SOCIO-ECONOMIC & INFRASTRUCTURAL DETERMINANTS OF ROAD ACCIDENTS IN BANGLADESH

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ABSTRACT

Road accidents are one of the most severe public safety concerns in Bangladesh. Rapid urbanization, fast-growing yet poorly regulated motorization, and significant socioeconomic disparities all interact to increase exposure and vulnerability on the road. This study investigates how road accident risk varies across space and time using publicly available secondary datasets. To determine spatial risk, the Entropy Weight Method (EWM) was used to create a district-level Accident Risk Index (ARI). The index includes socioeconomic, infrastructure, and environmental factors such as population density, literacy rate, urban population share, road density, hospital accessibility, and $PM_{2.5}$ concentration. When compared to real accident records, the ARI showed great spatial alignment: districts such as Dhaka, Chattogram, Gazipur, and Narayanganj emerged as the most vulnerable, whereas many rural and hilly districts showed significantly lower risk due to reduced exposure. The study also includes a 44-year time-series analysis (1980-2023) that revealed a significant structural break in 2006, which marks a reversal from long-term improvement to renewed deterioration in road safety, coinciding with rapid economic expansion and rapid urban growth. Correlation tests and VAR analysis indicate that, while accident trends rise in line with broader socioeconomic development, they are influenced more strongly by internal systemic elements within the transportation and regulatory environment than by short-term macroeconomic changes. Overall, the findings show that the country's road safety crisis emerges from a structural imbalance between the rate of development and the institutions' capacity for control. The study, hence, recommends incorporating socioeconomic and spatial diagnostics into national road safety policies, developing uniform and reliable data systems, and implementing proactive, evidence-based policy mechanisms. Such changes are required if Bangladesh is to make significant progress toward meeting the SDG target of reducing road traffic fatalities by 2030.

Keywords: *Road Accident, Socio-economic, Infrastructural, Risk Index, Bangladesh*

1. INTRODUCTION

Globally, road traffic accidents (RTAs) are the leading cause of death and injury, threatening public health, mobility, and sustainable development. Over 1.35 million people die and over 50 million are injured in automobile accidents annually, according to the (WHO, 2023). Alarmingly, 92% of these deaths occur in low- and middle-income nations (LMICs), which own only 60% of the global motor vehicle fleet. Transportation safety is imbalanced, with economic and infrastructural inequalities increasing exposure and susceptibility (Grimm & Treibich, 2010). Bangladesh has one of the highest road death rates in South Asia, with 25,000 annual fatalities. Eighty percent of fatalities include walkers, cyclists, and three-wheeler passengers, underlining road design, enforcement, and emergency services issues (BRTA, 2024).

Socio-economic and infrastructural factors have long been recognized as critical drivers of the likelihood and severity of road traffic accidents worldwide (Amiri, et al., 2021), (Anderson, 2010), (Roshanfekr & Khodaie-Ardakani, 2019). A substantial body of research indicates that people with lower socio-economic status encounter disproportionately increased risks. For example, (Sehat, et al., 2012) found that people with low incomes in Tehran are much more likely to encounter accident rates and fatalities, and (Haghighi, et al., 2020) found that factors like education level, household income, and vehicle condition are very significant in road crashes. Likewise, (Zeng, et al., 2022) discovered that China's swift economic expansion resulted in growing traffic volumes and congestion, subsequently leading to a rise in accident rates. Research from South Asia underscores that marginalized populations experience increased vulnerability due to poor, inadequate infrastructure, and identity-based disparities (Nanjunda, 2021); (Ghee, et al., 1997). These studies collectively underscore a critical understanding that road accidents are not arbitrary incidents; rather, they are fundamentally entrenched in extensive social, economic, and spatial inequities.

The road safety scenario evolves with a country's economic and infrastructural growth.(Bishai, et al., 2006) noted that in developing nations, traffic fatalities generally increase with economic expansion, as rapid motorization heightens exposure, and subsequently decrease as institutional safety measures evolve. Their findings show that poor income, inadequate governance systems, and consistently high death rates are all interlinked. Environmental and infrastructural considerations are also quite important, in addition to economic ones. (Haulle, 2016) found that poor-conditioned roads, lax enforcement, and vehicle overloading were major causes of accidents in Tanzania. These studies show that for a whole picture of accident risk, comprehension of socio-economic, infrastructural, and environmental characteristics is necessary. Spatial analyses enhance this comprehension by illustrating the unequal distribution of accident risks across regions. A GIS-based hotspot analysis in Muscat, Oman, found that Mutrah, Bawshar, and Al-Amerat had a lot of crashes because there were a lot of people living there, heavy traffic flow, and certain road features (Alhajri, et al., 2024). A similar study by Abdullah and Sipos (2023) in Duhok combined socio-economic data like literacy rates and medical access with accident locations to show how public awareness and regional infrastructure affect the severity of crashes (Abdullah & Sipos, 2023). Mahato and Htike (2025) utilized spatial econometric models in Nepal to demonstrate that high-risk districts constitute unique geographic clusters, especially in fast urbanizing regions such as the Kathmandu Valley (Mahato & Htike, 2025). These results demonstrate the significance of spatially disaggregated analyses in elucidating the influence of urbanization, density, and accessibility on local accident exposure and outcomes.

Urbanization, unregulated transportation, and institutional shortcomings exacerbate road safety issues in Bangladesh. The National Road Safety Strategic Action Plan (NRSSAP) (BRTA, 2010) emphasizes engineering, enforcement, education, and emergency response, but its implementation remains disorganized and largely reactive. Interventions often focus on immediate hazards, such as installing speed bumps or barriers, and overlook the broader social, economic, and environmental issues that affect the likelihood of accidents. Strategies for prevention often fail to take into account how things work in the area, such as changes in land use, divergent income, and job patterns. For instance, the fact that there are a lot of garment manufacturers in peri-urban areas means that a lot of people move about there, yet this fact is rarely taken into account when making decisions about roads or policies. The lack of comprehensive, region-specific data makes it hard to interpret these patterns. Accident records are usually kept apart from the socio-economic, land-use, and environmental data that would help us understand why hazards are different in places. As a result, most of the studies that have been done thus far have focused on micro-level factors like reckless driving, vehicle behavior, or road layout. Structural inequalities, on the other hand, have not been studied as much. This gap makes it hard for policymakers to find systemic areas of concern or develop targeted, evidence-based initiatives since they don't know what causes the differences in accident rates at the district level.

This study evaluates regional and temporal road accident risk factors in Bangladesh using the Entropy Weight Method to develop a district-level Accident Risk Index (ARI) incorporating different socio-economic. Analysing national accident data from 1980 to 2023, the study identifies long-term patterns and structural breakpoints in macroeconomic and social indices. By combining district-level spatial analysis with national-level temporal assessment, this research fills a critical policy gap and demonstrates how secondary data can create an evidence-based, reproducible road safety evaluation system in resource-limited contexts. The findings aim to help policymakers prioritize high-risk areas, develop equitable safety strategies, and align with the 2030 SDG target of reducing traffic fatalities.

2. METHODOLOGY

2.1 Study Area

Bangladesh is one of the most densely populated countries in the world. It is located in South Asia between latitudes 20°34′ N and 26°38′ N and longitudes 88°01′ E and 92°41′ E. The country is about 147,570 km² in size and is divided into eight administrative divisions and sixty-four districts. The districts are the primary spatial unit for planning and reporting statistics, which is why they are the analytical unit for this study. The country's transportation system consists primarily of a large network of roads that carry roughly 86 percent of passenger-kilometers and 73 percent of freight ton-kilometers (WB, 2022). Even while cities are growing rapidly, vehicle ownerships is increasing, and the road system is improving, road safety, enforcement, and planning have not improved. Accidents on the road are becoming an enormous concern for public safety and growth. Bangladesh has a wide range of physical and socioeconomic characteristics, from the floodplains of the Ganges-Brahmaputra-Meghna delta to the mountainous hills in the southeast and the coastal areas in the south. The probability of road accidents is influenced by population distribution, settlement design, and traffic patterns.

2.2 Data Sources & Variables

The analysis utilized publicly available secondary datasets representing socio-economic, infrastructural, and environmental conditions across all districts. The variables included Population Density, Literacy Rate, Urban Population, Road Density, Number of Hospitals, and $PM_{2.5}$ concentration as proxies for traffic intensity and urban activity. The total number of road accidents in each district was used for the validation of the index.

Table 1: Selected variables and their sources

Variable	Category	Description	Source	Year
Population Density	Socio-economic	Persons per km²	BBS	2022
Literacy Rate (%)	Socio-economic	Literate population aged 7+	BBS	2022
Urban Population (%)	Socio-economic	Share of population in urban areas	BBS	2022
Road Density (km/km²)	Infrastructure	Total road length per unit area	RHD	2022
Number of Hospitals	Infrastructure	Proxy for emergency/health access	OpenStreetMap	2022

$PM_{2.5}$ (µg/m³)	Environmental	Proxy for traffic and urbanization	Satellite Imagery	2022
Total Road Accidents	Validation purpose	Reported accidents per district	BBS	2022

The time-series study utilized data from 1980 to 2023, representing the entire country rather than specific districts.

2.3 Data Processing and Normalization

All variables were standardized to ensure comparability and remove unit effects. The min–max normalization technique was applied as:$X'_{ij} = \frac{X_{ij}-minX_{ij}}{maxX_{ij}-minX_{ij}}$; where; X'_{ij} represents the normalized value of indicator j for district i. Indicators with positive influence on accident risk (e.g., population density, road density) were normalized directly, whereas those with an inverse relationship (e.g., literacy rate) were inversely scaled. This process ensured that higher normalized values consistently represented higher relative risk levels.

2.4 Entropy Weight Method (EWM)

The Entropy Weight Method (EWM) was used to assign indicator weights objectively, based on district-level variability. Unlike subjective methods such as AHP, EWM is fully data-driven, minimizing human bias and ensuring transparency (Jahan, et al., 2016). Built on the concept of information entropy, EWM assumes that indicators with greater variation carry more discriminatory power; thus, variables that differ widely between districts receive higher weights, while more uniform indicators receive lower weights. EWM calculates a normalized proportion for each district–indicator value, derives indicator entropy to measure uncertainty, and then computes a diversification coefficient that reflects informational contribution. The final weight is obtained by normalizing these diversification values so that indicators with higher variability exert greater influence on the composite index. This makes EWM well suited for multidimensional, static, and non-parametric datasets and explains its wide application in fields such as water quality assessment (Zou et al., 2006), environmental vulnerability (Zhang, et al., 2014), heat and health risk analysis (Guo, et al., 2024), (Mehrin, et al., 2024), and traffic prediction (Qu, et al., 2024).

For each district i and normalized indicator j, the proportion was computed: $p_{ij} = \frac{X'_{ij}}{\sum_{i=1}^{n} X'_{ij}}$. Where n is the number of districts. Indicator entropy was then calculated to measure uncertainty:$e_j = -k\sum_{i=1}^{n} p_{ij} \ln p_{ij};\ \ k = \frac{1}{\ln{(n)}}$. A small positive number replaced zeros to avoid undefined logarithms. Indicators with uniform values have higher entropy (lower discriminatory power), while more variable indicators have lower entropy (higher discriminatory power). The diversification degree was computed as: $d_j = 1 - e_j$

Finally, weights were normalized: $w_j = \frac{d_j}{\sum_{j=1}^{m} d_j}$. Indicators with higher variability contribute more to the composite ARI. EWM's objectivity and ability to capture spatial heterogeneity made it ideal for integrating socio-economic, infrastructural, environmental, and accident-related factors into a statistically robust district-level Accident Risk Index.

2.5 Construction of the Accident Risk Index (ARI)

The Accident Risk Index (ARI) was developed as a composite metric that amalgamates essential socio-economic, infrastructural, environmental, and accident-related variables to assess road accident risk at the district level. The index includes population density, literacy rate, urban population, road density, number of hospitals, and $PM_{2.5}$ concentration—factors that signify exposure, mobility pressure, service accessibility, and environmental intensity. Data on accidents (total incidents, fatalities, and injuries) were utilised to build a comprehensive accident indicator, representing the direct expression of risk. Collectively, these variables encapsulate both the fundamental determinants and the observed consequences of road accident susceptibility throughout Bangladesh. the normalized values of all indicators were combined using their respective weights to compute the ARI for each district: $ARI_j = \sum_{j=1}^{m} w_j . X_{ij}^{'}$; ARI_j= Accident Risk Index for district I; $X_{ij}^{\prime}$= normalized value of variable j for district I; w_j= weight of variable j derived from EWM; m = total number of variables. This weighted aggregation ensures that each variable contributes proportionally to the ARI according to its variability, while also maintaining consistency with the direction of risk (higher values = higher risk).

2.6 Statistical Modeling

To complement the spatial analysis, a time-series modeling framework was applied to examine the long-term dynamics of road accidents in Bangladesh. This component of the study utilized a longitudinal dataset spanning 44 years (1980–2023), compiled from national transport and socioeconomic statistics. The dataset integrates accident indicators with macro-level development variables to explore structural changes and causal interactions over time. The variables included total accidents and fatalities as dependent measures; several categories of injury severity (serious, minor, moderate, and severe injuries) as secondary injury indicators; and a set of socioeconomic predictors such as Gross Domestic Product (GDP), healthcare spending, literacy rate, unemployment rate, and urban population.

2.7.1 Data Preprocessing and Feature Engineering

Data preprocessing was performed in R (version 4.4.3) using the dplyr and tidyverse packages to ensure standardisation and analytical consistency. The process entailed selecting precisely the variables relevant to the analytical framework and converting all non-temporal features into numeric representations appropriate for statistical modelling. Exploratory diagnostics indicated significant gaps in specific socioeconomic indicators—47.7% in healthcare expenditure, 63.6% in literacy rate, and 25% in unemployment rate. To preserve temporal continuity, absent observations were addressed by paired deletion. Subsequently, various derived indicators were calculated to improve interpretability and account for exposure, including a comprehensive injuries metric (Total_Injuries), accident severity quantified as fatalities per accident, and exposure-adjusted measures such as accidents per 100,000 population and deaths per 100,000 population, utilising urban population as a proxy. A categorical "Period" variable was established to divide the complete period into four phases (1980–1990, 1991–2000, 2001–2010, and 2011–2023), facilitating comparative trend analysis across decades.

2.7.2 Analytical Framework

A multi-method statistical modeling strategy was adopted to investigate the temporal evolution and determinants of accident risk. The analysis began with descriptive statistics and long-term trend visualizations to document fluctuations in accident counts, fatalities, and key socioeconomic indicators. These descriptive patterns helped reveal periods of escalation or stagnation and highlighted decadal shifts in road safety outcomes. To identify statistically significant structural changes in accident trajectories, the Bai–Perron multiple breakpoint test was applied using the strucchange package. A segmented regression model was then estimated to determine the specific year in which the slope of the accident trend changed. This provided empirical evidence of turning points potentially associated with infrastructural transformation, policy interventions, or rapid phases of motorization. Following the breakpoint analysis, correlation matrices were generated to examine bivariate relationships among the variables. Ordinary Least Squares (OLS) regression models were subsequently estimated separately for the pre- and post-breakpoint periods, allowing for comparison of how socioeconomic determinants—such as GDP, literacy, and healthcare spending—exerted different influences on accident counts across distinct stages of national development. Finally, to capture dynamic interdependencies and potential causal relationships, a Vector Autoregression (VAR) model was estimated using the vars package. This enabled the study to conduct Granger causality tests to assess whether past values of GDP or healthcare spending predict current accident levels. Impulse Response Functions (IRFs) were used to trace how accident frequency responds over time to shocks in socioeconomic drivers, while Forecast Error Variance Decomposition (FEVD) quantified the contribution of each variable—GDP, healthcare spending, and the accident series itself—to the forecast variance of future accidents. Together, this comprehensive modeling framework offered both statistical rigor and temporal interpretability, revealing not just correlations but also dynamic pathways through which national development patterns shape long-term accident trends.

3. RESULT & DISCUSSION

3.1 Accident Risk Index (ARI)

The Accident Risk Index (ARI) developed in this study integrates demographic, infrastructural, and environmental indicators to represent the relative spatial exposure to road accident risk across 64 districts of Bangladesh. The ARI values theoretically range between 0 and 1, where higher scores indicate greater risk. The index was constructed using the entropy-weighted method, incorporating population density, literacy rate, road density, urban population, hospital density, and $PM_{2.5}$ concentration as explanatory indicators. Accident frequency data were used only for validation to assess whether districts with high ARI scores correspond to areas of observed accident intensity.

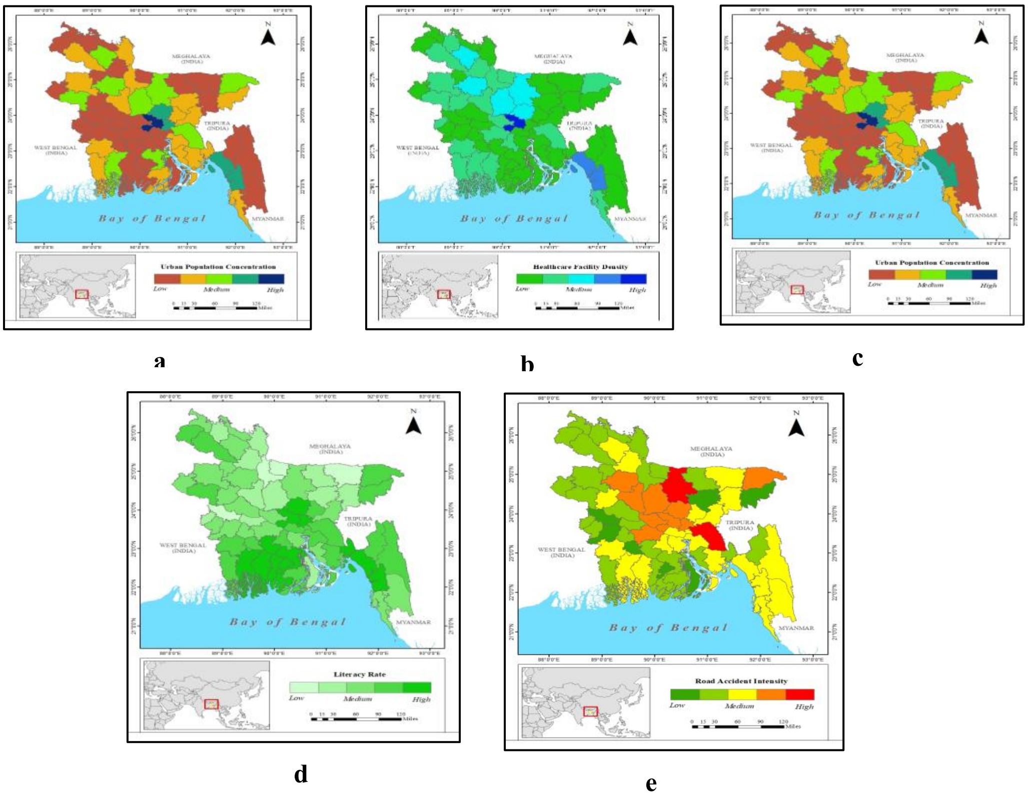


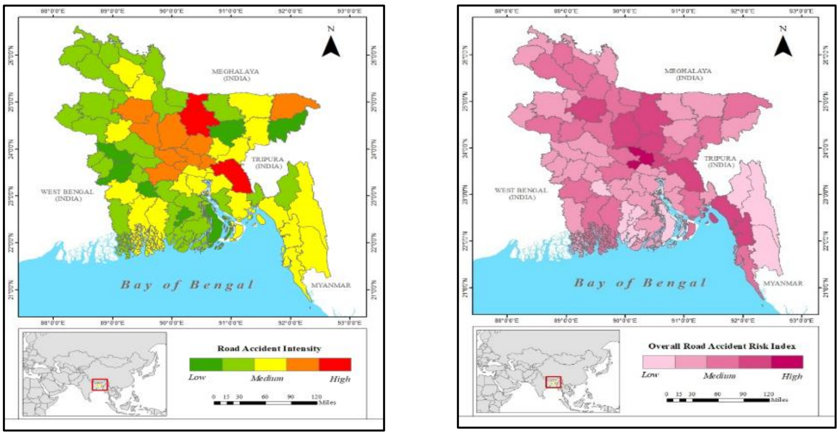
Figure 1: Spatial distribution of **a.** population exposure, **b.** healthcare facility, **c.** urban population, **d.** literacy rate to Road Accident Risk, **e.** road density

3.1.1 Spatial Distribution of Accident Risk

Based on the composite ARI scores, Bangladesh's districts can be interpreted into four risk levels:

Table 2: Classification of Districts by Accident Risk Index (ARI) Levels

ARI Level	Criteria	Districts
Very High Risk	ARI > 0.15	Dhaka, Chattogram, Gazipur, Narayanganj, Mymensingh, Comilla, Bogura, Tangail
High Risk	0.08–0.15	Sylhet, Rangpur, Manikganj, Sirajganj, Narsingdi, Brahmanbaria, Faridpur, Sherpur, Cox's Bazar
Moderate Risk	0.04–0.08	Rajshahi, Jashore, Bagerhat, Noakhali, Dinajpur, Chandpur, Gaibandha, Khulna, Natore, Naogaon, Moulvibazar, Kushtia, Sunamganj, Madaripur, Nawabganj, Shariatpur, Netrakona, Meherpur, Rajbari, Munshiganj
Low to Very Low Risk	ARI < 0.04	All other districts including Barguna, Jhalokati, Rangamati



a

b

Figure 2: Spatial Distribution of a. road accident intensity, **a.** road density, **b**. overall accident risk

3.1.2 District-Level Insights

Dhaka (ARI 0.792) exhibits the highest accident risk, driven by extreme population density, intense urbanization, and concentrated socio-economic activity patterns confirmed by its high accident counts. Chattogram (0.305) follows as the second-highest risk district, reflecting its role as the country's major port and economic hub, with dense transport flows and heavy road usage. Gazipur (0.228) and Narayanganj (0.208), the industrial satellites of Dhaka, show clear peri-urban spillover risks linked to rapid industrial growth, high workforce density, and expanding but overstressed road networks. Emerging regional centers such as Mymensingh (0.243) and Bogura (0.172) also rank high due to their strategic positions along major transport corridors. In contrast, Sylhet (0.112) and Rangpur (0.116) represent secondary risk clusters shaped by moderate urbanization and increasing motorization.

At the lowest end of the spectrum, hilly districts such as Bandarban (0.024), Rangamati (0.002), and Khagrachhari (0.018), along with coastal districts like Barguna and Jhalokati, show minimal exposure due to sparse populations, limited road infrastructure, and low vehicle volumes. Overall, the ARI map reveals three key risk concentrations: the Dhaka metropolitan–industrial belt, divisional capitals and regional growth centers, and major transport corridors such as Dhaka–Mymensingh–Bogura–Tangail. These patterns confirm that accident risk in Bangladesh is primarily shaped by urbanization intensity, population pressure, and infrastructural concentration.

3.1.3 Validation and Methodological Rationale

The ARI's validity is confirmed by its alignment with 2022 accident data. High-risk districts like Dhaka, Chattogram, Gazipur, and Narayanganj show the highest accident frequencies, while moderate-risk areas such as Tangail, Mymensingh, and Rajshahi exhibit corresponding levels, supporting the index's predictive power. Some high-ARI districts with lower reported accidents (e.g., Gazipur, Mymensingh) may reflect underreporting or emerging risk. Low-ARI districts like Jhalokati, Rangamati, and Barguna show minimal accidents, consistent with the index. Figures 1 and 2 illustrate the spatial distribution of ARI alongside observed accident intensity.

Table 3: Spatial Validation of the ARI Using Observed Accident Data

Case	ARI level	Accident index	Interpretation
Dhaka, Chattogram, Narayanganj, Gazipur	High ARI	High accident index	ARI accurately reflects actual high accident risk — strong validation.
Comilla, Tangail, Mymensingh	High ARI	High–moderate accident index	Also validated; these are major corridor zones with dense traffic.
Rajshahi, Rangpur, Khulna	Moderate ARI	Moderate accident index	Consistent — mixed urban–rural character.
Sylhet	Moderate ARI	Slightly higher accident index	Suggests local highway/topography effect not fully captured by indicators.
Jhalokati, Barguna, Rangamati, Bandarban, Bhola	Very low ARI	Very low accident index	Validation of low-risk classification.
Jessore, Tangail, Manikganj	Moderate ARI	Higher accident index	May indicate through-traffic corridors (risk underestimated by static exposure variables).

3.2 Descriptive Statistics and Long-Term Trends

The longitudinal statistics reveal a distinct U-shaped pattern in traffic accidents and fatalities in Bangladesh over the 44 years from 1980 to 2023. Figure 3 shows that the number of accidents reached its highest point in the early 1980s (around 1,500 in 1980) and then gradually dropped until it reached its lowest point in 2006, when there were only about 200 incidents. Subsequently, there is a clear rise, with the number of accidents climbing back up over 1,000 by 2023.

The number of deaths per accident also follows a periodic pattern: it declines downward at first, then goes back up after 2006, which suggests that accidents have become more severe in recent years. This change is similar to how quickly Bangladesh's economy and society are changing and how quickly cities are growing. Table 2 highlights the most important characteristics for each time period. It shows that the total number of accidents and deaths declined at first and then up again. However, the number of deaths per accident has lately gone above historical levels, which shows that crashes are getting worse even while economy is improving.

3.3 Identification of a Structural Break and the Reversal Phenomenon

To statistically validate the visual turning point observed in Figure 3A, a segmented regression model was applied following Bai–Perron multiple breakpoint testing. The analysis identified a significant structural break in 2006 ($p < 0.05$), dividing the series into two statistically distinct regimes:
Pre-2006 Era (1980–2005): Marked by a strong negative trend in accident frequency, corresponding to an overall improvement in road safety. Post-2006 Era (2006–2023): Defined by a positive trend, indicating the resurgence of road accidents despite sustained economic growth.
A t-test confirmed that the mean number of accidents was significantly lower post-break ($M = 625$) compared to the pre-break period ($M = 875$), yet the positive slope post-2006 signals a rapidly closing gap between the two phases.

3.4 Relationship with Socioeconomic Factors

A correlation matrix was computed to quantify associations between accident indicators and socioeconomic variables. As shown in Figure 5, road accidents exhibit strong positive correlations with GDP ($r = 0.97$), healthcare spending ($r = 0.96$), and literacy rate ($r = 0.93$). This pattern indicates that

as Bangladesh's economy and social development advanced, accident counts rose in parallel, suggesting that development, while improving infrastructure, also intensified mobility-related risk exposure. Regression models estimated separately for each structural regime revealed key contextual shifts:
Pre-2006 Model: Accidents were negatively associated with urban population ($p < 0.001$), implying that early phases of urbanization may have coincided with structured transport planning or limited vehicular density.
Post-2006 Model: The relationship reversed, showing a strong positive association between accidents and urban population ($p < 0.001$) and a negative link with GDP, reflecting that rapid, unregulated urban growth and motorization now act as primary accident risk amplifiers.

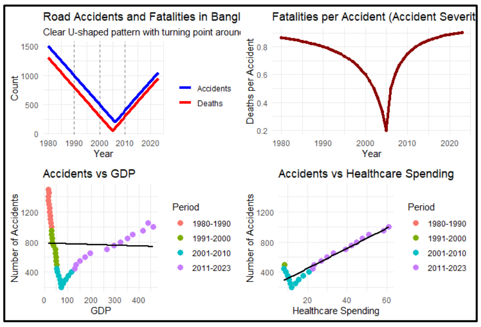


Figure 3: Longitudinal Trends and Bivariate Relationships in Road Accidents, Bangladesh (1980–2023). A) Primary U-shaped trend of accident counts and fatalities. (B) Accident severity (fatalities per accident). (C & D) Scatter plots showing positive associations between accidents and GDP (C) and healthcare spending (D), colored by period.

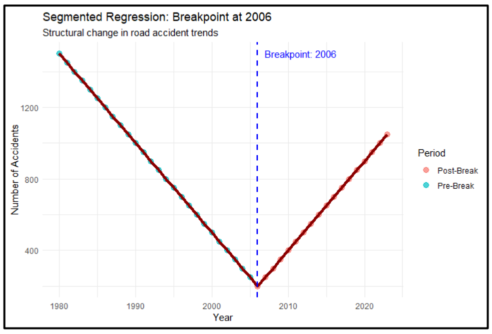


Figure 4: Segmented Regression Analysis Identifying a Structural Breakpoint in 2006. The solid red line represents the model's fitted trend, while the dashed blue line marks the breakpoint. Distinct slopes before and after 2006 demonstrate the reversal in trend dynamics.

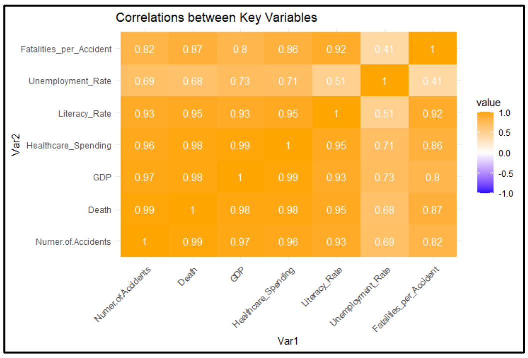


Figure 5: Heatmap of Correlation Matrix between Key Variables. Color intensity represents Pearson's r. Dark orange hues indicate strong positive correlations among accidents, fatalities, and socioeconomic indicators.

3.5 Causal Dynamics and Variance Decomposition

A Vector Autoregression (VAR) model was used to assess causal dynamics. Granger causality tests showed that neither GDP ($p = 0.94$) nor healthcare spending ($p = 0.40$) significantly predict future accident counts, indicating that accident trends are primarily driven by their own past values.
Forecast Error Variance Decomposition (FEVD) confirmed this pattern, with over 99% of future accident variance explained by shocks within the accident series itself, and less than 1% attributable to GDP or healthcare spending. Impulse Response Functions (Figures 6 and 7) similarly showed no statistically significant responses, as confidence intervals encompassed zero.

Table 4: Period-Wise Summary of Key Variables

Period	Avg. Accidents	Avg. Deaths	Fatalities/Accident	Avg. GDP (Billion USD)

1980–1990	1,250	1,050	0.84	22.6
1991–2000	725	525	0.71	41.7
2001–2010	325	175	0.53	76.4
2011–2023	750	650	0.86	285.0

3.6 The Central Phenomenon: Structural Reversal in Accident Trends

The most significant finding of this research is the identification of a structural reversal in national road accident trends beginning around 2006, marking a fundamental shift in Bangladesh's development–safety relationship. Prior to 2006, the steady decline in accidents likely reflected improvements in infrastructure, enforcement, public awareness, and relatively slower motorization. However, the post-2006 surge coincides with accelerated GDP growth, rapid urban expansion, and sharp increases in vehicle ownership; factors that collectively overwhelmed existing safety systems. This turning point suggests that once development surpasses institutional capacity, unregulated urbanization and motorization reintroduce systemic vulnerabilities, especially where enforcement, road design, and emergency response capabilities fail to keep pace. The rising fatalities-per-accident ratio further reinforces this pattern, indicating not only more frequent accidents but also escalating severity.

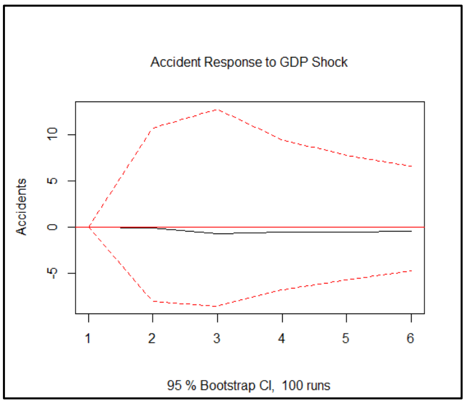


Figure 6: Impulse Response of Accidents to a One-Standard-Deviation Shock in GDP. The shaded region indicates the 95% confidence interval. The lack of a statistically significant deviation confirms that GDP fluctuations do not predict subsequent accident changes.

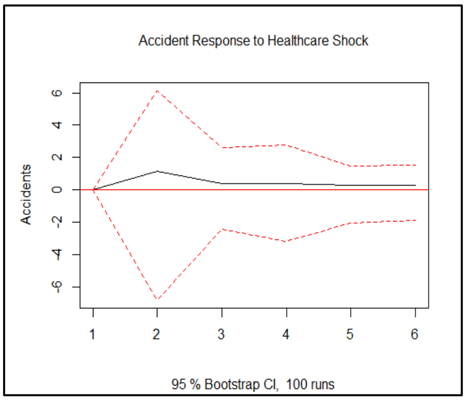


Figure 3: Impulse Response of Accidents to a One-Standard-Deviation Shock in Healthcare Spending. Similar to GDP, shocks in healthcare spending show no statistically meaningful effect on accident counts, highlighting the limited predictive influence of macroeconomic variables.

4. CONCLUSIONS

This study combined district-level spatial analysis with national time-series modeling to develop a comprehensive understanding of road accident risk in Bangladesh. The Accident Risk Index (ARI), constructed using the Entropy Weight Method, revealed pronounced spatial disparities driven by population density, urban concentration, infrastructural intensity, and environmental pressure. Districts such as Dhaka, Chattogram, Gazipur, and Narayanganj consistently emerged as high-risk zones, while remote rural and hilly districts showed negligible exposure. Although the ARI is not a direct measure of accident probability, its strong alignment with actual accident patterns demonstrates its value as a relative exposure metric derived from publicly available secondary data.

The time-series analysis validated these spatial results with evidence that national accident trends changed direction in a big way about 2006, going from long-term improvement to continued deterioration. This tipping point occurred at the same time as fast GDP development, rapid urbanisation, and more cars on the road—conditions that were too much for institutions to handle. The similarity between spatial ARI patterns and long-term accident trajectories demonstrates that the same socioeconomic and infrastructural factors that cause disparities within districts also affect the overall pattern of accidents in the country. The results show that Bangladesh's road safety problem has changed from one of underdevelopment to one of growth that is uneven and not sustainable. This means that the country needs to move from infrastructure-led measures to a more comprehensive approach to safety governance.

Several policy implications emerge from the findings of the research. Road safety planning must integrate socio-economic factors instead of depending exclusively on engineering solutions. High-risk urban-industrial corridors, such as the Dhaka-Gazipur-Narayanganj-Chattogram corridor, necessitate coordinated inter-agency actions, enhanced enforcement capabilities, improved trauma treatment systems, and ongoing monitoring of exposure patterns. The creation of a national, comprehensive road safety database that connects crash locations with socio-economic and infrastructure attributes is equally crucial for facilitating data-driven decision-making.

This study acknowledges limitations related to its reliance on cross-sectional secondary data, which constrains causal interpretation and temporal depth. The ARI, therefore, serves as a relative index rather than an absolute predictor of accident likelihood. Future research could incorporate dynamic spatial variables such as built-up density, vehicle ownership, and traffic flow, as well as primary data through safety audits, driver perception surveys, or real-time traffic counts. Incorporating spatial regression or GWR could further quantify variable-specific impacts. Overall, the findings underscore that the future of road safety in Bangladesh depends not only on mechanical or enforcement interventions but also on systematic socio-economic analysis and integrated planning. As the country continues to urbanize and motorize, proactive, evidence-based policies grounded in spatial and temporal risk diagnostics will be essential for achieving sustainable and equitable improvements in road safety.

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DECLARATION OF USE OF AI

The entire manuscript, including the conceptualization, analytical work, methodology development, results interpretation, and literature review, was developed solely by the author. No AI tools were used in the research design, data processing, analysis, or generation of academic content. For refinement of language only, limited support from a paraphrasing tool (QuillBot) was used to improve clarity and readability. All uses of AI were fully supervised by the author, and no AI-generated content was accepted without careful verification and revision. This declaration is made in the interest of transparency and adherence to ethical publishing guidelines.

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