SAFE STREETS FOR ALL

Appendix B: Data Support Technical Memorandum

Executive Summary

This document contains the Data Sustainability Plan, Regional Safety Needs, Performance Measures, and Data Action and Implementation Plan setting the groundwork for continued safety analysis and the development of a targeted Safety Action Plan.

The analysis, grounded in rigorous examination of 2018 – 2022 crash data through historic injury, future risk, and community need. The efforts aim to identify factors contributing to severe crashes and prioritize interventions for improving safety. Using a data-driven approach, we focused on patterns and correlations to pinpoint emphasis areas requiring attention. Our findings highlight the importance of actionable strategies based on clear trends in crash data.

From the analysis, we identified the following key emphasis areas:

Causation vs. Correlation

This analysis identifies features that are correlated with higher numbers of fatalities and serious injuries. This does not necessarily mean that the presence of the characteristic is contributing to crashes. This may be particularly true of characteristics that are likely acting as proxies for other features (e.g., the presence of more lanes may be a surrogate for higher speeds).

Emphasis Areas	Description
Speeding	Speeding significantly increases crash severity, making fatal or serious injuries **6.95 times more likely**. When combined with high-risk driving or specific demographics, the risk rises further.
Motorcycles* (Motorcycles, Mopeds, ATVs, etc.)	The rise in crashes involving motorcycles is notable where **crash totals have nearly doubled in 2022** compared to previous years (from 369 in 2021 to 685 crashes in 2022), however this fortunately has not translated to a significant rise in fatalities and serious injuries.
Younger Drivers (Ages 25 and under)	Fatal and serious injury crashes involving young drivers **have been nearly halved** – in 2017, 187 fatal and serious injury crashes involved a young driver as compared to 99 in 2022. Yet the share of fatal and serious injury crashes involving a young driver has held steady. Meaning fatal and serious injury crashes are down across the board but the **proportion** affecting younger drivers has **remained relatively level**.
Impaired Driving	Fewer but still too many crashes involving drivers under the influence – calendar year 2022 marked a steep decline in crash totals involving drivers under the influence, from a high of 843 in 2021 to a low of 735 in 2022. These crashes still account for **7.4% of all fatal and serious injury crashes**.

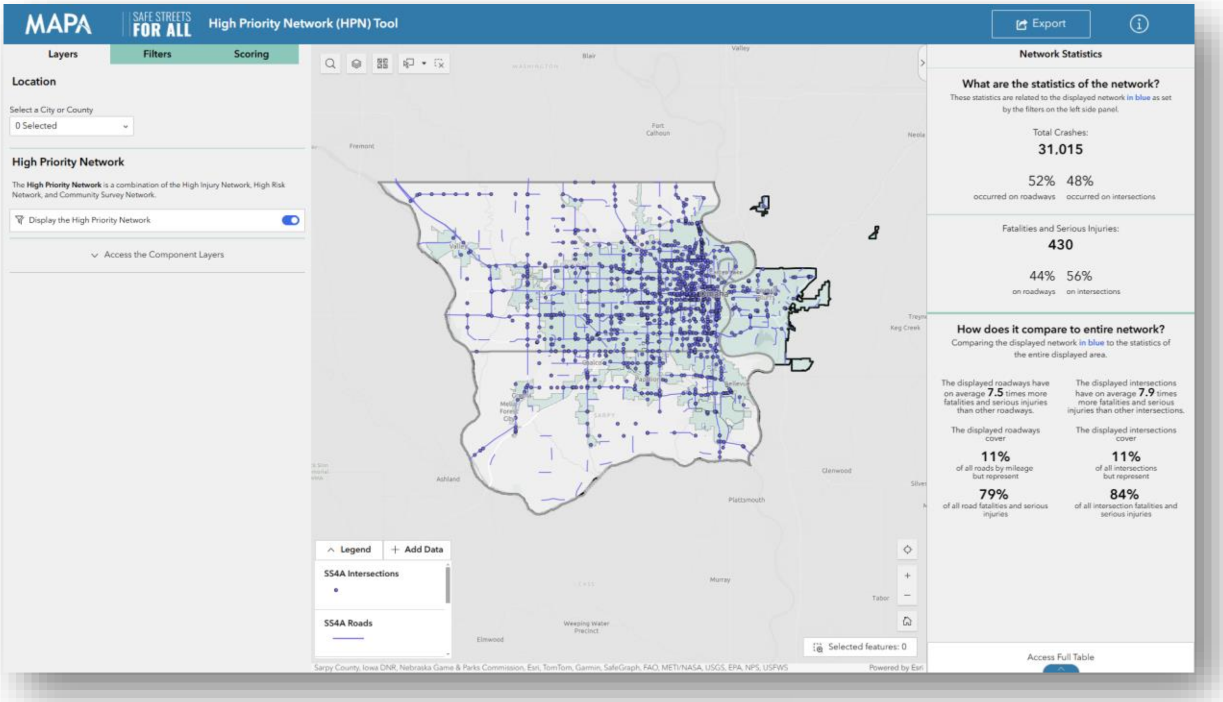
The memo underscores the critical areas where interventions can significantly enhance road safety and reduce fatal and serious injury crashes.

The High Priority Network and Tool

The culmination of the analysis is the High Priority Network (HPN) that prioritizes roads and intersections through a combination of need, risk, and community concern. It combines a hotspot analysis of high fatal and serious injury crash rates, a causality analysis of roadway characteristics, and the results of a survey of safety conditions in the MAPA region.

This network can be displayed via the link below to an interactable ESRI Tool:

https://mapacog.github.io/hpn-tool/



Location

Select a City or County: 0 Selected

High Priority Network

The **High Priority Network** is a combination of the High Injury Network, High Risk Network, and Community Survey Network.

Display the High Priority Network ●

Access the Component Layers

Network Statistics

What are the statistics of the network?

These statistics are related to the displayed network in blue as set by the filters on the left side panel.

Total Crashes: **31,015**

52% occurred on roadways; 48% occurred on intersections

Fatalities and Serious Injuries: **430**

44% on roadways; 56% on intersections

How does it compare to entire network?

Comparing the displayed network in blue to the statistics of the entire displayed area.

The displayed roadways have on average **7.5** times more fatalities and serious injuries than other roadways.

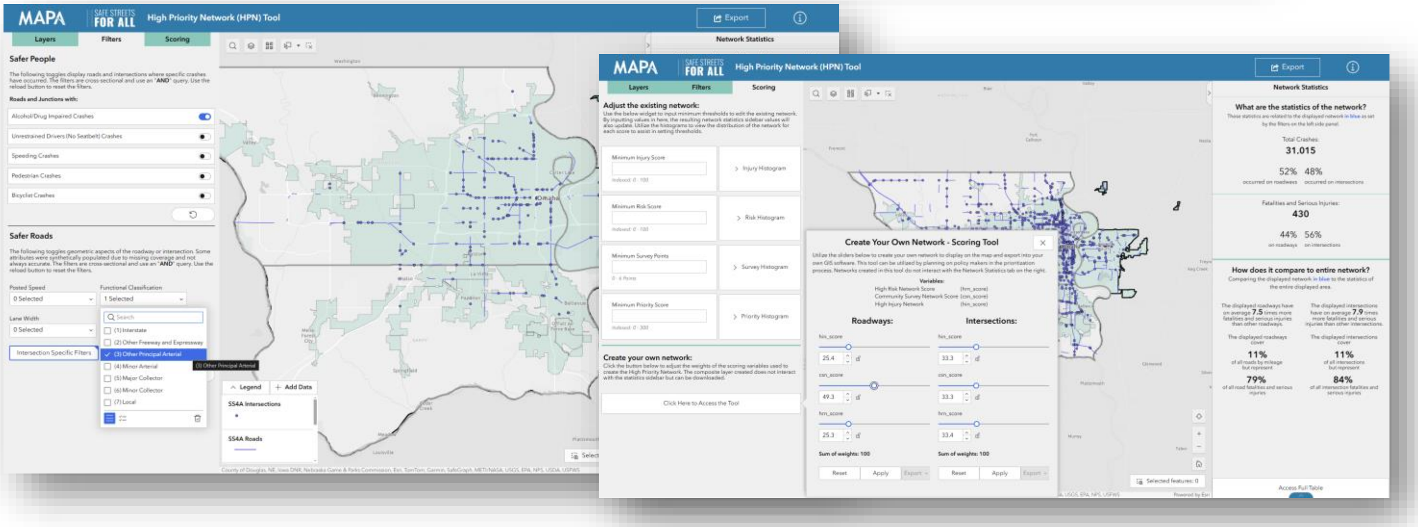
The displayed intersections have on average **7.9** times more fatalities and serious injuries than other intersections.

The displayed roadways cover **11%** of all roads by mileage but represent **79%** of all road fatalities and serious injuries

The displayed intersections cover **11%** of all intersections but represent **84%** of all intersection fatalities and serious injuries

Sarpy County, Iowa DNR, Nebraska Game & Parks Commission, Esri, TomTom, Garmin, SafeGraph, FAO, METI/NASA, USGS, EPA, NPS, USFWS

Powered by Esri



Safer People

The following toggles display roads and intersections where specific crashes have occurred. The filters are cross-sectional and use an "**AND**" query. Use the reload button to reset the filters.

Roads and Junctions with:

- Alcohol/Drug Impaired Crashes ●
- Unrestrained Drivers (No Seatbelt) Crashes ○
- Speeding Crashes ○
- Pedestrian Crashes ○
- Bicyclist Crashes ○

Safer Roads

The following toggles geometric aspects of the roadway or intersection. Some attributes were synthetically populated due to missing coverage and not always accurate. The filters are cross-sectional and use an "**AND**" query. Use the reload button to reset the filters.

Posted Speed: 0 Selected

Functional Classification: 1 Selected

- ☐ (1) Interstate
- ☐ (2) Other Freeway and Expressway
- ☑ (3) Other Principal Arterial
- ☐ (4) Minor Arterial
- ☐ (5) Major Collector
- ☐ (6) Minor Collector
- ☐ (7) Local

Lane Width: 0 Selected

Intersection Specific Filters

Adjust the existing network:

Use the below widget to input minimum thresholds to edit the existing network. By inputting values in here, the resulting network statistics sidebar values will also update. Utilize the histograms to view the distribution of the network for each score to assist in setting thresholds.

Minimum Injury Score

Minimum Risk Score

Minimum Survey Points

Minimum Priority Score

Create your own network:

Click the button below to adjust the weights of the scoring variables used to create the High Priority Network. The composite layer created does not interact with the statistics sidebar but can be downloaded.

Create Your Own Network - Scoring Tool

Utilize the sliders below to create your own network to display on the map and export into your own GIS software. This tool can be utilized by planning on policy makers in the prioritization process. Networks created in this tool do not interact with the Network Statistics tab on the right.

Variables:

High Risk Network Score (hrn_score)
Community Survey Network Score (csn_score)
High Injury Network (hin_score)

Roadways:		**Intersections:**	
hin_score	25.4	hin_score	33.3
csn_score	49.3	csn_score	33.3
hrn_score	25.3	hrn_score	33.4
Sum of weights: 100		**Sum of weights: 100**	

Introduction

The USDOT adopted a Safe System Approach (SSA) to roadway safety to address and mitigate the risks that are inherent in a complex transportation system. It is a shift from the conventional safety approach because it focuses on human mistakes and vulnerability with the goal of designing a system with multiple protective redundancies. Further, an effective safe system requires buy-in and shared responsibility across all stakeholders, including all levels of government, industry, non-profit/advocacy, researchers, and the general public.

Using **High-injury Networks (HINs)** for traffic safety planning is an example of the **Safe System Approach** in practice. Before the most effective interventions are implemented, it is essential to understand the most critical areas of need in a region's transportation network.

The MAPA Regional Safety Action Plan (RSAP) includes a data-driven analysis of existing conditions and historical trends to establish a baseline understanding of safety performance on the region's multimodal roadway system. To accomplish this important task, the consultant team (High Street) conducted a fatal and serious injury analysis that resulted in a region-wide high-priority network (HPN). Moving towards a vision of zero deaths requires an understanding of where the most severe collisions are occurring (i.e., crashes resulting in fatalities and serious injuries). Additionally, there may be aspects of the network that correlate to more severe crashes as a result of specific roadway design features or risky driver behavior. A defensible and objective HPN highlighting the areas of the roadway system in the most need of safety improvements can help agencies continue making progress with limited resources.

Safe System Approach

The team integrated the Safe System Approach (SSA) into the analysis by careful consideration of all available quality data that align with five SSA objectives of Safer People, Safer Vehicle, Safer Speeds, Safer Roads, and Post-Crash Care. The full list of data sources collected can be found in the Data Inventory Spreadsheet. The figure below shows the data elements used by the team in this analysis while organized by SSA objective.

Safer People

Census ACS Age
Pedestrian Crossings
Bikeable Streets
Bicycle Infrastructure
Crashes - Age

Safer Vehicles

DMV Registered Vehicles
Percent Truck Volume
Crashes – Vehicle Type

Post Crash Care

Hospital Locations
Iowa NEMSIS
Nebraska NEMSIS

Safer Roads

Facility Characteristics
Crashes

Safer Speeds

Streetlight Data
Facility Characteristics – Posted Speed
Crashes – Speeding Flag

Data Sustainability Plan

Methodology

This section describes the methodology of the analysis for understanding and reproducibility. The High Priority Network (HPN) was constructed through a methodical process that integrates both location-specific and systemic analyses as shown in Figure 1. Crash data was analyzed in conjunction with roadway and crash attributes to identify areas of concern. All active mode or non-motorized crashes were analyzed to identify and analyze vulnerable road users crashes.

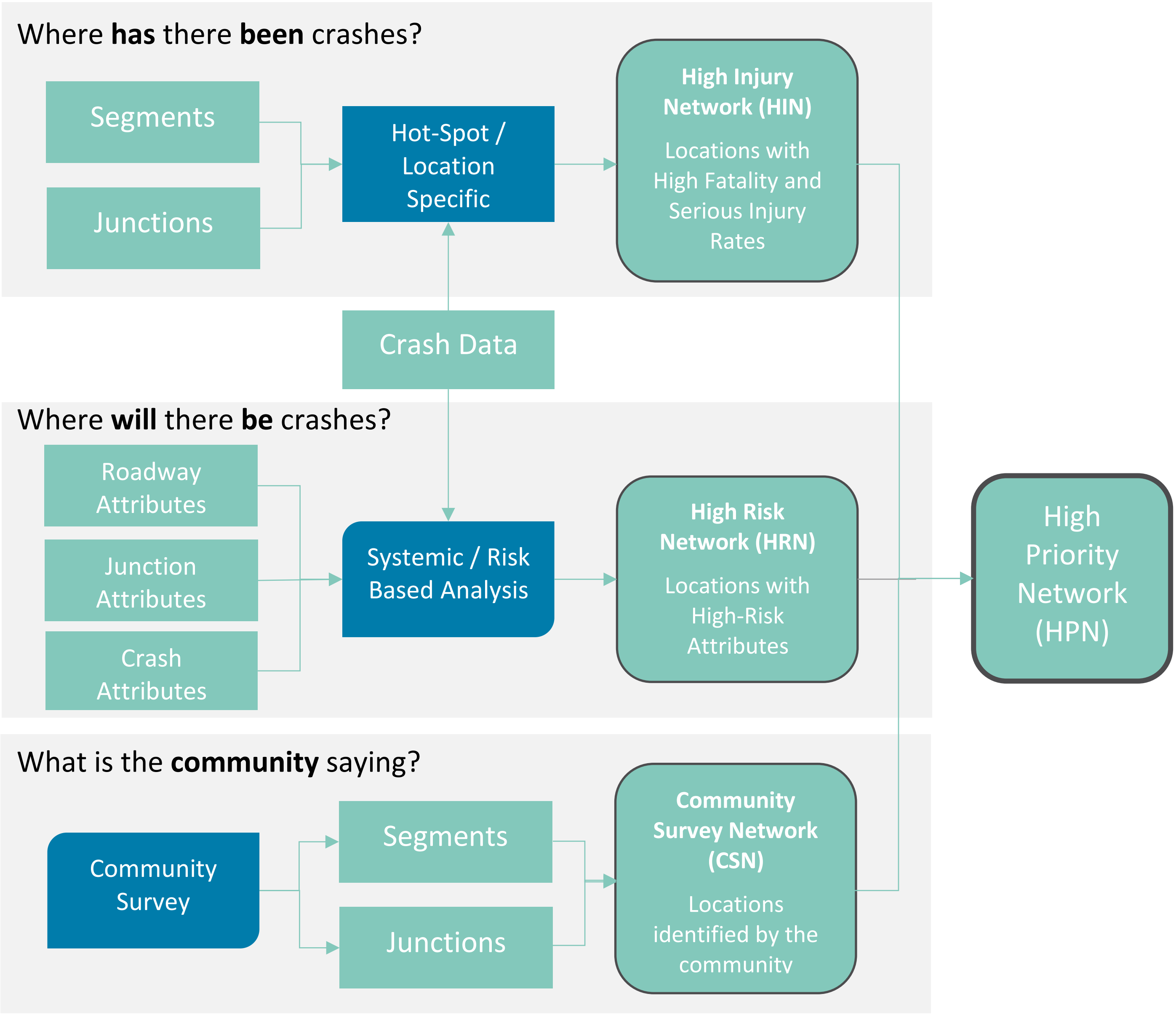


Figure 1. Three-Prong High Priority Network Process

We conducted a systematic process to organize, process, and analyze the data. **Error! Reference source not found.** below shows a 5-step process of data management, location analysis, systemic analysis, community survey, and weighting in order to arrive at our HPN Layer.

1. **High Injury Network:** Conducting a hot spot analysis reactively identifies roadway junctions and segments with higher concentrations of observed fatal (K) and serious injuries (A) crashes. This traditional “hot spot” analysis focuses investments at locations where a higher preponderance of severe crash events have occurred in the past five years. The resulting data shows high fatalities and serious injury (ksi) rate and a “Injury Score”, which ranks features based on the ksi crash rate in the five-year period of 2018 to 2022. The top 98th percentile is chosen and the result of this is the High Injury Network (HIN).
2. **High Risk Network:** Conducting a systemic based casual risk analysis consists of using a machine learning model (Random Forest) that identifies features of the regional roadway that correlate with fatalities and serious injuries regardless of whether such events occurred recently. The goal is to flag infrastructure with roadway features (e.g., lane count) and driver behaviors (e.g., speeding) that may increase the likelihood of future severe incidents on the network. The resulting attribute of this work is a “Risk Score” that calls attention to particularly risky roadway and junction facilities. The top 98th percentile risk score indicates the High Risk Network (HRN).
3. **Community Survey Network:** Collecting input from the community through a survey that notes intersections and segments of safety concern to the public. The result is a network that defines where there has been more than one complaint of safety.

The combination of these three scores results in a high-priority network score that ranks the county’s roadway segments through a score of features with the highest frequency of fatal and serious injury crash rate, and features with variables that contribute most to high risk, and areas of community need. This ensured that the network reflects both the granular details of specific sites, the broader systemic risks of the county, and the areas where data may not capture the safety need. A segment or junction will be placed on the **High Priority Network (HPN)** if it is found on either of the three networks mentioned above; HIN, HRN, or CSN.

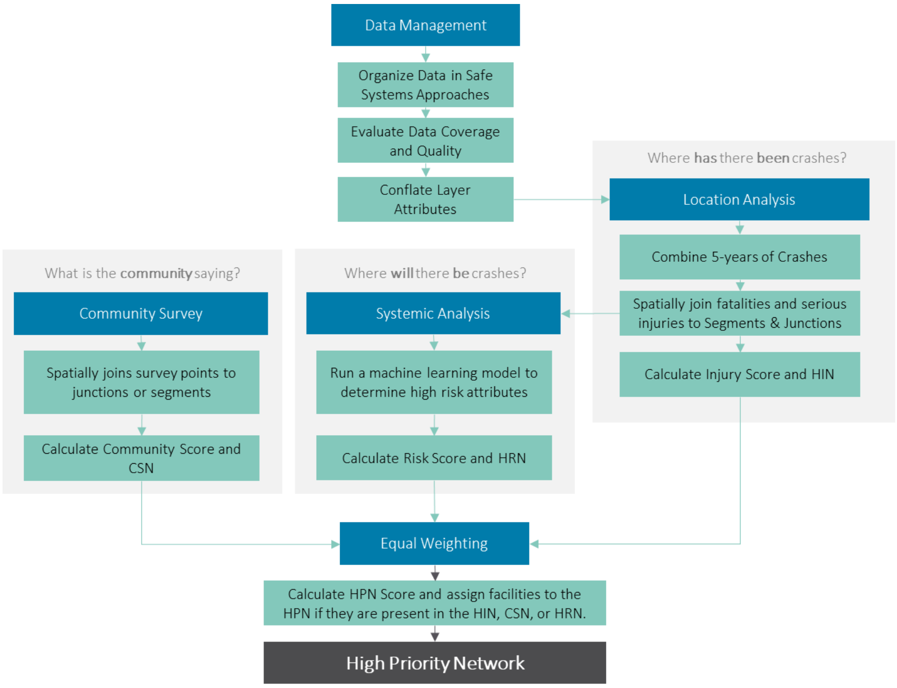


Figure 2: A general flowchart for the High Priority Network

Data Management (Crash Conflation)

The crash data for this analysis was sourced from three locations:

1. Iowa Crash Analysis Tool (ICAT) portal for Iowa crashes
2. NDOT-provided fixed-width column text files for Nebraska crashes prior to 2021
3. NDOT-provided Excel files for Nebraska crashes from 2021 onward

Pre-Processing: Each dataset underwent separate pre-processing steps, which included importing the raw data, defining or renaming columns, and applying general formatting. After pre-processing, the data was passed through a script designed to map corresponding attributes across the datasets, generate new columns or data fields, and merge the three datasets into a single, cohesive file.

Attribute Aggregation: Several data fields were common across all three datasets, allowing for attribute mapping, although some values needed adjustments to conform to a consistent scheme. For instance, each dataset included a field for the first harmful event.

Some values were identical (e.g., "Jackknife"), while others were consolidated into broader categories (e.g., 14 and 15 from Nebraska pre-2021, 22, 24, and 25 from Nebraska post-2021, and "non-motorist (see...)" from Iowa, all merged into "Collision with non-motorist").

Person Level Information: Crash dates were used to calculate the ages of drivers, occupants, pedestrians, and vehicles where these were not already provided (some datasets included one or more of these).

- The age columns, along with existing data, were used to create new columns. Flags were created as binary indicators for crash characteristics based on specific conditions in one or more columns (e.g., whether an unrestrained adult was involved, determined by checking restraint use and occupant age).
- Counts were generated to count different entities involved in the crash, such as the number of single-unit trucks or the number of pedestrians with KA injury severity.
- Finally, lists were compiled to show each value within a data field (e.g., vehicle action) and the frequency of each value for a given crash (e.g., the total number of vehicles noted as slowing/stopped at the time of the crash).

In all instances of personal information, we are never displaying personally identifiable information.

Final Aggregation: The three datasets were then trimmed to the final set of columns and merged. The primary output was a single Excel file containing combined Nebraska and Iowa crash data for the MAPA region, with one row per crash (aggregating driver, occupant, vehicle, and pedestrian data) and latitude and longitude information.

Additionally, separate files were created for disaggregated driver, vehicle, and occupant data (one row per entity) to allow for detailed analysis of their characteristics.

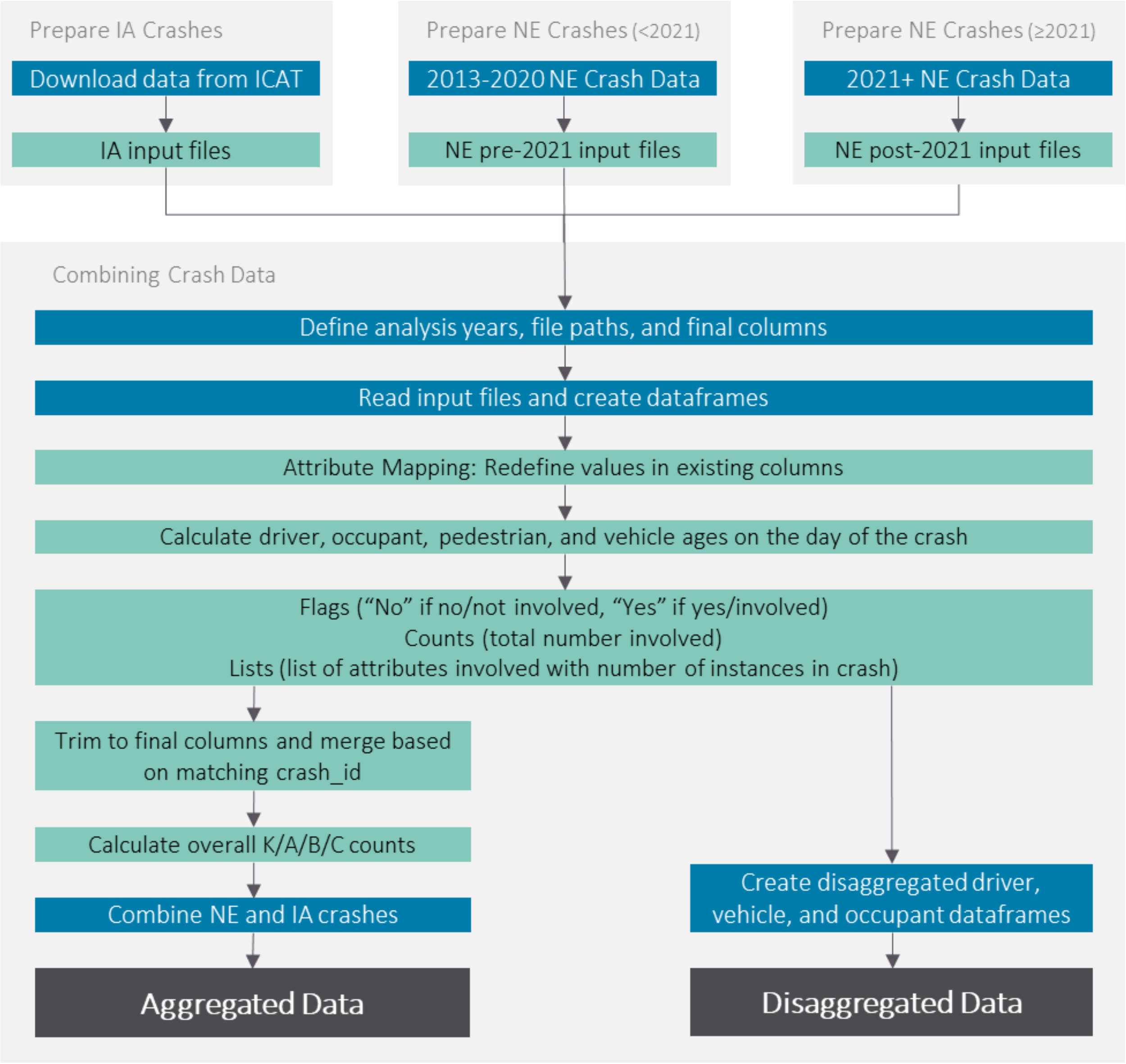


Figure 3. Data Workflow Diagram

Data Management (Feature Layer Conflation)

Accurate intersection and roadway data is essential for the analysis however data from different sources often vary in accuracy, coverage, and attribute details. Conflation is the process of integrating these diverse datasets into a single, reliable representation, ensuring consistency and completeness in roadway networks. This step particularly develops a usable data layer is to conflate all road and intersection information into one linear referencing system that we have called “conflated segments” in Figure 3 below and a consistent point layer which is called “conflated junctions” below.

Conflated Segments

The ffc_2024 layer from NDOT, which contains the most up-to-date functional classification information, was used as the primary source for the segments layer, as per MAPA's request. Additional sources, including HPMS layers and county centerline segments from Douglas and Sarpy counties, were incorporated to supplement any missing attributes. To determine whether a segment already existed in the ffc_2024 dataset, a buffer was applied, and spatial selection was performed using the "within" relationship. This ensured that county road classifications aligned with MAPA’s functional classification system.

Once the full road network was assembled for the MAPA SS4A project area, segments were dissolved and then split at key locations:

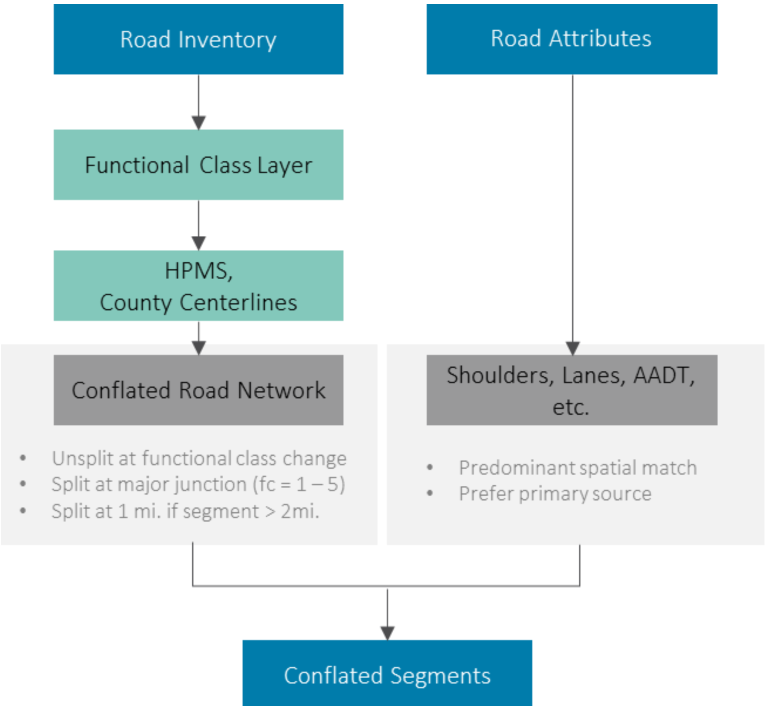


Figure 4 Segment Conflation Flow chart

1. **Functional class changes** to ensure that each segment retains a consistent classification.
2. **Major junctions** (functional classes 1 through 5) to reflect critical connectivity points.
3. **Segments exceeding two miles in length** were further split at one-mile intervals to create manageable segment lengths for analysis.

To enrich the segment dataset with key attributes, various data sources were conflated to the segmented road network using ArcGIS Pro’s Transfer Attributes tool. This tool was configured to match target segments to the longest overlapping source segment, ensuring that the predominant attributes were transferred. For each dataset, an appropriate search distance was determined based on the degree of spatial misalignment between the target and source data.

Before attribute transfer, source datasets were pre-processed:

- **Dissolved by key attributes** to reduce fragmentation and ensure a cleaner transfer.
- **Reprojected and clipped** to the SS4A boundary to ensure spatial consistency.
- **Standardized field names** to maintain attribute consistency across different sources.

Ten key attributes were transferred. For more information see the *Data Inventory spreadsheet*.

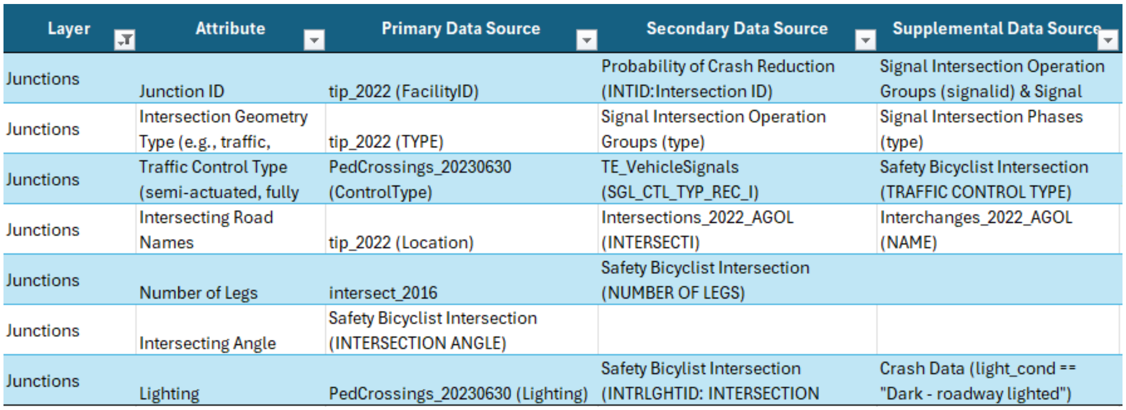
1. **Functional Classification** *(f_system)*: Derived from NDOT ffc_2024 and adjusted for county roads to match MAPA's classification.
2. **Facility Type** *(facility_type)*: Conflated from HPMS and validated against NDOT records.
3. **Through Lanes** *(through_lanes)*: Extracted from HPMS, supplemented by Iowa's road network where applicable.
4. **Lane Width** *(lane_width)*: Standardized based on available records.
5. **Shoulder Attributes** *(shoulder_type_left, shoulder_type_right, shoulder_width_left, shoulder_width_right)*: Integrated from HPMS and additional sources like AWS GIS Shoulder Width.
6. **Speed Limit** *(speed_limit)*: Pulled from HPMS, supplemented by county centerline data.
7. **AADT** *(aadt)*: Extracted primarily from HPMS with secondary validation from Iowa's road network.
8. **Median Information** *(median_type, median_width)*: Derived from HPMS and AWS GIS Median Divided Width datasets.
9. **Road Name** *(road_name)*: Merged from NDOT ffc_2024, HPMS, and county centerline datasets to ensure completeness.
10. **Bike and Pedestrian Facilities** *(trail_type)*: Integrated from MAPA's Bikeable Streets dataset.

To ensure accuracy and completeness, missing attributes were backfilled using the *Data Inventory spreadsheet* hierarchy of secondary and supplemental sources. The *merge_values()* function was used to fill in gaps where primary sources lacked information.

Before finalizing the dataset, the existing segments layer was archived with a timestamp to preserve previous versions. Temporary datasets and intermediate layers were deleted to optimize storage, and the geodatabase was compacted to enhance performance.

Conflated Junctions

The process of creating conflated junctions integrates multiple data sources to generate a refined and standardized dataset of intersection points. Each intersection is represented by a single, authoritative point while merging attributes from multiple sources, prioritizing primary data listed in the Data Inventory spreadsheet when available. Additional corrections and enhancements are applied to address inconsistencies in the underlying road network data.



Layer	Attribute	Primary Data Source	Secondary Data Source	Supplemental Data Source
Junctions	Junction ID	tip_2022 (FacilityID)	Probability of Crash Reduction (INTID:Intersection ID)	Signal Intersection Operation Groups (signalid) & Signal
Junctions	Intersection Geometry Type (e.g., traffic,	tip_2022 (TYPE)	Signal Intersection Operation Groups (type)	Signal Intersection Phases (type)
Junctions	Traffic Control Type (semi-actuated, fully	PedCrossings_20230630 (ControlType)	TE_VehicleSignals (SGL_CTL_TYP_REC_I)	Safety Bicyclist Intersection (TRAFFIC CONTROL TYPE)
Junctions	Intersecting Road Names	tip_2022 (Location)	Intersections_2022_AGOL (INTERSECTI)	Interchanges_2022_AGOL (NAME)
Junctions	Number of Legs	intersect_2016	Safety Bicyclist Intersection (NUMBER OF LEGS)	
Junctions	Intersecting Angle	Safety Bicyclist Intersection (INTERSECTION ANGLE)		
Junctions	Lighting	PedCrossings_20230630 (Lighting)	Safety Bicylist Intersection (INTRLGHTID: INTERSECTION	Crash Data (light_cond == "Dark - roadway lighted")

Figure 5 Data Inventory Primary, Secondary, and Supplemental Data Sources for Junctions

To begin, various datasets containing intersection and roadway information are downloaded and stored in the *mapa_ss4a_conflation* geodatabase. These datasets come from multiple sources and may have different spatial references, data structures, and levels of completeness. To standardize the data, the configuration settings, including the spatial reference, are stored in the *data/conflation/conflation.json* file. Ensuring a consistent projection system is critical because spatial misalignment between datasets can lead to inaccurate conflation. If any dataset is in a different projection, it is reprojected to match the defined project coordinate system using the *project()* function.

Prepare Datasets: Once the datasets are prepared, the road network is processed to extract intersection points. The segments layer is unsplit to create a uniform representation of the network, ensuring that overlapping segments do not create artificial breaks in the data. Intersection points are then generated by identifying locations where road segments overlap using *arcpy.analysis.Intersect()*. Clipping is performed using the *MAPA SS4A boundary layer*.

Merge Attributes: The next step involves merging intersection data from multiple sources into a single dataset called *merged_junction_sources*. Since different datasets may report the same intersection with slight positional variations, duplicate intersection points are removed using *arcpy.management.DeleteIdentical()*, evaluating identical geometries and key attributes such as *FacilityID*, *TYPE*, and *INTID*. A spatial join is performed to align *merged_junction_sources* with the closest intersection points from the processed road network using *arcpy.analysis.SpatialJoin()*. The joined data is then dissolved based on *JOIN_FID*, with attribute values concatenated to preserve data integrity.

To ensure each junction point has complete and accurate information, attributes such as *ControlType*, *Location*, and *Lighting* are populated based on a hierarchical data preference system. Missing attributes are backfilled from secondary and tertiary sources using the *merge_values()* function. Intersection points that lack key attributes, such as *Number_of_Legs* or *Intersecting Road Names*, are supplemented using information from road segments. This is done by running *arcpy.analysis.Intersect()* between the *mapa_junctions_draft* layer and the *segments_split_every_intx* layer, which allows for automatic attribute backfilling.

Fixing Alignment: Some intersection points do not align perfectly with the road network due to inconsistencies in road segment geometry. To address this, a *150-foot buffer* is created around processed junctions using *arcpy.analysis.Buffer()*, identifying unaligned points. These points are snapped to the nearest *segments_split_every_intx* endpoint first and, if necessary, to the nearest edge using *arcpy.edit.Snap()*. Once repositioned, these points undergo the same duplicate removal and attribute merging processes as the primary intersections.

Supplemental Data: Special attention is given to roundabout intersections, which do not behave like typical intersections in terms of connectivity and control. Their points are added separately while maintaining their original locations. A supplemental section was added at the end of the script to incorporate new data such as Douglas' *Traffic_Intersections_View* and *SarpyStreetIntersections*. These datasets undergo projection, merging, and deduplication following the same methodology, ensuring consistency with the existing junctions.

Standardize Naming: To standardize attributes across sources, field names are updated to maintain consistency. The *arcpy.management.AlterField()* function is used to rename fields such as *CONCATENATE_FacilityID* to *junction_id* and *CONCATENATE_Lighting* to *lighting*. Code dictionaries are applied to translate numerical values into meaningful categorical descriptions. For example, the *traffic_control_type and lighting* field use a mapping system to classify them such as:

Traffic Control Type:

- 1: Signalized *(with pedestrian signal)*
- 2: Signalized *(without pedestrian signal)*
- 3: All-way stop
- 4: Two-way stop
- 5: One-way stop
- 6: Yield sign
- 7-10: Various railroad crossings
- 11: Uncontrolled
- 77: Not reported
- 88: Other
- 99: Unknown

Intersection Lighting:

- 1: Intersection lighting
- 2: Destination lighting
- 3: No destination lighting
- 77: Not reported
- 88: Other
- 99: Unknown
- 0: No lighting

Before finalizing the dataset, the existing junctions layer is archived with a timestamp to preserve previous versions. Intermediate datasets, temporary layers, and unnecessary feature classes are deleted using *arcpy.management.Delete()*, optimizing storage. The geodatabase is then compacted with *arcpy.management.Compact()* to improve performance.

Updating the Junction & Segments Datasets

Below are five ways that the junctions dataset may typically be updated:

1. **Road Network Change:** Re-run the full script whenever *ffc_2024*, *HPMS*, or *county centerline* layers are updated. This ensures junctions snap to modified road segments and that functional class splits remain accurate.
2. **New Data Sources:** Add new datasets to *conflation.json* to ensure they are reprojected to match the project's spatial reference, clipped, merged into *merged_junction_sources* or *ready_for_attr_transfer* layers, and deduplicated before integration.
3. **Attribute Enhancements:** If higher-quality data for attributes such as lane configurations, speed limits, AADT, or intersection control types becomes available, rerun the *conflate_predominant()* function with updated search distances and refine *merge_values()* logic to prioritize new sources.
4. **Adjusting Spatial Tolerances:** If segment attributes are misaligned or junctions fail to snap correctly, modify buffer distances in the script (e.g., *100 Feet* for segment realignment and *150 Feet* for junction snapping) and refine the *SelectLayerByLocation* settings.
5. **Refine Attribute Prioritization:** Improve data accuracy by updating the hierarchy in *merge_values()*, weighting primary, secondary, and supplemental sources based on reliability, or incorporating heuristic ranking to resolve conflicts in overlapping datasets.

Location-Specific Hot Spot Scoring (High Injury Network)

The next is the process is to filter, combine, and spatially join our crashes to segments and junctions within 150 feet of the roadway; matching recommendations from the Highway Safety Manual.

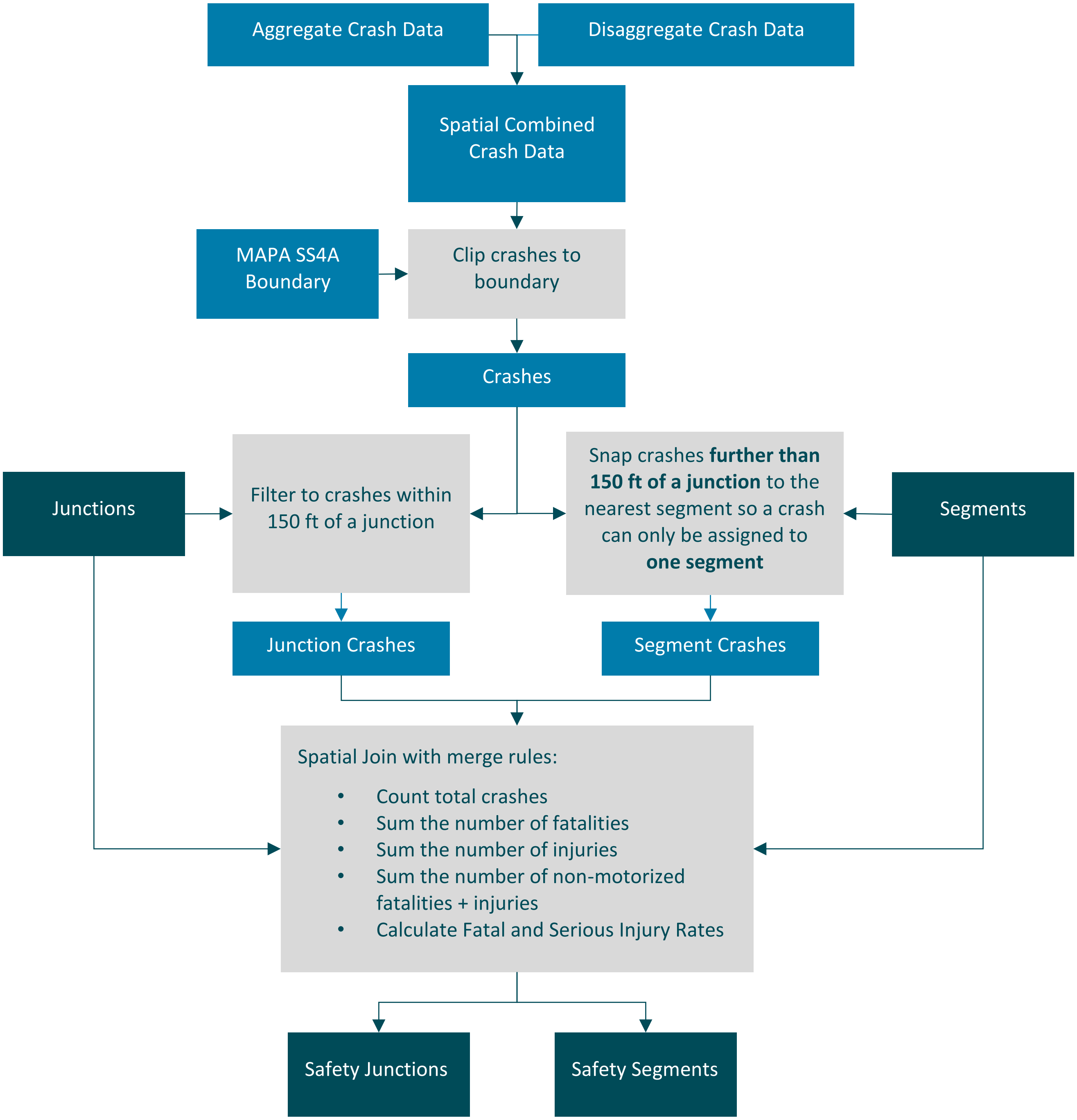


Figure 6. Calculating the injury score by assigning crashes to segments

Systemic-Based Scoring (High Risk Network)

Using the conflated segments layer with crashes, we've conducted a statistical regression analysis that determines which roadway or driver attributes (derived from either the roadway inventory or the crash data) are correlated fatalities and serious injuries.

Regression Analysis: We employed regression analysis for a comprehensive understanding of how multiple factors simultaneously influence crash frequencies. This approach not only identifies associations but also quantifies the strength and direction of these relationships, enabling predictions and a deeper insight into the complex interplay of road safety variables. This involved exploring various types of regression models:

1. **Linear Regression** was tested to examine continuous data relationships, where we could predict the number of crashes based on linear combinations of road attributes.
2. **Logistic Regression** was considered for binary outcomes, especially useful in scenarios where the outcome is a crash occurrence (yes/no).
3. **Poisson Regression** was particularly apt for count data, which aligns well with crash frequency analysis, where the response variable is a count (number of crashes).
4. **Random Forest Regression** was ultimately used to capture complex, non-linear relationships between road safety variables and crash frequencies by leveraging an ensemble of decision trees.

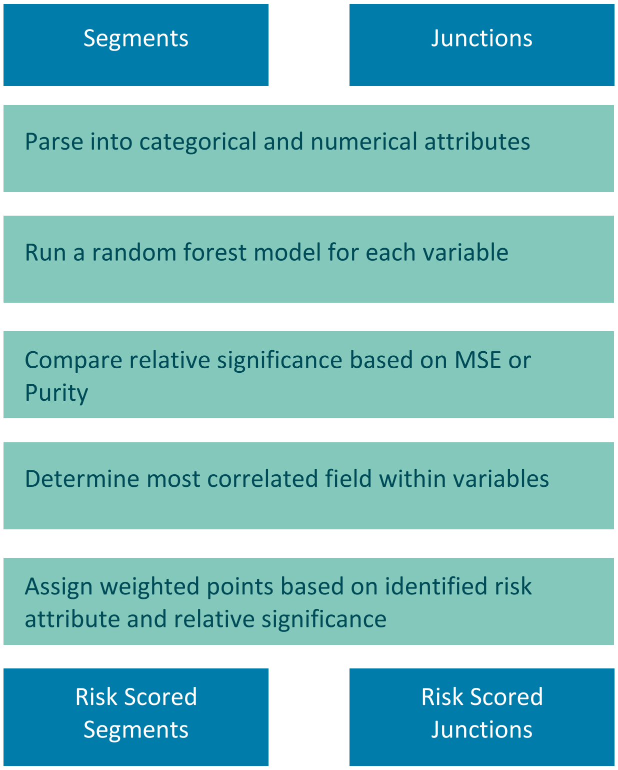
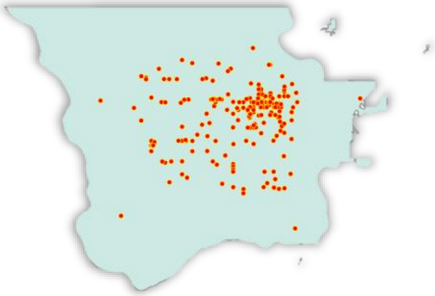


Figure 7. Calculating the risk/systemic score by finding roadway attributes of high risk

Correlation Analysis: We then identified correlations between various road attributes, such as the number of lanes and speed limits, and the number of KA crashes. This analysis is crucial for pinpointing single-to-single variable correlations to crash occurrences. By examining the relationships between these variables, we can better understand how certain road features may contribute to higher crash counts. Specific correlations with high variable importance from the regression analysis can be found in the analysis findings section. All other correlation plots can be found in Appendix B.

These models allowed us to integrate multiple variables and assess their collective impact on KSI crash rates. The most effective model was found to be Random Forest Regression and was utilized for the systemic based risk analysis. This method is a type of ensemble learning (a subset of machine learning), where multiple decision trees are combined to improve predictive accuracy and control over-fitting. Random Forest operates by constructing a multitude of decision trees during training and outputting the mean prediction of the individual trees. This technique is particularly beneficial in handling large datasets with numerous variables, as it can capture complex, non-linear relationships that traditional regression models might miss. We developed five distinct Random Forest models to cater to different roadway systems and account for the diversity in vulnerable road user types. These models proved to be more robust and provided a better fit for our complex and varied data sets. This was particularly useful when having different coverages of datasets like shoulder and median widths.

Community Network



Input from the community was gathered through a survey that notes intersections and roads of safety concern to the public. The result is a network that defines where there have been one or more complaints of safety.

High Priority Network Scoring

Our final step is to combine the community survey, high injury, and high-risk networks into a High Priority Network that will help us determine which segments to prioritize. This process equally weighed the risk and injury scores. Scores greater than three (3) or four (4) standard deviations are assigned to a high priority network (HPN) for all crashes, crashes involving non-motorized users, and crashes involving large trucks. Separate HPNs were prepared for all roads within the county and for roadways that are owned by the county or municipalities the intersect the county. Three and four standard deviations were selected as the threshold because it produced HPNs that were distinct from one another, highlighting key locations for each crash and ownership group.

Community Survey Score	Injury Score	Risk Score
Normalized count of **survey points** on a segment or junction. (0-100)	Normalized fatal and serious injury **crash rate** per million entering and vehicle miles traveled. (0-100)	∑ (Presence of identified high risk field in each variable * Variable Significance Percentage). (0-100)

CSN, HIN, and HRN all take the 98th percentile of each score. Only the top 2% are within the network.

High Priority Network Score = Sum of normalized community, injury, and risk scores.

High Priority Network = Any Feature on either the CSN, HIN, or HRN.

High Priority Network (HPN)

Figure 8. High Priority Network scoring process

Regional Safety Needs

Through a better understanding of system safety needs and trends, MAPA will be able to more effectively implement strategies to reduce fatalities and serious injuries. Included in this section is a summary of recent fatal and serious injury trends in the MAPA region including a breakdown of the most prevalent characteristics of those crashes, benchmarking MAPA regional safety performance relative to other geographies, and using data to identify where crashes are occurring and why.

Regional Safety Performance

Over the most recent five years for which crash data is available (2018-2022) the region has experienced an annual average of:

82,476	**2,326**	**296**
Reported motor vehicle involved crashes	Serious [incapacitating] Injuries	Fatalities

Despite a 32% increase in VMT between 2018 and 2022 [per the Regional Traffic Patterns reports], the MAPA region has seen a 10% reduction in combined fatal and serious injuries - from 555 in 2018 to 497 in 2022 (Figure 9). The onset of COVID-19 in 2020 did correlate with an uptick in more severe crashes but has since been on the decline. At that time, fatal and serious injury crashes represented 3.8% of all crashes as compared to the 2.4% number observed in 2022 (Figure 10).

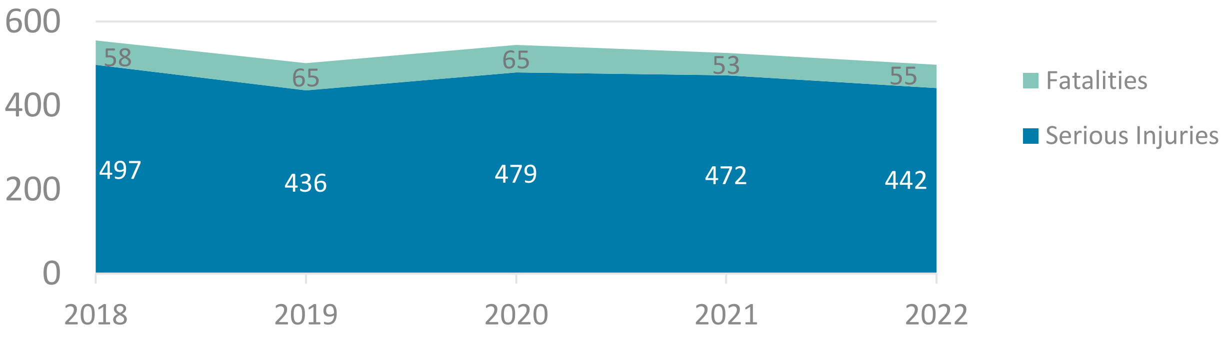


Figure 9. MAPA Fatality and Serious Injury Crash Trends Over Time

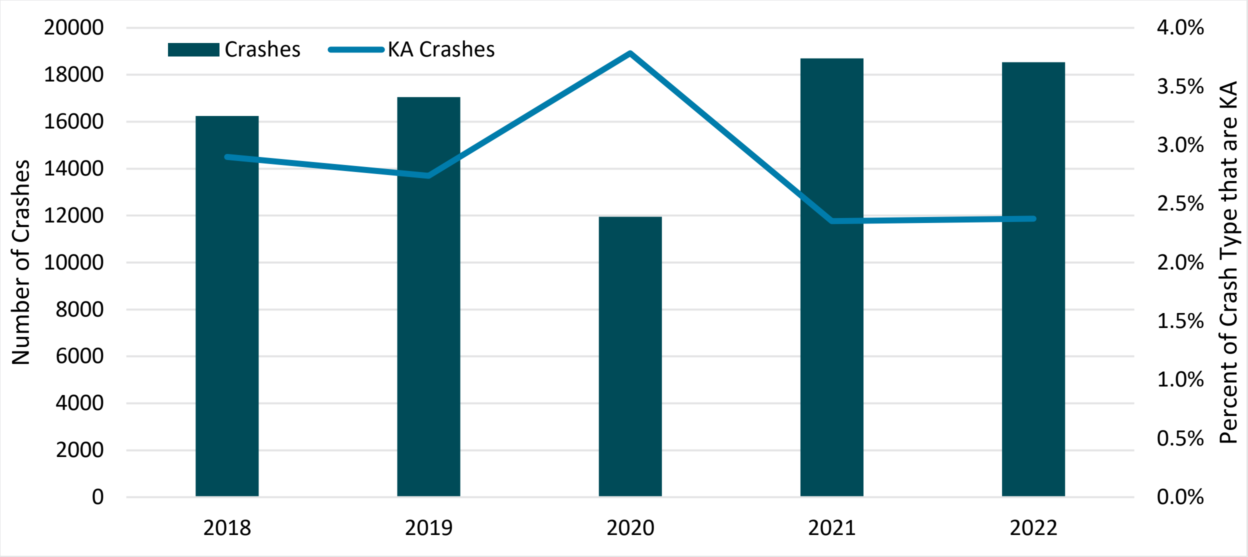


Figure 10. MAPA Crash Totals and Share of Fatal (K) and Serious Injury (A) Crashes Over Time

Crashes involving non-motorists have further decreased from 69 fatal and serious injury crashes in 2018 to 47 in 2022 (). On average, nearly one in five fatal and serious injury crashes have involved a non-motorist in the past five years.

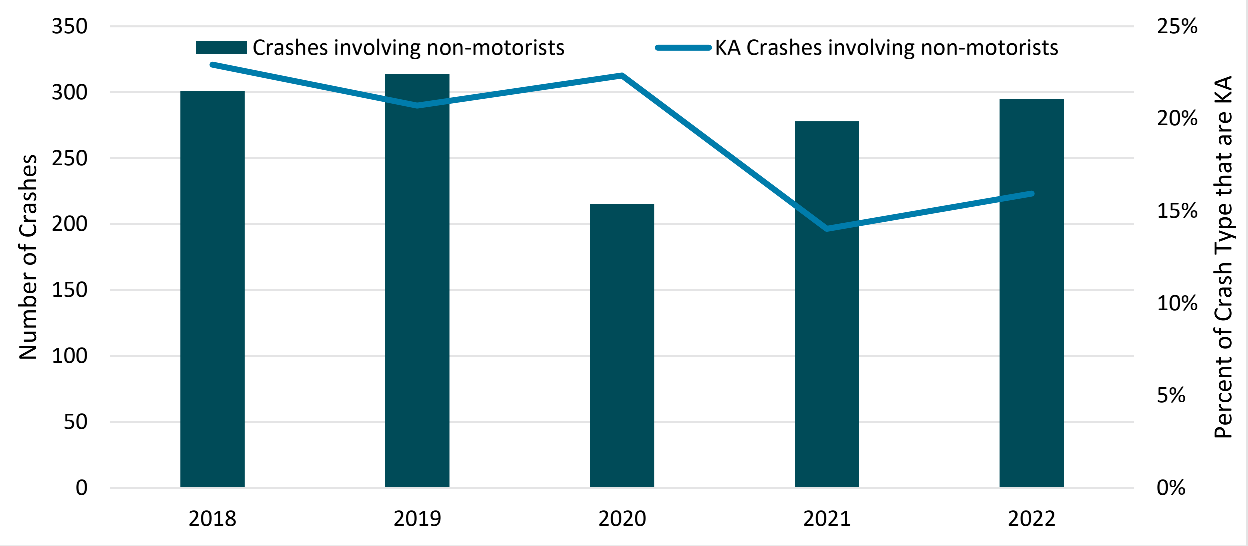


Figure 11. MAPA Non-Motorized Crash Totals and Share of Fatal (K) and Serious Injury (A) Non-Motorized Crashes Over Time

Most (61%) fatal and serious injury crashes have occurred along road segments with 39% occurring at junctions. The most commonly observed fatal and serious injury crash types over the past five years have involved only a single vehicle – be it a run-off the road, collision with a fixed object, or non-motorist involved crash (Table 1). This is closely followed by angle crashes that have predominantly occurred at intersections.

Table 1. Breakdown of 2018-2022 Crashes by Type

Crash Type	Count of Fatal and Serious Injury Crashes	Percent
Single-vehicle (Run Off Road, Fixed Object, Non-Motorist Crash)	854	**37.6%**
Angle (Left Turn, Broadside)	833	**36.7%**
Rear-end	279	12.3%
Sideswipe (Same Direction, Opposite Direction)	110	4.9%
Head-on	74	**3.3%**
Other	120	5.3%

Notable Trends

Single Vehicle and **Angle** crashes are the region's top fatal and serious injury crash types and have the greatest impact on severity.

While **rear-end** crashes are the top 3rd KA crash type, the likelihood of the crash being severe is low.

The likelihood of **head-on** crashes occurring is low, but the severity is high.

Other notable trends have included:

- **The rise in crashes involving small vehicles** – crash totals have nearly doubled in 2022 compared to previous years (from 369 in 2021 to 685 crashes in 2022), however this fortunately has not translated to a significant rise in fatalities and serious injuries.
- **Fewer but still too many crashes involving drivers under the influence** – calendar year 2022 marked a steep decline in crash totals involving drivers under the influence, from a high of 843 in 2021 to a low of 735 in 2022. These crashes still account for 7.4% of all fatal and serious injury crashes.
- **Fatal and serious injury crashes involving young drivers have been nearly halved** – in 2017, 187 fatal and serious injury crashes involved a young driver as compared to 99 in 2022. Yet the share of fatal and serious injury crashes involving a young driver has held steady. Meaning fatal and serious injury crashes are down across the board but the proportion affecting younger drivers has remained relatively level.

Crash Type vs. Contributing Factor

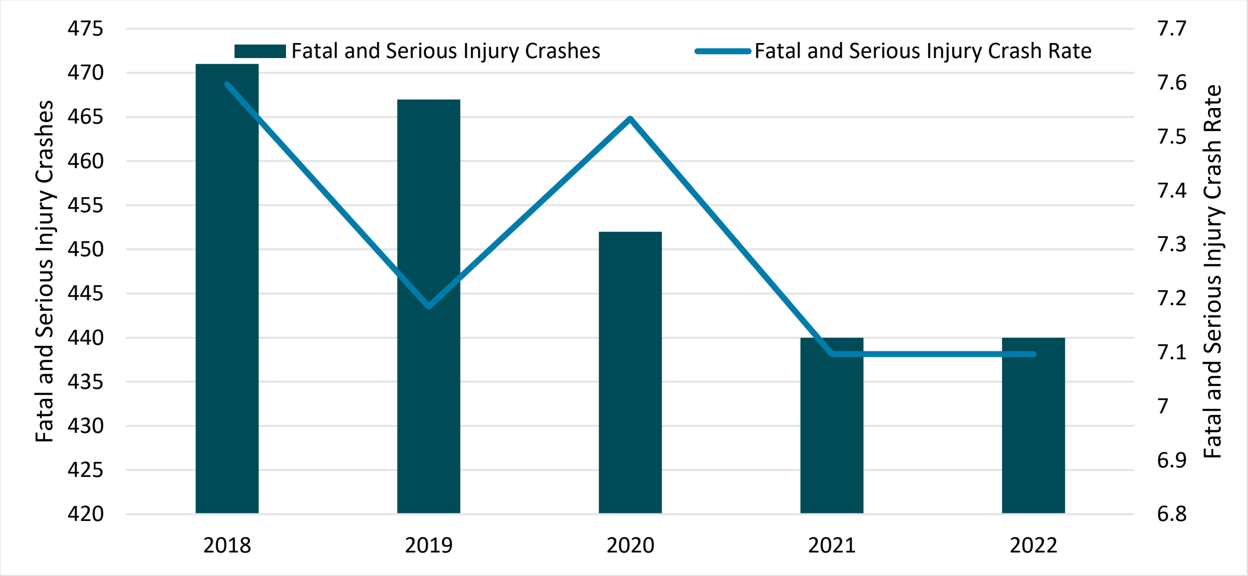
Crash Type describes how a crash happens (e.g., rear-end, angle), offering an objective classification based on observable evidence. Countermeasures can be identified to target specific crash types.

In contrast, Contributing Factor (e.g., distracted driving) involves subjective judgment about why a crash occurred, such as distracted driving or weather conditions, which can be unreliable due to reporting inaccuracies or cross-cutting across multiple crash types and not informative for strategy development.

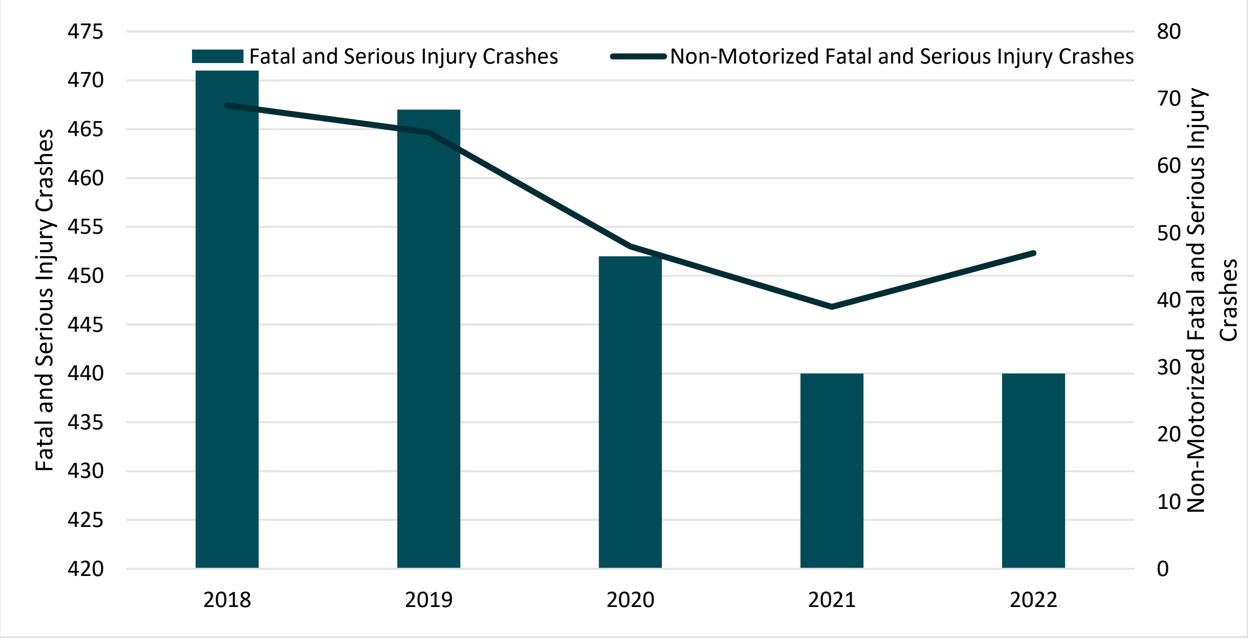
Focusing on crash types allows the plan to identify countermeasures targeted to the most common crash patterns.

	2018	2019	2020	2021	2022
Fatal and Serious Injury Crashes	471	467	452	440	440
Average Vehicle Miles Traveled	6,200	6,500	6,000	6,200	6,200
Fatal and Serious Injury Crash Rate	7.60	7.18	7.53	7.10	7.10
Non-Motorized KA Crashes	69	65	48	39	47

Over the past 5 years, both the rate and count of crashes have stayed low since 2020.



However, non-motorized fatal and serious injury crashes have risen when compared to all fatal and serious injury crashes.



Benchmarking Regional Safety Performance

Relative to statewide and national trends, MAPA has seen fatalities and serious injuries remain relatively level with a slight decrease by the end of the five-year period (Figure 12). Iowa has seen a slight increase in fatalities and serious injuries over the studied data range but a significant drop in fatalities from 2021 to 2022. Nebraska overall has seen totals fluctuate with more visible gains in reducing serious injuries than fatalities. Nationally, fatalities and serious injuries have been coming down with bigger gains in reducing fatalities than serious injuries.

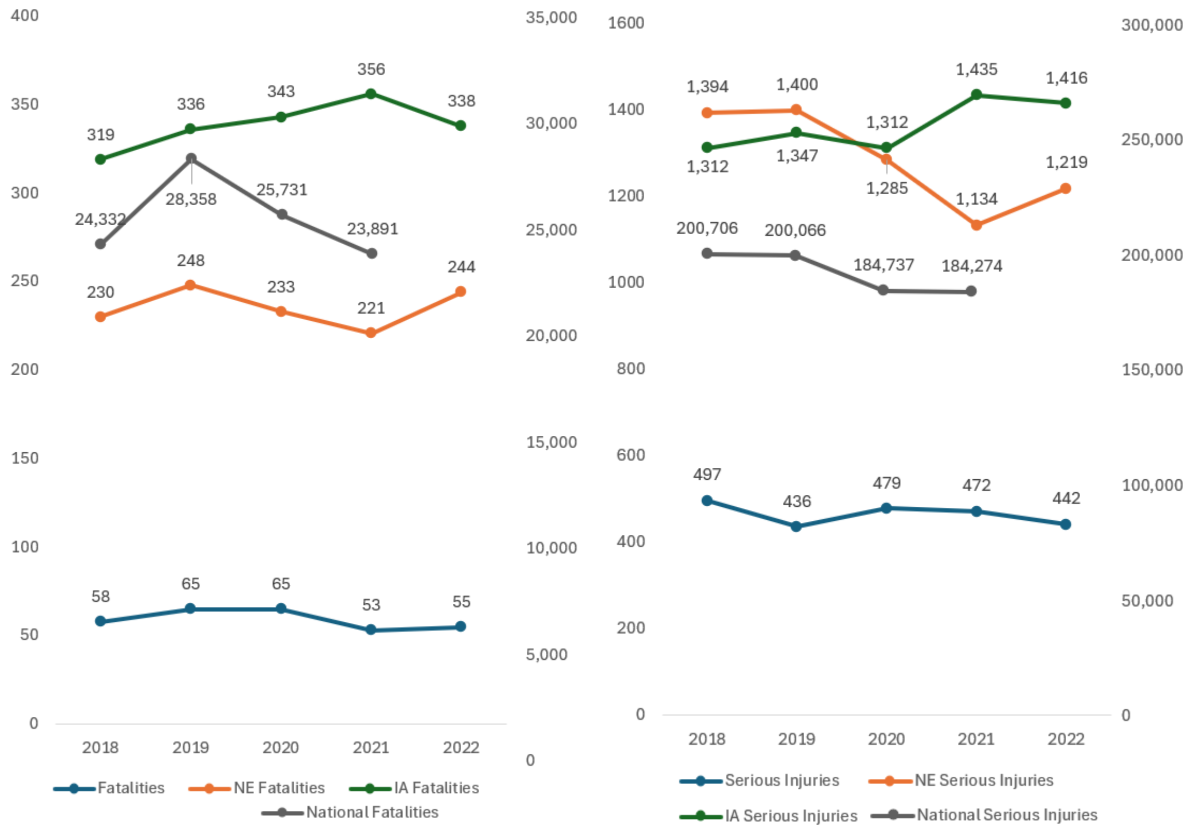


Figure 12. MAPA Fatality and Serious Injury Trends relative to Statewide and National Totals

Through this regional safety action plan update, the intent is to further define strategies to keep trends heading in the right direction, even in spite of increased traffic volumes that result in more potential exposure to crashes.

Location [High Injury] Analysis

The analysis looked at the fatal and serious injury rate for the road segment expressed as crashes per 100 million vehicle-miles of travel and intersections expressed as crashes per 100 million entering vehicles. The High Injury Network utilized this injury rate and selected the top 2% of roads and intersections, excluding interstates.

While the distribution of top **intersections centered around Omaha**, there were a significant portion of **roads outside of cities**. Aligning with the top crash type of angle for intersections and roadway departure on roadways. Looking at the top 2% of roads and intersections with high KSI rates, **94%** of them had crashes with **no seatbelt use** and **57%** of them had **Alcohol/Drug Impaired** crashes.

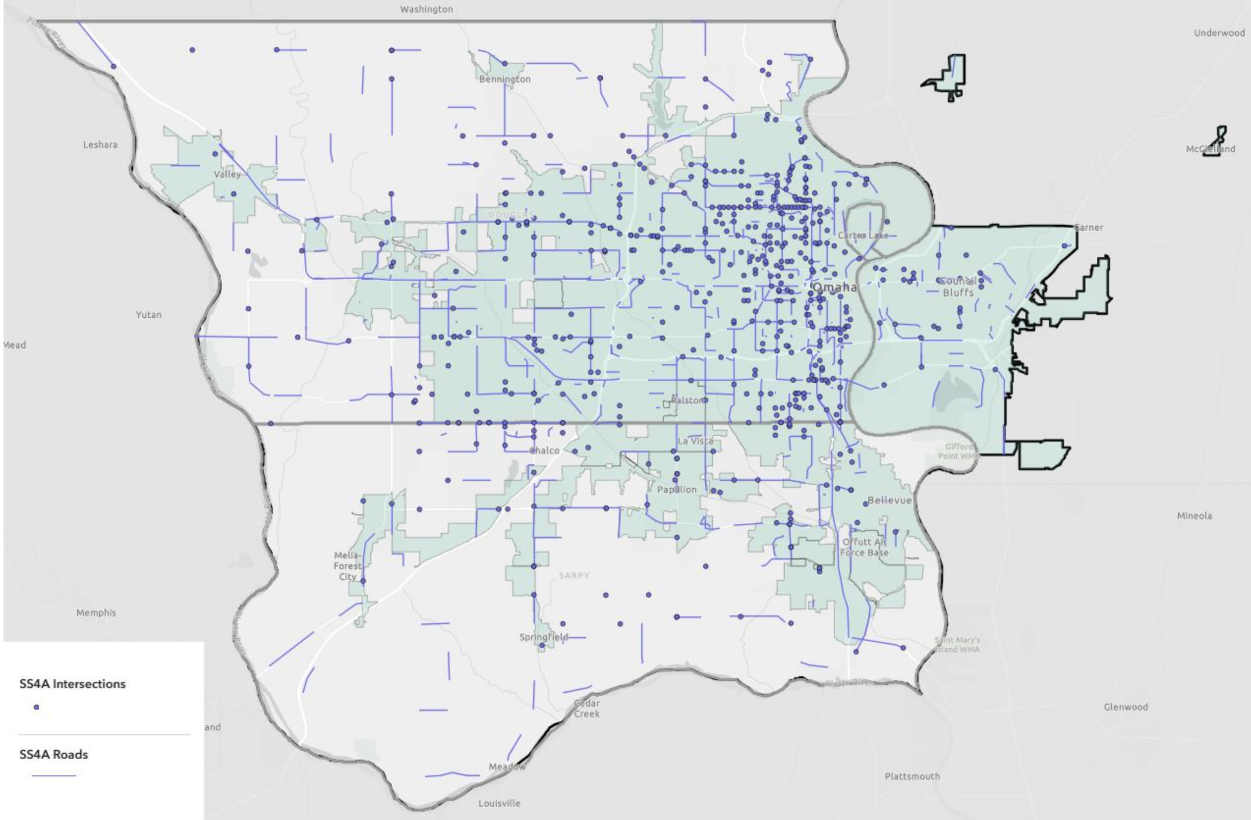


Figure 13 - The High Injury Network: Top 2% of Roads and Intersections with high KSI rates (2018-2022 Crash Data)

Systemic Risk [Causality] Analysis

Safer Roads

Crash Review

The machine learning model was broken into four models of urban segments, urban junctions, rural segments, and rural junctions. The model output the most significant variables that correlated to fatal and serious injury crashes. We can consistently see that speed, functional classification, and lane width are all significant correlations regardless of location. While urban segments correlate more to speed as a risk factor, rural segments find more correlation in lane width.

Urban Segments:	Speed, Functional Classification, and Lane Width.
Rural Segments:	Lane Width, Functional Classification, and Bike Facility Type.
Urban Junctions:	Lane Width, Functional Classification, and Speed.
Rural Junctions:	Lane Width, Functional Classification, and Speed.

We then looked at the fatal and serious injury crashes by category for the total amount of facilities within that category. Basically, the rate of injuries relative to the total amount of injuries at the count of the specific category. We included this to account for instances where there were a large number of injuries due to the large amount of that facility type (i.e. 12ft lane segments, or 35 mph intersections).

An example shown in the figure below shows that when speeds in rural junctions exceed 65 miles per hour, fatal and serious injuries drastically rise. The full details can be found in Appendix B and variable_importance.xlsx in the hpn-scripts repo. The table below is a summary of the top three most significant variables:

Urban Segments	Speed limit ≥ 35, Other Freeways and Expressways, and Lane width 12 or 13 feet.
Rural Segments	Lane width 12, Lane width 16 feet, Other Freeways and Expressways, Other Principal Arterials, and Right shoulder width 10–12 feet.
Urban Junctions	Lane width 13–16 feet, Other Principal Arterials, Speed limit 55 or 65 mph.
Rural Junctions	Lane width 12–15 feet, Speed limit 65–75 mph.

We also noted that the more through lanes a facility has the more likely to incur fatal or serious injury crashes over total length.

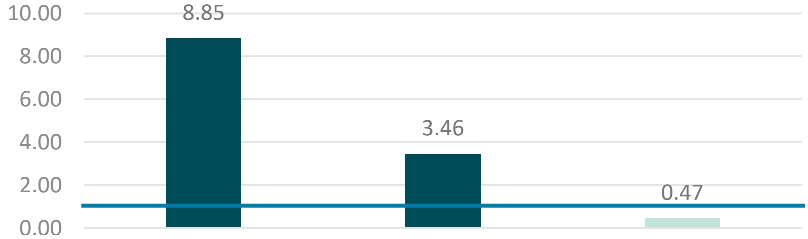


Figure 14 Risk Ratio of Number of Through Lanes

Lighting was marked as significant from the machine learning model and even though less than 30% of crashes are at night, they are 1.4x likely to result in a fatal or serious injury crash.

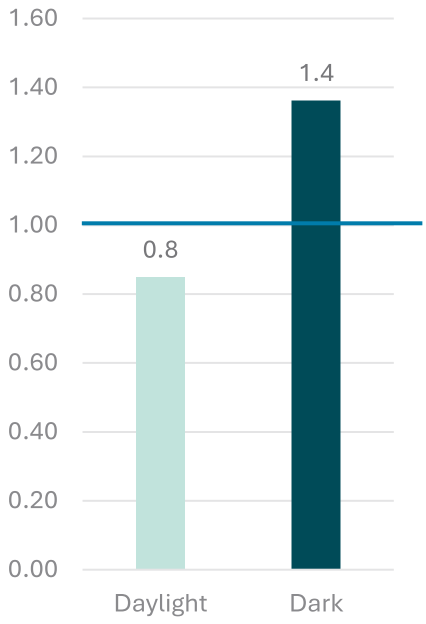


Figure 15 Risk Ratio of Roadway Lighting Conditions

Other Regional Plans & Studies

Safer roads strategies and goals are covered in the Omaha Vision Zero, Connect Omaha Active Mobility Plan, Nebraska Strategic Highway Safety Plan, Southside Terrace-Indian Hills Multi-Modal Study, Iowa Vulnerable Road User Safety Assessment, Iowa Strategic Highway Safety Plan, Pottawattamie County Local Road Safety Plan (anticipated), La Vista Active Mobility Plan (anticipated), and Western Sarpy Transportation Enhancement Plan (anticipated).

Examples of safer road initiatives recommended in other plans include expanding and updating pedestrian and bicycle facilities, implementing context-sensitive approaches to design, using roadway safety audits to identify countermeasures, installing roundabouts, implementing road diets, improving street lighting, updating signal phasing, and adding speed feedback signs.

More details on the comparison between this analysis and the safety plans in the region can be found in Appendix A.

Safer People

Crash Review

Younger Drivers

In the MAPA region, younger drivers—those under the age of 25—make up about 16% of the driving population. However, their involvement in fatal or serious injury crashes is disproportionately high. Drivers under 25 are 1.6 times more likely to be involved in such crashes compared to their counterparts in other age groups. Between 2018 and 2022, for every 693 younger drivers on the road, one was involved in a fatal or serious injury crash, in contrast to 1 in 907 for those aged 25 to 65 and 1 in 2,426 for those over 65.

The contributing factors in crashes involving younger drivers often relate to risky behaviors. Younger drivers are notably 4.1 times more likely to be involved in crashes due to speed-related factors, such as exceeding the speed limit or driving too fast for conditions. Additionally, they are more likely to engage in aggressive or erratic driving, fail to yield the right of way, disregard traffic control devices, and follow other vehicles too closely.

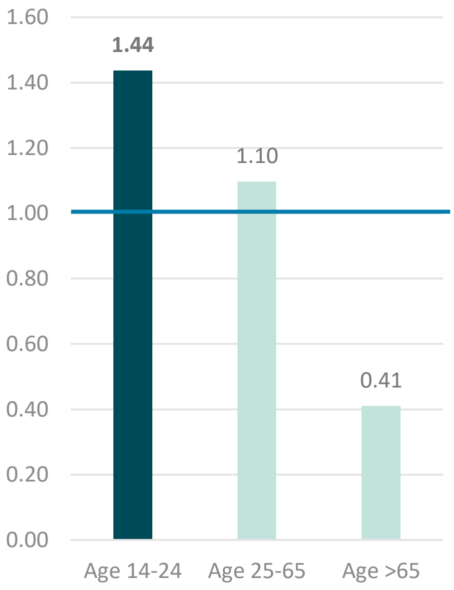


Figure 16 Risk Ratio of Driver Age

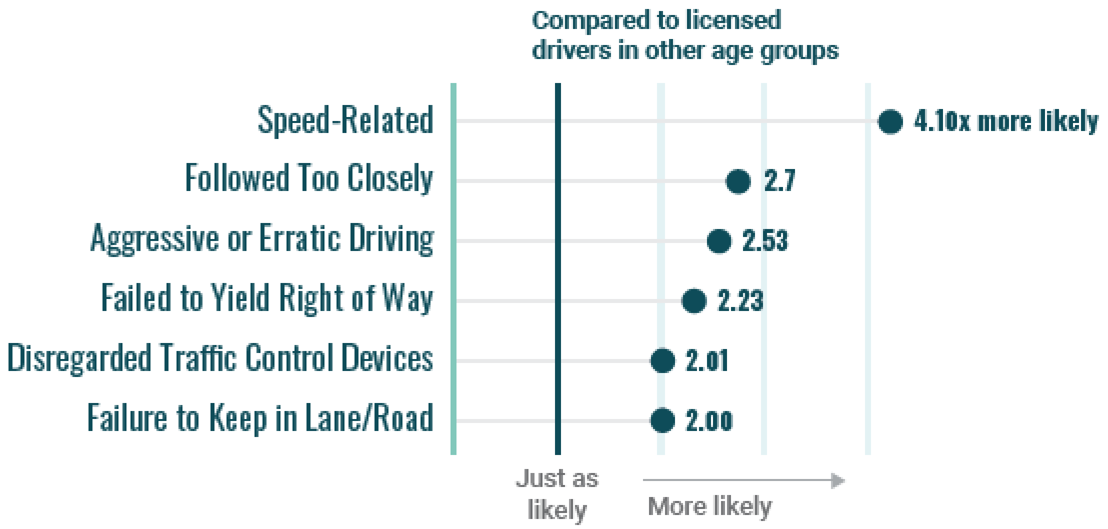


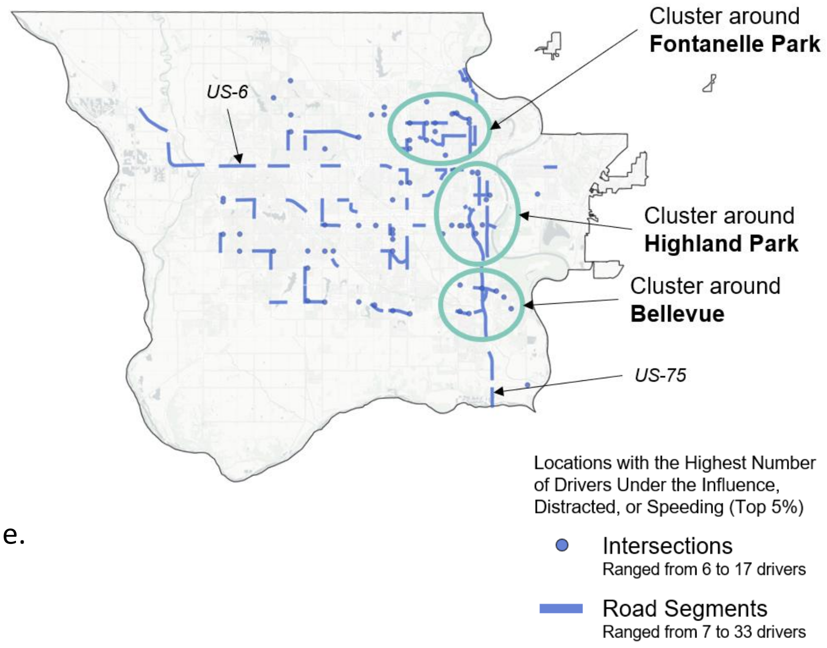
Figure 17 Risk Ratio of Young Driver Contributing Factors at Time of Crash (All Crashes)

Impaired Drivers

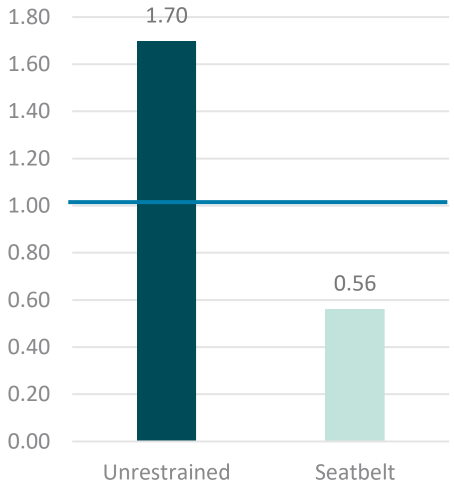
In the MAPA region, impaired driving is a significant factor in fatal and serious injury crashes. Approximately 60% of impairment-related crashes involve drivers who are "under the influence," compared to smaller percentages for other impairment conditions, such as emotional distress, physical illness, fatigue, or medical issues, which collectively account for around 21%. Notably, drivers under the influence are 3.8 times more likely to be involved in a fatal or serious injury crash compared to unimpaired drivers, underscoring the heightened danger they pose. 26% of fatalities and serious injuries were linked to under the influence, distracted, or speeding factors, with 17% of these incidents involving alcohol impairment.

When impaired drivers are involved in crashes, their behavior is significantly more erratic than that of unimpaired drivers. They are 14.23 times more likely to drive erratically, 6.19 times more likely to fail to stay within their lane or on the roadway, and 3.09 times more likely to exceed the speed limit or drive too fast for conditions. Additionally, these drivers are 1.77 times more likely to disregard traffic control devices.

Enforcement efforts should target clusters along major corridors such as US-75 and US-6, and particularly near Fontanelle Park, Highland Park, and Bellevue.



Unrestrained Occupants



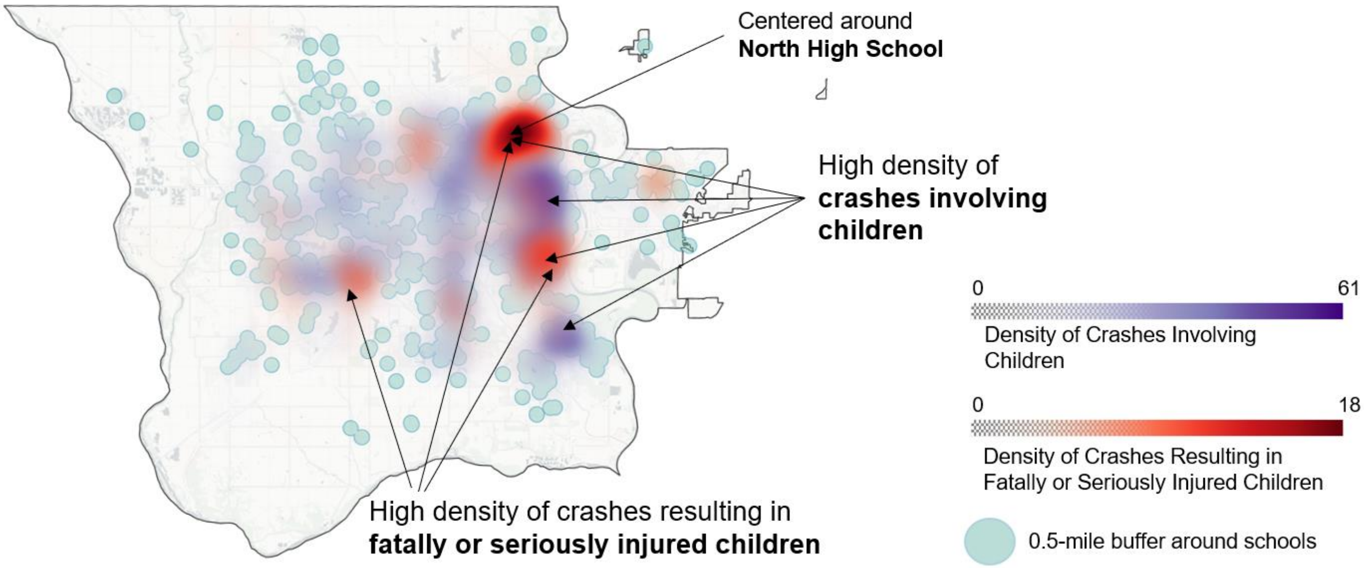
Unrestrained occupants in motor vehicle crashes are at significantly higher risk for fatal or serious injuries. Crashes that involve at least one unrestrained adult are 1.70 times more likely to result in fatalities or serious injuries compared to those where all adults are properly restrained. The risk is even higher for crashes involving children. In incidents where at least one child is unrestrained or improperly restrained, the likelihood of fatal or serious injury crashes increases by 1.852 times.

Proper restraint use is critical in preventing severe outcomes. Unrestrained adults are 3.66 times more likely to be fatally or seriously injured compared to their properly restrained counterparts. For children, this risk increases to 3.98 times. Furthermore, unrestrained occupants are 23.07 times more likely to be ejected from the vehicle during a crash, significantly elevating their risk of severe injury or death.

Despite the general perception that adults are more likely to use restraints, they are actually 1.31 times more likely to be unrestrained than children. This disparity becomes more pronounced in the back seat, where 73% of adults were unrestrained compared to only 24% of children. This difference can be attributed to the fact that children are 10.5 times more likely to be seated in the back seat than adults. Overall, these statistics emphasize the importance of consistent seatbelt use for all occupants, regardless of seating position or age, to reduce the likelihood of severe outcomes in crashes.

School Safety

Crash data indicates heightened risks near schools, with 4% of the region is within 0.5-miles of a school but encompassing 46% of all fatalities and serious injuries. Additional findings highlight:



- **Children's Vulnerability:** Children represented 18.8% of all fatally or seriously injured pedestrians and bicyclists and 8.6% of vehicle occupants. 11.6% of all crashes resulting in fatally or seriously injured children
- **Mode of Travel:** Crashes involving walking or biking children near schools resulted in a fatal or serious injury rate of 13%.
- **High-Risk Areas:** North High School and its surrounding neighborhoods show a significant density of crashes involving children.

Other Regional Plans & Studies

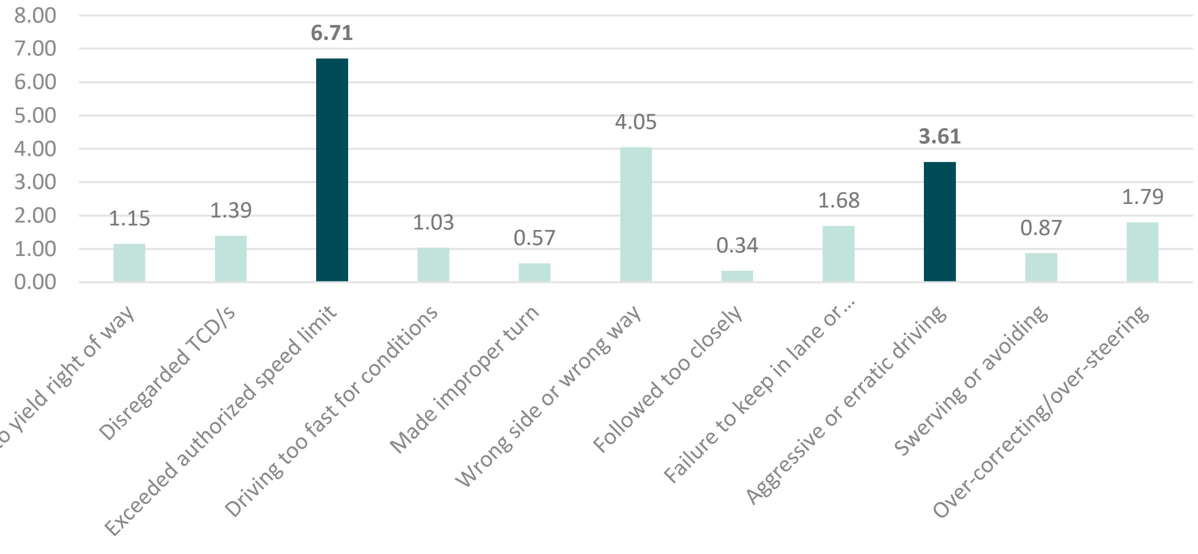
Safer people strategies and/or goals are identified in the Omaha Vision Zero, Nebraska Strategic Highway Safety Plan, and Iowa Strategic Highway Safety Plan.

Examples of safer people initiatives include using communication and education strategies to help increase seat belt usage, reducing impaired driving, and reducing red light running. Another strategy identified was in increasing or focusing enforcement on key safety issues.

Safer Speeds

Crash Review

Speeding is a critical factor in the severity of crashes, significantly increasing the likelihood of fatal or serious injuries. Crashes involving at least one vehicle exceeding the authorized speed limit are 6.71 times more likely to result in fatal or serious injury compared to other crashes. The risk becomes even more pronounced when the speeding vehicle is involved in high-risk driving behaviors or driven by specific demographics. For instance, speeding crashes often are flagged as also aggressive or erratic driving. These crashes are on average 3.6x likely to result in a fatal or serious injury crash and are 2.26 times more likely to result in disabling damage to the speeding vehicle.



Certain driver groups are more prone to speeding. Male drivers involved in crashes are 3.26 times more likely to be exceeding the speed limit compared to other drivers, and young drivers under 25 are 2.38 times more likely to do so. The risk is even higher for young male drivers, who are 3.39 times more likely to be speeding when involved in a crash. These statistics highlight the importance of targeted interventions aimed at young male drivers, who are disproportionately represented in speed-related crashes.

Impairment also plays a significant role in speeding-related crashes. Drivers under the influence of alcohol or drugs are nearly 12 times more likely to be exceeding the speed limit when involved in a crash, compared to unimpaired drivers. This combination of impairment and speeding drastically increases the likelihood of severe crash outcomes.

Small vehicles are particularly correlated in speed-related crashes. A small vehicle is 7.06 times more likely to exceed the speed limit compared to other vehicles. Given their already high risk of serious injury in crashes (see following section), the propensity for speeding further elevates the danger for small vehicle occupants. These findings emphasize the need for comprehensive speed management strategies that consider the unique risks posed by different vehicle types and driver demographics.

Other Regional Plans & Studies

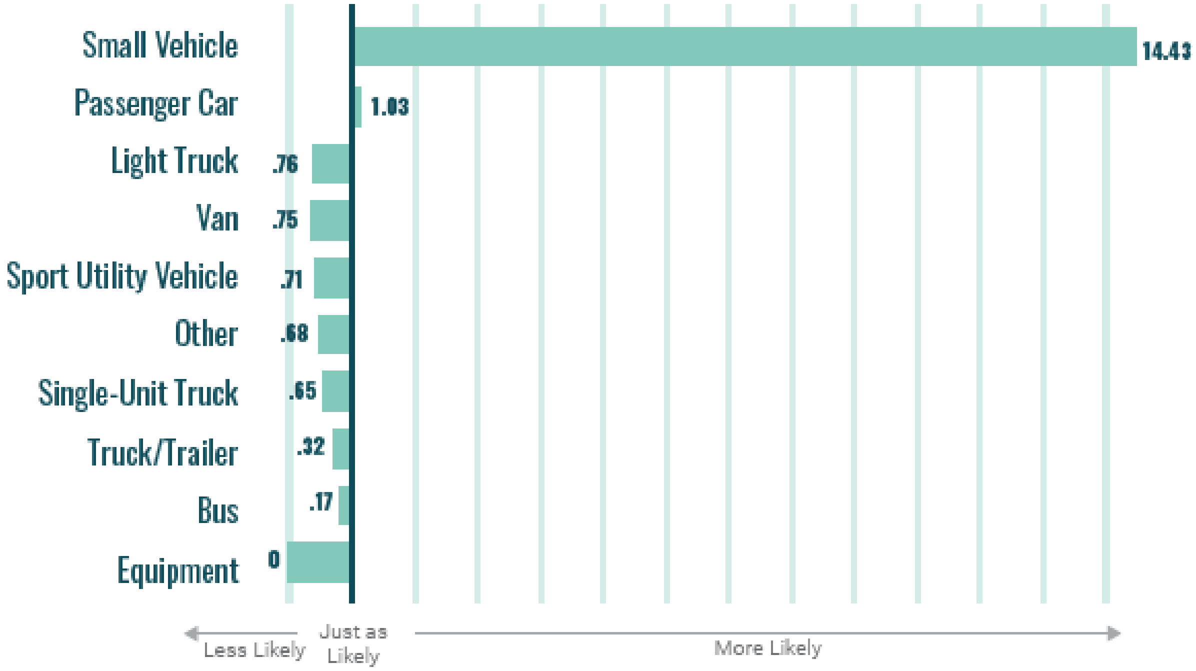
Safer speeds strategies and goals are covered in the City of Omaha Vision Zero Action Plan, Iowa Strategic Highway Safety Plan, Western Sarpy Transportation Enhancement Plan (anticipated), and Pottawattamie County Local Road Safety Plan (anticipated).

Examples of the strategies include implementing comprehensive speed limit policies looking at context, installing traffic calming devices, reconfiguring lanes, and implementing traffic calming programs.

Safer Vehicles

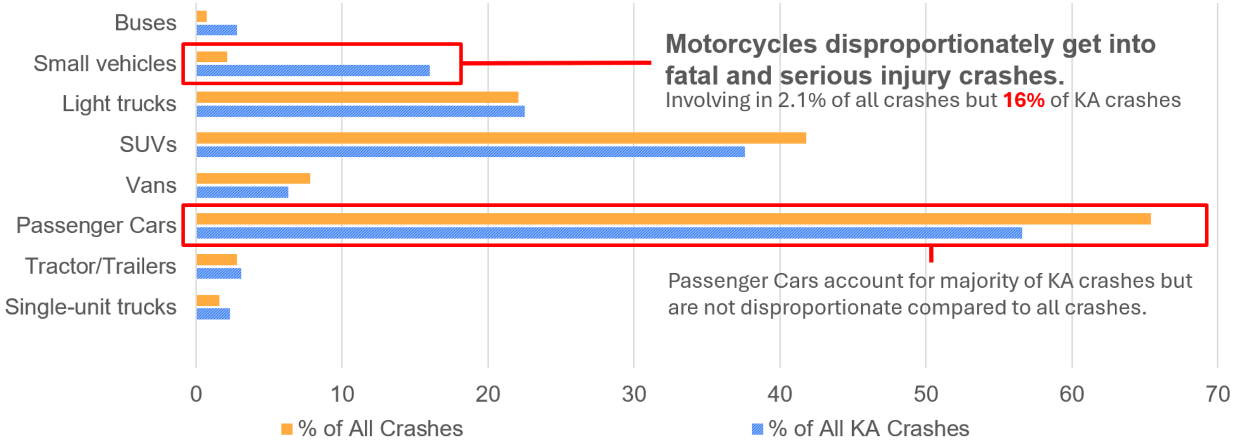
Crash Review

Small vehicle occupants, including those on motorcycles, mopeds, and all-terrain vehicles, face a significantly higher risk of severe injury or death in crashes compared to occupants of other vehicle types. Data from the MAPA region indicates that small vehicle occupants are 14.4 times more likely to be fatally or seriously injured in a crash when compared to total registered vehicles from the DMV. Beyond the risk of injury, small vehicles are also more likely to be engaged in certain driving behavior at the time of a crash. They are 2.9 times more likely to be involved in overtaking or passing maneuvers compared to other vehicle types.



This risk varies significantly with vehicle age. Newer small vehicles, those 10 years old or less, are 7 times more likely to be involved in such crashes. This risk increases for small vehicles aged between 11 and 20 years, which are 9.1 times more likely to be involved in fatal or serious crashes. The highest risk is seen in small vehicles over 20 years old, which are 12 times more likely to be involved in these severe crashes compared to vehicles of any other type or age. This drastic increase of risk with vehicle age is not observed with any other vehicle types.

If we look at the proportion of fatalities and serious injuries compared to all crashes, motorcycles involve 2% of all crashes but 16% of fatal and serious injury crashes.



Motorcycles disproportionately get into fatal and serious injury crashes.
Involving in 2.1% of all crashes but **16%** of KA crashes

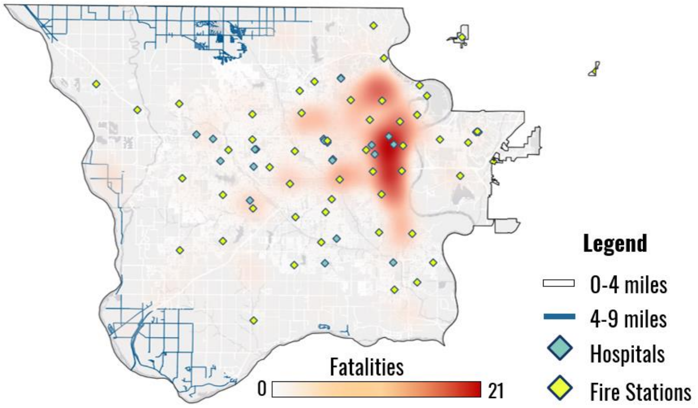
Passenger Cars account for majority of KA crashes but are not disproportionate compared to all crashes.

Post Crash Care

Crash Review

Crash data sourced from the Fatality Analysis Reporting System (FARS) (2018-2022) underscores critical insights into post-crash care within the region. While statistics specific to post-crash care are limited due to a lack of access to the National Emergency Medical Services Information System (NEMSIS), the following patterns were identified:

- **Response Times:** Emergency Medical Services (EMS) arrived on average within 7 minutes, with a maximum reported time of 20 minutes.
- **Outcome Data:** Approximately 45% of individuals transported to medical facilities succumbed within the first hour, yet no fatalities were reported during transport.
- **Crash Severity:** 51% of crashes necessitated emergency transport to medical facilities.
- **Fatality Hotspots:** High concentrations of fatalities occurred within a 0–4 mile radius of emergency facilities, with reduced rates observed in areas 4–9 miles away.



Transportation and the Unhoused

Transportation systems have a profound impact on individuals experiencing homelessness, as well as safety in public rights-of-way (ROW). Drawing from federal guidance and case studies, the following best practices are recommended:

1. **Engagement:** Direct involvement of individuals experiencing homelessness in transportation planning processes.
2. **Data Utilization:** Enhanced data collection and analysis to identify connections between homelessness and transportation risks.
3. **Housing and Services:** Leveraging transportation resources to support affordable housing and transitional services.
4. **Infrastructure and Design:** Prioritizing safety and accessibility in transportation infrastructure for vulnerable populations.
5. **Dignified Interaction:** Coordinated outreach, provision of health and hygiene services, and safe storage solutions for personal belongings.

Data Action and Implementation Plan

Summary of Analysis

The culmination of the analysis results in a High Priority Network (HPN) that prioritizes segments with fatalities and serious injuries through a combination of need and risk.

The general trends identified that were associated with higher fatalities or high risk, with respect to VRUs, were wide streets, such as principal and minor arterials, with more lanes and higher speeds. However, in addition to roadway characteristics, road users also play a role in helping ensure safer roads for all users such as avoiding distracted driving, impaired driving, using occupant protection. Older road users were also identified as an emphasis area. Finally, the trends to larger and heavier vehicles pose a greater risk to VRUs and there is a need to improve the post-crash care outcomes for those involved in a collision with a serious injury.

Data Action and Implementation

The results of this analysis provide a foundation for informed decision-making and strategic safety improvements. The key to effective implementation is leveraging the priority scores generated in this analysis to guide investments and focus resources where they can have the greatest impact. The approach integrates network performance statistics, safety risk ratios, and stakeholder needs to ensure targeted, data-driven solutions. Below, we outline a structured process for translating the findings into actionable strategies, incorporating the potential applications highlighted in the analysis.

Implementation in the Prioritization Framework

- **Utilize Priority Scores:** The priority scores derived from this analysis serve as the baseline for ranking and prioritizing corridors and intersections within the network. These scores integrate historical crash performance, systemic risk factors, and community concern, ensuring an equitable and data-informed approach to decision-making.
- **Incorporate Network Performance Statistics:** Use performance metrics, such as the crash rates and tool’s risk ratios, to evaluate the potential safety impact of specific corridors or locations. For example, high-risk roadways with elevated fatality and serious injury concentrations can be flagged for countermeasure deployment or design improvements.
- **Stakeholder-Specific Filtering:** Tailor the tool to address stakeholder priorities. For instance:
    - Identify corridors with high incidences of speeding and impairment for enhanced enforcement strategies.
    - Highlight pedestrian and bicycle crash corridors for Vulnerable Road User (VRU) safety studies or infrastructure enhancements.

Implementation of Network Screening

To facilitate implementation, three key network screening methods are employed:

1. **High Injury Network (HIN):**
    - **Purpose:** Identifies where the highest concentrations of fatalities and serious injuries rates occur.
    - **Applications:** Use this network to guide countermeasure selection, prioritize projects under funding programs like PPPP, and track performance management outcomes. Focus interventions on the highest-performing locations, such as known hotspots for severe crashes.
2. **High Risk Network (HRN):**
    - **Purpose:** Predicts where future crashes may occur using machine learning models that assess roadway characteristics correlated with crash risk.
    - **Applications:** Inform regional Safety Performance Function (SPF) development and identify locations with excess expected crashes through the Empirical Bayes (EB) method. Proactively implement countermeasures on high-risk corridors, prioritizing investments before crashes occur.
3. **Community Survey Network (CRN):**
    - **Purpose:** Incorporates community feedback to identify safety concerns that may not be fully reflected in available crash data.
    - **Applications:** Address missing data areas or equity concerns and integrate community insights into Safety Action Plans or community-driven projects. Engage local stakeholders to validate findings, refine scoring methodologies, and prioritize projects that address community-identified needs.

Implementation in Scoring and Weighting Efforts

- **Multi-Network Scoring:** Allow stakeholders to assign weights to the three networks—HIN, HRN, and CRN—based on their specific safety goals.
- **Provide Corridors of Concern:** Use the HPN to output corridors for Enforcement agencies of speeding and impairment. Use the HPN tool to emphasize pedestrian and bicycle safety in the action plan by showcasing corridors of historic non-motorized crashes.
- **Risk-Based Filtering:** Use safety risk ratios to refine project prioritization further. High-risk locations, as determined by the comparison of KSIs and network coverage, should receive greater emphasis in the scoring process.
- **Stakeholder Collaboration:** Provide stakeholders with the HPN tool to apply custom filters on person and road characteristics, enabling the prioritization of projects based on both quantitative data and qualitative input.

Implementation Strategies

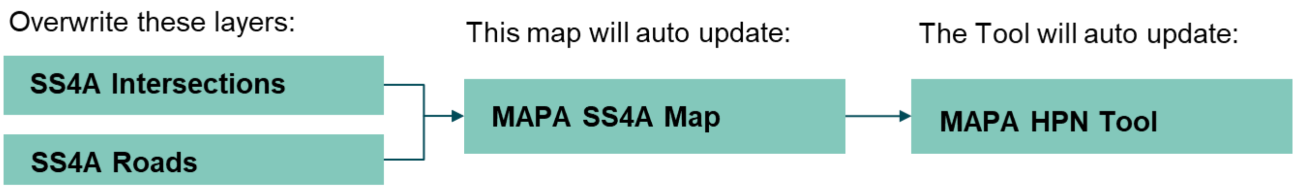
The implementation of this analysis involves aligning identified priorities with funding, planning, and operational processes. Specific actions include:

- **Countermeasure Selection:** Identify appropriate countermeasures for high-risk corridors and intersections, using crash type and contributing factor data to tailor interventions.
- **Project Prioritization (PPPP Funding):** Use the HPN score to guide funding applications and programming decisions, prioritizing projects based on the score.
- **Performance Management:** Establish metrics to monitor the effectiveness of implemented countermeasures and track progress toward safety goals. A common non-state and federal metric often requested by the CSAP team was Risk Ratio.

By leveraging priority scores, integrating the network screening analysis, and aligning risk ratio needs efforts with performance measuring, stakeholders can systematically reduce crashes, fatalities, and serious injuries across the network.

Expected Data Formats

The data is stored as two layers within the MAPA ArcGIS Online (AGOL).



SS4A Roads:	https://mapa.maps.arcgis.com/home/item.html?id=364d3fe6270849288266b7c9de0aea80
SS4A Intersections:	https://mapa.maps.arcgis.com/home/item.html?id=1332f5f24035439ca3cbf8f686cce5b7
MAPA SS4A Map:	https://mapa.maps.arcgis.com/home/item.html?id=9fe19a059a3d4d2aa1dc5ccadbf7208c
MAPA HPN Tool:	https://mapacog.github.io/hpn-tool/

All underlying sources, conflation methods, data dictionaries, and aggregation methods are described in the Data Inventory spreadsheet.

How To Run The Developed Geoprocessing Tools

The process to run the scripts to aggregate crashes, conflate roadways, conflate intersections, and score the networks are described in the Data Sustainability Slides and the README in the MAPA hpn-scripts repo. https://github.com/mapacog/hpn-scripts

Details On Tool Features

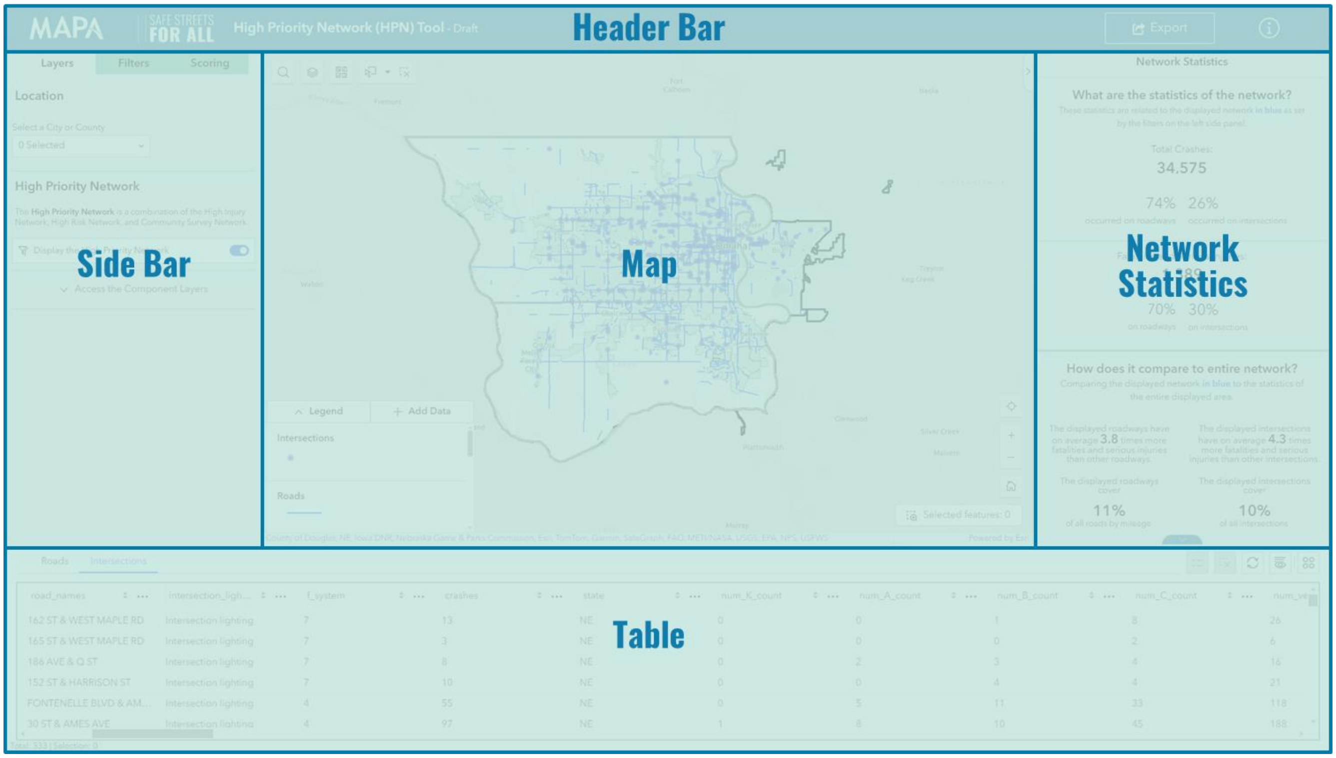
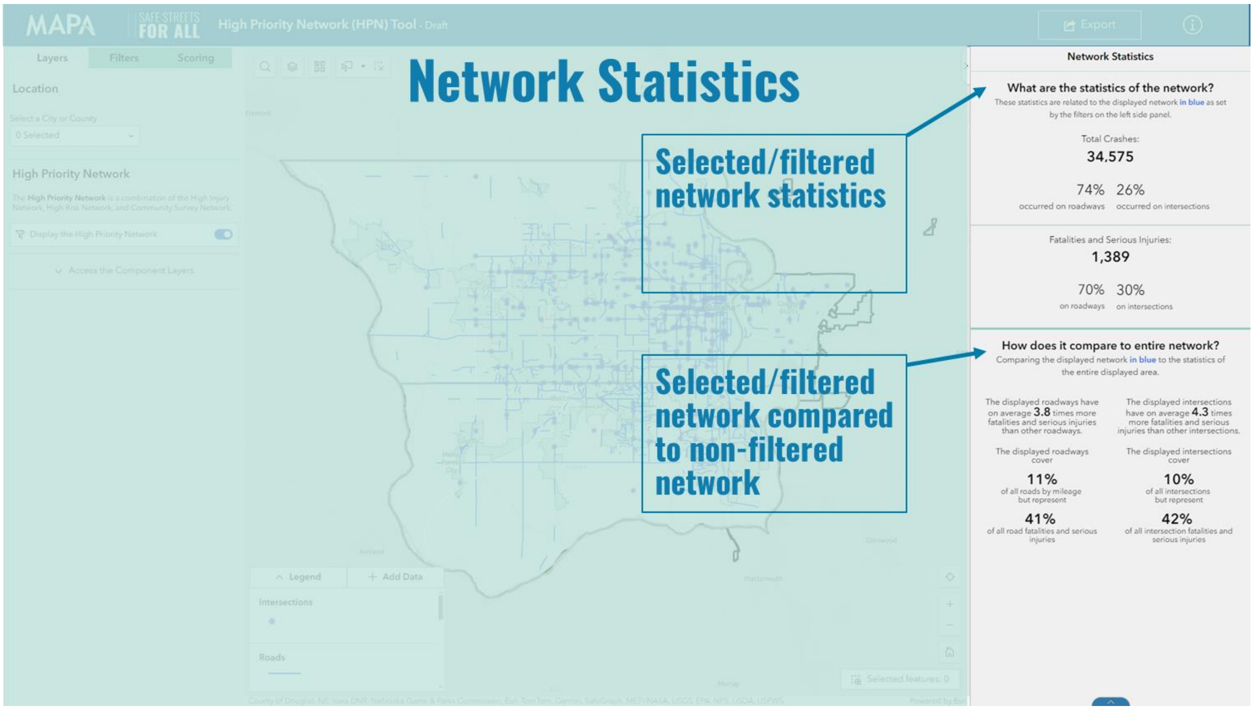


Figure 18 The Tool's five sections containing the nine features available to the user

The tool has **nine** main features available to all users. More details can be found in the Data Support Workshop slides.

1. **View the Networks:** Use the map to zoom in/out, select, and explore the region.
2. **Select a specific region:** In the Layers sidebar, select a specific city or county to filter the data to.
3. **Select different Networks:** In the Layers sidebar, select the safety network you would like displayed on the map.
4. **View the Underlying Data:** In the Layers sidebar, under Underlying Networks, show crash data or survey points directly on the map.
5. **Filtering the Networks:** In the Filters sidebar, select driver characteristics, driver behavior, or road characteristics to filter to.
6. **Scoring**: Adjust the MAPA High Priority Network or create your own network based on a selection of sliders.
7. **View Safety Performance Statistics:** See how your region or selected network performs on safety statistics.
8. **Export**: Download a csv or geojson file of the filtered and selected data.
9. **View the Table:** View specific details on the network in a table view.

How To Interpret the Statistics Sidebar



Network Statistics

Selected/filtered network statistics

Selected/filtered network compared to non-filtered network

Network Statistics

What are the statistics of the network?

These statistics are related to the displayed network in blue as set by the filters on the left side panel.

Total Crashes:
34,575

74% occurred on roadways
26% occurred on intersections

Fatalities and Serious Injuries:
1,389

70% on roadways
30% on intersections

How does it compare to entire network?

Comparing the displayed network in blue to the statistics of the entire displayed area.

The displayed roadways have on average 3.8 times more fatalities and serious injuries than other roadways.	The displayed intersections have on average 4.3 times more fatalities and serious injuries than other intersections.
The displayed roadways cover	The displayed intersections cover
11%	10%
of all roads by mileage but represent	of all intersections but represent
41%	42%
of all road fatalities and serious injuries	of all intersection fatalities and serious injuries

The safety performance network statistics tab summarizes information on the performance of the selected region and network displayed on the map. It is divided into two sections:

Displayed Network Statistics

This summarizes safety performance for the selected network, divided into two categories: roadways and intersections. Key metrics include the total number of crashes and the proportion of fatalities and serious injuries (KSIs) occurring on each type of facility type. This section is intended to give a high-level understanding of where crashes and severe outcomes occur within the selected network over the five years (2018-2022).

Total Crashes: The data includes all reported crashes spatially joined to the displayed network, categorized by whether they occur on roadways or at intersections. It's important to note that this is the sum of crashes on roads and junctions, not a sum of crash points.

Fatalities and Serious Injuries (KSIs): The count of KSIs on the network. Categorized to highlight the relative severity of crashes by roadways or at intersections. It's important to note that this is the sum of fatalities and serious injuries on roads and junctions, not a sum of KSI crashes or a sum of fatal and serious injury points.

What are the statistics of the network?

These statistics are related to the displayed network in blue as set by the filters on the left side panel.

Total Crashes:
31,015

52% occurred on roadways
48% occurred on intersections

Fatalities and Serious Injuries:
430

44% on roadways
56% on intersections

Figure 19 Displayed Network Statistics for Safety Performance tab

Displayed Network Comparison

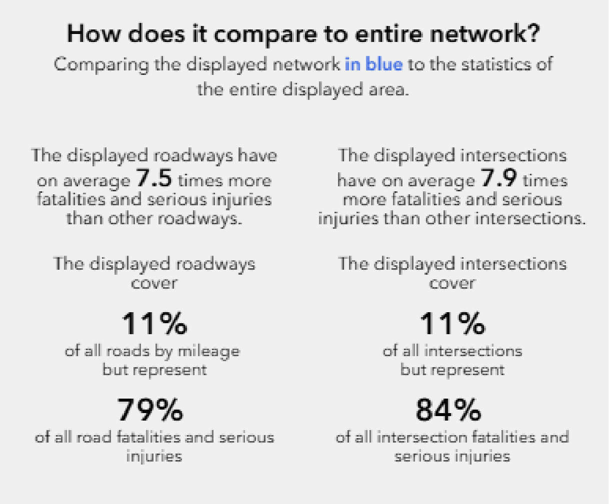
This section contextualizes the crash data by comparing the displayed network to the performance of the entire network in that region. The analysis highlights the relative risk of the selected network in terms of crash severity and facility coverage.

Safety Risk Ratio: The relative risk of severe crashes on the displayed network is quantified, indicating how many times more likely fatalities and serious injuries are to occur in the selected network compared to other parts of the system in that region. This metric helps identify high-risk locations for prioritization and the safety potential this network can have.

- It is calculated as the Relative Severity Percentage divided by the Network Coverage Percentage.

Network Coverage Percentage: The analysis examines the proportion of the total roadway mileage and intersection inventory represented by the selected network compared to the total in that region.

- For Roads: It is calculated as the total miles of displayed road divided by the total miles of roads within the selected region.
- For Intersections: It is calculated as the total count of intersections divided by the total count of intersections within the selected region.



How does it compare to entire network?

Comparing the displayed network **in blue** to the statistics of the entire displayed area.

The displayed roadways have on average **7.5** times more fatalities and serious injuries than other roadways.

The displayed roadways cover

11%

of all roads by mileage but represent

79%

of all road fatalities and serious injuries

The displayed intersections have on average **7.9** times more fatalities and serious injuries than other intersections.

The displayed intersections cover

11%

of all intersections but represent

84%

of all intersection fatalities and serious injuries

Figure 20 Displayed Network Comparison Safety Performance Tab

Relative Severity Percentage: The displayed roadways and intersections are evaluated based on the concentration of KSIs compared to their representation in the overall network in that region. This provides an indication of how overrepresented severe crashes are in the selected network compared to the rest of the roadway and intersection system.

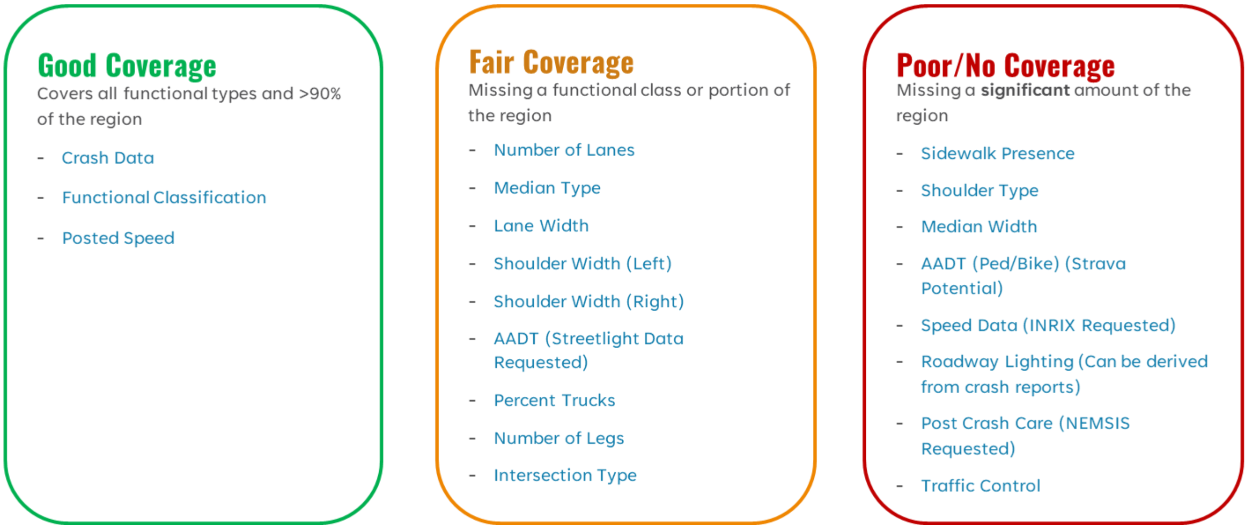
- It is calculated as the total KSI of displayed road/intersection divided by the total KSI of roads/intersections within the selected region.

Additional Data to Consider Collecting

The data collection effort provided a solid foundation for understanding the existing conditions and identifying key areas for intervention within the region. The lack of data coverage limited comprehensive analysis, leaving us constrained by data limitations. To enhance this high standard of safety planning, we recommend further developing the linear referencing system and considering the integration of additional data sources in future analyses. These sources can offer new dimensions of insight, further refining our understanding of traffic safety dynamics and enabling even more targeted and effective interventions.

Safer Roads

Road and Intersection coverage is limited in the MAPA region and more efforts to collect MIRE data are recommended. See the data evaluation slides for details and the coverage summary figure below. More efforts in collecting accurate and fully coverage roadway characteristics give the opportunity to conduct more detailed data science and safety performance predictions.



Good Coverage
Covers all functional types and >90% of the region

- Crash Data
- Functional Classification
- Posted Speed

Fair Coverage
Missing a functional class or portion of the region

- Number of Lanes
- Median Type
- Lane Width
- Shoulder Width (Left)
- Shoulder Width (Right)
- AADT (Streetlight Data Requested)
- Percent Trucks
- Number of Legs
- Intersection Type

Poor/No Coverage
Missing a **significant** amount of the region

- Sidewalk Presence
- Shoulder Type
- Median Width
- AADT (Ped/Bike) (Strava Potential)
- Speed Data (INRIX Requested)
- Roadway Lighting (Can be derived from crash reports)
- Post Crash Care (NEMSIS Requested)
- Traffic Control

Figure 21 Coverage of different roadway attributes within MAPA SS4A Region

- Junction/Intersection Data: More attributes of an intersection can help identify high risk attributes. The current dataset lacks a full regional coverage of intersections and attributes such as turn lanes, left-turn phase, and other items noted in FHWA's MIRE elements.
- Land Use Data: Detailed zoning and land use patterns can help understand how the built environment influences traffic flow and safety. This can guide the design of safer roads that accommodate all users.
- Public Transportation Usage Data: Information on public transportation ridership and service coverage can highlight areas where enhancements in vulnerable road user safety can be most effective.
- Pedestrian and Bicyclist Volume Data: This data can enhance studies and targeted action in vulnerable road user safety. Non-Motorized users are more likely to incur a fatality or serious injury in a crash.

Post Crash Care

- National Emergency Medical Services Information System (NEMSIS): MAPA was denied access to this data during this analysis. Retrieving this data can open more opportunities for involvement from hospital and EMS provider stakeholders.
- Hospital Trauma Center Data: Detailed data from hospital trauma centers on patient outcomes can help evaluate the effectiveness of post-crash care and identify areas for medical intervention improvement, ultimately reducing fatalities and severe injuries.

Safer Speeds

- Connected Vehicle Data: Real-time data from connected vehicles can offer insights into prevailing speed patterns and hard breaking events across different road types and conditions, aiding in the identification of spots where speed management measures are most needed.

Safer Vehicles

- Insurance Claim Data: Aggregated data from insurance claims can provide another layer of detail regarding the types of vehicles and safety features most commonly involved in crashes, offering a unique perspective on vehicle safety performance.

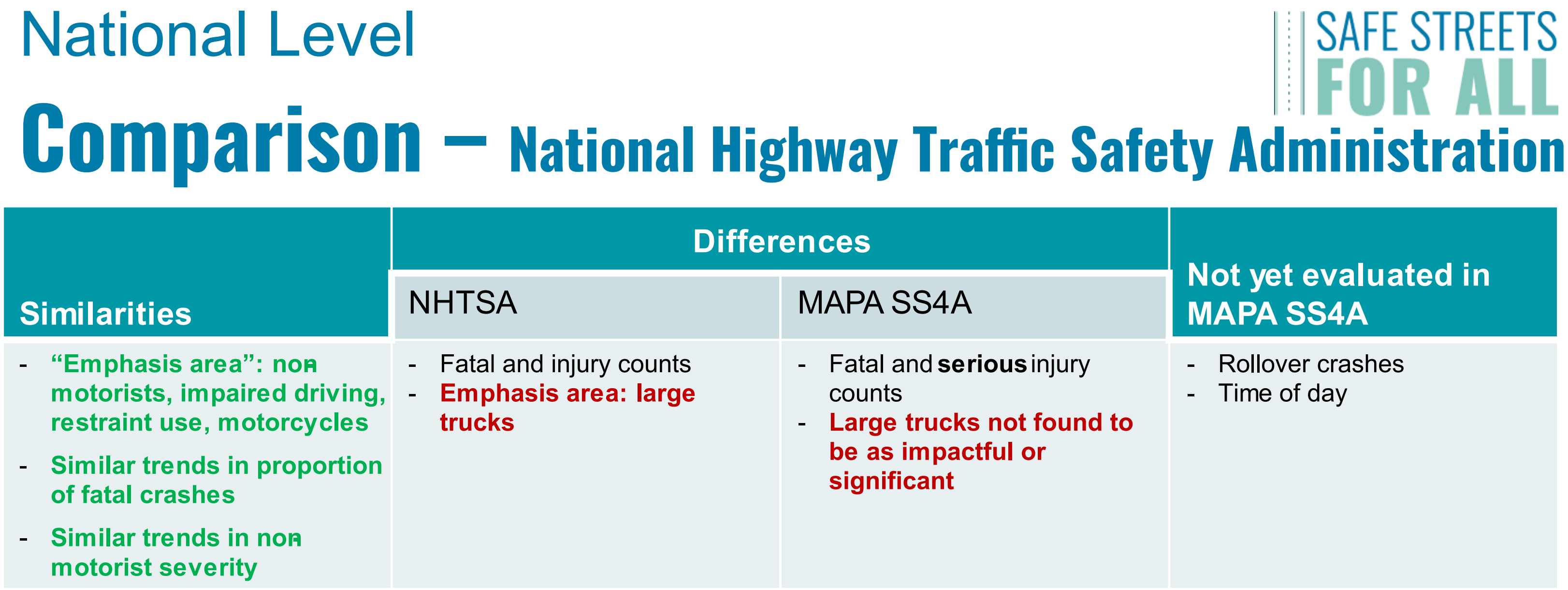
Safer People

- Mobile App Data: Analyzing anonymized data from traffic-focused mobile apps (such as Waze and Google Maps) can provide insights into public perceptions of road safety and hazardous locations.
- Health Department Records: Data on alcohol and drug consumption patterns from health departments can help identify correlations with crash occurrences, informing targeted interventions for impaired driving.

Appendix

Appendix A: Safety Plan Comparison (Plan and Process Inventory Review)

The following appendix summarizes the differences and similarities between the SS4A analysis and other regional plans.



National Level

SAFE STREETS FOR ALL

Comparison – National Highway Traffic Safety Administration

Similarities	Differences		Not yet evaluated in MAPA SS4A
	NHTSA	MAPA SS4A	
- **"Emphasis area": non-motorists, impaired driving, restraint use, motorcycles** - **Similar trends in proportion of fatal crashes** - **Similar trends in non-motorist severity**	- Fatal and injury counts - **Emphasis area: large trucks**	- Fatal and **serious** injury counts - **Large trucks not found to be as impactful or significant**	- Rollover crashes - Time of day

State Level

Comparison – Nebraska Strategic Highway Safety Plan

SAFE STREETS FOR ALL

Similarities	Differences		Not yet evaluated in MAPA SS4A
	Nebraska SHSP	MAPA SS4A	
- **Emphasis area: restraint use, lane departures, impaired driving, young drivers, non-motorists** - **Similar trends in restraint use and crash severity**	- **Emphasis area: older drivers** - Emphasis area: intersections - **KAB crashes considered** - Run-off road crashes were most common for young drivers - 34% of fatal crashes were alcohol-related	- **Older drivers were not found to be as significant as younger drivers** - More specific intersection emphasis area/s - **KA crashes considered** - Following too closely was more common than run-off road crashes for young drivers - 18% of KA crashes were alcohol-related	- Time of day - Unrestrained occupant gender - Location of lane departure crashes

MAPA

State Level

Comparison – Iowa Strategic Highway Safety Plan

Similarities	Differences		Not yet evaluated in MAPA SS4A
	Iowa SHSP	MAPA SS4A	
- **Emphasis area: non-motorists, young drivers, impaired driving, restraint use, lane departures, motorcycles** - **Similar trends in impaired driving, young drivers, motorcycles, and non-motorists (in KA crashes)**	- **Emphasis area: older drivers, work zones, distracted driving, heavy trucks** - Emphasis area: intersections - **37% of KA crashes had improper restraint use** - **15% of KA crashes involved distracted driving**	- **These areas were not found to be as impactful or significant** - More specific intersection emphasis area/s - **65.5% of KA crashes had unrestrained adult** - **3.7% of KA crashes involved distracted driving (not significant)**	- Train-related crashes - Winter conditions - Post-crash care - Local roads

City Level

Comparison - Omaha Vision Zero

Similarities	Differences		Not yet evaluated in MAPA SS4A
	Omaha Vision Zero	MAPA SS4A	
- **Male vs. Female proportion in KA crashes** - **Age distribution in KA crashes** - **Emphasis areas: restraint use, impaired driving, non-motorists** - **Mode share (vehicle vs. non-motorist) in population vs. KA crashes**	- **27.2% of KA crashes had improper restraint use** - Red light running as an emphasis area - Over 25% of **fatal** crashes involved alcohol	- **65.5% of KA crashes had unrestrained adult** - Disregard of TCDs (includes red light running) was not significant - 18% of **KA** crashes involved alcohol	- Race/ethnicity - Time of day - Safe routes to school (school zone TCDs were considered but not significant) - Speed of vehicle - Motorcycle helmet use

Neighborhood Level

SAFE STREETS FOR ALL

Comparison – Southside Terrace-Indian Hills Multi-Modal Study

Similarities	Differences		Not yet evaluated in MAPA SS4A
	Southside Terrace - Indian Hills	MAPA SS4A	
- Similar proportion of KA crashes overall [and for junctions/segments] - Similar proportion of crashes occurring on weekend days - Emphasis area: non motorists	- 2.5% of crashes involved non-motorist/s - 23.8% of non-motorist crashes were KA	- 1.7% of crashes involved non-motorist/s - 19.1% of non-motorist crashes were KA	- Time of day - Month of year - Crash density per mile - Comparison to city-wide crash rate for segments and junctions

MAPA

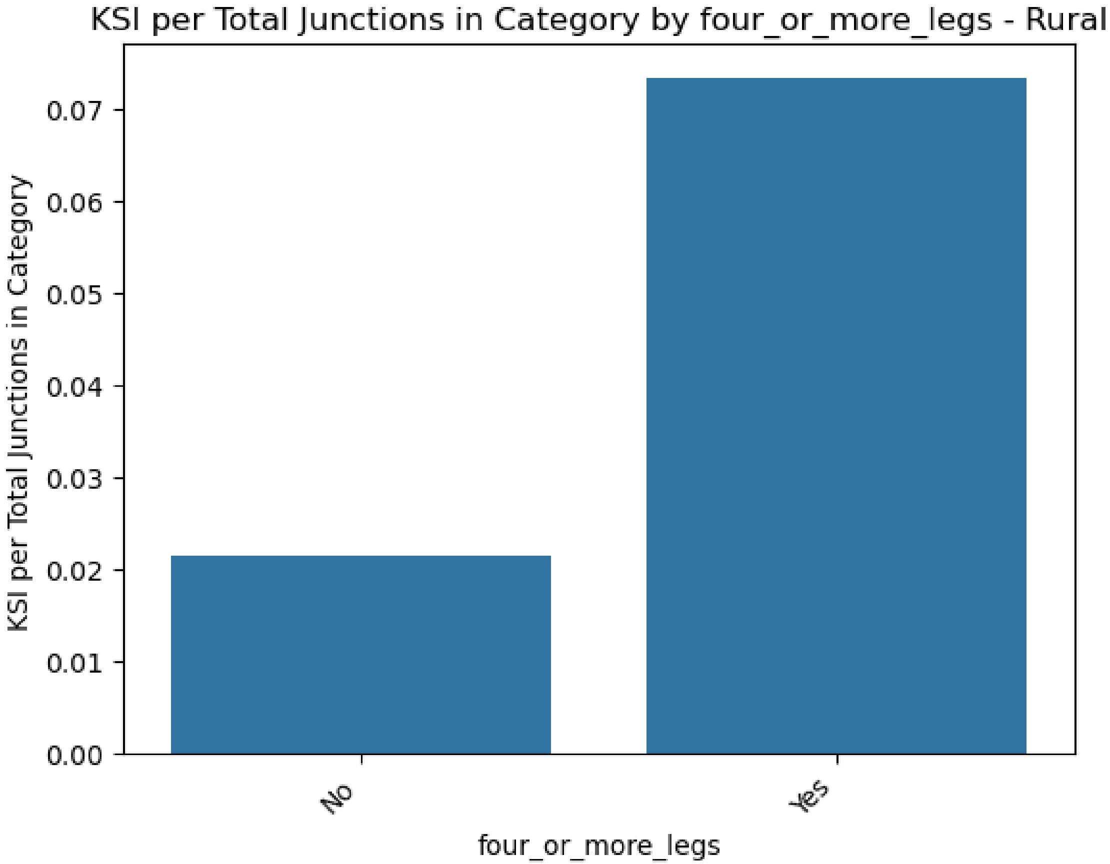
Corridor Level

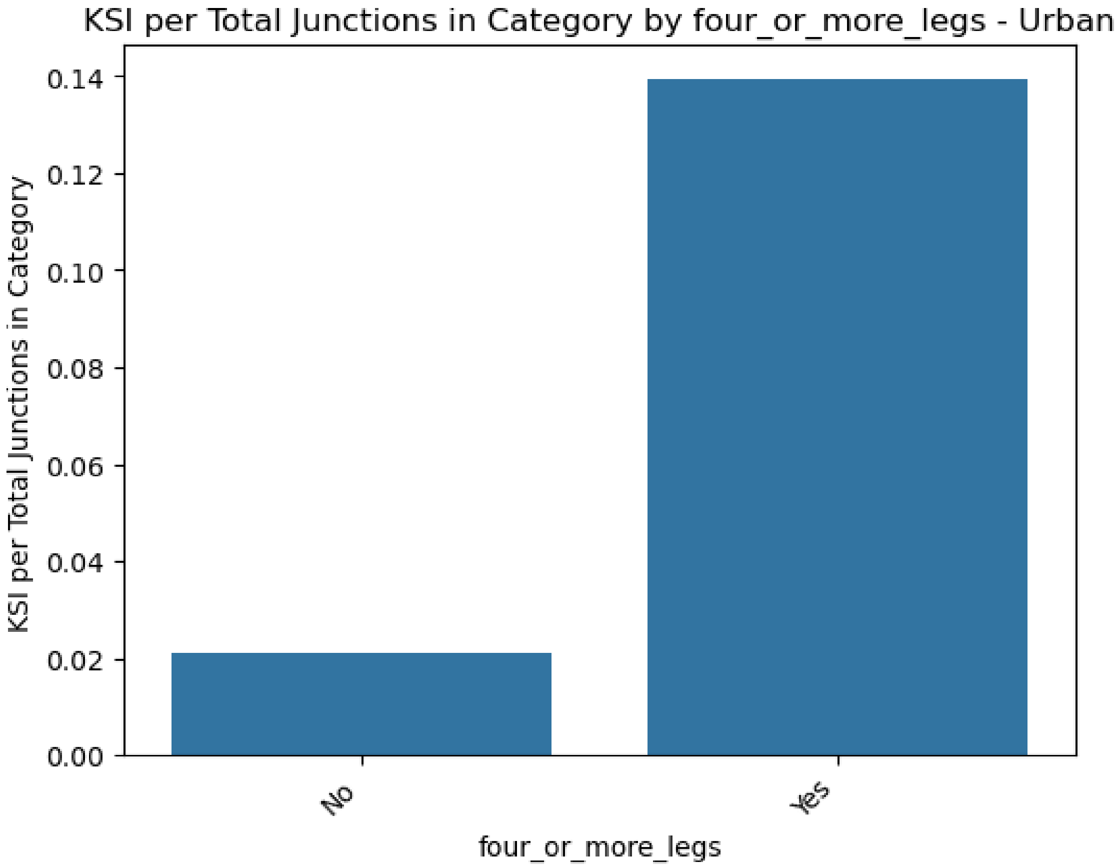
Comparison – Highway 75 Corridor and Freight Study

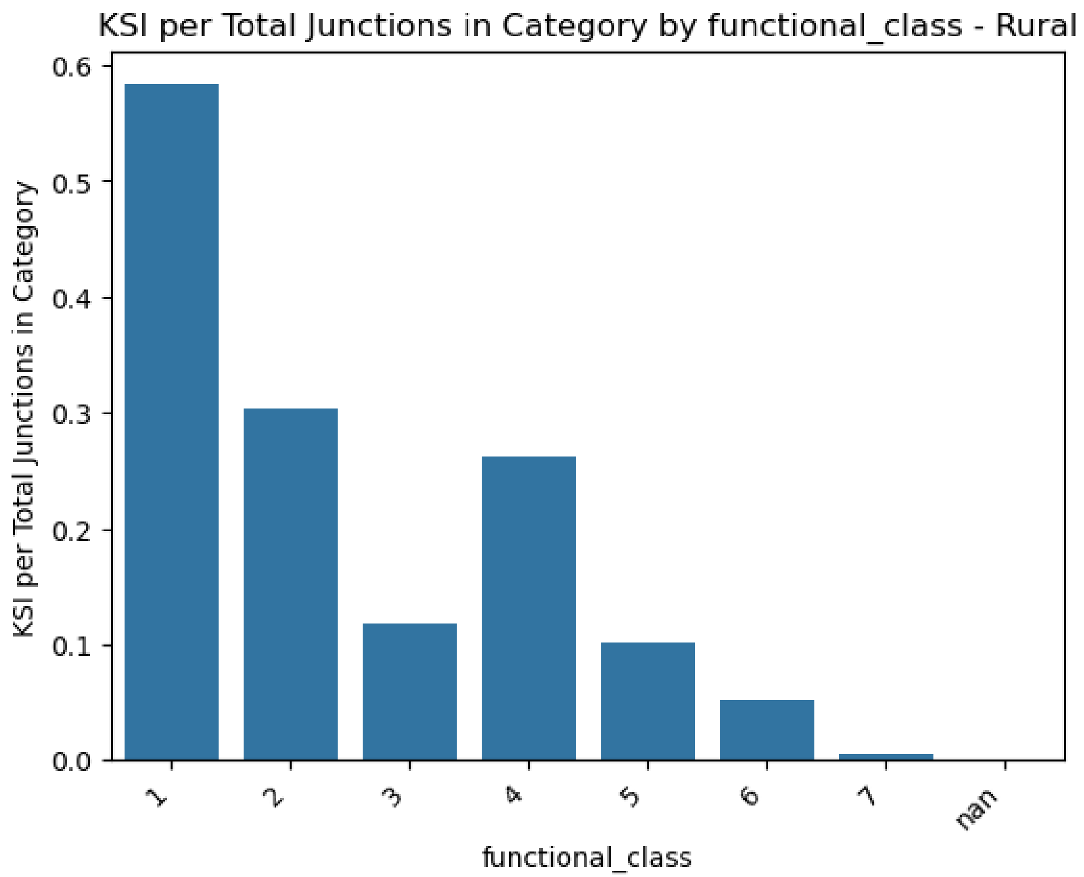
Similarities	Differences		Not yet evaluated in MAPA SS4A
	Highway 75	MAPA SS4A	
- **Emphasis areas: non motorists**	- 4.7% of crashes were KA - 4.1% of crashes involved non-motorist/s - 51.7% of non-motorist crashes were KA - No safety-specific recommendations given	- 2.6% of crashes were KA - 1.7% of crashes involved non-motorist/s - 19.1% of non-motorist crashes were KA	- Freight-related safety mentioned but no statistics given

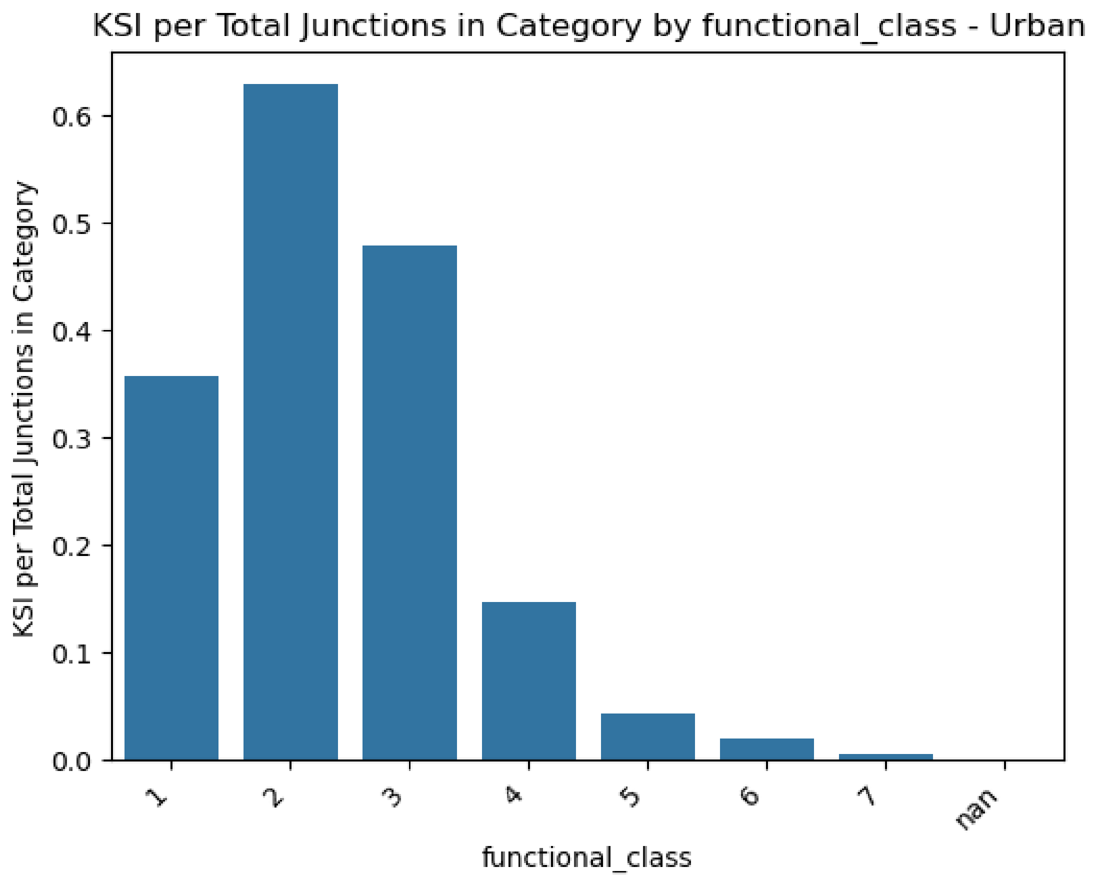
Appendix B: Risk Analysis – Variable Importance Plots

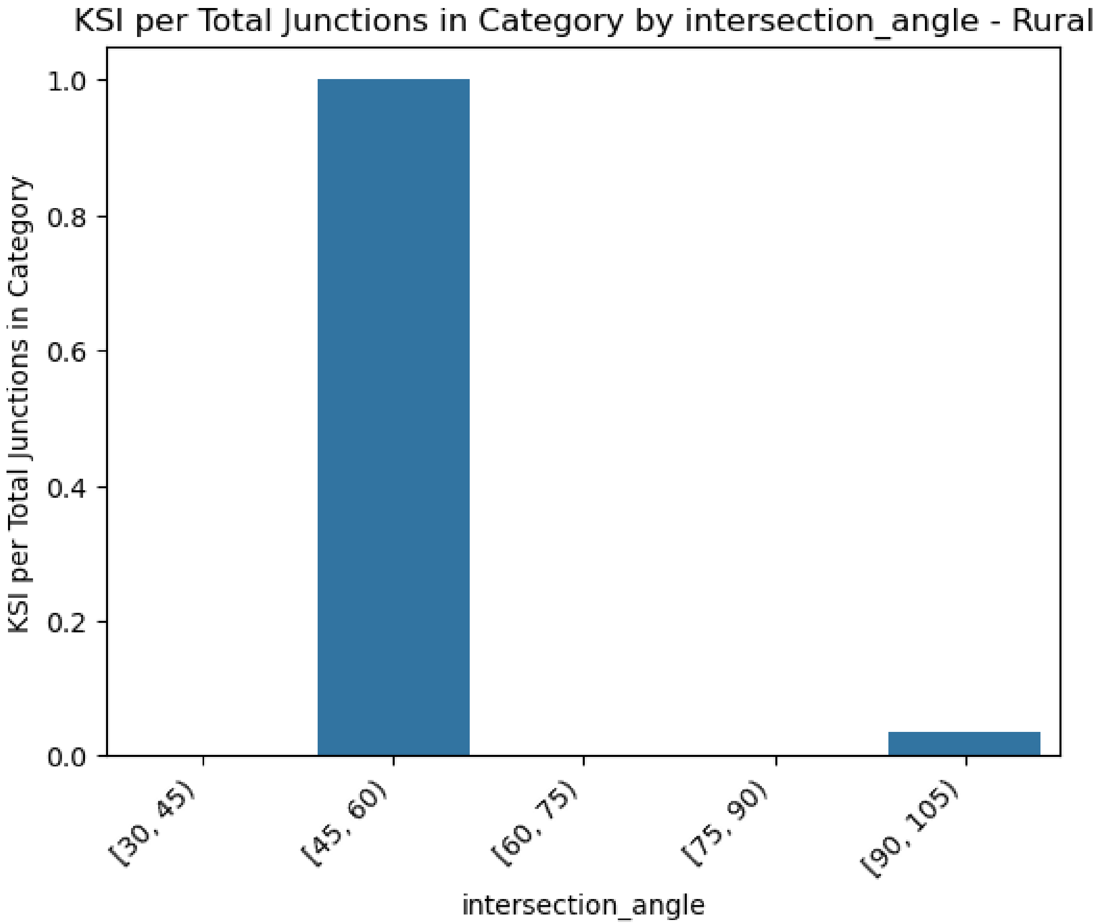
The following are plots of all the roadway characteristics used in the risk analysis and HRN selection.

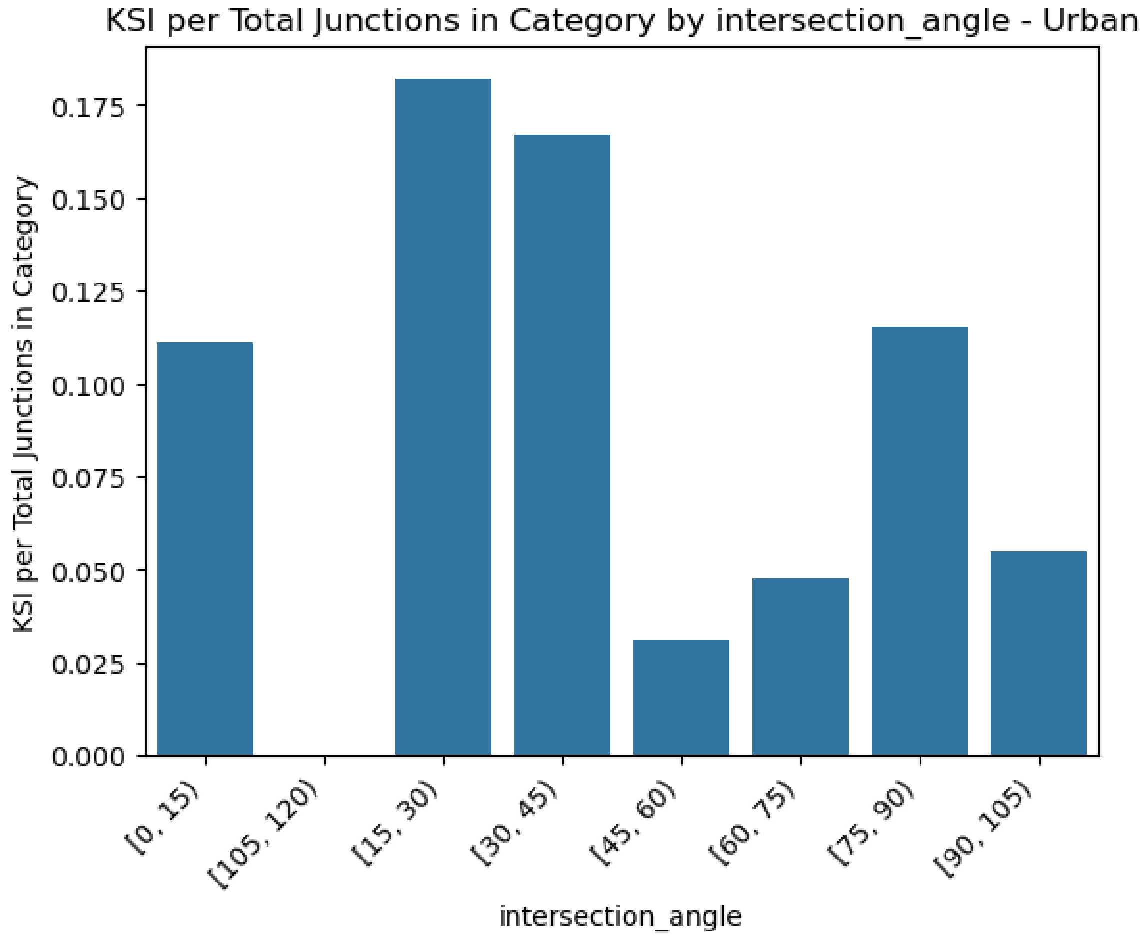


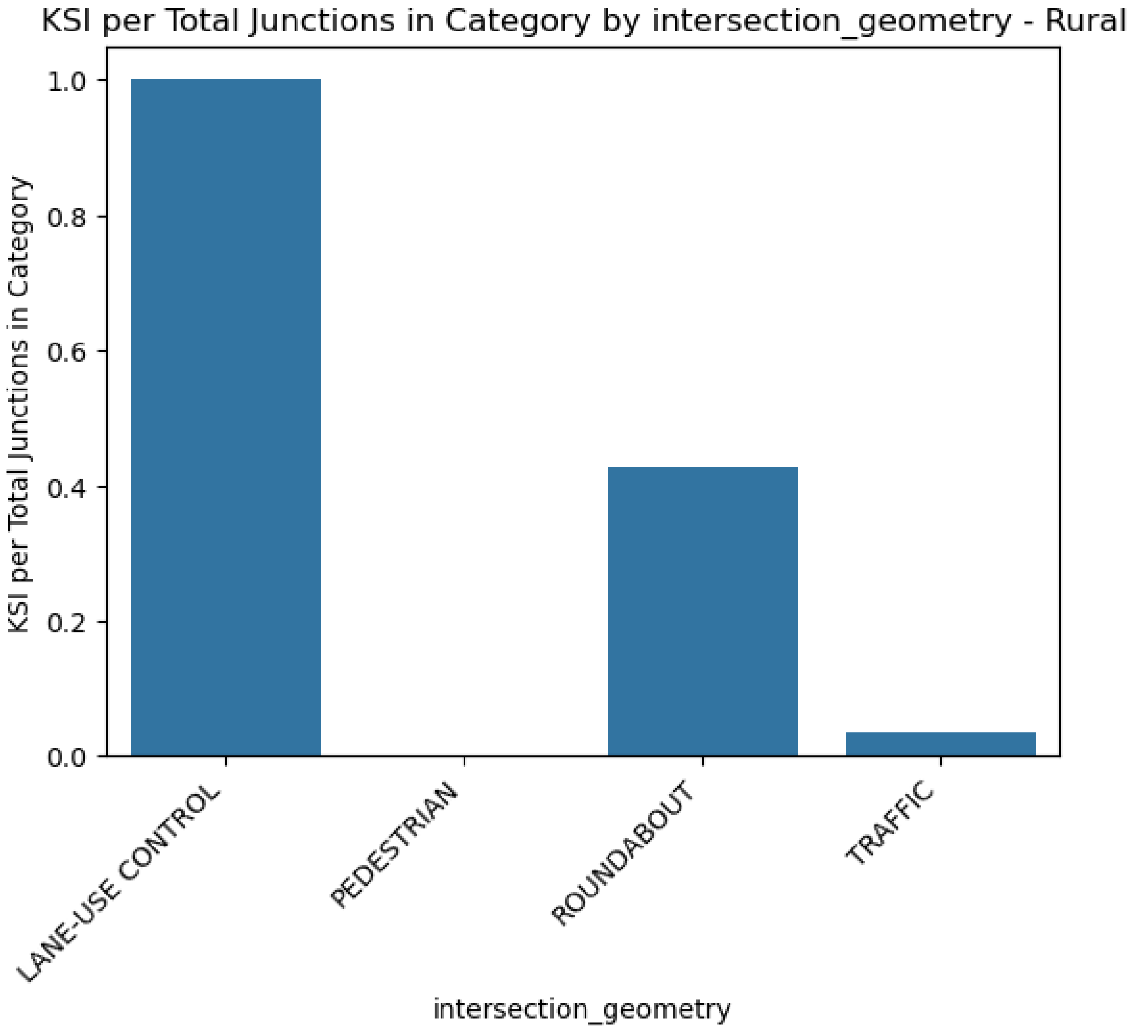

KSI per Total Junctions in Category by four_or_more_legs - Urban
KSI per Total Junctions in Category
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0.14
No
Yes
four_or_more_legs

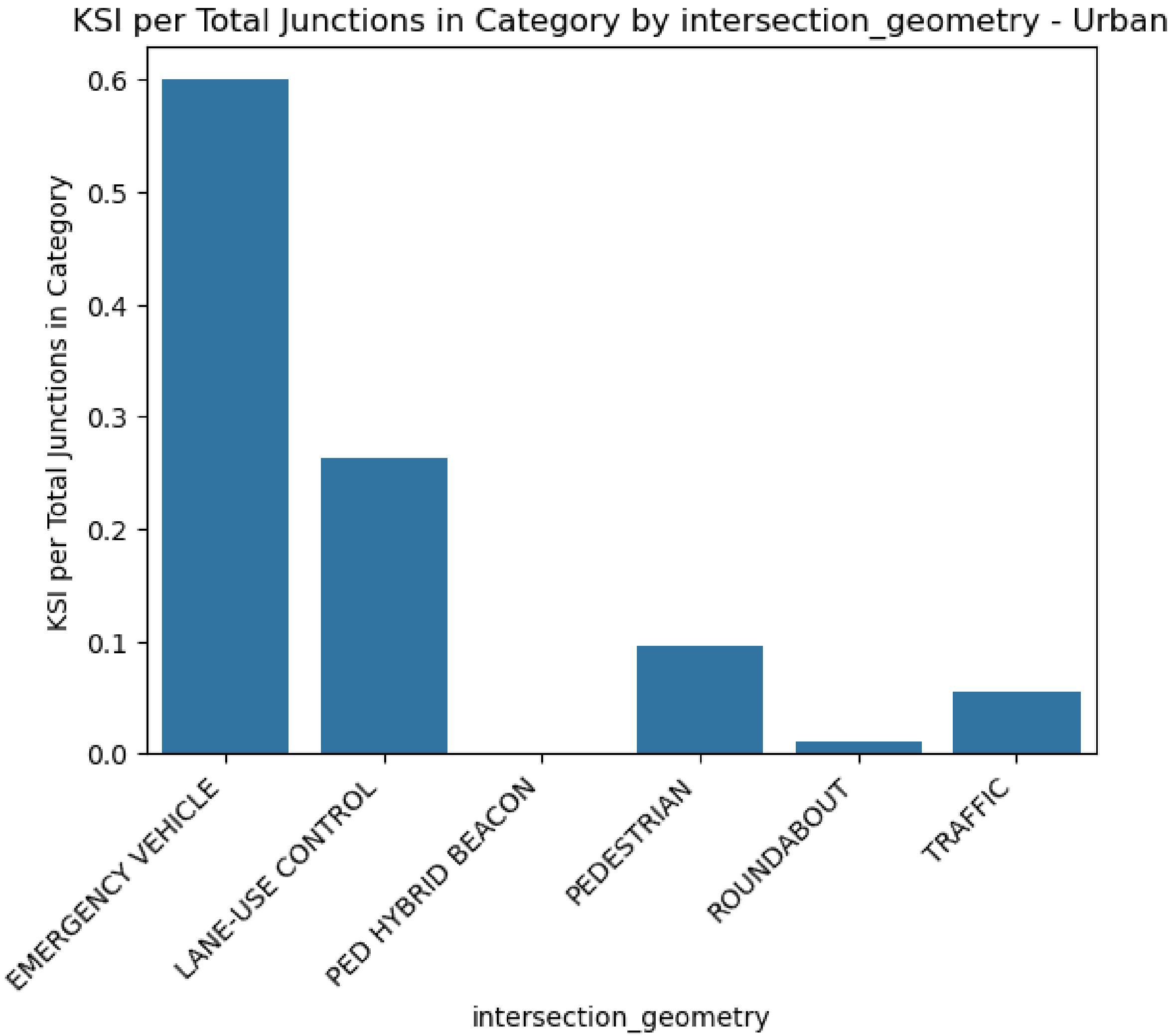

KSI per Total Junctions in Category by functional_class - Rural
KSI per Total Junctions in Category
0.0
0.1
0.2
0.3
0.4
0.5
0.6
1
2
3
4
5
6
7
nan
functional_class

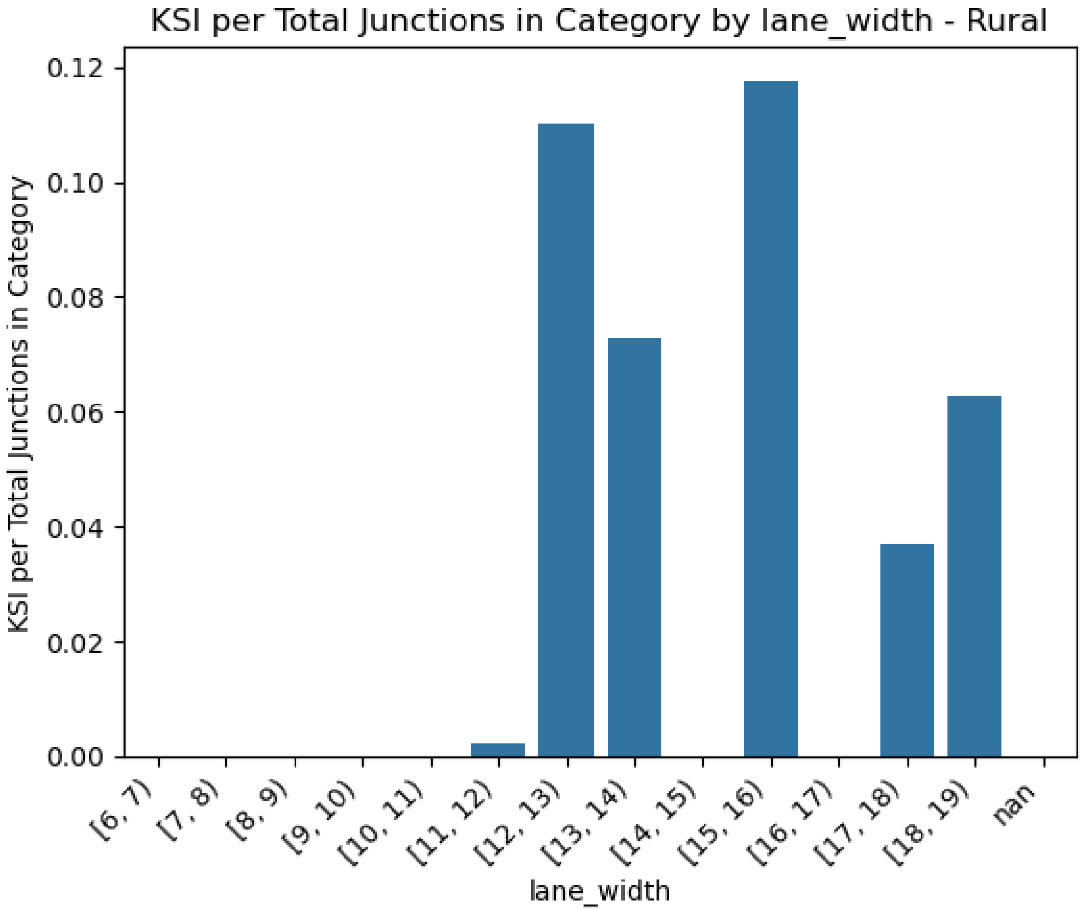

KSI per Total Junctions in Category by functional_class - Urban
KSI per Total Junctions in Category
0.0
0.1
0.2
0.3
0.4
0.5
0.6
functional_class
1
2
3
4
5
6
7
nan

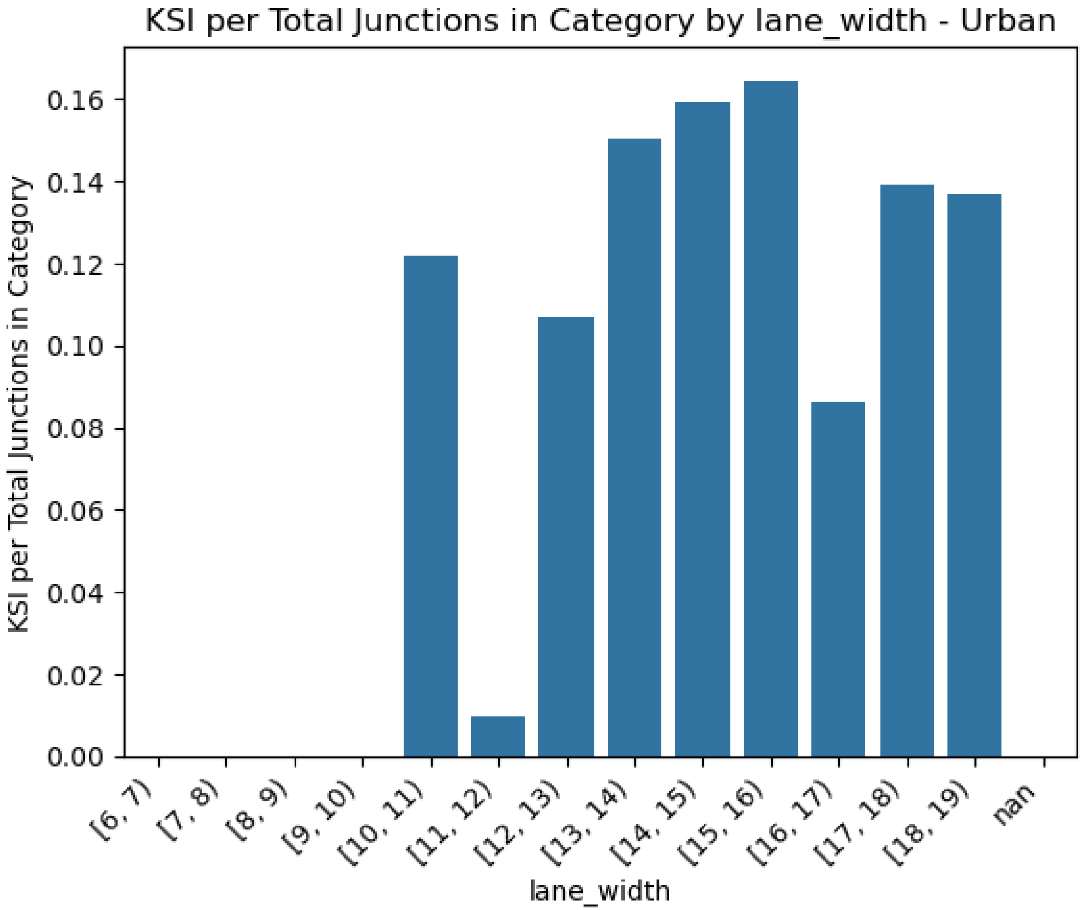

KSI per Total Junctions in Category by intersection_angle - Rural
KSI per Total Junctions in Category
1.0
0.8
0.6
0.4
0.2
0.0
[30, 45)
[45, 60)
[60, 75)
[75, 90)
[90, 105)
intersection_angle

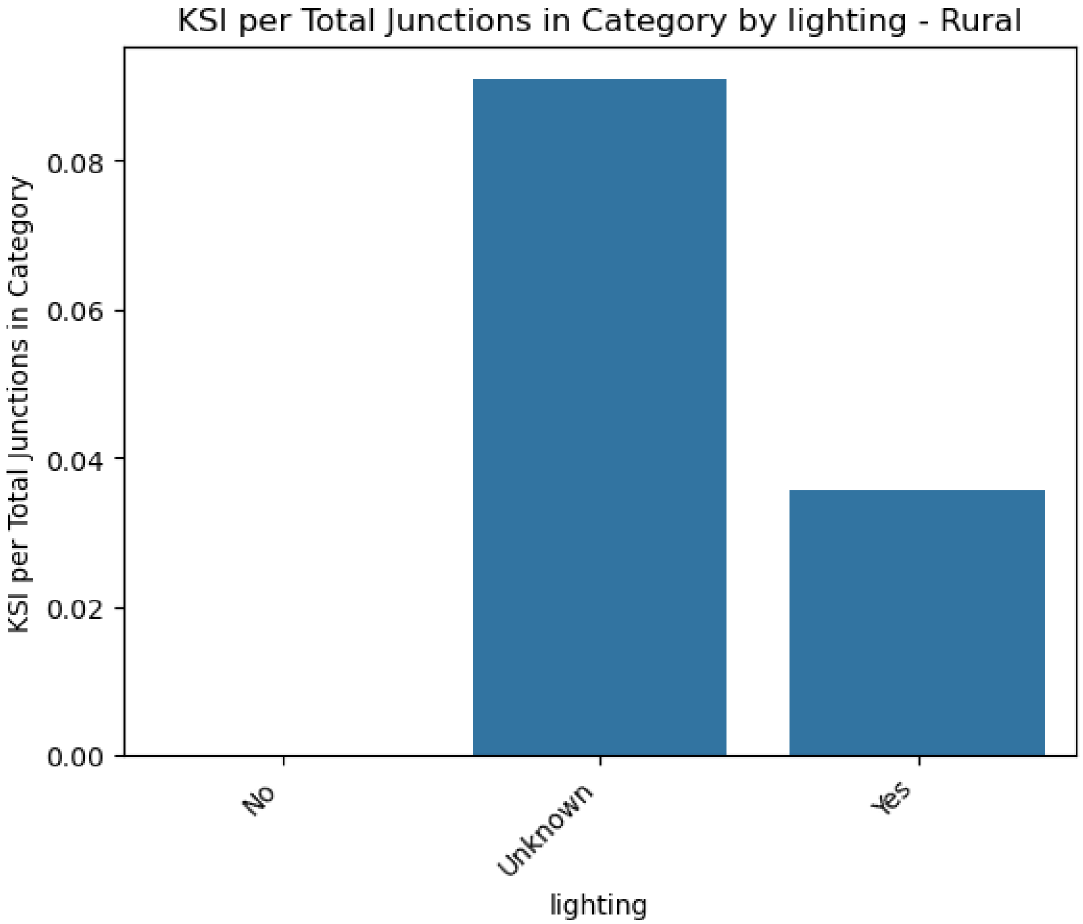

KSI per Total Junctions in Category by intersection_angle - Urban
KSI per Total Junctions in Category
0.000
0.025
0.050
0.075
0.100
0.125
0.150
0.175
[0, 15)
[105, 120)
[15, 30)
[30, 45)
[45, 60)
[60, 75)
[75, 90)
[90, 105)
intersection_angle

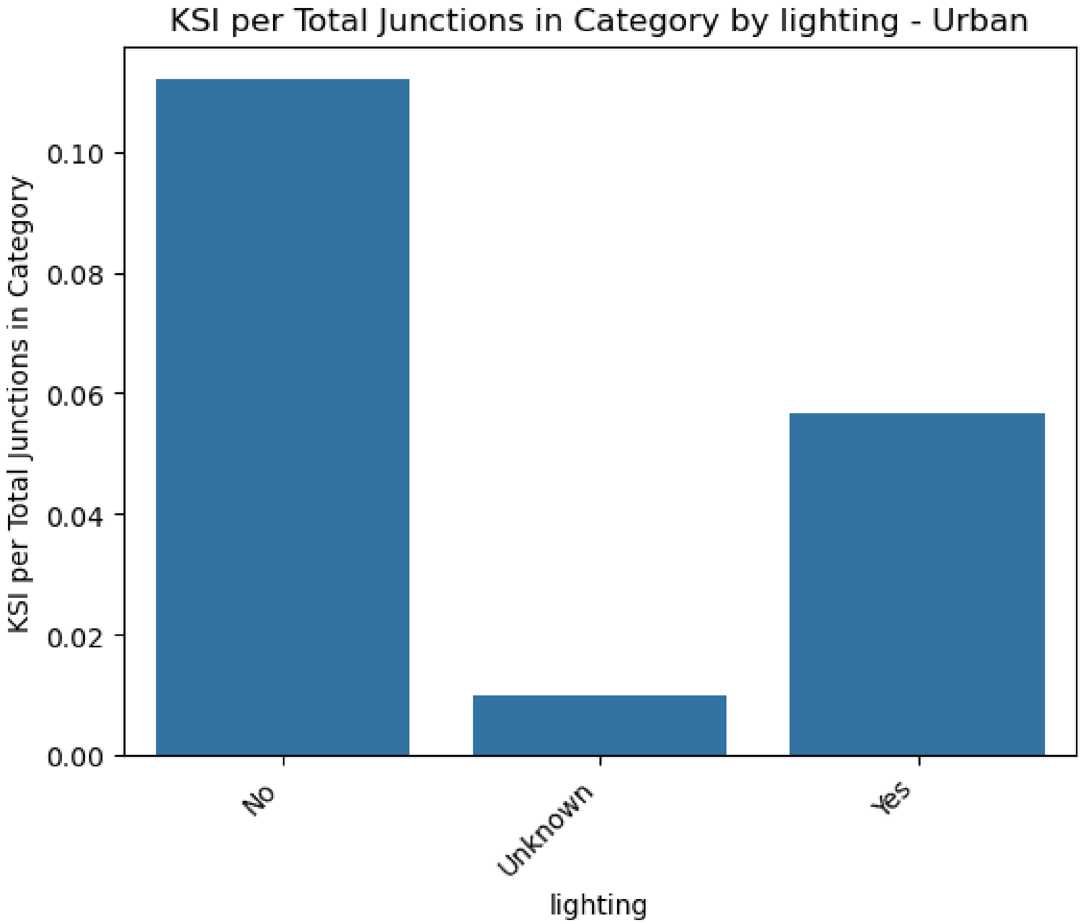

KSI per Total Junctions in Category by intersection_geometry - Rural
KSI per Total Junctions in Category
1.0
0.8
0.6
0.4
0.2
0.0
LANE-USE CONTROL
PEDESTRIAN
ROUNDABOUT
TRAFFIC
intersection_geometry

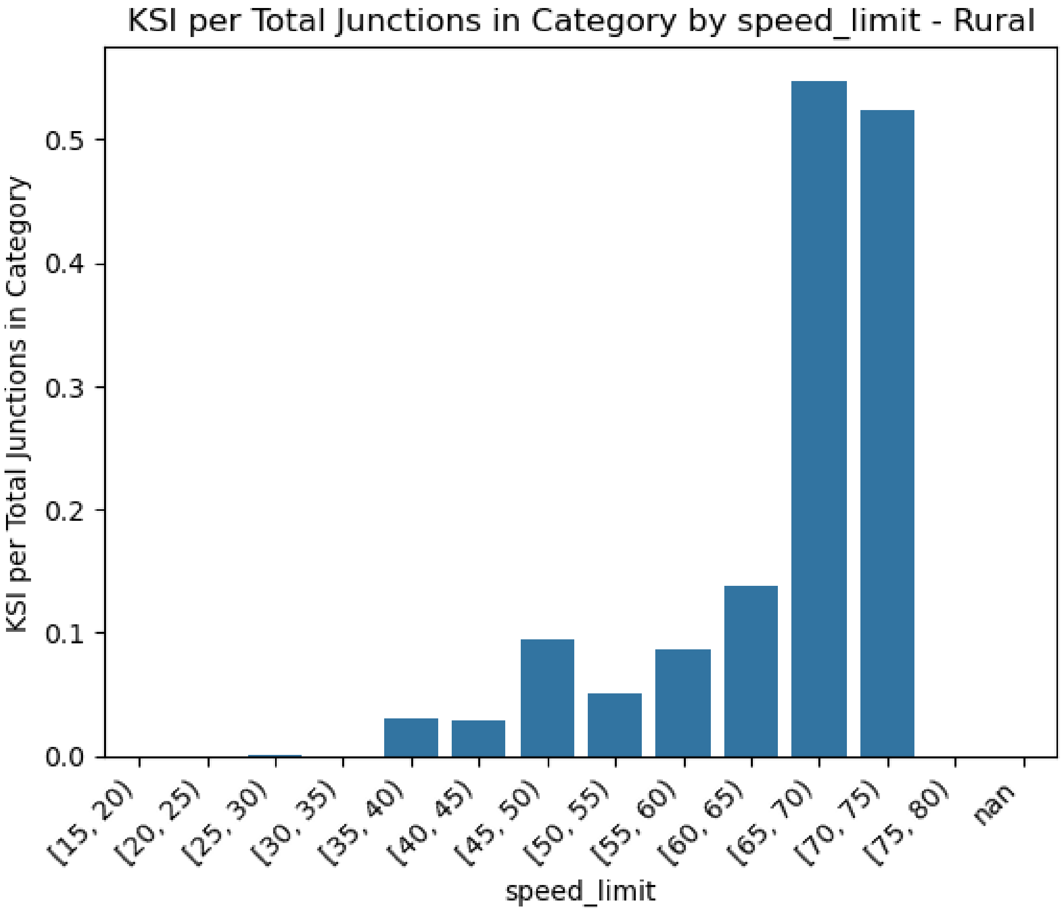

KSI per Total Junctions in Category by intersection_geometry - Urban
KSI per Total Junctions in Category
0.0
0.1
0.2
0.3
0.4
0.5
0.6
EMERGENCY VEHICLE
LANE-USE CONTROL
PED HYBRID BEACON
PEDESTRIAN
ROUNDABOUT
TRAFFIC
intersection_geometry

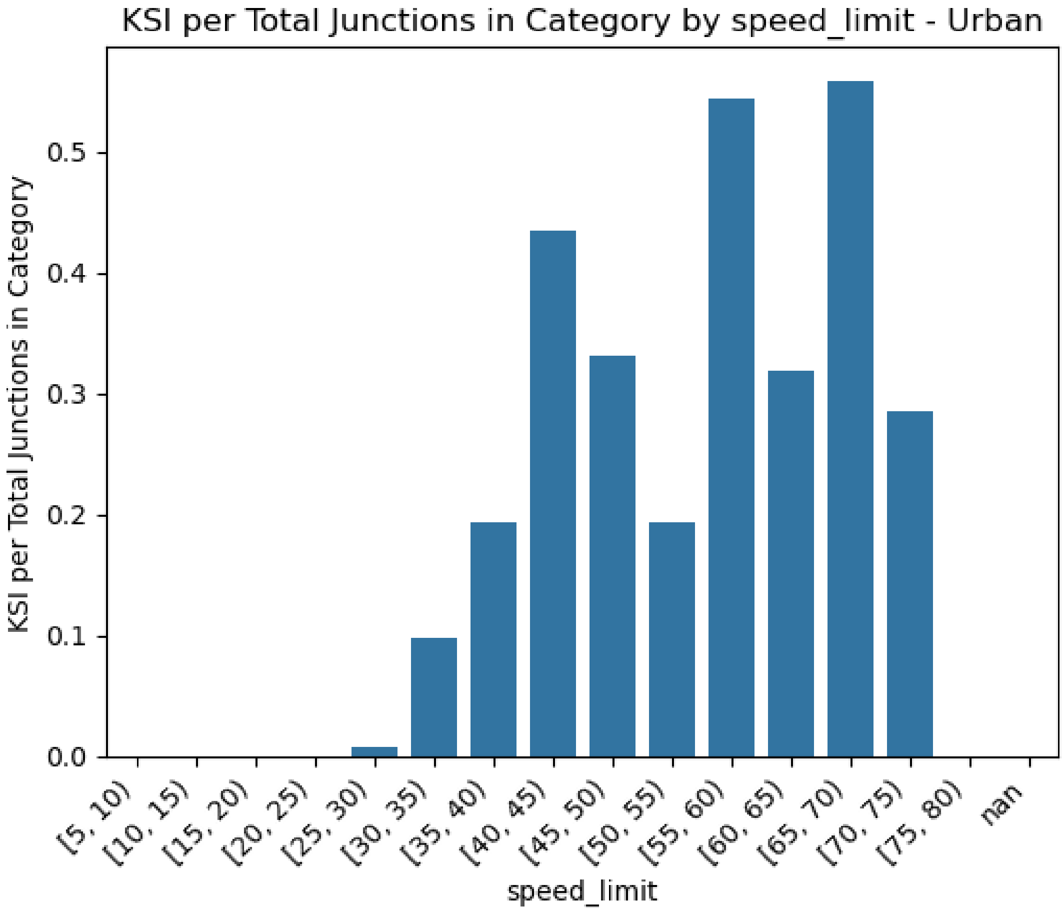

KSI per Total Junctions in Category by lane_width - Rural
KSI per Total Junctions in Category
0.00
0.02
0.04
0.06
0.08
0.10
0.12
[6, 7)
[7, 8)
[8, 9)
[9, 10)
[10, 11)
[11, 12)
[12, 13)
[13, 14)
[14, 15)
[15, 16)
[16, 17)
[17, 18)
[18, 19)
nan
lane_width

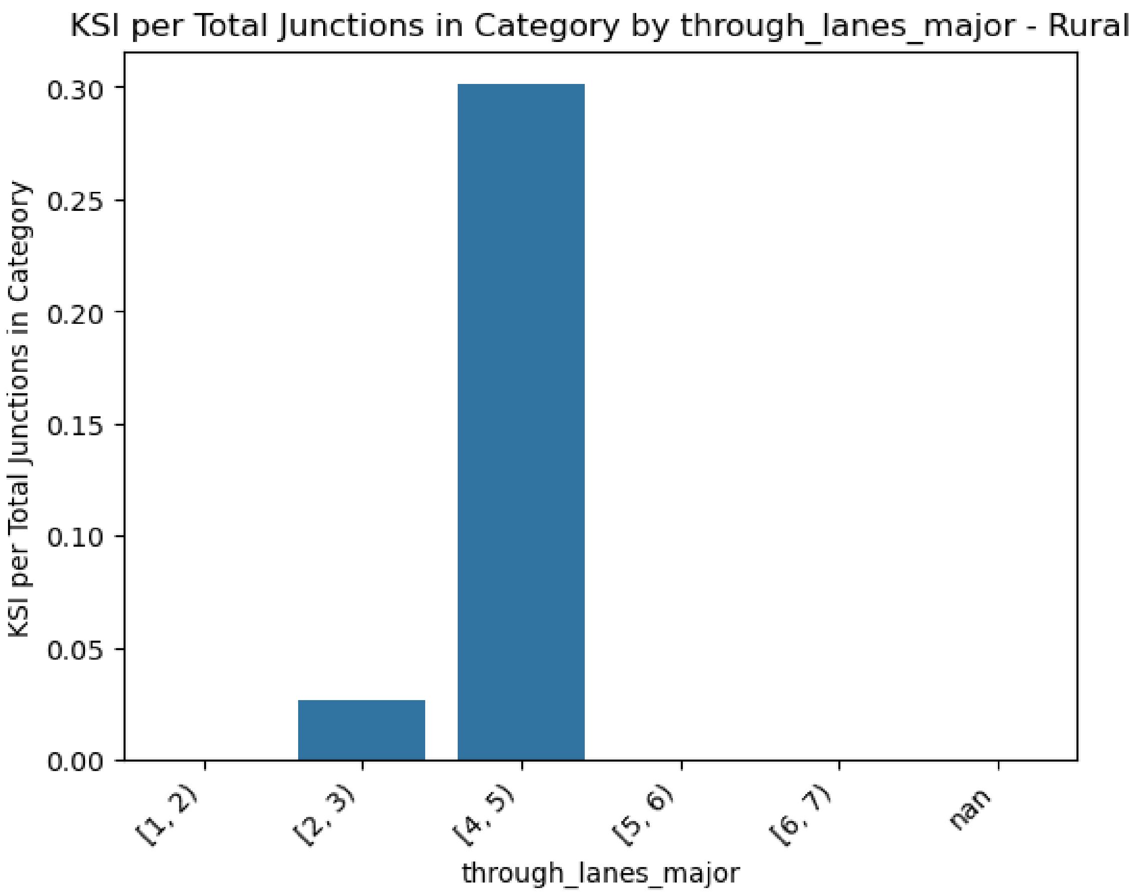

KSI per Total Junctions in Category by lane_width - Urban
KSI per Total Junctions in Category
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0.14
0.16
[6, 7)
[7, 8)
[8, 9)
[9, 10)
[10, 11)
[11, 12)
[12, 13)
[13, 14)
[14, 15)
[15, 16)
[16, 17)
[17, 18)
[18, 19)
nan
lane_width

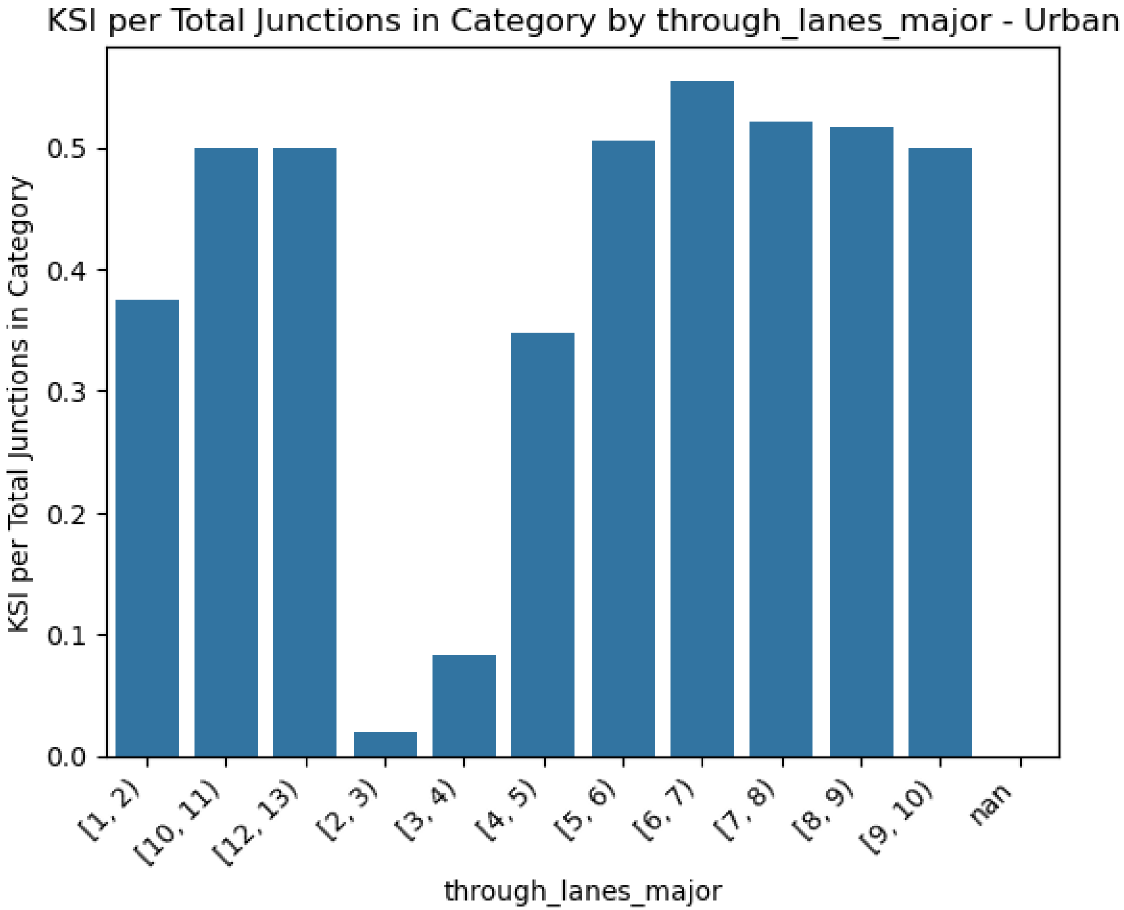

KSI per Total Junctions in Category by lighting - Rural
KSI per Total Junctions in Category
0.00
0.02
0.04
0.06
0.08
No
Unknown
Yes
lighting

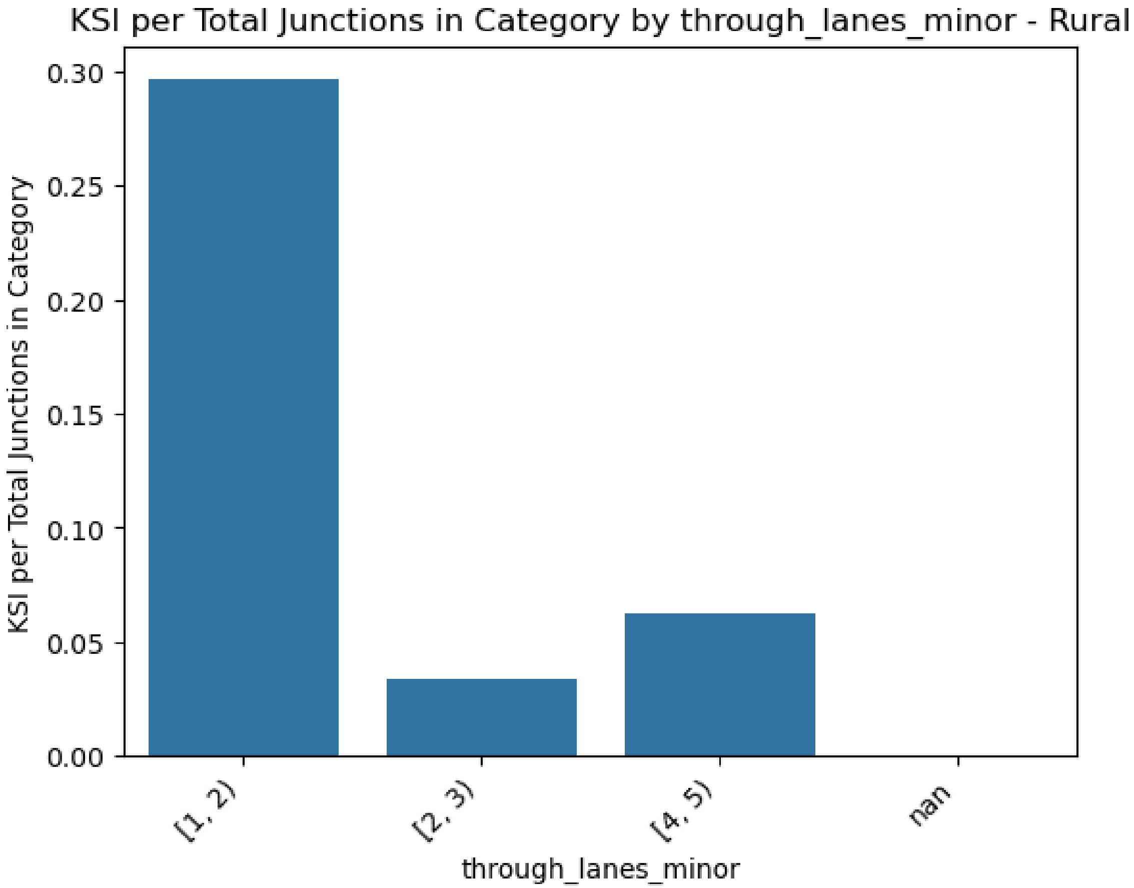

KSI per Total Junctions in Category by lighting - Urban
KSI per Total Junctions in Category
0.00
0.02
0.04
0.06
0.08
0.10
No
Unknown
Yes
lighting

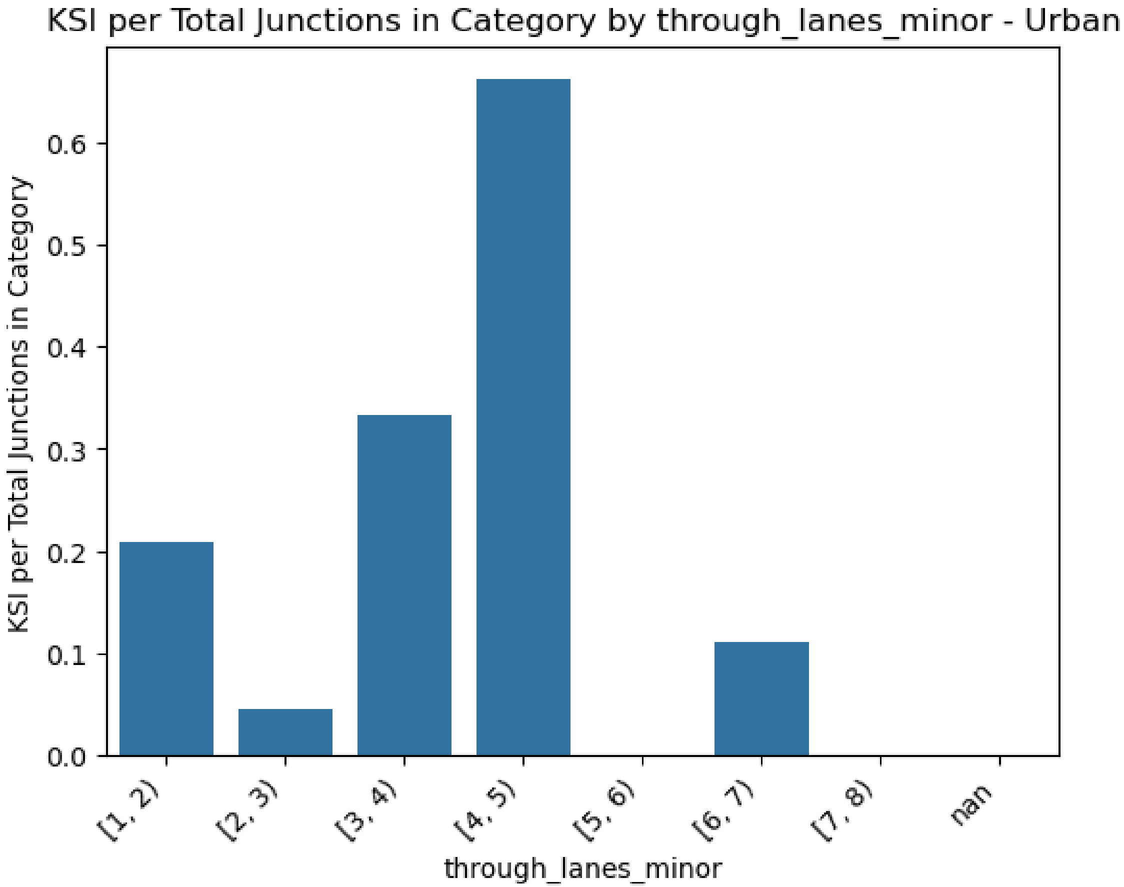

KSI per Total Junctions in Category by speed_limit - Rural
KSI per Total Junctions in Category
0.0
0.1
0.2
0.3
0.4
0.5
[15, 20)
[20, 25)
[25, 30)
[30, 35)
[35, 40)
[40, 45)
[45, 50)
[50, 55)
[55, 60)
[60, 65)
[65, 70)
[70, 75)
[75, 80)
nan
speed_limit

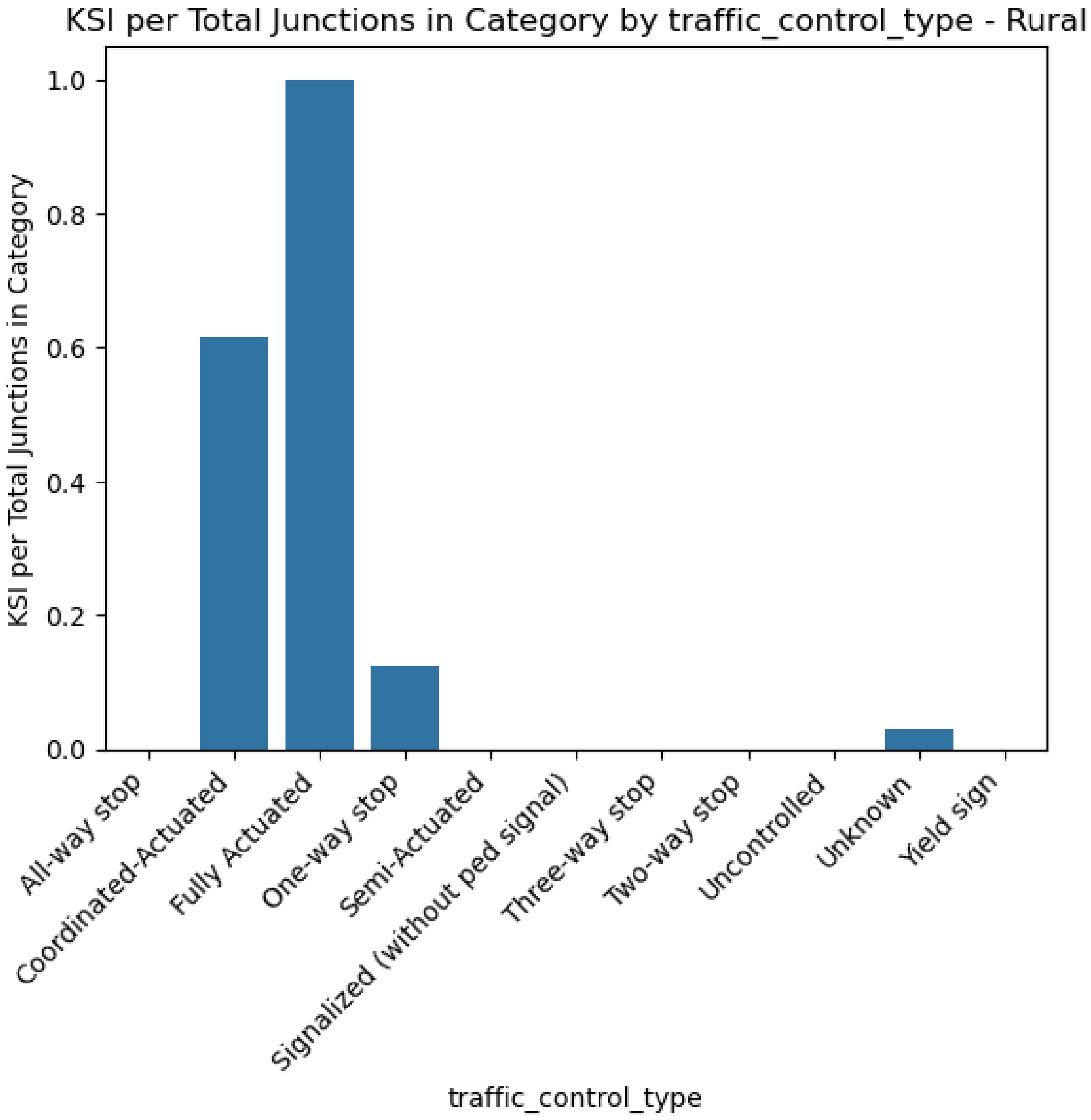

KSI per Total Junctions in Category by speed_limit - Urban
KSI per Total Junctions in Category
0.0
0.1
0.2
0.3
0.4
0.5
[5, 10)
[10, 15)
[15, 20)
[20, 25)
[25, 30)
[30, 35)
[35, 40)
[40, 45)
[45, 50)
[50, 55)
[55, 60)
[60, 65)
[65, 70)
[70, 75)
[75, 80)
nan
speed_limit

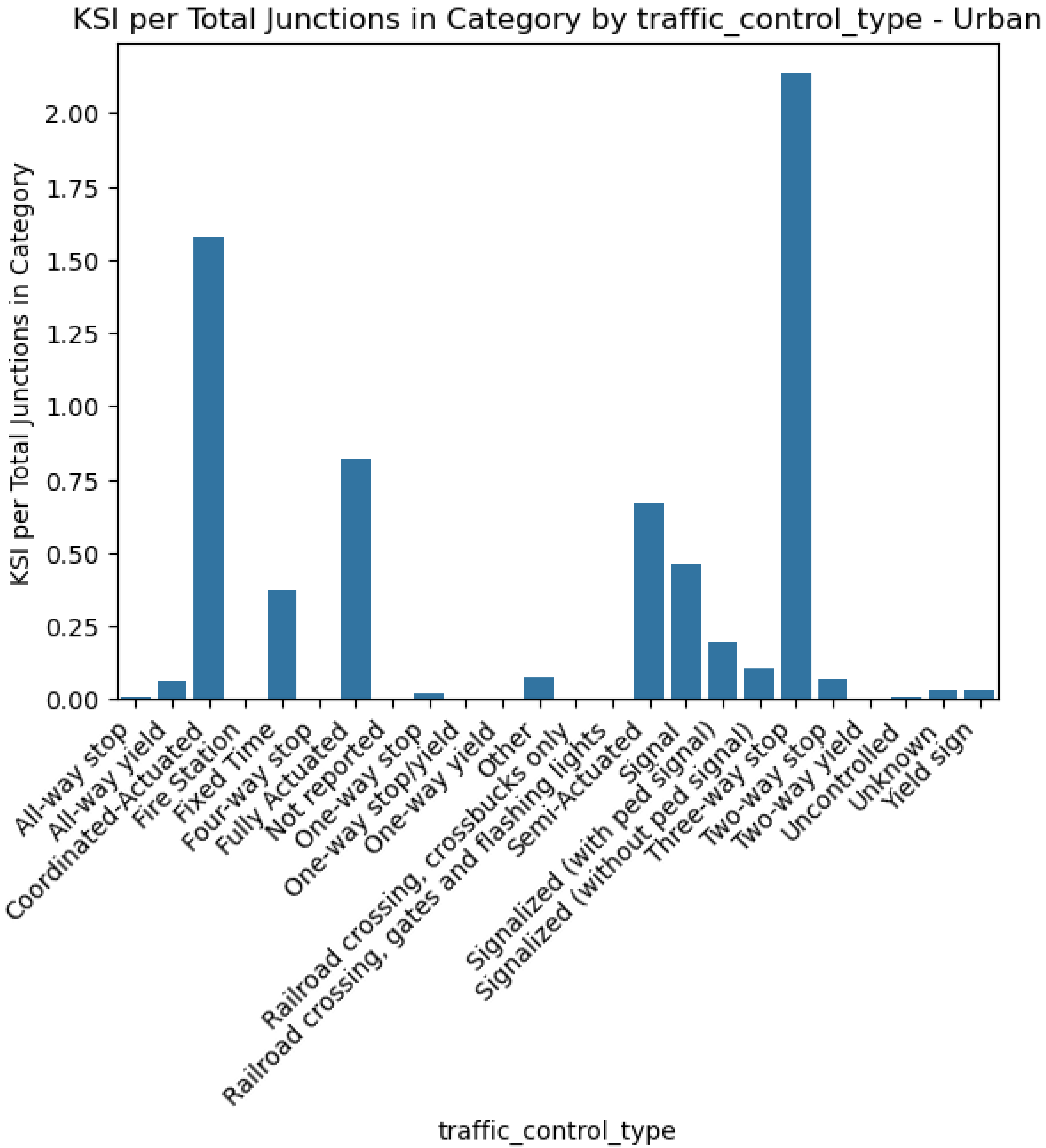

KSI per Total Junctions in Category by through_lanes_major - Rural
KSI per Total Junctions in Category
0.30
0.25
0.20
0.15
0.10
0.05
0.00
[1, 2)
[2, 3)
[4, 5)
[5, 6)
[6, 7)
nan
through_lanes_major

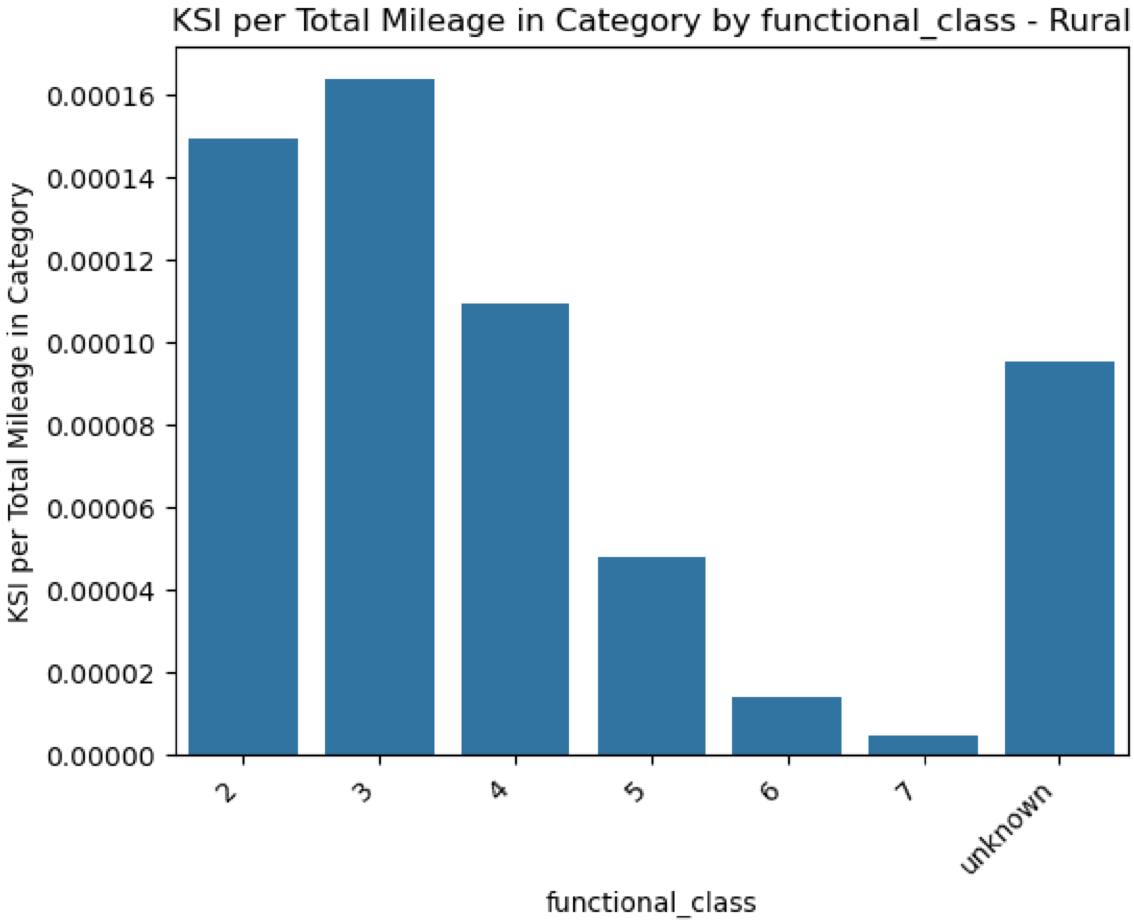

KSI per Total Junctions in Category by through_lanes_major - Urban
KSI per Total Junctions in Category
0.0
0.1
0.2
0.3
0.4
0.5
[1, 2)
[10, 11)
[12, 13)
[2, 3)
[3, 4)
[4, 5)
[5, 6)
[6, 7)
[7, 8)
[8, 9)
[9, 10)
nan
through_lanes_major

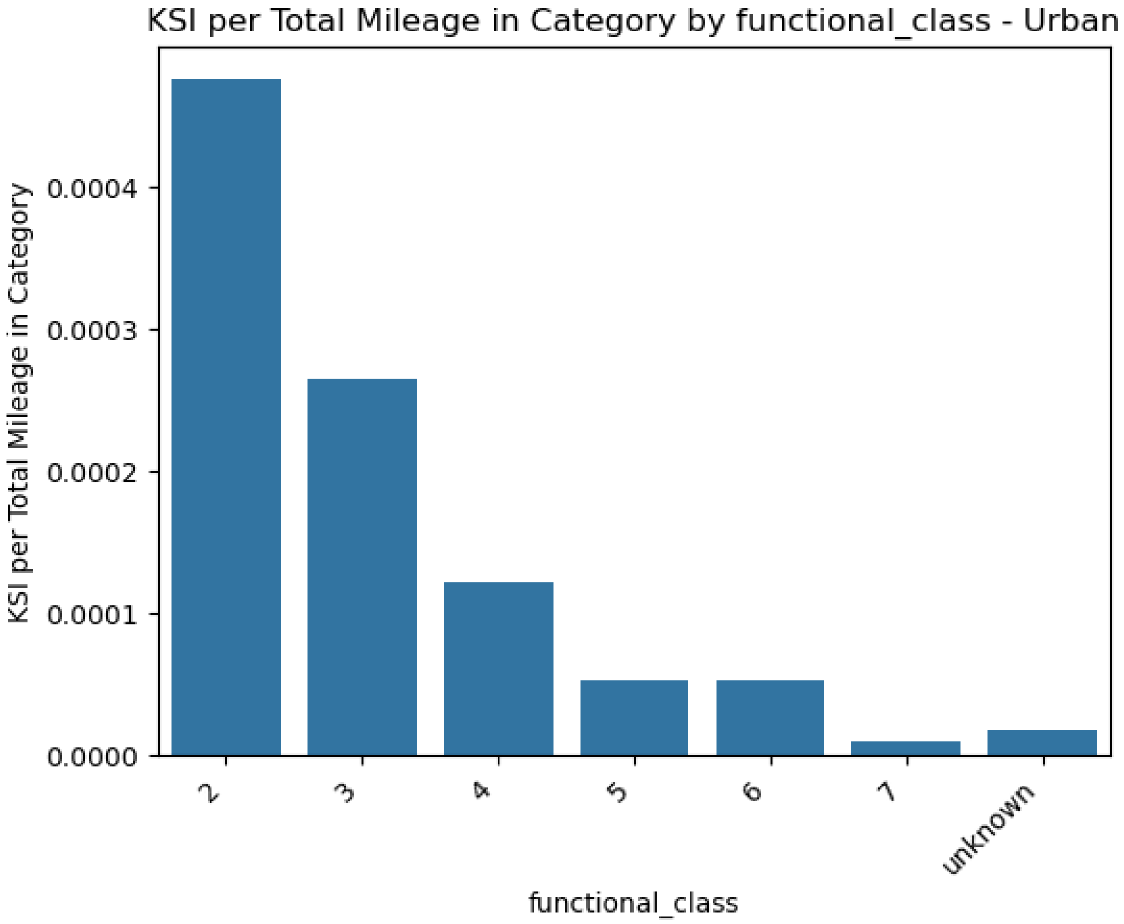

KSI per Total Junctions in Category by through_lanes_minor - Rural
KSI per Total Junctions in Category
0.30
0.25
0.20
0.15
0.10
0.05
0.00
[1, 2)
[2, 3)
[4, 5)
nan
through_lanes_minor

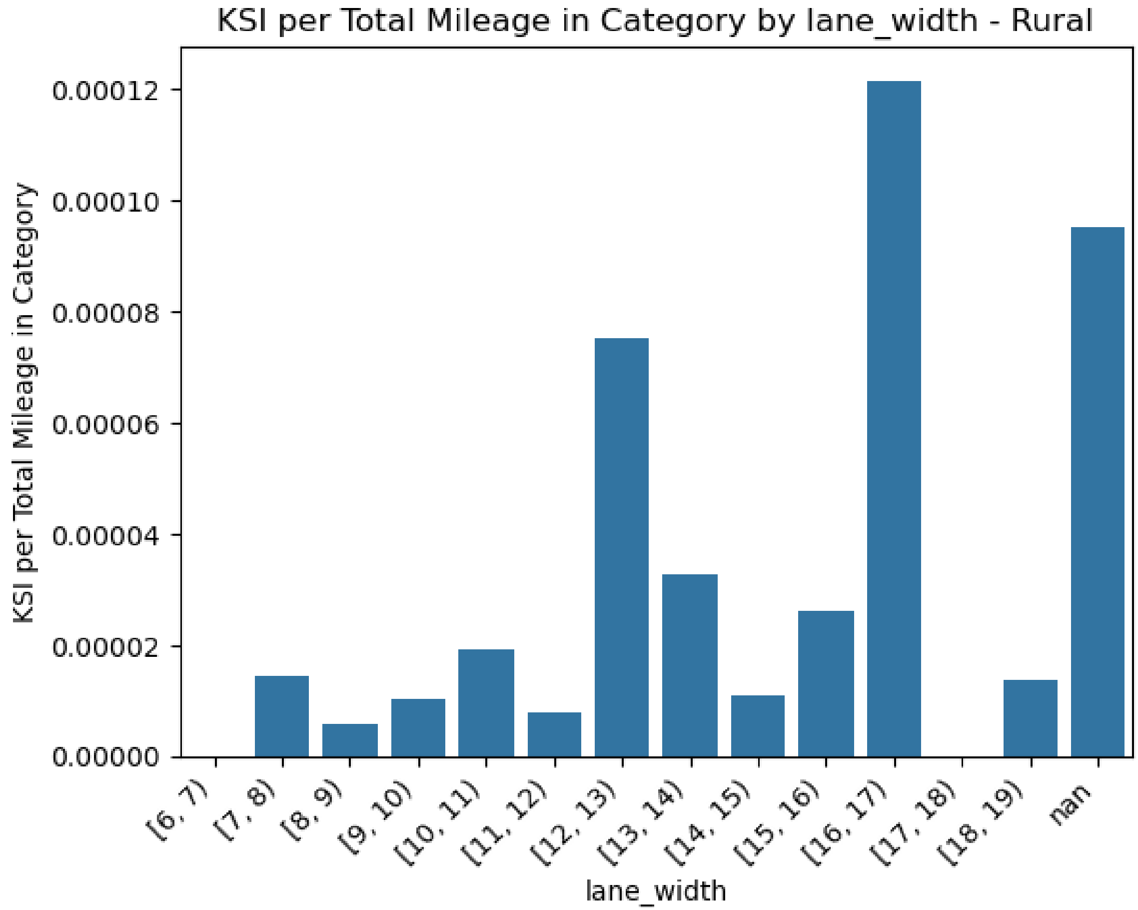

KSI per Total Junctions in Category by through_lanes_minor - Urban
KSI per Total Junctions in Category
0.0
0.1
0.2
0.3
0.4
0.5
0.6
[1, 2)
[2, 3)
[3, 4)
[4, 5)
[5, 6)
[6, 7)
[7, 8)
nan
through_lanes_minor

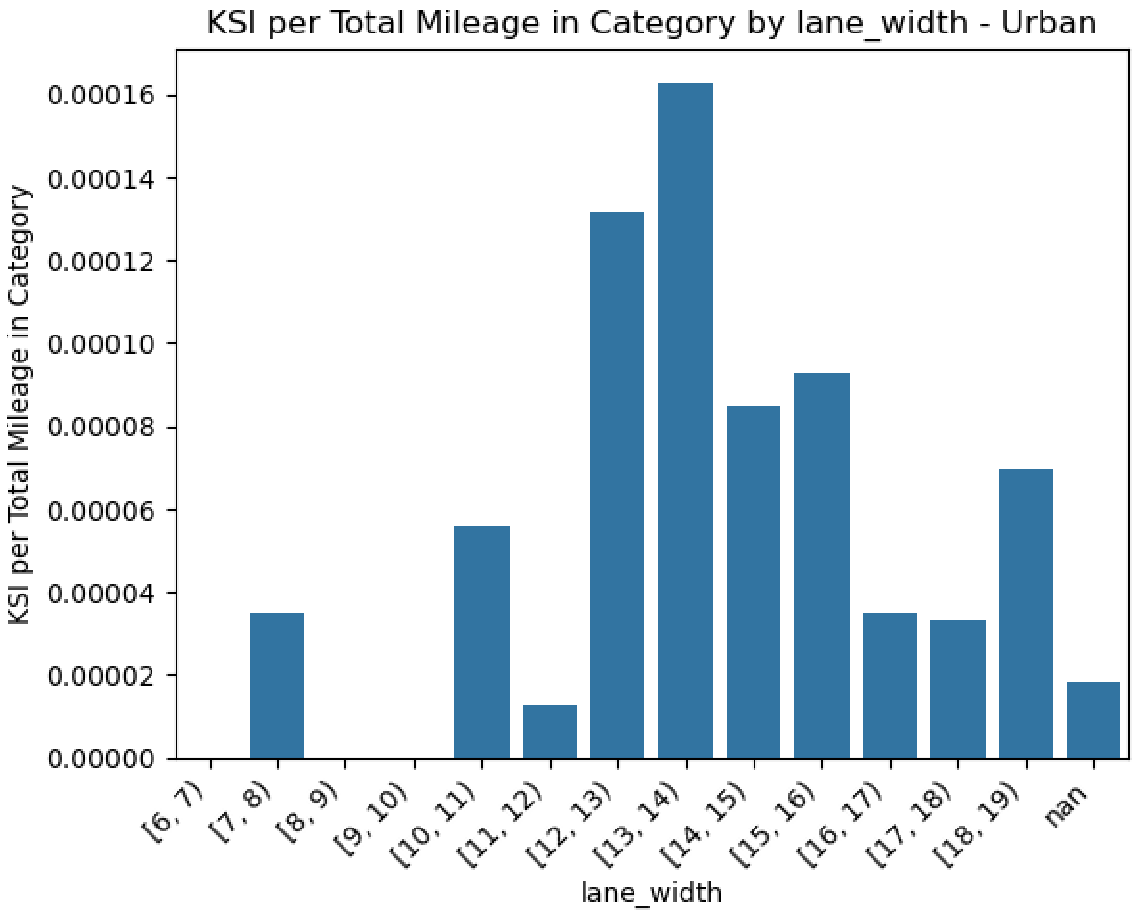

KSI per Total Junctions in Category by traffic_control_type - Rural
KSI per Total Junctions in Category
1.0
0.8
0.6
0.4
0.2
0.0
All-way stop
Coordinated-Actuated
Fully Actuated
One-way stop
Semi-Actuated
Signalized (without ped signal)
Three-way stop
Two-way stop
Uncontrolled
Unknown
Yield sign
traffic_control_type

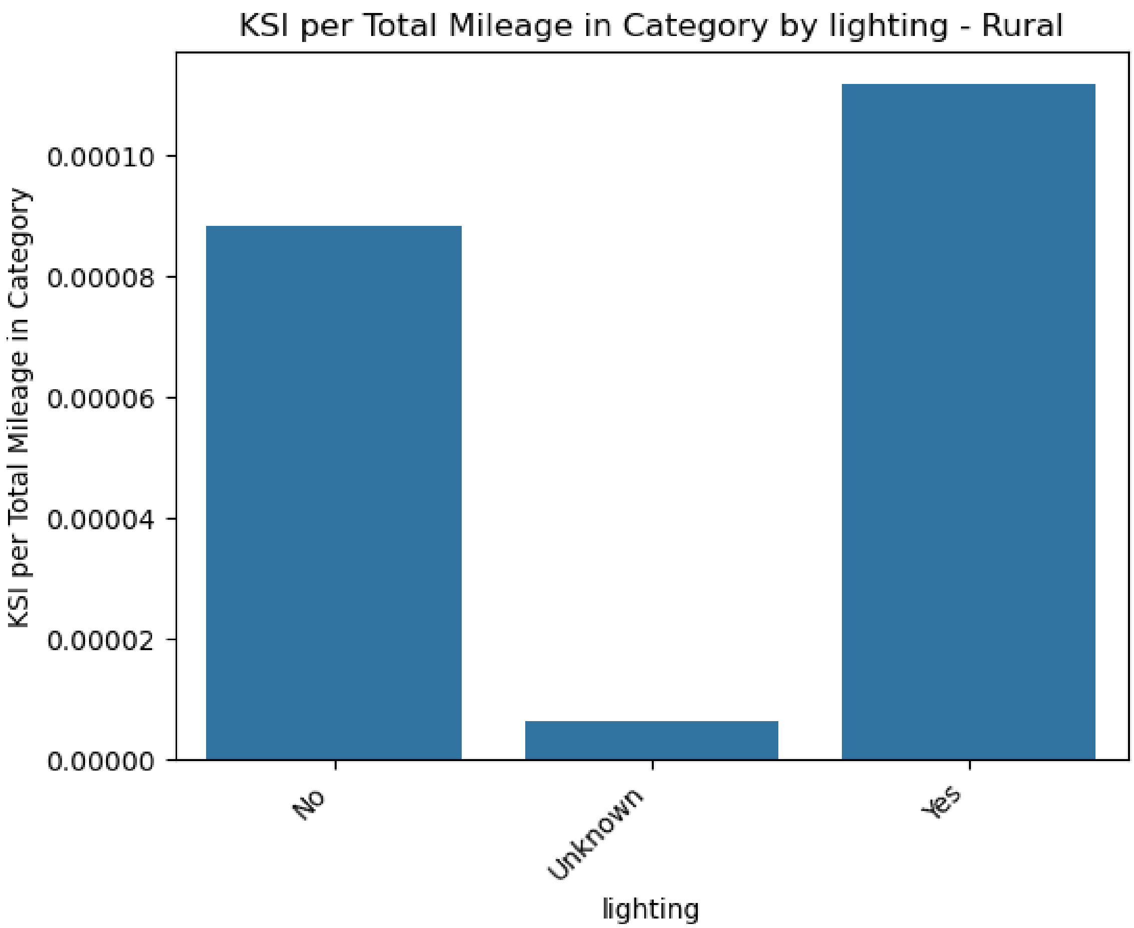

KSI per Total Junctions in Category by traffic_control_type - Urban
KSI per Total Junctions in Category
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
All-way stop
All-way yield
Coordinated-Actuated
Fire Station
Fixed Time
Four-way stop
Fully Actuated
Not reported
One-way stop
One-way stop/yield
One-way yield
Other
Railroad crossing, crossbucks only
Railroad crossing, gates and flashing lights
Semi-Actuated
Signal
Signalized (with ped signal)
Signalized (without ped signal)
Three-way stop
Two-way stop
Two-way yield
Uncontrolled
Unknown
Yield sign
traffic_control_type

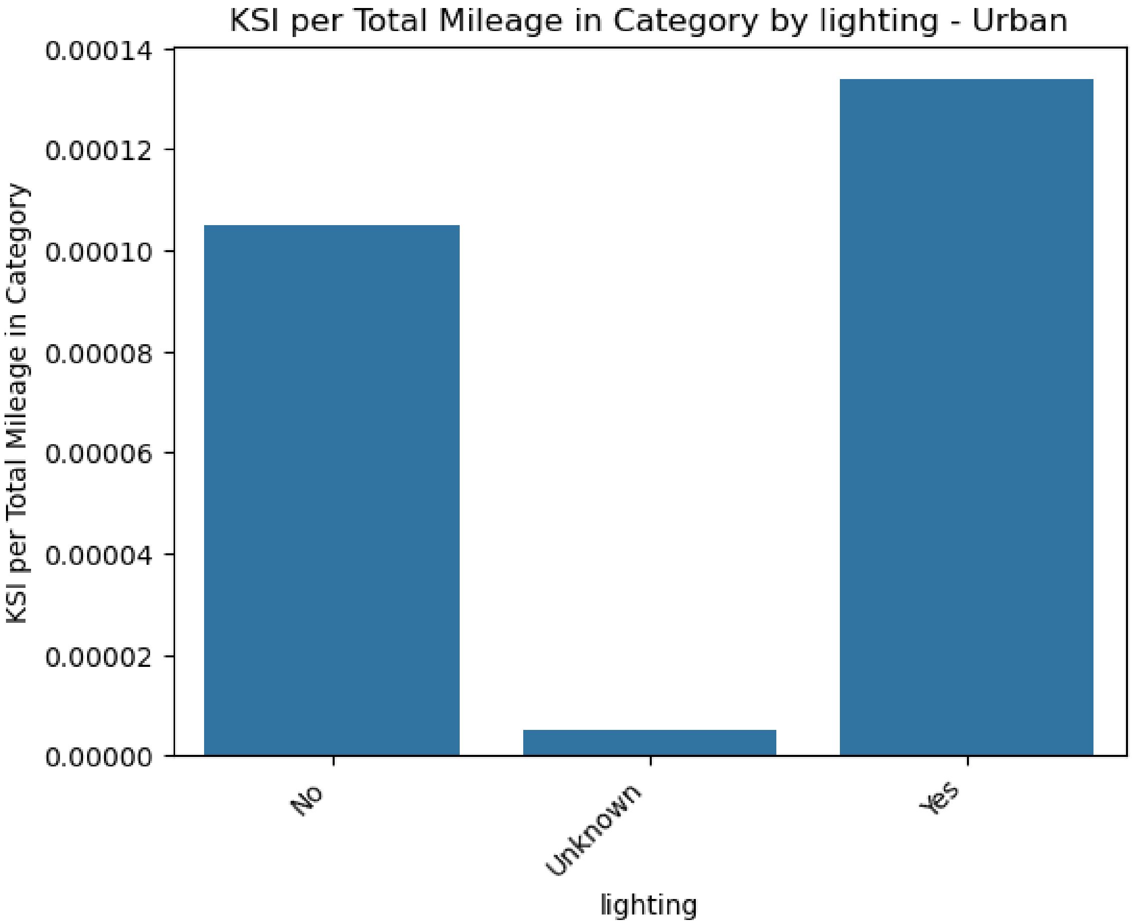

KSI per Total Mileage in Category by functional_class - Rural
KSI per Total Mileage in Category
0.00016
0.00014
0.00012
0.00010
0.00008
0.00006
0.00004
0.00002
0.00000
2
3
4
5
6
7
unknown
functional_class

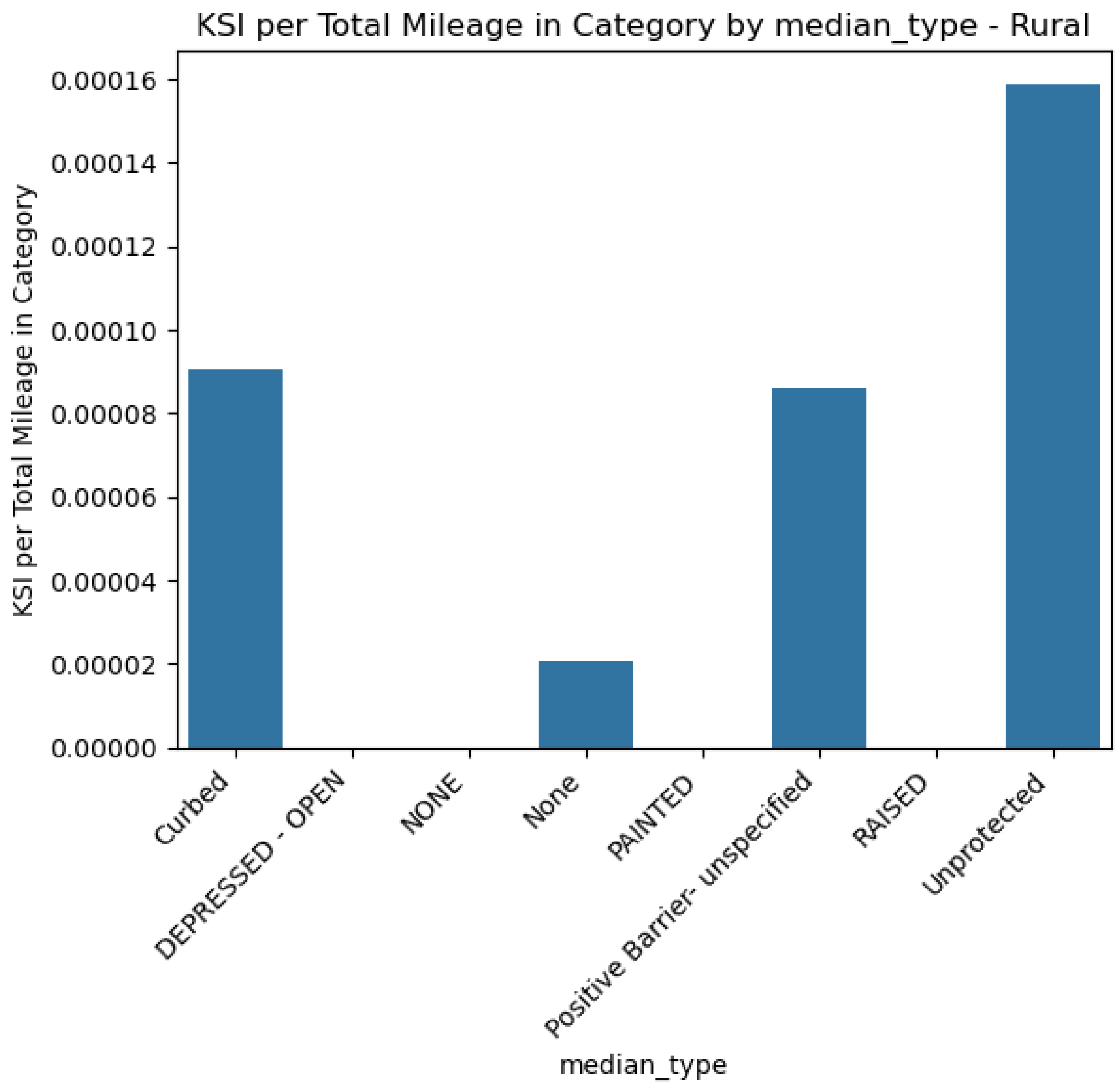

KSI per Total Mileage in Category by functional_class - Urban
KSI per Total Mileage in Category
0.0000
0.0001
0.0002
0.0003
0.0004
2
3
4
5
6
7
unknown
functional_class

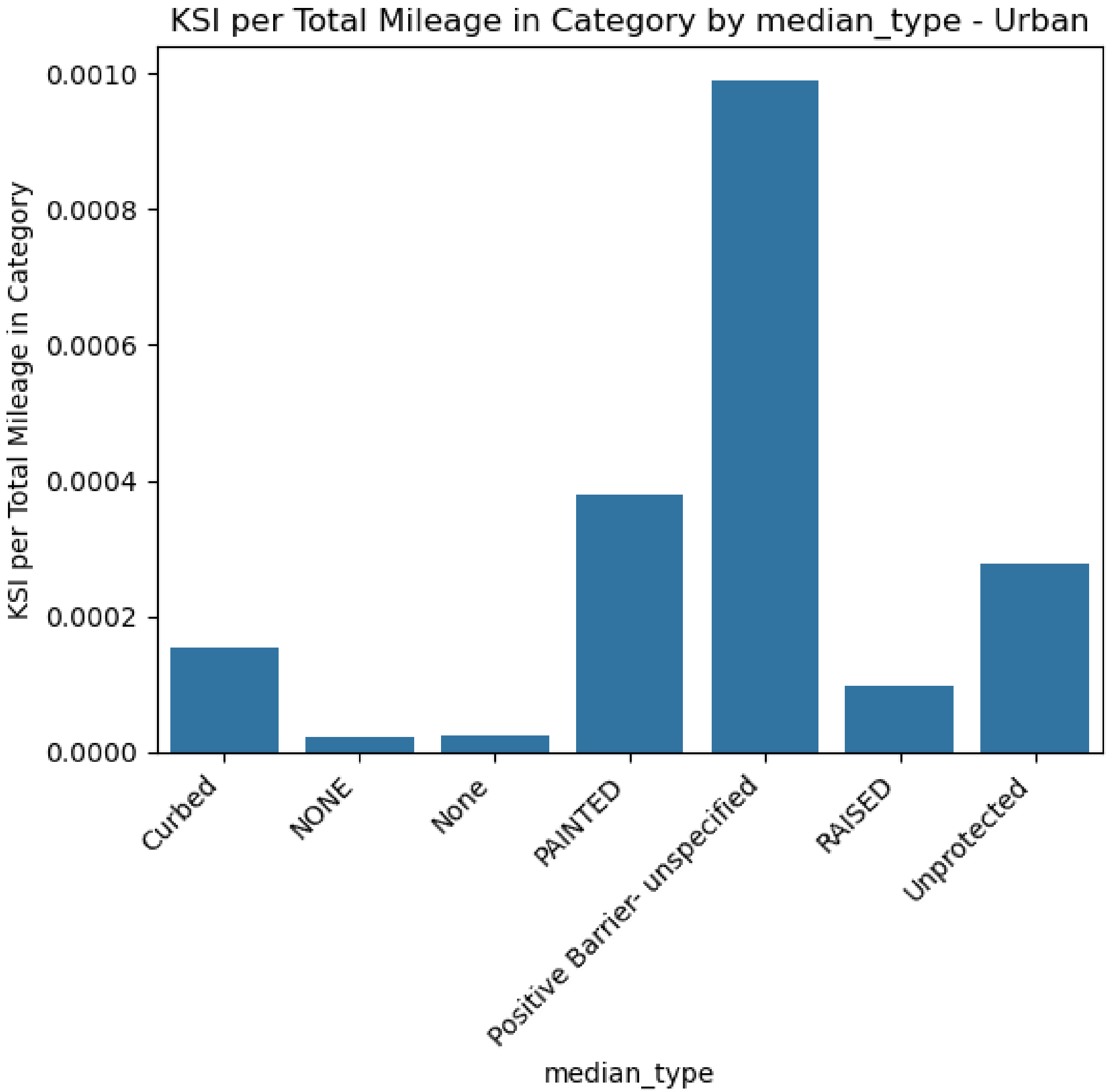

KSI per Total Mileage in Category by lane_width - Rural
KSI per Total Mileage in Category
0.00012
0.00010
0.00008
0.00006
0.00004
0.00002
0.00000
[6, 7)
[7, 8)
[8, 9)
[9, 10)
[10, 11)
[11, 12)
[12, 13)
[13, 14)
[14, 15)
[15, 16)
[16, 17)
[17, 18)
[18, 19)
nan
lane_width

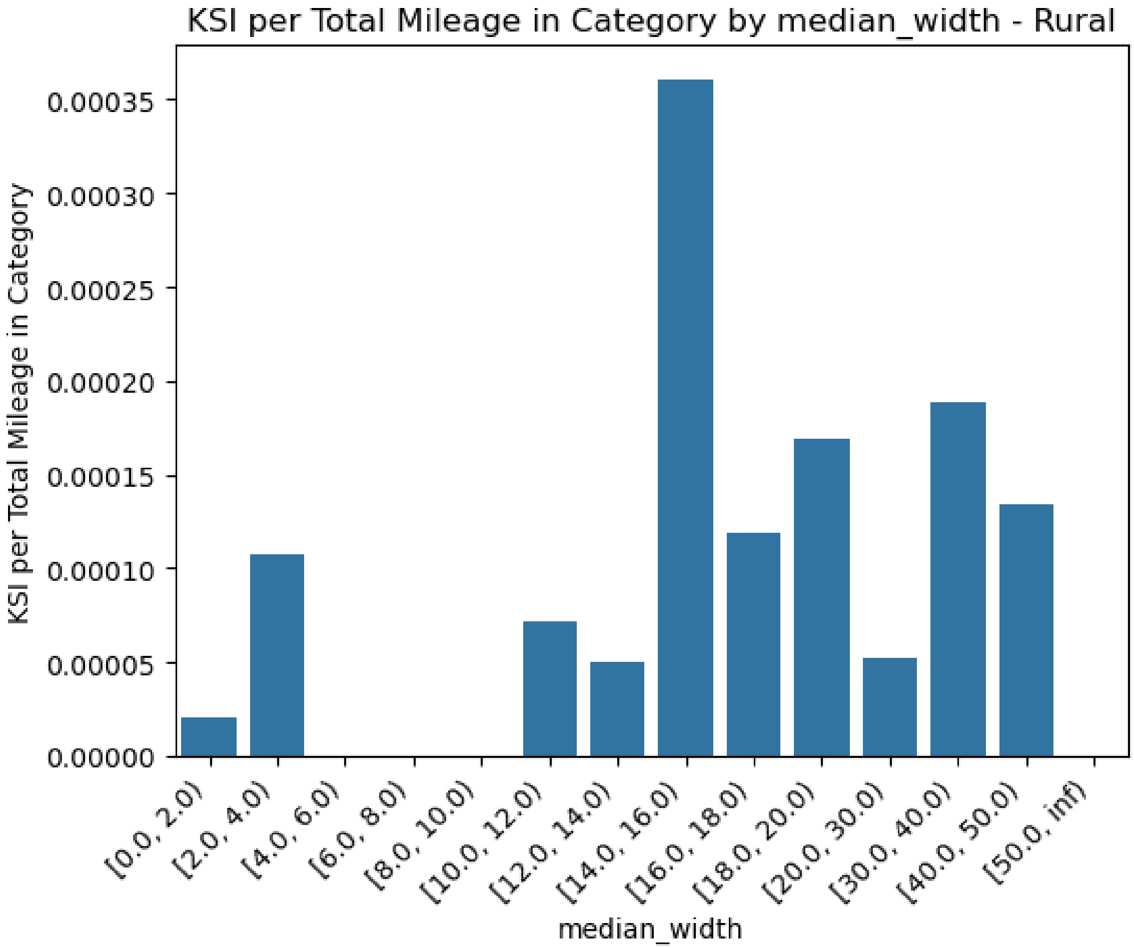

KSI per Total Mileage in Category by lane_width - Urban
KSI per Total Mileage in Category
0.00016
0.00014
0.00012
0.00010
0.00008
0.00006
0.00004
0.00002
0.00000
[6, 7)
[7, 8)
[8, 9)
[9, 10)
[10, 11)
[11, 12)
[12, 13)
[13, 14)
[14, 15)
[15, 16)
[16, 17)
[17, 18)
[18, 19)
nan
lane_width

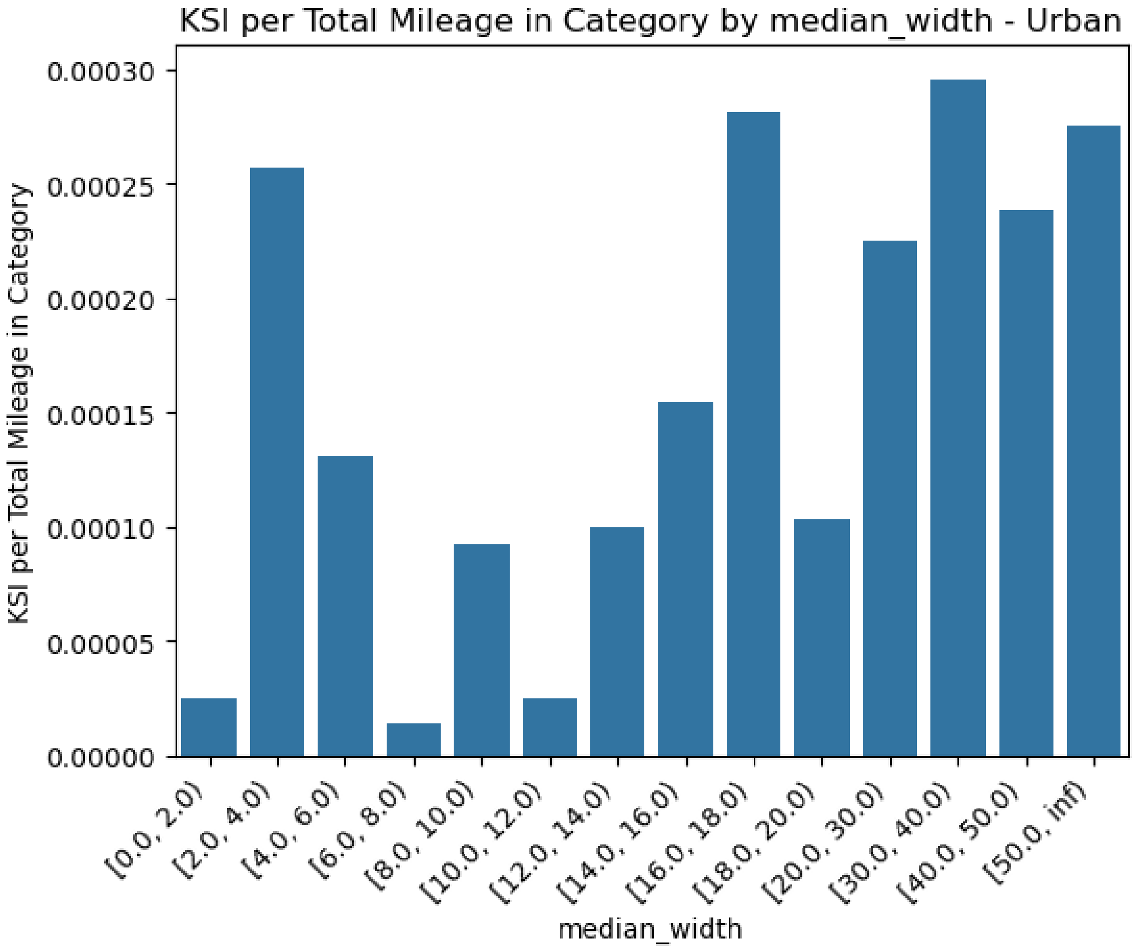

KSI per Total Mileage in Category by lighting - Rural
KSI per Total Mileage in Category
0.00010
0.00008
0.00006
0.00004
0.00002
0.00000
No
Unknown
Yes
lighting

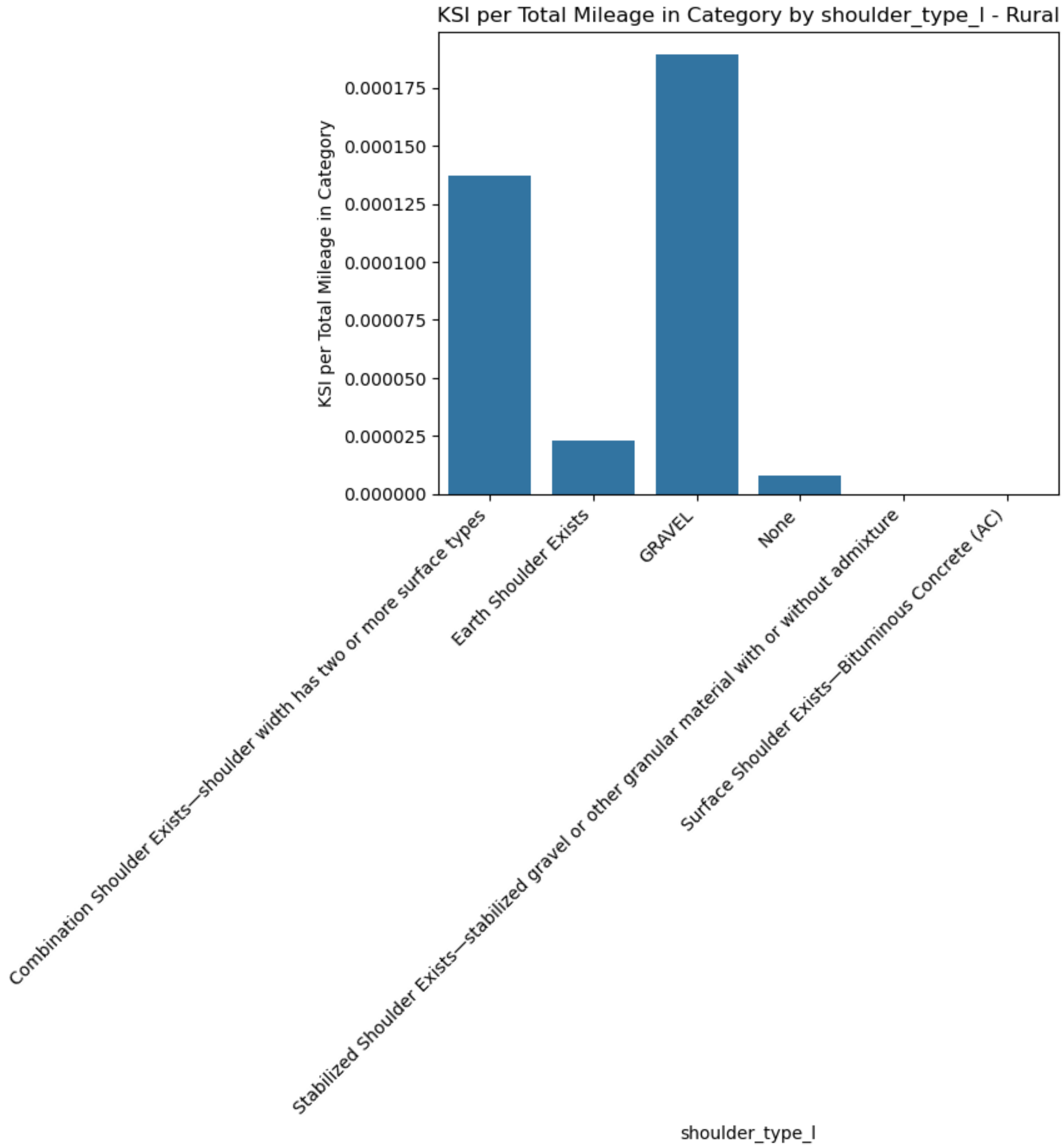

KSI per Total Mileage in Category by lighting - Urban
KSI per Total Mileage in Category
0.00014
0.00012
0.00010
0.00008
0.00006
0.00004
0.00002
0.00000
No
Unknown
Yes
lighting

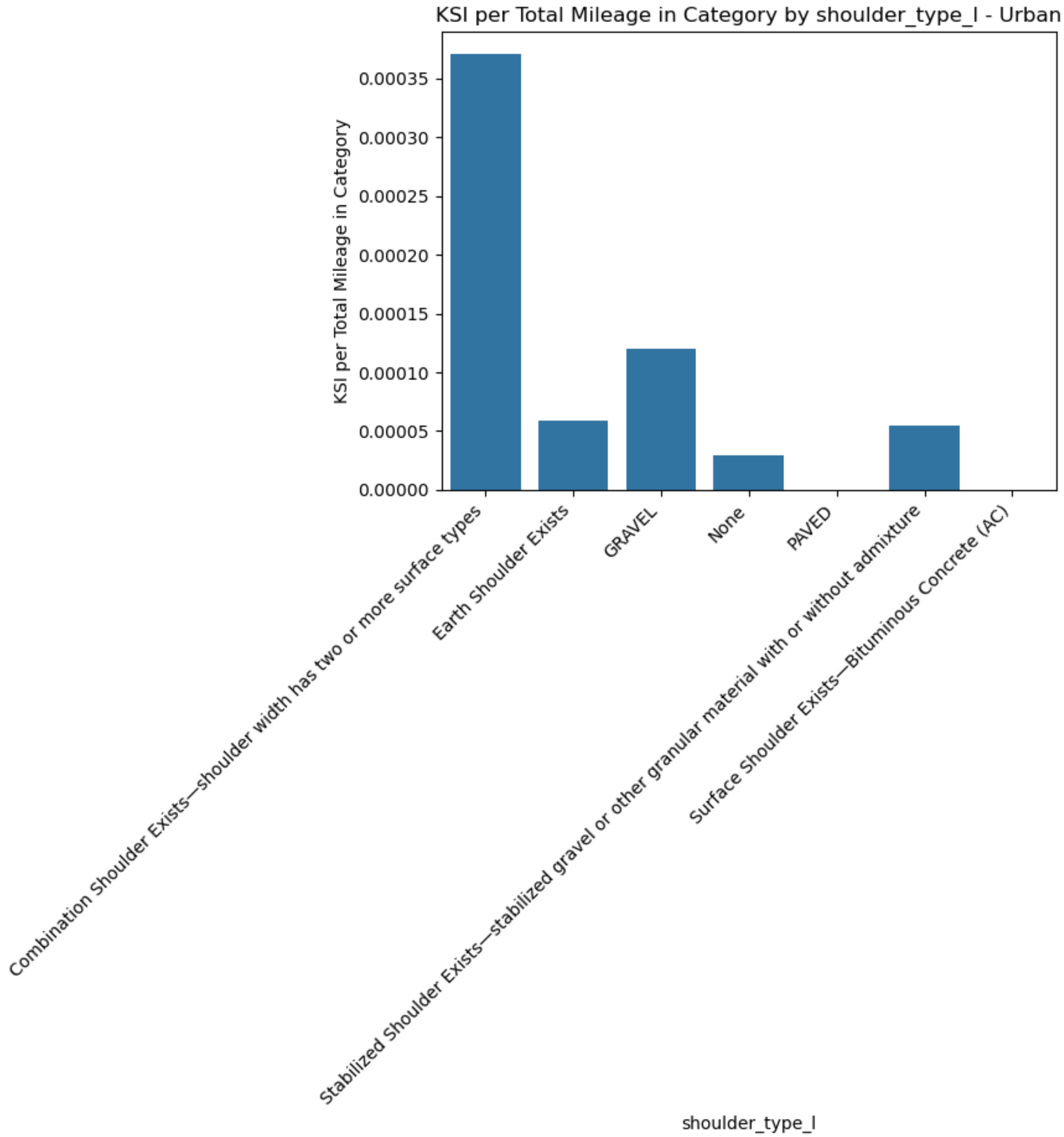

KSI per Total Mileage in Category by median_type - Rural
KSI per Total Mileage in Category
0.00016
0.00014
0.00012
0.00010
0.00008
0.00006
0.00004
0.00002
0.00000
Curbed
DEPRESSED - OPEN
NONE
None
PAINTED
Positive Barrier- unspecified
RAISED
Unprotected
median_type

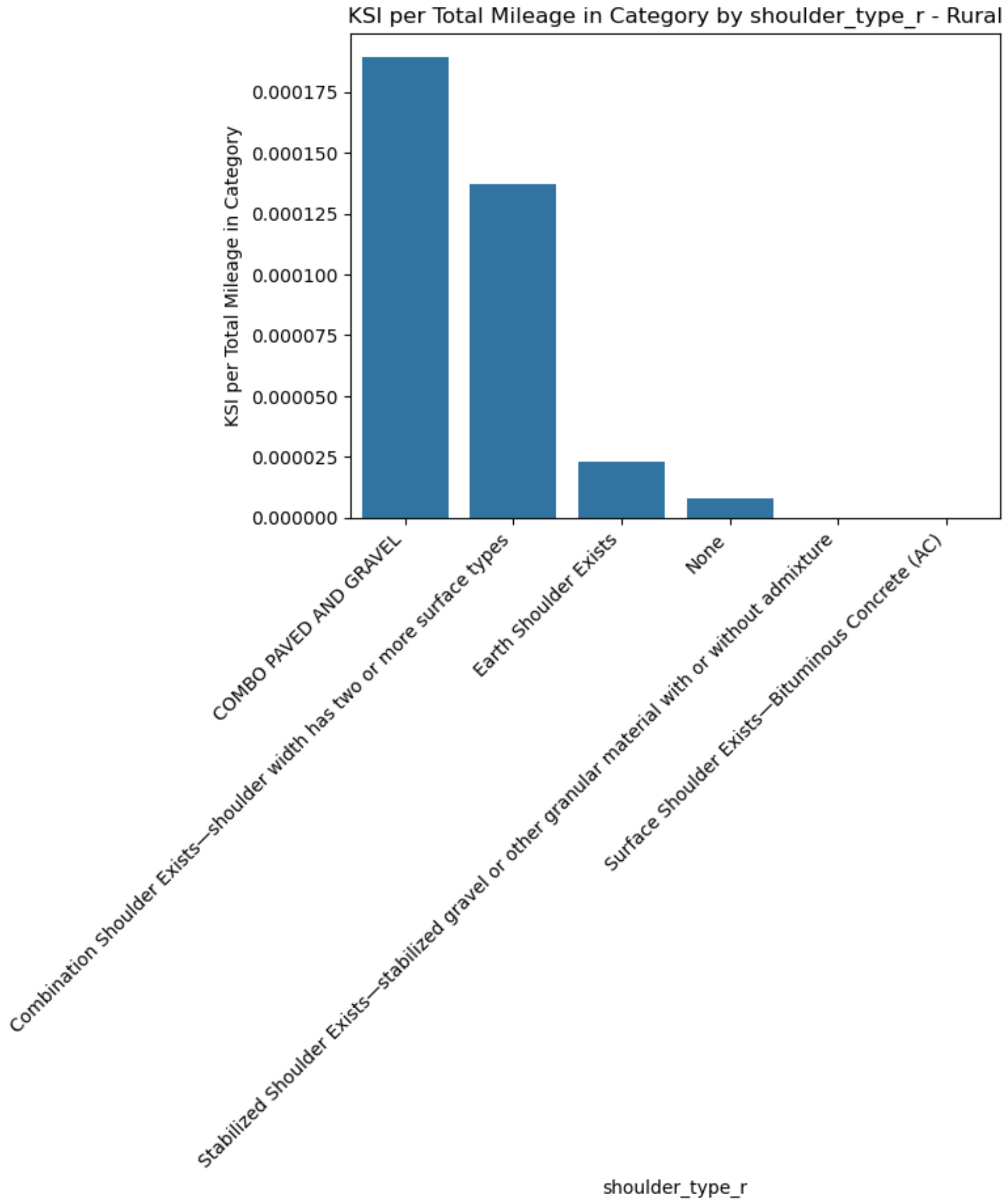

KSI per Total Mileage in Category by median_type - Urban
KSI per Total Mileage in Category
0.0010
0.0008
0.0006
0.0004
0.0002
0.0000
Curbed
NONE
None
PAINTED
Positive Barrier- unspecified
RAISED
Unprotected
median_type

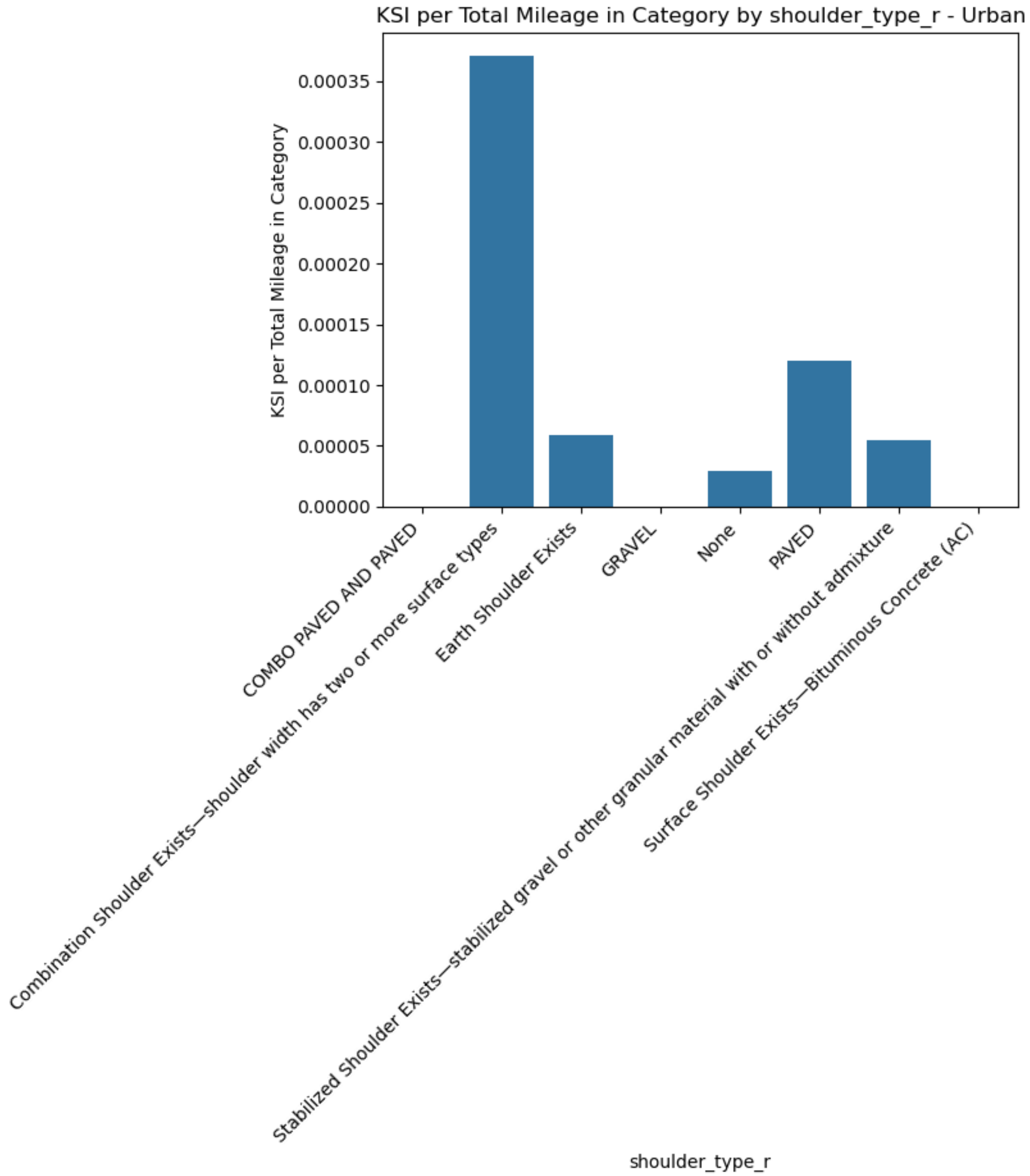

KSI per Total Mileage in Category by median_width - Rural
KSI per Total Mileage in Category
0.00035
0.00030
0.00025
0.00020
0.00015
0.00010
0.00005
0.00000
[0.0, 2.0)
[2.0, 4.0)
[4.0, 6.0)
[6.0, 8.0)
[8.0, 10.0)
[10.0, 12.0)
[12.0, 14.0)
[14.0, 16.0)
[16.0, 18.0)
[18.0, 20.0)
[20.0, 30.0)
[30.0, 40.0)
[40.0, 50.0)
[50.0, inf)
median_width

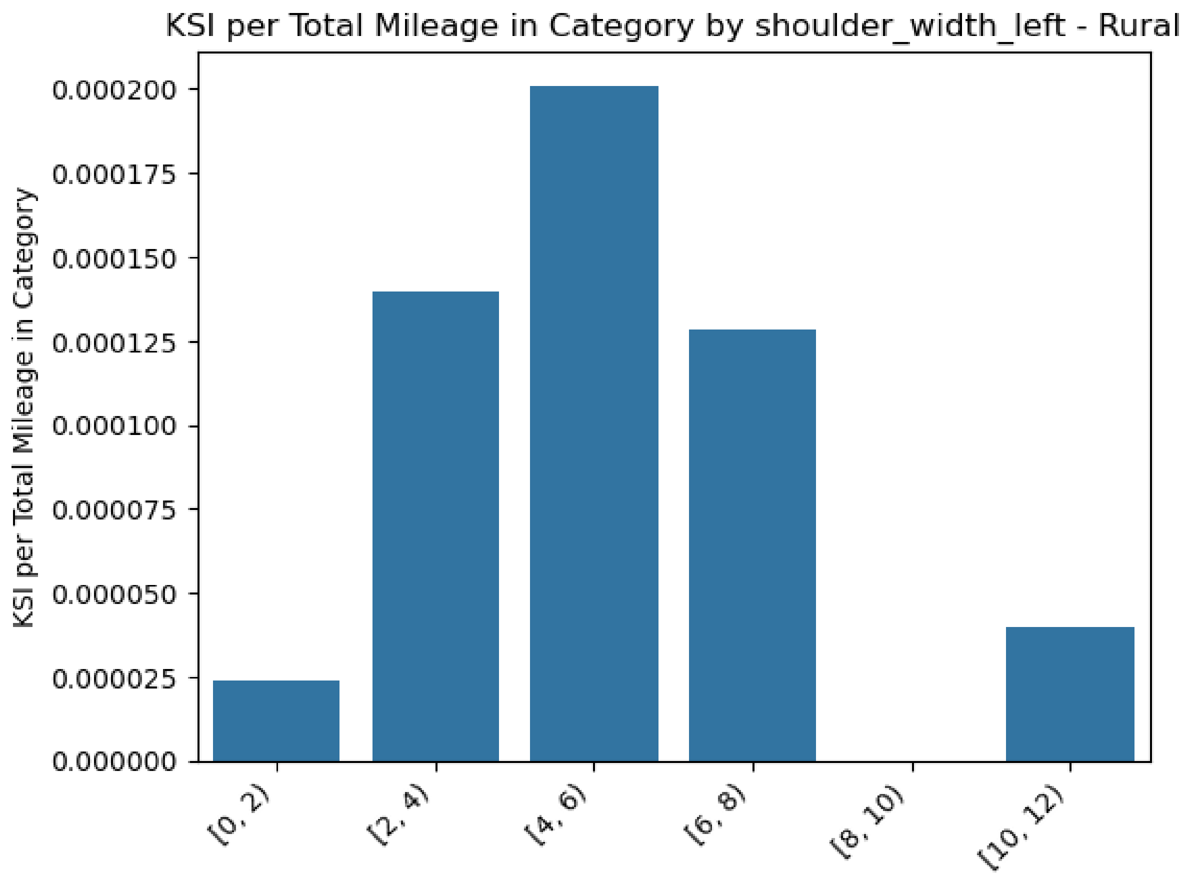

KSI per Total Mileage in Category by median_width - Urban
KSI per Total Mileage in Category
0.00030
0.00025
0.00020
0.00015
0.00010
0.00005
0.00000
[0.0, 2.0)
[2.0, 4.0)
[4.0, 6.0)
[6.0, 8.0)
[8.0, 10.0)
[10.0, 12.0)
[12.0, 14.0)
[14.0, 16.0)
[16.0, 18.0)
[18.0, 20.0)
[20.0, 30.0)
[30.0, 40.0)
[40.0, 50.0)
[50.0, inf)
median_width

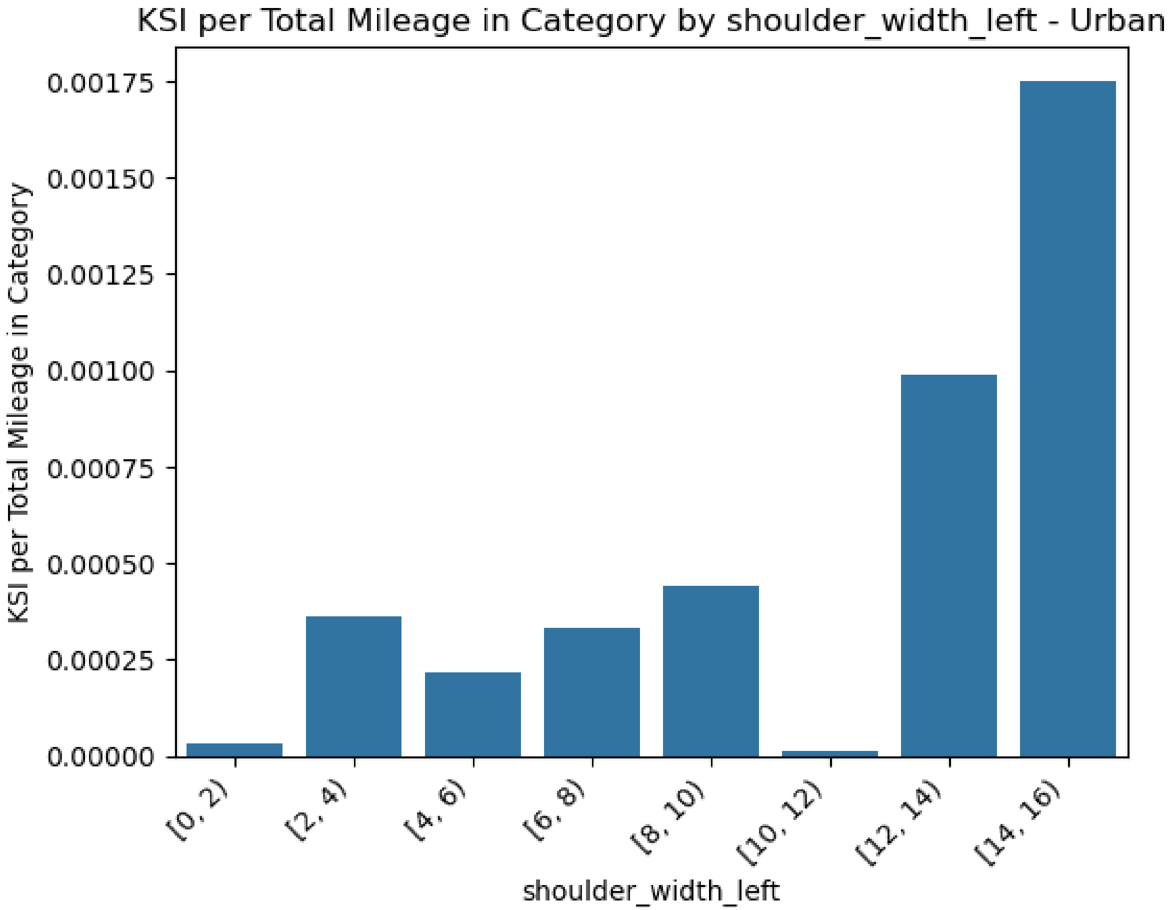

KSI per Total Mileage in Category by shoulder_type_I - Rural
KSI per Total Mileage in Category
0.000000
0.000025
0.000050
0.000075
0.000100
0.000125
0.000150
0.000175
Combination Shoulder Exists—shoulder width has two or more surface types
Earth Shoulder Exists
GRAVEL
None
Stabilized Shoulder Exists—stabilized gravel or other granular material with or without admixture
Surface Shoulder Exists—Bituminous Concrete (AC)
shoulder_type_I

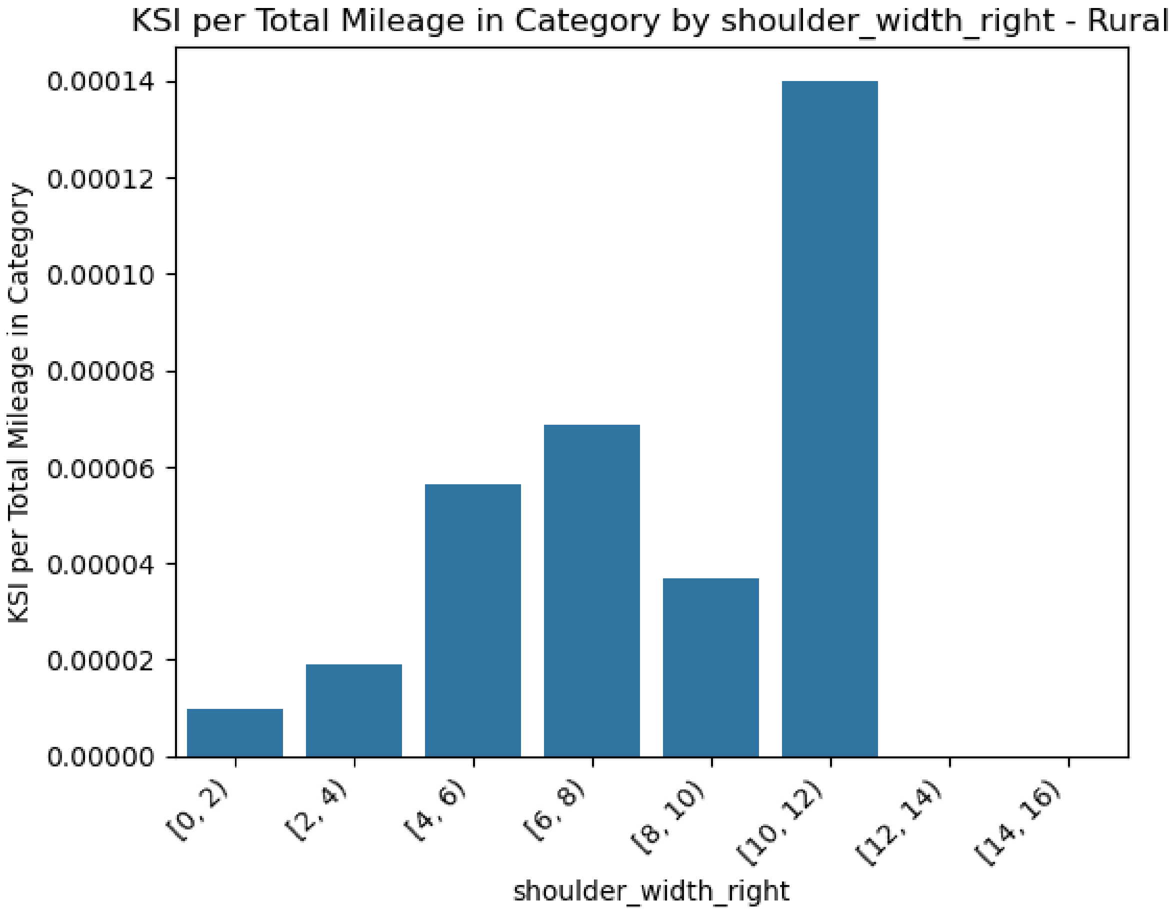

KSI per Total Mileage in Category by shoulder_type_I - Urban
KSI per Total Mileage in Category
0.00035
0.00030
0.00025
0.00020
0.00015
0.00010
0.00005
0.00000
Combination Shoulder Exists—shoulder width has two or more surface types
Earth Shoulder Exists
GRAVEL
None
PAVED
Stabilized Shoulder Exists—stabilized gravel or other granular material with or without admixture
Surface Shoulder Exists—Bituminous Concrete (AC)
shoulder_type_I

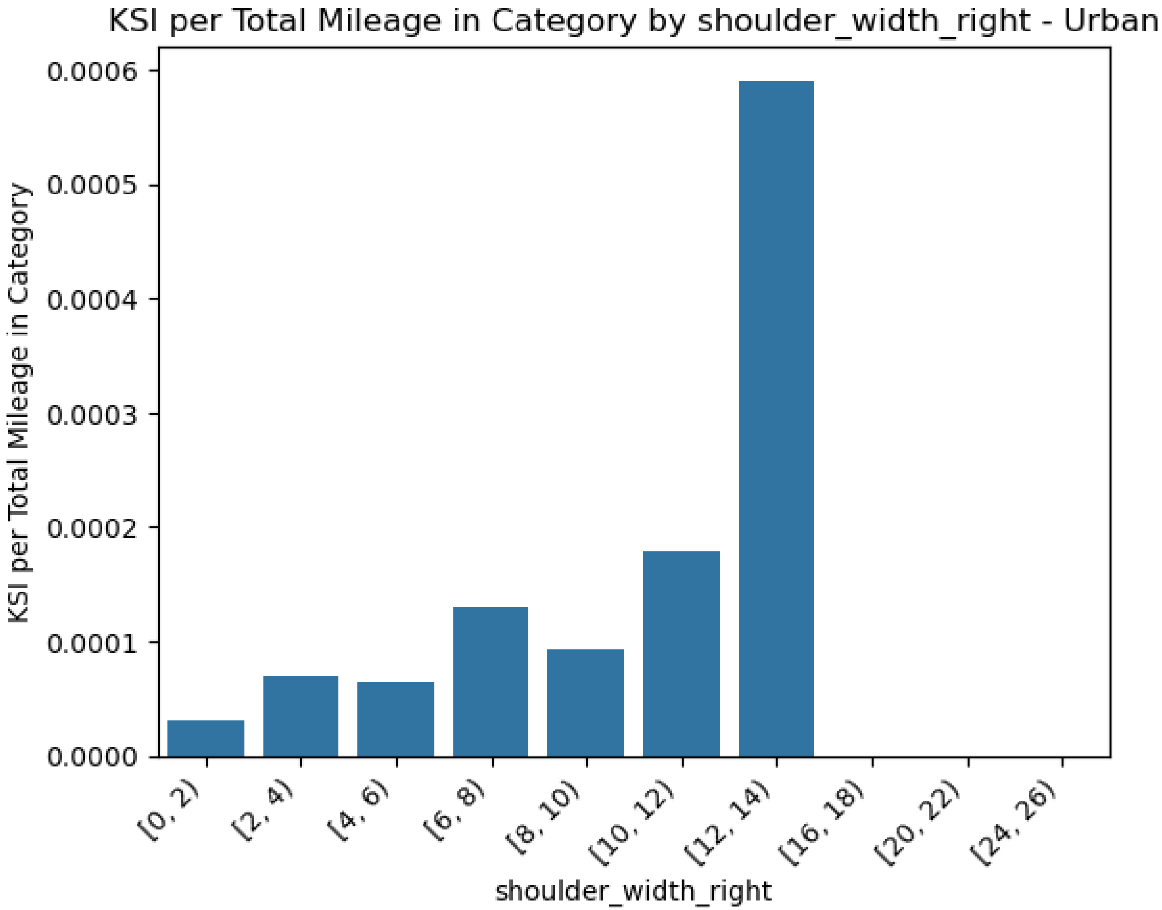

KSI per Total Mileage in Category by shoulder_type_r - Rural
KSI per Total Mileage in Category
0.000000
0.000025
0.000050
0.000075
0.000100
0.000125
0.000150
0.000175
COMBO PAVED AND GRAVEL
Combination Shoulder Exists—shoulder width has two or more surface types
Earth Shoulder Exists
None
Stabilized Shoulder Exists—stabilized gravel or other granular material with or without admixture
Surface Shoulder Exists—Bituminous Concrete (AC)
shoulder_type_r

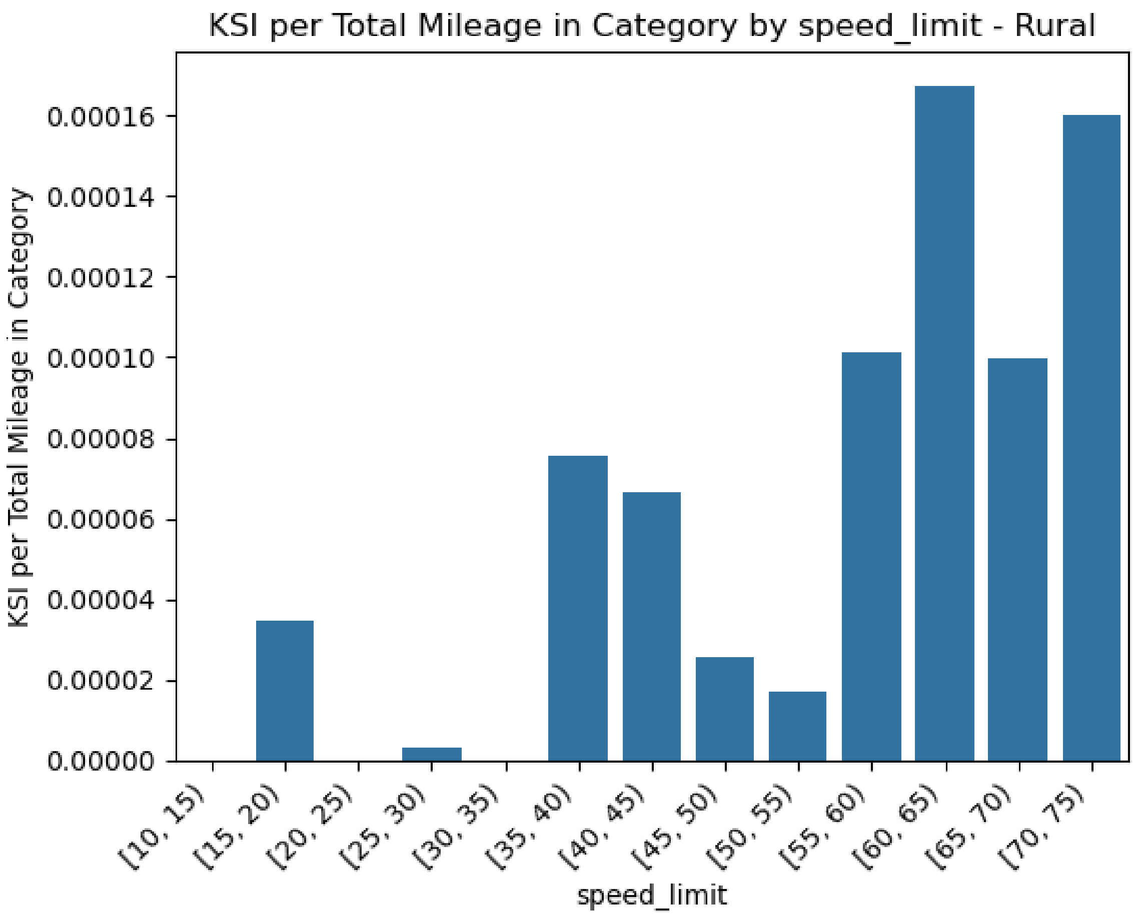

KSI per Total Mileage in Category by shoulder_type_r - Urban
KSI per Total Mileage in Category
0.00035
0.00030
0.00025
0.00020
0.00015
0.00010
0.00005
0.00000
COMBO PAVED AND PAVED
Combination Shoulder Exists—shoulder width has two or more surface types
Earth Shoulder Exists
GRAVEL
None
PAVED
Stabilized Shoulder Exists—stabilized gravel or other granular material with or without admixture
Surface Shoulder Exists—Bituminous Concrete (AC)
shoulder_type_r

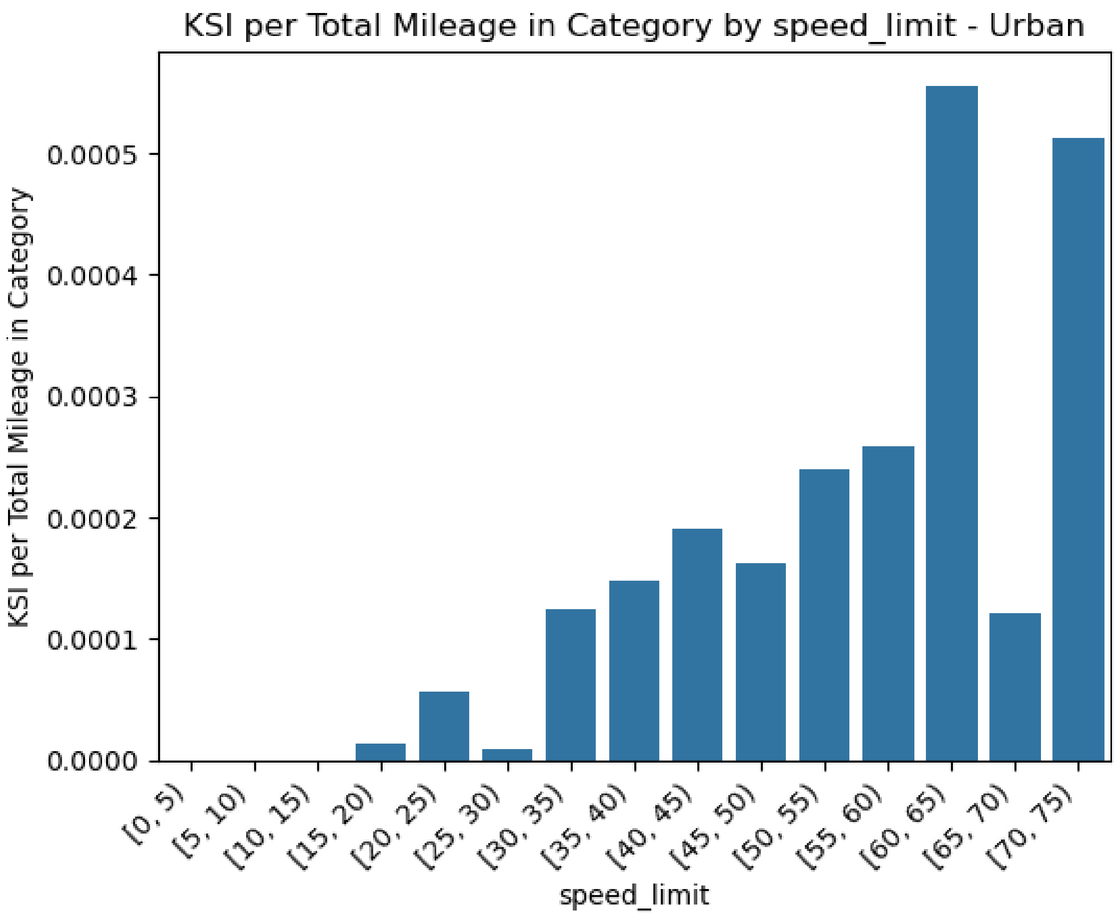

KSI per Total Mileage in Category by shoulder_width_left - Rural
KSI per Total Mileage in Category
0.000200
0.000175
0.000150
0.000125
0.000100
0.000075
0.000050
0.000025
0.000000
[0, 2)
[2, 4)
[4, 6)
[6, 8)
[8, 10)
[10, 12)
shoulder_width_left

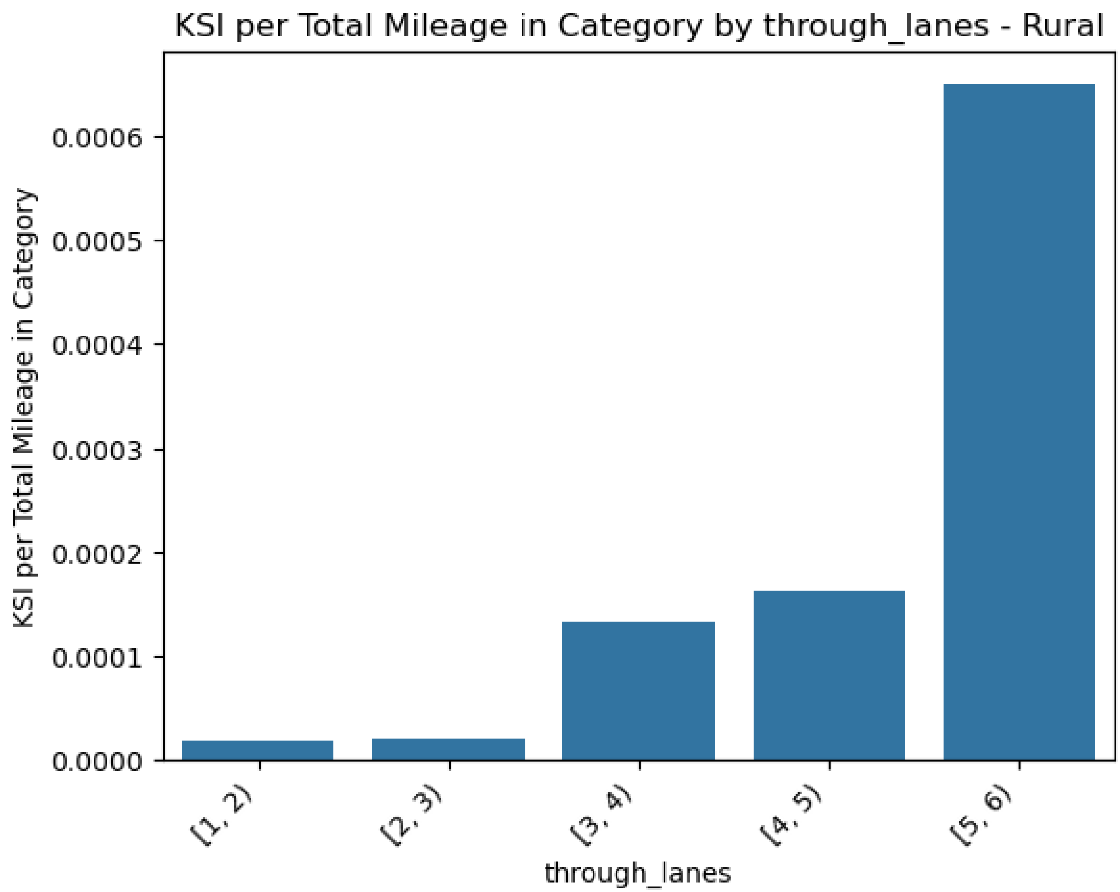

KSI per Total Mileage in Category by shoulder_width_left - Urban
KSI per Total Mileage in Category
0.00175
0.00150
0.00125
0.00100
0.00075
0.00050
0.00025
0.00000
[0, 2)
[2, 4)
[4, 6)
[6, 8)
[8, 10)
[10, 12)
[12, 14)
[14, 16)
shoulder_width_left

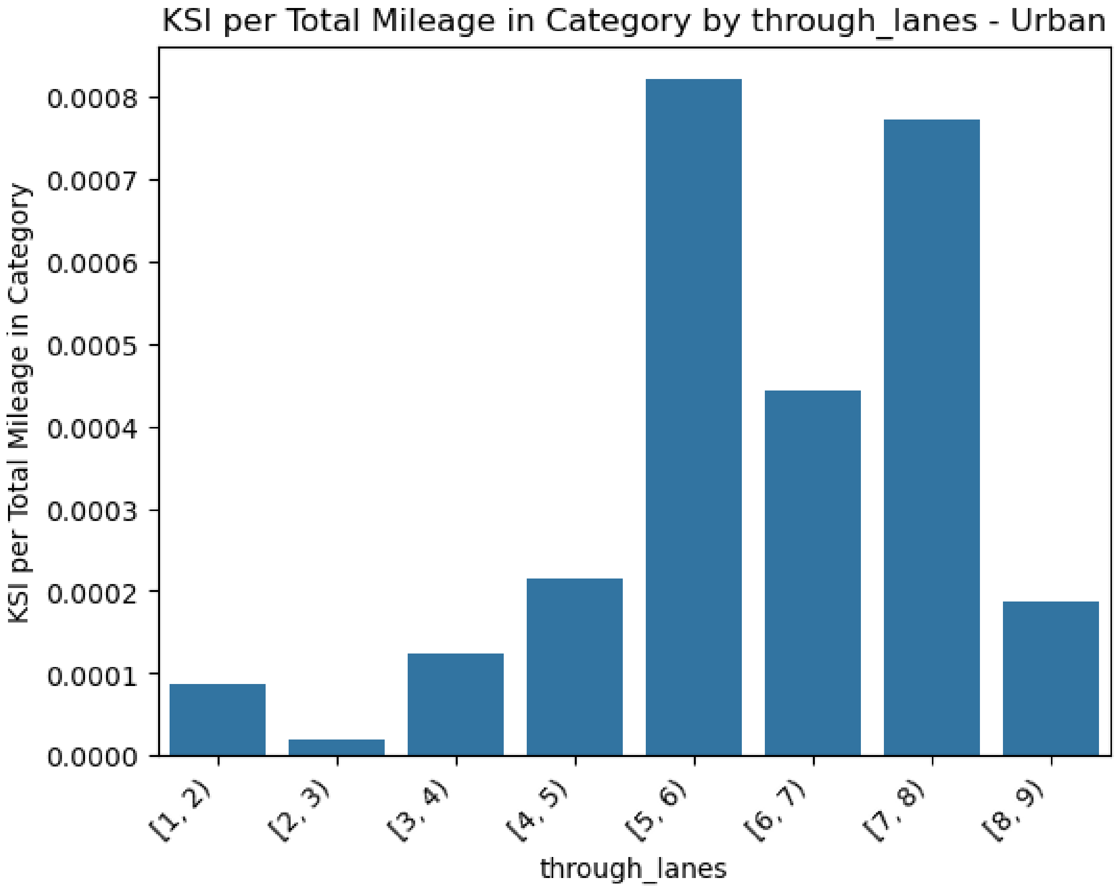

KSI per Total Mileage in Category by shoulder_width_right - Rural
KSI per Total Mileage in Category
0.00014
0.00012
0.00010
0.00008
0.00006
0.00004
0.00002
0.00000
[0, 2)
[2, 4)
[4, 6)
[6, 8)
[8, 10)
[10, 12)
[12, 14)
[14, 16)
shoulder_width_right

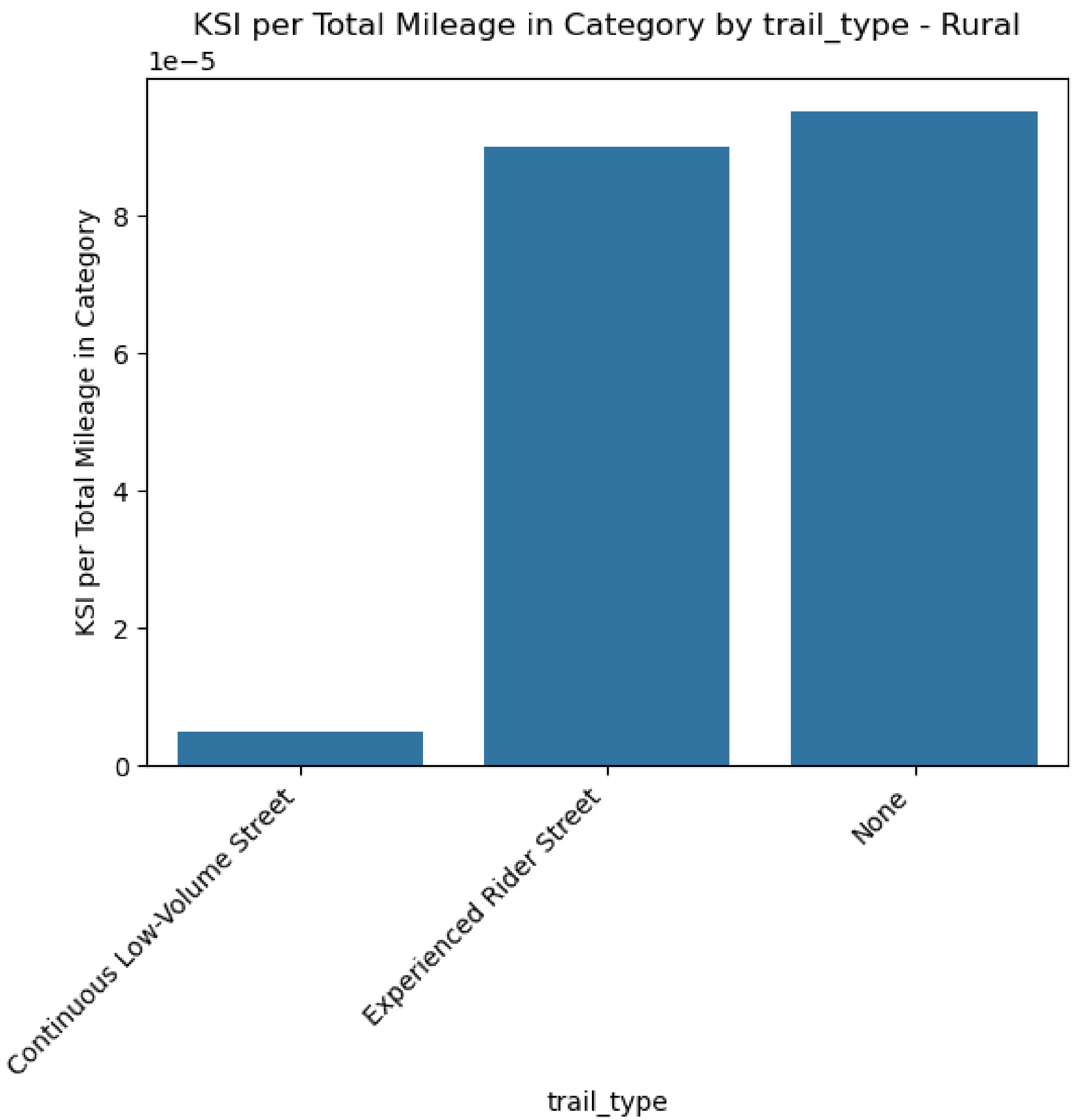

KSI per Total Mileage in Category by shoulder_width_right - Urban
KSI per Total Mileage in Category
0.0006
0.0005
0.0004
0.0003
0.0002
0.0001
0.0000
[0, 2)
[2, 4)
[4, 6)
[6, 8)
[8, 10)
[10, 12)
[12, 14)
[16, 18)
[20, 22)
[24, 26)
shoulder_width_right

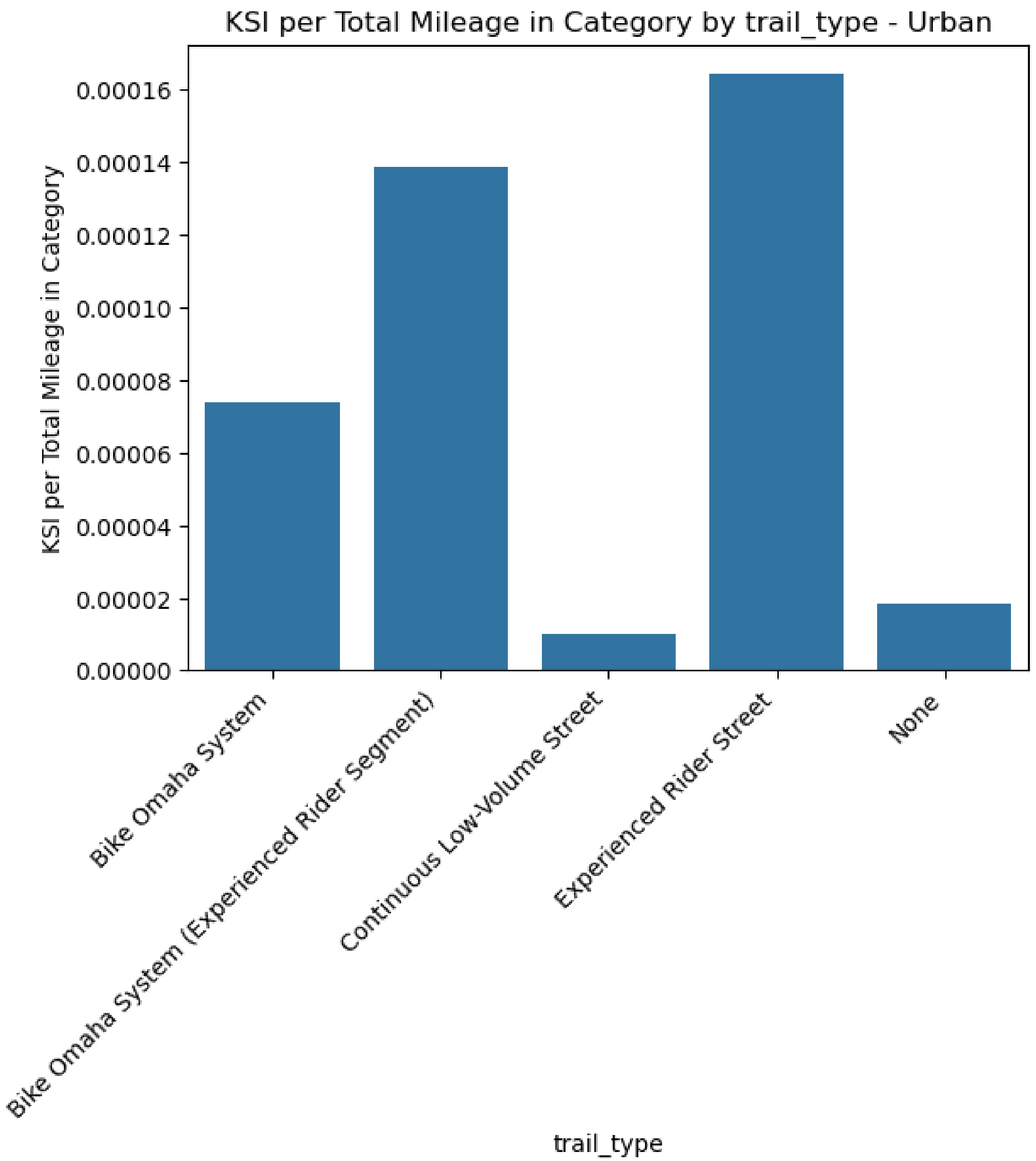

KSI per Total Mileage in Category by speed_limit - Rural
KSI per Total Mileage in Category
0.00000
0.00002
0.00004
0.00006
0.00008
0.00010
0.00012
0.00014
0.00016
[10, 15)
[15, 20)
[20, 25)
[25, 30)
[30, 35)
[35, 40)
[40, 45)
[45, 50)
[50, 55)
[55, 60)
[60, 65)
[65, 70)
[70, 75)
speed_limit


KSI per Total Mileage in Category by speed_limit - Urban
KSI per Total Mileage in Category
0.0000
0.0001
0.0002
0.0003
0.0004
0.0005
[0, 5)
[5, 10)
[10, 15)
[15, 20)
[20, 25)
[25, 30)
[30, 35)
[35, 40)
[40, 45)
[45, 50)
[50, 55)
[55, 60)
[60, 65)
[65, 70)
[70, 75)
speed_limit


KSI per Total Mileage in Category by through_lanes - Rural
KSI per Total Mileage in Category
0.0000
0.0001
0.0002
0.0003
0.0004
0.0005
0.0006
[1, 2)
[2, 3)
[3, 4)
[4, 5)
[5, 6)
through_lanes


KSI per Total Mileage in Category by through_lanes - Urban
KSI per Total Mileage in Category
0.0008
0.0007
0.0006
0.0005
0.0004
0.0003
0.0002
0.0001
0.0000
[1, 2)
[2, 3)
[3, 4)
[4, 5)
[5, 6)
[6, 7)
[7, 8)
[8, 9)
through_lanes


KSI per Total Mileage in Category by trail_type - Rural
1e−5
KSI per Total Mileage in Category
0
2
4
6
8
Continuous Low-Volume Street
Experienced Rider Street
None
trail_type


KSI per Total Mileage in Category by trail_type - Urban
KSI per Total Mileage in Category
0.00000
0.00002
0.00004
0.00006
0.00008
0.00010
0.00012
0.00014
0.00016
Bike Omaha System
Bike Omaha System (Experienced Rider Segment)
Continuous Low-Volume Street
Experienced Rider Street
None
trail_type

Appendix C: Data Science 1-Pagers

The following attached pages include the summarized 1-pagers in Post-Crash Care, Safer People: Driver Characteristics, Safer People: Driver Behavior, and Safer speeds.