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Identifying the Critical Golden-Hour Zones in Rural Kansas

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16 Abstract

This study developed a data-driven geospatial tool to optimize emergency response strategies for vehicle crashes in Kansas. The tool analyzed more than a decade of crash data from the Kansas Department of Transportation (KDOT) and the Fatality Analysis Reporting System (FARS) to provide insight into T1 (crash to emergency medical services [EMS] notification), T2 (EMS notification to EMS arrival), and T3 (EMS arrival to hospital) intervals. The tool emphasized the importance of timely and efficient post-crash care, particularly in rural areas, where 36.6% of fatal crashes have response times that exceed 60 minutes, compared to only 10% in urban areas.

Leveraging Python-based mapping and data analysis libraries, including OpenStreetMap and Dijkstra's algorithm for shortest path calculations, the interactive tool allows users to visualize crash locations, EMS dispatch points, and hospital/trauma center locations. The tool also identifies high-crash regions with delayed response times and helps decision-makers improve emergency response strategies by simulating real-time EMS routing. Through its dynamic interface, the tool offers planning and assessment capabilities to decrease the number of fatalities and improve emergency care, especially in rural settings. This application specifically addresses the disparity in response times between rural and urban regions and can be adapted for similar efforts in other states, supporting life-saving strategies to enhance road safety.

17 Key Words
Post-crash Care, Emergency Response, Transportation Safety, Golden Hour

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Identifying the Critical Golden-Hour Zones in Rural Kansas

Final Report

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PREFACE

The Kansas Department of Transportation's (KDOT) Kansas Transportation Research and New-Developments (K-TRAN) Research Program funded this research project. It is an ongoing, cooperative and comprehensive research program addressing transportation needs of the state of Kansas utilizing academic and research resources from KDOT, Kansas State University and the University of Kansas. Transportation professionals in KDOT and the universities jointly develop the projects included in the research program.

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Abstract

This study developed a data-driven geospatial tool to optimize emergency response strategies for vehicle crashes in Kansas. The tool analyzed more than a decade of crash data from the Kansas Department of Transportation (KDOT) and the Fatality Analysis Reporting System (FARS) to provide insight into T1 (crash to emergency medical services [EMS] notification), T2 (EMS notification to EMS arrival), and T3 (EMS arrival to hospital) intervals. The tool emphasized the importance of timely and efficient post-crash care, particularly in rural areas, where 36.6% of fatal crashes have response times that exceed 60 minutes, compared to only 10% in urban areas.

Leveraging Python-based mapping and data analysis libraries, including OpenStreetMap and Dijkstra's algorithm for shortest path calculations, the interactive tool allows users to visualize crash locations, EMS dispatch points, and hospital/trauma center locations. The tool also identifies high-crash regions with delayed response times and helps decision-makers improve emergency response strategies by simulating real-time EMS routing. Through its dynamic interface, the tool offers planning and assessment capabilities to decrease the number of fatalities and improve emergency care, especially in rural settings. This application specifically addresses the disparity in response times between rural and urban regions and can be adapted for similar efforts in other states, supporting life-saving strategies to enhance road safety.

Acknowledgments

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Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction

1.1 Problem Definition

In 2022, the U.S. Department of Transportation (DOT) adopted the Safe System Approach as the guiding paradigm to address roadway safety. One of the five objectives of the Safe System Approach is Post-Crash Care, which seeks to enhance the survivability of crashes through expedient access to emergency medical care. According to the National EMS Information System (NEMSIS), 40% of people in crashes were alive at the scene of the crash but later died. This study will inform the update of Kansas's Drive to Zero (DTZ) Plan, otherwise known as its Strategic Highway Safety Plan (SHSP). Post-crash emergency care is a critical aspect of traffic safety, especially when dealing with severe crashes. Here, time plays a vital role in saving lives.

While urban areas often benefit from faster emergency medical services (EMS) response times, rural areas may face significant challenges. In many rural areas, response times frequently exceed 60 minutes, which can greatly impact the chances of survival for crash victims. There is a 26.6% disparity between rural and urban response times to crashes which result in fatal injury. In rural areas, 36.6% of response times are greater than 60 minutes compared to 10% in urban settings. The term "golden hour" refers to the critical period following a traumatic injury during which medical intervention is most likely to save lives. The "golden hour" varies depending on the nature of the injuries and the timeframe before they become fatal. This study focuses on reducing response times to improve survival chances within this critical window. This delay is largely due to geographical isolation and the limited availability of EMS personnel and emergency infrastructure.

Improving response times in these critical situations is essential for reducing fatalities and injuries caused by traffic crashes. Currently, there is a lack of accessible tools that can help visualize and optimize emergency services' placement and response strategies. Emergency responders and planners need a data-driven solution that can identify high-risk areas and suggest efficient routes to reduce response delays, especially in rural areas.

1.2 Objective

The objective of this research was to develop a comprehensive geospatial tool that enhances the efficiency of EMS responses during post-crash situations by integrating and visualizing critical data such as crash locations, EMS dispatch points, and nearby hospitals. This interactive platform is intended to support decision-making by enabling emergency responders to plan effective, timely responses. By analyzing historical crash data and response times, the tool highlights areas with delayed emergency responses and suggests ways to reduce delays.

This comprehensive tool also serves as a planning and assessment module for stakeholders, such as EMS, law enforcement, and transportation authorities, by providing a user-friendly interface to visualize crash hotspots, locate EMS and hospital facilities, and calculate the shortest routes for emergency services to reach crash sites. The primary goal is to reduce response times, particularly in rural areas. This ensures that EMS can reach crash victims faster, potentially saving lives and minimizing long-term injuries – ultimately improving post-crash care and enhancing traffic safety in rural areas.

Chapter 2: Related Work

2.1 Literature Review

Various studies have confirmed the significance of timely intervention by law enforcement and emergency response teams after a crash. Delays in response times, particularly delayed notification of emergency services, have been correlated with increased numbers of fatalities. For example, a study in Missouri found that a delay of 5 min or more in notifying ambulance dispatchers significantly increased the fatality rate in 10%–20% of fatal crashes (Brodsky, 1990). Another study from Spain examined more than 1,400 crashes in May 2004 and concluded that decreasing the time between the crash and EMS arrival by 10 min significantly decreased the probability of death (Sánchez-Mangas et al., 2010).

Similarly, a study that analyzed post-crash police response times in Pennsylvania between 2008 and 2017 determined that long response times are directly linked to increased fatality rates, highlighting significant factors such as day of the week, weather conditions, roadway type, and crash location (Liu, 2022). Another study focused on ambulance rescue times in Riyadh, Saudi Arabia, where an analysis of 874 emergency calls revealed an average rescue time of 35.84 min, with an average response time of 10.23 min (Al-Ghamdi, 2002). Factors such as scene time, travel time to hospitals, and average ambulance speed (34.21 mph) were also considered.

Further research has focused on EMS response times specifically for pedestrian-related crashes. Data from the Fatality Analysis Reporting System (FARS) between 2015 and 2018 was used to model EMS response times through a geographically and temporally weighted truncated regression model. This study observed that survival time and reaction time are closely linked, with shorter response times significantly improving survival rates for more severe crashes (Mahdinia et al., 2022). Another key study explored how various factors such as crash notification time influenced rural fatality rates. It found that the elasticity of rural fatalities with respect to crash notification time was 0.14 (Evanco, 1999). The same study suggested that if a rural Mayday system (an in-vehicle emergency notification system) was fully implemented, the potential monetary benefits could reach around USD 1.83 billion annually, with comprehensive benefits valued at USD 6.37 billion. The Mayday system is designed to automatically alert emergency services immediately upon detecting a crash, significantly reducing notification delays and, consequently, overall response times. By minimizing the time from crash occurrence to EMS notification, such systems can improve survival rates in rural areas where delays in reporting are more prevalent.

Moreover, long-term analysis of FARS data from 1975 to 2017 found that national response times improved by 50% during that period; although, rural areas demonstrated longer response times than urban regions. The study emphasized the importance of improved data collection to increase understanding of response time variabilities in different geographic regions (Lee et al., 2018). Another study used Florida data to apply log-logistic and gamma models to analyze crash reporting and EMS arrival intervals, proving that highway infrastructure, environmental conditions, and socioeconomic factors significantly impact EMS reporting and arrival times (Adeyemi et al., 2022).

Overall, although emergency response times have improved in urban areas, rural regions continue to face significant delays, leading to disproportionately higher fatality rates. Studies have consistently shown the need for improved data collection, strategic resource allocation, and the implementation of advanced notification systems to bridge the gap between urban and rural emergency services (Fu et al., 2022).

2.2 Established Methods and Approaches

Geospatial tools and geographic information systems (GISs) have proven to be highly effective at managing traffic safety and optimizing emergency response strategies. Several GIS-based traffic safety applications have been developed to map crash locations, visualize EMS resources, and optimize routes for emergency vehicles. For example, statewide GIS models have been used to analyze traffic patterns and help allocate EMS resources efficiently (Kumaresan et al., 2009; Schultz et al., 2012). GIS tools have also been integrated with traffic simulation and optimization engines, providing real-time updates on travel times and route conditions (Aghasi, 2019).

A novel approach discussed by researchers integrates GIS with optimization engines to reduce EMS response times. This method utilizes GIS as the primary user interface, while the optimization engines gather real-time data to compute the shortest travel times for emergency vehicles, which has shown to reduce response times significantly (Huang & Pan, 2007). Similarly, a dynamic ambulance routing system has been developed, which integrates GIS with real-time traffic conditions. This system computes the shortest path for ambulances based on current traffic congestion, offering a significant improvement in response times, especially during unexpected traffic delays (Panahi & Delavar, 2009).

A geographical analysis in Kano, Nigeria, utilized Global Positioning System (GPS) surveying and satellite images to analyze the location of emergency healthcare facilities, crash hotspots, and existing ambulances. The study emphasized the need for strategically placed ambulances to improve emergency response times in high-risk areas (Yunus & Abdulkarim, 2022). Another methodology, developed for urban emergency medical services (uEMS) in Porto, Portugal, consisted of two steps: a demand assessment to calculate the frequency and priority of emergency events, and an optimization model to maximize vehicle coverage by strategically placing ambulance stations (Amorim et al., 2017).

Further efforts in the field have included optimization-based approaches to ambulance location management, which focus on maximizing coverage while minimizing response times. Studies have also considered fairness (Grot et al., 2022) in the distribution of EMS resources, ensuring that all regions receive equitable emergency response services (Andersson et al., 2020; Mohri & Haghshenas, 2021). Other research has explored decision-support systems (Hajiali et al., 2022; Yıldırım & Soylu, 2023) that help in the strategic planning of EMS services and resource allocation (Hashemi et al., 2022; Khoshgehbari et al., 2023).

These established approaches have contributed significantly to reducing response times and optimizing the deployment of emergency services. However, the challenge remains in applying these methods effectively to rural areas, where the logistical issues are more complex due to geographic isolation, limited resources, and longer distances to medical facilities. Therefore, this research aims to bridge this gap by developing an interactive geospatial tool that not only visualizes crash data but also integrates real-time EMS routing, helping to optimize emergency responses in rural regions.

Chapter 3: Data Preprocessing and Analysis

3.1 Datasets

This research utilizes two primary datasets to perform a comprehensive analysis of crashes and emergency response times: the Kansas Department of Transportation (KDOT) dataset and the Fatality Analysis Reporting System (FARS) dataset. The analysis is classified into two modules: the planning module and the assessment module. The KDOT dataset is used for the planning module, which is detailed in Chapter 4.1, while the FARS dataset is utilized for the assessment module, as discussed in Chapter 4.2.

The KDOT dataset spans from 2013 to 2022 and contains detailed records of crash incidents within the state of Kansas. This dataset includes various attributes related to crash circumstances such as location (latitude and longitude), time, road conditions, and whether the crash occurred in a rural or urban area, which was identified using the "Urban Area Boundary (UAB)" field. With 606,915 crash records, the dataset provides extensive coverage, enabling in-depth analysis of spatial and temporal crash patterns. Additionally, supplementary data such as hospital locations and EMS response times were included for analysis of emergency services' response times to rural crashes.

The FARS dataset offers a nationwide view, with data spanning from 2012 to 2021, focusing specifically on fatal crashes. While the dataset covers all U.S. states, for this project, the focus was on crash records relevant to Kansas. The FARS dataset includes comprehensive details on fatal crashes; categorized by crashes, vehicles involved, and individuals. Key variables like crash location, EMS response intervals, roadway conditions, and other environmental factors were used to analyze the effectiveness of emergency responses. The FARS data provides the necessary information to evaluate three critical intervals: T1 (time from crash occurrence to EMS notification), T2 (time from EMS notification to EMS arrival), and T3 (time from EMS arrival to hospital arrival).

Together, these datasets form the basis of the geospatial tool developed in this research, enabling the identification of high-risk zones, the calculation of emergency response times, and the proposal of improved strategies for faster and more efficient EMS deployment, especially in rural Kansas.

3.2 Data Preprocessing

This research utilizes two primary datasets to analyze crashes and emergency response times comprehensively: the Kansas Department of Transportation (KDOT) dataset and the Fatality Analysis Reporting System (FARS) dataset. The analysis is classified into two modules: the planning module and the assessment module. The KDOT dataset is used for the planning module, while the FARS dataset is utilized for the assessment module.

3.2.1 KDOT Dataset Processing

The KDOT dataset initially comprised yearly folders (2013-2022), each containing multiple text files delineated by a pipe ('|') delimiter. The preprocessing of these files involved several steps aimed at ensuring data consistency and usability. First, the text files were converted into comma-separated value (CSV) file format while retaining their original filenames. The CSV files were stored in new folders corresponding to each year (e.g., "new2013" for the 2013 data), and files with identical structures were merged across the entire period to create consolidated datasets. For example, the "Accidents.csv" files from 2013-2022 were merged into a single file, "Merged_Accidents.csv," using Pandas to facilitate longitudinal analysis.

To maintain data integrity and avoid errors related to data types, columns such as 'ACCIDENT_KEY' were standardized by converting them to string format. This was especially important for columns with mixed data types to ensure consistency across the dataset. Additionally, the dataset was filtered to include only crash records within Kansas, based on latitude (36.5 to 40.5) and longitude (-102.5 to -94.5) boundaries, using the GeoPandas and Shapely libraries to manage geospatial data.

Further, the classification of crashes as "urban" or "rural" (denoted by the "UAB" field) was a crucial feature in this dataset. However, missing values for latitude, longitude, and the "UAB" classification needed to be addressed. Approximately 4.48% of the records (27,220 out of 606,915) had missing latitude or longitude values. These missing values were imputed using the centroid values of the corresponding county, which were flagged as approximations. Additionally, 3.09% of the records (18,741 out of 606,915) lacked an "Urban" or "Rural" classification, and

0.90% (168 out of 18,741) of these had valid latitude and longitude data, allowing for further imputation.

Descriptive and exploratory analyses were performed to understand temporal trends, correlations, and data completeness. No significant correlations were observed between missing data and other variables. Finally, supplementary data such as Kansas hospital and EMS locations were integrated into the dataset to facilitate the visualization and analysis of EMS response times, especially in rural areas. Folium and GeoJSON were used to create geospatial maps, providing visual insights into crash locations and the spatial distribution of emergency services.

3.2.2 FARS Dataset Processing

The FARS dataset contained multiple files across yearly folders (2012-2021), specifically focusing on fatal crashes. For this project, only the 'accident', 'vehicle', and 'person' files were used. Each file was processed to ensure consistency and accuracy. A unique 'ACCIDENT_KEY' column was created by combining the year and 'ST_CASE' (the unique case identifier) to ensure that records could be merged seamlessly across the years without duplicating or losing data.

The FARS files were merged across the entire period to create comprehensive datasets for further analysis. Feature engineering was performed to derive three critical EMS response intervals: T1 (time from crash occurrence to EMS notification), T2 (time from EMS notification to arrival at the crash scene), and T3 (time from EMS arrival to the hospital). These intervals are essential for evaluating EMS efficiency and identifying areas with delayed responses.

Basic descriptive statistics were calculated for T1, T2, and T3, and the analysis was performed to differentiate between urban and rural areas. The data was also grouped into 15-minute intervals to observe trends in response times. Furthermore, the analysis showed differences in response times across various environmental factors such as roadway conditions, weather, and lighting.

Data cleaning was a crucial step in preparing the FARS dataset for analysis. Records with placeholder or negative time values were removed to maintain data quality. Complex categorical data, such as vehicle types and crash causes, were transformed into simplified categories to improve the clarity and interpretability of the dataset. Exploratory data analysis was performed on the key intervals, with various statistical models (exponential, gamma, log-normal, log-logistic, and Weibull) fitted to the T1, T2, and T3 intervals. The log-logistic model was found to provide the best fit for T1, while the exponential model was identified as the best fit for T2, based on the mean absolute deviation (MAD) comparisons between the models.

Table 3.1: Comparison of Mean Absolute Deviation Values between Models

Model	MAD for T1	MAD for T2	MAD for T3
Exponential	2.7186	3.1965	9.4409
Gamma	3.0000	7.9362	10.5751
Log-Normal	1.9870	3.2325	10.3688
Log-Logistic	1.8191	3.3044	10.1036
Weibull	2.2361	3.9917	10.9309

3.3 Exploratory Data Analysis

Exploratory Data Analysis (EDA) was conducted on both the KDOT and FARS datasets to explore the distribution and patterns within the data. The FARS dataset, spanning 10 years (2012-2021), provided detailed records of 3,076 fatal crashes in Kansas. Figures 3.1- 3.13 illustrate the trends and spatial distribution of response times at the county level.

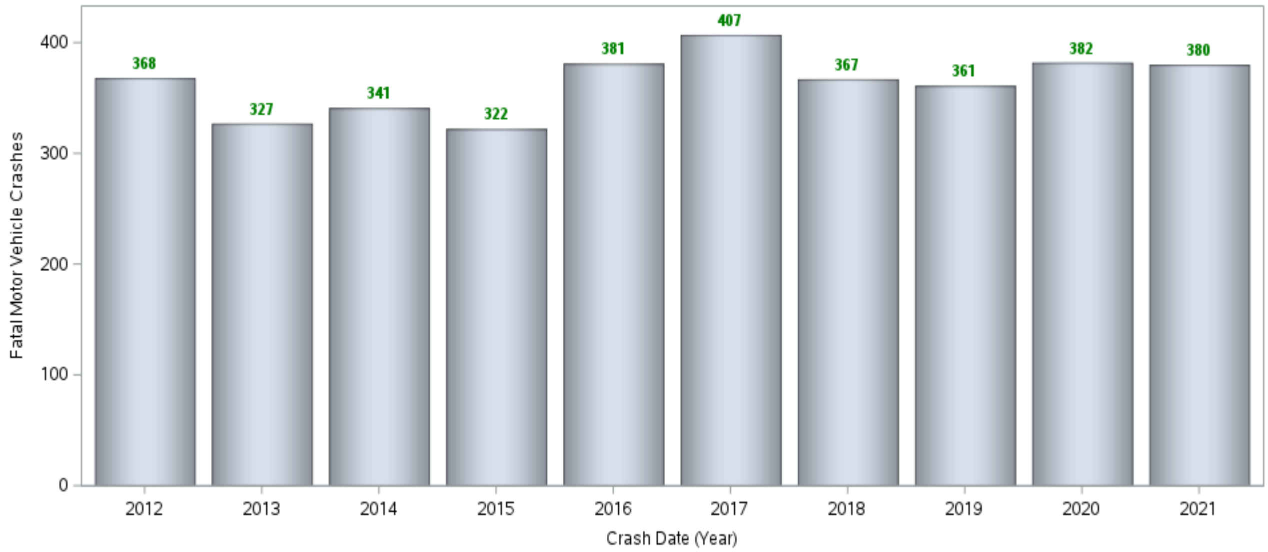


Figure 3.1: The Number of Fatal Crashes in Kansas over the Years 2012 – 2021
(Data Source: NHTSA FARS)

Figure 3.1 presents the graph showing fatal motor vehicle crashes in Kansas from 2012 to 2021. The number of fatal crashes fluctuated significantly over the years, with a notable dip around 2013 and a sharp increase peaking in 2017. After 2017, fatal crashes dropped substantially in 2018, reaching a low point before gradually increasing again from 2019 to 2021. The data suggests variability in fatal crash numbers over time, with some years experiencing significant changes, indicating potential factors impacting road safety in Kansas across these years.

Figures 3.2-3.4 present box-whisker plots showing the distribution of the three critical response intervals (T1, T2, and T3) across Kansas from 2012 to 2021. Figures 3.5-3.7 display radial diagrams that highlight the variation in response times across different counties within the state. Figures 3.8-3.13 present box-whisker plots showing the distribution of the three critical response intervals (T1, T2, and T3) across the months and time of the day.

3.3.1 Yearly Trends in Kansas

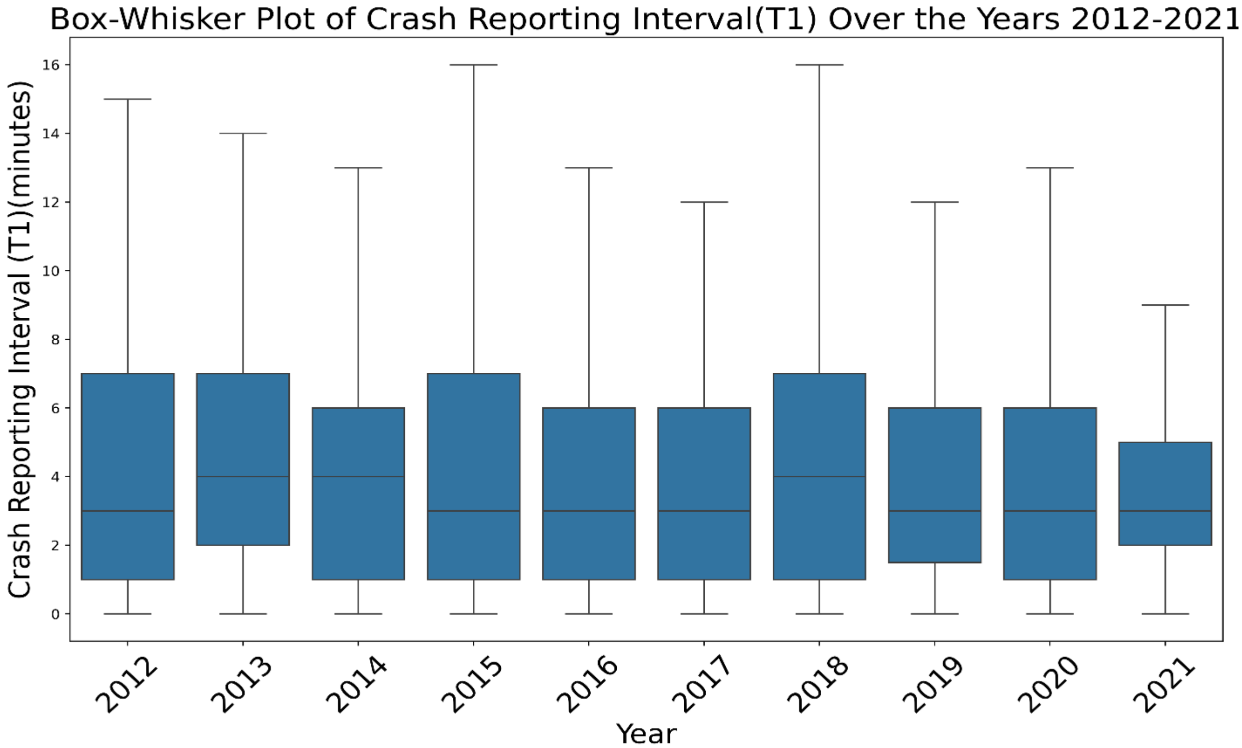


Figure 3.2: Box-Whisker Plot of T1 in Minutes (Crash Occurrence to EMS Notification) over the Years 2012- 2021

This box-whisker plot in Figure 3.2 illustrates the crash reporting interval (T1) from crash occurrence to EMS notification over the years 2012 to 2021. Each box represents the median and interquartile range of T1 intervals annually, while the whiskers indicate the variability outside the upper and lower quartiles. The median T1 interval remains relatively consistent over the years, though the variability is more prominent in some years, particularly in 2018, where a higher upper range is visible. This visualization highlights the stability in the reporting interval, with occasional fluctuations, suggesting a steady but variable response in the notification time across the decade.

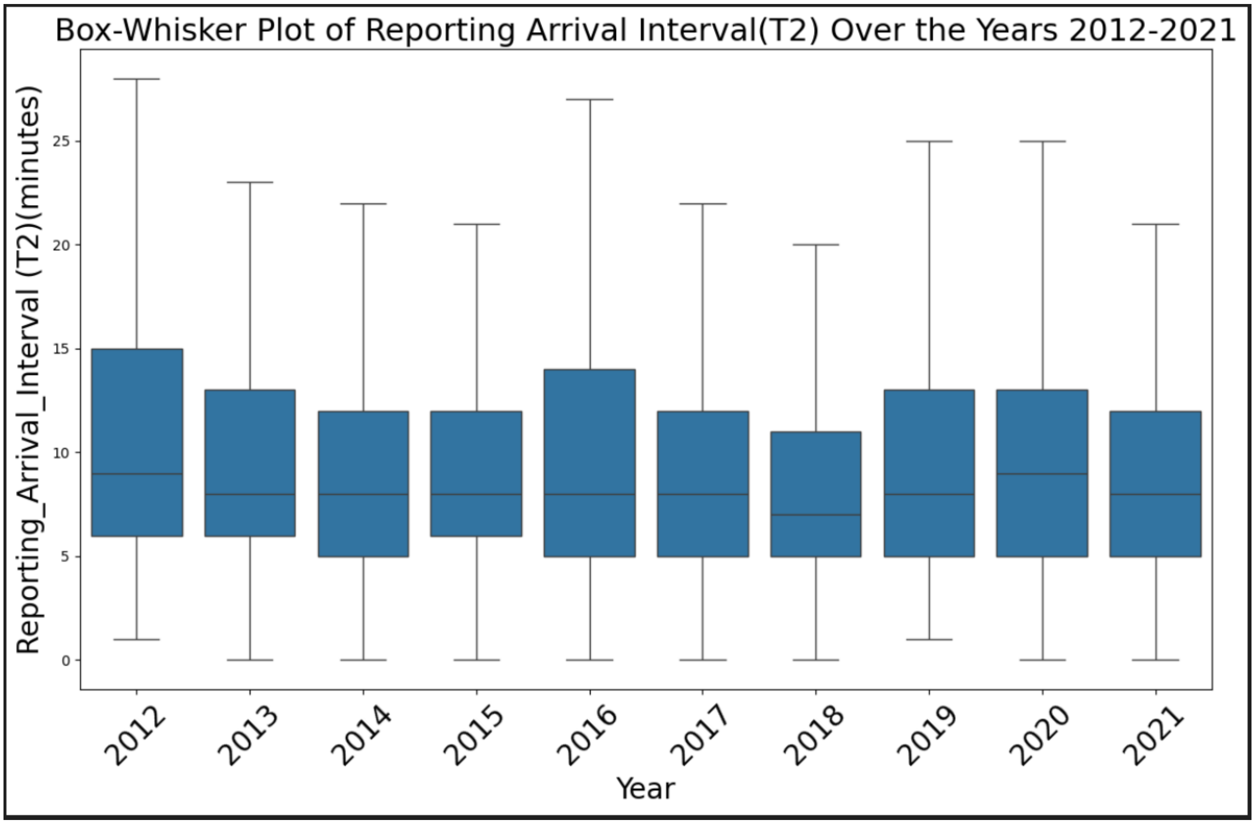


Figure 3.3: Box-Whisker Plot of T2 (EMS Notification to EMS Arrival) over the Years 2012 - 2021

This box-whisker plot in Figure 3.3 displays the distribution of the reporting arrival interval (T2), which measures the time from EMS notification to EMS arrival at the crash site, over the years 2012 to 2021. The median T2 interval remains stable across the years, though there is some variation in the interquartile range, with 2012 and 2016 showing wider variability in response times. The whiskers indicate the range of intervals outside the interquartile range, with several years showing relatively high maximum values, particularly in 2016. This visualization suggests that while the central tendency of arrival times has remained steady, there are occasional years with greater fluctuation in response intervals.

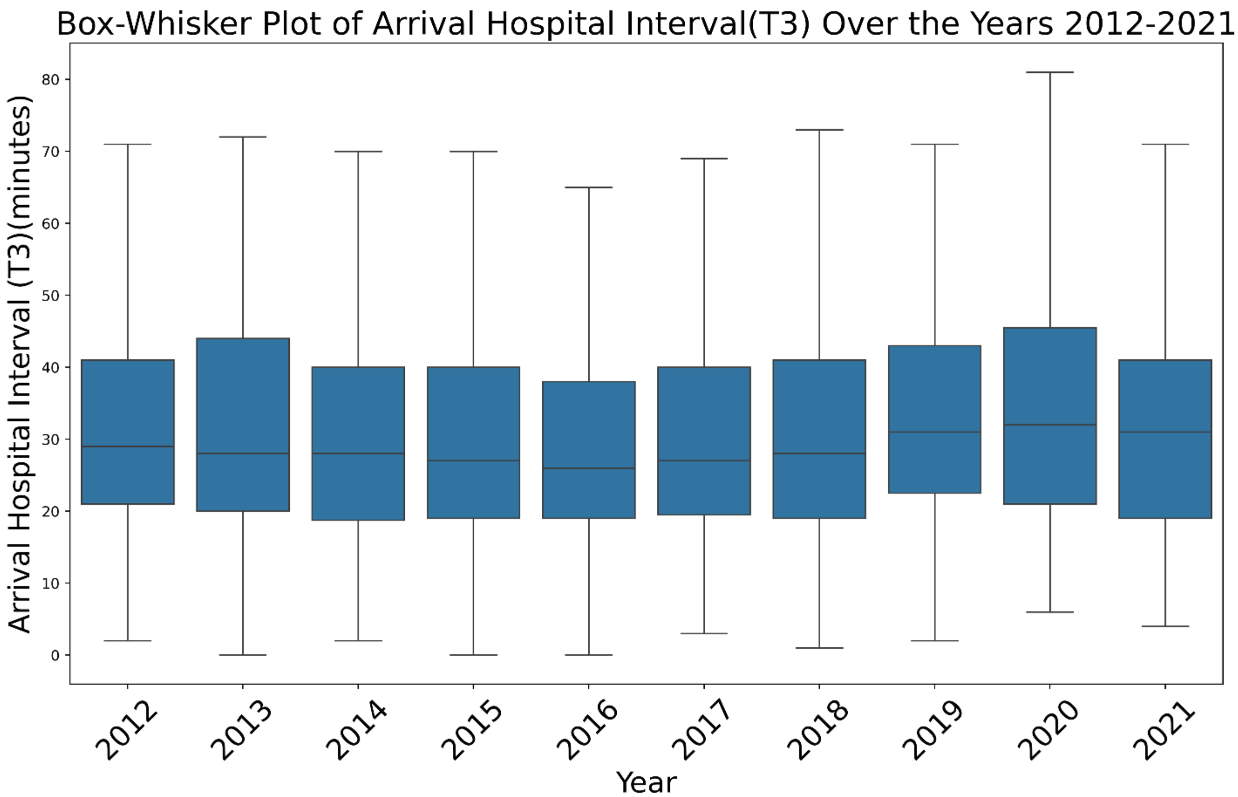


Figure 3.4: Box-Whisker Plot of T3 (EMS Arrival to Patient Arrival at the Hospital) over the Years 2012- 2021

This box-whisker plot in Figure 3.4 illustrates the distribution of the arrival hospital interval (T3), which measures the time from EMS arrival at the crash site to hospital arrival, over the years 2012 to 2021. The median T3 interval is relatively consistent across the years, hovering around 30 minutes. The interquartile range varies slightly each year, with 2016 showing a somewhat wider spread. The whiskers represent the range of intervals outside the interquartile range, with some years, such as 2016 and 2020, showing higher maximum values. Overall, this plot indicates stable central tendencies in hospital arrival times, with occasional variability in longer intervals.

3.3.2 Response Time: Spatial Patterns in Kansas Counties

The table below displays the 21 counties with the longest average T1 intervals in minutes, which shows the distribution of time taken from the crash occurrence to the EMS notification.

Table 3.2 Counties with the Highest Average T1 Intervals (in Minutes)

County	Average of T1: Time between Crash Occurrence and EMS Notification (Minutes)
COMANCHE	64.40
MORRIS	31.18
ROOKS	29.00
CHEYENNE	20.80
SHERIDAN	19.23
PHILLIPS	17.50
ATCHISON	15.80
HODGEMAN	15.14
GREELEY	15.00
WALLACE	14.50
ELLIS	14.15
NORTON	13.86
SHERMAN	13.18
JEWELL	13.00
KEARNY	12.50
GREENWOOD	12.30
HASKELL	12.22
CRAWFORD	11.12
KINGMAN	11.09
LEAVENWORTH	11.09
ELLSWORTH	11.07

The table below displays the 10 counties with the longest average T2 intervals in minutes, which shows the distribution of time taken from the EMS notification to EMS arrival at the crash site. Most counties are clustered around lower intervals, though some display longer arrival intervals, reaching up to around 35 minutes. This pattern suggests variability in EMS arrival times across counties, with certain areas experiencing delays compared to others. The chart highlights counties with potentially higher EMS response times, which could be areas for further investigation or improvement.

Table 3.3 Counties with the Highest Average T2 Intervals (in Minutes)

County	Average of T2: Time between EMS Notification and Arrival to the Crash Site (Minutes)
WABAUNSEE	36.9500
KINGMAN	24.6400
PHILLIPS	23.0000
KIOWA	20.5000
JEWELL	19.5000
GREELEY	19.5000
OSAGE	19.4800
SHERIDAN	19.3100
HASKELL	19.1100
LINN	19.0000

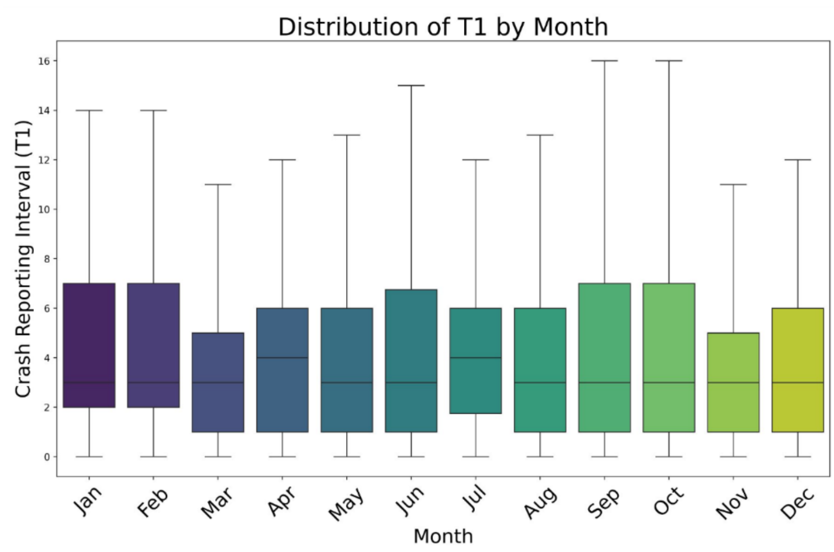
The table below displays the 10 counties with the longest average T3 intervals in minutes, which shows the distribution of time taken from EMS's arrival at the crash site to the patient's arrival to the hospital. Most counties display intervals clustered closer to the center, suggesting shorter arrival times, while a few counties show higher values, reaching up to around 50 minutes. The chart highlights differences in hospital arrival times between counties, indicating that some regions may face delays in getting patients to hospitals after EMS arrival. These variations could suggest areas where improvements in transport time to hospitals may be beneficial.

Table 3.4 Counties with the Highest Average T3 Intervals (in Minutes)

County	Average of T3: Time from Arrival at Crash Site to Hospital (Minutes)
WOODSON	66.3300
LINN	63.6400
NEOSHO	54.0900
LYON	52.9100
KINGMAN	51.0000
MARION	49.6400
CHASE	46.1800

3.3.3. Distribution by Month & Time of the Day

Figure 3.8 displays the monthly distribution of the crash reporting interval (T1) in minutes, showing variation throughout the year. The median T1 remains relatively stable, though there is slightly more variability observed in the summer and fall months, particularly in September and October.



Distribution of T1 (minutes): Month of the Year

Figure 3.8: Distribution of T1 by Month

Figure 3.9 illustrates the distribution of T1 by time of day, with intervals remaining consistent during most daytime hours. However, the T1 interval shows higher variability and slightly longer times in the early morning hours (12 AM - 5 AM), suggesting delays in crash reporting during late-night and early-morning periods. Both figures highlight time-based patterns in crash reporting intervals.

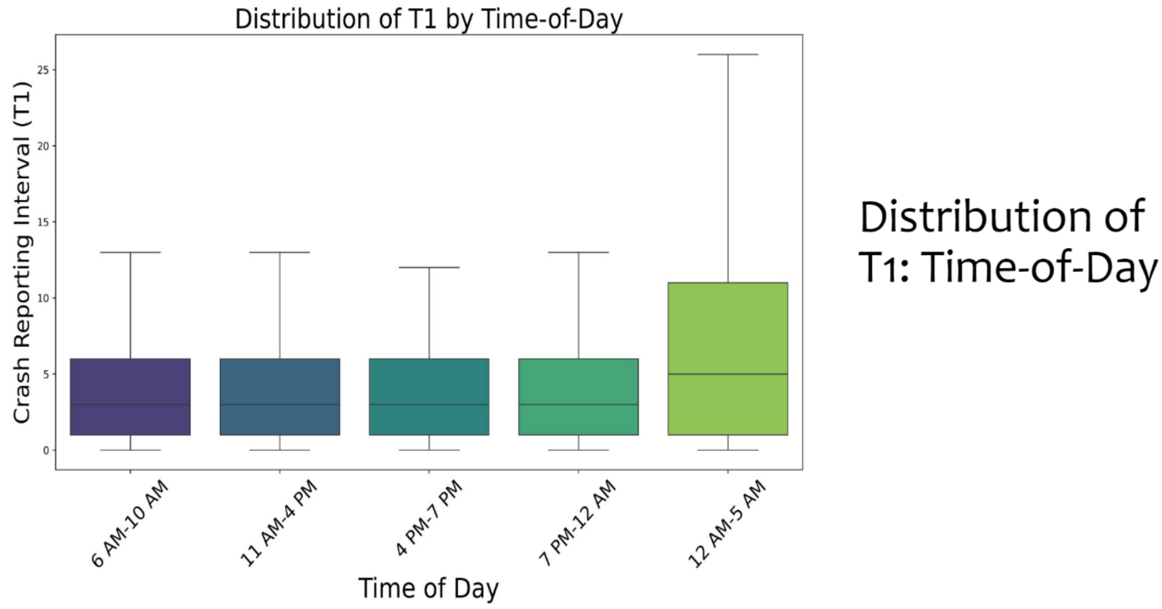


Figure 3.9: Distribution of T1 by Time of Day

Figure 3.10 shows the monthly distribution of the reporting arrival interval (T2) in minutes, indicating the time from EMS notification to arrival at the crash site. Median T2 intervals are consistent across the year.

Distribution of T2 (minutes): Month of the Year

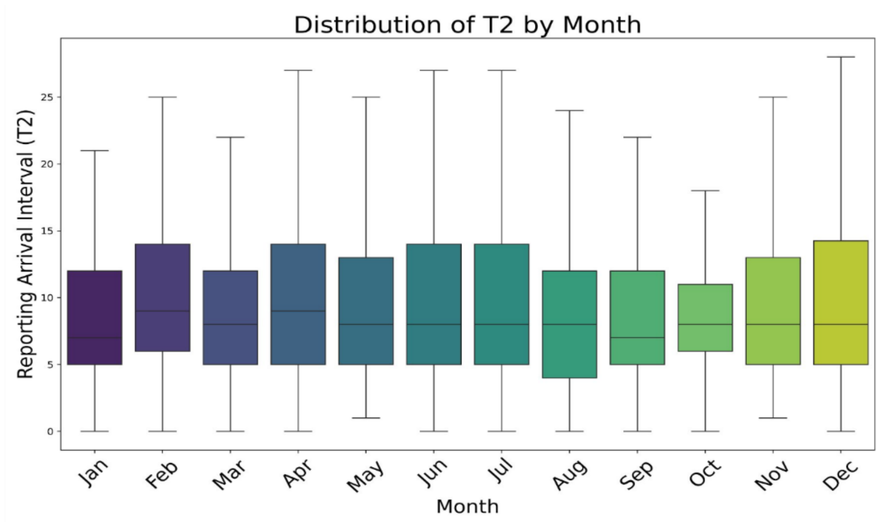


Figure 3.10: Distribution of T2 by Month

Figure 3.11 presents the distribution of T2 at different times of the day. Together, these figures suggest that seasonal and time-of-day factors may have a minor influence on EMS arrival times.

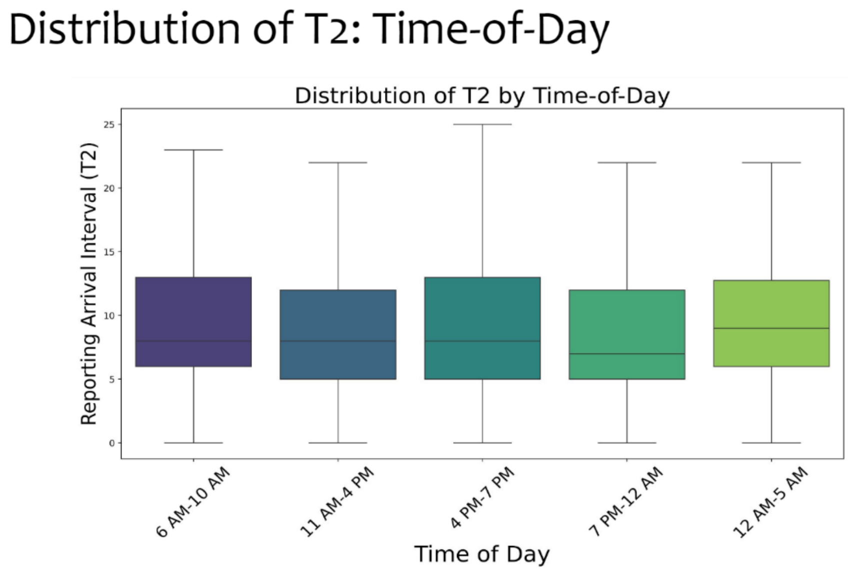


Figure 3.11: Distribution of T2 by Time of Day

Figure 3.12 shows the monthly distribution of the hospital arrival interval (T3) in minutes, representing the time from EMS arrival at the crash site to the patient's arrival at the hospital. The median T3 interval is generally stable throughout the year, though slightly higher variability is observed during winter months, particularly in January and December.

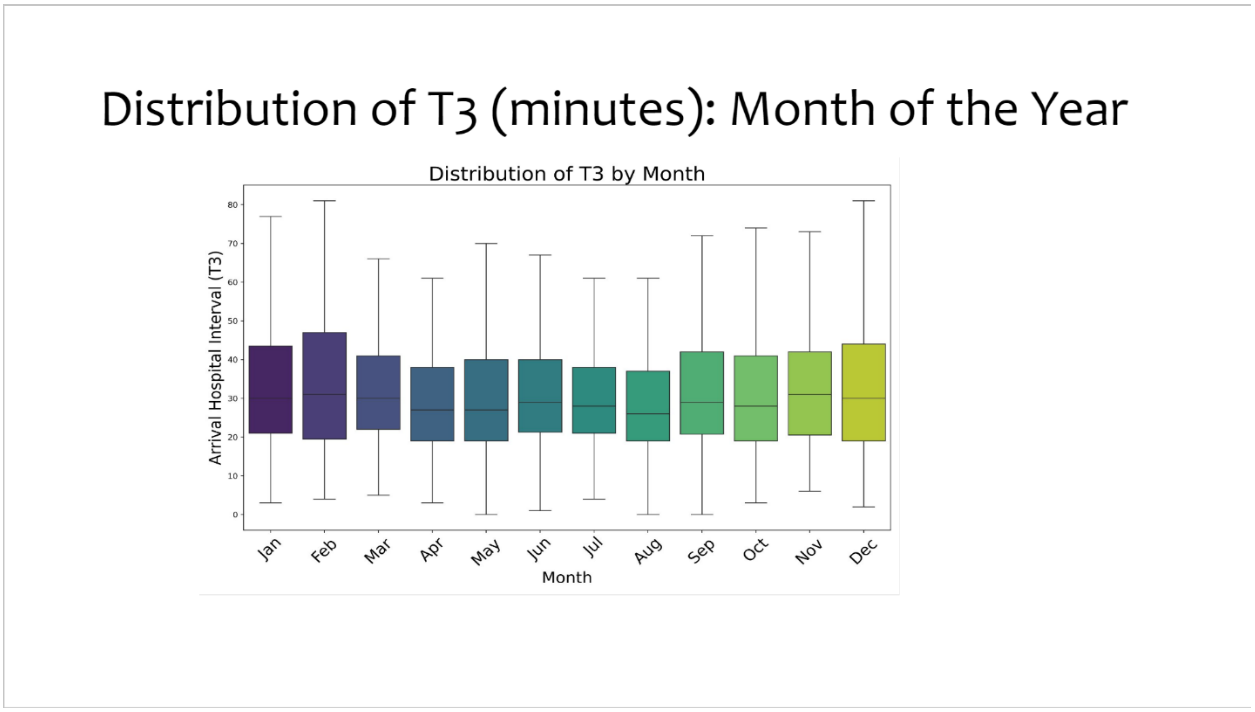


Figure 3.12: Distribution of T3 by Month

Figure 3.13 illustrates the distribution of T3 across different times of the day, with intervals remaining consistent across most periods. However, T3 intervals tend to be somewhat higher in the early morning hours (12 AM - 5 AM), indicating potential delays in hospital arrival during this period. Both figures suggest that seasonal and time-of-day factors may have minor impacts on hospital arrival times.

Distribution of T3: Time-of-Day

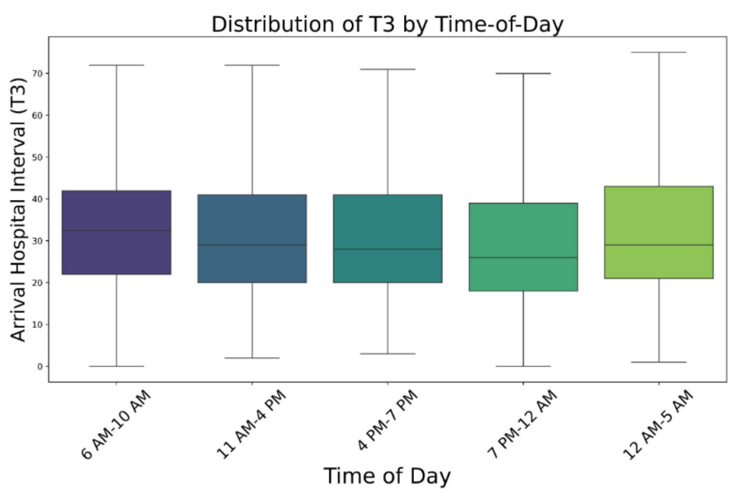


Figure 3.13: Distribution of T3 by Time of Day

Chapter 4: Methodology

The processed data from KDOT and FARS was used to develop an interactive web-based tool to plan efficient emergency responses and assess historic emergency responses based on fatal crash data.

4.1 Planning Module

The planning module (Figure 4.1) was developed to create an interactive and visual tool for optimizing emergency response strategies in Kansas. This application leverages the processed KDOT dataset and provides a user-friendly interface that allows emergency planners and responders to assess crash locations, EMS facilities, and hospitals, while also estimating emergency response times based on geospatial data.

The planning module was built using Python in the Streamlit environment, which provides an accessible and dynamic web-based interface. To display the geographic data, OpenStreetMap was used for map visualizations, with the Kansas state boundary plotted using GeoJSON files for clarity. The geospatial data manipulation, which involved handling crash data, hospital locations, and EMS dispatch points, was performed using the GeoPandas library. Folium, a Python library used for creating Leaflet maps, was employed to visualize crash locations on an interactive map.

The KDOT data was filtered to only include crashes within Kansas by defining the state's boundary. To enhance usability and optimize performance, the interface incorporated a dropdown menu that allowed users to select specific counties within Kansas. Upon selecting a county, all crashes within that region were marked on the Folium map based on their geographical coordinates. The crash markers, shown in red, provided users with additional details, such as the accident key and the rural or urban status (based on the UAB field), through pop-ups that appeared when clicking on a marker. For better performance and visualization, the application used clustering functionality at higher zoom levels, while individual crash points were visible at lower zoom levels.

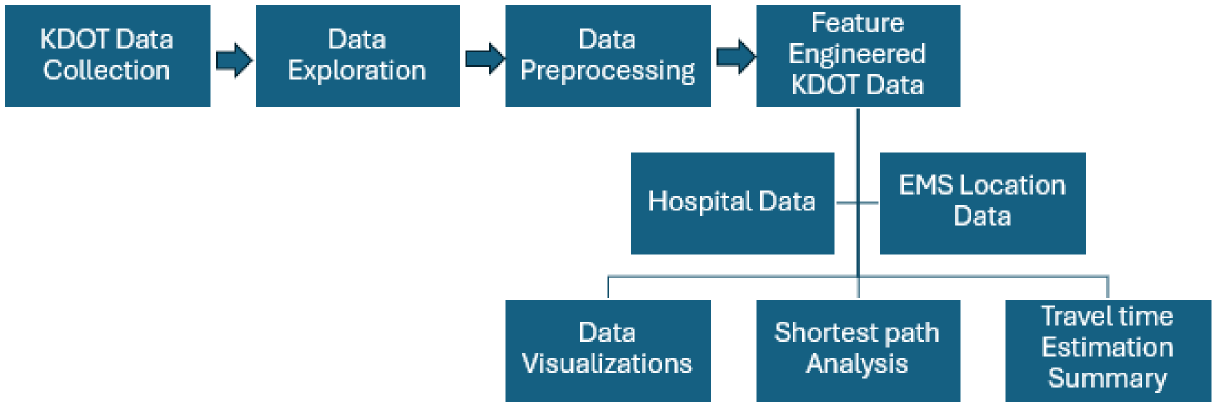


Figure 4.1: Schematic of the Planning Module

Beyond crash locations, the planning module also integrated hospital and EMS dispatch locations onto the map. Users had the option to display or hide these markers through checkboxes. When the "Show Crashes" option was selected, crash locations in the specified county were displayed, while selecting the "Show Hospital" and "Show EMS" checkboxes enabled users to visualize the locations of all hospitals and EMS facilities across Kansas. Clicking on these markers provided users with detailed information about each hospital, including the hospital name, trauma level, and the location of EMS dispatch centers.

To further enhance the planning capabilities, a shortest path analysis feature was implemented. This feature allowed users to estimate EMS response times for specific crash locations by defining a radius around the crash site. Users could input the crash key and a radius to identify the nearest EMS and hospital facilities. The NetworkX and OSMnx libraries were employed to compute the shortest driving routes between the crash site and the nearest EMS and hospital nodes. Using Dijkstra's algorithm, the shortest distance between the crash location and the EMS or hospital was calculated, and the route was displayed on the map with distinct colors representing EMS and hospital paths.

The planning module also provided a summary of the total travel time and distance for the shortest paths, allowing users to make informed decisions on how to optimize emergency response strategies. This tool, with its geospatial mapping, route optimization, and real-time crash location data, offers a robust framework for improving the effectiveness of emergency services in Kansas.

The flexibility of this module also ensures that it can be adapted for other regions facing similar challenges in rural and urban emergency response.

4.2 Assessment Module

The assessment module (Figure 4.2) was designed to evaluate historic emergency responses to fatal crashes using the FARS dataset. This module aims to provide a detailed analysis of response times, allowing users to assess the efficiency of EMS responses in various regions over the past decade. The assessment tool enables users to select statewide or county-specific data, visualize crash data, and explore key EMS response intervals.

Upon selecting the statewide or county data via dropdown menus, the application displayed crash markers based on their geographical coordinates. The GeoJSON files for the selected statewide and county data were also plotted on the map, providing clear geographical context. This visualization of crashes and state boundaries helped users understand the spatial distribution of crashes and how response times varied across regions.

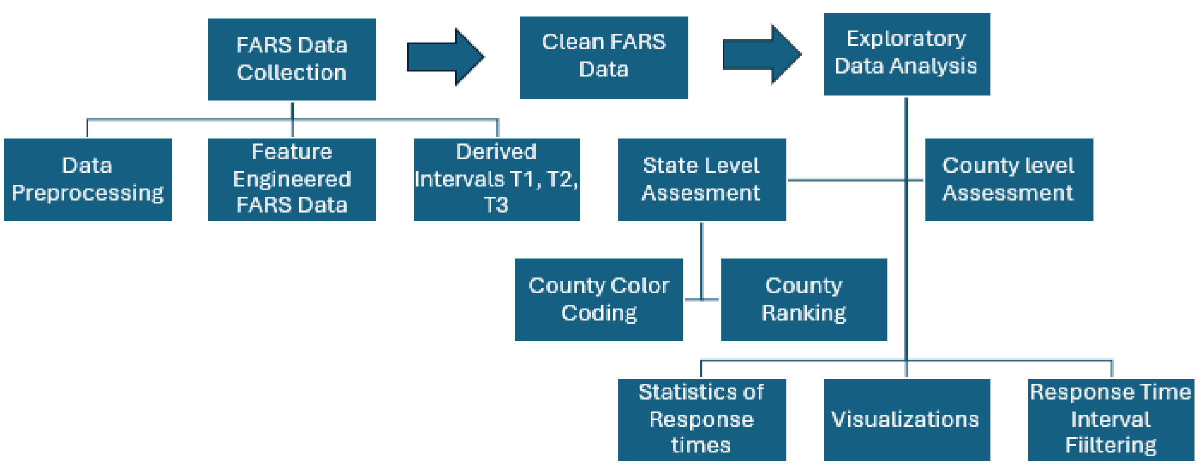


Figure 4.2: Schematic of the Assessment Module

The primary focus of the assessment module was to calculate and visualize the three key EMS response intervals: **T1** (time between crash occurrence and EMS notification), **T2** (time between EMS notification and arrival at the crash site), and **T3** (time between EMS arrival at the crash site and patient arrival at the hospital). When the application is first loaded, it provides summary statistics for these intervals at the state level, including the average, minimum, and maximum values for each interval. When a specific county is selected, the assessment tool recalculates and displays these statistics for that county, offering a more granular analysis.

To enhance the visualization, counties within Kansas were color-coded based on the selected EMS response interval. A dropdown menu allowed users to toggle between the T1, T2, and T3 intervals, updating the map's color coding to reflect average, maximum, and minimum values for the selected interval. Additionally, a ranking feature was implemented to display counties by their average response times, allowing users to quickly identify areas with faster or slower EMS response times. This visual representation provided a clear picture of the efficiency of emergency services in different regions.

The assessment module also included a filtering feature to allow for the analysis of specific time intervals. For example, users could input a time range (such as 5-10 minutes for T1), and the application would highlight crashes that fell within that range by marking them with a red ring around the crash marker. This feature provided users with the ability to conduct a more targeted analysis of response times and to focus on particular regions or time intervals of interest.

When users clicked on a highlighted crash marker, a popup displayed detailed information about the crash, including the exact values of T1, T2, and T3. This feature enabled users to gain deeper insights into individual crashes and evaluate EMS response times in those cases. By filtering the data in this way, emergency planners and analysts could better understand the challenges in response times and identify areas for potential improvement.

Together, the planning and assessment modules form a comprehensive tool that enables users to both optimize future emergency response strategies and evaluate the performance of past emergency responses. The combination of real-time geospatial mapping, route optimization, and detailed historical analysis makes this tool a valuable resource for improving road safety and reducing fatalities in Kansas.

Chapter 5: Results & Use Cases

5.1 Planning

To view specific markers (e.g., only hospitals), use the checkboxes to select or deselect crash locations, hospital locations, and EMS locations.

Figure 5.1: Check Boxes to Select the Modules

5.1.1 Inventory Assessment

Users can view the locations of historical, as well as EMS stations and hospitals, for selected regions. Additionally, users can deselect certain assets and zoom in on specific types, such as the spatial distribution of hospitals and trauma centers across Kansas.

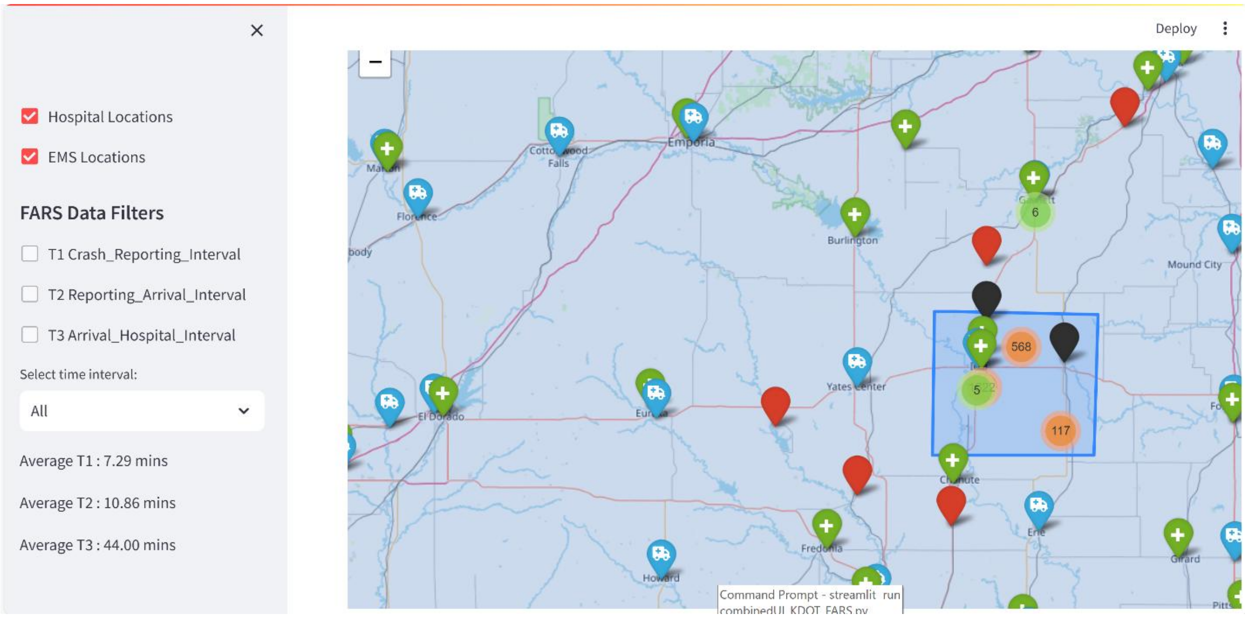


Figure 5.2: Spatial Visualization of Assets and Crash Locations for Post-Crash Management [Blue: EMS; Green: Hospital; Red: Crash Locations (Black Indicates Multiple Crashes)]

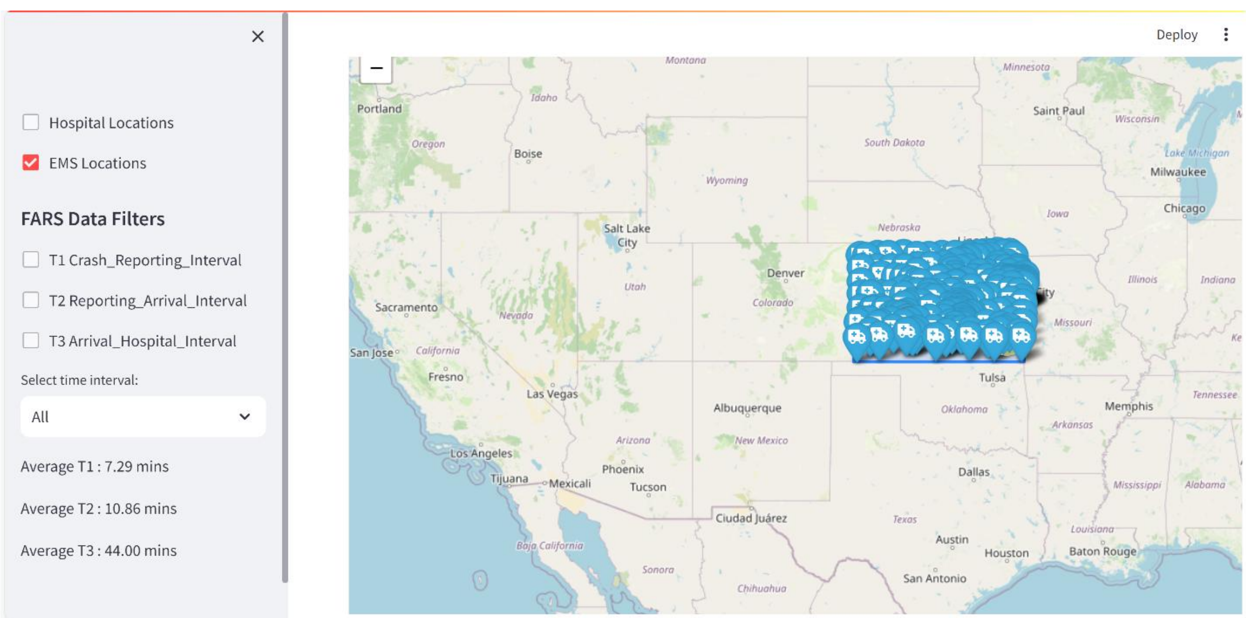


Figure 5.3: EMS Locations

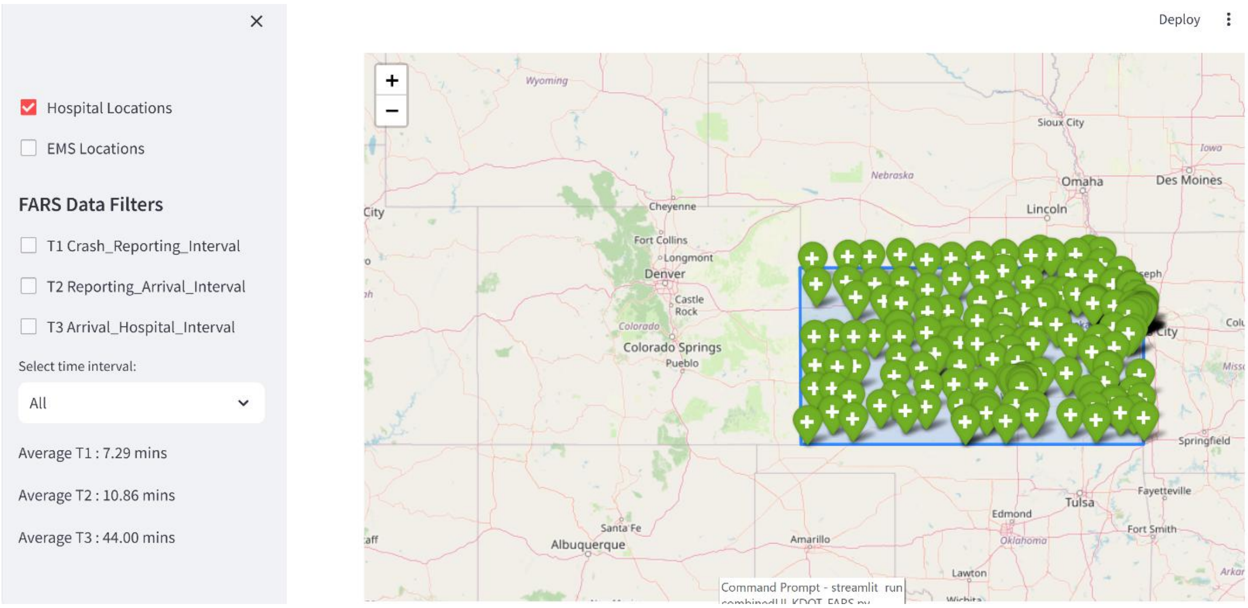


Figure 5.4: Hospital Locations

5.1.2 County-Specific Analysis

To view crash locations, users can see clusters of crashes or individual crash sites depending on the zoom level for a selected county. By choosing the desired county number from the dropdown menu, users can focus on a specific region. For example, selecting county number 81 will display all reported crashes in Riley County.

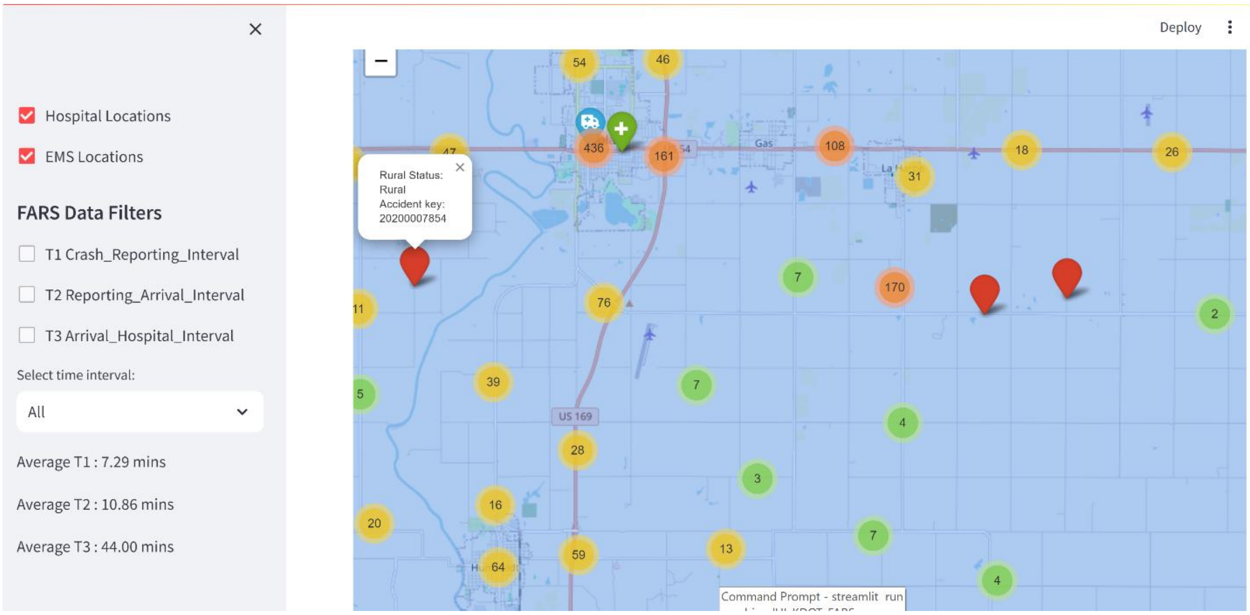


Figure 5.5: County Specific Data (Riley County, KS) [Blue: EMS; Green: Hospital; Red: Crash Locations (Black Means Multiple Crashes)]

To find the nearest hospital to a specific crash location within a certain radius, enter the accident key in the provided input field and adjust the radius as needed. The map will then display the nearest hospital and the path from the crash location. This same methodology can be used to find the nearest EMS location to the crash location. By default, the radius is set to 50 miles and the accident key is an empty field. If the accident key is empty, the user can view all the crash locations in the selected county.

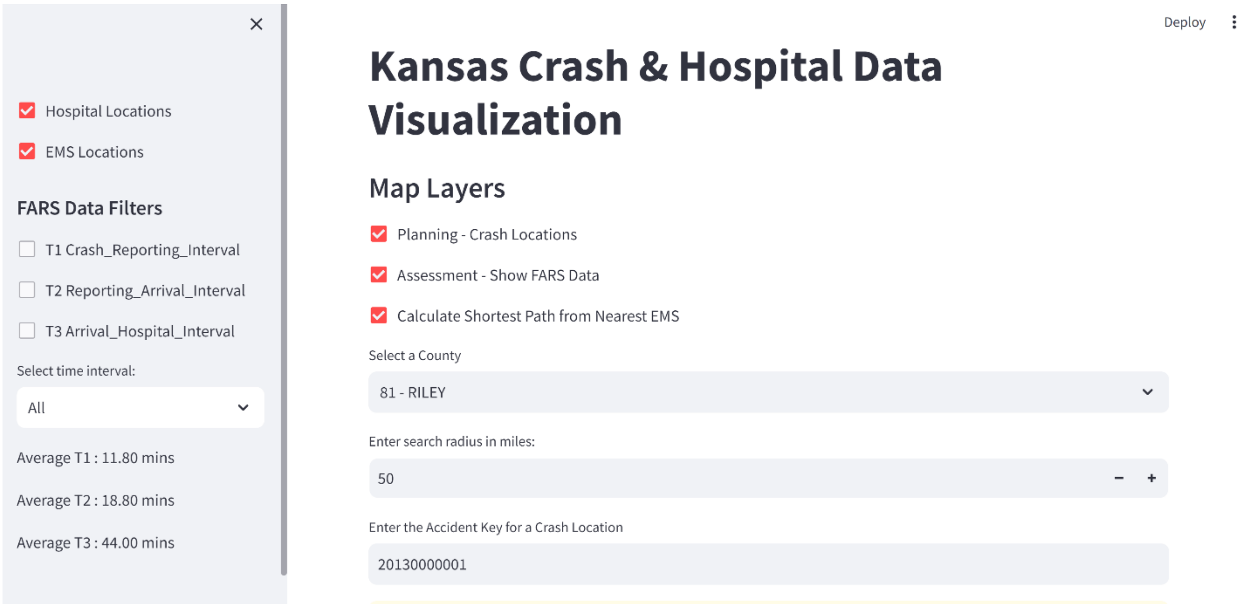


Figure 5.6: Input Fields for Radius and Accident Key

Figure 5.6 shows an example of how to query for a specific crash using an accident key of 20130000001 and determine the path from the crash location to the nearest hospital. For example, enter the accident key as the value in the input field. It will display that specific crash location and path to the nearest hospital.

5.1.3 Routing to Nearest Trauma Center

After selecting a crash location (either a specific point or a historical crash), users can compute the estimated average travel time. To find the nearest hospital to a crash site within a specified radius, users can enter the accident key (or exact location) in the provided input field and adjust the radius as needed. The map will then display the nearest hospital and the route from the crash location. Similarly, users can find the nearest EMS dispatch center to the crash site. By default, the radius is set to 50 miles, and the accident key field is left empty. When the accident key field is empty, all crash locations in the selected county will be displayed. Selecting a specific crash will show its location and the route to the nearest hospital. Additionally, clicking on any marker will display further details, such as the hospital's name, trauma level, and whether the crash occurred in a rural or urban area.

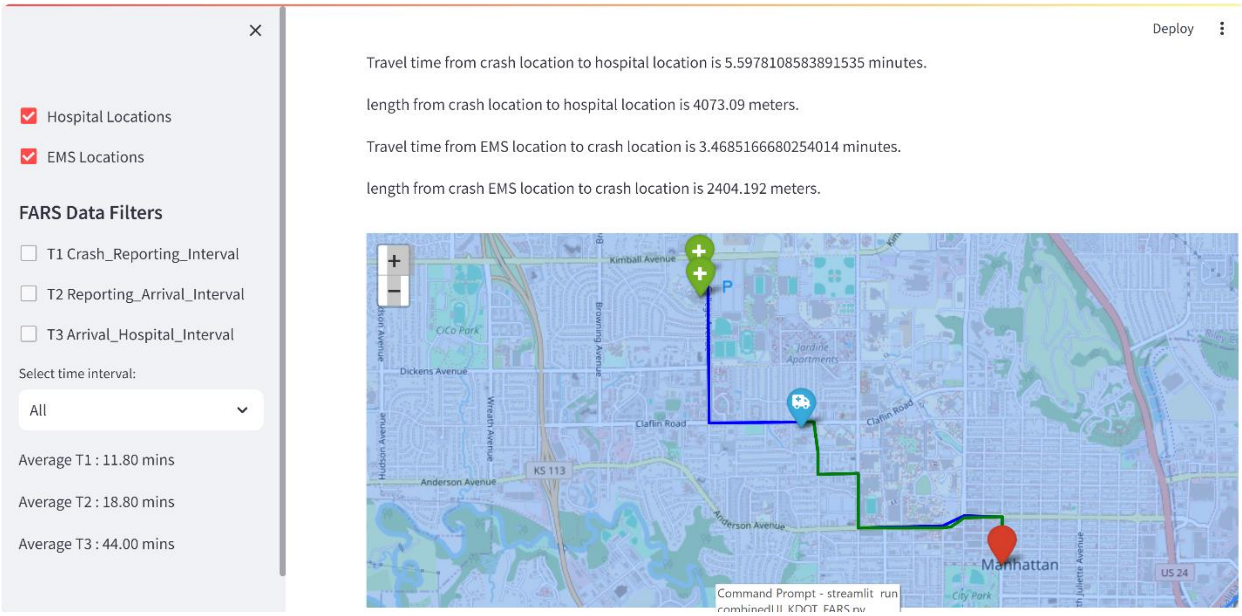


Figure 5.7: Travel Time Estimation Using the Shortest Path from EMS to Crash Location & Crash to Hospital Location

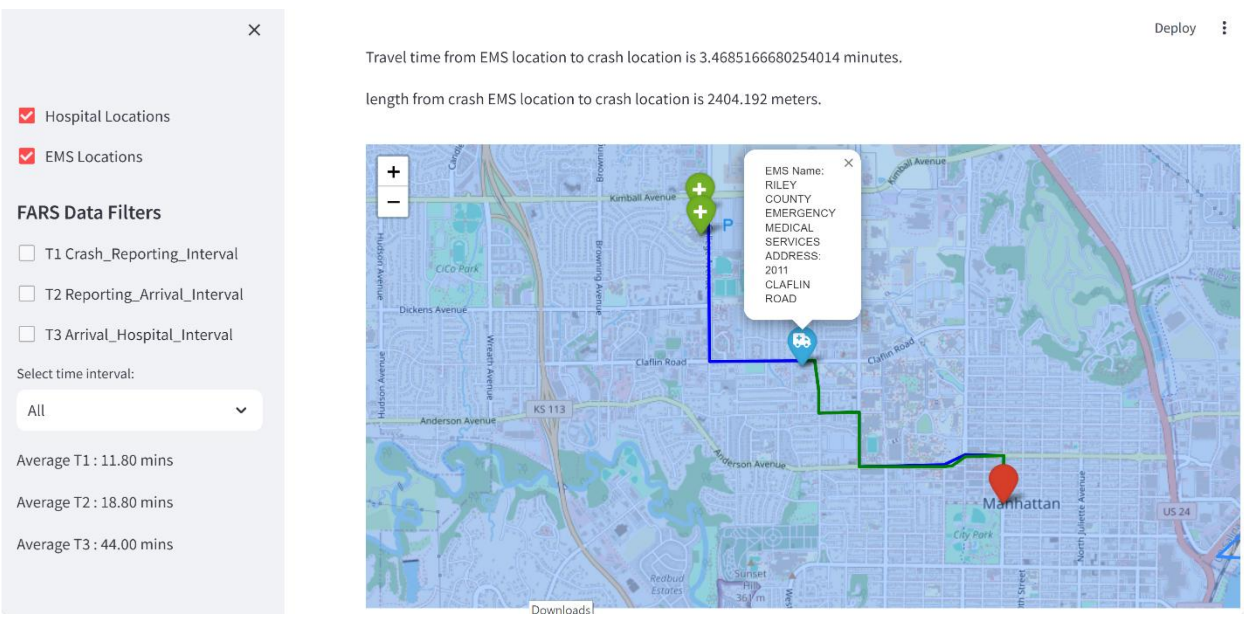


Figure 5.8: Pop-Up to Display Details of EMS/Hospital

5.2 Assessment

5.2.1 Response Time (T1, T2, &T3) Statistics

The assessment module is built using FARS data and provides statistics at the state and county level, with options to filter fatal crashes based on time intervals (T1, T2, T3) and geographical boundaries (state and county filters). For example, when Kansas is selected from the dropdown menu, the Graphic User Interface (GUI) displays FARS data for the state. It displays statistics for the state of Kansas including the minimum, maximum, and mean values for the T1, T2, and T3 intervals.

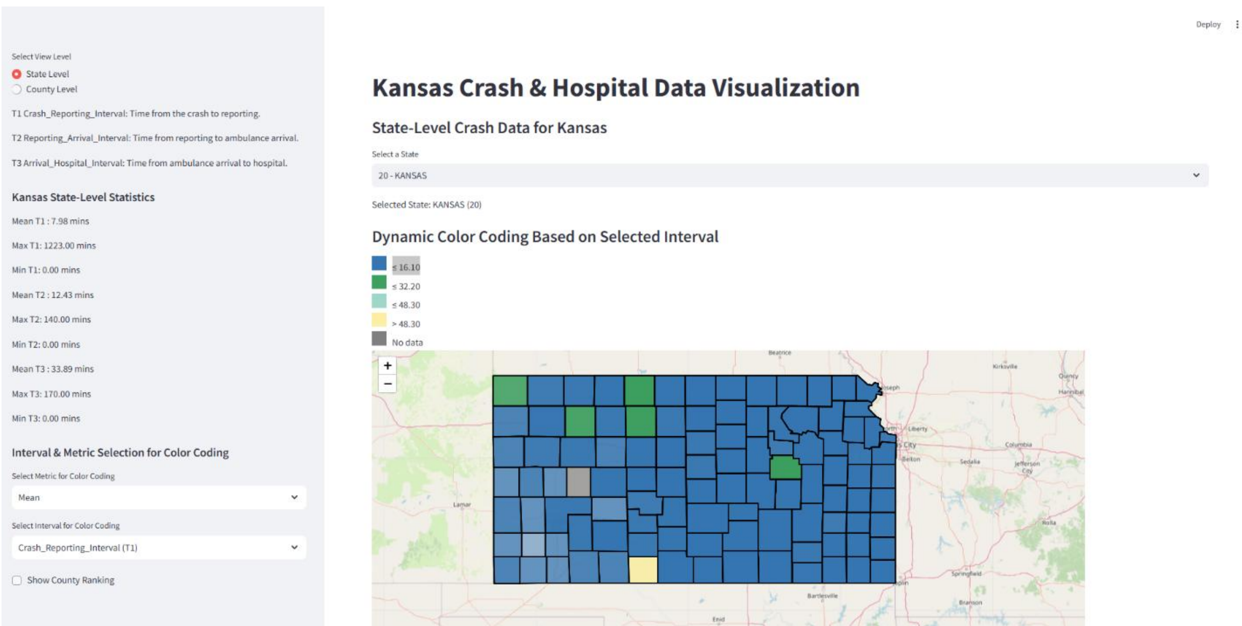


Figure 5.9: State Level Statistics of Kansas

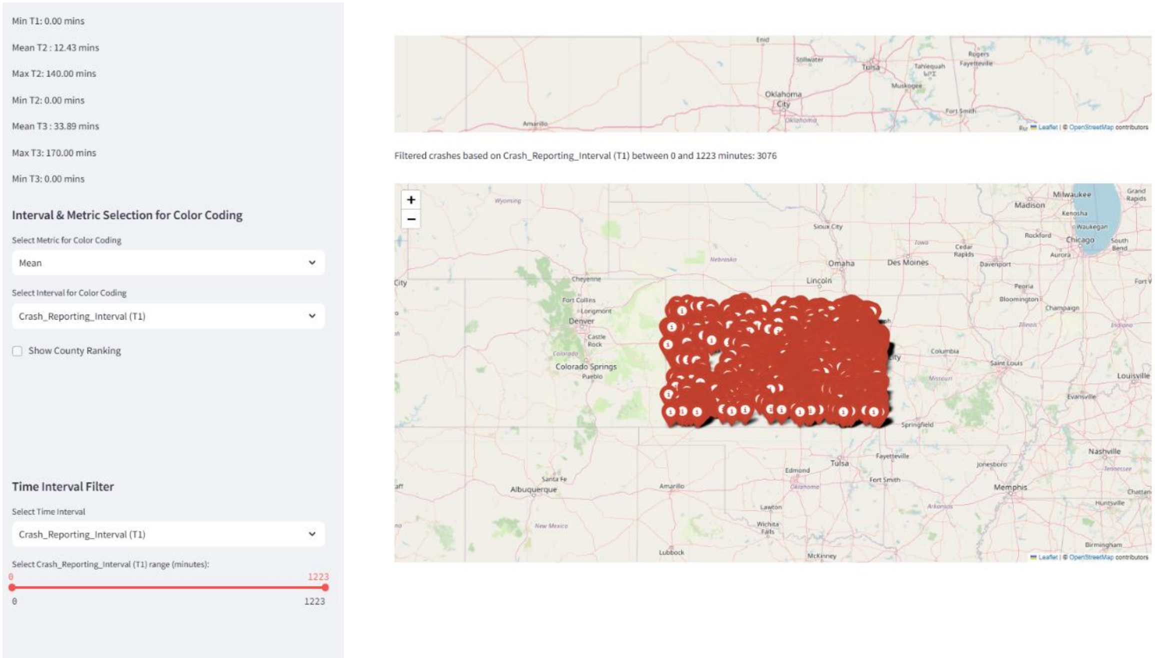


Figure 5.10: State Level FARS Data for Kansas

The main display features a map of Kansas, with state and county boundaries outlined, using color coding to represent the mean, max and min values of the intervals T1, T2 and T3. A legend is provided to help interpret the color-coded data.

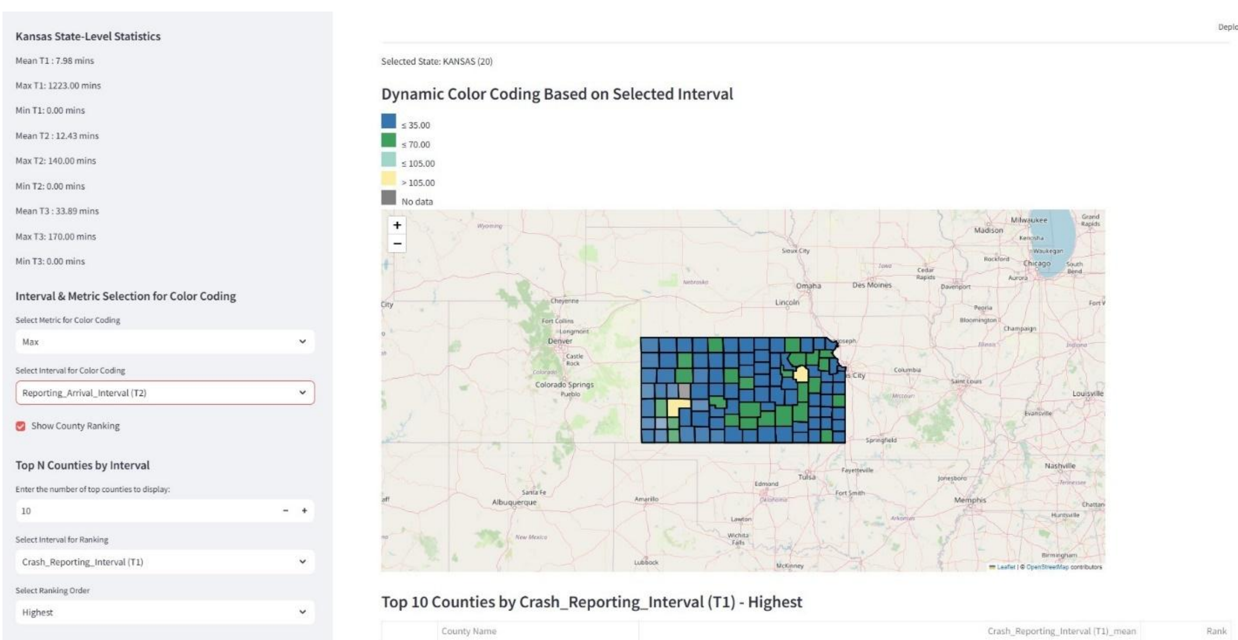


Figure 5.11: Spatial Mapping for Minimum Values of T2

The GUI displays the list of counties based on the maximum, minimum, and mean values of intervals T1, T2, and T3 sorted in ascending or descending order.

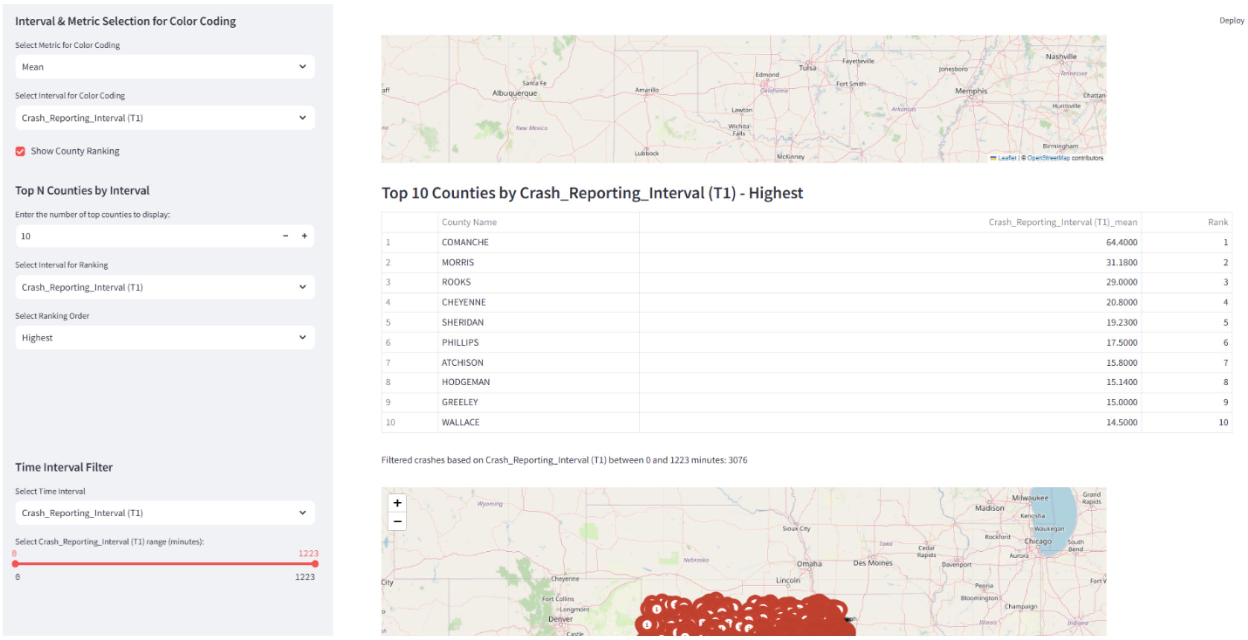


Figure 5.12: Ranking of Counties in Kansas Based on Selected Interval Values

5.2.2 Response Time (T1, T2, & T3) Spatial Mapping with User-Defined Ranges

The module can display a map of FARS crash data for the state, utilizing a clustering approach that shows varying levels of detail depending on the zoom level. Additionally, a slider allows users to adjust the time intervals, ranging from 0 to the maximum value found for the T1, T2, and T3 intervals. Users can adjust the slider to specify a desired time range (e.g., 101-310 minutes for T3), and select the relevant column by checking a box in the sidebar (e.g., T3 values). Once the filter is applied, crashes that fall within the selected time range are visually highlighted on the map with red circles. The interface also updates to display the total number of crashes that meet the specified criteria.

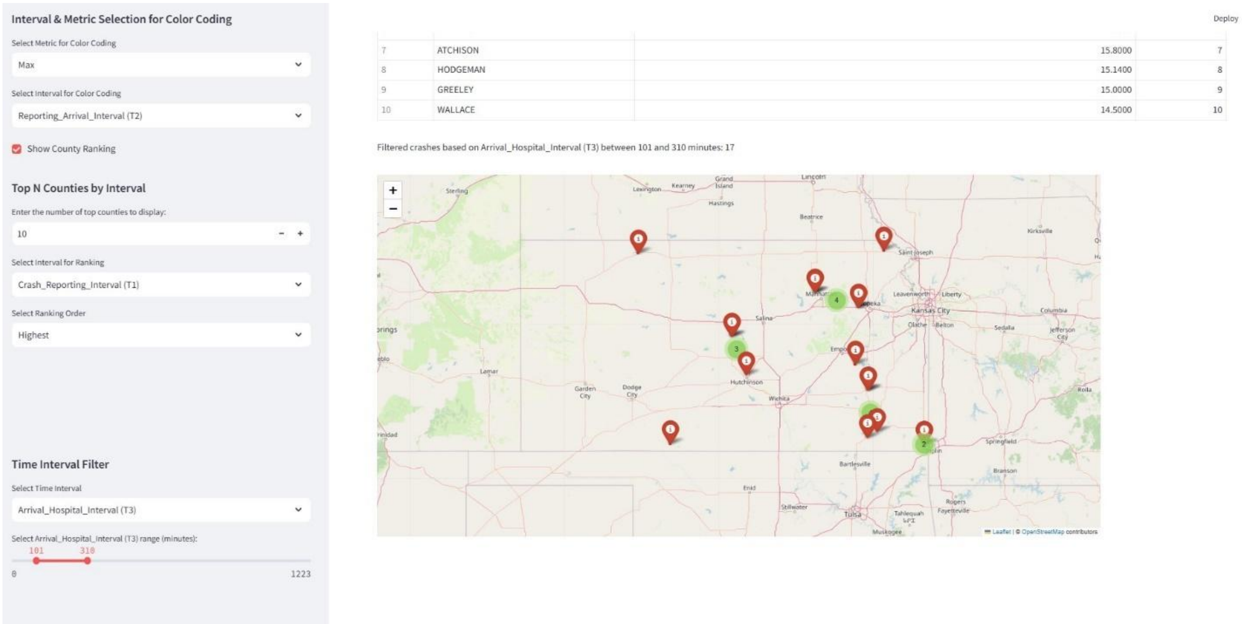


Figure 5.13: Filtering and Mapping Crashes with a Specified Range for T3

Similarly for the county level, once the county level is selected, a second dropdown menu lists its corresponding counties. Upon selecting a county, the sidebar displays statistics for the chosen county, including the county code, county name, and the minimum, maximum, and mean values for the T1, T2, and T3 intervals. The display focuses only on the crashes in the selected county.

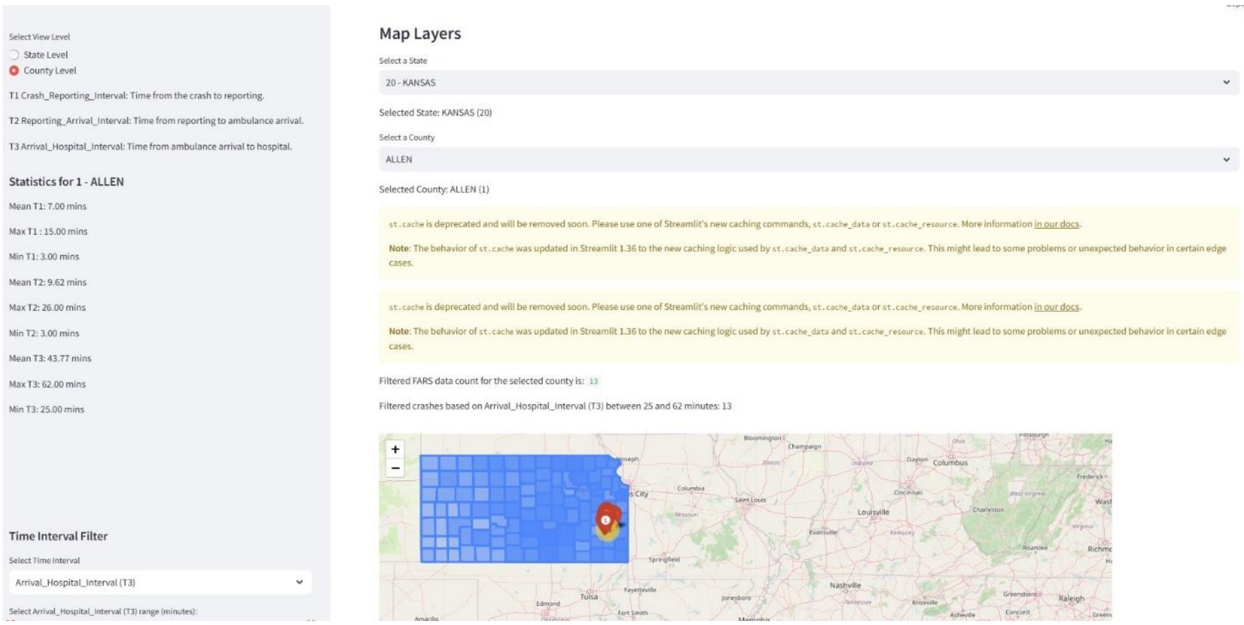


Figure 5.14: County Level Statistics with Crashes in the Specific County

The map displays FARS crash data for the selected county, using a clustering approach that allows for varying levels of detail at different zoom levels. Additionally, a slider controls the selection of time intervals, with a range from minimum to the maximum value found across T1, T2, and T3 intervals. Users can adjust this slider to specify a desired time interval (e.g., 0-31 minutes for T1) and choose the relevant column in the dropdown (e.g., T1 Crash_Reporting_Interval). Once applied, this filter visually highlights the relevant crashes with red circles on the map, indicating these incidents fall within the selected time interval. The interface also updates to display the count of crashes that meet the specified criteria for the selected county.

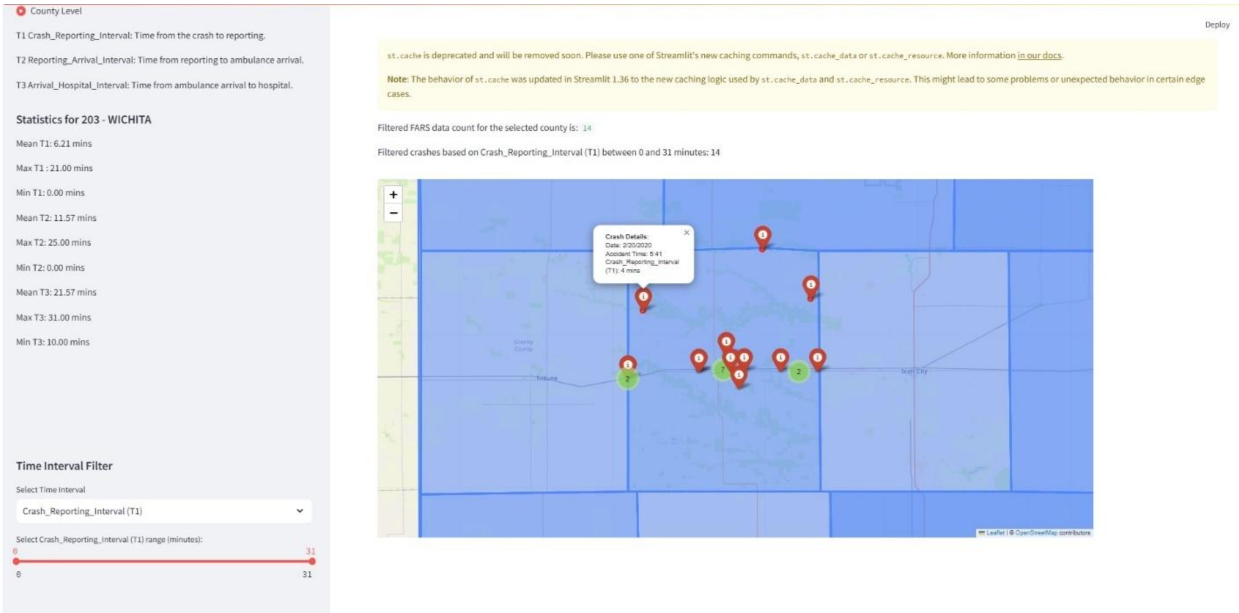


Figure 5.15: Customizing Response Time Range to Identify Crashes within the Chosen Spatial Boundary (e.g., Wichita, KS)

Chapter 6: Conclusion and Future Work

6.1 Conclusion

This research has developed a comprehensive web-based tool aimed at improving emergency response strategies, with a focus on reducing response times and fatalities, particularly in rural areas. By leveraging the Kansas Department of Transportation (KDOT) and Fatality Analysis Reporting System (FARS) datasets, we were able to create a geospatial tool that allows for the visualization of crash locations, EMS dispatch points, and hospitals, while providing analysis of emergency response routes.

The planning module enables users to visualize crash hotspots and efficiently map EMS dispatch locations and hospitals, offering actionable insights for emergency responders and law enforcement agencies. By utilizing shortest path algorithms and route optimization, the tool supports the dynamic adjustment of EMS routes, targeting faster response times. The assessment module, on the other hand, provides a historical analysis of fatal crash data, allowing stakeholders to assess past EMS responses and identify areas that require improvement.

The tool's capacity to identify critical corridors and high-priority areas for EMS dispatching offers a direct benefit to state and local transportation safety entities. The insights generated by the tool can assist these agencies in strategically improving EMS coverage, ultimately contributing to the improvement of post-crash care across the state or in specific counties.

Overall, the web-based tool provides a practical solution for addressing the disparity in emergency response times between urban and rural regions, enhancing post-crash care and reducing fatalities across Kansas. This framework has the potential to be adapted for use in other geographic regions and could serve as a valuable resource for first responders across the nation.

6.2 Future Directions

Looking ahead, there are several key enhancements that could be implemented to improve the functionality and scalability of the geospatial tool. One of the most promising directions for future work is the incorporation of machine learning (ML) techniques. By integrating ML models, the tool could be used to predict high-risk crash zones and forecast the estimated time of occurrence for traffic crashes based on historical data. Once trained and validated, these predictive models would allow for more accurate identification of critical geographic areas, such as safety corridors and counties with higher crash risks.

Future enhancements may include further the optimization of EMS routing by incorporating real-time traffic data into the tool. Real-time traffic conditions, such as congestion or road closures, would be invaluable in dynamically adjusting EMS routes, reducing response times even further. This enhancement would allow emergency responders to navigate the most efficient routes based on current traffic patterns, providing an even greater level of service for crash victims.

Another future improvement involves ensuring the scalability and user-friendliness of the tool. To achieve this, the system's ability to handle an increase in user activity and website traffic will be consistently evaluated. Another key component of the tool will be compatibility across various platforms, including smartphones, notebooks, and desktops, to ensure that first responders can access the tool from multiple devices.

By incorporating these future enhancements, the tool will continue to evolve, providing even more powerful insights into crash patterns, EMS response times, and road safety. With the addition of ML-driven forecasting and real-time traffic integration, the tool will play an even more critical role in saving lives and improving traffic safety outcomes.

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Appendix

Note that the table does not report data for Lane County. The FARS dataset used for analysis did not have the required data to estimate the values.

Table A.1: Mean Crash Reporting Interval (T1) in Minutes for 105 Counties in Kansas

County Name	**Crash Reporting Interval (T1) Mean** Time from Crash Occurrence to EMS Notification
COMANCHE	64.4000
MORRIS	31.1800
ROOKS	29.0000
CHEYENNE	20.8000
SHERIDAN	19.2300
PHILLIPS	17.5000
ATCHISON	15.8000
HODGEMAN	15.1400
GREELEY	15.0000
WALLACE	14.5000
ELLIS	14.1500
NORTON	13.8600
SHERMAN	13.1800
JEWELL	13.0000
KEARNY	12.5000
GREENWOOD	12.3000
HASKELL	12.2200
CRAWFORD	11.1200
KINGMAN	11.0900
LEAVENWORTH	11.0900
ELLSWORTH	11.0700

STANTON	9.3300
LYON	9.0900
RAWLINS	9.0000
MCPHERSON	8.9700
BOURBON	8.8200
DOUGLAS	8.3000
DICKINSON	8.0400
LINCOLN	8.0000
RILEY	7.8400
WYANDOTTE	7.7500
FRANKLIN	7.7200
DONIPHAN	7.4500
TREGO	7.3800
WABAUNSEE	7.2500
MARSHALL	7.2300
RICE	7.1600
FINNEY	7.0200
ALLEN	7.0000
MONTGOMERY	6.9400
OSAGE	6.8800
PAWNEE	6.8100
BROWN	6.7300
SUMNER	6.4400
MITCHELL	6.4300
SHAWNEE	6.4200
RUSSELL	6.3300
BUTLER	6.2200
LABETTE	6.2100

WICHITA	6.2100
RENO	6.1400
NEOSHO	6.0900
JEFFERSON	6.0500
FORD	5.9600
SEDGWICK	5.9500
SALINE	5.9400
MEADE	5.7600
SCOTT	5.7500
NESS	5.7500
LINN	5.7300
ANDERSON	5.3800
WOODSON	5.3300
MORTON	5.2500
BARBER	5.2500
HARPER	5.2500
MARION	5.1600
HAMILTON	5.0700
JACKSON	5.0500
REPUBLIC	5.0000
SMITH	5.0000
POTTAWATOMIE	4.9500
CHEROKEE	4.9000
PRATT	4.8400
GRANT	4.8300
CLAY	4.8000
CHASE	4.6400
GEARY	4.6300

GRAHAM	4.5000
HARVEY	4.4900
CLARK	4.4400
RUSH	4.4400
MIAMI	4.3000
STEVENS	4.2200
NEMAHA	4.1400
GOVE	4.0000
WASHINGTON	4.0000
OTTAWA	3.9500
THOMAS	3.7600
STAFFORD	3.7500
GRAY	3.7300
WILSON	3.7300
COWLEY	3.7100
COFFEY	3.6900
JOHNSON	3.5600
OSBORNE	3.5000
CLOUD	2.9000
CHAUTAUQUA	2.8900
LOGAN	2.8000
ELK	2.7500
BARTON	2.2000
EDWARDS	2.1700
KIOWA	2.1200
SEWARD	1.7000
DECATUR	0.6700

Table A.2: Mean Reporting Arrival Interval (T2) in Minutes for 105 Counties in Kansas

County Name	**Reporting Arrival Interval (T2) Mean** Time from EMS Notification to EMS Arrival
WABAUNSEE	36.9500
KINGMAN	24.6400
PHILLIPS	23.0000
KIOWA	20.5000
JEWELL	19.5000
GREELEY	19.5000
OSAGE	19.4800
SHERIDAN	19.3100
HASKELL	19.1100
LINN	19.0000
GREENWOOD	17.9100
LYON	17.7700
ELK	17.7500
WOODSON	17.6700
ATCHISON	16.7300
RAWLINS	16.5000
GOVE	16.4000
DECATUR	15.6700
CHAUTAUQUA	15.6700
PRATT	15.3100
JEFFERSON	14.8600
CHASE	14.8200
FINNEY	14.6400
KEARNY	14.5000
ELLSWORTH	14.2500
BUTLER	14.0300

SCOTT	13.8800
MORTON	13.8800
MEADE	13.8600
HODGEMAN	13.8600
EDWARDS	13.8300
LOGAN	13.6000
GRAY	13.5900
NESS	13.5000
BARBER	13.5000
CLARK	13.3300
NEOSHO	13.0900
MARSHALL	13.0800
FORD	12.7000
COFFEY	12.6900
PAWNEE	12.6900
SUMNER	12.6800
COMANCHE	12.4000
BOURBON	12.2700
LABETTE	12.2400
SMITH	12.0000
TREGO	11.7700
SHERMAN	11.7300
MITCHELL	11.7100
STANTON	11.6700
WICHITA	11.5700
DOUGLAS	11.5100
RENO	11.4600
CRAWFORD	11.4200

NORTON	11.2900
DONIPHAN	11.1800
MONTGOMERY	11.1000
NEMAHA	11.0000
SEWARD	10.9500
RICE	10.9500
MARION	10.7600
BROWN	10.5300
GRANT	10.5000
MCPHERSON	10.4700
JACKSON	10.4300
HARPER	10.4200
CLAY	10.4000
MORRIS	10.3600
RUSSELL	10.3300
ROOKS	10.2400
GEARY	10.1400
LEAVENWORTH	10.0400
WALLACE	10.0000
COWLEY	9.9000
SALINE	9.8900
STEVENS	9.7800
RILEY	9.7300
THOMAS	9.6200
ALLEN	9.6200
MIAMI	9.5700
OTTAWA	9.5000
GRAHAM	9.5000

CHEROKEE	9.3300
POTTAWATOMIE	9.1400
ANDERSON	9.0600
LINCOLN	9.0000
HARVEY	8.9400
FRANKLIN	8.7800
DICKINSON	8.7500
WILSON	8.5900
STAFFORD	8.3800
ELLIS	8.3300
HAMILTON	8.0700
RUSH	7.8900
SHAWNEE	7.6800
CHEYENNE	7.6000
BARTON	7.4300
SEDGWICK	7.3100
OSBORNE	7.0000
WYANDOTTE	6.6000
REPUBLIC	6.5500
WASHINGTON	6.4400
JOHNSON	6.4000
CLOUD	6.0000

Table A.3: Mean Arrival Hospital Interval (T3) in Minutes for 105 Counties in Kansas

County Name	Arrival Hospital Interval (T3) Mean Time from EMS Arrival to Hospital Arrival
WOODSON	66.3300
LINN	63.6400
NEOSHO	54.0900
LYON	52.9100
KINGMAN	51.0000
MARION	49.6400
CHASE	46.1800
ELLSWORTH	45.4600
COMANCHE	45.4000
DECATUR	45.0000
RENO	44.9400
GREENWOOD	44.6500
MIAMI	44.5700
WALLACE	44.5000
OSAGE	44.1200
ALLEN	43.7700
LEAVENWORTH	43.6100
JEWELL	43.5000
MCPHERSON	43.3300
POTTAWATOMIE	43.0500
BUTLER	42.8300
CHEROKEE	42.8300
HASKELL	42.7800
NORTON	42.7100
MORRIS	41.8200
ELK	41.5000

WABAUNSEE	41.4500
LINCOLN	40.0000
SUMNER	39.4700
JACKSON	39.1400
JEFFERSON	39.0800
HARVEY	39.0600
TREGO	38.8500
LOGAN	38.8000
FORD	38.5300
PRATT	38.5000
ANDERSON	38.1200
MONTGOMERY	38.1000
DOUGLAS	38.0900
ATCHISON	37.3300
SHERIDAN	36.9200
STAFFORD	35.9400
RILEY	35.7500
COWLEY	35.7100
NEMAHA	35.4300
ROOKS	35.2400
FRANKLIN	35.0300
GRAY	34.8600
PHILLIPS	34.8600
CLAY	34.8000
GEARY	34.5700
RUSSELL	34.0800
CHEYENNE	33.8000
RUSH	33.5600

CLARK	33.3300
BARTON	33.1000
HAMILTON	32.4300
OTTAWA	32.2700
CRAWFORD	31.8200
BROWN	31.5300
THOMAS	31.1900
BOURBON	30.6400
LABETTE	30.5200
MARSHALL	30.1500
DONIPHAN	29.7300
HARPER	29.5000
COFFEY	29.0000
MORTON	28.5000
PAWNEE	27.8800
DICKINSON	27.8600
FINNEY	27.8400
SEDGWICK	27.6800
CHAUTAUQUA	27.5600
ELLIS	27.4800
BARBER	27.2500
STEVENS	27.0900
GRANT	27.0000
GRAHAM	27.0000
RICE	26.8400
KIOWA	26.5000
RAWLINS	26.5000
SMITH	26.2500

MITCHELL	26.0000
SHAWNEE	25.8800
JOHNSON	25.1200
STANTON	24.3300
WILSON	24.2700
SALINE	24.1100
SEWARD	22.8400
WYANDOTTE	22.6800
MEADE	22.6700
HODGEMAN	21.7100
WICHITA	21.5700
WASHINGTON	20.8900
SCOTT	19.8800
EDWARDS	19.8300
OSBORNE	19.7000
GREELEY	19.5000
SHERMAN	19.0900
KEARNY	18.3300
GOVE	17.3000
REPUBLIC	16.6400
CLOUD	15.3000
NESS	13.7500

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KANSAS TRANSPORTATION RESEARCH AND NEW-DEVELOPMENT PROGRAM

Kansas
Department of Transportation