

Review on Assessing Urban Traffic Crash Risk and its Impact on Mode Choice using Safety Performance Functions

Trupti Narkhede¹, Lokesh Gupta², Prasun Chakrabarti³ and Arvind Sharma⁴

¹Civil Engineering, Faculty of Integrated & Advanced Technology, Sir Padampat Singhanian University, Udaipur, India
Email: narkhede.phd2023@spsu.ac.in

²Civil Engineering, MGM's College of Engineering and Technology, Kamothe, Navi Mumbai, India
Email: lokesh.gupta

³Faculty of Computing and Informatics, Sir Padampat Singhanian University, Udaipur, India
Email: prasun.chakrabarti

⁴Faculty of Data Science and Analytics, Sir Padampat Singhanian University, Udaipur, India
Email: arvind.sharma@spsu.ac.in

Abstract— As cities rapidly expand and traffic congestion intensifies, urban road safety has emerged as a major concern. Vulnerable road users such as pedestrians, cyclists, two-wheeler riders, and car passengers face different levels of crash risk. This paper reviews research on the use of Safety Performance Functions (SPFs) to quantify urban traffic crash risks. These statistical models describe the relationship between crash frequency and factors such as population, traffic density, and road characteristics. By analyzing historical crash data and road geometry, researchers can estimate crash likelihoods at intersections, mid-blocks, and roundabouts. High-risk zones are often those with heavy traffic and inadequate pedestrian infrastructure. Similarly, poor visibility and high-speed traffic contribute to increased crash severity. The review highlights the importance of reducing vehicle speed, improving street lighting, and providing pedestrian-friendly infrastructure to enhance urban road safety.

Index Terms— traffic crash risk, safety performance functions, urban roads, road safety, predictive modeling.

I. INTRODUCTION

Urban transportation systems are evolving with increasing investments in flyovers, road expansions, and intersection improvements. However, these developments have not been accompanied by a proportional decrease in severe accidents and fatalities. With rising population and income levels, cities are investing heavily in transportation infrastructure. To ensure safe mobility for all road users, it is crucial to quantify actual crash risk at different urban locations. Understanding real crash risks allows for targeted interventions to pre-vent accidents. Moreover, perceived risk significantly influences people's travel mode choices.

This review focuses on understanding crash risk in medium and large cities, examining how people perceive crash risk, and analyzing how it affects their transportation mode choices.

A. Rationale of the Study

If current trends in urban traffic growth continue, crash risks are likely to escalate. Risk varies across user types and road segments such as intersections, mid-blocks, and roundabouts. Predictive modeling using crash data and road typologies can help identify high-risk locations. However, comprehensive crash data including location, severity, time, vehicle type, and victim profile are often difficult to obtain. In this case, we can use of police records, road and traffic surveys, and household surveys are useful how citizens will perceive and experience traffic crash risks.

B. Problem Statement

Urban infrastructure upgrades such as intersection redesigns, construction of flyovers, and road widening have enhanced the overall efficiency of transport systems. However, these developments have coincided with a rise in safety risks for vulnerable road users, including pedestrians, cyclists, two-wheeler riders, and public transport users. As urban populations and incomes continue to grow in the coming decades, investments in transport infrastructure are expected to increase significantly. To align with sustainability objectives, these investments must prioritize the development of safe and inclusive transport systems that ensure secure mobility for all users.

Accurately assessing the risk levels faced by various types of road users across different road environments is essential. Scientific identification and mitigation of actual traffic accident risks can lead to targeted interventions and significant improvements in road safety. Additionally, the perceived risk associated with different travel modes and infrastructure types plays a key role in individuals' mode choice. Therefore, it is equally important to evaluate how safety perceptions influence travel behavior. Travel mode decisions should account not only for factors such as travel time and convenience but also for the safety of all road users.

This thesis addresses the issue of road safety in the context of a medium-sized city, with a particular focus on evaluating the risk of fatal accidents across various modes of transport. Additionally, the study aims to examine how different categories of road users perceive traffic accident risk and how these perceptions influence their travel mode choice behavior.

II. CURRENT STATUS OF KNOWLEDGE, METHODS AND RESULTS: A REVIEW

Previous research on road safety has focused on three main areas: (1) the development of Safety Performance Functions (SPFs) to model the relationship between expected traffic crashes and factors such as road geometry, traffic volume, and demographics; (2) the relationship between perceived and actual traffic crash risks; and (3) how perceived risk influences travel mode choice.

Vinayaraj, V. S., and Vedagiri Perumal. (2024) This study investigates factors influencing crash risk and develops a severity model for rear-end and angle collisions at roundabouts, particularly in non-lane-based, heterogeneous traffic environments [32]. For rear-end collisions, key factors influencing severity include posted speed limits, type of violation, collision partner, whether the collision involved a single vehicle, and the age of the vehicle. In contrast, for angle collisions, the severity is mainly affected by violation type, collision partner, and road surface conditions. The analysis of angle collisions revealed that the likelihood of fatal injuries increased by 28% in incidents involving heavy vehicles and vulnerable road users. In the case of rear-end collisions, risk factors such as collision partners (especially heavy vehicles and vulnerable road users) and single-vehicle collisions were associated with a 25% and 18% increase in fatal injury severity, respectively. Interestingly, rear-end collisions generally resulted in higher severity compared to angle collisions. The findings offer useful insights for formulating strategies to reduce the severity of collisions at roundabouts .

Vinayaraj and Vedagiri Perumal (2023) developed Safety Performance Functions (SPFs) and Crash Modification Factors (CMFs) to evaluate safety at roundabouts, focusing on entry, exit, and circulating lanes [34]. Their study analyzed crash data from 21 roundabouts and 78 approaches across major Indian cities from 2015 to 2019. Using negative binomial and cross-sectional models, they identified several key factors influencing crash occurrences, including the proportion of motorized two-wheelers, average daily traffic volumes, central island diameter, entry and exit angles, lane widths at various sections, posted speed limits, road surface conditions, and number of circulatory lanes. Among these, circulating roadway width, traffic volume, and speed limits emerged as the most critical contributors to crash risk. The analysis also revealed that crash rates vary significantly across different roundabout sections, reflecting the uneven influence of geometric and traffic variables. These findings offer valuable input for updating roundabout design standards with enhanced safety considerations and demonstrate how SPF and CMF models can guide safety improvements in non-lane-based, mixed traffic conditions.

In a subsequent study (2023), the authors examined crash severity at 20 Indian roundabouts with heterogeneous traffic using an ordered-probit model [33]. Key factors impacting severity included roundabout geometry (e.g.,

inscribed circle diameter, central island height), traffic control features, collision types, and victim demographics. Marginal effects revealed fatal injury probabilities rising significantly with angle collisions, pedestrian involvement, certain collision patterns, and collision partners. Rear-end and sideswipe collisions were linked to higher severe injury risks. These findings support targeted safety enhancements and design improvements to reduce crash severity at roundabouts.

Vinayaraj and Vedagiri Perumal (2022) highlighted the limited research on roundabout safety in non-lane-based traffic due to scarce crash data and assessment tools [35]. They developed Safety Performance Function (SPF) models using crash data from 19 roundabouts (2015–2019) to analyze factors influencing crash frequency. Their negative binomial models showed that higher shares of two-wheelers, heavy vehicles, steeper entry angles, and longer weaving sections increased crashes, while more circulatory lanes, larger inscribed circle diameters, and lane markings reduced them. This work provides useful insights for improving roundabout safety, especially in developing countries.

Prajapati and Tiwari (2013) examined rising fatality rates in Indian cities linked to rapid urban growth, highlighting the variability of crash risk depending on infrastructure type and user exposure [29]. Using police-reported fatal crash data, they analyzed six common transportation modes such as walking, cycling, motorized two-wheelers, auto-rickshaws, cars, and buses across different road environments such as mid-blocks and intersections. Household surveys were conducted to assess perceived risks, allowing comparison between actual crash occurrences and public perception.

In a related study, Prajapati and Tiwari (2013) assessed safety on mid-block segments of urban arterial roads in Vadodara, India, through fatal crash data collected over six years [28]. The analysis incorporated traffic volumes, segment lengths, number of unsignalized intersections, and median presence. Results showed that higher traffic volumes were associated with increased crash risk, though risk decreased on roads with lower traffic. Interestingly, segments with more unsignalized intersections exhibited reduced crash risk, while those with medians experienced higher crash occurrences compared to segments without medians.

Nevelsteen et al. (2012) undertook a study focussed on 6 to 12 year old children in Belgium to evaluate factors of the parental safety perception on their travel mode choice [22]. The effect of real and perceived traffic safety. Parental allowance probability was calculated for each travel mode for children using infrastructure characteristics. A binary logistic model was developed using age, gender and traffic infrastructure characteristics near origin and destination of the trip.

Ma et al. (2010) analyzed severe crashes on arterial roads in Beijing with mixed traffic using Negative Binomial regression and Generalized Estimating Equations (GEE) [20]. Data from signalized intersections and road segments were used to model crash predictors. At intersections, significant factors included traffic volumes, lane configurations, speed limits, medians, bike and pedestrian facilities, and signals. For road segments, length, lane count, intersection density, posted speed, median type, land use, and bus stop proximity were important predictors.

Cafiso et al. (2010) developed NB regression crash prediction models for two-lane rural highways, excluding intersection crashes, using five years of data [5]. Key variables affecting crashes included traffic flow, driveway density, curvature ratio, roadside hazard ratings, speed profile, and segment length. The study recommended these models for Empirical Bayes accident prediction applications.

Hadayeghi et al. (2010) investigated the relationship between traffic crash counts and factors such as land use, demographics, and traffic patterns by comparing Geographically Weighted Poisson Regression (GWPR) with traditional Generalized Linear Models (GLM) [14]. Their findings indicated that GWPR models more effectively capture spatial variability in crash rates compared to GLMs, suggesting that accounting for geographic heterogeneity improves crash prediction accuracy.

Cho et al. (2009) examined the relationship between perceived and actual crash risks for pedestrians and cyclists, incorporating survey data, official crash records, GIS, and street audits [8]. Using factor analysis and path modeling, they found that residents in low-density, single-use areas perceived higher crash risks despite lower actual crash rates compared to compact, mixed-use areas. The study suggested that heightened risk perception in less dense areas may promote cautious behavior, reducing actual crashes.

Klobucar and Fricker (2007) focused on improving both actual and perceived bicycle safety [16]. They noted that cyclists' route choices were influenced by perceived safety and trip length. Tools like the Bicycle Compatibility Index and Bicycle Level of Service were used to evaluate infrastructure based on user feedback, helping planners assess perceived safety from the cyclist's perspective.

Parkin et al. (2007) investigated how perceived crash risk affects cyclist behavior, particularly at roundabouts and intersections [24]. In a study involving 144 commuter cyclists shown first-person cycling videos, perceived

risk ratings were modeled using nonlinear regression. The study found that cyclists felt safer on traffic-free paths and at signalized junctions, with less concern for dedicated cycle facilities on heavily trafficked roads.

Caliendo et al. (2007) developed crash prediction models using Poisson, NB, and Negative Multinomial regressions for multilane highways based on five years of data [6]. The models excluded crashes involving ramps, toll booths, and non-motorized users. Variables such as segment length, traffic volume, road gradient, alignment, friction, and intersection density were included. Due to overdispersion in the data, the Negative Binomial model performed better than Poisson, with the Negative Multinomial model being the most suitable.

Lord and Bonneson (2007) described in their paper the development of accident prediction model and accident modification factor for rural frontage road segments in Texas [17]. Five years non-intersection crash data (1997-2001) were used in the study to see the effect of variables in the model developed by Poisson-gamma distribution. The results indicated that mid-block crashes reduced because of wider lane and shoulder. It was recommended 16 further work to assess safety benefits of pavement markings. The study also stated that the risk of severity on rural frontage roads and rural highways were almost equal [17].

Bhalla et al. (2007) presented a risk-based framework for predicting traffic fatalities, assuming crash frequency proportional to exposure [4]. They analyzed fatality ratios for vehicle-vehicle and pedestrian-vehicle crashes, observing that fatalities had declined in industrialized countries but increased in areas dominated by motorized two-wheelers and mixed traffic. Fatal crash probability was modeled as the product of crash occurrence and fatality likelihood.

Petritsch et al. (2006) determined factors affecting bicycle safety and found side-path width, distance between side-path and main roadway, posted speed and number of lanes on the main roadway as significant [26]. Authors suggested that their study can assist transportation planners to review existing side-paths and to identify safety issues to bicyclists.

El-Basyouny and Sayed (2006) proposed two Negative Binomial (NB) regression models for predicting traffic crashes using data from 392 arterial segments in British Columbia [9]. The traditional NB model assumed a fixed shape parameter, whereas their modified approach allowed the shape factor to vary by location. Using the Empirical Bayes (EB) method, they identified accident-prone areas more accurately by incorporating both historical crash data and traffic/roadway characteristics. The modified NB model outperformed the traditional one, especially for high-crash locations.

Elvik and Bjørnskau (2005) conducted a survey in Norway with 1,000 participants to study the accuracy of perceived risk across various transport modes [10]. Using only fatal crash data (due to limited injury data), they compared numerical translations of perceived safety ratings with actual fatality rates per billion kilometers traveled. Strong correlations were observed, indicating that public perceptions often align with statistical crash risk across modes.

Hauer et al. (2004) used Negative Multinomial regression to develop crash prediction models for undivided four-lane urban roads, focusing on non-intersection crashes [15]. Based on four years of crash data from 196 km of roads in Washington State, the study found that off-road crashes decreased as average daily traffic volumes increased. However, geometric features such as lane width, shoulder width, and curve degree were not statistically significant.

Lord and Persaud (2004) developed tools that help in planning process to estimate traffic crashes for urban transportation network [18]. Separate models for intersection and mid-block were developed using NB regression. The tools assist the planners to evaluate different road network alternatives on computerised transportation networks [18].

Allen-Munley et al. (2004) and Allen-Munley and Daniel (2006) developed multivariate logistic model for urban bicycle routes to predict the severity of an injury from traffic crash to a bicyclist [2],[3]. Four years (1997-2000) crash data of Hudson County having 314 bicycle motor vehicle crashes were analysed in the study. Various variables including carriageway width, traffic volume, income level, one-way streets, population density, vertical and horizontal alignment, grade, pavement condition, parking, classification of road, bus, modelling. Significant variables were carriageway width, traffic volume, population density, one-way streets, gradient, pavement condition, classification of road, truck route and daylight.

Cervero and Duncan (2003) developed discrete logit models to estimate the probability of walking or bicycling [7]. Factor analysis was adopted for variables on street supply, intersection type, city block size, socio-economic characteristics. It was concluded that deterrent variables to walking were longer trip length, steep terrain, rain and nightfall. The model also observed pedestrians tended to avoid lower-income environments probably because of safety concerns. Land use diversity at trip origin was significant for pedestrian. Topography, darkness, and rainfall had stronger influence than factors including well connected street network, small city blocks, mix land use and close proximity to retail activities.

Greibe (2003) developed Poisson-based crash prediction models for urban intersections and mid-block segments, using data from over 1,000 intersections and 142 km of urban roads [12]. Traffic flow variables were most significant for intersection crashes, while mid-block models responded to additional factors such as nearby junctions, parking facilities, road environment, and speed limits. The study concluded that mid-block crash modeling is generally less complex than intersection modeling.

Hadayeghi et al. (2003) applied Negative Binomial regression to crash data from 463 traffic zones in Toronto [13]. Recognizing the rarity and unpredictability of crashes, they favored NB models over Poisson and linear models due to data overdispersion. The study incorporated crash severity, time of occurrence, and socio-demographic data, developing separate models for total annual crashes, severe crashes, and morning peak-hour incidents. Key predictors included vehicle-kilometers traveled, road length, household and employment density, speed limits, and volume-to-capacity ratios. Crashes increased with higher travel volumes and population density, while fewer crashes were observed in areas with higher posted speeds and v/c ratios, possibly indicating better road conditions.

Lord D. (2002) explored the link between safety and risk, defining $\text{Risk} = \text{Safety} / \text{Exposure}$, and applied crash prediction models to a hypothetical network built on the traditional four-stage transport model [19]. His findings suggested that individual crash risk declines as overall traffic flow increases.

Sawalha and Sayed (2001) created crash prediction models for arterial roads in Vancouver and Richmond using both Poisson and Negative Binomial regressions [31]. Their analysis covered 58 roads and 391 segments, incorporating variables like daily traffic volume, road segment length, intersection and crosswalk density, driveway and access point frequency, median design, land use, and the presence of bus stops. Key predictors of crash frequency included traffic volume, land use type, and infrastructure characteristics.

In the domain of predictive crash modeling, Poch and Mannering (1996) used seven years of crash data from 63 intersections in Bellevue, Washington to develop Negative Binomial regression models [27]. These models estimated various crash types such as total, rear-end, angle, and turning crashes based on intersection-level factors. They emphasized the societal costs of crashes and recommended broader studies for improving intersection safety.

Noland (1995) explored how perceived crash risk affects individuals' commuting choices [23]. He found that people are more likely to avoid transport modes they consider unsafe, with perceived risk acting as a key behavioral driver. His study, based on survey data, also highlighted the role of travel time, cost, comfort, and personal demographics in mode choice decisions. The study concluded that higher perceived risk associated with a particular transport mode could lead to a decreased likelihood of individuals choosing that mode for commuting [25].

Many researchers (Poch and Mannering, 1996 [27]; Sawalha and Sayed, 2001 [31]; Greibe 2003 [12]; Hadayeghi et al., 2003 [13]; Hauer et al., 2004 [15]; Lord and Persaud, 2004 [18]; El-Basyouny and Sayed, 2006 [9]; Caliendo et al., 2007 [6]; Ma et al., 2010; Cafiso et al., 2010) [5] have employed Generalized Linear Modeling (GLM) techniques, particularly Poisson and Negative Binomial (NB) regression, in their studies. Other approaches, such as multinomial logistic regression, have also been applied to predict traffic crash severity (Allen-Munley, 2004 [3]; Caliendo et al., 2007 [6]). These studies generally acknowledge that road accidents are infrequent and unpredictable events, making the frequency of accidents on a particular road or area fluctuate significantly within a short time frame. This characteristic of accident data, coupled with the non-negative and discrete nature of accident counts, makes traditional linear regression with a normal error distribution unsuitable for analyzing accident data. Consequently, Poisson and Negative Binomial regression models have become more common in these analyses.

Typically, variables used in crash prediction models include traffic flow, road segment length, land use, lane density, median presence, collector street density, parking availability, volume-to-capacity ratio, shoulder width, road classification, gradient, posted speed, and traffic signal presence. One study noted that increased perceptions of risk associated with a particular transportation mode can decrease the likelihood of individuals using that mode. This underscores the need for a study in India focused on the perceived risk of traffic crashes and its impact on mode choice. Previous research by Klobucar and Fricker (2007) [16] and Cho et al. (2009) [8] explored the relationship between perceived and actual crash risks for bicycles and pedestrians. Elvik and Bjørnskau (2005) [10] compared perceived and estimated crash risks across different modes of transport and found a strong correlation between the two.

Additionally, mode choice is influenced by factors such as perceived travel time, cost, comfort of alternative modes, and demographic characteristics. The findings suggest that higher perceived risk of a given transportation mode can reduce its usage.

III. PROPOSED METHODOLOGY

This study introduces a comprehensive modelling framework that integrates traditional Safety Performance Functions (SPFs) with machine learning approaches to improve the prediction of traffic crash risk in urban settings across various road locations. The methodology involves the following key components:

A. Data Collection and Preprocessing

Traffic Crash Data: Historical records of traffic accidents including information on crash locations, types, and severity will be obtained from official traffic databases and police reports.

Roadway Characteristics: Geometric design features, traffic volumes, and infrastructure components (e.g., pedestrian crossings, cycle tracks) will be collected using Geographic Information Systems (GIS) and other urban data sources.

Perception Data: Surveys will be conducted to capture commuters' perceptions of crash risk, taking into account different roadway environments and infrastructure conditions.

B. Model Development

Safety Performance Function (SPF): A baseline SPF will be constructed using Negative Binomial regression to estimate the expected number of crashes per year at specific types of urban road locations, based on traffic flow characteristics and roadway features.

C. Model Validation and Evaluation

Cross-Validation: The developed models will be tested on independent validation datasets to assess their predictive reliability and generalizability.

Performance Assessment: Statistical metrics will be used to evaluate the accuracy and effectiveness of both the traditional SPF and machine learning models.

D. Influence of Perceived Risk on Mode Choice

A mode choice model will be formulated to analyse how both actual and perceived traffic crash risks influence travel behaviour, particularly decisions involving walking, cycling, public transit, and private vehicle use.

E. Planned Simulation and Modelling for Mumbai

Building on methodologies successfully applied in Vadodara[28], [29], this study plans to implement Safety Performance Functions (SPFs) and simulation-based analysis for Mumbai's urban road network. Using SUMO (Simulation of Urban MObility), synthetic traffic environments will be developed to reflect key locations such as intersections, mid-blocks, and roundabouts in Mumbai. The simulation will incorporate local traffic volume, vehicle composition, and geometric features collected through GIS and municipal datasets. Statistical modeling, particularly Negative Binomial regression[6], [31], will be used to estimate crash frequency based on these variables. Perception surveys will also be designed to capture how Mumbai commuters perceive crash risk across different infrastructure types. These combined approaches aim to assess both actual and perceived crash risks and their impact on mode choice in Mumbai.

IV. APPLICATIONS

- Assess traffic crash risk at different location type and further provides insights in to mode choice models [30].
- Using crash prediction model, it is possible to understand the risk of fatal crash to different road users in cities and planners can decide how best the funds for transportation infrastructure can be used for improving safety.
- To calculate the risk of traffic crashes for various road users at various road sites.
- To create Safety Performance Functions (SPFs) for road accidents that result in death.
- To comprehend and establish the connection between the actual and perceived risk of traffic crashes.
- To ascertain how the choice of transport mode is influenced by the danger of traffic crashes.

V. RESULTS AND DISCUSSION

While previous research in Vadodara demonstrated the effectiveness of SPFs in identifying high-crash zones using six years of fatal crash data [28], [29], this study aims to replicate and expand the methodology for

Mumbai. The future analysis will focus on arterial roads, intersections, and roundabouts in Mumbai using crash records (2018–2023), road geometry, and traffic volume data.

Based on existing literature, significant variables likely to influence crash frequency include average daily traffic, presence of medians, lane count, intersection density, and pedestrian infrastructure [6], [31]. The study will apply Negative Binomial regression to account for overdispersion in crash data, which was shown to outperform Poisson regression in similar contexts [6].

Simulation Component: A planned simulation in SUMO will replicate real-world traffic scenarios in Mumbai. The simulation will help evaluate how interventions such as pedestrian crossings, speed control measures, or roundabout redesign might influence crash occurrence, similar to methods used in earlier SPF studies [29], [31].

Perceived vs. Actual Risk in Mumbai: A survey targeting a representative sample of road users in Mumbai will be conducted to capture perceived safety across various modes and locations. The results will be compared with modeled crash risk, building on approaches followed in previous perception-based studies [8], [10], [29].

Planned Mode Choice Analysis: Using binary logistic regression, the study will analyze how perceived crash risk influences people's willingness to walk, cycle, or use public transport. The goal is to determine how improving perceived safety can shift mode choice toward more sustainable options, as observed in previous studies on risk perception and mode choice [10], [23].

The anticipated outcome is to develop data-driven recommendations for improving urban safety and guiding future infrastructure investments in Mumbai.

VI. CONCLUSION

Most reviewed studies use Generalized Linear Models (GLM), especially Poisson and Negative Binomial regressions, to account for the discrete and sparse nature of crash data [1]. Perceived crash risk significantly affects travel behaviour, especially among pedestrians and cyclists. In India, localized studies on perceived risk and mode choice remain limited. Future research should integrate both actual and perceived risk to guide investments in safe, inclusive, and sustainable transportation systems. The proposed extension of the SPF modeling and simulation-based framework to Mumbai aims to provide localized insights into crash risk and traveler behavior. Although the results are yet to be generated, the methodology builds on proven approaches [28], [29], [6], [31] and aligns with Mumbai's ongoing need for safer, more inclusive transportation systems. Future work will focus on data collection, model calibration, and validation to support evidence-based urban mobility planning.

REFERENCES

- [1] A. Agresti, *Categorical Data Analysis*, 2nd ed., Hoboken, NJ: Wiley, 2002, pp. 115–164.
- [2] C. Allen-Munley and J. Daniel, "Urban Bicycle Route Safety Rating Model Application in Jersey City, New Jersey," *Journal of Transportation Engineering*, vol. 132, no. 6, pp. 499–507, 2006. Available: <http://ascelibrary.org/teo/resource/1/jtpedi/v132/i6/p499s1>
- [3] C. Allen-Munley, J. Daniel, and S. Dhar, "Logistic Model for Rating Urban Bicycle Route Safety," *Transportation Research Record*, no. 1878, pp. 107–115, 2004. doi: 10.3141/1878-13.
- [4] K. Bhalla, M. Ezzati, A. Mahal, J. Salomon, and M. Reich, "A Risk-Based Method for Modeling Traffic Fatalities," *Risk Analysis*, vol. 27, no. 1, pp. 125–136, 2007. doi: 10.1111/j.1539-6924.2006.00864.x.
- [5] S. Cafiso, A. Di Graziano, G. Di Silvestro, G. La Cava, and B. Persaud, "Development of Comprehensive Accident Models for Two-Lane Rural Highways Using Exposure, Geometry, Consistency, and Context Variables," *Accident Analysis and Prevention*, vol. 42, no. 4, pp. 1072–1079, 2010. doi: 10.1016/j.aap.2009.06.020.
- [6] C. Caliendo, M. Guida, and A. Parisi, "A Crash-Prediction Model for Multilane Roads," *Accident Analysis and Prevention*, vol. 39, no. 4, pp. 657–670, 2007.
- [7] R. Cervero and M. Duncan, "Walking, Bicycling, and Urban Landscapes: Evidence from the San Francisco Bay Area," *American Journal of Public Health*, vol. 93, no. 9, pp. 1478–1483, 2003.
- [8] G. Cho, D. A. Rodriguez, and A. J. Khattak, "The Role of the Built Environment in Explaining Relationships Between Perceived and Actual Pedestrian and Bicyclist Safety," *Accident Analysis and Prevention*, vol. 41, no. 4, pp. 692–702, 2009.
- [9] K. El-Basyouny and T. Sayed, "Comparison of Two Negative Binomial Regression Techniques in Developing Accident Prediction Models," *Transportation Research Record*, no. 1950, pp. 9–16, 2006. doi: 10.3141/1950-02.
- [10] R. Elvik and T. Bjørnskau, "How Accurately Does the Public Perceive Differences in Transport Risks? An Exploratory Analysis of Scales Representing Perceived Risk," *Accident Analysis and Prevention*, vol. 37, no. 6, pp. 1005–1011, 2005.
- [11] P. Finn and B. W. E. Bragg, "Perception of the Risk of an Accident by Young and Older Drivers," *Accident Analysis and Prevention*, vol. 18, no. 4, pp. 289–298, 1986.

- [12] P. Greibe, "Accident Prediction Models for Urban Roads," *Accident Analysis and Prevention*, vol. 35, no. 2, pp. 273–285, 2003.
- [13] A. Hadayeghi, A. Shalaby, and B. Persaud, "Macrolevel Accident Prediction Models for Evaluating Safety of Urban Transportation Systems," *Transportation Research Record*, no. 1840, pp. 87–95, 2003. doi: 10.3141/1840-10.
- [14] A. Hadayeghi, A. S. Shalaby, and B. N. Persaud, "Development of Planning Level Transportation Safety Tools Using Geographically Weighted Poisson Regression," *Accident Analysis and Prevention*, vol. 42, no. 2, pp. 676–688, 2010.
- [15] E. Hauer, F. Council, and Y. Mohammedshah, "Safety Models for Urban Four-Lane Undivided Road Segments," *Transportation Research Record*, no. 1897, pp. 96–105, 2004. doi: 10.3141/1897-13.
- [16] M. Klobucar and J. Fricker, "Network Evaluation Tool to Improve Real and Perceived Bicycle Safety," *Transportation Research Record*, no. 2031, pp. 25–33, 2007. doi: 10.3141/2031-04.
- [17] D. Lord and J. Bonneson, "Development of Accident Modification Factors for Rural Frontage Road Segments in Texas," *Transportation Research Record*, no. 2023, pp. 20–27, 2007.
- [18] D. Lord and B. N. Persaud, "Estimating the Safety Performance of Urban Road Transportation Networks," *Accident Analysis and Prevention*, vol. 36, no. 4, pp. 609–620, 2004.
- [19] D. Lord, "Application of Accident Prediction Models for Computation of Accident Risk on Transportation Networks," *Transportation Research Record*, no. 1784, pp. 17–26, 2002.
- [20] M. Ma, X. Yan, M. Abdel-Aty, H. Huang, and X. Wang, "Safety Analysis of Urban Arterials Under Mixed-Traffic Patterns in Beijing," *Transportation Research Record*, no. 2193, pp. 105–115, 2010.
- [21] D. Mohan, O. Tsimhoni, M. Sivak, and M. J. Flannagan, *Road Safety in India: Challenges and Opportunities*, UMTRI-2009-1, Ann Arbor, MI: University of Michigan Transportation Research Institute, 2009.
- [22] K. Nevelsteen, T. R. S. Steenberghen, A. Van Rompaey, and L. Uyttersprot, "Controlling Factors of the Parental Safety Perception on Children's Travel Mode Choice," *Accident Analysis and Prevention*, vol. 45, pp. 39–49, 2012.
- [23] R. B. Noland, "Perceived Risk and Modal Choice: Risk Compensation in Transportation Systems," *Accident Analysis and Prevention*, vol. 27, no. 4, pp. 503–521, 1995.
- [24] J. Parkin, M. Wardman, and M. Page, "Models of Perceived Cycling Risk and Route Acceptability," *Accident Analysis and Prevention*, vol. 39, no. 2, pp. 364–371, 2007.
- [25] J. Parkin, M. Wardman, and M. Page, "Estimation of the Determinants of Bicycle Mode Share for the Journey to Work Using Census Data," *Transportation*, vol. 35, no. 1, pp. 93–109, 2008.
- [26] T. Petritsch, B. Landis, H. Huang, and S. Challa, "Sidepath Safety Model: Bicycle Sidepath Design Factors Affecting Crash Rates," *Transportation Research Record*, no. 1982, pp. 194–201, 2006.
- [27] M. Poch and F. Mannering, "Negative Binomial Analysis of Intersection-Accident Frequencies," *Journal of Transportation Engineering*, vol. 122, no. 2, pp. 105–113, 1996.
- [28] P. Prajapati and G. Tiwari, "Evaluating Safety of Urban Arterial Roads of Medium Sized Indian City," *Proceedings of the Eastern Asia Society for Transportation Studies*, vol. 12, 2013.
- [29] P. Prajapati and G. Tiwari, "Study of Relation Between Actual and Perceived Crash Risk," *Procedia - Social and Behavioral Sciences*, vol. 104, pp. 1095–1104, 2013. Presented at the 2nd Conference of Transportation Research Group of India (CTRG), Agra, India.
- [30] S. d. P. Sanches and F. Serra de Arruda, "Incorporating Non-Motorised Modes in a Mode Choice Model," *Transportation Research Record*, no. 1818, pp. 89–93, 2002.
- [31] Z. Sawalha and T. Sayed, "Evaluating Safety of Urban Arterial Roadways," *Journal of Transportation Engineering*, vol. 127, no. 2, pp. 151–158, 2001. doi: 10.1061/(ASCE)0733-947X(2001)127:2(151).
- [32] V. S. Vinayaraj and P. Vedagiri, "Analysis of Crash Severity in Rear-End and Angled Collisions on an Urban Roundabout in Heterogeneous Non-Lane Based Traffic Conditions," *Transport Letters*, 2024. doi: 10.1080/19427867.2024.2338325.
- [33] V. S. Vinayaraj and P. Vedagiri, "Analysing the Factors Affecting the Crash Severity at Urban Roundabouts in Non-Lane-Based Traffic," *International Journal of Injury Control and Safety Promotion*, pp. 1–13, 2023. doi: 10.1080/17457300.2023.2279967.
- [34] V. S. Vinayaraj and P. Vedagiri, "Developing Safety Performance Function and Crash Modification Factor for Urban Roundabouts in Heterogeneous Non-Lane-Based Traffic Conditions," *Transportation Research Record*, 2023. doi: 10.1177/03611981231157727.
- [35] V. S. Vinayaraj and P. Vedagiri, "Safety Evaluation of Urban Roundabouts in India: A Safety Performance Function Based Approach," *Traffic Safety Research*, vol. 3, no. 15, 2022. doi: 10.55329/bylj4120.
- [36] World Health Organization, *Global Status Report on Road Safety: Time for Action*, Geneva: WHO, 2009.