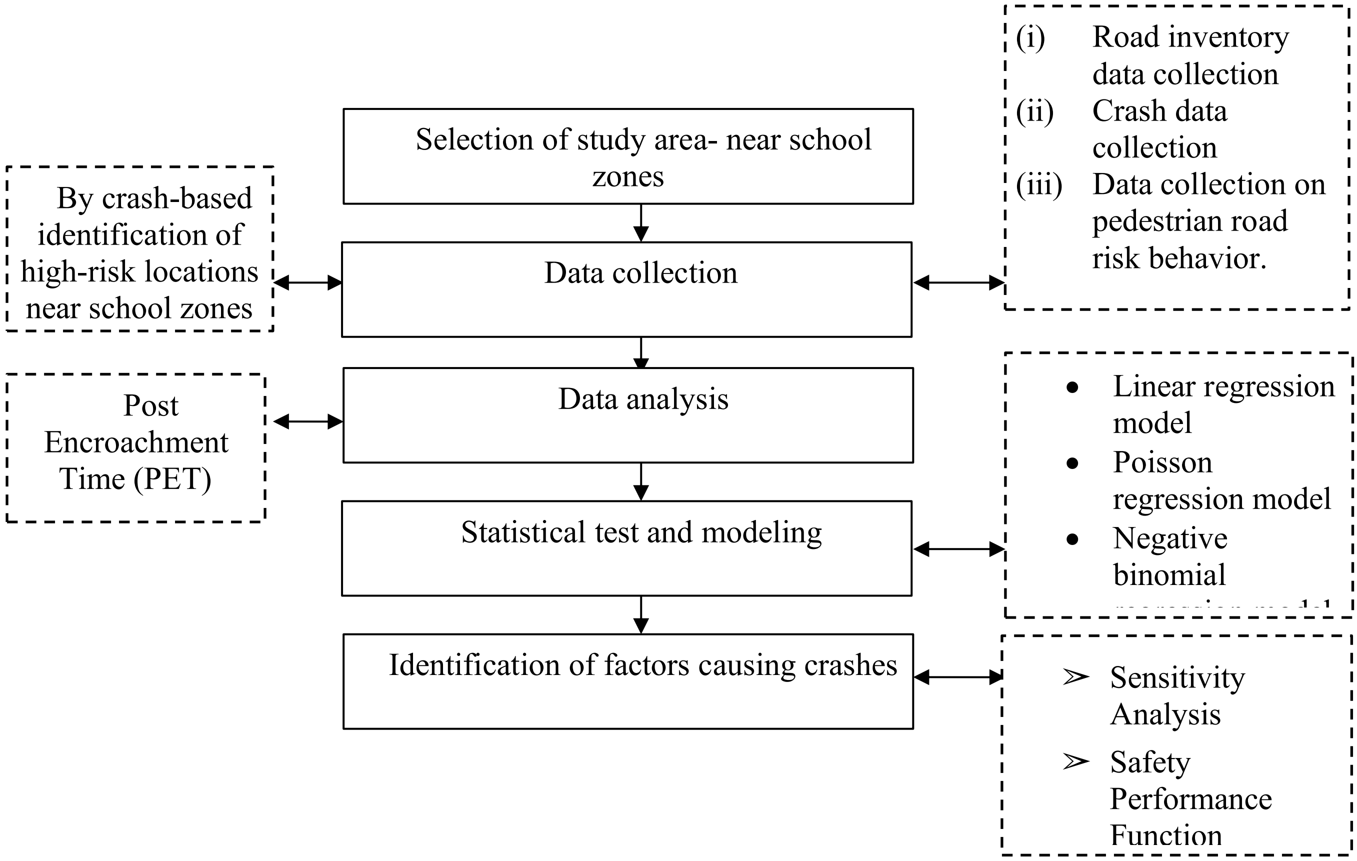

Figure 1 Study methodology

DATA COLLECTION

This section presents the data collection process adopted for developing the crash prediction model to improve pedestrian safety in school zones**. Figures 2(a)** and **2(b)** show a typical school zone in Nemom, located in the city of Thiruvananthapuram, which falls within the municipal corporation. The study location is characterised by substantial traffic problems and an increase in the number of school-age pedestrians and cyclists injured and killed throughout the years. The other school zones selected also exhibited illegal crossing behaviors and traffic violations with high accident rates and accident severity.

One-year accident data for the year 2022 was collected from District Crime Records Bureau (DCRB) and Kerala Road Safety Authority (KRSA) for thirty school zones. Data collection included road inventory data, children-related crash data at selected locations, and data on pedestrian road risk behavior. The crash data obtained for the year 2022 included the location details, date, time of occurrence of crash, type of vehicle involved, and type of injury. As per DCRB statistics, in Thiruvananthapuram, 979 accidents were recorded in September in the city limit, while 51 people died in the mishaps in 2022. The KRSA identified high-priority black spots in the city. Based on the reports of KRSA, out of the 341 black spots, 65 were located in the school zones in Thiruvananthapuram city. The 30 school zones in Thiruvananthapuram city, identified for the study was selected from the 65 black spots.

Video camera footage was used to capture data on pedestrian crossing behavior, traffic volume, speed, and post-encroachment time, which served as essential inputs for developing the crash prediction model. Traffic volume data was collected using manual counting methods, and the annual average daily traffic (AADT) was computed based on the peak hour flow and equivalency factors as per (*12*).

Pedestrian behavior data was collected to analyze behavior at crossings (using and not using crossing facilities) and on sidewalks (using and not using footpaths) using a video graphic survey. The study monitored pedestrian speed and post-encroachment time (PET) during peak hours (8:00 a.m. to 9:00 a.m.) when school timings were in effect.

Geometric data on road infrastructure was gathered to identify road features such as lane width, number of lanes, distance to pedestrian crossings, availability of sidewalks, sidewalk width, availability of guardrails, and elevation of sidewalks.

Figure 2 (a) School zone in Nemom

Figure 2(b) Barrier opening 30m away from school resulting in illegal crossing behaviour

DATA ANALYSIS

The study utilized traffic volume (expressed as AADT), vehicle speeds, accident data, pedestrian behavioral risk data, pedestrian volume, and road data. One-year accident data from 2022 was used for model development.

Based on data analysis, it was observed that the AADT values ranged from 542 veh/hr to 5090 veh/hr, indicating varying traffic volumes at different school zones. Vehicle speed analysis revealed speeds between 21 km/hr to 42 km/hr, with potential safety concerns in areas with higher speeds. Accidents were classified into fatal, grievous, non-grievous, and damages-only accidents for different school zones (indicated as School ID serially numbered from 1 to 30) in **Figure 3**. It can be observed that there are significant contributions of accidents of different categories at the selected school locations.

To analyze the pedestrian behavioral risk analysis, factors such as availability and accessibility of pedestrian crossings and sidewalk usage was monitored at selected school locations. Based on data analysis, it was observed that the majority of pedestrians, including the school children, were not using designated facilities (**Figures 4** and **5**). The data were obtained from video recordings, and it was observed that, on average, 71% of pedestrians were not using designated crossing facilities, and 51% were not using sidewalks in the selected school zones. This behavior poses significant risks, especially in high-traffic volume areas or where vehicles are traveling at high speeds.

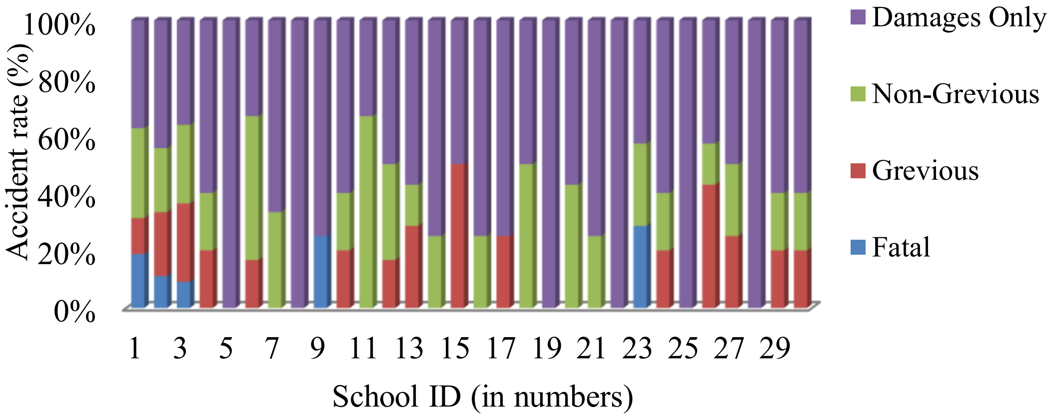

Figure 3 Category-wise classification of accidents at selected school locations

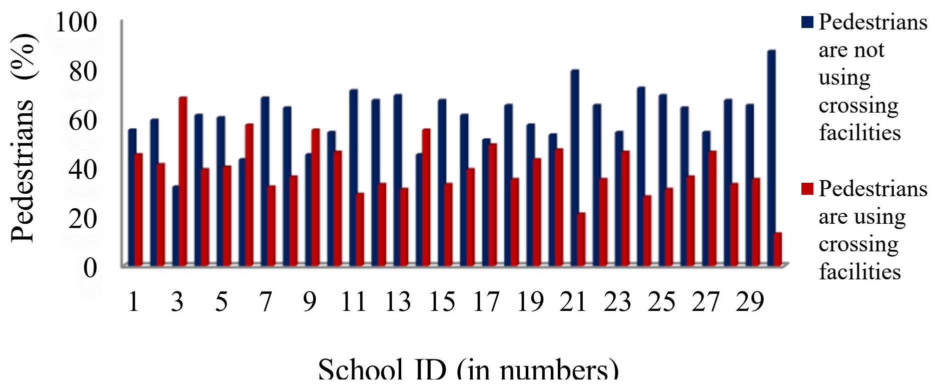

Figure 4 Comparison of the number of pedestrians using and not using crossing facilities at selected school locations

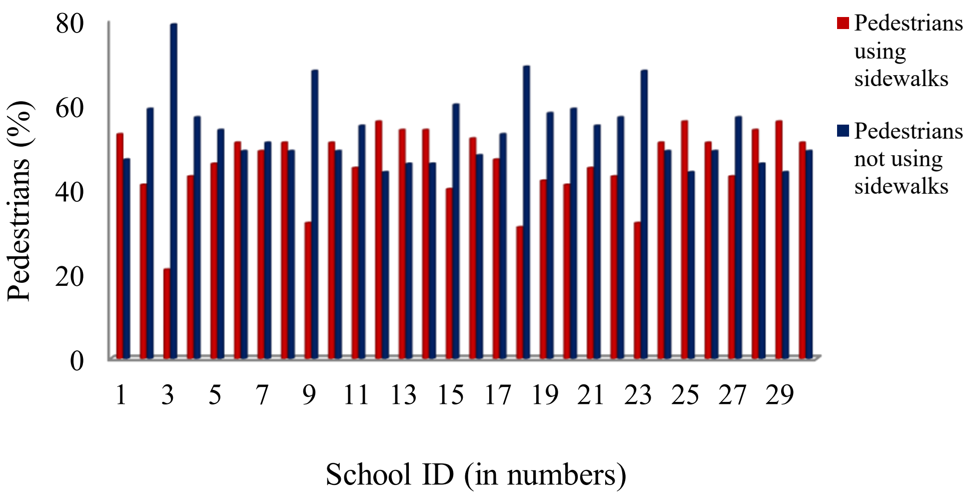

Figure 5 Comparison of the number of pedestrians using and not using sidewalks at selected school locations

Post-Encroachment Time (PET) was determined at the selected school locations to analyze the pedestrian behavioral risk. Post-Encroachment Time (PET) is a critical parameter used to assess pedestrian safety at intersections.
PET used to assess pedestrian-vehicle conflict is expressed as

$$PET = T_c - T_r ,$$

(1)

where T_c = time required for the pedestrian to leave the conflict area, *and* T_r = time when the vehicle enters the conflict area (*13*).

The smaller PET value implies a greater proximity of collision. If the PET value is zero, it shows that both road users (pedestrians and vehicles) are in the conflict area, representing the accident condition. Previous studies suggest that a PET value below 2 seconds indicates a higher risk of collision for pedestrians, as it implies that they have a shorter time to clear the intersection safely before oncoming vehicles start moving (*13*).

In this study, the PET values were observed to be in the range of 1.1 to 5.1 seconds (**Figure 6**). A shorter PET value indicates a higher risk of collision for pedestrians, as it implies that they have less time to clear the intersection safely before oncoming vehicles start moving. Therefore, locations with lower PET values (e.g., below 2 seconds) were considered to have a higher severity in terms of pedestrian safety, as pedestrians may face challenges in crossing the road safely. Based on data analysis, it was observed that eight school locations had PET values below 2 seconds, indicating a higher risk of collision for pedestrians in these locations.

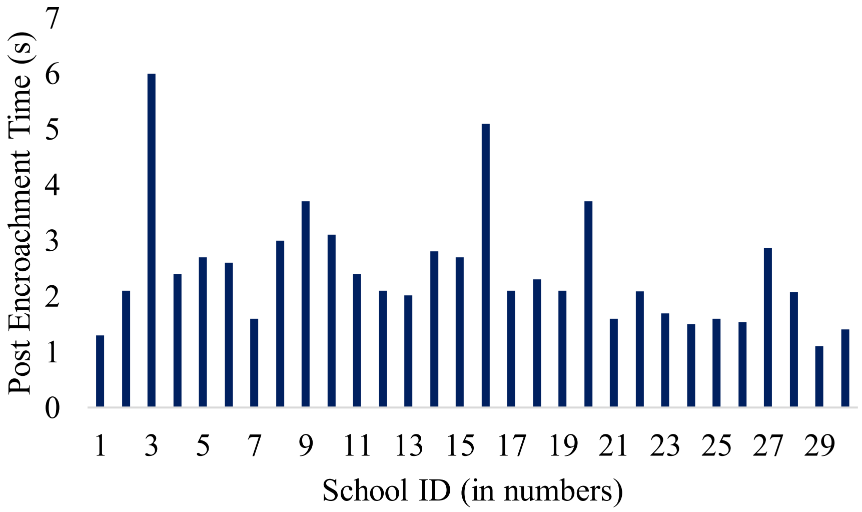

Figure 6 PET values for selected school location

MODEL DEVELOPMENT

Various statistical methods were employed to develop reliable crash frequency models with variables, as shown in **Table 1**. Correlation analysis was used to identify relationships between variables, and three models, namely linear regression, Poisson regression, and negative binomial regression, were developed for crash prediction. The best-fitting model, negative binomial regression, was used to predict crash frequency based on traffic flow, pedestrians not using crossing facilities, footpath width, and post-encroachment time (PET).

Pearson's correlation coefficient was determined to identify relationships between crash frequency and various factors. Based on the analysis, it was observed that traffic flow and pedestrians not using crossing facilities showed significant positive correlations, while footpath width and PET exhibited negative correlations. Three models were developed: linear regression, Poisson regression, and negative binomial regression using these variables. In the linear regression model, the PET value was excluded from the model development because its inclusion resulted in a significance value exceeding 0.05, indicating that the variable did not have a statistically significant effect on the outcome variable. The negative binomial regression was found to be the best fit for the data due to the presence of over-dispersion, which means that the variance in crash frequency was greater than the mean. The negative binomial regression model indicated that crash frequency was significantly influenced by several factors, including traffic flow, pedestrians not using crossing facilities, footpath width, and post-encroachment time (PET). **Table 2** shows the crash frequency model developed using a multiple linear regression model.

Table 1 Dependent and independent variables for the model development

Characteristics	Variables	Data collection methods	Type of variables	Description
Dependent Variable				
Crash data	Pedestrian crash statistics	From selected locations, police stations.	Integer value	The overall pedestrian crashes in school zones for the year 2022.
Independent Variables				
Exposure factors and operational characters.	Average daily traffic volume(Veh/hr)	Video-graphic survey	Continuous	Number of vehicles that pass through a particular location considered.
	Average daily pedestrian volume (Ped/hr)	Video-graphic survey	Continuous	Number of pedestrian that pass through a particular location on an average day considered
	Speed (kmph)	Spot speed survey	Continuous	The average vehicular speed of each location.
Infrastructure and road way factors	Road width (m)	Road inventory survey	Continuous	Distance between the edges of a traffic lane on a road.
	Footpath Width (m)	Road inventory survey	Continuous	Distance between the edge of a sidewalk or footpath and nearest adjacent property curb.
	Median Width (m)	Road inventory survey	Continuous	Distance between the edges of the median, separating two directions of traffic on the road

	Number of lanes	Road inventory survey	Continuous	Total number of travel lanes available for vehicles in one direction.
Pedestrian Behavioral characteristics	Pedestrian Crossing facility and sidewalk facility	Video-graphic survey.	Categorical	In which crossing facility and sidewalk is there in the selected location
	Pedestrian not using crossing facilities (%)	Video-graphic survey.	Continuous	Percentage of pedestrians' illegal behaviour on crossing the road.
	Pedestrian not using sidewalk facilities	Video-graphic survey.	Continuous (%)	Percentage of pedestrians' illegal behaviour on not using footpath.

Table 2 Coefficients: Multiple Linear Regression Model

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
Constant	-4.580	1.650	-	-2.775	0.007
Traffic Flow (*v*)	0.002	0.000	0.690	8.488	0.000
Pedestrian not using crossing Facilities (*PNCF*)	0.093	0.024	0.304	3.827	0.000
Width of footpath (*WF*)	-1.077	0.536	-0.121	-2.007	0.048

Since crash frequency is count data, an approach was taken to develop a Poisson regression model for predicting crash frequency, as shown in **Table 3**. The negative binomial regression model was identified as the best model, as shown in **Table 4**, based on log-likelihood and AIC values.

Table 3 Parameter estimates: Poisson regression

Variables	Coefficient	Standard Error	p-value
Intercept	-1.852	0.5034	0.000
Traffic flow	0.001	0.0001	0.000
WF	0.002	0.0003	0.001
PNCF	0.001	0.0007	0.004
PET	0.195	0.1230	0.003

Table 4 Parameter estimates: Negative Binomial Regression

Variables	Coefficient	Standard Error	p-value
Intercept	-1.852	0.5034	0.000
Traffic flow	0.001	0.0001	0.000
WF	0.002	0.0003	0.001
PNCF	0.001	0.0007	0.004
PET	0.195	0.1230	0.003

The negative binomial regression model revealed that traffic flow and post-encroachment time positively influence the crash frequency, while the width of the footpath and pedestrians not using crossing facilities have a negative impact.

MODEL VALIDATION

To validate the developed models, statistical measures such as Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE) were used. The Mean Absolute Percentage Error is obtained using the;

$$\text{MAPE} = \left(\frac{1}{N}\sum_{k=1}^{N}\frac{|O(k)-P(k)|}{O(k)}\right) \times 100\%, \tag{2}$$

where $P(k)$ and $O(k)$ are the predicted and the observed crash frequency of the study location k, with N being the total number of study locations. MAPE meets most of the criteria required for a summary measure, such as measurement validity, reliability, ease of interpretation, clarity of presentation, and support for statistical evaluation. However, as noted by most researchers (*14*), the distribution of MAPE is often asymmetrical or right-skewed and undefined for zero values. Hence, a scale-dependent measure called Root Mean Square Error (RMSE) is also used, which is often helpful when different methods applied to the same set of data are compared.

However, there is no absolute criterion for a "good" value of any of the scale-dependent measures as they are on the same scale as the data (*15*). The Root Mean Square Error is given by:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{k=1}^{N}[O(k) - P(k)]^2}, \quad (3)$$

where $P(k)$and $O(k)$ are the predicted and the observed crash frequency of the study location k, with N being the total number of study locations

Based on Lewis's scale of interpretation of estimated accuracy, a MAPE value of less than 10% is considered highly accurate, 11%–20% as good, 21%–50% as reasonable, and 51% or more as inaccurate. RMSE expresses the expected value of the error and has the same unit as the data, which makes the size of a typical error visible. The lesser the value of RMSE, the better the forecast obtained. For model validation, 20% of the collected data was used, while the remaining 80% was employed for model development. **Table 5** shows the validation results of the crash frequency models using MAPE and RMSE.

Table 5 Model validation results

Model	RMSE (crashes/year)	MAPE (%)
Linear Regression Model	0.820	42.16
Poisson Regression Model	0.811	25.78
Negative Binomial Regression (NBR) Model	0.587	11.13

Based on RMSE and MAPE values, the linear regression model and Poisson regression model were classified as reasonable models for crash frequency prediction. The negative binomial regression model (NBR) showed the best performance among them, making it a good model for accurately predicting crash frequency on the study roads.

Sensitivity analysis

Sensitivity analysis (**Table 6**) was performed on the NBR model to understand the effect of changes of independent variables in crash frequency by varying each of the independent variables while keeping the other variables constant. Sensitivity analysis revealed a notable correlation between traffic flow and crash frequency. Manipulating factors like post-encroachment time (PET) and width of footpath while holding others constant also affected the crash frequency. These findings underscore the interconnection of various factors in influencing road safety outcomes.

Table 6 Sensitivity analysis results

Variable Name	Percentage change in the variable	Percentage change in crash frequency	Remarks
Traffic Flow (Veh/hr)	Increased by 10%, 20%, 30%	Increase of 24%, 56%, 87%	This trend reflected the inherent risk associated with greater vehicle density, which heightened the likelihood of collisions due to increased interaction between vehicles and potential congestion.
	Decreased by 10%,20%,30%	Decrease of 20%, 35%, 51%	This inverse relationship underscored the safety benefits of lower traffic volumes, reducing the chance of accidents by decreasing vehicle interactions and congestion.
Pedestrians Not Using Crossing Facilities (%)	Increased by 10% ,20%, 30%	Increase of 28%, 54%, 85%	This finding highlighted the heightened risk posed by pedestrians not using designated crossing points, which led to higher accident rates as drivers may not have anticipated or reacted effectively to pedestrian crossings.
	Decreased by 10%, 20%, 30%	Decrease of 25%, 31%, 56%	This demonstrated the effectiveness of improving pedestrian adherence to crossing facilities in reducing accidents, emphasizing the importance of pedestrian infrastructure and enforcement.
Width of footpath (meters)	Increased by 10%, 20%, 30%	Decrease of 10%, 16%, 27%	Wider footpaths improved pedestrian safety by providing more space for walking, reducing the likelihood of pedestrians interacting with vehicle traffic.
	Decreased by 10%, 20%, 30%	Increase of 14%, 26%, 45%	This highlighted the critical role of adequate footpath width in ensuring pedestrian safety and mitigating accident risks.
Post encroachment time (seconds)	Increased by 10%, 20%, 30%	Decrease of 26%, 53%, 82%	This indicated that allowing more time for pedestrians to clear the crossing could significantly reduce the likelihood of accidents, as it reduced the risk of collisions between pedestrians and vehicles.

	Decreased by 10%, 20%, 30%	Increase of 31%, 57%, 87%	This result underscored the importance of providing adequate time for pedestrians to safely cross, as insufficient time increased the risk of accidents.

Safety Performance Functions

Additionally, Safety Performance Functions (SPFs) (**Table 7**) were developed to assess crash risk factors related to road infrastructure planning and land use, traffic operational characteristics, and pedestrian behavior and perception by correlation analysis. The first set focused on road infrastructure planning and land use, where parameters like road width, median width, number of lanes, and footpath width were considered. It was observed by empirical evidence indicating a correlation that roads with inadequate design, signage, and poor conditions resulted in increased accident numbers.

The second set examined traffic operational characteristics, including traffic flow, post-encroachment time (PET), vehicle speed, and the presence of traffic police. High traffic flow and shorter PET were found to increase crash frequency. Vehicle speed also strongly influenced crash frequency, with speeding vehicles contributing to around 40% of pedestrian accidents.

The third set focused on pedestrian behavior and perception. Pedestrian non-compliance with designated crossing facilities and sidewalk usage significantly affected crash frequency. Pedestrians choosing not to use designated crossings and walking on the roadway with baggage increased the risk of collisions with vehicles. The study identified significant risk factors ($p<0.05$) as road width, median width, number of lanes, vehicle speed, and pedestrian non-compliance with crossing facilities in the selected locations.

Table 7 Safety Performance Function results based on correlation analysis

Variable Name	Correlation Coefficient(r)
Road Width	-0.55
Median Width	-0.47
Number of lanes	-0.43
Vehicle speed	0.672
Pedestrians not using the sidewalk	0.452
Pedestrian baggage effect	0.540

Based on the findings, a set of remedial measures were recommended to improve pedestrian safety in these areas. These measures include installing visible and accessible crosswalks with proper signage, implementing speed humps to slow down vehicles, improving lighting for better visibility, and using automated speed cameras to monitor traffic violations. Education campaigns and enforcing laws to promote responsible pedestrian behavior can also contribute to reducing the risk of accidents. In conclusion, the negative binomial regression model showed the highest predictive accuracy for crash frequency, and the sensitivity analysis provided valuable insights into the factors influencing crash frequency. By implementing the recommended remedial measures and considering the findings of the safety performance functions, safer and more walkable communities can be created near school zones, thus reducing the occurrence and severity of pedestrian crashes.

CONCLUSIONS

The study focused on pedestrian safety in school zones, particularly analyzing the impact of behavioral risk factors on pedestrian crashes. The compliance of traffic regulations and infrastructure regulations recommended by codal provisions on school zone safety are not often followed in India, thereby validating the findings from the study that school zones are vulnerable due to the increasing traffic congestion and the presence of pedestrians, including schoolchildren, who may not always adhere to road rules.

According to pedestrian behavior analysis results from the study, an average of 70% of pedestrians are not using the designated crossing facilities, and 53% of pedestrians were not using the sidewalks, exacerbating crash risks. PET values determined from the study indicated that selected school zones were unsafe for pedestrians, necessitating urgent improvements in pedestrian safety. Three crash prediction models were developed. The multiple linear regression model highlighted key variables affecting crash frequency, including traffic flow, pedestrian behavior, and footpath width. Following this, Poisson and negative binomial regression models were employed to account for the count nature of crash data. The negative binomial regression emerged as the most robust model, as evidenced by its superior log-likelihood and AIC values. This model underscores that increased traffic flow and longer post-encroachment times are associated with higher crash frequencies, while wider footpaths and reduced pedestrian non-compliance with crossing facilities contribute to fewer crashes. These findings provide actionable insights for urban planning and traffic management, emphasizing the need for targeted interventions to enhance pedestrian safety and optimize traffic flow.

The study's sensitivity analysis and safety performance functions identified critical factors contributing to pedestrian crashes and injuries. The sensitivity analysis results effectively validated the model's predictions and offered valuable insights for practical interventions. By highlighting how variations in traffic flow, pedestrian behavior, footpath width, and post-encroachment time influenced crash frequency, these findings supported targeted measures to enhance road safety and pedestrian infrastructure. The correlation analysis based on safety performance functions effectively highlighted the relationships between various road and pedestrian factors and safety performance. The negative correlations with road width, median width, and number of lanes indicated that these factors generally contributed to safer road conditions. In contrast, the positive correlations with vehicle speed, pedestrian non-compliance with sidewalks, and pedestrian baggage effect underscored the increased risks associated with these variables. Overall, the study emphasizes the importance of addressing behavioral risk factors and implementing safety measures to enhance pedestrian safety, especially in school zones.

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