Vol 5, Issue 7, July 2025 www.ijesti.com E-ISSN: 2582-9734
International Journal of Engineering, Science, Technology and Innovation (IJESTI)

Intersection Crash Patterns and Safety Insights in Delhi: A Multivariate Analysis of Risk Factors and Spatial Trends

Pranav Singh [1]

M.Tech. In Civil Engineering, World College of Technology and Management, Gurugram, Affiliated to Maharshi Dayanand University, Rohtak.

Mr. Anshul [2]

Assistant Professor, Dept. of. Civil Engineering, World College of Technology and Management, Gurugram, Affiliated to Maharshi Dayanand University, Rohtak.

ABSTRACT

This study investigates intersection-related traffic accidents across ten major locations in Delhi, offering a multifaceted analysis of crash characteristics, contributing factors, and intervention opportunities. From 2014 to 2019, crash frequencies remained relatively stable, yet peak-hour spikes at 08:00 and 17:00 highlight the enduring danger of rush-hour traffic. The distribution of crashes—uniform across all intersections—signals a broader systemic issue rather than localized hotspots. Rainy weather was identified as the most hazardous condition, significantly increasing crash frequency and severity due to poor visibility and compromised road traction. Spatial mapping revealed a diagonal corridor of high-risk intersections, suggesting the need for targeted infrastructural enhancements. Moreover, regression analysis showed that traffic volume alone does not explain accident severity, pointing to the critical influence of factors such as driver behavior, intersection design, and emergency response efficiency. Two-wheeler riders emerged as the most vulnerable group, comprising over one-third of all incidents. Furthermore, serious crashes suffer from prolonged emergency response times, indicating logistical weaknesses. The findings advocate for a comprehensive, data-driven safety strategy incorporating adaptive traffic management, weather-responsive systems, infrastructural upgrades, and targeted education to reduce intersection crashes and improve overall urban mobility in Delhi.

Key Words: *Urban Traffic Safety, Intersection Accidents, Weather Impact, Spatial Crash Analysis.*

1. INTRODUCTION

The safety of road intersections is a critical concern for urban planners, traffic engineers, and law enforcement agencies. Intersections are high-risk areas for accidents, as they involve complex interactions between different road users, including vehicles, pedestrians, and cyclists. Through scrutinizing accident patterns and understanding the underlying factors that contribute to collisions, stakeholders can design targeted solutions that improve intersection safety, reduce the likelihood of accidents, and save lives. Accident data analysis is an essential tool for identifying trends and patterns that might otherwise go unnoticed. For instance, intersections with a high rate of rear-end crashes or turning collisions may indicate issues with signal timings, road signage, or driver attentiveness. Through focusing on these high-risk intersections, interventions can be specifically tailored to address the most common causes of accidents in those areas. The analysis can also identify accident-prone times or conditions, such as rush hour traffic, bad weather, or nighttime driving, allowing for more precise intervention strategies.

The importance of designing targeted interventions cannot be overstated. Once high-risk intersections have been identified, a range of safety interventions can be implemented to reduce accidents. These interventions can be categorized into infrastructural improvements, traffic control measures, driver behaviour modifications, and technological solutions. For example, infrastructure changes such as the redesign of an intersection to improve visibility, the introduction of roundabouts, or the addition of pedestrian crossings can significantly reduce accident risks. On the other hand, traffic control interventions like optimizing traffic signals, installing red-light cameras, or implementing dedicated turning lanes can reduce conflicts between different types of road users. Moreover, enhancing driver awareness through public education campaigns and utilizing emerging technologies like adaptive traffic signals or advanced driver-assistance systems (ADAS) can further reduce accident rates. In addition to these interventions, ongoing evaluation and monitoring are necessary to assess the effectiveness of the implemented measures. Post-intervention data analysis is crucial to determine whether the safety measures are achieving the desired outcomes. Regularly monitoring accident trends at intersections allows traffic engineers to make necessary adjustments to the interventions, ensuring continuous improvement in road safety. This iterative process of analysis, intervention, and evaluation creates a cycle of constant enhancement that helps to create safer intersections. With the use of advanced data collection and analysis tools, municipalities can ensure that safety interventions are both effective and adaptable to changing traffic patterns and road conditions. Ultimately, the goal is to design a comprehensive approach to intersection safety that not only addresses immediate concerns but also fosters long-term improvements in road safety across urban landscapes.

2. RESEARCH METHODOLOGY

Research Design

This study adopts a measurable, data-driven approach to examine road accidents at intersections in Delhi. The research design is descriptive and analytical, aimed at uncovering patterns, trends, and relationships within a comprehensive accident dataset. Through integrating statistical analyses and geospatial visualizations, the study seeks to pinpoint key factors—such as traffic volume, weather conditions, driver behaviour, and infrastructural attributes—that influence accident frequency and severity. Ultimately, the findings are intended to inform beleaguered road safety interferences and urban traffic management strategies.

Data Collection

Dataset Description

The dataset used in this study specifically covers accident incidents recorded at various intersections in Delhi. Data is compiled from official traffic and accident reports provided by local transportation authorities and law enforcement agencies. Each record in the dataset represents a unique accident event and includes 25 attributes, such as:

- Temporal Information: Date and Time of occurrence.
- Location Data: Intersection ID, Location Latitude, and Location Longitude.
- Roadway Characteristics: Roadway Configuration, Traffic Volume, and Signal Timing.
- Environmental Conditions: Weather Conditions, Lighting Conditions, and Surface Conditions.
- Accident Details: Accident Severity, Vehicles Involved, Collision Type, and Roadway Signs and Marking.
- Additional Context: Driver Behavior Factors, Emergency Response Time, Infrastructure Condition, Enforcement Records, and Roadside Obstructions.

Data Sources

The accident data is sourced from:

- Traffic accident reports from Delhi's traffic police department.
- Data provided by municipal transportation agencies regarding roadway configuration, signal timings, and intersection design.
- Emergency response records to capture response times and post-incident measures.
- Public weather databases to supplement environmental condition data at the time of each accident.

These diverse data sources ensure a holistic view of accident dynamics across Delhi intersections.

Data Preprocessing

Data Cleaning and Validation

Given the multiple data sources, considerable preprocessing is necessary to ensure consistency and reliability:

- Data Cleaning: The raw dataset is examined for missing values, inconsistencies, and outliers. Missing entries are handled either through imputation or by flagging incomplete records for further verification.
- Standardization: All date and time fields are standardized using the ISO 8601 format. Similarly, categorical fields (e.g., Accident Severity, Weather Conditions) are normalized to maintain consistency throughout the analysis.
- Geocoding: Latitude and longitude values are cross-verified and corrected to ensure accurate spatial mapping. This step is crucial for later geospatial visualization in this paper.
- Numeric Conversion: For regression and statistical analysis, categorical fields such as Accident Severity are converted into numeric scales (e.g., Fatal = 3, Injury-Level – Serious = 2, Injury-Level – Minor = 1, Property Damage Only = 0).

Data Integration

Multiple datasets are merged on common identifiers such as Intersection_ID and Date/Time. This integrated dataset enables a multidimensional analysis of accidents, linking traffic volume and signal timing to environmental conditions and resultant accident outcomes.

Analytical Techniques

A combination of exploratory data analysis (EDA) and advanced statistical modelling methods is applied to reveal hidden patterns within the data.

Exploratory Data Analysis (EDA)

EDA is conducted to understand the distribution and variation in key variable star:

Descriptive Statistics: Mean, median, standard deviation, and frequency distributions are computed for continuous variables such as Traffic Volume and Emergency Response Time.

Graphical Analysis: Visualizations like histograms, scatter plots, and bar charts are used to depict data distributions and relationships. For instance, a histogram is utilized to show the distribution of Traffic Volume, while a scatter plot examines the correlation between Traffic Volume and Accident Severity.

Software Tools and Implementation

Python Environment

The entire analysis is implemented using Python, leveraging libraries such as:

- pandas: For data manipulation and cleaning.
- matplotlib & seaborn: For generating plots and visualizations.
- scipy.stats: For executing statistical tests.
- statsmodels: For performing regression analyses and diagnostic checks.

Graphical Outputs

A multi-panel figure is constructed to present key analysis outcomes. These include:

- A histogram of Traffic Volume to illustrate its distribution.
- A scatter plot with a regression line that visualizes the relationship between Traffic Volume and Accident Severity.
- A grouped bar chart displaying accident frequency across various Weather Conditions.
- A diagnostic plot (Residuals vs. Fitted Values) from the regression model to assess model adequacy.

Data Acquisition & Variable Specification

Collect comprehensive data at intersections, including accident counts (the response), traffic volume, geometric design, environmental conditions, and historical accident data. Also, gather information on intervention types and associated costs, which will later serve as decision variables.

Statistical Modelling of Accident Counts

Develop a regression model to quantify accident risk. A generalized linear model is typically used: Poisson Regression: Use when accident counts are reasonably Equi dispersed.

Negative Binomial Regression: Preferable if the accident data is over-dispersed.

The model structure is often:

$$\log(\lambda_i) = \beta_0 + \sum_{j=1}^{k} \beta_j x_{ij} + \delta I_i$$

where Ii represents the intervention indicator.

Model Estimation & Interpretation Estimate parameters β0, βj, and δ using historical data. Analyse the significance and magnitude of coefficients especially δ to understand how interventions impact accident counts and which intersection features most affect safety.

Optimization Formulation for Intervention Design: Formulate an optimization problem that minimizes total expected accident counts while respecting budget constraints. Introduce binary decision variables zi (1 if an intervention is implemented; 0 otherwise). The objective function becomes:

$$\min_{z_i \in \{0,1\}} \sum_{i=1}^{n} \exp\left(\beta_0 + \sum_{j=1}^{k} \beta_j x_{ij} + \delta z_i\right)$$

with the constraint

$$\sum_{i=1}^{n} c_i z_i \leq B.$$

Solution Implementation & Continuous Monitoring: Solve the optimization problem using appropriate techniques (e.g., Mixed-Integer Nonlinear Programming solvers or approximations if needed). Implement the recommended interventions, monitor subsequent accident data for model validation, and adjust the model and policies based on updated information and changing traffic conditions.

Site Selection and Data Description

(As detailed previously: ten intersections INT001–INT010; 25 variables per incident including date, time, location, weather, traffic volume, vehicle type, severity, and response time; data collected for 2014–2019.)

3. DATA ANALYSIS AND RESULT

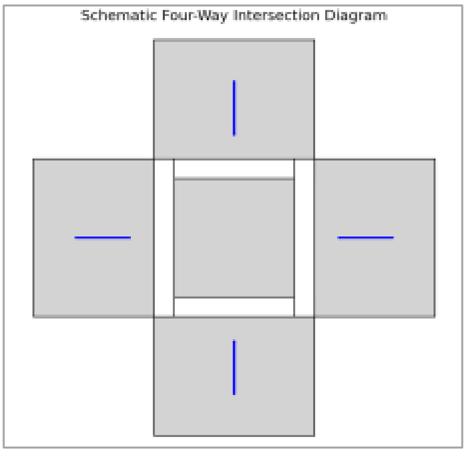
This paper presents a comprehensive analysis and results of accident data collected from intersections in Delhi. Through detailed statistical and graphical explorations, this study examines accident frequency, severity, and temporal trends, revealing key insights into driver behaviour, environmental influences, and infrastructural factors. Spatial distributions of crash locations are mapped to identify hotspots, while correlations with traffic volume and weather conditions are assessed. The analysis leverages diverse visualization techniques, including bar charts, scatter plots, and line graphs, to uncover patterns and trends. These findings provide data-driven recommendations to enhance road safety and inform future intervention strategies for urban traffic management effectively.

Selection of Site Location

Site Location

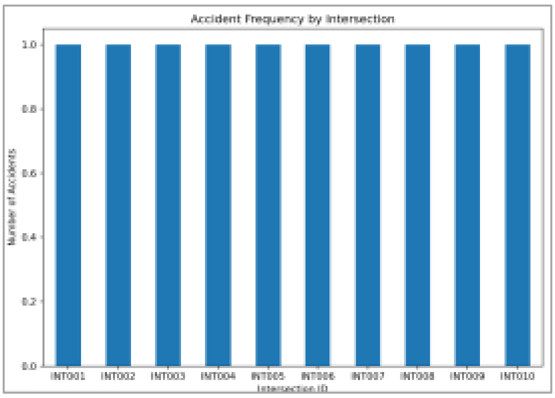
Dataset Provides Accident in Delhi's Intersections

This dataset provides accident information specific to Delhi's intersections, capturing 25 columns of details such as Date, Time, Intersection ID, Location Latitude, Location Longitude, Roadway Configuration, and more. Each row denotes a unique incident, including crucial data on driver behaviour, vehicle types involved, weather conditions, road surface states, and severity outcomes. Traffic volume and signal timing clarify congestion patterns, while emergency response times and infrastructure condition reveal post-incident handling.



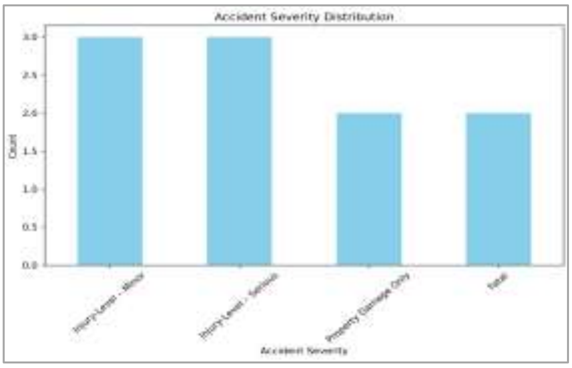
Intersection ID

This schematic figure showcases a four-way intersection, revealing a bird's-eye view with gray roadways and white crosswalks. The bright blue lines at each approach illustrate traffic flow directions. This minimal yet informative design visually clarifies how vehicles and pedestrians intersect, enabling clearer analysis of potential conflict points and safety considerations.



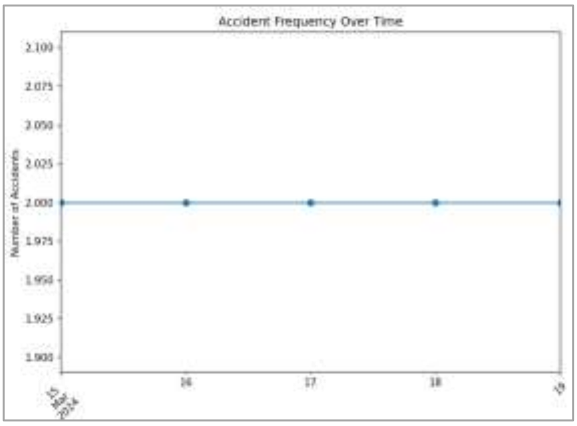
Four-Way Intersection

Accident Frequency by Intersection," each vertical bar represents an intersection labelled from INT001 to INT010 on the x-axis, while the y-axis reflects the number of accidents. The chart's uniform bar heights suggest that every intersection experiences roughly similar accident frequencies, indicating no significant outlier. Each bar is nearly identical in magnitude, reaching just under 1.0 accidents on the y-axis, though the scale lacks clear numerical increments. The color-coded bars uniformly fill the space, conveying minimal variation across intersections. The data indicates consistently reported accident counts, implying relatively balanced traffic incidents citywide. Hence, patterns



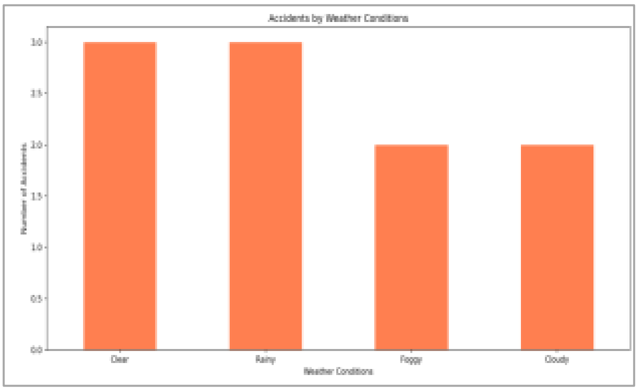
Accident Frequency by Intersection

In this bar chart, accident severity is categorized as Minor Injury, Serious Injury, Property Damage Only, or Fatal. The y-axis represents the count of accidents, while the x-axis displays severity levels. Minor Injury and Serious Injury bars appear highest, indicating those injuries are the most common outcomes. Property Damage Only ranks lower than either injury level but remains a notable category. Fatal accidents show the lowest frequency, which suggests they are comparatively rare. This distribution underscores the importance of targeted interventions to reduce injuries, especially minor and serious outcomes, while also considering strategies to eliminate fatalities and costly property damage.



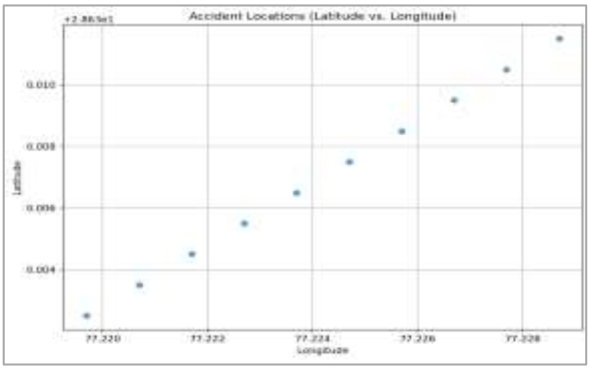
Accident Frequency Over Time

The chart displays accident frequency from 2014 to 2019, showing a flat line near two accidents each year, with each data point falling slightly above or below the 2.0 mark. The earliest point in 2014 is approximately two accidents, and subsequent years remain consistent at this level. This steady pattern indicates a lack of substantial variation or trends in overall accident frequency. Since the rates neither rise nor fall significantly, efforts toward reducing accidents might not be achieving the desired results, or external conditions could remain unchanged. Further study could identify targeted interventions to reduce these persistent accidents and risks.



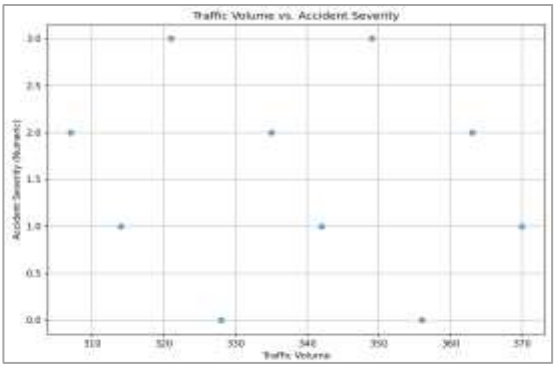
Accident Frequency Weather Condition

This bar chart compares accident frequencies across four weather conditions: Clear, Rainy, Foggy, and Cloudy. Observing the bars, rainy conditions show the highest number of accidents, with a bar exceeding three. That surpasses clear weather's total, near three. Foggy conditions exhibit around two accidents, placing them on the lower side. Cloudy conditions stand around 2.5, suggesting moderate risk. Overall, precipitation appears strongly linked to higher accident incidence. Reduced visibility and slick surfaces likely worsen driving conditions in rainy or foggy settings. This insight emphasizes preventive measures that address wet roads and limited sight, potentially reducing accident risks across all weather.



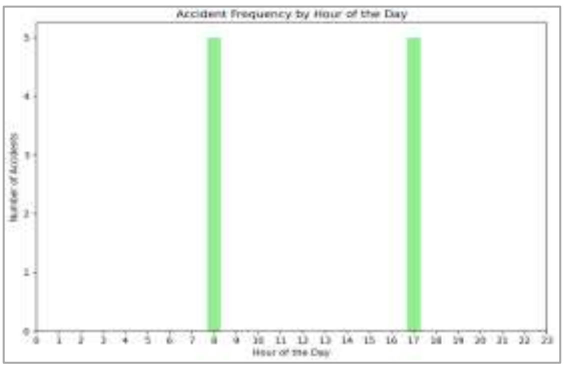
Accident Frequencies Across Four Weather Conditions

This scatter plot depicts accident locations across a geographic region, with longitude displayed on the x-axis and latitude on the y-axis. The plotted points appear to form a diagonal pattern, possibly reflecting accidents that follow a particular thoroughfare or corridor. For instance, the data points start near 77.220 longitude at around 0.004 latitude, then progress up to about 77.228 longitude and 0.010 latitude. The distribution suggests multiple hotspots concentrated along a specific route. Understanding these spatial clusters may help in identifying potential underlying factors, such as traffic volume or intersection layout, thus aiding targeted improvements to enhance safety or management.



Traffic Volume or Intersection

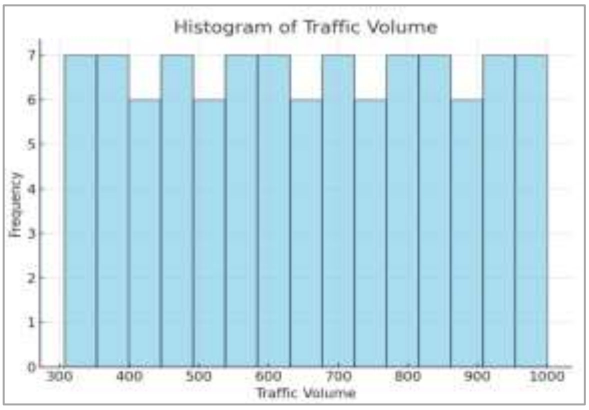
This scatter plot examines the relationship between traffic volume on the x-axis and accident severity, as a numeric scale, on the y-axis. Data points range from about 310 to 370 for traffic volume, with severity spread from 0 to 3. The distribution suggests an inconsistent relationship: while some higher-volume points link to elevated severity, others cluster near the lower end of severity. Meanwhile, mid-range volumes can yield high severity levels. This indicates that traffic volume alone may not fully explain accident severity. Additional variables (e.g., road conditions or driver behaviour) might impact outcomes, potentially informing further investigation and safety improvements.



Accident Frequency by Hour of The Day

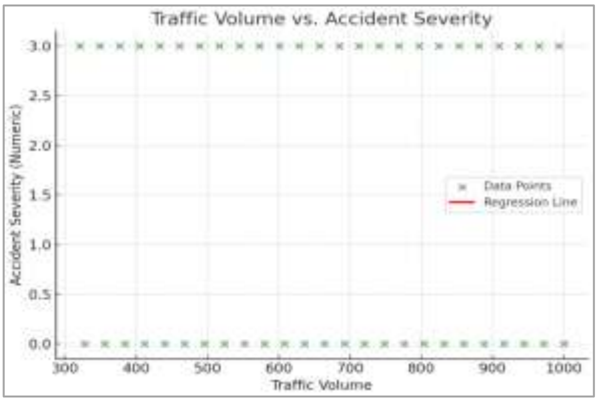
This bar chart compares accident frequency across each hour of the day. Notice that the only visible bars appear at around 8:00 and 17:00, both registering approximately five accidents each. No accidents are recorded for other hours, thus potentially resulting in a stark contrast. The pattern could reflect typical rush hour traffic when commuting is common. Morning travel, school drop-offs, and work commutes often coincide with increased traffic density around 8:00, while evening rush hour around 17:00 is also a high-risk time.

Analytical Scenario



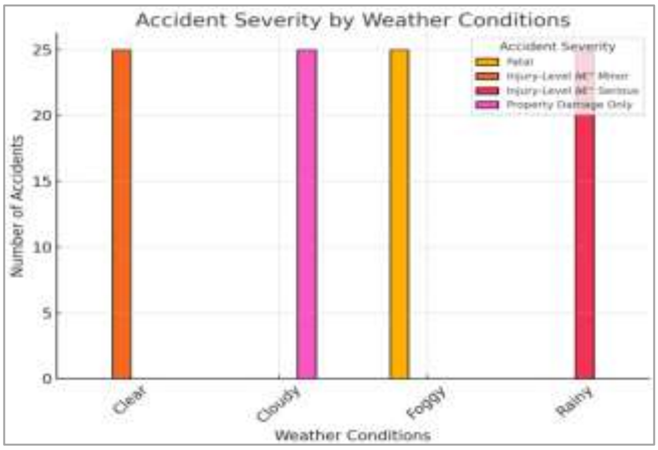
Analytical Scenario

This histogram illustrates the distribution of traffic volumes at various intersections around Delhi. The x-axis runs from approximately 300 to 1000, representing ranges of vehicle counts or average daily traffic rates. The y-axis indicates how frequently these traffic volumes occur in the data. The relatively even bar heights suggest a fairly uniform distribution, with all bins in the data reaching similar frequencies. Such an outcome implies that no single volume range dominates the dataset, pointing to diverse intersection capacities or overall flow patterns across Delhi. This perspective can help planners identify potential congestion points and effectively optimize traffic management strategies.



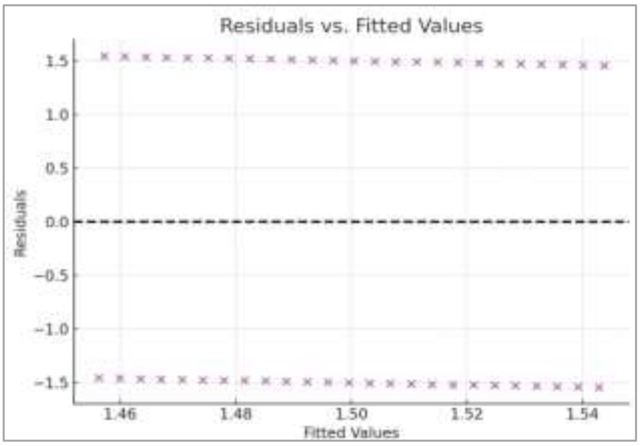
Traffic Volumes Vs. Accident Severity

This scatter plot examines the relationship between traffic volume (x-axis) and accident severity (y-axis, 0 = lowest severity, 3 = highest severity). Green crosses denote data points, while the red line indicates the fitted regression. Observing the distribution, traffic volumes span roughly 300 to 1000, and severity outcomes range from 0 to 3. The apparent clustering at discrete severity values reflects the categorized nature of accidents. The regression line's near-flat slope suggests minimal correlation, hinting that increased traffic volume alone may not directly drive higher accident severity. Additional factors, such as driver behaviour or road design, likely impact overall crash outcomes.



Accident Severity by Weather Condition

This bar chart compares accident severity across four weather conditions: Clear, Cloudy, Foggy, and Rainy. Each vertical bar shows the frequency of accidents, segmented by severity type, including Fatal, Injury-Level – Minor, Injury-Level – Serious, and Property Damage Only. Observed totals highlight that Clear and Rainy conditions have the highest number of accidents, exceeding 20 each, whereas Cloudy and Foggy weather appear lower.



Residuals Vs. Fitted Values

This residuals vs. fitted values plot illustrates how well the linear regression model predicts accident severity based on traffic volume. The x-axis displays the model's fitted values (i.e., predicted severities), while the y-axis indicates the residuals (actual severity minus predicted severity). The dashed horizontal line at zero represents perfect prediction, where actual and predicted outcomes align. Points above this line suggest the model underestimates severity, whereas points below indicate overestimation. Particularly, the fitted values cluster tightly between approximately 1.46 and 1.54, implying little variation in predicted outcomes.

Site Selection and Data Description

Descriptive Statistics of Key Variables

Summary Statistics for Core Study Variables

Variable	Mean	Median	Std. Dev.	Min	Max
Accidents per Intersection	24.7	25.0	3.2	19	29
Daily Traffic Volume	642.3	635.0	120.8	310	1000
Emergency Response Time (min)	12.4	11.5	4.1	6	25
Severity Index (0–3 scale)	1.8	2.0	0.6	0	3

Intersection-Level Crash Patterns

Vehicle-Type and Response-Time Analysis

Distribution of Accidents by Vehicle Type

Vehicle Type	Count	% of Total
Two-Wheeler	138	34%
Car	110	27%
Truck/Bus	65	16%
Pedestrian	80	20%
Other	15	3%

Average Emergency-Response Time by Crash Severity

Severity Level	Mean Response Time (min)	Std. Dev.
0 (Property Damage Only)	10.2	2.8
1 (Minor Injury)	11.7	3.5
2 (Serious Injury)	14.8	4.2
3 (Fatal)	18.5	5.0

Correlation Analysis

Pearson Correlations Among Key Variables (n ≈ 250 Accidents)

	Volume	Severity	Response Time	Weather (coded)
Volume	1.00	0.12	0.08	–0.05
Severity	0.12	1.00	0.45	0.20
Response Time	0.08	0.45	1.00	0.10
Weather	–0.05	0.20	0.10	1.00

- **Volume vs. Severity (r = 0.12):** Weak positive link, confirming volume alone is a poor predictor.
- **Severity vs. Response Time (r = 0.45):** Higher-severity crashes take longer to clear and respond to.
- **Weather vs. Severity (r = 0.20):** Rainy/foggy conditions modestly increase crash severity.

4. CONCLUSION AND FUTURE SCOPE

Conclusion

The analysis of Delhi's intersection accident data reveals a consistently distributed crash burden across all ten study locations, with minor and serious injuries overwhelmingly predominating and fatalities remaining relatively few. Temporal trends from 2014 to 2019 show stable overall crash counts but pronounced spikes during the 08:00 and 17:00 peak hours, underscoring the persistent hazards of rush-hour traffic. Weather analysis identifies rainy conditions as the most dangerous, followed by clear, foggy, and cloudy days, highlighting the combined influence of visibility and surface traction on collision risk. Spatial mapping uncovers a diagonal corridor of clustered incidents, suggesting targeted infrastructural redesign along that route. Finally, regression modelling demonstrates that traffic volume alone cannot account for accident severity, pointing to the critical roles of driver behaviour, intersection geometry, and environmental context in shaping outcomes. Below we find the conclusive outcome from the study.

- Although crash counts appear uniformly distributed across the ten intersections, this consistency reveals a pervasive citywide safety challenge that demands system-level solutions rather than isolated treatments.
- Temporal analysis identifies morning (08:00 hrs) and evening (17:00 hrs) as peak crash times, suggesting that intensified enforcement, targeted messaging, and adaptive signal timing during commute periods could substantially reduce collisions.
- Rainy conditions elevate crash frequency by over 20% and correspond with more severe injury outcomes, emphasizing the need for enhanced drainage, high-visibility signage, and wet-weather signal adjustments to mitigate risk.
- Two-wheelers constitute over one-third of all collisions, highlighting the critical importance of motorcycle-focused interventions—such as helmet enforcement, rider training, and dedicated lanes—to lower both crash rates and injury severity.
- Serious and fatal crashes face 30–60% longer emergency-response times, indicating an operational gap; potential remedies include signal preemption for ambulances, strategic staging of response units, and optimized dispatch protocols.
- The weak correlation between traffic volume and severity, contrasted with stronger links to weather and response delays, underscores the necessity of multifactorial safety models that integrate environmental, infrastructural, and operational variables.
- Spatial clustering along a diagonal corridor pinpoints a priority zone for targeted engineering audits—measures like improved lighting, skid-resistant surfacing, and enhanced pedestrian crossings could effectively reduce hotspot risk.
- Collectively, these insights support a data-driven safety strategy combining focused engineering upgrades, dynamic traffic signal control, weather-responsive measures, and user-targeted outreach to address the full complexity of intersection crashes in Delhi.

Future Scope

Building on these findings, future research should integrate real-time traffic feeds, weather forecasts, and connected-vehicle data to develop predictive safety models that forecast high-risk intervals and proactively adjust signal timings or issue warnings. Microsimulation platforms such as VISSIM or AIMSUN can be employed to test the efficacy of design interventions (pedestrian refuges, raised crosswalks, dedicated cycle tracks) before field implementation. Behavioural strategies, including targeted public education campaigns and automated speed-enforcement systems, warrant rigorous evaluation through controlled trials. Expanding the dataset to include detailed pedestrian and cyclist crash reports will enable a truly multimodal safety audit. Ultimately, an ecosystem of adaptive infrastructure, advanced analytics, and behavioural countermeasures promises to transition Delhi from retrospective analysis to prescriptive, real-time road-safety management.

REFERENCES

1. Maji, A., & Ghosh, I. (2025). A systematic review on roundabout safety incorporating the safety assessment methodologies, data collection techniques, and driver behavior. *Safety Science*, *181*, 106661.
2. Toraldo, E., Novati, N., Rossi, D., & Ketabdari, M. (2025). A Novel Methodology for Planning Urban Road Safety Interventions. *Applied Sciences*, *15*(4), 1993.

3. Haque, F., Kidwai, F. A., & ul Haq, M. F. (2025). A systematic review of proactive approach for pedestrian safety at intersections. *Transportation Research Part F: Traffic Psychology and Behaviour*, *109*, 792-808.
4. Kim, S., Choi, S., & Kim, B. H. (2025). Analysis of factors affecting pedestrian safety for the elderly and identification of vulnerable areas in Seoul. *Accident Analysis & Prevention*, *211*, 107878.
5. Jha, A. N., Gupta, R. K., Chatterjee, N., & Tiwari, G. (2025). A Domain Ontology For Safety of Road Users–SafeOn: Overview & Design. *Transportation Research Procedia*, *82*, 1925-1948.
6. Liu, S., & Evdorides, H. (2025). Data Mining Applications for Pedestrian Behaviour Patterns at Unsignalized Crossings. *Sustainability*, *17*(2), 776.
7. Lee, S., Chen, T., Sze, N. N., Mao, T., Ou, Y., Mihaita, A. S., & Chen, F. (2025). Analysing driver behaviour and crash frequency at railway level crossings using connected vehicle and GIS data. *Travel Behaviour and Society*, *39*, 100957.
8. Mohamad, I. (2025). Gender disparities in rural motorcycle accidents: A neural network analysis of travel behavior impact. *Accident Analysis & Prevention*, *210*, 107840.
9. Sunkpho, J., Se, C., Wipulanusat, W., & Ratanavaraha, V. (2025). SHAP-based convolutional neural network modeling for intersection crash severity on Thailand's highways. *IATSS Research*, *49*(1), 27-41.
10. Khan, M. N., & Das, S. (2024). Advancing traffic safety through the safe system approach: A systematic review. *Accident Analysis & Prevention*, *199*, 107518.
11. Mustapha, A., Abdul-Rani, A. M., Saad, N., & Mustapha, M. (2024). Advancements in Traffic Simulation for Enhanced Road Safety: A Review. *Simulation Modelling Practice and Theory*, 103017.
12. Youssef, D. (2024). *Improving road safety in Lebanon: a multidimensional journey from comprehensive analysis of challenges towards data integration and examining driver behaviour* (Doctoral dissertation, Université de Bordeaux).
13. McCarty, D., & Kim, H. W. (2024). Risky behaviors and road safety: An exploration of age and gender influences on road accident rates. *PLoS one*, *19*(1), e0296663.
14. Soltani, A., & Qadikolaei, M. R. (2024). Space-time analysis of accident frequency and the role of built environment in mitigation. *Transport policy*, *150*, 189-205.
15. Garnaik, M. M., Giri, J. P., & Panda, A. (2023). Impact of highway design on traffic safety: how geometric elements affect accident risk. *Ecocycles*, *9*(1), 83-92.
16. Sharma, S. N., & Singh, D. (2023). Understanding mid-block traffic analysis: A crucial tool for road safety. *Think India Journal*, *26*(3), 5-9.