Assessing the Visual and Built Environment Risk on Pedestrian-Vehicle Crash Severity in Absence of Detailed Roadway Inventory: A Deep Learning Based Framework Harnessing Public Geospatial Data

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Objective: Pedestrian-vehicle crashes remain a major public health concern, yet the contribution of drivers' visual environments to crash severity has received limited attention. While built-environment factors have been widely examined, many developing countries lack detailed roadway inventories that are necessary for traditional analysis. This study aimed to develop a data-driven framework that integrates visual and built-environment features using publicly accessible geospatial data to predict pedestrian crash severity and support context-specific safety planning in resource-constrained settings.

Methods: Police-reported pedestrian crash data from Dhaka were combined with multiple open data sources, including Google Street View imagery, Overture Maps, OpenStreetMap, and Meta's sociodemographic datasets. Built-environment variables such as land use ratio, network density, and demographic attributes were extracted. Visual characteristics including Green View Index, Signage Index, Street Openness, Buildingview Index, and Streetscape Complexity were derived through semantic segmentation of street-level imagery. Four machine learning models were trained for binary crash severity prediction: Random Forest, XGBoost, AdaBoost, and CatBoost. Model interpretability was assessed using SHAP values. K-means clustering was applied to SHAP outputs to identify groups of road segments with similar risk patterns.

Results: XGBoost achieved the best predictive performance with an F1 score of 79%. Network density and commercial, institutional, residential, and industrial land use showed positive associations with fatal crashes. Recreational land use, signage presence, greenery, building visibility, Relative Wealth Index, and the density of schools, hospitals, and bus stops showed negative associations. Streetscape Complexity demonstrated a nonlinear effect. Low complexity reduced fatality risk, while moderate and high complexity increased the likelihood of a fatal outcome. SHAP clustering revealed three distinct roadway environments: segments with strong commercial activity and high building visibility, dense neighborhoods with greenery and high-speed traffic, and open, low-income corridors where vehicles travel at higher speeds. These patterns confirmed strong spatial heterogeneity in the influence of built environmental variables on crash severity.

Conclusions: The findings show that both visual and built-environment characteristics significantly affect pedestrian crash severity and that their impacts vary across different street contexts. The integration of open geospatial datasets with interpretable machine learning provides a practical framework for analyzing crash severity in cities that lack detailed roadway inventories. The demonstrated spatial heterogeneity underscores the need for location-specific interventions rather than uniform safety strategies. This framework can support planners and policymakers in designing safer streets and prioritizing targeted safety measures in rapidly urbanizing regions.

Keywords: traffic crash severity; urban planning; built environment; visual environment; open geospatial data; computer vision

Word Count: 5772 words, 3 tables & 9 figures

Introduction

Pedestrian-vehicle crashes pose a significant health concern worldwide. Approximately 1.19 million people die each year as a result of road traffic crashes, and pedestrians account for 21% of fatalities worldwide (World Health Organization 2023). In order to implement effective countermeasures, it is essential to understand the factors contributing to pedestrian crashes. Researchers have investigated the underlying factors of pedestrian crashes through numerous studies (Nogueira Silva et al. 2022; Ahmed et al. 2023; Sedigh Bavar et al. 2023). Different approaches are often needed to reduce crash occurrence and minimize crash severity. For this reason, researchers typically develop separate models for crash frequency and severity analysis (Savolainen et al. 2011; Liu and Fan 2020). Urban traffic crash severity is significantly influenced by the built environment, which shapes regional traffic patterns, vehicle speeds, and the frequency of potential crashes (Ewing and Dumbaugh 2009).

However, despite evidence that visual surroundings can affect driving behaviour (Edquist et al. 2012; Anciaes 2023), current research has predominantly focused on built environment factors. While a few studies have explored how visual environment affects crash

occurrence (Cai et al. 2022; Liu et al. 2023a; Yue 2024), its impact on crash severity remains underexplored. Pedestrian crash severity analysis examines how possible crash-inducing variables relate to severity outcomes (Prato et al. 2018; Zafri and Khan 2023). It is important to understand how the built and visual surroundings affect the severity of pedestrian crashes in order to design well-planned road landscapes and enhance pedestrian and traffic safety.

In the absence of comprehensive roadway inventories, often in the case of developing countries, innovative approaches leveraging emerging data sources are essential. However, only a handful of studies focused on crash severity, considering the built and visual environment, and utilizing emerging data sources for analysis in developing countries. The visual environment is the combination of all visual elements along a street, including buildings, sidewalks, trees, furniture, and open spaces that create its unique character and appearance. The primary visual elements of urban streetscape can be measured through Green Looking Ratio, Street Openness, Buildingview Index, and Streetscape Complexity (Liu et al. 2023a), which influence crash risk through affecting driver attention, decision-making (Jiang et al. 2021), and heart rate (Liu et al. 2023a). As a megacity of a developing country, Dhaka offers a unique visual and built environment due to its dense population, rapid urbanization, diverse land use, heterogeneous traffic flow, and limited public infrastructure (Cervero 2013), which necessitates a comprehensive analysis of its streetscape elements to enhance the understanding of how streetscape can influence crash severity.

In Bangladesh, a few studies have analyzed crash severity using police data and traditional models such as ordered probit and logistic regression (Barua and Tay 2010; Kamruzzaman et al. 2014), leaving gaps due to limited built-environment variables and little attention to visual variability.

Built-environment studies based on the 3D/5D frameworks show that density, land-use mix, roadway design and transit accessibility strongly influence pedestrian safety

(Cervero 2002). Recent work using spatial models demonstrates that these effects vary across geographic locations, including Dhaka, confirming the importance of accounting for spatial heterogeneity (Prato et al. 2018; Zafri and Khan 2023).

A newer line of research examines the driver's visual environment using Google Street View and deep learning, linking visual features such as greenery, sky openness and roadside complexity to speeding behavior and crash occurrence (Cai et al. 2022; Stiles et al. 2022). Machine learning and SHAP-based interpretability have improved in recent crash studies (Yang et al. 2021; Ahmed et al. 2023), but no research in Bangladesh has integrated built-environment features, visual-environment attributes and crash severity in a single framework. This leaves a methodological and contextual gap that the present study aims to address.

The major contribution of this study is threefold. First, this paper adds to the existing literature by incorporating both the visual and built environmental parameters in pedestrian crash severity analysis. Secondly, by introducing a framework that can leverage publicly accessible, open, and crowd-sourced geospatial data sources to complement traditional crash data, particularly useful in data-scarce regions. Lastly, by creating a map of road segment clusters with similar crash fatality risk and characteristics to facilitate planners and decision-makers design well-planned streetscape and implement targeted interventions to enhance pedestrian and traffic safety.

Methods

Study Area

The study encompasses the entire Dhaka Metropolitan Area covering an area of 1530 km^2 with a population of about 23.9 million (Greater Dhaka 2025). It covers the Dhaka Municipal Corporation area along with several surrounding municipalities: Savar and Keraniganj, as

well as Narayanganj Sadar, Bandar, Rupganj, Gazipur Sadar and Kaliakair.

Data Collection

Accident Data

Traffic Crash data for the four years 2017 to 2020 were collected from the Accident Research Institute, BUET, for the Dhaka Metropolitan Area. There were 1,021 reported traffic crashes on roads recorded by the Dhaka Metropolitan Police. After filtering for pedestrian-vehicle crashes and removing duplicate entries, 623 data points were obtained. Since locations are vital for this study, data with missing crash locations were discarded, and 426 crash data points were retrieved, as shown in the map in Figure 1.

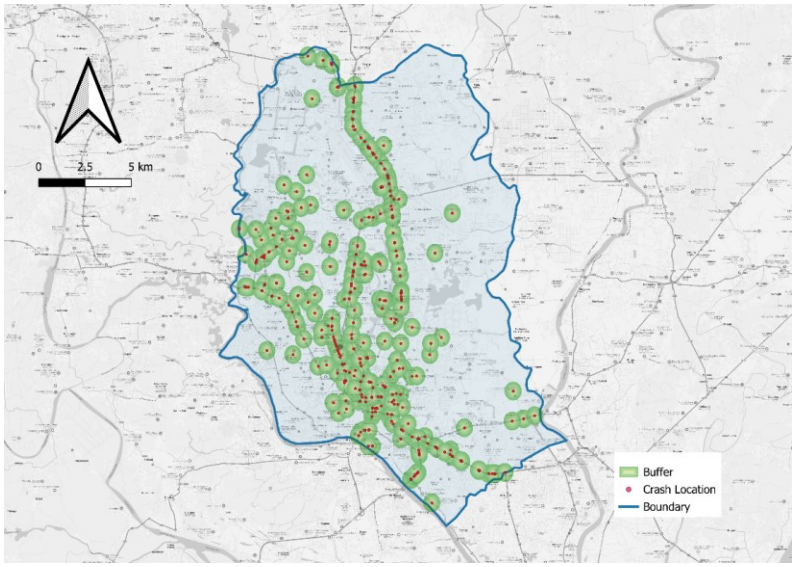


Figure 1 Map of study area, buffer zone and crash locations

Land Use Data

Due to a lack of accurate land use data for developing countries like Bangladesh, most of the studies conducted in the past relied on Detailed Area Plan for approximating land use variable, which is often not representative of real land use. Recently, a global trend has emerged towards utilizing Points-of-Interest (POI) from map data to determine land use

variables (Andrade et al. 2020; Li et al. 2021). Point of Interest (POI) data highlight key locations on maps and offer valuable locational attributes for urban analytics and city science.

Despite the global availability of Google Maps, its associated API costs and the limited access of points of interest (POI) per location make it unsuitable for comprehensive land use analysis. The recent emergence of open data platforms, such as Overture Maps, is opening new opportunities. Overture Maps is an open data mapping collaboration that offers high-quality data for locations worldwide. In this study, the Overture Places dataset is utilized to extract 78,878 points of interest (POI) covering the entire Dhaka Metropolitan Area.

Amazon Web Service Command Line Interface were used to download Overture Places data from Amazon S3 bucket. The downloaded GeoParquet files were filtered using the bounding box co-ordinate of Dhaka Metropolitan Area using DuckDB query engine. Overture Maps offers POI data approximately across more than 813 categories. To enhance usability and better define the land use of road segments, similar POIs were grouped and reclassified into seven categories, as outlined in Table 1.

Table 1 Classification of POI categories for enhancing usability

Reclassified POI Category	**Description**	**Overture Maps POI Category**
Commercial	Commercial businesses and their offices	shopping_center, grocery_store, furniture_store, books`tore, department_store, jewelry_store etc.
Institutional	Places used for institutional purposes and religion	college_university, school, religious_school, elementary_school, medical_school, vocational_and_technical_school, religious_organization etc
Residential	Guest house, hotels, accommodation, residential dwellings	accommodation, hotel, hostel, cottage, inn, housing_authorities, real_estate_service etc.

Reclassified POI Category	Description	Overture Maps POI Category
Public Service	Government buildings and government offices, services, non-profits, social services	public_service_and_government, post_office, charity_organization, local_and_state_government_offices, youth_organizations, fire_department, public_utility_company etc.
Industrial	Workshops, factories, or warehouses and those produce goods	chemical_plant, industry, appliance_manufacturer, glass_manufacturer, mattress_manufacturing, iron_and_steel, industrial_company eetc.
Recreational	Places used for entertainment or recreational purposes	park, spas, theatre, arts_and_entertainment, gym, soccer_field, museum, zoo, cricket_ground, botanical_garden, travel, lake, meditation_center, swimming_pool, fort, playground, golf_course, resort, circus, dance_club, fair, topic_concert_venue etc.
Transportation	Places used for transportation system and infrastructure	airport, gas_station, bus_station, train_station, airport_terminal, rental_service, automotive_repair, bridge, motorcycle_repair etc.

Using the DuckDB query engine, the Point-of-Interest (POI) and densities of Educational Institutions, Bus Stops, and Hospitals within 500m of each location with a confidence level exceeding 0.7 were count, as shown in Figure 2. These filtered counts, helped remove lower-accuracy records. For determining the land use ratio, most studies in the past relied on the total count of POI over a defined radius (Li et al. 2021; Yue 2024); however, since POI data is highly imbalanced on online maps, such methodology may not be appropriate.

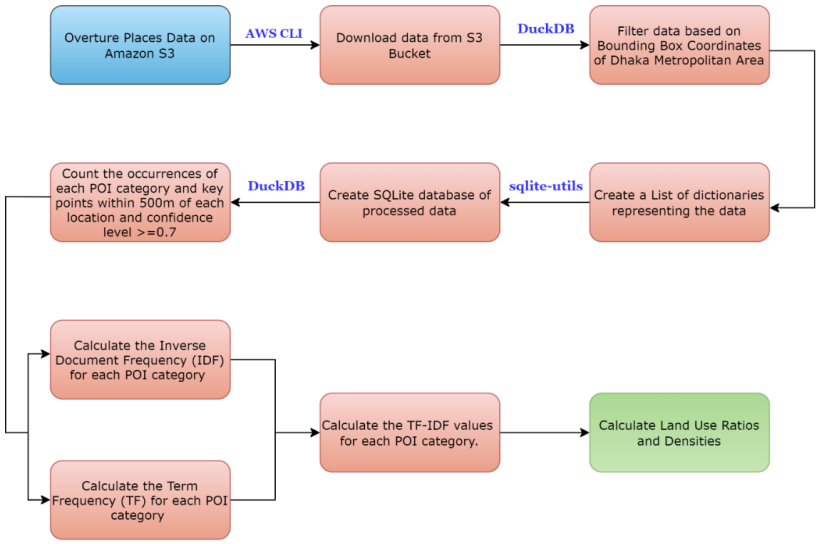


Figure 2 Collection of Point-of-Interest data from Overture Maps and calculating land use variables

In this study, the concept of relative frequency is employed. Commercial POIs are reported more frequently than residential or recreational POIs on online mapping services. By applying the concept of relative frequency, we weight the Term Frequency (TF) with the Inverse Document Frequency (IDF) to ensure that POI categories appearing frequently across all the buffer zones are assigned a lesser weight. This methodology of determining land use ratio is consistent with the methodology followed by Gao et al. (2021). TF and IDF for POI category *p* for buffer zone *i* are given by equations 1,2, and 3 shown below.

$$tf = \frac{N_{pi}}{\sum_{i=1}^{P} N_{pi}} \tag{1}$$

$$idf = \log \frac{\sum_{i=1}^{Z} \sum_{i=1}^{p} N_{pi}}{\sum_{i=1}^{Z} N_{pi}} \tag{2}$$

$$tfidf = tf.idf \tag{3}$$

Where, *tf* is the term frequency of POI category p, N_{pi} is the number of p POI category for *i*th buffer zone, P is the total number of POI category. *idf* is the inverse document frequency and Z is the total number of buffer zones in the study area. It is clear from the equation that, as the value of $\sum_{i=1}^{Z} N_{pi}$ increases, the *idf* value decreases. Land Use Ratio for POI category p is then calculated using the equation, $R_{pi} = \frac{tf\ .\ idf}{\sum_{p=1}^{P} tfidf_{pi}}$. Similarly, Land Use Mix Level is determined using $\frac{-\sum_{i=1}^{P} R_p \cdot \ln(R_p)}{\ln(P)}$.

Visual Environment Data

Collection of GSV Images: The coordinates of the accident location were identified based on the location description available at the ARI accident dataset using Google's geocoding API. Due to the imprecise nature of these descriptions, accurately pinpointing accident locations was challenging. Consequently, road segments, defined as the part of the street that runs between two intersections or dead ends (Boeing 2017), corresponding to each crash, were used for further calculations. Google's Street View Static API was used to download images at 640×640 resolution along these road segments. Using this API, the GSV image in the desired pitch, field of view, and heading can be requested. The field of view was set to 60°, as suggested in past studies (Cai et al. 2022), and is shown in Figure 3.

Heading was calculated based on the bearing angle and the direction of the road using OSMNx (Boeing 2024). After removing images with defects, total 12,108 images were stored for further analysis.

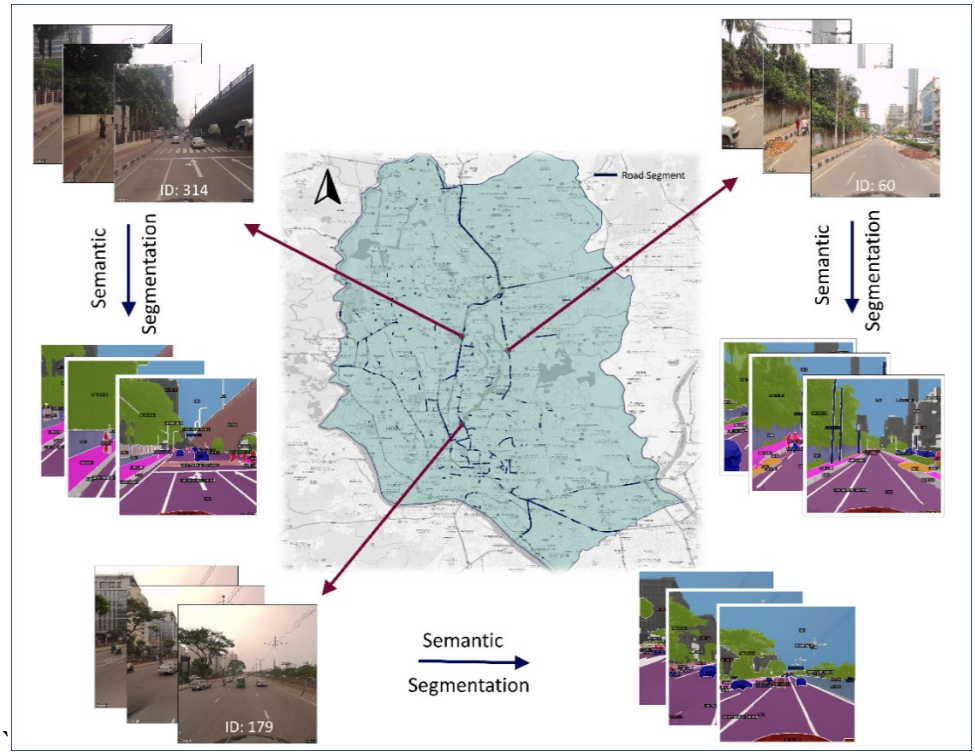


Figure 3 Semantic segmentation of collected GSV images at 5m interval of identified road segments

Extraction of Streetscape Features

In this study, Detectron2 (Wu et al. 2019) along with Mask2former, a universal image segmentation architecture, pretrained on the Mapillary Vistas dataset, has been utilized to perform semantic segmentation on downloaded GSV images (Cheng et al. 2022). Both the architecture and pretrained model have been carefully chosen to perform best on streetscapes of Dhaka. The Mapillary Vistas dataset street-level images from all over the world, covering 6 continents (Neuhold et al. 2017).

Streetscape features, such as, pixel proportion of road, building, sidewalk, sky, vegetation, etc. were extracted by semantic segmentation. Dynamic elements that change frequently including persons, bicycles, buses, cars, motorcycles etc. excluded from this analysis. Using the extracted features, various streetscape contextual variables (Liu et al.

2023b) were derived by calculating the average values of all collected images for each road segment, as shown in Table 2.

Table 2 Streetscape's contextual features

Variable	Definition	Expression
Street Openness	Proportion of sky pixels to total image pixels.	$\frac{\sum Pixel_{sky}}{\sum Pixel_{image}}$
Buildingview Index	Proportion of building pixels to total image pixels.	$\frac{\sum Pixel_{building}}{\sum Pixel_{image}}$
Green Looking Ratio	Proportion pixels of greeneries to total image pixels.	$\frac{\sum Pixel_{vegetation}}{\sum Pixel_{image}}$
Signage Index	Proportion of traffic sign, banner, billboard to total image pixels.	$\frac{\sum Pixel_{sign}}{\sum Pixel_{image}}$
Visual Complexity	Proportion of static streetscape elements (sidewalk, sky, vegetation, traffic sign, vegetation pole etc) to total pixels of building and road class. (Liu et al. 2023b)	$\frac{\sum Pixel_{static\ elements}}{\sum Pixel_{building} + \sum Pixel_{road}}$

Sociodemographic Data

Sociodemographic data, Population Density (per 30 m^2), and Relative Wealth Index (per 2.4 km^2) were collected from the 'Data for Good' project of Meta.

Road Network Data

Roadway network data was collected from OpenStreetMap using the OSMnx Python library (Boeing 2024). Road network density was calculated by summing up the total roadway length in each buffer area and dividing by the buffer area.

Lane Data

A Python script was written to collect traffic lane count from OpenStreetMap using the Nominatim web service. For road segments where the lanes tag was missing in OpenStreetMap, lane count was imputed using the modal value of the corresponding road class.

Weather Data

The crash dataset did not have accurate weather classification, so weather data was collected for stated latitude, longitude and crash time using the historical weather API of open-meteo (Zippenfenig 2024).

Traffic Speed Data

Traffic speed data for developing countries often unavailable due to lack of necessary infrastructure and associated cost. Google Typical Traffic's Color Codes have been utilized to estimate the traffic speed of road segments. A Python script was developed to automatically download images of traffic color at each crash location for the specific week-days and times. By analyzing the images, Congestion Color Codes were extracted. The five Color Codes were then converted into an ordinal variable called "Relative Vehicle Speed", similar to the scale previously outlined by (Hilpert et al. 2019). For the Relative Vehicle Speed categories, the colors Dark Red, Red, Orange, Green and Grey correspond to the values 1, 2, 3, 4 and 5. A value of 1 indicates heavily congested conditions, 2 indicates congestion, 3 represents slow-moving traffic, 4 reflects free-flowing conditions and 5 indicates light traffic.

Density of Features

the density of three key features, which were previously found to be linked to pedestrian crash severity (Xin et al. 2017; Zafri et al. 2020), such as Hospital Density, Educational Institute Density and Bus Stop density were calculated for each buffer. The summary of the data collection process is shown in Figure A3 of Appendix. The descriptive statistics of the independent variables along with the sources are attached in Table A1 of Appendix.

Binary Classification Model for Accident Severity

In this study, crash severity prediction is considered to be a binary classification problem that classifies crash severity into fatal and non-fatal categories. Four ensemble machine learning models, (1) Random Forest, (2) AdaBoost, (3) XGBoost, and (4) CatBoost were adopted for the crash severity prediction model, in consistent with most previous crash severity studies.

Random Forest: Random Forest is an ensemble learning method that combines multiple decision trees to reduce overfitting and improve prediction accuracy. It uses a technique called bagging to randomly select training samples. A single decision tree has low bias and high variance. Random Forest addresses this issue by averaging predictions from multiple trees to reduce variance while keeping bias low (Tin Kam Ho 1995).

AdaBoost: Boosting is an ensemble learning technique that combines multiple weak learners to create a strong learner. Boosting methods provide more importance to misclassified instances which allows the model to adapt and improve iteratively. One of the most popular boosting algorithms is Adaptive Boosting, introduced by (Freund and Schapire 1997).

XGBoost: Extreme Gradient Boosting is based on gradient boosting that is designed for speed and efficiency (Chen and Guestrin 2016). It improves upon gradient boosting through

incorporating optimization techniques and algorithmic enhancements. XGBoost focuses on fitting new models to the residual errors of the previous ones instead of adjusting weights.

CatBoost: CatBoost is an open-source library for gradient boosting on decision trees that offers high performance with minimal parameter tuning, specifically while handling categorical features. It natively supports categorical data and eliminates the need for manual encoding (Prokhorenkova et al. 2018).

Interpreting Model Predictions

SHAP (SHapley Additive exPlanations) is an explainable algorithm that provides a systematic and objective method for understanding how machine learning models generate predictions. For a feature i, the SHAP value can be obtained by equation 4 given below,

$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!\,(|F| - |S| - 1)!}{|F|!} \left[f_{S \cup \{i\}}\left(x_{S \cup \{i\}}\right) - f_S(x_S) \right] \qquad (4)$$

Where, |F| is the set of all features, S denotes any subset of features excluding the ith feature, $|S|$ is the size of that subset. $f_{S \cup \{i\}}\left(x_{S \cup \{i\}}\right)$ refers to the model trained with the ith feature, while $f_S(x_S)$ represents the model trained without it (S.M. Lundberg and Lee 2017).

Clustering of SHAP Values using K-means Clustering

To identify patterns and group similar data points, K-Means clustering was applied on SHAP values of top 20 feature. K-Means clustering utilizes a four-step iterative algorithm for grouping similar data points. The first step involves choosing K initial cluster centroids. The second step is assigning each data point to its nearest cluster from the selected metric. Once

all the points are assigned, the center of each cluster is recalculated based on the mean calculation of the data points in each cluster. These update and assignment steps are iteratively repeated until the clusters are stable.

Results

Performance of Crash Severity Model

The dataset exhibited mild class imbalance, so a cost-sensitive learning approach was applied by assigning class weights inversely proportional to class frequencies. Balanced weights were computed by dividing the total number of samples by the product of the number of classes and the number of instances in each class. All models were trained using an 80:20 split along with stratified 10-fold cross-validation. Hyperparameters were tuned using Bayesian optimization implemented through Optuna. During optimization, each candidate model was evaluated using five-fold stratified cross-validation, and model quality was summarized with a composite objective function that combined discrimination and class-balanced performance. The objective was defined as $0.6 \times \mathrm{AUC} + 0.4 \times \mathrm{F1}$, giving slightly greater weight to class separation while still accounting for imbalance.

To determine the optimum features for the model, an initial Random Forest model was trained and features with very low or zero importance were removed. After feature refinement, four models were trained, and their performance metrics are reported in Table 3.

Table 3 Performances of the models trained

Model	Accuracy	Precision	Recall	F1	AUC
Random Forest	69.0	85.0	63.0	72.0	67.0
XGBoost	72.0	85.0	74.0	79.0	70.0
AdaBoost	67.0	79.0	74.0	77.0	62.0

Model	Accuracy	Precision	Recall	F1	AUC
CatBoost	65.0	83.0	65.0	73.0	66.0

The XGBoost classifier achieved the best overall performance, with an accuracy of 72.0 , a AUC of 70.0, and an F1 score of 79.0. The final model used (XGBoost) the hyperparameters identified through Optuna optimization which includes a maximum depth of 18, a learning rate of 0.15, 160 boosting rounds, a subsample rate of 0.30, a column-sampling rate of 0.54, and regularization terms of 9.65 (L1) and 0.48 (L2). For imbalanced datasets, accuracy score is not be the best metric for model comparison, for which AUC and F1 scores were also calculated. Considering all these metrics, XGBoost model was selected as the best performing model.

Discussion

Feature Analysis using SHAP

In order to unveil the impact of contributing factors for crash severity analysis, feature analysis was performed using SHAP. SHAP framework was first introduced by Lundberg and Lee (S. Lundberg and Lee 2017), which is based on Shapley values. Global and local interpretability, then clustering of SHAP values were performed to better understand the non-linear characteristic of features and crash severity.

Global Interpretability of Model

For global interpretability SHAP values aggregate the contributions of each feature across all observations in the dataset. This helps determining the most influential features for the model's prediction on average.

Analyzing Feature Importance: Feature importance provides insight into the most influential features on model prediction. Plot in Figure 4 shows important features in descending order of importance. The most important feature affecting the model outcome is recreational land use ratio, followed by signage index, streetscape complexity, educational institute density, public service land use ratio, network density, no. of lanes, population density, Street Openness etc.

Among the key feature densities, educational institute density has more impact on model prediction than hospital and bus stop densities. Among contextual streetscape features, the model prediction is more impacted by Signage Index, Streetscape Complexity, Street Openness than Green Looking Ratio and Buildingview Index. Regarding land use, the model prediction is less impacted by commercial, industrial, institutional land use compared to recreational, public service and residential land use. Among the street design related parameters, network density, no. of lanes, primary road category, relative vehicle speed impacts the model prediction most.

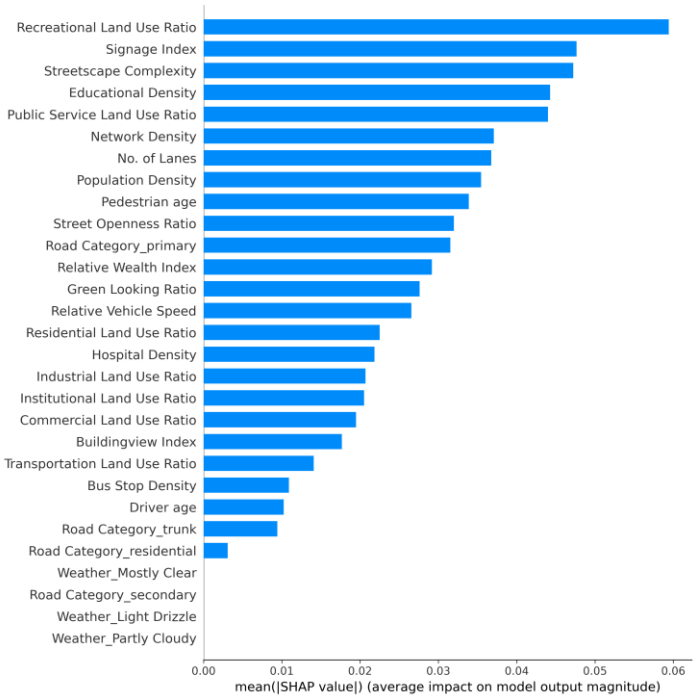


Figure 4 SHAP feature importance

Analyzing Correlation with Summary plot: SHAP summary plot shown in Figure 5 offers global explainability by displaying both key features and the range of their effects across the entire dataset. Positive value of SHAP indicates positive correlation of a feature with fatal crashes while negative value of SHAP indicates negative correlation with fatal crashes for a given observation. For instance, road segments with higher recreational land use ratio are found to be negatively correlated with fatal crashes.

Street segments with higher value of signage index are found to be less prone to fatal pedestrian crashes. Streetscape's visual complexity from global perspective have been found to be positively contributing to fatal crashes. This is due to the fact that visually complex environments may increase driver's cognitive load. While relation between streetscape and crash severity have not been studied much in the past, previous studies have found both positive (Cai et al. 2022) and negative correlation with streetscape complexity and crash occurrences (Liu et al. 2023b).

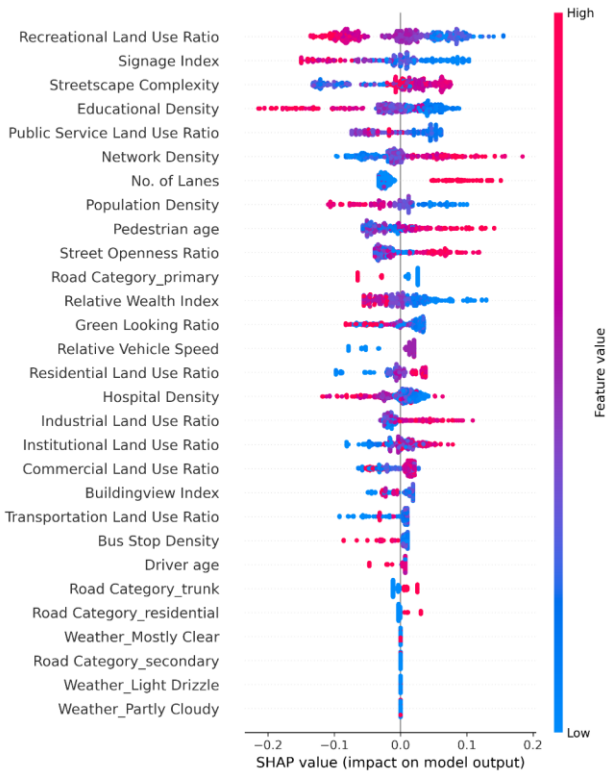


Figure 5 SHAP summary plot for global interpretability

Network density also positively contributes to fatal crashes, which is in consistent with previous studies conducted by (Zafri and Khan 2022) although contrary to studies conducted by (Wang et al. 2023). Commercial land use ratio increase the probability of fatal crashes, which is also consistent with previous study (Wang et al. 2023). Institutional, residential and industrial land use is found to increase the likelihood of fatal crashes. While the findings for institutional land use are in consistence with previous study (Zafri and Khan 2023), for residential and industrial land use are contrary to past studies (Aziz et al. 2013; Zafri and Khan 2023). Also, the SHAP summary plot shows the mean average of SHAP values and the correlation may differ for individual street segments.

Lower values of population density is found to be associated with increased likelihood of fatal crashes which is in consistent with previous study (Clark 2003). Features that are negatively correlated with fatal crash for the XGBoost model are: educational institution density (in consistent with past study (Xin et al. 2017)), public service land use ratio, Relative Wealth Index, Green Looking Ratio (aligns with findings of past studies (Calvi 2015; Cai et al. 2022)), hospital density, buildingview index and bus stop density (similar to findings of study (Xin et al. 2017) and in contrary to the findings of study (Zafri and Khan 2023)).

Analyzing non-linearity with Feature Dependence plot: SHAP feature dependence plot shows how changing a specific feature impacts the model's output as well as the distribution of that feature's SHAP values. Figure 6 shows SHAP dependence plot for top 4 most important features.

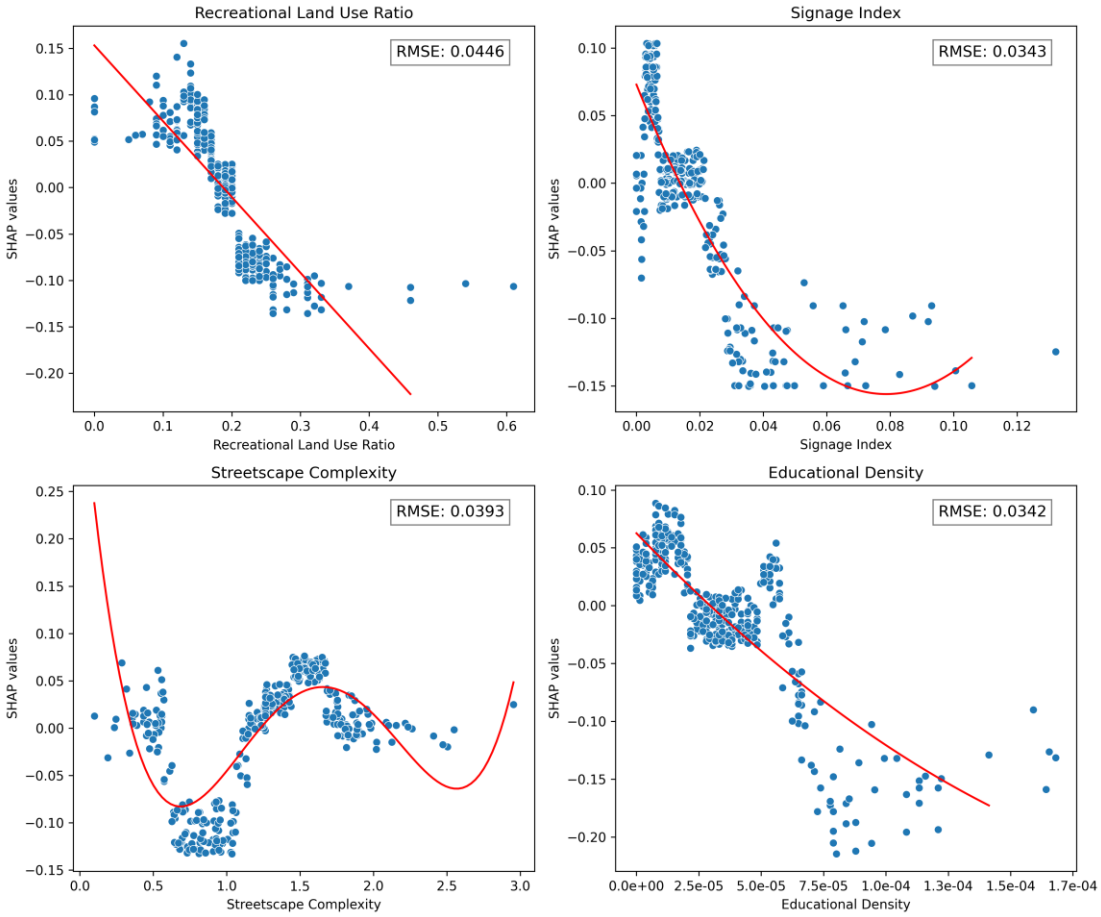


Figure 6 SHAP dependence plot for 4 most important feature causing fatal crashes

Recreational land use ratio vs SHAP values plot shows a trend of linear negative relationship with fatal crashes. The dependence plot for signage index shows a slightly non-linear relationship. This suggests that areas with more signage might have better traffic control, improved driver awareness and potentially safer road conditions. However, too much traffic signs can distract drivers increasing likelihood of fatal crash.

The educational institute density vs SHAP values plot also shows a negative correlation with fatal crashes. However, the streetscape complexity dependency plot shows a complex non-linear relationship. For smaller values of complexity, the likelihood of fatal crash decreases. This may happen because street segments with smaller complexity have simple layout and a smaller number of distracting elements. There is a cluster of data points with positive SHAP values in the middle range of Streetscape Complexity suggesting that

moderate and very high levels of Streetscape Complexity might be associated with an increased risk of fatal crash. However, the relationship is likely influenced by various other factors requiring in-depth analysis.

Local Interpretability of Model

Local interpretability provides information about how individual feature value impacts a specific prediction made by a machine learning model. For the first observation, the bar plot is shown in Figure 7.

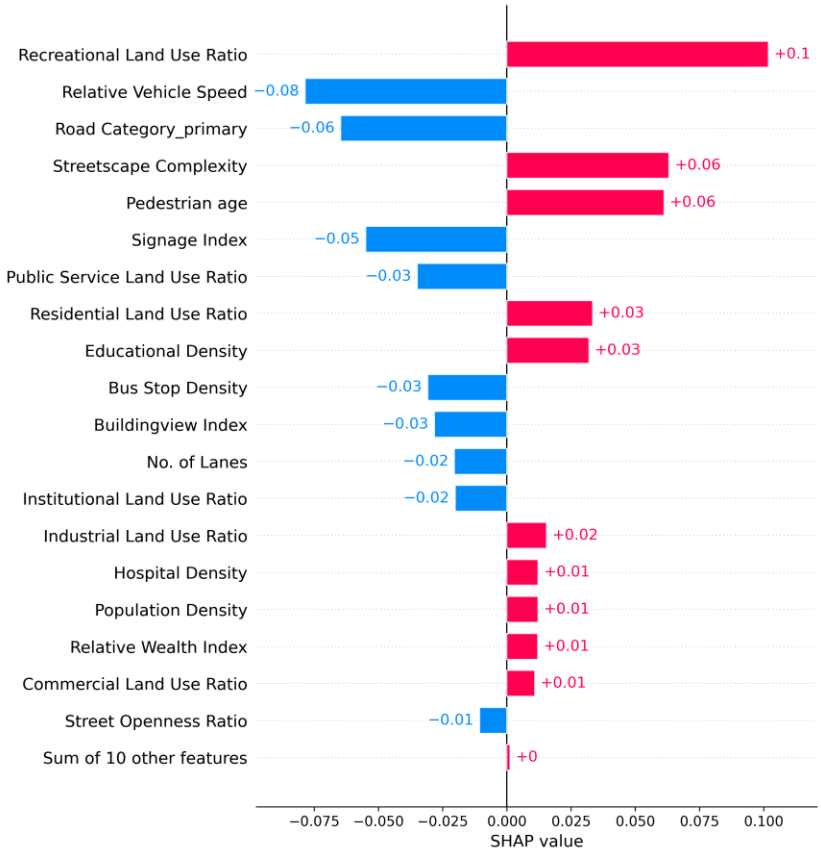


Figure 7 Local feature importance for observation 1

The bars represent SHAP value for each feature. Bars colored red indicates the feature increase the likelihood of fatal crashes where blue indicates the decrease of likelihood of fatal

crashes. For observational 1, recreational land use, streetscape complexity, pedestrian age, residential land use, educational inst. density etc. are found to be increasing the likelihood of fatal crashes.

Interpreting Results of SHAP Clustering

K-Means clustering was applied to the SHAP values obtained of the top 20 features with optimum number of clusters selected as, K = 3 focusing on Silhouette score and easier interpretability. SHAP values quantify the importance of each feature by determining how much each feature contributes to the prediction, both positively and negatively.

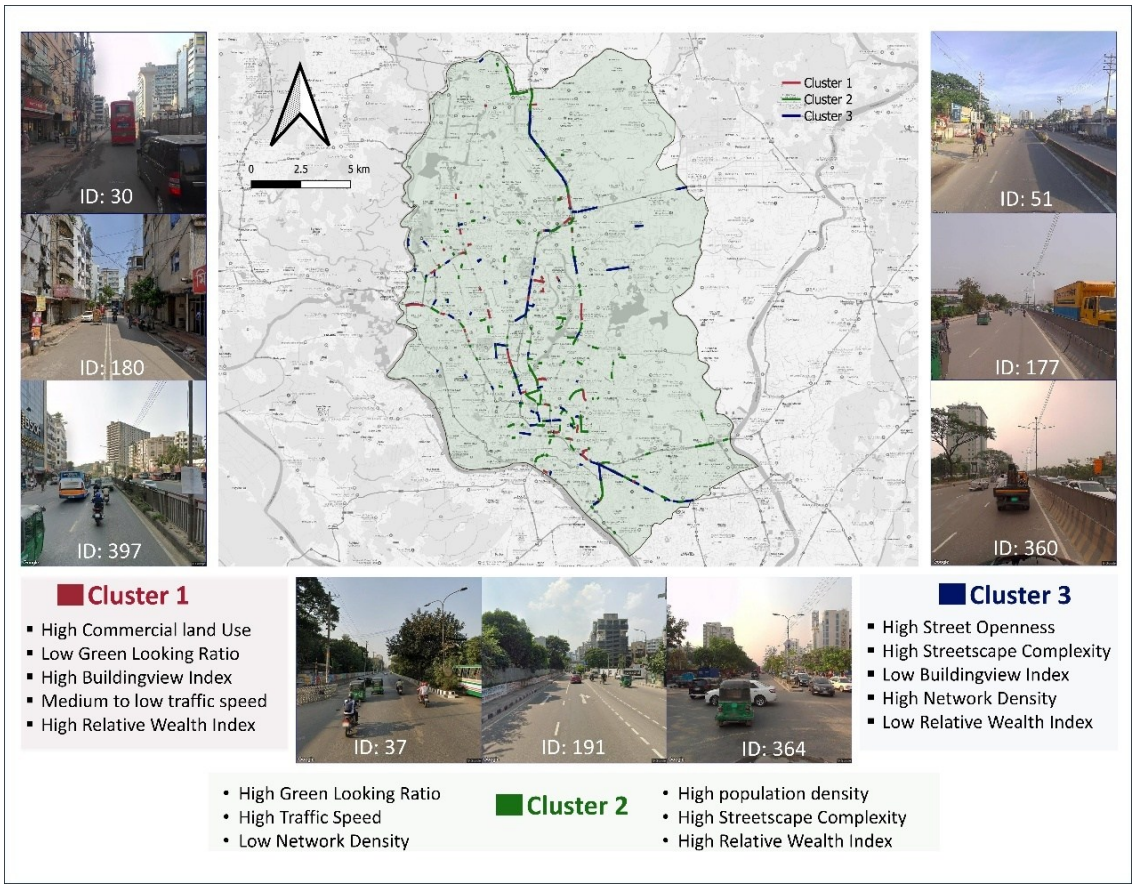


Figure 8 Clustering of SHAP values and cluster characteristics

SHAP summary plot shows an aggregated view of feature importance. SHAP clustering can overcome this issue by showing feature contribution in road segments with similar SHAP values. Sample images of each cluster are shown in Figure 8.

Figure 9 below shows average SHAP value corresponding to each cluster for top 20 of most important features. For cluster 1, features that positively contribute to fatal crashes are: recreational land use ratio, public service land use ratio, relative wealth index, recreational and institutional land use ratio. On the other hand, educational institute density, streetscape complexity, signage index, hospital density, street openness, population density, industrial land use ratio, building view index and pedestrian age. Some of these features affects positively to model outcomes for one cluster, but negatively to other clusters.

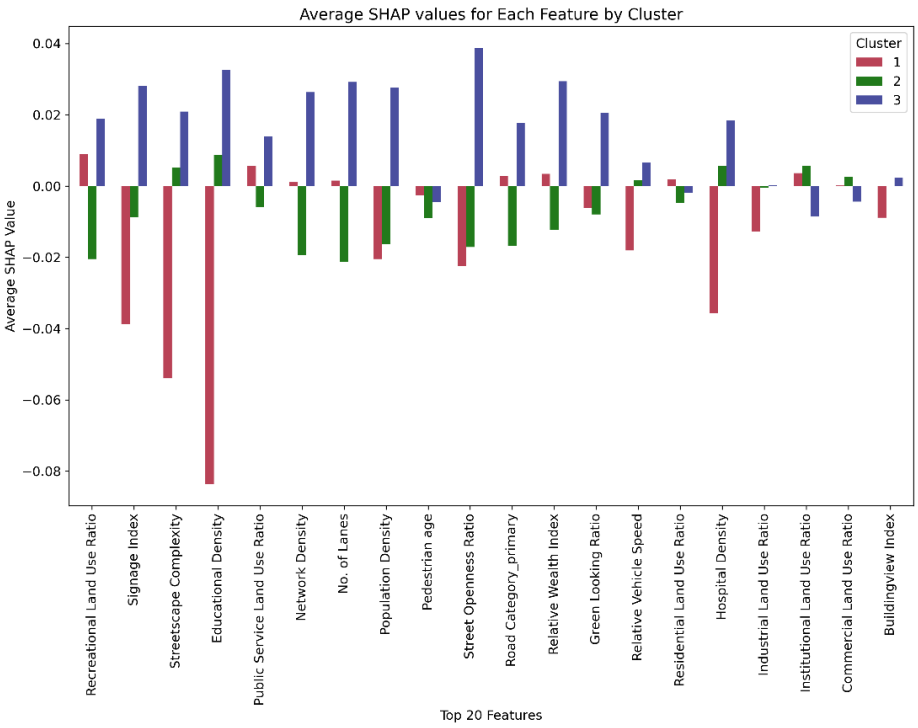


Figure 9 Average SHAP values corresponding to each cluster for top 20 features

For cluster 2, features that increase the likelihood of fatal crashes are: streetscape complexity, educational institute density, hospital density, institutional and commercial land use ratio. Negatively correlated features are: no. of lanes, network density, recreational land use ratio, network density, street openness, pedestrian age, public service and recreational land use ratio. Pedestrian age is negatively correlated to all three clusters meaning younger pedestrians tend to face more fatal crashes.

For cluster 3, most of the features are positively correlated with fatal crashes except for pedestrian age, recreational, industrial and commercial land use ratio.

Cluster 1 is characterized by areas with a high Building View Index (0.2), high commercial land use (0.25), a high density of educational institutions and hospitals, occasional congestion, and high Relative Wealth Index (1.35).

Cluster 2 is characterized by high greeneries (0.12), dense population (52) and elevated speeds. These road segments have high relative vehicle speed since the network density is low. Cluster 3 includes by open streets (0.36) in relatively low-income (1.02) areas with high network density and speedy traffic. Box plot of each cluster for top 20 features are shown in Figure A2 of Appendix.

Policy Implications for Pedestrian and Traffic Safety

Critical Features are determined by deeply analysing Figure 10, Figure A2 of Appendix and identifying features that increase the likelihood of fatal crashes and are prevalent (exceeding dataset median) in respective clusters of road segments.

For cluster 1, recreational and public service land use, network density, no. of lanes, residential and institutional land use are critical features which are positively associated with fatal crashes. To improve pedestrian safety, pedestrian-priority zones should be designated near recreational land use zones. Near schools, colleges and major public institutions, Neighbourhood Slow Zones should be implemented. Superblock Design can be implemented to simplify road networks. Besides. Context-Aware Signage can be implemented in these streets.

For cluster 2, Educational Institute, Hospital Density, Streetscape Complexity, Relative Vehicle Speed, and Industrial and Commercial land use are identified as critical features. In these streets, Speed-Controlled Corridors with enough signage and well-marked

pedestrian crossings should be implemented near schools and colleges. Green Buffers around school, colleges and hospitals should be implemented to naturally slow down traffic (Calvi 2015; Cai et al. 2022). Besides, the Dynamic Lane Management technique should be implemented to ensure the slower and orderly flow of traffic around industrial zones. Near markets, shopping malls and hospitals adaptive street lights should be installed to control speeding behavior.

For Cluster 3, the identified critical features are Street Openness, Number of Lanes, Network Density, Streetscape Complexity, and Relative Vehicle Speed. To ensure pedestrian safety, Variable Speed Limits should be implemented on wide open road. Frontage Roads can be developed on high-speed arterials. Besides, mixed-use catalyst zones can be implemented through encouraging mix land use along open corridors. Finally, upgradation of existing pedestrian infrastructures can improve pedestrian and traffic safety. The summary of critical features and suggested policy measures for planners and policymakers is summarized in Figure A1 of Appendix.

Limitations

This study has several limitations. Crash location data obtained from ARI often contained imprecise textual descriptions, which may have introduced positional errors when mapping events to street segments. Some road segments also lacked Google Street View coverage, requiring the use of the nearest available imagery and potentially reducing accuracy in derived visual features. Due to underreporting, incomplete location information, and variable data quality, only 426 crashes could be used, limiting statistical power. Land-use measures were derived from the 2023 Overture Places dataset as the closest available temporal match to the study period, though newer releases may better reflect current conditions.

Conclusions

This study presents a data-driven framework for analyzing the risk factors influencing the severity of pedestrian-vehicle crashes, with a special focus on the interplay between built and visual environmental characteristics in developing urban settings. By integrating multiple open geospatial data sources, this research addresses several key gaps in the existing literature related to data scarcity, spatial heterogeneity, and model interpretability in road safety studies. Through machine learning predictive modeling and SHAP-based interpretability analysis spatial heterogeneity and complex, non-linear associations between crash severity and both traditional built environment factors visual variables were uncovered. The clustering of street segments based on SHAP values further reveals that the influence of these factors differs markedly across urban contexts, affirming the need for localized and context-sensitive policy interventions. The demonstrated spatial heterogeneity in risk factors underscores that a one-size-fits-all approach is inadequate for predicting and mitigating crash severity. In summary, the results from this study provide a robust foundation for the development of context-aware, data-driven interventions to enhance road safety in developing urban environments and contribute to the broader goal of sustainable, people-centered urban mobility. Despite some limitations, the study offers a structured and transferable framework that can be strengthened with larger datasets and extended in future research on pedestrian crash severity in resource-constrained settings.

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During the preparation of this work, the authors used ChatGPT and Claude only to enhance the readability and language of the manuscript. Following the use of these tools, the authors thoroughly reviewed and revised the content to ensure accuracy and take full responsibility for the final version of the manuscript. All content, analysis and interpretations are original and their factual accuracy have been verified by the authors and have been ensured that the work is free from bias and plagiarism risks associated with AI generated texts.

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Data availability

Data will be made available on request.

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