# A Comparative Analysis of Road Surface Conditions and Traffic Crash Outcomes

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**ABSTRACT**

This study investigates the impact of road surface conditions on traffic accident frequency and severity. Different surface conditions, including dry, wet, pothole-affected, gravel-covered, oil-contaminated, and ice/snow-covered roads, were analyzed to understand their influence on vehicle control and crash outcomes. The findings revealed that wet surfaces recorded the highest accident frequency (32%) and severity index (35%), while dry surfaces showed the lowest accident severity. Poor road conditions were found to increase stopping distances, reduce traction, and elevate the risk of severe injuries and fatalities. The study emphasizes the importance of regular road maintenance, improved drainage systems, and proactive pavement management to enhance road safety and reduce accident-related losses.

***Keywords:*** *Traffic Safety, Road Surface, Accident Severity, Pavement Condition, Crash Analysis.*

## I. INTRODUCTION

### 1.1 Traffic Crash Analysis

Traffic crash analysis is the systematic study of road accidents to identify their causes, patterns, and severity. It helps transportation engineers and policymakers understand how factors such as driver behavior, vehicle characteristics, roadway conditions, and environmental influences contribute to accidents. Modern crash analysis utilizes statistical methods, machine learning, and GIS technologies to improve road safety and reduce accident-related injuries and fatalities. Recent studies have shown that advanced analytical techniques can significantly enhance crash severity prediction and support effective safety interventions (Kotsyubynska et al., 2026; Zhen & Yang, 2025).

### 1.2 Road Surface Condition

Road surface condition refers to the physical quality of pavement, including factors such as roughness, potholes, cracks, skid resistance, and surface contamination. A good road surface provides sufficient friction between tires and pavement, allowing safe braking, steering, and acceleration. However, deteriorated surfaces reduce vehicle control and increase accident risks. Research has demonstrated that poor pavement conditions are strongly associated with higher crash frequencies and greater injury severity, highlighting the importance of regular maintenance and pavement management programs.

### 1.3 Impact of Surface Conditions on Traffic Safety

Road surface conditions significantly influence traffic safety by affecting vehicle stability and driver control. Wet, icy, oily, or damaged surfaces reduce tire-road friction, leading to longer stopping distances, skidding, and loss of control. Adverse weather conditions further worsen these risks by accelerating pavement deterioration and reducing visibility. Studies have reported that crashes occurring on compromised surfaces often result in more severe injuries and fatalities than those on dry roads. Therefore, maintaining safe road surfaces is essential for reducing accident severity and improving overall transportation safety (Ye et al., 2025; Gedamu et al., 2024).

## II. FINDING FROM RESEARCH STUDY

| Author & Year | Study Area / Objective | Methodology / Tools Used | Key Findings | Research Contribution |
|---|---|---|---|---|
| Kotsyubynska et al. (2026) | Crash injury severity prediction using ML and DL models | Systematic Review & Meta-analysis; PRISMA 2020; 74 studies; 2,127,059 crash records | Deep Learning achieved higher prediction performance (F1-score 78.6%) than conventional ML. SMOTE/ADASYN improved minority-class prediction. | Demonstrated effectiveness of AI-based approaches for crash severity prediction and emphasized balanced datasets and interpretability. |
| Li et al. (2026) | Autonomous Vehicle (AV) crash scenario analysis | Analysis of 774 California AV crash reports; automated mapping rules | Identified 27 pre-crash scenarios with 98.1% accuracy. Rear-end and intersection crashes were dominant. | Provided insights for AV safety testing, regulation, and algorithm improvement. |
| Bhat (2026) | Statistical modelling of traffic injury severity | Multivariate flexible bimodal distribution; Texas crash database | Developed a novel distribution for modeling asymmetric crash severity patterns. | Improved econometric modelling capability for crash injury severity analysis. |
| Ye et al. (2025) | Road safety analysis using Street View Imagery (SVI) | Literature review; Computer Vision & ML techniques | SVI-derived road design features significantly influenced crash frequency and risk. | Established SVI as an effective tool for roadway safety assessment. |
| Zhen & Yang (2025) | Contextual crash severity prediction | CrashSage Framework; LLaMA3-8B; LLM-based analysis | Outperformed traditional ML and DL models; improved explainability of crash mechanisms. | Introduced LLM-based interpretable crash severity analysis framework. |
| Gedamu et al. (2024) | Spatial crash severity analysis in Addis Ababa and Berlin | Moran's I, ANN, Local Moran's I | Significant crash clustering observed; stronger spatial autocorrelation in Addis Ababa. | Demonstrated importance of spatial analysis in identifying high-risk crash zones. |
| Mounica & Lavanya (2024) | Social media-based traffic analysis | Big Data Architecture, Twitter Analytics, Ensemble ML | Classification accuracy improved from 56% to 88%. | Showed effectiveness of social media data for traffic condition monitoring. |
| Alam & | Crash hotspot | GIS, Moran's I, | Identified major crash | Supported evidence- |

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|---|---|---|---|---|
| Tabassum (2023) | identification in Ohio | Getis-Ord Gi*, Crash Severity Index | hotspots in Cleveland, Cincinnati, Toledo, and Columbus. | based highway safety planning. |
| Li et al. (2023) | Outlier treatment in crash severity datasets | Robust Bayesian Regression (Robit Model) | Improved robustness and accuracy of crash severity estimation. | Addressed data quality challenges in crash analysis. |
| Bougna et al. (2022) | Socio-economic costs of traffic crashes | Literature Review; Econometric Analysis | WTP estimates were higher than Human Capital estimates; underreporting remained a major issue. | Highlighted economic burden of road accidents and methodological gaps. |
| Sun et al. (2022) | Crash duration analysis in Houston | Geostatistical Analysis; ArcGIS Kernel Density | Crash duration influenced by night-time, holidays, residential locations, and roadway factors. | Contributed to traffic incident management strategies. |
| Tola et al. (2021) | Crash hotspot analysis in Ethiopia | ArcGIS 10.5, Moran's I, Getis-Ord Gi* | Major crash hotspots located near Addis Ababa entry and exit corridors. | Demonstrated effectiveness of GIS-based crash severity mapping. |
| Chand et al. (2021) | Review of traffic accident prediction techniques | Literature Review | Identified major accident risk factors, prediction algorithms, and research gaps. | Provided comprehensive overview of accident analysis methodologies. |
| Freeman & Leith (2020) | Crash-related cervical spine injuries | Comparative analysis of national injury databases | Estimated 869,000 annual cervical spine injuries; substantial underreporting identified. | Highlighted limitations of existing injury databases and reporting systems. |
| Angeline et al. (2020) | Traffic congestion and jam clustering | Traffic Simulation; 300 samples; 5 km roadway | Proposed algorithm improved travel time by 1.96–7.96%. | Demonstrated traffic management strategies for congestion reduction. |

## III. PROPOSED MATHEMATICAL MODEL FOR ROAD SURFACE CONDITION AND

**ACCIDENT SEVERITY**

**Let:**

- $AS$= Accident Severity Index
- $RF$= Road Surface Factor
- $WS$= Weather Severity Factor
- $VC$= Vehicle Control Factor
- $SA$= Speed Adaptation Factor
- $\alpha, \beta, \gamma, \delta$= Weight coefficients

The accident severity model can be expressed as:

$$AS = \alpha RF + \beta WS + \gamma VC + \delta SA$$

Where:

- $RF$: Surface condition score (Dry = 1, Wet = 2, Pothole = 3, Gravel = 4, Ice/Snow = 5)
- $WS$: Weather impact factor
- $VC$: Vehicle control loss factor
- $SA$: Speed adaptation factor

Severity Risk Function

A more comprehensive risk model may be written as:

$$R = \frac{V^2 \times S}{F}$$

Where:

- $R$= Accident Risk
- $V$= Vehicle Speed (km/h)
- $S$= Surface Hazard Index
- $F$= Tire–Road Friction Coefficient

## IV. ANALYSIS OF ROAD SURFACE CONDITION AND ACCIDENT SEVERITY

This paper presents the analysis of the relationship between road surface conditions and traffic accident severity. The objective of this analysis is to evaluate how different pavement conditions influence accident frequency and the level of crash severity. Various surface categories, including dry, wet, pothole-affected, gravel-covered, oil-contaminated, and ice/snow-covered roads, were examined to assess their impact on vehicle control and road safety. The findings provide valuable insights into the role of surface conditions in accident occurrence and severity, thereby supporting the need for effective road maintenance, hazard mitigation, and traffic safety management strategies. The results are presented in the following table and graph for better interpretation and comparison.

| Road Surface Condition | Accident Frequency (%) | Severity Index (%) |
|---|---|---|
| Dry Surface | 18 | 15 |
| Wet Surface | 32 | 35 |
| Pothole Surface | 21 | 24 |
| Gravel Surface | 12 | 14 |
| Oil Spill Surface | 8 | 10 |
| Ice/Snow Surface | 9 | 22 |

Wet road surfaces recorded the highest accident frequency (32%), while wet and ice/snow surfaces showed the greatest accident severity. Dry surfaces exhibited the lowest severity, indicating better vehicle control and safety. The results confirm that deteriorated and slippery road conditions substantially increase crash risks and accident severity.

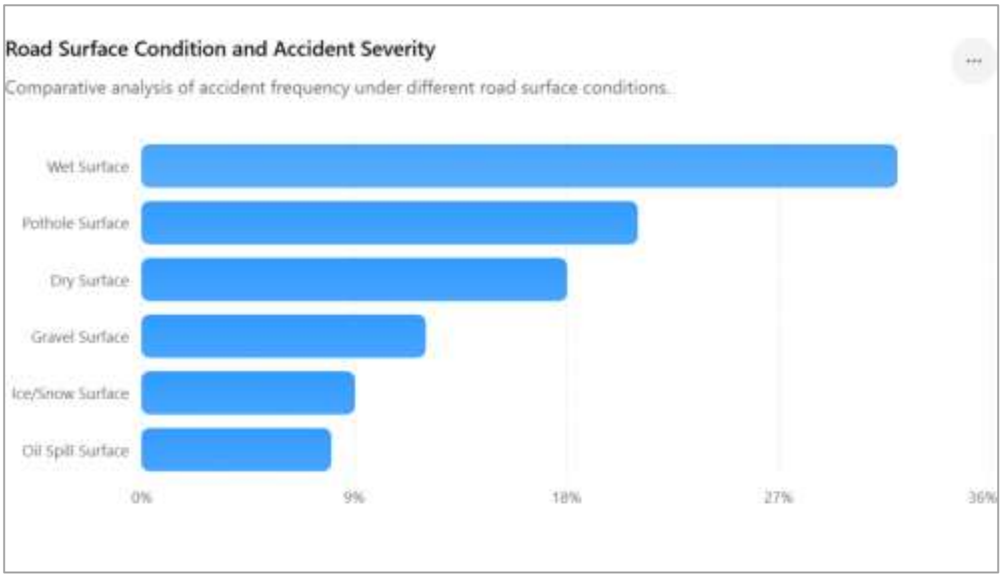


**Figure 1: Road Surface Condition and Accident Severity**

The figure 1 as above presents a comparative analysis of accident frequency under different road surface conditions. The results indicate that wet surfaces recorded the highest accident frequency (32%), demonstrating the substantial impact of reduced tire-road friction and poor vehicle control during rainy conditions. Pothole-affected surfaces accounted for 21% of accidents, highlighting the dangers associated with uneven pavements and sudden vehicular manoeuvres. Dry surfaces contributed 18% of accidents and exhibited relatively safer driving conditions due to better traction and stability. Gravel surfaces represented 12%, while ice/snow surfaces accounted for 9% of accidents, reflecting the risks associated with slippery conditions. Oil spill surfaces showed the lowest accident frequency (8%). Overall, the analysis confirms that deteriorated and slippery road conditions significantly increase accident occurrence and severity, emphasizing the importance of regular road maintenance and effective surface management strategies.

## V. CONCLUSION

The study concludes that road surface condition is a significant factor influencing traffic accident severity. Wet, pothole-affected, and slippery surfaces substantially increase crash risks by reducing vehicle stability and driver control. Dry and well-maintained roads provide safer driving conditions and lower accident severity. The findings highlight the need for timely road maintenance, pothole repair, high-friction surface treatments, and weather-responsive traffic management strategies. Improving pavement quality can significantly reduce accident frequency, injuries, fatalities, and economic losses while enhancing overall transportation safety and efficiency.

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