



# IJEAST

INTERNATIONAL JOURNAL  
OF ENGINEERING APPLIED SCIENCE  
AND TECHNOLOGY



**VOLUME : 11    ISSUE : 02    Print / Issue Publication Date: June 2026**



**ISSN : 2455-2143**



**DOI : 10.33564/IJEAST.2026.v11i02.014**

Indexed In



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# GLOBAL ROAD TRAFFIC INJURY ANALYTICS: EVALUATING SYSTEMIC RISKS, DATA REALITIES, AND VISUALIZING COLLABORATIVE SAFETY TRENDS

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**Abstract**—Every year, road traffic accidents claim roughly 1.35 million lives worldwide. Although government data is crucial for monitoring progress toward SDG Target 3.6, frequent under-reporting routinely distorts public safety policies. To uncover these hidden vulnerabilities, this paper examines a 2020 dataset of 74,881 traffic collisions using Tableau-driven visual analytics. By cross-referencing environmental, demographic, and financial variables, our analysis reveals that wet and icy road conditions trigger massive economic losses topping \$98 million, motorists between the ages of 41 and 60 suffer the highest mortality rates, and medical expenditures peak at nearly \$193 million. Ultimately, this study highlights how interactive business intelligence can fill critical information gaps and support targeted, proactive interventions for global injury prevention.

**Keywords**— Road traffic injuries, Traffic mortality, Healthcare expenditures, Collision patterns, Accident demographics, Tableau, Public health policy, Visual analytics

## I. INTRODUCTION

Road traffic injuries are a global health challenge. The number of road traffic deaths continues to rise steadily, from 1.15 million in 2000 to 1.35 million in 2018. Of the 56.9 million deaths worldwide, road traffic injuries account for about 2.37% and are the eighth cause of global death [1]. In response, the United Nations released the Global Plan for the Decade of Action for Road Safety 2011–2020 in 2011 [2] and included road traffic injury prevention as Target 3.6 of the Sustainable Development Goals (SDG) in 2015 [3]. Road traffic injury statistics is the foundation to monitor the

progress and evaluate the effectiveness of road traffic injury prevention efforts nationally and globally. Official road traffic injury data which were delivered by governments worldwide are often believed reliable and valid, and are used for a variety of official and unofficial purposes. Unfortunately, it has been demonstrated that the data deviate from reality in several countries. In fact, the quality of official data has even been suggested to deteriorate recently in a few countries[4]. Road traffic data with problems may mislead resource allocation and strategic decision-making, ultimately create unwanted risk for evaluating the effectiveness of road traffic injury prevention. They may also bias the research findings. This paper summarized the documented problems in government statistics on road traffic injury, discussed the potential mechanisms behind the invalid and unreliable data, and suggested solutions to the challenges..

## II. LITERATURE REVIEW

The global landscape of road safety is defined by a persistent tension between rising populations and the slow evolution of protective measures. According to the World Health Organization [1], road traffic injuries remained a premier global public health crisis, claiming approximately 1.35 million lives as of 2016. While international road safety measures prevented the death rate from skyrocketing relative to the population, the progress was insufficient to meet the ambitious Sustainable Development Goal (SDG) 3.6, which targeted a 50% reduction in fatalities. This shortfall suggested that the problem was not merely one of traffic volume, but of systemic gaps in policy and management. These gaps were most visible at the clinical level, where the human cost of these statistics was tallied. Deresse E et al., conducted a hospital-based study in Adama, Ethiopia, and identified road



traffic accidents as the dominant cause of trauma, accounting for over half of all cases [2]. The profile of the victim was strikingly consistent: young males aged 20–29 remained the most vulnerable demographic. However, the struggle for safety was further complicated by geography; many victims traveled from rural areas to seek care, highlighting a critical disconnect between where accidents happened and where life-saving treatment was available.

The ability to bridge these gaps was fundamentally dependent on the quality of the data being collected, yet the global record was fraught with inconsistency. Chang et al. [3] argued that the very foundation of road safety monitoring was often built on unreliable official statistics, plagued by under-reporting and a lack of detail regarding specific road user types. This "data silence" was often systemic either because victims did not enter the formal healthcare system or because performance-based policies inadvertently encouraged local authorities to under-report deaths to avoid administrative scrutiny. This lack of transparency was a global phenomenon; a massive longitudinal study of 195 countries by Huang et al. [4] revealed that only 39% possessed synchronized data across both health and non-health sectors, leaving low-income nations particularly blind to the true scale of their mortality rates.

When the data was available, it revealed that the causes of accidents were often a cocktail of environmental and behavioral factors. In Lithuania, Mamčič and Sivilevičius [5] found that the safety of regional gravel roads was dictated by a shifting balance of traffic volume, speed, and seasonal weather patterns that saw accident rates climb from spring through autumn. To combat these multifaceted risks, the field of emergency management evolved from simple observation to advanced risk reduction. In regions as diverse as Tanzania and the United States, researchers such as Shanmugam, Raheem, and Batcha [6] employed data analytics to move beyond reactive measures. By utilizing the Knowledge Discovery in Databases (KDD) process and machine learning models like Random Forest, authorities were able to classify accident severity with high precision, allowing for more strategic decision-making in emergency response.

This technological shift represented a broader trend in the literature, where a comprehensive review by Behboudi et al. [7] confirmed that machine learning and deep learning became the gold standards for predicting accident risk and duration. These advanced models offered a path toward the 2030 global safety goals by integrating complex datasets that traditional statistics simply could not parse. Yet, despite this digital evolution, the fundamental killers remained: overspeeding, alcohol impairment, and poor infrastructure continued to result in 1.3 million annual deaths and up to 50 million injuries globally [8]. In Central India, Ganveer and Tiwari [9] noted that these injuries frequently manifested as severe fractures and blunt trauma among young men, often the result of side-swipe collisions involving two-wheelers.

Ultimately, the future of road safety lies in the marriage of local empirical evidence and high-level artificial intelligence. Córdova, de Saint Pierre, and Montt [10] demonstrated this in Chile's Metropolitan Region; by applying  $k$ -means clustering and Neural Networks to years of pedestrian crash data, researchers identified specific high-fatality zones in urban centers. This transition from broad statistics to localized, AI-driven prevention represented the most promising frontier in the global effort to ensure that road travel no longer carries a mandatory risk of fatality.

Further strengthening the global understanding of road traffic injuries, Peden, Scurfield, Sleet, Mohan, Hyder, Jarawan, and Mathers [11], through the World Report on Road Traffic Injury Prevention, emphasized that road traffic accidents had evolved into one of the leading causes of preventable mortality worldwide. The report highlighted that rapid urbanization, increasing motorization, weak enforcement of traffic regulations, and inadequate infrastructure collectively intensified the global road safety crisis, particularly within low- and middle-income nations. Their findings reinforced the growing international consensus that road safety must be treated not merely as a transportation issue, but as a major public health and developmental challenge requiring coordinated governmental intervention.

The unequal burden of this crisis was particularly visible across developing countries, where Nantulya and Reich [12] described road traffic injuries as a "neglected epidemic." Their study revealed that nations experiencing rapid economic growth often faced rising vehicle ownership without corresponding improvements in infrastructure, trauma-care systems, or traffic regulation enforcement. As a result, vulnerable populations in developing regions continued to experience disproportionately high mortality and disability rates, demonstrating how socioeconomic disparities further amplified the human consequences of road traffic accidents. Despite the increasing global attention toward road safety, researchers continued to identify major weaknesses within accident reporting and monitoring systems. Jacobs, Aeron-Thomas, and Astrop [13] examined global road fatality estimation methods and found that official statistics frequently underestimated the true scale of traffic-related deaths due to inconsistent reporting standards and incomplete national databases. This lack of standardized surveillance systems created significant barriers for policymakers attempting to measure the real effectiveness of road safety interventions and international prevention strategies.

As road traffic datasets became more extensive, researchers increasingly shifted toward analytical approaches capable of understanding accident occurrence patterns more systematically. Abdel-Aty and Radwan [14] explored statistical models for traffic accident occurrence and involvement by analyzing roadway characteristics, environmental conditions, and traffic flow variables. Their findings demonstrated that accident occurrence was strongly influenced by measurable external conditions rather than by



random events alone, thereby reinforcing the importance of data-driven transportation planning and predictive traffic analysis.

The evolution of road safety research subsequently encouraged broader methodological improvements in crash-frequency analysis. Lord and Mannering [15] reviewed several statistical approaches used in traffic safety studies and argued that conventional observational methods often failed to capture the complex variability present within accident datasets. Their work highlighted the growing importance of advanced analytical frameworks capable of handling over-dispersion, heterogeneity, and inconsistencies in crash data, thereby improving the reliability of accident frequency estimation and transportation safety evaluation.

This analytical progression further extended into injury-severity assessment, where Savolainen, Mannering, Lord, and Qudus [16] examined statistical methodologies used for highway crash-injury severity analysis. The authors emphasized that accident severity is shaped by the interaction of multiple contributing factors including driver behavior, roadway infrastructure, environmental conditions, and vehicle characteristics. Their review demonstrated that severity-focused analytical models provide deeper insights into how and why certain accidents result in fatal or critical injuries, thereby supporting more targeted road safety policies and emergency management strategies.

As transportation safety research matured, attention increasingly shifted toward improving the predictive reliability of accident risk estimation systems. While recent transportation safety research increasingly emphasizes predictive machine learning and statistical modeling approaches, the present study focuses specifically on exploratory visual analytics and descriptive trend interpretation using Tableau dashboards. Elvik [17] evaluated the predictive validity of Empirical Bayes methods in road safety analysis and found that traditional observational evaluations were often distorted by regression-to-the-mean effects and random statistical fluctuations. By introducing more stable estimation techniques, the study demonstrated how analytical refinement could improve the accuracy of identifying genuinely hazardous road segments, ultimately contributing toward more evidence-based infrastructure planning and long-term accident prevention strategies.

### III. METHODS

This research employs a data visualization and exploratory analytics methodology using Tableau to investigate patterns associated with road traffic injuries and accident severity. The study focuses on transforming large-scale accident records into interpretable visual representations that facilitate comparative analysis across demographic, environmental, temporal, and economic dimensions. The objective of the methodology is the identification of observable trends and risk distributions through interactive analytical visualization.

The analytical process began with the acquisition and integration of the Road Accidents 2020 dataset into Tableau. Data preprocessing procedures were performed to improve consistency and analytical usability, including verification of categorical attributes, removal of duplicate entries where necessary, handling of incomplete values, and standardization of variable formats. Key variables selected for analysis included crash dates, road conditions, weather conditions, driver age groups, injury counts, fatality records, medical expenditures, economic losses, and geographic indicators.

After preprocessing, the dataset was explored using multiple visualization techniques designed to support descriptive and comparative analysis. These visual methods included line charts for temporal trend evaluation, bar graphs for categorical comparison, heat maps and highlight tables for regional intensity assessment, funnel charts for demographic ranking, and dual-axis charts for comparative trend analysis between multiple variables. Interactive dashboards were then constructed by integrating these visual components into a consolidated analytical framework capable of filtering and cross-referencing accident-related attributes dynamically.

The methodological framework emphasizes visual interpretation and analytical observation to better understand how environmental conditions, demographic factors, and infrastructural variables are associated with injury occurrence and financial impact. By employing dashboard-oriented visual analytics, the study seeks to provide a clearer representation of hidden traffic safety patterns and support evidence-based understanding of road accident trends and public safety challenges.

### IV. MATERIALS

The dataset utilized in this study was obtained from an open-access repository containing structured traffic collision records for the year 2020. The dataset was selected due to its extensive coverage of accident-related variables and its suitability for exploratory visual analytics. A total of 74,881 collision records were analyzed to examine patterns associated with road safety, injury occurrence, environmental conditions, and contributing behavioral factors.

The dataset is organized as a comprehensive event-based traffic collision log designed to support transportation and public safety analysis. It contains multiple categories of structured attributes that collectively describe the circumstances surrounding each incident. Temporal attributes include variables such as crash date and crash time, enabling the analysis of daily, weekly, and seasonal traffic patterns. Locational attributes provide geographic context through area identifiers, postal codes, roadway names, intersecting streets, and coordinate-based references that assist in identifying spatial accident distributions and high-risk zones.

In addition to spatial and temporal information, the dataset includes categorical variables documenting contributing factors associated with collisions, such as driver inattention, failure to yield, improper lane usage, and other roadway



behaviors linked to accident occurrence. Vehicle-related fields classify the modes of transportation involved in each event, including sedans, sport utility vehicles, taxis, bicycles, and other vehicle categories. Each collision record is further associated with a unique identification number to maintain traceability and support systematic analysis.

The dataset also contains injury and impact-related measures describing the number of motorists, pedestrians, and cyclists injured or killed in each incident. Supplementary analytical attributes, including road condition, weather condition, medical cost, economic loss, driver age group, and driver gender, provide additional dimensions for evaluating the broader social and financial implications of traffic collisions. The integration of temporal, geographic, behavioral, demographic, and economic variables makes the dataset suitable for descriptive trend analysis and interactive visual interpretation using dashboard-oriented analytical tools.

## V. ANALYSIS AND DISCUSSIONS

Analyzing 74,881 traffic collision records from 2020 reveals a complex web of overlapping risk factors that threaten global transit systems. By mapping how weather conditions, driver ages, and financial consequences intersect, these visual analytics move past the limitations of traditional government data to expose where public safety networks are failing.

### 1. Spatial and Geographic Risk Densities

Evaluating accident volumes across primary road classifications—Highways, Main Roads, and Streets—reveals a uniform risk distribution, with each registering between 6,500 and 6,800 motorist injuries. This uniform baseline proves that traffic vulnerability is not exclusive to high-speed corridors; rather, regular municipal streets carry an almost identical injury burden. Geographically, clear spatial clustering appears: the boroughs of Brooklyn and Queens account for the vast majority of injuries across all road categories, indicating that broad safety policies must be replaced by highly localized urban engineering interventions.

**2. Vulnerable Road Users and Traffic Volatility** The safety profiles of vulnerable road users display different risk patterns than those of protected motorists. International metrics for cyclist injuries remain highly consistent across nine of the ten tracked nations, maintaining a predictable baseline of 310 to 350 total injuries, with the United States acting as a clear upward outlier. Interestingly, the gender balance for cyclist injuries remains evenly split near a 50:50 ratio in almost every territory.

Conversely, pedestrian casualties show intense temporal volatility. Rather than showing a steady daily baseline, pedestrian fatalities fluctuate sharply across calendar months. The data highlights acute spikes, such as a single-day peak of 7 pedestrian deaths on March 14, 2020. This indicates that pedestrian risk is driven by transient, situational factors rather than uniform daily risk exposure.

**3. Demographic Anomalies and Healthcare Economics** Cross-referencing driver age groups against casualty metrics reveals an inverse relationship that challenges traditional safety assumptions. Funnel chart analytics ranking driver age by fatality counts prove that mature drivers aged 41–60 constitute the largest high-risk cohort, accounting for 36 deaths. In contrast, drivers under the age of 18 represent the lowest mortality segment with 22 deaths.

While older cohorts suffer higher immediate mortality due to physiological frailty during impacts, the under-18 driver group generates the highest running sum of cumulative medical costs. This trend implies that younger drivers are involved in high-velocity, non-fatal accidents that result in complex, long-term clinical trauma and extensive critical care, placing a massive long-term financial burden on healthcare systems.

| Driver Age Group | Fatalities Count    | Cumulative Medical Impact Cost       |
|------------------|---------------------|--------------------------------------|
| Under 18         | 22 deaths (Lowest)  | \$372M – \$382M (Highest Sum)        |
| 41–60            | 36 deaths (Highest) | Intermediate Expenditure Bracket     |
| 61+              | Intermediate Count  | Minimum Expenditure Bracket (Lowest) |

### 4. Environmental Hazards as Risk Multipliers

Environmental conditions act as clear catalysts for severe physical injuries and extensive economic damage. The highest concentration of human injuries occurs on Main Roads during snow-covered conditions, whereas dry municipal streets show the lowest overall injury baseline. While total injuries across changing weather states remain bounded between 2,199 and 2,397 cases, adverse weather heavily shifts simple accidents toward high-severity outcomes.

This pattern is mirrored in regional economic loss metrics, where wet and icy road conditions generate the highest financial drain, climbing up to \$100 million globally. In India's specific domain (spanning approximately 8,000 accidents and 15 fatalities), wet roads caused the highest economic loss at over \$98 million, whereas dry conditions resulted in the minimum baseline of roughly \$91 million. This confirms that poor wet-weather drainage and reduced tire friction serve as immediate economic drains, amplifying the financial severity of collisions.

### 5. Temporal Traffic Anomalies and Pandemic Shifts

The chronological tracking of daily injuries from January through August 2020 clearly captures the impact of the COVID-19 pandemic on global mobility. Line charts mapping daily injury totals reveal a severe, unprecedented drop starting in mid-March 2020, directly matching the implementation of state-level lockdowns and travel restrictions.



Following this historic decline, the data displays a gradual, steady climb through late spring and early summer, returning completely to pre-pandemic injury baselines by late July. Dual-axis monitoring reveals that as cities reopened during June and July, cyclist injuries spiked dramatically due to summer recreation, though cyclist fatalities remained close to zero. Concurrently, motorist injuries followed a matching upward vector in later weeks. This rapid return to pre-March injury baselines proves that as economic activity and traffic volume returned, legacy road risks quickly re-emerged, moving faster than the implementation of modern, collaborative safety measures.

**VI. INFERENCES FROM VISUAL ANALYTICS**

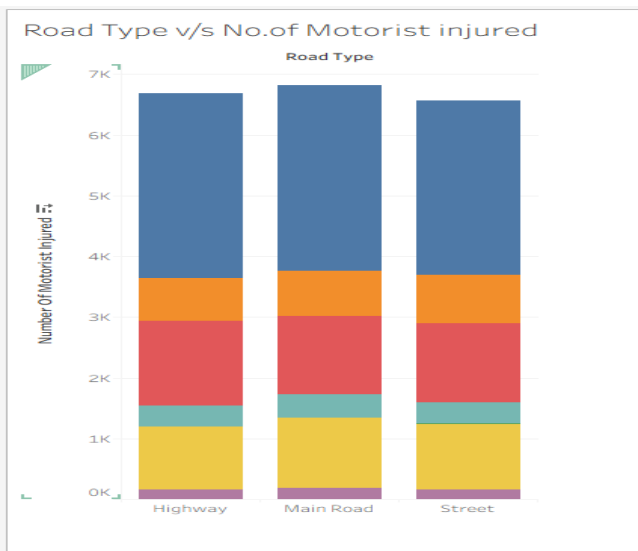


Fig.1.1 Road type v/s number of motorists Injured

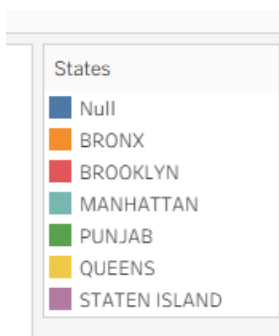


Fig.1.2 colour coded States

1. Across three types of roads—Highways, Main Roads, and Streets—the number of injured motorists is very similar, with about 6,500 to 6,800 injuries each. While the road types differ, the location data shows a clear pattern: Brooklyn and Queens account for most of these injuries across every category.

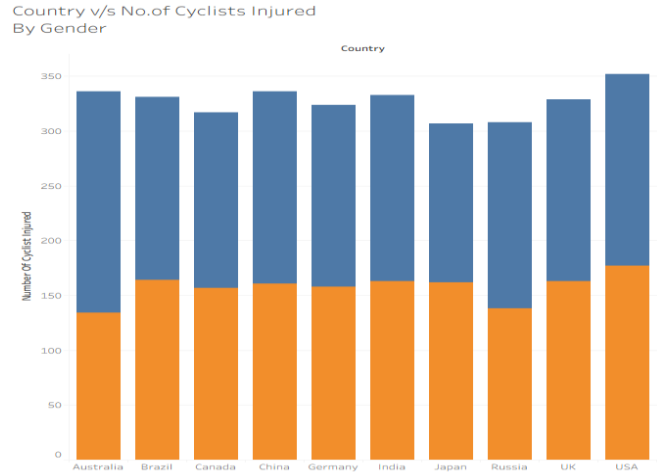


Fig.2. Country versus number of cyclist injured by gender

2. This chart tracks cyclist injuries across ten countries, showing that most nations record between 310 and 350 total injuries. The USA stands out with the highest overall number. Despite these differences in totals, the gender balance remains very consistent, with injuries split fairly evenly between both groups in almost every country.

**Country vs sum of medical costs**

| Country   | Sum of Medical Costs |
|-----------|----------------------|
| Australia | 190,998,299          |
| Brazil    | 185,849,830          |
| Canada    | 193,321,397          |
| China     | 188,827,388          |
| Germany   | 192,816,108          |
| India     | 188,412,463          |
| Japan     | 182,839,927          |
| Russia    | 184,657,168          |
| UK        | 188,728,613          |
| USA       | 190,216,515          |

Fig.3. Country versus sum of medical costs

3. This table represents total medical expenditures for ten different countries ranging from approximately **182 million to 193 million**. **Canada** shows the highest total cost in this dataset, while **Japan** represents the lowest.

**Driver Age Grp vs Medical costs**

| Driver Age .. | Medical Costs |
|---------------|---------------|
| 18-25         | 373,633,605   |
| 26-40         | 379,144,704   |
| 41-60         | 379,296,967   |
| 61+           | 372,200,706   |
| <18           | 382,391,727   |

Fig.4. Driver age group versus medical costs



4. This table contains total medical costs based on the age group of the driver with all totals between **372 million and 382 million**. Interestingly the **under 18** age group accounts for the highest sum of medical costs, while the **61+** group are the lowest.

Road Conditions vs Persons injured

| Road Condition | Road Type | Persons Injured |
|----------------|-----------|-----------------|
| Dry            | Highway   | 2,293           |
|                | Main Road | 2,383           |
|                | Street    | 2,199           |
| Icy            | Highway   | 2,308           |
|                | Main Road | 2,243           |
|                | Street    | 2,245           |
| Snow-covered   | Highway   | 2,231           |
|                | Main Road | 2,397           |
|                | Street    | 2,217           |
| Wet            | Highway   | 2,239           |
|                | Main Road | 2,366           |
|                | Street    | 2,327           |

Fig.5. Road conditions vs persons injured

5. This table compares the number of persons injured across different **road conditions** and **road types**. Overall, injuries are fairly similar across conditions, generally ranging from about **2,199 to 2,397** cases. The highest number of injuries occurs on **main roads under snow-covered conditions**, while **streets in dry conditions** show the lowest number.

Country vs no.of persons killed

| Country   | No. of Persons Killed |
|-----------|-----------------------|
| Australia | 12                    |
| Brazil    | 13                    |
| Canada    | 18                    |
| China     | 13                    |
| Germany   | 22                    |
| India     | 15                    |
| Japan     | 14                    |
| Russia    | 4                     |
| UK        | 20                    |
| USA       | 13                    |

Fig.6. country vs number of persons killed

6. This table shows how many people were killed in accidents across different countries. **Germany** has the highest number at 22, while **Russia** has the lowest at 4.

Heat map  
 [Country vs pedestrians Injured]

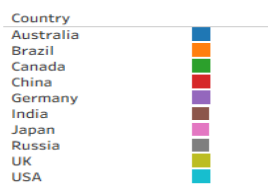


Fig.7. Country vs pedestains injured

7. This Heatmap uses different colors to represent the number of pedestrians injured in each country. It lists the same ten countries, with **each color** likely corresponding to a specific range or value of injuries.

Country vs sum of medical costs

| Country   | Sum of Medical Costs |
|-----------|----------------------|
| Australia | 190,998,299          |
| Brazil    | 185,849,830          |
| Canada    | 193,321,397          |
| China     | 188,827,388          |
| Germany   | 192,816,108          |
| India     | 188,412,463          |
| Japan     | 182,839,927          |
| Russia    | 184,657,168          |
| UK        | 188,728,613          |
| USA       | 190,216,515          |

Fig.8. Country versus sum of medical costs

8. This Highlight Table uses different colors to show the total amount spent on medical costs in ten countries. **Dark green** highlights the countries with the highest costs like **Canada**, which spent over 193 million. **Dark red** marks the countries with the lowest costs, with **Japan** having the smallest total at 182 million.

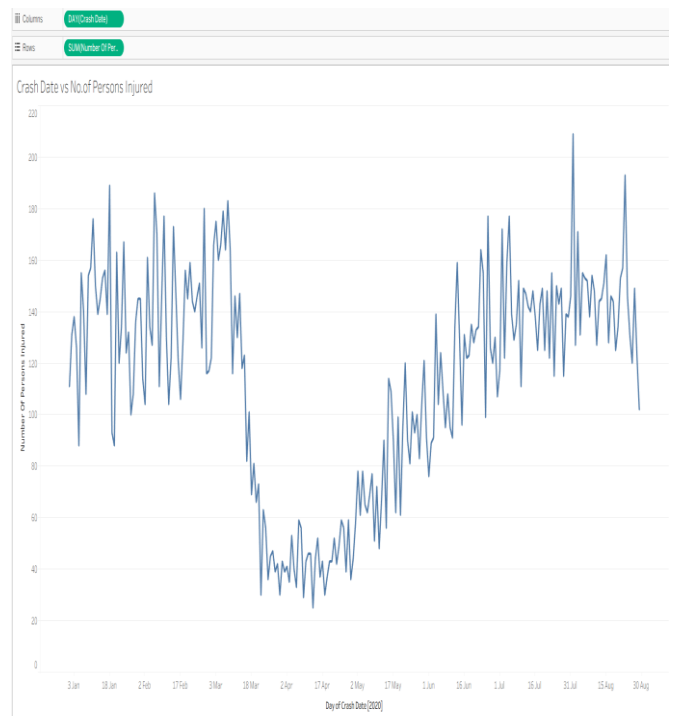


Fig.9. Crash Date vs No. of Persons Injured

9. This line chart, titled "**Crash Date vs No. of Persons Injured**," tracks daily injury totals from January through August 2020. It shows a significant drop in injuries starting in



mid-March, followed by a steady climb back to pre-March levels by late July.

Crash dates vs No. of cyclists injured

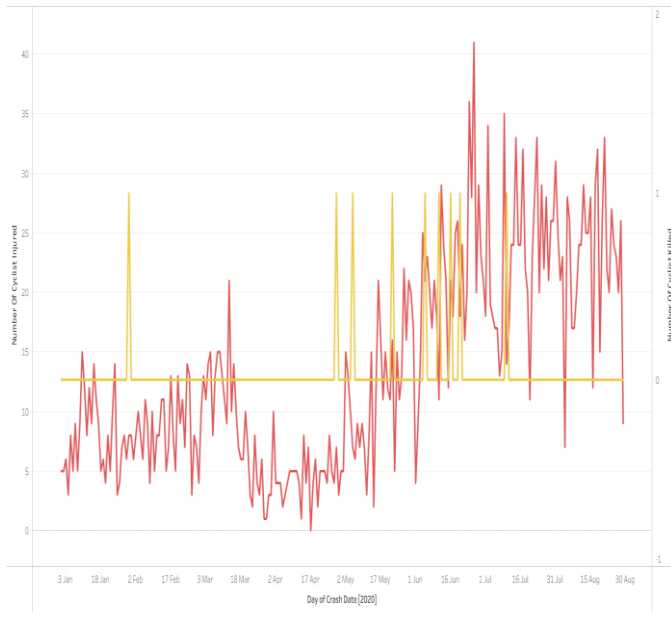


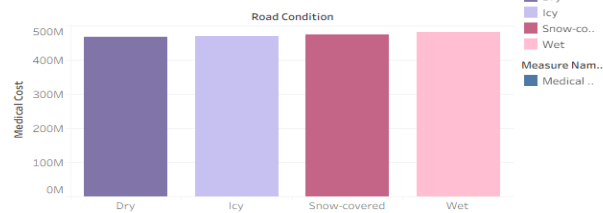
Fig.10. Dual Axis

10. This graph shows how many cyclists were injured or killed in crashes between January and August 2020. The **red line** shows that injuries increased significantly in the summer, while the **yellow line** shows that deaths remained rare, usually staying at zero.

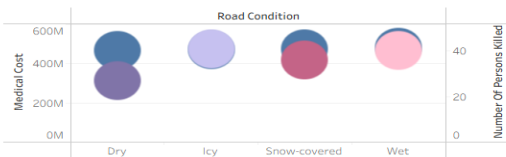
**Dashboards**

Comparison based on medical costs

Road conditions vs Medical costs



No. of cyclists killed vs no. of pedestrians killed



Crash dates vs No. of cyclists injured

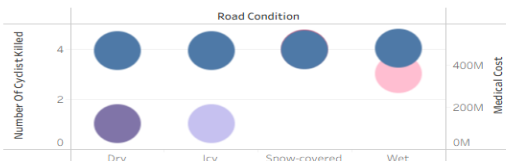
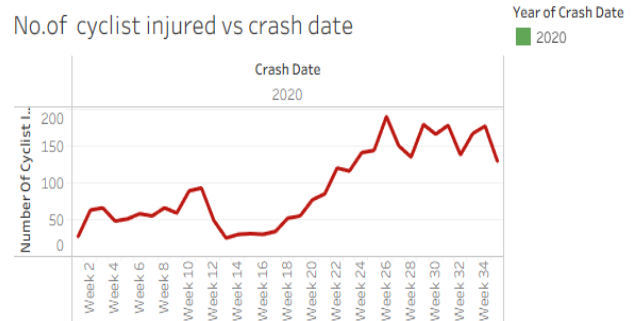


Fig.11. Comparison based on medical costs

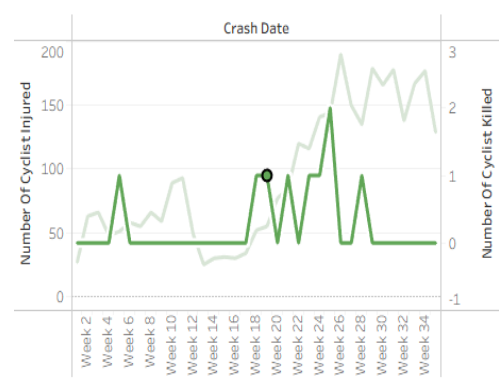
11. This dashboard visualizes the relationship between **road conditions** (dry, icy, snow-covered, wet) and various metrics including **medical costs**, fatalities, and injuries. It uses a combination of bar and bubble charts to compare how these environmental factors impact the severity and financial burden of traffic accidents.

Comparison based on crash dates

No. of cyclist injured vs crash date



Weekly cyclist injuries and Fatalities Trend



Weekly cyclist vs Motorist injured trend(2020)

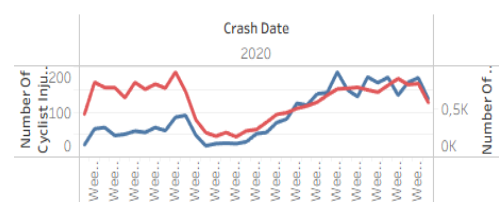


Fig.12. Comparison based on crash dates

12. The dashboard compares cyclist injuries, fatalities, and motorist injuries across weekly crash dates in 2020. Cyclist injuries show a dip around mid-year followed by a steady rise toward later weeks. Cyclist fatalities remain low and relatively stable with occasional small spikes. Motorist injuries are consistently higher than cyclist injuries and follow a similar upward trend in later weeks.

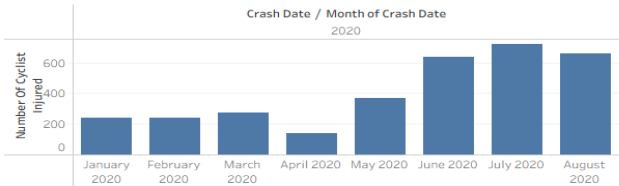


**Time-Based Analysis of Cyclist Injuries and Motorist Deaths**

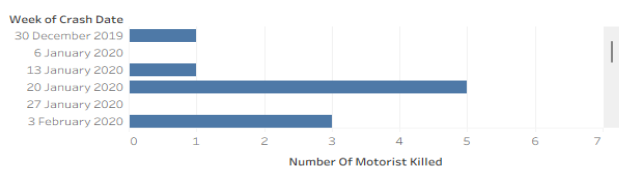
Based on Crash Date Country vs Number of Cyclist Killed

| Country   | Quarter of Crash Date |         |         |
|-----------|-----------------------|---------|---------|
|           | 2020 Q1               | 2020 Q2 | 2020 Q3 |
| Australia | 86                    | 103     | 147     |
| Brazil    | 78                    | 112     | 141     |
| Canada    | 87                    | 107     | 123     |
| China     | 70                    | 139     | 127     |
| Germany   | 76                    | 116     | 132     |
| India     | 72                    | 120     | 143     |
| Japan     | 79                    | 108     | 120     |
| Russia    | 73                    | 110     | 125     |
| UK        | 58                    | 104     | 167     |
| USA       | 76                    | 124     | 152     |

Crash date vs No.of Cyclist injured



Week of Crash Date vs No.of Motorist Killed

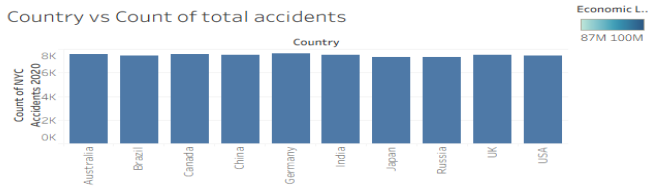


Sum of Number Of Motorist Killed for each Crash Date Week. The data is filtered on Action (QUARTER(Crash Date),Country), which keeps 30 members.

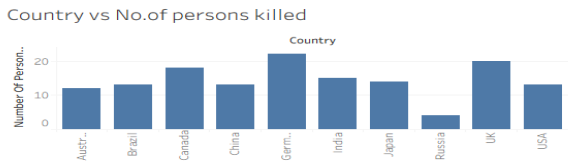
**Fig.13.**

13. No cyclist fatalities were recorded in the data. Cyclist injuries decreased around April and then increased steadily, reaching a peak in July before slightly declining. Motorist fatalities showed weekly fluctuations, with higher occurrences observed in late January and early February

**Analyzing Accidents, Fatalities, and Economic Loss by Country**



Count of NYC Accidents 2020 for each Country. The data is filtered on Action (Country), which keeps 10 members.



Sum of Number Of Persons Killed for each Country.

Country wise road condition vs Economic loss

| Country   | Road Condition |            |              |            |
|-----------|----------------|------------|--------------|------------|
|           | Dry            | Icy        | Snow-covered | Wet        |
| Australia | 90,885,465     | 92,099,547 | 96,652,844   | 98,417,553 |
| Brazil    | 90,885,465     | 92,099,547 | 96,652,844   | 98,417,553 |
| Canada    | 90,885,465     | 92,099,547 | 96,652,844   | 98,417,553 |
| China     | 90,885,465     | 92,099,547 | 96,652,844   | 98,417,553 |
| Germany   | 90,885,465     | 92,099,547 | 96,652,844   | 98,417,553 |
| India     | 90,885,465     | 92,099,547 | 96,652,844   | 98,417,553 |
| Japan     | 90,885,465     | 92,099,547 | 96,652,844   | 98,417,553 |
| Russia    | 90,885,465     | 92,099,547 | 96,652,844   | 98,417,553 |
| USA       | 90,885,465     | 92,099,547 | 96,652,844   | 98,417,553 |

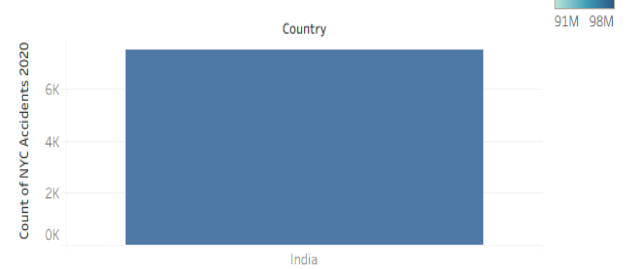
Sum of Economic Loss broken down by Road Condition vs. Country. Color shows sum of Economic Loss. The marks are labeled by sum of Economic Loss. The data is filtered on Action (Country), which keeps 10 members.

**Fig.14.1. Analysing accidents , fatalities, and economic loss by country**

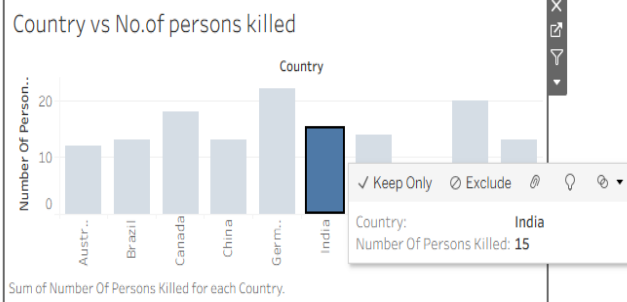
14.1. Global data across ten countries shows that while total accident numbers are similar, fatalities vary significantly, with **Germany** and the **UK** recording the highest death rates. Financial losses are also analyzed by **road condition**, revealing that wet and icy weather often lead to the highest economic costs, reaching up to **\$100 million**.

**Analyzing Accidents, Fatalities, and Economic Loss by Country**

Country vs Count of total accidents



Count of NYC Accidents 2020 for each Country. The data is filtered on Action (Country), which keeps 1 member.



Sum of Number Of Persons Killed for each Country.

Country wise road condition vs Economic loss

| Country | Road Condition |            |              |            |
|---------|----------------|------------|--------------|------------|
|         | Dry            | Icy        | Snow-covered | Wet        |
| India   | 90,885,465     | 92,099,547 | 96,652,844   | 98,417,553 |

Sum of Economic Loss broken down by Road Condition vs. Country. Color shows sum of Economic Loss. The marks are labeled by sum of Economic Loss. The data is filtered on Action (Country), which keeps 1 member.

**Fig.14.2. Analysing accidents , fatalities, and economic loss by country**

14.2. India recorded approximately 8,000 total accidents and 15 fatalities. The economic impact varies significantly by road condition, with wet roads causing the highest financial loss at over \$98 million, while dry conditions resulted in the lowest at roughly \$91 million.

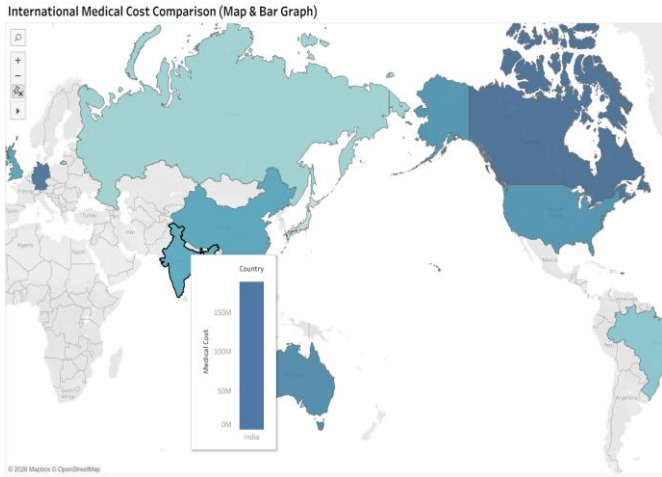


Fig.15. International Medical Costs Comparison

15. India shows a medical cost of approximately **\$190 million**. This is represented by a **darker blue shade** on the global map, indicating it is one of the higher-cost regions compared to countries like Russia or Brazil. The accompanying bar chart confirms this peak value, placing India at the top of the scale for this specific dataset.

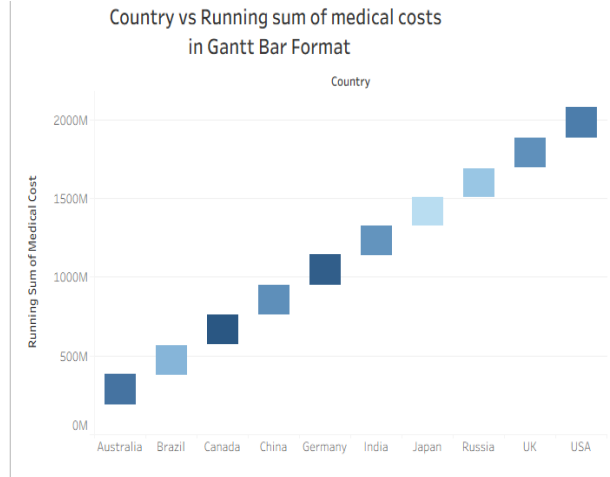


Fig.17. Country versus running sum of medical costs in Gantt bar format

17. This chart uses a **Gantt bar** technique to create a **waterfall effect**, showing how medical costs accumulate country by country. Each bar represents a single country's contribution, positioned to start exactly where the previous country's cost left off. This "floating" structure visually maps the step-by-step growth of the total global expenditure.

Crash date vs No.of pedestrians killed(Timeline chart with highlight box)

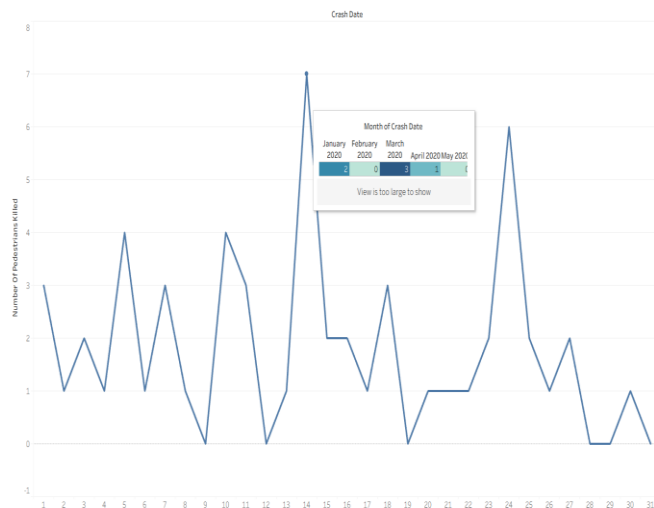


Fig.16. Crash date vs No.of pedestrians killed (Timeline chart with highlight box)

16. Pedestrian fatalities fluctuated throughout the month, peaking sharply at **7 deaths** on the **14th**. While most days saw **0 to 4 fatalities**, **March 2020** was the deadliest month highlighted with **3 deaths**.

Funnel chart for analyzing Driver Age Grp and no.of persons killed

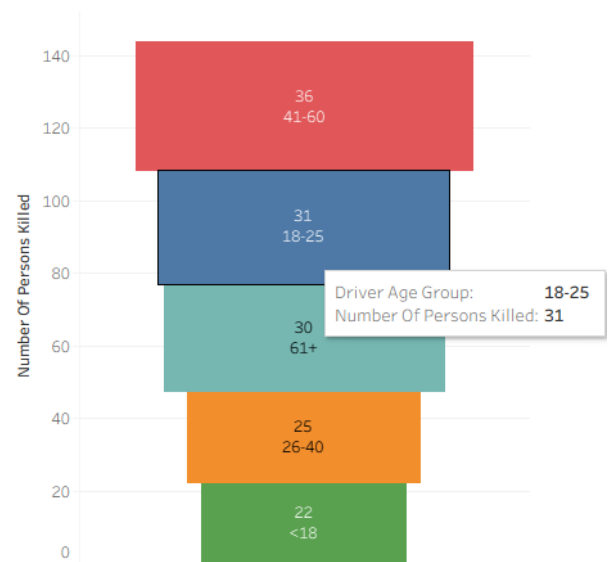


Fig.18. funnel chart for analysing driver age group and Number of persons killed

18. This funnel chart ranks driver age groups by number of fatalities they are linked to. The 41-60 group represents largest segment with 36 deaths, while drivers under 18 account for the smallest at 22.

Running Sum of medical cost VS Driver Age Group in Gantt Bar

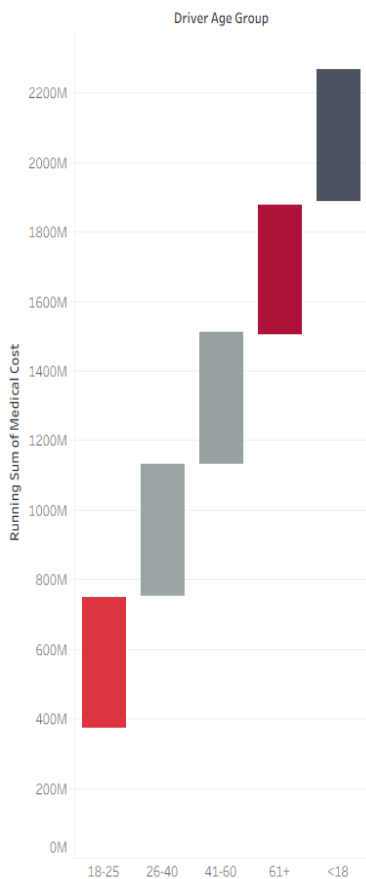


Fig 19. Running sum of medical cost versus driver age group in Gantt bar

19. This chart shows medical costs across driver age groups. It uses a running sum to display total expenses. Each bar represents an age category. Costs increase with age. The gantt format highlights differences clearly. It shows overall cost trends.

## VII. CONCLUSION

This study successfully demonstrates the utility of interactive business intelligence and visual analytics in unmasking systemic road safety risks and addressing the pervasive issue of "data silence" in global accident reporting. By analyzing 74,881 records from the Road Accidents 2020 dataset within Tableau, this research bridges the gap between raw statistical data and actionable policy insights. The empirical findings reveal that environmental factors function as significant risk multipliers, with wet and icy road conditions generating up to \$100 million in economic losses globally and over \$98 million in India alone. Demographically, the analysis challenges conventional assumptions by identifying drivers aged 41–60 as the segment tied to the highest fatality rates, while unexpected healthcare burdens were observed in under-

18 driver categories. Furthermore, chronological analysis accurately captured the impact of external societal shifts, tracking a distinct decline in traffic injuries during mid-March 2020 lockdowns followed by a steady resurgence by late July. Ultimately, these insights indicate that passive, disjointed data reporting is insufficient to achieve Sustainable Development Goal (SDG) Target 3.6. To significantly reduce traffic mortality, regional governments must transition to synchronized, cross-sector visual analytics platforms that enable proactive infrastructure investments, targeted demographic safety campaigns, and optimized emergency medical resource allocation.

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