Factors Affecting Traffic Crash Survivors' Accessibility to a Trauma Center within the Golden Hour

By

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Submitted to the graduate degree program in Civil Engineering and the Graduate Faculty of the University of Kansas in partial fulfillment of the requirements for the degree of Master of Science.

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Date Defended: August 30, 2023

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Date Accepted: August 31, 2023

Abstract

The Golden Hour has been used as an ideal measure of patients' access to trauma centers. It is the one hour after any traumatic event, including a traffic crash. It was shown that if patients can arrive at the hospital within one hour after a traumatic injury, the chances for survival increase. Therefore, this study aimed to identify the determining factors for patients involved in a traffic crash to arrive at the trauma center within the Golden Hour. For this, four years (2018-2021) of Kansas traffic crash data were investigated. Among the eight factors analyzed in the study, the time of the crash and lighting conditions were found to be the most important factors. The result showed that crashes that occurred when it was dark with no streetlights experienced the highest total transport time (TTT), which was 61.3 minutes. It may be an indication that crashes with longer TTT occurred in rural remote locations. TTT did not exceed the Golden Hour for any other factor. This study also showed that the distance between the crash location and the trauma center was not the only factor for increased total transport time (TTT). For example, crashes occurring within 5 miles of trauma centers can experience TTT higher than 60 minutes. This could happen if a crash goes unnoticed for a long period of time or if time is needed to extricate the patients.

Dedication

I would like to dedicate this work to the millions of people from developing countries like Bangladesh who do not have good health care, and who even do not have the concept of the Golden Hour, and to my paternal uncle, Babul Mojumder, who died in a traffic crash in May 2013.

Acknowledgments

This thesis work would not be completed without the help and continuous support of some people. It is my pleasure to have a chance to acknowledge them here. Therefore, I would like to mention the following persons:

- Dr. Steven D. Schrock: Throughout the last two and half years, Dr. Schrock guided me toward the journey of my master’s degree. His continuous mentoring helped me to approach a problem in a realistic and easy way. I will be grateful to him for instructing me to develop an insight into research problems and my personal life too.
- Dr. Hemin J. Mohammed: I had the opportunity to be in touch and work with Dr. Hemin Mohammed in the first year of my master’s degree. He involved me in writing a journal article, reviewed my writing sample, and guided me. Without his guidance, it would be tough to get introduced to the world of transportation engineering research.
- Elsit Mandal & Haley Dougherty: Elsit and Haley are the staff from the Kansas Department of Transportation (KDOT) who helped me to get the traffic crash report, districts’ map and participated in the discussion on the crash report. Active engagement of Haley in my queries on the traffic crash report was necessary to answer my questions and clean the data for analysis.
- Thesis committee members: I would like to thank my thesis committee members for their valuable review of my thesis proposal and thesis which improved the final outcome.

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Chapter 1: Introduction

Thousands of people die annually across the United States (U.S.) from road traffic crashes. According to the National Highway Traffic Safety Administration (NHTSA), 42,795 people died in road traffic crashes in the United States (U.S.) in 2022, while this number was 42,939 in 2021 (National Highway Traffic Safety Administration, 2023). Data from the Centers for Disease Control and Prevention (CDC) showed that road traffic crash was the second largest cause of unintentional deaths (accounting for 22.6% of total unintentional death from 2015-2020) in the US (Centers for Disease Control and Prevention, 2020). As a result, many initiatives have been taken to reduce traffic crashes and mitigate post-crash trauma on road users. Recently, NHTSA proposed the “Safe System Approach (SSA)” to confront traffic crashes (Ritter et al., 2022). Post-crash care is one of the critical components of this SSA.

One of the strategies of post-crash care is the idea of the “Golden Hour.” The Golden hour is a concept used in trauma and emergency management (Rogers et al., 2015). It refers to the first hour after a crash (e.g., traffic crash, fire). It is believed that if trauma patients are given proper treatment within the first hour of a crash, then the chances of survival increase.

Although the Golden Hour concept was widely accepted, no concrete evidence supported or negated this. A paper (Lerner and Moscati, 2001) reviewed the previous articles that mentioned Golden Hour . The goal was to find the origin and scientific evidence supporting the Golden Hour concept. After reviewing some of the earliest articles on Golden Hour, the authors reported that they found little evidence to support the Golden Hour concept. They reported that the Golden Hour could neither be proven nor disproven.

A recent study (Hashmi et al., 2019) in the US analyzed the number of possible traumatic deaths which could be preventable by timely access (within one hour after the incident) to a trauma center. The study collected state-level adult (≥15 years old) traumatic death data between 1999-2016 from multiple sources, including the Centers for Disease Control and Prevention. Deaths from drowning, fire/flame, hot objects/substances, natural/environmental, overexertion, poisoning, and suffocation were excluded from the analysis. In total, 1,949,375 adult trauma deaths were included in the analysis. The statistical analysis showed an inverse correlation ($r=-0.64$) between the proportion of the population with access to Level I/II trauma centers within one hour and the ratio of prehospital deaths to in-hospital deaths. The result also found an inverse correlation ($r=-0.71$) between the ratio of prehospital death to in-hospital death and age-adjusted mortality rate per 100,000 population. Both results were statistically significant ($p<0.05$).

1.1 Problem Statement

A study (Branas et al., 2005) in the US estimated the percentage of the population getting access to trauma centers. The study collected trauma centers and population data on all 50 states and the District of Columbia. The result showed that nationally 69.2% and 84.1% of the population had access to Level I or II trauma centers within 45 and 60 minutes, respectively. However, had lower numbers, with 48.5% and 62.3% of the Kansas population have no access to Level I or II trauma centers within 45 and 60 minutes, respectively. The study was conducted in 2005 and did not differentiate between injury due to traffic crashes and other types of traumas.

A recent study (Hu et al., 2018) estimated the travel distances from Level I or II trauma centers for fatal traffic crashes. The result showed that in the Midwest, the average route and linear distance from the trauma center was 33.6 miles (54.1 kilometer (km)) and 27.6 miles (44.4 km), respectively. For Kansas, these distances were 62.6 miles (100.7 km) and 53.4 miles (85.9 km), respectively.

These two studies showed that Kansas had lower access to Level I or II trauma centers than the national average, and the distances of traffic crashes from trauma centers were also more than its neighboring states. Increased distance will tend to increase the transport time to a trauma center, Therefore, it is essential to understand how faster road traffic trauma patients can access trauma centers and possible measures to improve accessibility. For this, it is necessary to know the factors affecting accessibility to trauma centers.

1.2 Research Objectives

The objective of this study was to investigate the accessibility of road trauma patients to trauma care within the Golden Hour. To do so, this study analyzed factors that affect accessibility.

1.3 Research Benefits

This analysis will help to target any factors that delay accessibility to trauma care. In addition, the study will highlight road networks that are not reachable within the Golden Hour. By doing so, this study can answer what percentage of road trauma patients can have access to trauma centers within the Golden Hour. This will guide to help better post-crash management and future distribution of trauma care infrastructure.

1.4 Thesis Organization

This thesis is divided into six chapters. The first chapter is ‘Introduction.’ This discussed the thesis's objective, problem statement, and research benefits. The second chapter, ‘Literature

Review,’ shows previous research studies related to the thesis topic. This chapter also finds the literature's limitations, emphasizing this thesis's importance. The third chapter is about the applied methodology to conduct research and the source of data collection. A short description of the data is also included in this chapter. The fourth chapter discusses the results of the data analysis and compares the results with the findings from previous research. The Conclusion and Recommendation’ is the final chapter. This chapter recommends the application of the results and possible future works. In addition, the final chapter also shows the limitations in conducting the research and the possible ways to improve the outcome.

Chapter 2: Literature Review

Throughout the last few decades, many studies have been conducted to investigate the accessibility of people to trauma centers across the world. Those studies investigated all types of traumatic incidents, including traffic crashes. Studies analyzed accessibility to trauma centers from different points of view. Most studies focused on the travel time and distance of incidents from emergency centers as deciding factors for trauma center accessibility. Studies also analyzed the impact of the location of emergency vehicles (ambulance) centers, the location of the incident, traffic congestion, the number of emergency calls on ambulance response time (ART), and on-time admission to the hospital. While some studies focused on a single factor that affects trauma center accessibility and ART, most studies investigated the influence of multiple factors.

Based on the literature review, studies can be organized under the following broad categories:

- Influence of travel-distance and travel-time;
- Influence of traffic volume;
- Influence of emergency centers location;
- Influence of rural and urban areas;
- Others; and
- Conclusions.

This literature review did not include all the studies related to trauma center accessibility conducted throughout the last few decades worldwide. Yet the literature review was intended to reflect an understanding of this field. As field triage patterns and emergency services (e.g., modernization of emergency vehicles) might change significantly every decade, recent works were reviewed with special emphasis. A particular interest of the literature review was focused on studies that included traffic crash data to analyze trauma center accessibility. While road traffic fatalities accounted for a significant portion of traumatic deaths, only a handful of studies were found to investigate the accessibility to a trauma center for patients involved in a traffic crash. When a study involves road traffic crash data, it will be specifically mentioned to differentiate it from other trauma.

Throughout the literature review, a few terms like “response time,” “notification time,” and “transport time interval” will be noticed. As the study location for reviewed studies were not the same, the definition and meanings of these terms were not the same for each country. To avoid ambiguity and confusion, definitions of any relevant term will be given right after mentioning a term, if needed.

2.1 Influence of Travel-Distance and Travel-Time

A significant portion of the reviewed studies focused on the travel distance between the crash location and emergency service center (ambulance center and trauma center) locations. Sometimes travel time was also used to see if the patients had access to the trauma center within the Golden Hour. Travel time was estimated using the travel distance and road speed limit. ESRI ArcGIS Network Analyst tools made this estimation possible. Hence, travel distance and travel time are interrelated and discussed here.

A recent United States (U.S.) study compared the estimated time from the crash location to the trauma center (Hu et al., 2020). Estimated time was the travel time from the crash location to the trauma center estimated using ArcGIS. The study used FARS data from 2013-2017 for all states in the U.S. The study found that some rural areas' actual time (transport interval) was less than the estimated interval. This indicates that those patients were taken to local hospitals instead of a Level I or II trauma center. The same study also analyzed the correlation between mortality rates and time intervals. The investigated time intervals, commonly known as rescue intervals, were; notification time, transport interval, and arrival interval. Among these time intervals, the estimated interval (estimated using ArcGIS) showed the strongest correlation with mortality rates. Conversely, the actual transport interval did not show a statistically significant correlation for most of the states. The study concluded that adhering to the Golden Hour without considering distance may not be helpful. This study was also limited to fatal crashes, and injury crashes were not considered. Involvement in injury crashes might yield different results.

A study published in 2017 analyzed access to a trauma center after road crashes in the U.S. (Hu et al., 2018). The study used 2013-2014 Fatality Analysis Reporting System (FARS) data. FARS data records fatal crashes, including notification, dispatch, and transport time from the crash location to the trauma center. Using ArcGIS, the study investigated the effects of travel distance on trauma care access. Two distances, namely linear and routed distance, from the crash location to the trauma center were estimated. The result showed that these distances were 53.4 miles (85.9 km) and 62.6 miles (100.7 km) in Kansas. These were average for all fatal crashes. Among Midwestern states, these distances were higher in South Dakota and North Dakota. For some states, these distances were less than half of Kansas's. These longer distances indicated a longer transport time in Kansas from the crash location to a Level I/II trauma center, possibly due to the spread of crash locations. However, this study did not include injury crashes in the analysis.

A case study in South Africa investigated the spread of fatal crashes and access to a trauma center within the Golden Hour (Vanderschuren and McKune, 2015). The study assumed notification and admission times were zero, considering the best possible scenario after a traffic crash. Dispatch, stabilization, and loading times were loaded from the Provincial Government of Western Cape Town (PGWC). Then, transport time was estimated by subtracting all these available times (e.g., dispatch time, admission time) from one hour. Among the 13,037.3 miles (20,981.5 km) of road analyzed, the study found that 9,123.2 miles (14,682.4 km) was outside the Golden Hour. The study also showed that 53.1% of fatal crashes occurred outside of Golden Hour. One of the study's drawbacks was that it assumed ambulance speed to be the same as the road speed limit.

In Taiwan, a 2021 study (Wiratama et al., 2021) applied multivariate logistic regression on two years of traffic crash data (2017-2019) to measure the effect of travel distance and trauma center level on traffic crash fatalities. The study used Euclidean distance (not the actual travel distance) from the crash location to the nearest trauma center. A GIS-based nearest neighbor analysis measured the distance between the crash location and trauma centers. A 3.1 miles (five km) cut-off value was used to categorize the distance into ≥ 3.1 miles and < 3.1 miles. This study found that the 3.1 miles cut-off value was associated with the highest odds ratio than any other value (e.g., 0.62 miles (1 km), 1.3 miles (2 km), 3.7 miles (6-km), 4.3 miles (7 km)). Therefore, the 3.1 miles cut-off value was used to categorize crashes into two categories: crashes located ≥3.1 miles from the nearest trauma center and crashes located < 3.1 miles from the nearest trauma center. The logistic regression result indicated that crashes located ≥3.1 miles from the nearest trauma center were nearly two times more likely (odds ratio: 1.98) to sustain fatal injuries than crashes located <3.1 miles from the nearest trauma center.

While the above studies mentioned above were focused on the distance between trauma centers and incident locations, US-based research (Concepcion et al., 2022) investigated the impact of distance between trauma centers and the nearest highway exit (TC-HW distance) at the county level. A total of 2019 trauma centers were included in the analysis few of these were verified by the American College of Surgeons (ACS). Prehospital traffic fatalities from 2014-2019 were collected from Fatality Analysis Reporting System (FARS). The statistical analysis found no strong and significant correlation between prehospital fatalities and TC-HW distance at the county level. A moderate positive and significant correlation was observed between fatalities and trauma centers with TC-HW distance ≤ 5 miles. However, the study found that counties with TC-HW length ≤ 5 miles reported 17.7 prehospital fatalities, while this number was 101.2 for counties with TC-HW distance > 5 miles. In contrast to this result, counties with TC-HW lengths in between 10 to15 miles and 15 to 20 miles reported 48.3 and 12.8 prehospital fatalities, respectively. The study concluded that shorter distances between trauma centers and the nearest highway positively correlated with fewer prehospital fatalities for counties with trauma centers ≤ 5 miles from the nearest highway exit.

Conception et al. (2022) also showed that travel time to the trauma centers from the crash location increased with the increased TC-HW distance. Statistical analysis showed a positive correlation between travel time and prehospital fatalities for counties with TC-HW distances ≤ five miles. In contrast, an inverse correlation was observed between travel time and prehospital fatalities for counties with TC-HW distances from five to ten miles. In addition, K-nearest neighbor (KNN) analysis found that dispersed trauma centers were associated with increased prehospital fatalities. Using KNN, the nearest neighbor ratio (NNR) was estimated. NNR showed a positive correlation with prehospital fatalities. NNR was the distance between any single TC and its nearest TC neighbors.

A study (Sánchez-Mangas et al., 2010) in Spain analyzed 1463 traffic crashes. It was found that the mean response time was 25.4 minutes for motorways and 26.7 minutes for conventional roads. The response time was defined as the time interval between the traffic crash and the arrival of an emergency vehicle at the crash scene. The study established a probit model to estimate the influence of medical response time on crash fatality. According to the probit model results, longer medical response time was associated with a higher probability of death. The study estimated that death probability could decrease by one-third by a 10-minute reduction in medical response time.

A relationship between traffic fatality and ambulance response time was also established in the US. A study (O.J. Adeyemi et al., 2022) using FARS data from 2010-2019 applied a negative binomial regression model to estimate the relationship between response time and traffic fatality. Response time was used as the predictor variable, and fatality rate as an outcome variable. The result showed that with a one-minute increase in EMS notification time to scene arrival time, the fatality rate increased by 1% in rural areas. This percentage was 2% and 5% for micropolitan-urban and metropolitan-urban counties, respectively.

This section discussed studies investigating the effect of travel distance and time on prehospital mortality. A few takeaways from this section are summarized below:

- In the US, the correlation between transport time interval and prehospital traffic fatalities was not statistically significant (Hu et al., 2020).
- In the US, prehospital fatalities and TC-HW distance were not significantly correlated (Concepcion et al., 2022). For TC-HW distances ≤ five miles, distances affected traffic mortality significantly.
- Reduction of ambulance response time was associated with decreased probability of traffic fatality in the US and other countries (O.J. Adeyemi et al., 2022; Sánchez-Mangas et al., 2010).

2.2 Influence of Traffic Volume

Although emergency vehicles are given priority to drive, increased traffic volume can lead to traffic congestion and delays in vehicle movement. Typically, it takes work to get the traffic volume data while emergency vehicles are present. Hence, studies sometimes used surrogate measures to estimate increased traffic volume's impact on emergency vehicle response. Usually, traffic crashes on roadways can lead to traffic congestion in the nearby area, especially in urban areas, resulting in reduced speed. Following studies discussed the impact of traffic volume on emergency vehicles.

A study conducted in the Netherlands showed an effort to quantify the impact of traffic volume (Dijkink et al., 2020). Rush hours and low traffic hours were used as surrogate traffic volume measures. The time between 6:00 a.m.-9:00 a.m. and 4:00 p.m.-7:00 p.m. during weekdays were considered rush hours, and low traffic hours were between 12:00 a.m.– 6:00 a.m., 9:00 a.m. –

4:00 p.m., and 7:00 p.m. – 12:00 a.m. on weekdays and weekends. Using ArcGIS, the study estimated expected travel time, and from the actual data, the study found observed time. The result showed that during low traffic hours, the median observed and expected travel times 11.4 min and 11.1 min, respectively, while during rush hours, these times were 12.1 min and 12.0 min, respectively. This showed that travel time from the accident (not the traffic crash) location to the trauma center increased when traffic volume increased. Noticeably, the study assumed zip codes as accident locations, which was not the same as the traffic crash location. The same study also analyzed seven hypothetical scenarios considering the different distribution of trauma centers across the study area. The result showed that roughly 57% of the population could reach a trauma center within 15 minutes of accidents in a scenario of three trauma centers. In another scenario, populations served within 15 minutes were 53% and 51%. This indicates the same service range from two and three trauma centers. This analysis showed the potentiality of ArcGIS-based analysis in trauma center distribution and future planning.

To estimate the impact of traffic congestion on emergency medical services (EMS), a survey-based study was conducted in Alabama (Griffin and McGwin, 2013). the study took a survey from personnel of fire departments and ambulances. A total of 500 EMS providers (from the Alabama Department of Public Health) were selected, from which 112 responded to the survey. About 67.6% of responders were firefighters. Two-thirds of the responders served the urban areas. The survey result showed that the mean travel time due to traffic congestion increased by 2.5 minutes from the emergency center to the incident scene and 6.4 minutes from the incident scene to the final destination. Continuous median barriers on roads were reported by 75% of respondents to increase the EMS response at the scene. High occupancy lanes were reported by

70% of survey responders to have a beneficial impact on emergency response times. Among the in-vehicle technology, survey results showed that low-frequency sirens, GPS devices, and preemptive green lights could improve emergency response times. Responders (95.3%) also agreed that public education about how to react to an approaching emergency vehicle would reduce the response time.

A California-based study (Brent and Beland, 2020) used the actual traffic volume to estimate the impact of traffic congestion. The study analyzed the effect of traffic congestion and transportation policies on the response times of emergency vehicles. Response time was the interval between the incident notification and the emergency vehicle's arrival. Emergency response data were collected for California from 2008 to 2015, which contains fires, emergency medical services, and other hazards. A five-minute traffic data window was used just before the emergency alarm to estimate the traffic deciles and delays from free flows. Both the traffic deciles and delays were then merged with emergency response data. The study excluded traffic crashes from the analysis. The study found that traffic delays were lower in non-urban areas than in urban areas, but the response times were higher. The average response time was 6.2 minutes. For further analysis, regression analysis was conducted where response time was the outcome variable, and the independent variables were decile of traffic delays, year effect, and hour of the day. Regression results showed that traffic delays for emergency calls in the 9^{th} and 10^{th} deciles increased the response times by about 0.13 minutes (2.2% of response times) and 0.19 minutes (3.1 minutes of response times), respectively. However, this impact was heterogeneous across the different hours of the day. At peak hour, the response time increased by 9^{th} and 10^{th} deciles were 0.17 and 0.19 minutes. At an off-peak hour, the response times improved by 9^{th} and 10^{th}

deciles were 0.11 and 0.21 minutes. Unexpected traffic conditions (deciles of traffic delays) were also found to increase the response times weekly and monthly. All the results were statistically significant. The study also estimated that the zip codes with high occupancy vehicles and toll lanes had lower response times. In a zip code area with no HOV lanes, toll roads, rail, and metro stations, the response time was increased by 0.16 minutes, whereas a zip code area with any of these policies had lower response times. However, the number of fire stations was not a determining factor for response times. The authors explained that fire stations in Los Angeles were well-distributed, hence the distance between the fire station and the incident was not a predictor for response times.

The studies reviewed in the section (Brent and Beland, 2020; Dijkink et al., 2020; Griffin and McGwin, 2013) did not include traffic crash data. A study by Brent and Beland (2020) mentioned that traffic crashes could increase traffic congestion, which can be a factor in a traffic crash. Therefore, traffic congestion and the occurrence of a traffic crash might be correlated with each other.

From the discussion of this section, the following points can be summarized:

- Delays in emergency vehicle travel were higher in urban than non-urban areas (Brent and Beland, 2020).
- In Alabama, traffic congestion increased the emergency response time to the scene by 2.5 minutes (Griffin and McGwin, 2013).
- Travel time of emergency vehicles during rush hours was higher than at other times (Dijkink et al., 2020).

2.3 Influence of Emergency Centers Location

The location of emergency service centers and trauma centers can be another critical factor to affect trauma center accessibility because depending on the site of emergency centers, travel distance and travel time to the incident scene changes. A previous literature review found a lower probability of prehospital death with decreased travel time (Sánchez-Mangas et al., 2010). Conversely, the chance of prehospital deaths increases with the increase in response time (O. J. Adeyemi et al., 2022) and transport time from the incident scene to the trauma center.

A US-based (Brown et al., 2016) study conducted a nationwide analysis of trauma center (Level I & II) distribution. Each state's injury fatality rates per 100,000 population were collected to do this. Using Moran's I statistics, auto-correlation among injury rates was estimated. Results showed that injury fatality rates were spatially autocorrelated, meaning that neighboring states had similar fatality rates. In addition, the nearest neighbor ratio (NNR) was estimated for each state using GIS-based analysis. NNR measures how clustered or dispersed the existing trauma centers are. An NNR<1 indicates that the trauma center is clustered, and NNR>1 indicates dispersed trauma centers. Finally, the Spearman correlation, ordinary least square regression, and Spatial-lag regression were estimated to measure the correlation between NNR and injury fatality rates. Results found that the NNR and fatality rates were positively correlated. They indicated that increasing the NNR increased the fatality rates. Increasing the NNR means increasing the dispersion of trauma centers. However, the study hypothesized that more dispersion of trauma centers would yield better outcomes by decreasing the fatality rate. This could be due to the ununiform distribution across land areas, and clustered trauma center best serves the clustered population center. These results also held for motor vehicle collisions.

Another study in the US (Horst et al., 2017) proposed new approaches to finding suitable locations for new trauma centers of Level I or Level II. Trauma-related data were collected from the Pennsylvania Trauma Systems Foundation. Assuming that trauma incidents occur in border areas, patients can be taken to trauma centers in surrounding states; the study collected road network data with speed limits from Pennsylvania and the surrounding states of Pennsylvania. The Network Analyst Location-Allocation function in ArcGIS Desktop was used to run the analysis. The parameters included in the Network Analyst function were 60 minutes of travel time from the centroid of zip codes to TC, facilities of hospitals, and distance from existing TC. Thirteen years of trauma-related data (2003-2015) were collected from the study location. The results showed that adding six new TCs increased the trauma cases within 60 minutes of the nearest TCs from 91.6% to 96.2%.

A Singapore-based study (Lam, Zhang, et al., 2015) investigated a new way of reducing response time by dynamic reallocation of ambulances. This study investigated system status management (SSM) using GIS and mathematical programming (MP) -based models. SSM is the process of dynamically reallocating ambulances across time and space. Six months of emergency calls data (total observations of 995) were collected. Using GIS and MP-based analysis, the study found a dynamic reallocation strategy, which reduced the median response time by 13 seconds and 44 seconds, respectively. Among the two strategies, the MP-based strategy covered a higher percentage of emergency calls than the GIS-based strategy. Both models showed improvement in coverage than the static allocation of ambulances. An example of ambulance relocation using GIS-based analysis was that optimal performance was achieved if there was one ambulance between 23:00 to 03:00 hours in postal district 78 (an area in Singapore). If the ambulance number was two, the best locations were postal districts 55 and 67. The study found that the centroids of hotspots were not static and tended to expand in the southwestern direction during working hours.

From this section, the following are the key takeaways:

- Dispersed trauma centers were associated with increased prehospital mortality (Brown et al., 2016). This could be due to the result of people living clustered in cities. Because traumatic injury occurs where people live and travel centered in areas where people live.
- Addition of new trauma centers can increase people's access to trauma centers (Horst et al., 2017). GIS-based analysis can help find the locations of new trauma centers.
- Dynamically relocating ambulances can reduce the ambulance response time (Lam, Zhang, et al., 2015).

2.4 Influence of Rural and Urban Areas

The traveling speed of emergency vehicles may change in urban and rural areas due to traffic volume and roadway geometric design. Therefore, driving speed in rural and urban areas may differ so that the response times can vary. Many studies investigated this factor. The studies (O.J. Adeyemi et al., 2022) reviewed in previous sections that reported the difference in response time and prehospital mortality between rural and urban areas would not be repeated in this section.

For example, a study in Sweden (Petzäll et al., 2011) compared the difference in ambulance speed between emergency and non-emergency driving. Emergency ambulance transportation data were collected from thirty emergency centers from May 2008 to February 2009. Experimental driving was conducted from September 2008 to February 2009, which served as non-emergency services. The experimental driving was a repetition of emergency driving and was conducted to match the emergency driving as possible (e.g., driving on the same day of the week, same time). Both datasets contain data from urban and rural areas. Urban areas were larger towns with inhabitants of nearly 100,000, and rural areas were the areas with 10,700 to 24,000 population. The result showed that emergency driving saved 3 minutes in urban areas, and in rural areas, this was nearly 9 minutes. The study reported that all the emergency driving was faster than the experimental non-emergency driving. The patient's need for emergency care or clinical status showed no variation in the emergency vehicle speed. Therefore, the study recommended developing procedures to identify the patient's condition for high-speed ambulance transportation, as high-speed transit can lead to a traffic crash.

In the US, a study (Byrne et al., 2019) analyzed 2,214,480 ambulance responses which contain information from 2268 counties. The study found that counties with longer response times in rural areas had more on-scene and transport time. Counties with response times of 12 minutes had a mortality rate of 11.9 per 100,000 populations per year. This mortality rate was 4.9 for counties with 7 minutes response times. The study reported that median response times in rural or wilderness areas was 10 minutes, while this number was 7 minutes for urban areas.

To report the prehospital time interval for urban and rural emergency medical services, a study (Alruwaili and Alanazy, 2022) reviewed 37 articles published between 1991 to 2022, among which 17 studies were conducted in the United States. The result showed that a difference in response time between rural and urban areas was reported in 29 studies. Response time for crashes in rural areas was higher than in urban areas in 27 studies. In conclusion, all of these studies reported that pre-hospital time was shorter for crashes occurring in urban areas than in rural areas. In addition to these findings, the study reported that mean response time for urban and rural regions differed for each study.

This section identified that:

- In Sweden, emergency driving was 9 minutes faster in rural areas and 3 minutes faster in urban areas than non-emergency driving (Petzäll et al., 2011).
- In the US, rural areas had an increased traffic crash mortality rate (Byrne et al., 2019).
- Emergency vehicle response time for crashes occurring in rural areas was longer in the US and other countries (Alruwaili and Alanazy, 2022).

2.5 Others

The term “others” includes all other factors except travel time, travel distance, location of emergency centers, traffic volume, and rural and urban areas. During the literature review, factors like weather, age groups, emergency call numbers, transportation policies, and lighting conditions also affected trauma center accessibility. Studies (Brent and Beland, 2020; Griffin and McGwin, 2013) already reviewed in previous sections reported a few of these and were mentioned during the review of those studies. Therefore, those studies will not be repeated here again.

A study (Vanga et al., 2022) in the US investigated the influence of factors that affect emergency vehicles' response time (ERT) (ERT was the time interval between the time of crash occurrence and the time of the emergency service's arrival at the crash scene). For this, one county in Alabama was selected as a study location. This county had only a single EMS center. Motor vehicle collision data from 2016-2019 (214 automobile crashes) were collected. Traffic Crash data contained severity, ERT, actual travel time, day of the week, time of the day, weather, and lighting conditions. The fastest travel time was estimated using Google Maps. The descriptive analysis showed that ERT was longer for crashes occurring on dark roads not lighted, from 6:00 p.m. to 6:59 p.m., with suspected serious injury, during mist or foggy weather conditions, and on weekends. Among the different crash severities, ERT was longer for suspected minor and suspected severe injuries. In addition, as the travel time increased, ERT also increased. The study estimated travel time using Google Maps from the location of the crash to the location of emergency medical services. Results showed that to travel the same distance, ERT was longer than the travel time. This was because of delays during the travel of emergency vehicles. However, in general, delays in ERT decreased as the travel time increased.

in Saudi Arabia investigated the impact of weather and other factors on emergency vehicle response time and rescue time. A total of 57,928 emergency call data from the Kingdom of Saudi Arabia were used in this study. These data were the road traffic crash data that occurred in 2019. These data contained information regarding ambulance dispatch time, EMS arrival time, hospital admission time, and other information. A linear regression model showed that geographical region, time of the crash, number of injured people, type of injury, and weather conditions affected the response and rescue time. These results were statistically significant (p-values<

0.05). Factors such as crash day, academic calendar, and visibility range were found to be nonsignificant. However, the R-square value (less than 2.76%) was found to be low, indicating that although the factors were significant, these factors cannot explain variability in response time. The addition of two factors (traffic level and traveled distance) improved the R-square value (more than 70%) for the region Al-Riyadh. The study found that rescue and response times increased as the number of injured people increased and during rainy weather conditions.

Another study (Cabral et al., 2018) reviewed scientific articles using the terms “Response Time” and “Emergency Medical Services” from different countries between 2007 and 2017. This study defined response time as the time interval between the notification of the incident and ambulance arrival at the scene. The study found that response time in Europe and North America was nearly 8 minutes, whereas, in Asia and Africa, this time was higher than eight minutes. However, no correlation between GDP and response time was found. Traffic volume, demographic density, localities, and public health policies were reported to influence the response time. The study recommended investigating the factors affecting response time to understand the measures for reducing response time.

A Singapore-based study (Lam, Nguyen, et al., 2015) investigated the factors affecting ambulance response times (ART). ART was defined as the interval between ambulance dispatch and arrival at the incident scene. “Dispatch time” was when an ambulance left the EMS station. The study investigated risk factors such as age, gender, ethnicity, weather, location of the incident, and traffic. Ideal travel time (ITT) was also included in the analysis of risk factors. ITT was the time based on travel distance and road speed limit. The study was conducted using a multinomial logit model (MLM). For analysis purposes, ART was categorized into three categories: short (less than 4 min), intermediate (4-8 min), and long (more than 8 min). For MNL analysis, short ART was considered as the baseline factor. MNL analysis identified that traffic conditions, weather, place of incident, gender, and ideal travel time affected the ambulance response times. For long ART, traffic was found to show the highest odds ratio (OR). Heavy and moderate traffic increased the Long ART more than the light traffic. For intermediate ART, the highest OR was shown by place of incident. Both for the long and middle ART, MNL analysis showed that any location of an incident was associated with increased ART than an incident location on the road. This indicated that traffic crashes had a higher chance of lower ART than incidents occurring at home and in buildings. The gender type “Female” increased the odds of Long and Intermediate ART. Ideal Travel Time (ITT) increased the odds of the Long and Intermediate ART. Weather (Heavy and Light Rain) was associated with increased OR for Long and Intermediate ART. Spoken language was also found to be a significant factor. If the callers spoke in a language other than Malay, Chinese, or Tamil, there was a higher chance of Long and Intermediate ART. This could be due to miscommunication resulting from inexperience in other languages.

In another study in Singapore (Do et al., 2013), ambulance response time was influenced by the volume of emergency calls in the last hour. Studies (Brent and Beland, 2020) also reported that the presence of HOV lanes and toll lanes decreased response times. Survey-based research (Griffin and McGwin, 2013) in the US reported that roadway geometry, like the median barriers, could increase the rescue time at the incident scene.

From the discussion in this section, the following points are identified:

- In the US, ambulance response times varied depending on weather, lighting conditions, and day of the week (Vanga et al., 2022).
- In the US, the presence of HOV lanes, toll lanes, and metro stations decreased the response time (Brent and Beland, 2020).
- Studies also mentioned demographic densities and public health policies (Cabral et al., 2018), age groups of 17-42 years (Byrne et al., 2019), volumes of emergency calls (Do et al., 2013), roadway geometry (Griffin and McGwin, 2013), gender, and spoken language (Lam, Nguyen, et al., 2015) as influential factors.

2.6 Conclusion

Over the years, studies have identified the influence of different factors on emergency vehicle response time and transport time. Those studies aimed to quantify the impact of factors on different prehospital time intervals and understand how factors were correlated with prehospital time intervals. Commonly studied factors were traveling distance, traffic congestion, location of emergency centers, and rural and urban areas. While a traffic crash can lead to traffic congestion and affect the ambulance response time, studies were not found to investigate the influence of traffic congestion (resulting from a traffic crash) on ambulance response time. The availability of traffic volume data after the traffic crash can be a factor in estimating the influence of traffic volume on ambulance response time. Although it is less likely that weather and lighting conditions will affect emergency vehicles traveling speed, some studies identified these factors as involving emergency vehicles' response time. Other factors were also investigated, such as the number of emergency calls, spoken language, demographic densities, and roadway median barrier. Among these, median barriers are an essential factor, as the location of traffic crashes can have a median barrier.

Some studies also focused on dynamically relocating ambulances to improve emergency services and found positive results. Based on GIS analysis, some studies tried to find the best locations for new trauma centers. It seems that most studies investigating factors affecting trauma center accessibility involved GIS-based analysis in estimating the closest facility and travel time. However, one drawback of this type of analysis is that GIS-based travel time was calculated using the road speed limit, and emergency vehicles are not bound to follow the road speed limit. A study (Petzäll et al., 2011) showed that emergency vehicles were always faster than non-emergency driving. However, the study did not mention if the driving speed exceeds the road speed limit. Studies also applied logistic regression, count data models (e.g., negative binomial regression), and correlation analysis (e.g., spearman correlation) to understand how the factors are related to emergency response time and prehospital mortality. However, only some studies involved traffic crash data and were done on other emergency service calls.

Chapter 3: Methodology

This chapter discusses the data, data collection, and methodology used in the research. Creating additional factors from the data during the analysis was also discussed. Finally, this chapter discusses the assumptions of the research.

3.1 Data Collection and Description of Data

This research used traffic crash data, trauma centers data, local hospital data, Kansas's road network data, and the Kansas Department of Transportation's (KDOT's) administrative districts data.

3.1.1 Traffic Crash Data: Collection, Cleaning, and Preparation for the Analysis

Traffic crash data were collected from the Kansas Accident Reporting System (KARS) database. KARS database stores traffic crash data occurring in the State of Kansas. Traffic crash data were collected for four years, from 2018 to 2021. Each traffic crash has information regarding crash time, crash type, causes of the crash, vehicle involved, weather, and demographic information. This information is called a factor. For this research, factors were selected based on previous studies and the purpose of the research. Each traffic crash was extracted along with the factors such as crash key, on-road speed limit, county name, weather, lighting conditions, latitude and longitude, year of the crash, date of the crash, time of the crash, day of the crash, police notification time, police arrival time, EMS notification time, EMS arrival at the crash scene, and EMS arrival at the hospital.

3.1.2 Trauma Center and Hospital Data

As this research aimed to identify the factors affecting access to trauma centers for fatal and severely injured patients, the location of trauma centers and hospitals was required. State-designated trauma center data were collected from a publicly available ArcGIS online database maintained by the Kansas Department of Health and Environment (KDHE). The database link was received through email from a staff working at the Kansas Geological Survey at the University of Kansas. The data were in a shapefile format, hence importable to the ArcGIS Desktop. The data contained information regarding the name of the trauma center, the state-designated level of the trauma center, email and phone number of the director of the trauma center. A trauma center can be designated as Level I, Level II, Level III, or Level IV trauma center, depending on the facilities of a trauma center. In total, there were 44 trauma centers listed in the shapefile.

Local hospital data were collected from the website of the Kansas Hospital Association (https://www.kha-net.org/KansasHospitals/HospitalListings/: Accessed on April 20, 2023). This website enlisted all hospitals, including trauma centers located in Kansas, U.S. A total of 124 hospitals were listed. However, the website only listed the names of the hospitals. The researcher was also interested to know if the hospital had emergency facilities, an intensive care unit (ICU), and a designation of trauma level.

Therefore, the researcher browsed the internet to find out the hospitals' websites and then interviewed the hospital staff (e.g., the emergency department director) to collect more information. For the hospitals that did not respond to the questions, the author browsed the website of these hospitals to see if those hospitals have emergency facilities.

Hospitals that were not state-designated trauma centers may have had emergency facilities. So, these hospitals can stabilize patients, and depending on the condition, they can transfer the patient to a state-designated trauma center if needed. One hospital (Greenwood County Hospital) was reported to have lost its trauma designation. Sometimes, the trauma level changes (e.g., Providence Medical Center). During the phone-call interview, hospital staff representatives reported that trauma designation is renewed every two years, and hospitals must apply for that designation. If any hospital can meet specific criteria designed by the state, then the hospital gains its trauma-level designation.

Finally, hospital data contained state-designated trauma centers and hospitals that were not state-designated trauma centers but had facilities such as emergency and ICU. The researcher only called some of the hospitals, because trauma levels for some hospitals were reported in the shapefile received from KUGIS. As mentioned before, 44 trauma centers were reported in that shapefile. So, the researcher talked to a representative of other hospitals to learn more about their facilities. After collecting all the information, the data showed that there are 53 trauma centers in Kansas. That indicates that nine trauma centers were not reported in the KDHE shapefile. This could be because, after the preparation of the KDHE shapefile, other hospitals got their designation as trauma centers.

The hospital data were collected in Microsoft Excel ‘CSV’ file. A ‘CSV’ file can be imported into ArcGIS Desktop from the ‘Add Data’ window. Once the ‘CSV’ file is added, these data can be plotted on the map by specifying latitude and longitude from ‘Display X-Y Data.’ This imported data does not contain an ‘object id’ and is not recommended for analysis. Hence, these data were exported as a shapefile and added to the layer.

3.1.3 Road Network and Administrative District Data

Road network data and KDOT’s administrative districts were collected from KDOT. The road network data were in shapefile format and importable to the ArcGIS Desktop. The road network data contained each road segment's speed limit and length. The unit of speed limit was miles per hour (mph), and the length unit was feet which was converted to miles.

KDOT divided the State of Kansas into six administrative districts: District 1, District 2, District 3, District 4, District 5, and District 6. Upon request, KDOT provided the shapefile of the district map and list of all counties within each district.

3.2 Geospatial Analysis

This study applied location-based analysis, which was conducted in ArcGIS Desktop 10.8.1. ArcGIS Desktop can be used for mapping and analysis of spatial data. Spatial data are the data with location information (latitude and longitude). Among the different types of spatial analysis tools available in ArcGIS Desktop, this research used the Network Analyst’s Closest facility, cliff, and buffer tools.

3.2.1 Network Analyst’s Closest Facility Tool

If there is any life-threatening injury, it is important to take the patients to the nearest trauma center as quickly as possible. Therefore, this research was also interested in identifying the closest trauma center to the location of a traffic crash and estimating the distance between these two (trauma center and traffic crash). This can be estimated by the ‘Closest Facility Tool’ in ArcGIS Desktop (ESRI, 2021b).

The ‘Network Analyst’ toolbar is not a default toolbar, and it can be enabled from ArcGIS Desktop extensions.

The ‘Closest Facility Tool’ uses Dijkstra’s algorithm to find out the closest facility (trauma center) from an incident (crash location) (ESRI, 2021a). Dijkstra’s algorithm is the most used in finding the shortest path problem. For example, ‘Google Maps’ also used this algorithm in destination route selection. A discussion on this algorithm is out of the scope of this research.

To enable the ‘Closest Facility Tool’ or any other tool available in the ‘Network Analyst’ toolbar, a network dataset must be created. A network dataset (ESRI, 2021d) models the road network, which takes the data such as the direction of movement (one or two-way), turn restrictions (right, left, or U-turn), overpass or underpass and connectivity (e.g., end-to-end connectivity). Multimodal transportation can also be specified in a network dataset. Creating a network dataset will be discussed in the following section.

Following steps discuss the analysis using the ‘Closest Facility’ tool:

- Step 1: Once the network dataset is created, it will be enabled in the ‘Network Analyst’ tool indicating that the ‘Closest Facility’ tool is ready for analysis.

- Step 2: A new window is opened when the ‘Closest Facility' is clicked. This has the option to ‘load locations’ for facilities, incidents, routes, point barriers, line barriers, and polygon barriers. This study used trauma centers and hospitals as facilities and traffic crash locations as incidents. No barriers were used because the information about turn restrictions and barriers was not available. ‘Routes’ info is not given because it stores the result (all incidents that find a trauma center) after completing the analysis.

- Step 3: There is additional information required to be provided before the analysis. This information is ‘Layer Properties.’ The most important properties are ‘Analysis Settings’ and ‘Accumulation.’ In the ‘Analysis Settings,’ there are two types of ‘Impedance’: ‘ Length’ and ‘Time.’ The ‘Length’ impedance allows a user to estimate the shortest path, and the ‘Time’ impedance will enable a user to estimate the quickest path. These ‘Length’ and ‘Time’ impedance come from the network dataset, and the network dataset is created from the road network shapefile. This research used road network data from KDOT, which had each road segment's length and on-road speed limit. Time (to pass through a road segment) was estimated from length and speed. However, this research used ‘Length’ as ‘Impedance.’ Because ‘Time’ impedance will calculate the quickest path and estimating the quickest path requires considering traffic volume on the road, ‘Time’ impedance was not used. In addition, time was estimated using the road speed limit; practically, emergency vehicles can travel more than the posted speed limit.

  One traffic crash requires one facility; therefore, ‘Facilities to Find’ was 1 (one). The vehicle travels from the location of the traffic crash to a trauma center; hence, ‘Travel From’ was ‘Incident to Facility.’ If the location of emergency vehicles were known, then this could be ‘Facility to Incident’ to estimate the shortest distance between the location of the traffic crash location and the location of emergency vehicles.

- Step 4: The last step was ‘Accumulation’ in ‘Layer Properties.’ This research was interested in extracting the shortest path length from a traffic crash location to a trauma center or hospital and the time to travel that distance. Therefore, ‘Length’ and ‘Time’ was selected in ‘Accumulation.’

3.2.2 Creating Network Dataset

Network dataset allows for analyzing a road network. In a road network, vehicles travel in a specific direction, turn in a specific way, stop at a ‘STOP’ sign or traffic signal, and slow down if there is congestion, emergency vehicle, or any incidents. The network dataset can specify all these things that affect vehicle movement (ESRI, 2021c). These were not used because the location of turn restrictions and traffic signals were unknown.

The following steps describe the process of creating a network dataset:

- Step 1: A ‘New Network Dataset’ dialogue box pops up when the road network shapefile in Arc Catalog is right-clicked.

- Step 2: After clicking on ‘New Network Dataset,’ a dialogue box pops up where all road network elements can be specified. First, it asks for a name which will be the name of the network dataset after adding in the layer. Then, it asks to specify the ‘Turns.’ Because ‘Turns’ features were unknown (these data were not collected), ‘No’ was selected.

- Step 3: Next, ‘Any Vertex’ was selected as a connectivity policy. This allows users to connect intersecting streets. An ‘End Point’ connectivity is chosen for an underpass or overpass, and intersecting streets are considered overpass or underpass. Overpasses or underpasses are created by setting elevation data along with latitude and longitude.

- Step 4: No elevation data was collected; hence ‘None’ was selected when network features required elevation data.

- Step 5: The attribute specified here will be available for accumulation in the ‘Closest Facility Analysis’ mentioned in ‘Step 4.’ The network dataset automatically identified the ‘Length’ attribute from the road network shapefile. However, the ‘Time’ attribute was not identified, and this can be added from the ‘Add’ tab at the top of the right side. ‘Units’ of these two attributes should be selected. This research used ‘miles’ for length and ‘minutes’ for time.

- Step 6: No input was provided when network features required to specify ‘Travel Mode’. This travel mode allows to specify multimodal transportation; however, multimodal transportation was not required for this research. This research only estimated the shortest distance between a crash location and a trauma center and the time to travel. Keeping travel mode and the following elements blank did not affect the result.

- Step 7: The default driving direction is both-way driving. Hence, no driving direction was given. Because traffic crashes considered here were fatal and incapacitating injuries, emergency vehicles were assumed to travel in both directions.
- Step 8: Then click on the ‘Finish’ tab to create the network dataset.

3.2.3 Cliff and Buffer tool

Cliff and buffer tools are geoprocessing tools available in the ArcGIS Desktop. A buffer tool is used to create a polygon (called ‘buffer zone’) around an input feature to a specified distance. This input feature could be point data, a line, or a polygon. For this research, a few buffer zones were created around hospital and trauma center data which were point data.

The cliff tool is used to extract input features that overlay cliff features. The cliff feature can be point, line, or polygon data depending on the input features. This research was interested in estimating the number of traffic crashes and the road network length within a certain distance from a hospital or trauma center. Therefore, a buffer zone was created around the hospital or trauma center, and this buffer zone was a cliff feature. Traffic crash data were input features.

The cliff tool only extracts the input features within a cliff feature. For example, cliff features can extract the road network data within a polygon, which is another road network data. However, this research required to estimate the length of the newly extracted road network data. This can be done from the attribute table. To do that, the attribute table of any layer (e.g., road network) was opened, and right-clicking in any field (e.g., length) opened a window showing ‘statistics’ and other functions.

3.3 Outlier Detection

Among many statistical tests, Grubb’s outlier test (Grubbs, 1969) and Walsh’s outlier test (Walsh, 1950) are two tests for detecting outliers. Grubb’s test is a parametric test and requires that the data should be normally distributed. Walsh’s test is non-parametric and does not require the data to be normally distributed.

Because the data were not normally distributed, this research used Walsh’s test for outlier detection. The ‘Test of Normality’ section will discuss the methodology for checking normality. Below are the steps for conducting Walsh’s test (Lipi et al., 2022):

- Step 1: Assume the number of outliers, r ≥ 1
- Step 2: Compute the following: c= ceil$\sqrt{(2n)}$), k= r+ c, $b^2 = \frac{1}{\alpha}$ and $a = \frac{1+b\sqrt{\frac{c-b^2}{c-1}}}{c-b^2-1}$

Here, n is the sample size, and ceil( ) indicates rounding up the value to the nearest integer (e.g., 2.1 becomes 3.0). If n>220, $\alpha = 0.05$. If 60 <n≤ 220, $\alpha = 0.1$. If n<60; the test is not recommended to apply.

- Step 3: The r smallest point is an outlier if;

$x_r - (1 + a)x_{r+1} + ax_k < 0$ ………………..(i)

- Step 4: The r largest point is an outlier if;

$x_{n+1-r} - (1 + a)x_{n-r} + ax_{n+1-k} > 0$ …………..(ii)

3.4 Test of Normality

Histogram and Q-Q plot (quantile-quantile plot) are the two graphical methods that can be used to test the normal distribution of the dataset. If a dataset is normally distributed, the histogram looks like a normal distribution curve (Bland, 2015). A histogram is the plot of the frequency of the observations against observations.

Q-Q plot (quantile-quantile plot) plots quantiles of the theoretical distribution against quantiles of the observed frequency distribution. If the dataset is normally distributed, the Q-Q plot shows a straight line; otherwise, it becomes some sort of curve (Bland, 2015). Below are the steps for drawing the Q-Q plot ((Bland, 2015)):

- **Step 1**: Order the data from smallest to largest.
- **Step 2**: Find the expected value of each ordered data using the following equation:

For i^{th} observation, $\Phi(z) = \frac{i}{n+1}, where\ n\ is\ the\ sample\ size.$ There are other methods to estimate $\Phi(z)$. r each $\Phi(z)$ estimate the corresponding z-score from the normal distribution table (see appendix). However, practically to estimate the z-score, NORM.S.INV( ) (a Microsoft Excel function) was used.

- **Step 3**: Now plot the observed data against the expected value of each ordered data.

3.5 Binary Logistic Regression

Logistic regression was proved to be an effective method to estimate the impact of dependent variables on the dichotomous categorical independent variable (Al-Ghamdi, 2002). Hence, logistic regression was used in this research to measure the influence of various variables on the transport time and estimate what factors are responsible for a crash to be within the Golden Hour or outside the Golden Hour. When the total transport time (discussed in section 4.1.1) of a crash exceeded 60 minutes it was defined as 'outside Golden Hour' crash, otherwise it was a 'within Golden Hour' crash.

If a categorical independent variable is coded as '1' or '0', then the conditional probability of that independent variable is written as follows (Hosmer and Lemeshow, 2000):

P(Y=1|x) = $\pi(x) = \frac{e^{\beta_0+\beta_1 x}}{1+e^{\beta_0+\beta_1 x}}$…………………(iii)

This represents the conditional mean of the dependent variable Y. By logit transformation of the equation (iii),

$g(x) = \ln\left[\frac{\pi(x)}{1-\pi(x)}\right] = \beta_0 + \beta_1 x$……………..(iv)

Equation (iv) has properties like linear regression. Thus, g(x) can be written as g(x)=Y, whereas Y is the outcome value for dependent variable.

If there are more than one independent variable,

Y= $g(x) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots \ldots \ldots \ldots . + \beta_n x_n$ ……………(v)

This equation gives a value of Y ranging from $-\infty$ to $+\infty$. Usually, a cut-off value is used to classify the category of Y. For example, for binary categorical dependent variable dependent variable is coded as '0' or '1.' A cutoff value of 0.5 indicates that if Y>0.5, the outcome is '1.'

There are several ways to measure how well the fitted model explains the variance and fit the data. These measures are called goodness-of-fit statistics. Model Chi-square, classification table, and Pseudo R-squares are used in this research.

Model Chi-square in logistic regression is analogous to the F-test in linear regression (Menard, 2002). If the model chi-square is statistically significant ($p \leq 0.05$), then it is concluded that the model with the independent variables predicts better than the model without the independent variables (Menard, 2002). The model chi-square is written as follows (Hosmer and Lemeshow, 2000):

Model chi-square= G = D(for the model without the variable) – D (for the model with the variable)

$$= -2 \ln\left[\frac{(likelihood\ of\ the\ model\ without\ the\ variable)}{(likelihood\ of\ the\ model\ with\ the\ variable)} \right]$$

'D' in the above equation is called deviance and (Hosmer and Lemeshow, 2000) provided a detailed description of the 'D' and how to estimate the model chi-square. The mathematical expression is not described here because the necessary estimation of logistic regression and goodness-of-fit statistics were calculated using software package IBM SPSS Statistics 28.0. (Menard, 2002) discussed the logistic regression estimation (section 1.4, page 14) using SPSS.

The classification table summarizes the values predicted by the fitted model and compares this against the observed values (Hosmer and Lemeshow, 2000). This table shows how many values (dependent variables) are correctly or incorrectly predicted. Hence, it offers the model accuracy. From this table sensitivity and specificity of the model can also be estimated. For binary logistic regression, sensitivity indicates how well the model predicts the Y=1, and specificity show how well the model predicts the Y=0. Mathematically, sensitivity is the total number of correctly predicted Y=1 divided by the total number of actual Y=1. Specificity is the total number of correctly predicted Y=0 divided by the total number of actual Y=0. Here, Y is the categorical dependent variable coded as '1' or '0' in binary logistic regression.

R-square indicates how much variance is explained (Menard, 2002). Analogous to the linear regression, several measures of R-square (R^2)have been proposed (Hosmer and Lemeshow, 2000; Menard, 2002). These R-squares are called Pseudo R-squares. However, there is no unanimous agreement on which R-square measures are perfect. This research estimated logistic regression in SPSS, producing two R-square measures such as Nagelkerke R-Square and Cox & Snell R-Square (Menard, 2002).

Cox and Snell (Cox and Snell, 1989) proposed R-square is expressed as follows:

$$R^2{}_{C\,\&\,S} = 1 - \left(\frac{L_M}{L_0}\right)^{2/n}$$

Here is the sample size. L_M is the likelihood of the fitted model and L_0 is the likelihood of the null model. The upper bound is always less than 1.0 (the maximum could be 0.75) and expressed as $1 - {L_0}^{2/n}$.

Nagelkerke R-square is a correction to the Cox & Snell R-square, resulting in the upper bound of the R-square equal to 1.0 (Nagelkerke, 1991). Its values range from 0 to 1.

Nagelkerke R-square= $R^2{}_N = \frac{[1-(L_0/L_M)^{2/N}]}{[1-(L_0)^{2/N}]}$

L_M and L_0 are the same as defined in the Cox and Snell R-square.

To test the significance of independent variables, Wald Statistic is used, which follows the chi-square distribution (Hosmer and Lemeshow, 2000; Menard, 2002). It is expressed as follows (Hosmer and Lemeshow, 2000):

Wald Statistic= $\frac{maximum\ likelihood\ estimate\ of\ the\ slope\ parameter}{standard\ error\ of\ the\ slope\ parameter}$

The logistic regression was estimated in IBM SPSS Statistics 28.0. The model was estimated using a backward and stepwise process.

3.6 Test of Proportion

A two-tailed hypothesis test was conducted to compare between the two groups of crashes. This online article (Penn State University, 2023) is found to be useful to conduct the test. The test estimates z-score and p-value for each z-score. Interested readers are referred to go through the article for more details.

3.7 Assumptions

Because of the limitations of the data, this research made the following assumptions:

- The designation of the trauma center level of each hospital was unchanged during the study period (2018-2021).
- No new trauma center, hospital, and road were constructed during the study period.
- Speed limit, geometry, and traffic volume of existing roads were unchanged.
- The location of trauma centers and emergency vehicles were the same.
- Emergency vehicles can travel in both directions.

Chapter 4: Analysis and Results

This chapter describes the data preparation and cleaning for the analysis, analysis of the data, and results. Data preparation and cleaning were carried out in Microsoft Excel. Part of the analysis was conducted in Microsoft Excel, and part of the analysis was carried out in ArcGIS Desktop 10.8.1. Therefore, analysis can be categorized into two broad categories: preliminary analysis (conducted in Microsoft Excel) and spatial analysis (conducted in ArcGIS).

First, all the data were collected, and then the traffic crash data were cleaned. Before preliminary analysis, the closest facility analysis was conducted to estimate the nearest trauma center and hospitals from the location of a traffic crash.

4.1 Data Cleaning and Preparation

In total, 5545 fatal and injury crashes were collected from the KARS database. Injury crashes were crashes with possible injury, suspected minor injury, or suspected serious injury. For more details about the injury severity, readers are referred to Kansas Motor Vehicle Accident Report Coding Manual (KDOT, 2014), which describes the injury severity. Fatal crashes result in at least one death within 30 days of a crash.

Among 5545 crashes, 2148 were duplicates and removed from the analysis. Duplicate crashes were those crashes that had the same ‘Accident Key,’ which would indicate multiple vehicles were involved in the same crash. After removing duplicates, 3397 crashes were included for analysis.

Each crash data had information (called ‘factor’) on latitude and longitude, time of crash occurrence, time of emergency management service (EMS) notification, time of emergency vehicle arrival, time of hospital arrival, weather, day of the week, lighting conditions, county, year of the crash, injury severity, on-road speed limit.

4.1.1 Estimating Time Intervals

Crash data recorded the time of the crash, time of EMS notification, time of EMS arrival at the crash scene, and EMS arrival at the hospital. However, this research required estimating the time in three time intervals, namely notification time interval (NTI), arrival time interval (ATI), and transport time interval (TTI). The NTI was the time between the time of the crash and the time of the EMS notification. The ATI was the time between the time of the EMS notification and the EMS arrival at the crash scene. The TTI was the time between the EMS arrival at the crash scene and the EMS arrival at the hospital. Finally, total transport time (TTT) was calculated by adding these three time intervals. The unit of these time intervals was minutes.

After deleting duplicates, 3397 crashes remained for analysis. Among these, 2072 crashes had no information regarding EMS notification time. In addition, the crashes with no info regarding EMS scene arrival time and EMS arrival at the hospital were 2122 and 2208, respectively. That means the ATI and TTI for these crashes were impossible to estimate, which does not have time information. Two crashes had no information on the time of crash occurrence; therefore, calculating NTI for these two crashes was impossible. Eventually, the crashes that had information regarding all the time intervals were 1166 (30 crashes had no information on latitude and longitude). That means 2231 (3397-1166=2231) crashes were not available for analysis. This necessitates the importance of estimating time intervals using ArcGIS. To do this in ArcGIS, crash data requires latitudes and longitudes. The crash data showed that 75 crashes needed information about latitude and longitude. Among these 75 crashes, 30 crashes had information for all three time intervals.

After estimating three time intervals, a time interval below zero was found for 51 crashes. These negative time intervals could be NTI, ATI, or TTI. Negative time intervals (below zero) were not acceptable, and time intervals could not be lower than zero. Therefore, the researcher requested the KDOT for the crash reports showing negative time to further analyze and extract the correct time intervals. In total, 39 crash reports were reviewed. However, no discrepancy in the time record was found between the crash reports and the KARS database.

A negative time interval was estimated because of the incorrect time of EMS arrival at the scene or EMS arrival at the hospital. For example, a crash (Accident Key is 20180003112) occurred in 2018 in Harvey County recorded that EMS arrival at the scene was 2345 and EMS arrival at the hospital was 2334 (time was in U.S. military time format). Table 1 shows the list of crashes with incorrect time intervals.

Three more crashes were found to have incorrect time intervals. These were listed and discussed in Appendix A. Therefore, 51 crashes with negative and three with incorrect time intervals were excluded from the analysis. After excluding these crashes, 1112 (1156-51-3=1112) were considered for a preliminary analysis. Table 2 shows the descriptive statistics of these 1112 crashes. Table 2 showed that zero was the minimum value of NTI, ATI, and TTI. Further analysis showed zero-time intervals existed for 127 NTI, six ATI, and one TTI.

Table 1. A Sample of Crashes with incorrect time intervals

Accident Key	Date of Accident	Time of Accident	Date Notified	Time Notified	Date Arrived	EMS Notified Time	EMS Arrived Time	EMS at Hospital Time
20180003112	2/19/2018	2239	2/19/2018	2239	2/19/2018	2340	2345	2334
20180011545	7/10/2018	0908	7/10/2018	0913	7/10/2018	0913	0937	0915
20180117320	7/21/2018	2231	7/21/2018	2234	7/21/2018	2231	2324	2254
20190011101	6/17/2019	0144	6/17/2019	0147	6/17/2019	0159	0203	0040
20190095133	7/24/2019	1434	7/24/2019	1440	7/24/2019	1437	1459	1452
20210103184	2/8/2021	1618	2/8/2021	1620	2/8/2021	1620	1640	1457
20180106656	3/26/2018	0225	3/26/2018	0231	3/26/2018	0239	0232	0258
20190115698	7/1/2019	1343	7/1/2019	1348	7/1/2019	1358	1345	1433
20200016289	9/6/2020	0405	9/6/2020	0410	9/6/2020	0410	0326	0437
20210095122	7/24/2021	0320	7/24/2021	0330	7/24/2021	0330	0329	0352

Table 2. Descriptive Statistics of the Time Intervals

	Notification Time Interval (minutes)	Arrival Time Interval (minutes)	Transport Time Interval (minutes)	Total Transport Time (minutes)
Mean	9.76	10.86	33.93	54.56
Median	4	9	29.5	47
Mode	0	5	30	34
Standard Deviation	39.99	7.99	22.73	47.44
Minimum	0	0	0	6
Maximum	1021	129	430	1061
Sample Size	1112	1112	1112	1112

4.1.2 Outlier Detection

Table *2* showed that a larger difference between the minimum and maximum value of each time interval existed. Therefore, the time intervals were checked for the possible presence of outliers. The outlier was only tested for TTT, and the outlier for all three other time intervals was not tested. Because TTT was the primary concern, and the goal of the EMS service was to minimize the TTT.

Walsh's test was selected to detect outliers because the TTT was not normally distributed. The methodology for testing normality and Walsh's test were described in Chapter 3, section 'Test of Normality' and 'Outlier Detection,' respectively. Figure 1 shows that the Q-Q plot did not fit a straight line. Hence the TTT was not normally distributed.

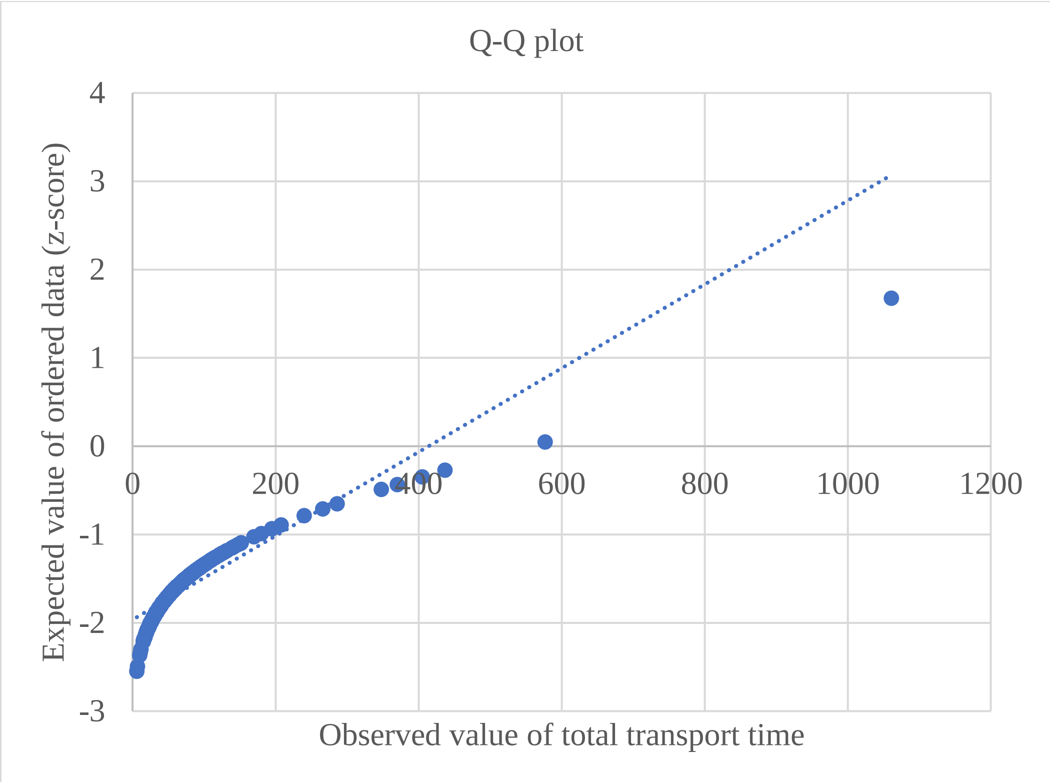

Figure 1. Q-Q Plot of Total Transport Time

Therefore, Walsh's test was applied. The following calculations showed a sample of selecting one outlier. The process was repeated four times to detect nine outliers.

First trial: r=10

For the first trial, it was assumed that r=10.

k= r+ c= 10+ 48=58

From the equation (i);

$x_r - (1+a)x_{r+1} + ax_k = x_{10} - (1+a)x_{11} + ax_{58}$

$= 16 - ((1 + 0.169362279)*16) + (0.169362279 * 24)$

= 1.354, which is not smaller than 0.

Therefore, the 10th smallest point is not an outlier.

Here, the total transport time was first rearranged from smallest to largest value, and then x_{10}, $x_{11,}$ and x_{58} were determined. x_{10}, x_{11} and x_{58} $were$ the 10th, 11th and 58th point of the rearranged dataset.

From equation (ii);

$x_{n+1-r} - (1+a)x_{n-r} + ax_{n+1-k} = x_{1103} - (1+a)x_{1102} + ax_{1055}$

$=208 - (1 + 0.169362279) * 195 + 0.169362279 * 97$

= -3.597, which is not larger than 0.

Therefore, the 10th largest point was not an outlier.

Table 3 shows the result of two equations for different values of ‘r.’

Table 3. Result of Outlier Detection from Walsh's Test

	Equation (i)		Equation (ii)	
	Result	Below '0'	Result	Above '0'
r=1	1.709	No		
r=8	1.524	No	2.119	**Yes**
r=9	0.354	No	13.370	**Yes**
r=10	1.354	No	-3.597	No

The above table shows that the 9th and 8th largest points were outliers, while the 10th largest point was not an outlier. Therefore, any value from the 9th to the 1st largest point was an outlier.

The test detected no outlier for any minimum value (minimum TTT was 6, see Table 2). If r=1, the equation (i) resulted in a number greater than 0 which did not satisfy the condition. Because r=1 represented the smallest point of the dataset, there was no minimum point for outliers. Thus, the minimum value of TTT remained unchanged after removing outliers, while the maximum value changed, as shown in Table 4.

Table 4. Descriptive Statistics of the Time Intervals without Outliers

	Notification Time Interval (minutes)	Arrival Time Interval (minutes)	Transport Time Interval (minutes)	Total Transport Time (minutes)
Average	7.23	10.87	33.27	51.38
Median	4	9	29	47
Mode	0	5	30	34
Standard Deviation	11.81	8.01	18.20	23.65
Minimum	0	0	0	6
Maximum	144	129	156	208
Sample Size	1103	1103	1103	1103

4.1.3 Creating New Factors: KDOT Districts

The original crash data extracted from the KARS database did not contain information on KDOT administrative districts. KDOT divides the State of Kansas into six districts (Districts 1 through 6) based on county boundaries. For analysis purposes, the district's name was necessary to see if there were any differences in time intervals among the districts. Therefore, the district's names and a GIS shapefile of the KDOT administrative districts were requested. KDOT provided the researcher with an ArcGIS shapefile containing the boundary of each district. The district name was assigned to each crash using this shapefile and traffic crash data. The 'Spatial Join' tool is available in ArcMap was used. The newly joined file contained the attributes of crash data (including Crash Key) and the district shapefile, which was copy-pasted to a Microsoft Excel file for further analysis.

The crash data file used had 3397 crashes where latitude and longitude were missing for 75 crashes. Because spatial join required latitude and longitude to plot on a map, district names for these 75 crashes were not extracted. Two more crashes did not find the district name. In total, 77 crashes missed the district name. However, KDOT also provided each district's county names, which were used to find the missing districts. Noticeably, the original crash data included the county name for each crash location. Because county names were not available for many crashes, county names alone could not assign district names for all crashes. A combination of both the ArcGIS spatially joined file and county names data were used. Finally, only 13 crashes (out of 3397) were not assigned to any county name due to a lack of data.

4.1.4 Closest Facility Analysis

Distances to the nearest trauma centers and hospitals from the location of crashes were used in this research to compare the distance and time intervals. Because a smaller distance would take less time to arrive at a trauma center, comparing the distance and time intervals is practical.

The closest facility tool in ArcGIS estimated distances to the closest facility (trauma center and local hospitals). A network dataset is required to enable and apply the 'new closest facility' tool in the Network Analyst in ArcGIS. The creation of a network dataset and the application of the closest facility tool was discussed in Chapter 3.

The reason for not finding the closest facility could be the availability of the route. For example, a crash might be located in a place, and the road shapefile provided by KDOT recorded no route connecting the place with another route. Further analysis to investigate the reasoning for not finding any facility was out of the scope of the research. In addition, only six crashes did not find any facility among 3322 (3397-75=3322) crashes. Table 5 shows the details of six crashes that did not find a facility.

4.2 Factor-by-Factor Analysis

This section shows the average of all time intervals during a specific factor. Selected factors were weather conditions, day of the crash, lighting conditions, year of the crash, injury

Table 5. Crashes Did Not Find a Facility, Although Located on the Map

Crash Key	On-Road Speed Limit	County Name	Weather Conditions	Light Conditions	Latitude	Longitude	Crash Year	Crash Severity
20180008792*	70	LYON	No adverse weather	Dark: streetlights on	38.4115972	-96.1361496	2018	Injury
20190095106 *	55	FRANKLIN	No adverse weather	Daylight	38.4966928	-95.1218743	2019	Fatal
20200120525	65	SEWARD	Rain	Dark: no streetlights	37.0171566	-100.9557795	2020	Injury
20200008197	55		No adverse weather	Daylight	37.1342942	-96.1097682	2020	Injury
20200121116*	65	SEWARD	Rain	Dark: no streetlights	37.0171566	-100.9557795	2020	Injury
20210004486	45		Rain	Daylight	39.3194123	-95.9609016	2021	Injury

*Crashes had all the three-time intervals

severity, on-road speed limit, time of the crash, and KDOT districts. These factors were selected based on previous studies and the study's objective. The study's objective was to identify and analyze the factors affecting trauma center accessibility for patients involved in motor vehicle crashes. Therefore, factors found in previous studies affecting time intervals were selected.

4.2.1 Weather Conditions

The traffic crash data contained information on weather conditions. For the analysis, the weather condition was categorized into four distinct categories. Weather conditions recorded as sleet, sleet and fog, snow, snow, and wind were categorized as 'Snow.' Weather conditions recorded as fog, freezing rain, rain and wind, and rain/mist/drizzle were categorized as 'Rain.'

‘No adverse weather’ and ‘Strong wind’ involved the weather conditions reported as ‘No adverse weather’ and ‘Strong winds.’

Table 6 shows that during snow and strong winds, TTT was higher than the other weather conditions. The highest NTI during snow implied less traffic on the roads to notice a crash and notify the EMS. However, the lowest TTT was experienced during rainy weather conditions. Therefore, according to Table 6, snow and strong winds increased the TTT.

Table 6. Average of the Time Intervals for Different Weather Conditions

Weather Condition	Sample Size	Notification Time Interval (minutes)	Arrival Time Interval (minutes)	Transport Time Interval (minutes)	Total Transport Time (minutes)
No adverse weather	851	7.09	10.72	33.95	51.76
Snow	69	8.40	13.44	33.21	55.07
Rain	167	7.64	9.99	29.87	47.51
Strong wind	16	5.75	17.18	32.81	55.75

Table 7 shows the 95% confidence interval of the time intervals estimated in Table 6. According to the Table 7, NTI during different weather conditions might be same as there are overlapping points between the upper and lower bounds. Snow and rainy weather conditions showed a difference in time intervals such as ATI cannot be the same during snow and rainy weather conditions.

Table 7. Confidence Interval (95%) of Mean of the Time Intervals for Different Weather Conditions

Weather Condition	NTI (minutes)		ATI (minutes)		TTI (minutes)		TTT (minutes)	
	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound
No adverse weather	6.37	7.82	10.17	11.27	32.71	35.20	50.19	53.35
Snow	4.00	12.82	11.42	15.47	28.02	38.41	47.87	62.27
Rain	5.52	9.77	9.13	10.86	27.60	32.15	44.22	50.81
Strong wind	3.63	7.87	10.37	24.01	25.06	40.56	44.63	66.87

4.2.2 Day of Crash

The day of the week of the crash occurrence was recorded in the crash data. For analysis, the day of the week was categorized as weekday and weekend. Table 8 showed that time intervals did not vary between weekdays and weekends. Table 9 also shows that time intervals during weekday and weekend can be the same because there are overlapping points between upper and lower bound. In contrast, a study in Alabama (Vanga et al., 2022) estimated that ERT (ERT=NTI + ATI) was nearly 17% longer on weekends than weekdays.

Table 8. Average of the Time Intervals during Different Days of the Week

Day of Week	Sample Size	Notification Time Interval (minutes)	Arrival Time Interval (minutes)	Transport Time Interval (minutes)	Total Transport Time (minutes)
Weekday	780	7.05	10.89	33.13	51.08
Weekend	323	7.68	10.82	33.61	52.12

Table 9. Confidence Interval (95%) of Mean of the Time Intervals during Different Days of the Week

Day of Week	NTI (minutes)		ATI (minutes)		TTI (minutes)		TTT (minutes)	
	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound
Weekday	6.25	7.86	10.31	11.48	31.84	34.42	49.43	52.74
Weekend	6.29	9.07	10.04	11.61	31.65	35.58	49.50	54.74

4.2.3 Lighting Conditions

The lighting conditions were recorded in four categories, as shown in Table 10. According to Table 10, TTT was the highest during light conditions that were dark with no streetlights. NTI was also the highest at dark with no streetlights. Among the four lighting conditions, TTT for crashes that occurred during dark with no streetlights was longer than the Golden Hour. The result suggested that during the night and dark light conditions, NTI and TTT were higher. Table **10** and Table 11 also show that NTI and TTT of daylight does not intersect with NTI and TTT of dark condition with no streetlights. A study from Alabama, U.S. (Vanga et al., 2022) also found that crashes occurring in the dark with no streetlight had the highest ERT (ERT= NTI + ATI) than other lighting conditions.

Table 10. Average of the Time Intervals at Different Lighting Conditions

Lighting Condition	Sample Size	Notification Time Interval (minutes)	Arrival Time Interval (minutes)	Transport Time Interval (minutes)	Total Transport Time (minutes)
Dark: no streetlights	246	9.78	13.19	38.41	61.39
Daylight	643	6.18	10.27	32.51	48.98
Dark: streetlights on	154	7.24	8.94	27.82	44.01
Dawn	35	7.82	14.91	33.71	56.45
Dusk	25	8.48	9.68	35.08	53.24

Table 11. Confidence Interval (95%) of Mean of the Time Intervals at Different Lighting Conditions

	NTI (minutes)		ATI (minutes)		TTI (minutes)		TTT (minutes)	
	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound
Dark: no streetlights	7.77	11.79	11.81	14.59	35.85	40.97	57.90	64.88
Daylight	5.54	6.83	9.76	10.79	31.19	33.85	47.40	50.56

Dark: streetlights on	5.59	8.90	8.07	9.83	25.13	30.52	40.80	47.22
Dawn	2.19	13.47	11.13	18.70	27.62	39.80	46.35	66.57
Dusk	-3.22	20.18	7.69	11.67	26.94	43.22	38.38	68.10

4.2.4 Year of Crash

As mentioned earlier, crash data were collected for four years, from 2018 to 2021. As per Table 12 and Table 13, TTT was almost the same across the study period. The sample size ranged from 259 to 290 each year. Therefore, the result suggested that TTT did not vary yearly. This could be due to the same number of trauma centers which remained unchanged during the study. This validated one of the assumptions (mentioned in Chapter 3) that trauma centers and hospitals remained unchanged over the study period.

Table 12. Average of the Time Intervals during Different Years of the Crash

Year of the Crash	Sample Size	Notification Time Interval (minutes)	Arrival Time Interval (minutes)	Transport Time Interval (minutes)	Total Transport Time (minutes)
2018	272	7.86	10.51	32.51	50.88
2019	282	7.06	11.78	32.79	51.64
2020	290	7.27	10.76	33.71	51.75
2021	259	6.73	10.39	34.09	51.22

Table 13. Confidence Interval (95%) of Mean of the Time Intervals during Different Years of the Crash

Year of the Crash	NTI (minutes)		ATI (minutes)		TTI (minutes)		TTT (minutes)	
	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound
2018	6.38	9.34	9.67	11.35	30.42	34.61	48.07	53.71
2019	5.64	8.49	10.54	13.03	30.75	34.84	48.84	54.44
2020	6.03	8.52	9.98	11.54	31.48	35.95	49.01	54.50
2021	5.27	8.20	9.55	11.24	31.84	36.35	48.36	54.10

4.2.5 Injury Severity

Fatal and injury crashes were analyzed for this research. Table 14 and Table 15 show the average and confidence intervals of time intervals for different injury severity. Although the average value of time intervals were not the same, the confidence intervals show that the time intervals can be same. Table 14 shows that TTT was nearly 1.8 minutes higher for fatal crashes than injury crashes, which contradicts the findings from Alabama (Vanga et al., 2022), where suspected serious injuries had the highest ERT than fatal crashes. This could happen because possible injury crashes could be taken to the local hospitals, while fatal crashes were more likely to be taken to the trauma center. Section 3.1.2 discussed that the total number of trauma centers was 53 and the total number of hospitals, including trauma centers, was 124. This indicated that trauma centers were not as abundant as local hospitals. Therefore, taking a patient to the trauma center might take a longer time than taking a patient to the local hospital. The later analysis (Section 4.2.8) found that among the 50 crashes in District 6, only one was taken to the state-designated trauma center (Level IV).

Table 14. Average of the Time Intervals of Different Injury Severity

Crash Severity	Sample Size	Notification Time Interval (minutes)	Arrival Time Interval (minutes)	Transport Time Interval (minutes)	Total Transport Time (minutes)
Injury	1032	7.15	10.95	33.16	51.27
Fatal	71	8.42	9.71	34.91	53.05

Table 15. Confidence Interval (95%) of Mean of the Time Intervals during Different Injury Severity

Crash Severity	NTI (minutes)		ATI (minutes)		TTI (minutes)		TTT (minutes)	
	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound
Injury	6.45	7.86	10.46	11.45	32.06	34.26	49.85	52.70
Fatal	4.76	12.09	8.19	11.25	30.15	39.68	46.29	59.82

4.2.6 On-Road Speed Limit

The posted speed limit at the location of crash occurrence was recorded as a numeric value and categorized into three categories in this research, as shown in Table 16. The table shows that TTT was the lowest (lower by more than 7 minutes) for the crashes that occurred on the roads with posted speed limits lower than or equal to 45 miles per hour (mph). The NTI was also lower on low-speed roads. This could be because high or higher-speed roads are usually interstates or highways. A higher traffic volume could decrease the travel speed of emergency vehicles. Previous studies showed that increased traffic volume increased emergency vehicles' response time (Griffin and McGwin, 2013). In addition, low-speed roads are likely to be in urban areas, and a study showed that emergency vehicles experienced higher delays in urban areas than in non-urban areas (Brent and Beland, 2020). Although travel time delays in urban areas are more likely due to the volume of traffic, emergency vehicle response times were found to be lower in urban areas than in rural areas (Alruwaili and Alanazy, 2022; Byrne et al., 2019). In this research, an analysis of time intervals based on urban and rural areas was not conducted. Therefore, future research can investigate the time intervals based on the posted speed limit and the presence of that road (in other words, the location of crash occurrence) in terms of urban or non-urban areas.

Table 17 emphasized the findings from the Table 16 by showing that the TTT confidence interval on low-speed roads did not intersect with the TTT confidence intervals for the higher speeds road categories.

Table 16. Average of the Time Intervals at Different Speed Limits

Posted Speed Limit	Sample Size	Notification Time Interval (minutes)	Arrival Time Interval (minutes)	Transport Time Interval (minutes)	Total Transport Time (minutes)
Higher Speed (≥65 mph)	258	7.57	10.53	31.94	50.06
High Speed (>45 mph, <65 mph)	751	7.18	11.29	34.32	52.81
Low Speed (≤45 mph)	94	6.72	8.44	28.50	43.67

Table 17. Confidence Interval (95%) of Mean of the Time Intervals during Different Speed Limits

Posted Speed Limit	NTI (minutes)		ATI (minutes)		TTI (minutes)		TTT (minutes)	
	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound
Higher Speed (≥65 mph)	6.01	9.15	9.63	11.44	29.79	34.10	47.12	53.01
High Speed (>45 mph, <65 mph)	6.37	8.00	10.70	11.89	32.98	35.67	51.10	54.52
Low Speed (≤45 mph)	4.10	9.35	7.00	9.89	25.64	31.36	39.77	47.57

4.2.7 Time of Crash

The time of the crash was categorized into 24 categories, each representing a one-hour interval of the day. Each crash record had information on the time of the crash, and from this information, a crash was taken into one category among the 24 categories. For example, if a crash occurred on 2312, the time of the crash was categorized as ‘2300-2359.’ Figure 2 and Figure 3 show the 24 categories of the time of the crash and the average TTT and NTI during these categories of time. The average values of all time intervals during the 24 categories at the time of the crash was shown in Appendix B.

From Figure 2 and Figure 3, it was noticed that during midnight to 0700 (7 a.m.), notification time was higher by approximately 7 minutes. During the same time period, total transport time was also greater than 50 minutes. The notification time interval from 0700 (7 a.m.) to 1900(7 p.m.) was lower than approximately 7 minutes. From 0700 to 1900, most of the TTT was lower than 50 minutes.

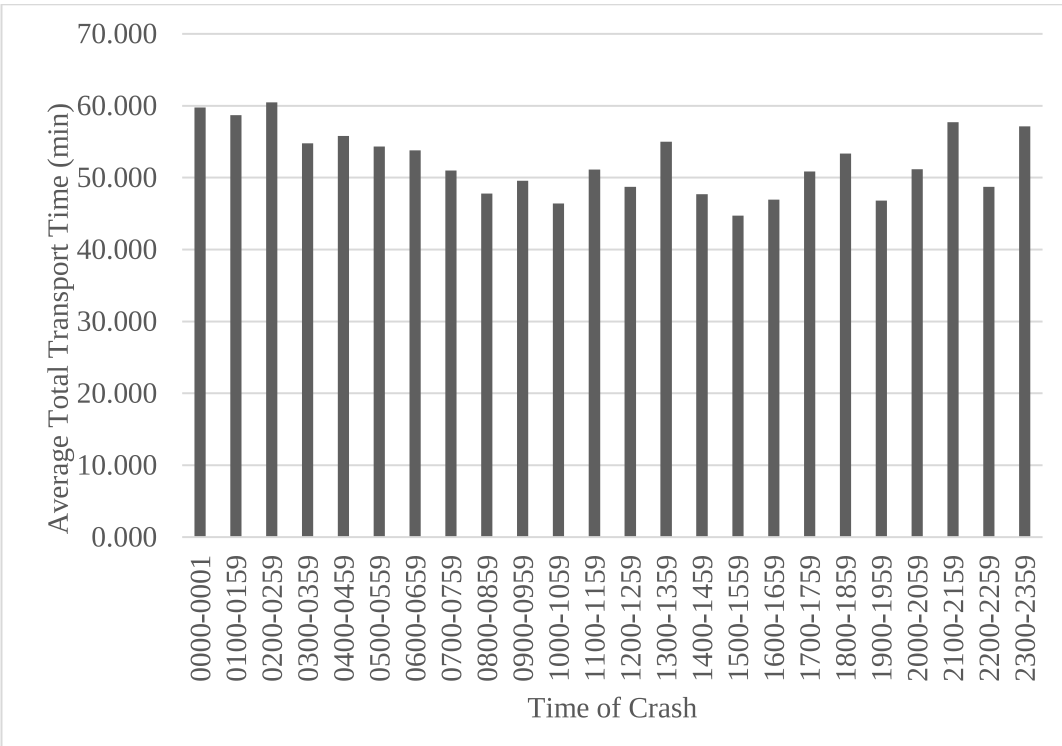

Figure 2. Average of the Total Transport Time at Different Times of the Crash

Notification and transport times did not decrease or increase linearly through the 24-hour intervals. However, noticeably higher TTT and NTI were observed from 1100 to 0700. To further verify these, time intervals were categorized into 1100-0659, 0700-1759, and 1800-2259. Table 18 shows the average of the time intervals at these three-time categories. Table 19 shows the confidence intervals of the time intervals at different times of the day.

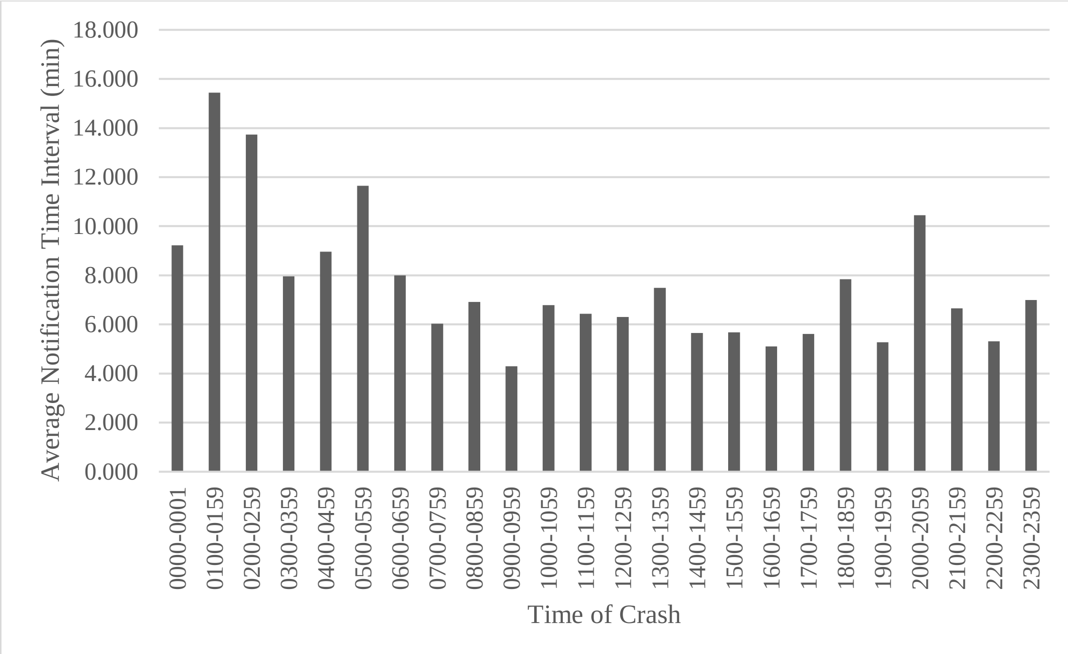

Figure 3. Average of the Notification Time Intervals at Different Times of the Crash

Table 18. Average of the Time Intervals at Different Times of the Crash

Time of Crash (U.S. military time)	Sample Size	Notification Time Interval (minutes)	Arrival Time Interval (minutes)	Transport Time Interval (minutes)	Total Transport Time (minutes)
2300-0659	279	**10.05**	12.17	34.22	56.45
0700-1759	617	6.02	10.32	32.65	49.0
1800-2259	207	7.07	10.74	33.82	51.64

Table 19. Confidence Interval (95%) of Mean of the Time Intervals during Different Times of the Crash

Time of Crash (U.S. military time)	NTI (minutes)		ATI (minutes)		TTI (minutes)		TTT (minutes)	
	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound
2300-0659	8.21	11.89	10.96	13.40	31.79	36.66	53.20	59.72
0700-1759	5.37	6.67	9.81	10.85	31.32	34.00	47.40	50.62
1800-2259	5.13	9.03	9.63	11.86	31.30	36.34	48.10	55.19

Table 18 shows that during the time interval 1100-0659, NTI and TTT were the maximum, followed by the time period 1800-2259. The same time period (6:00 p.m. – 6:59 a.m.) in Alabama was also found to have the highest ERT (Vanga et al., 2022). This time period is nighttime, and Table 10 also showed that the highest NTI and TTT were recorded during dark conditions with no streetlights. From Table 7 and Table 11, it can be concluded that crashes occurring at nighttime, especially during the time period 1100-0659 at roads with no street lights, can experience a higher TTT (possibly more than the Golden Hour) than other times of the day.

To see if time intervals vary by other time periods of the day, the time of the crash was categorized into six categories, and the result is shown in Table 20. According to the table, the highest NTI and TTT were recorded during the time period 2201-0200 and 0201-0600. This two-time period was represented in the time period 2300-0659.

Table 20. Average of the Time Intervals at Six Time Categories

Time of crash	Sample Size	Notification Time Interval (minutes)	Arrival Time Interval (minutes)	Transport Time Interval (minutes)	Total Transport Time (minutes)
0201-0600	130	11.07	11.73	33.44	56.26
0601-1000	211	6.30	11.86	32.88	51.04
1001-1400	213	6.79	10.36	33.31	50.46
1801-2200	164	7.03	10.59	34.01	51.65
1401-1800	256	5.88	9.78	32.12	47.79
2201-0200	129	8.57	11.76	35.01	55.34

4.2.8 KDOT Districts

The creation of a factor for KDOT Districts was discussed in section 4.1.3. Table 21 shows District 4 had the highest TTT, although the NTI was lower than the four other districts. This indicated that NTI was not the only factor to increase or decrease the total transport time.

Table 21. Average of the Time Intervals at Six KDOT Districts

KDOT Districts	Sample Size (1099)*	Notification Time Interval (minutes)	Arrival Time Interval (minutes)	Transport Time Interval (minutes)	Total Transport Time (minutes)
District 1	380	7.14	10.43	31.36	48.94
District 2	149	8.10	12.24	34.36	54.71
District 3	84	**9.09**	12.61	29.41	51.13
District 4	157	6.38	11.22	39.88	**57.49**
District 5	279	7.14	9.90	33.90	50.94
District 6	50	5.78	11.66	27.32	44.76

*Four crashes needed county name, latitude, and longitude information. Therefore, the district name for these four crashes was missing, resulting in a sample size of 1099 (1103-4=1099).

Table 22 shows that NTI of different districts can have intersecting values, however, TTT of District 4 cannot intersect with TT of District 1.

Table 22. Confidence Interval (95%) of Mean of the Time Intervals at Six KDOT Districts

KDOT Districts	NTI (minutes)		ATI (minutes)		TTI (minutes)		TTT (minutes)	
	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound
District 1	6.17	8.12	9.49	11.38	29.63	33.10	46.72	51.17
District 2	5.94	10.28	11.07	13.43	31.43	37.29	51.03	58.40
District 3	5.10	13.09	11.38	13.86	27.03	31.80	46.29	55.97
District 4	4.74	8.03	10.14	12.31	36.10	43.67	52.99	61.99
District 5	5.65	8.63	9.00	10.80	31.84	35.96	48.12	53.77
District 6	4.05	7.51	9.60	13.72	23.69	30.95	39.84	49.68

District 6 had the lowest NTI and TTT. To further investigate, crashes that occurred at District 6 were extracted. After a thorough investigation of each crash, it was found that out of 50 crashes, only one crash (at least one patient involved in that crash) was taken to a trauma center which was a level IV trauma center. Other crashes were taken to a local hospital. Because local hospitals were higher in number than the trauma centers, it was more likely that hospitals were closer to the location of the crash than the trauma centers. Figure 4 and Figure 5 showed the spread of the crash location, trauma centers, and hospitals in the KDOT districts. More analysis of the KDOT District was discussed in Appendix C. However, future research can investigate where (trauma center/hospital) patients were taken in reality and, if they were taken to the nearest hospital (or trauma center), what could be the TTT using the closest facility.

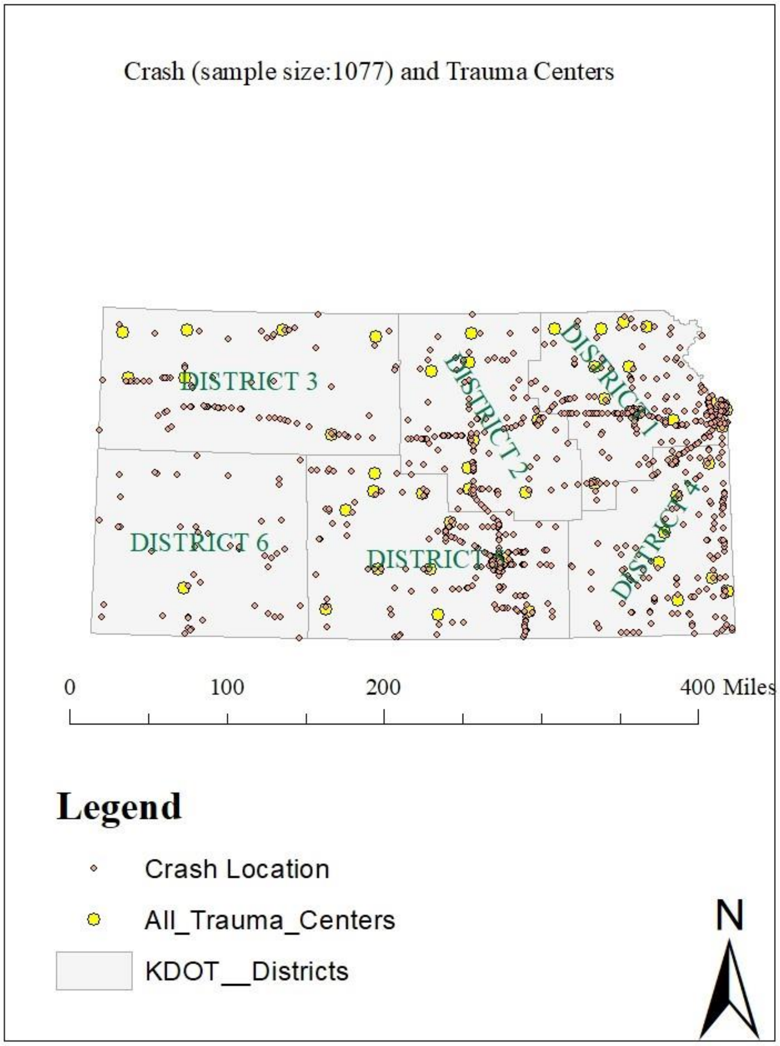

Figure 4. Crash and Trauma Centers in KDOT Districts

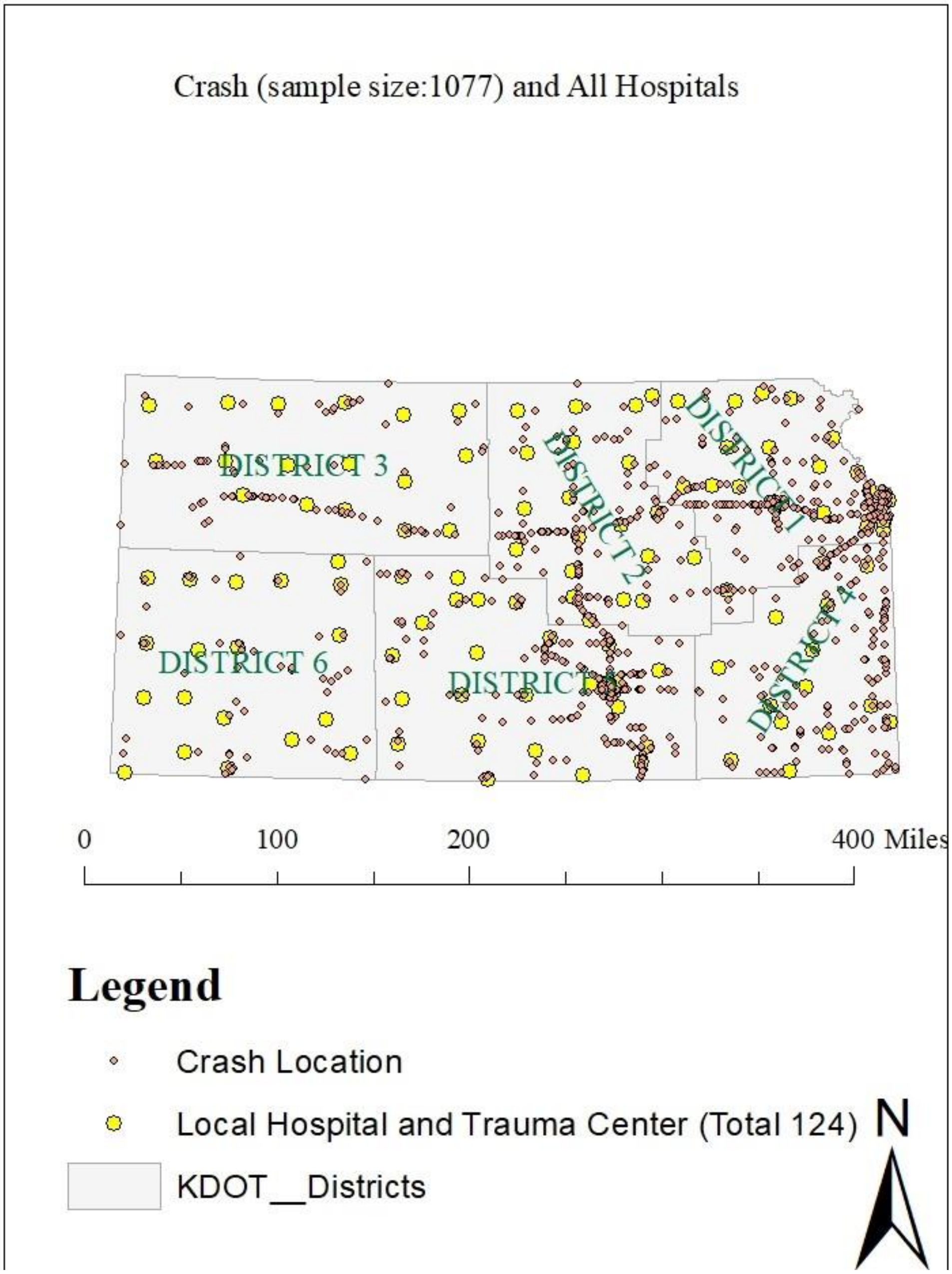

Figure 5. Crash and Hospitals in KDOT Districts

4.2.9 Influence Diagram

An influence diagram helps to visualize the impact of factors on the output. From the analysis of the eight factors, the following influence diagram is presented Figure 6. The

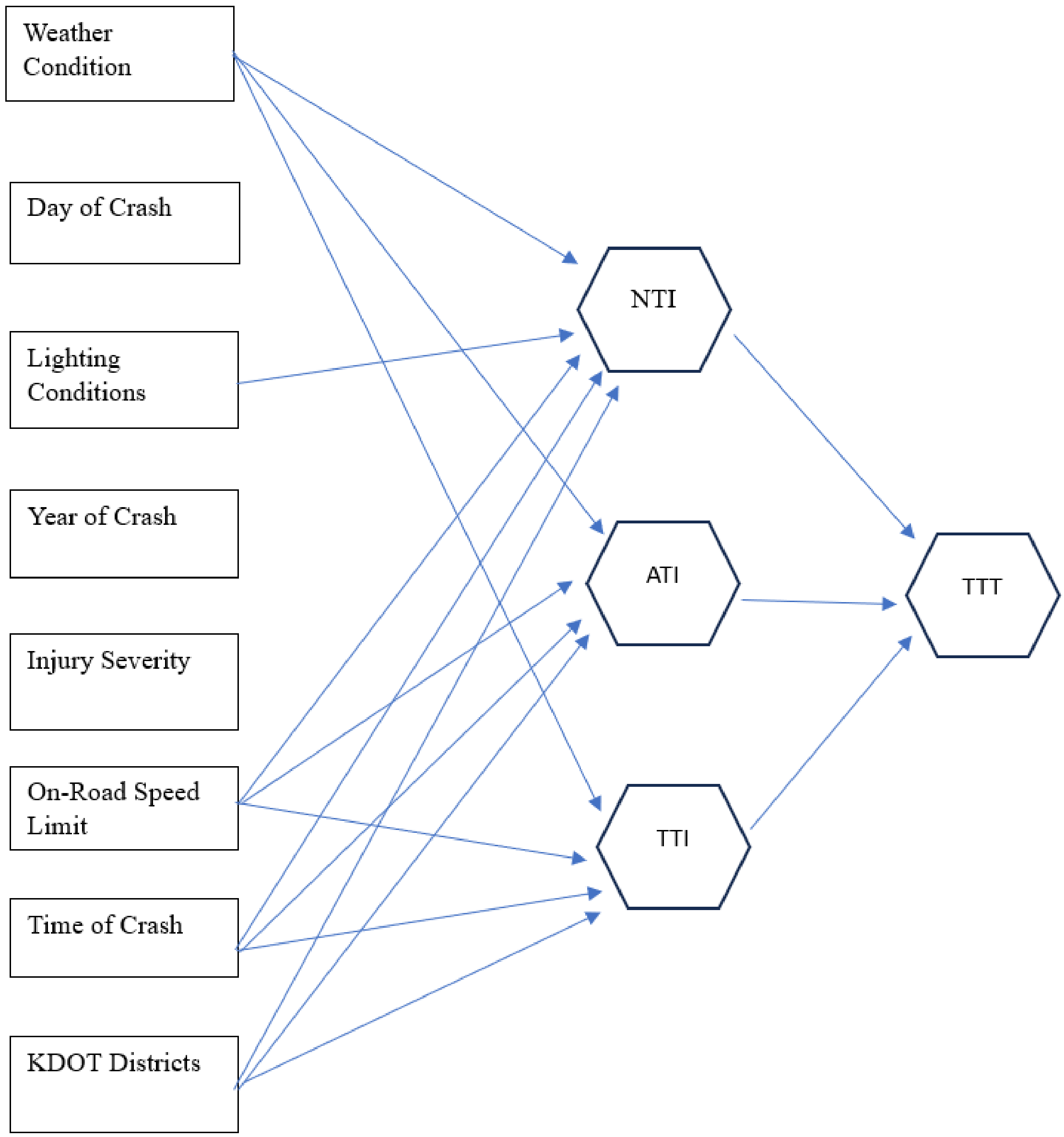

Figure 6. Influence Diagram of Eight Factors affecting Time Intervals

rectangular boxes indicate the factors, the hexagonal boxes indicate the output and the arrow signs indicate which factor is affecting which output.

4.3 ‘Within Golden Hour’ and ‘Outside Golden Hour’ crashes

To further investigate the factors that can increase the TTT above the Golden Hour the crash dataset was divided into groups: ‘within Golden Hour’ and ‘outside Golden Hour.’ Crashes with more than 60 minutes of TTT were grouped into ‘outside golden hour’ crashes, and other crashes (TTT≤ 60 minutes) were categorized as ‘within golden hour’ crashes.

Table 23 shows the average time intervals of these two crash categories. According to Table 23, the TTT of ‘outside golden hour’ crashes was two times more than the TTT of ‘within golden hour’ crashes. Among the three-time intervals, TTI was about 28.088 minutes higher in ‘outside golden hour’ crashes. In contradiction, the closest facility analysis shows (Table 15) that the average transport time from the crash location to the nearest trauma center was nearly six minutes longer for ‘outside golden hour’ crashes than the ‘within golden hour’ crashes.’ However, analysis of the crashes occurring at District 6 (section 4.2.8) showed that most were taken to the local hospital instead of a trauma center, resulting in lower TTI than the TTI estimated using the closest facility. Therefore, future research should investigate which hospitals the patients were taken to because analysis showed that if patients were taken to the trauma center, this resulted in a lower TTI.

Table 23. Average of the Time Intervals of Crashes Within or Outside the 'Golden Hour'

Golden Hour Indicator	Sample Size (1103)	Notification Time Interval (minutes)	Arrival Time Interval (minutes)	Transport Time Interval (minutes)	Total Transport Time (minutes)
Within Golden Hour	820	5.34	9.26	26.06	40.67
Outside Golden Hour	283	12.73	15.54	54.15	82.43

Table 24. Average of the Distances to the Closest Trauma Centers from the Crash Location

	Within the 'golden hour.'	Outside 'golden hour.'
Average distances to the closest trauma center from the crash location (miles)*	15.70	22.50
Average time to arrive at the closest trauma centers from the crash location (minutes)*	16.78	22.97

*Estimated using ArcGIS closest facility analysis.

According to Table 25, the percentage of each variable under a factor was almost equal in both groups (‘within golden hour’ and ‘outside golden hour’) except for the lighting condition dark with no streetlights. For ‘within golden hour’ crashes, 17.93% of total ‘within golden hour’ crashes occurred during dark lighting conditions with no streetlights. Conversely, this percentage was 34.98% for ‘outside golden hour’ crashes, meaning one-third of the ‘outside golden hour’ crashes occurred during dark with no streetlights.

Table 26 shows the results of statistical test for comparison proportion of crashes between ‘within Golden Hour’ and ‘outside Golden Hour’ crashes. The null hypothesis was that the percentage of crashes for each variable under a factor between the two groups is equal. The null hypothesis is rejected when the p-value is less than 0.05. According to the Table 26, percentage of crashes between two groups were different during dark condition with no streetlights, roads with higher speed limit (>65 mph), and two time period 2300-0659 and 1800-2259. This difference was statistically significant at 0.05 level. Therefore, lighting conditions, posted speed limit and time of the crashes were the significant factors.

Table 10 showed that NTI and TTT were significantly higher during dark with no streetlights than in other lighting conditions. Table 18 showed that NTI and TTT were higher during the time period 1100-0659 than at any other time. Therefore, a particular focus was given to see the average time intervals of both groups during different times of the day. Hence, Table 27 and Table 28 are presented.

Table 27 and Table 28 showed that 23.41% of ‘within Golden Hour’ crashes occurred during the time period 2300-0659, while this percentage was 30.74 for ‘outside Golden Hour’ crashes. Table 29 shows the differences in time intervals from ‘outside Golden Hour’ to ‘within Golden Hour.’ According to Table 29, the highest differences in time intervals were observed during the time period 2300-0659. During 2300-0659, the NTI of ‘outside Golden Hour’ crashes was 10.81 minutes higher than the NTI of ‘within Golden Hour’ crashes. During the time period 0700-1759, the difference in NTI was the lowest. Noticeably, the difference between ATI and TTI did not vary more than 2 minutes among the three periods. Differences in ATI were nearly six minutes during all time periods, and TTI was about 28 minutes during all the time periods. The only difference in NTI during dark hours (1800-0659) was nearly 10 minutes, while during 0700-1759, the difference was 4.04 minutes. The percentage difference also showed that 7.32% higher ‘outside golden hour’ crashes occurred during the time period1100-0659 than ‘within Golden Hour’ crashes, while 8.22% higher ‘within Golden Hour’ crashes occurred during time period 0700-1759. In other words, a higher percentage of ‘within Golden Hour’ crashes occurred during time period 0700-1759, and a lower percentage of ‘within Golden Hour’ crashes occurred during time period 1800-0659. This indicates that the time period 1800-0659, mainly 2300-0659,

Table 25. Descriptive Statistics of the 'Within golden hour' and 'Outside golden hour' Crashes

		'Within Golden Hour.'		'Outside Golden Hour'	
Factor	Variable	Frequency	Percentage	Frequency	Percentage
Weather condition	No adverse weather	629	76.71%	222	78.45%
	Rain	134	16.34%	33	11.66%
	Snow	46	5.61%	23	8.13%
	Strong wind	11	1.34%	5	1.77%
	Total	820	100.00%	283	100.00%
Lighting condition	Dark: no streetlights	147	17.93%	99	34.98%
	Dark: streetlights on	133	16.22%	21	7.42%
	Dawn	24	2.93%	11	3.89%
	Daylight	498	60.73%	145	51.24%
	Dusk	18	2.20%	7	2.47%
	Total	820	100.00%	283	100.00%
Year of crash	2018	204	24.88%	68	24.03%
	2019	206	25.12%	76	26.86%
	2020	215	26.22%	75	26.50%
	2021	195	23.78%	64	22.61%
	Total	820	100.00%	283	100.00%
Day of week	Weekday	586	71.46%	194	68.55%
	Weekend	234	28.54%	89	31.45%
	Total	820	100.00%	283	100.00%
Posted Speed Limit	Higher Speed (≥65 mph)	542	66.10%	209	73.85%
	High Speed (>45 mph, ≤ 60 mph)	196	23.90%	62	21.91%
	Low Speed ≤45 mph	82	10.00%	12	4.24%
	Total	820	100.00%	283	100.00%
Crash severity	Fatal	50	6.10%	21	7.42%
	Injury	770	93.90%	262	92.58%
	Total	820	100.00%	283	100.00%
Time of the crash	1001-1400	159	19.39%	54	19.08%
	1401-1800	203	24.76%	53	18.73%
	1801-2200	118	14.39%	46	16.25%
	201-600	89	10.85%	41	14.49%
	2201-200	93	11.34%	36	12.72%
	601-1000	158	19.27%	53	18.73%
	Total	820	100.00%	283	100.00%

Table 26. Test of Proportion of Crashes between 'Within Golden Hour' and 'Outside Golden Hour' Crashes

Factor	Variable	Z-Score	P-value
Weather condition	No adverse weather	0.53	0.60
	Rain	-0.67	1.50
	Snow	0.41	0.68
	Strong wind	0.07	0.95
Lighting condition	Dark: no streetlights	3.15	<0.001*
	Dark: streetlights on	-1.08	1.72
	Dawn	0.15	0.88
	Daylight	-2.04	1.96
	Dusk	0.04	0.97
Year of crash	2018	-0.14	1.11
	2019	0.30	0.77
	2020	0.05	0.96
	2021	-0.19	1.15
Day of week	Weekday	-0.77	1.56
	Weekend	0.51	0.61
Posted Speed Limit	Higher Speed (≥65 mph)	2.04	0.04
	High Speed (>45 mph, ≤ 60 mph)	-0.32	1.25
	Low Speed ≤45 mph	-0.67	1.50
Crash severity	Fatal	0.21	0.84
	Injury	-0.75	1.55
Time of the crash	1001-1400	-0.05	1.04
	1401-1800	-0.93	1.65
	1801-2200	0.30	0.76
	201-600	0.60	0.55
	2201-200	0.22	0.83
	601-1000	-0.09	1.07
Time of the crash	2300-0659	130.47	<0.001*
	0700-1759	-172.69	2.00
	1800-2259	14.65	<0.001*

*Indicates statistically significant at $\alpha = 0.05$ level of significance.

Table 27. Average of the Time Intervals of 'Within Golden Hour' Crashes at Different Times of the Day

Golden Hour Indicator	Time of Crash	Sample Size	Percentage of sample size	Notification Time Interval (minutes)	Arrival Time Interval (minutes)	Transport Time Interval (minutes)	Total Transport Time (minutes)
Within Golden Hour	2300-0659	192	**23.41**	6.67	10.09	25.35	42.13
Within Golden Hour	0700-1759	476	**58.04**	5.09	8.92	26.18	40.20
Within Golden Hour	1800-2259	152	18.53	4.42	9.27	26.59	40.30

Table 28. Average of the Time Intervals of 'Outside Golden Hour' Crashes at Different Times of the Day

Golden Hour Indicator	Time of Crash	Sample Size	Percentage of sample size	Notification Time Interval (minutes)	Arrival Time Interval (minutes)	Transport Time Interval (minutes)	Total Transport Time (minutes)
Outside Golden Hour	2300-0659	87	**30.74**	17.49	16.77	53.81	88.08
Outside Golden Hour	0700-1759	141	**49.82**	9.14	15.07	54.51	78.72
Outside Golden Hour	1800-2259	55	19.43	14.40	14.81	53.78	83.0

played the most crucial role in determining a crash to be ‘outside Golden Hour’. Sections 4.2.3 and 4.2.7 discussed crashes occurring during lighting conditions dark with no streetlights, and during the time period, 2300-0659 experienced the highest NTI and TTT. Therefore, among the eight factors analyzed in this research, the time of the crash and lighting conditions were found to be the most important in affecting the NTI and TTT, which resulted in a crash being ‘within Golden Hour’ or ‘outside Golden Hour.’

Table 29 shows that differences in NTI between the two groups of crashes were the highest during 2300-0659. The lowest differences in NTI were found in 0700-1759 (daytime). Table 31 shows that the average distances to the closest trauma centers from the ‘outside Golden Hour’ crashes were 20.99 miles during 2300-0659, while this distance was 23.16 miles during 0700-1759. That indicates that although ‘outside Golden Hour’ crashes occurred at a closer location during nighttime (2300-0659), the NTI was higher than daytime (0700-1759). This result further strengthens the research finding that time period 2300-0659 could be the most important determining factor for a crash to be in ‘within Golden Hour’ or ‘outside Golden Hour.’

Table 29. Differences in Time Intervals between the 'Within Golden Hour' and 'Outside Golden Hour' Crashes during Different Times of the Day

Times of the Day	Percentage (%)	Notification Time Interval (minutes)	Arrival Time Interval (minutes)	Transport Time Interval (minutes)	Total Transport Time (minutes)
2300-0659	7.327	**10.81**	**6.67**	**28.46**	**45.95**
0700-1759	-8.225[a]	4.04	6.14	28.32	38.51
1800-2259	0.898	9.97	5.54	27.18	42.69

[a]= A negative sign indicates that ‘within golden hour’ had a higher percentage than ‘outside Golden Hour.’

Table 30. Distances to the Closest Trauma Center for 'Within Golden Hour' Crashes Occurring at Different Times of the Day

Time of Crash	Sample Size (1074)*	Distance between trauma centers and crash location (miles)
2300-0659	189	15.352
0700-1759	461	15.785
1800-2259	146	15.852

*Out of 1103 crashes, 29 did not find the closest facility because of lack of latitude, longitude, and incorrect latitude and longitude.

Table 31. Distances to the Closest Trauma Center for 'Outside Golden Hour' Crashes Occurring at Different Times of the Day

Time of Crash	Sample Size (1074)	Distance between trauma centers and crash location (miles)
2300-0659	84	20.993
0700-1759	140	23.167
1800-2259	54	23.129

The average NTI during time period 1800-0659 was at least five minutes higher than the NTI during other times of the day. This could be due to less frequent following traffic to notice a traffic crash and notify the EMS. On the other hand, a higher amount of traffic (Griffin and McGwin, 2013), especially rush hour traffic (Dijkink et al., 2020), was found to increase the ATI and TTI. Therefore, future research should investigate the effect of traffic volume on NTI and other time intervals. The research should focus on identifying an optimum amount of traffic (considering roadway geometry) that can be associated with a lower NTI and will not delay travel time.

According to Table 28, ‘outside golden hour’ crashes experienced the highest TTT during the time period 2300-0659 than other times of the day. Table 31 shows that ‘outside Golden Hour’ crashes occurring at the time period 2300-0659 had the lowest distances from the crash locations to the closest trauma center. This implies that crashes with higher TTT might not necessarily happen at a greater distance from the trauma center. The following section (section 4.4) further sheds light on this.

4.4 Percentage of Crashes within a Buffer Zone

This section estimated the percentage of traffic crashes within a specified distance from the trauma center. The goal was to learn about the percentage of crashes that occur within 5, 10, 15, 20 and 30 miles of trauma centers. This would help to learn about the impact of distance between the crash location and trauma center on the patient’s access to trauma center within the Golden Hour.

The traffic crash data is point data. The buffer zone of the traffic crash data was a circular area around the location of a traffic crash. A buffer zone of 30 miles is estimated to be a circular area of 30 miles radius around a site of a traffic crash. Section 2.2.3 discussed using ArcGIS tools to create buffer zones and estimating the number of crashes within a buffer zone.

Figure 7 through Figure 11 show the location of traffic crashes and buffer zones of different radii around the area of traffic crashes. The total sample size was 1077 because 26 crashes had no latitude and longitude. When multiple buffer zones intersected, they were dissolved into one buffer zone so that only one boundary was shown for the intersecting buffers.

- **Case 01**: Percentage of crashes within 30 miles of a trauma center

The total number of crashes=1077.

The total number of 'within golden hour' crashes=798

The total number of 'outside golden hour' crashes= 279

Number of 'outside Golden Hour' crashes within 30 miles of a buffer from all trauma centers= 253

Percentage of 'outside Golden Hour' crashes within 30 miles of a buffer from all trauma centers= $\frac{253}{279} * 100 = 90.68\%$

Number of 'within Golden Hour' crashes within 30 miles of a buffer from all trauma centers= 741

Percentage of 'within Golden Hour' crashes within 30 miles of a buffer from all trauma centers= $\frac{741}{798} * 100 = 92.85\%$

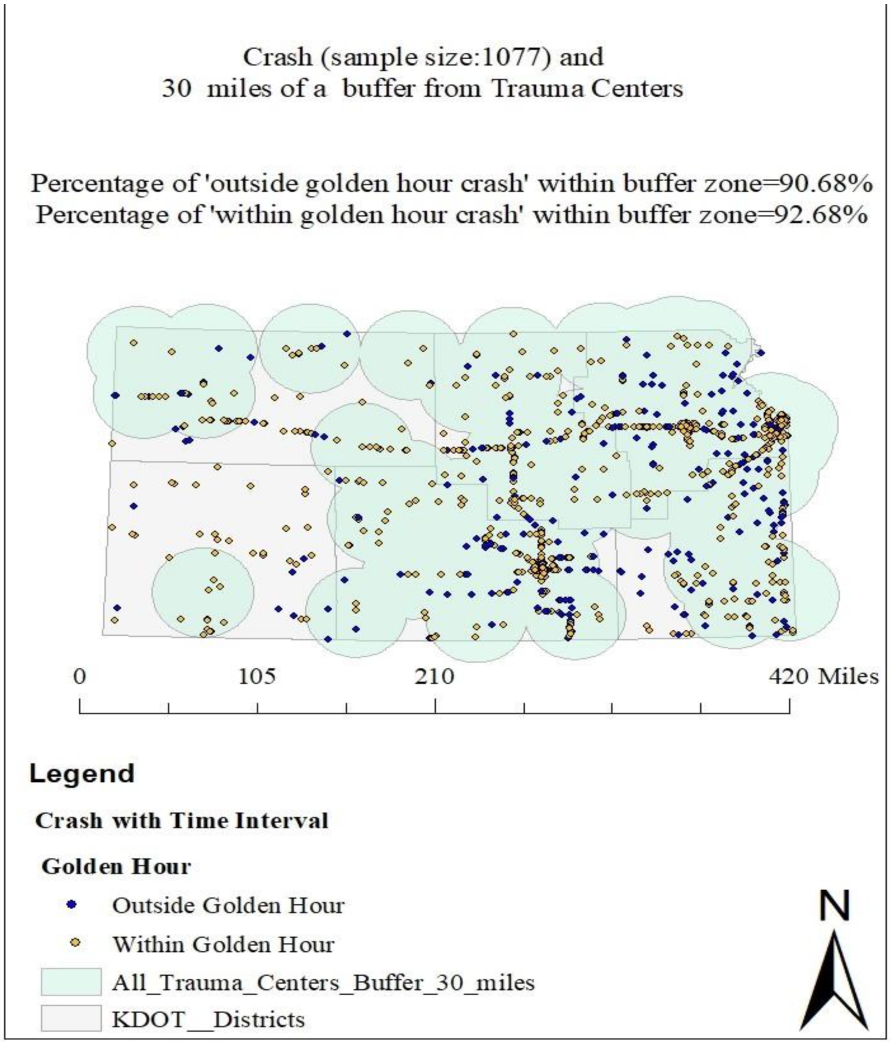

Figure 7. Percentage of Crashes within 30 miles of Trauma Center

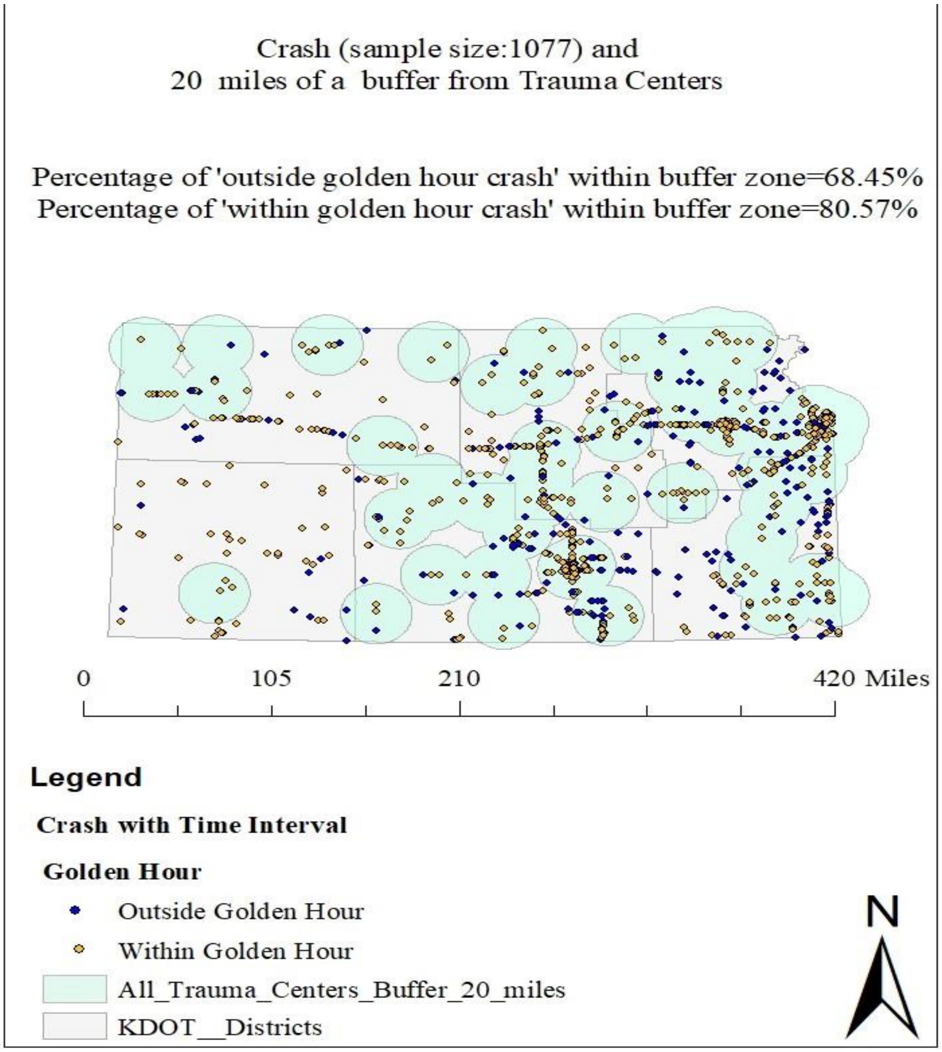

Figure 8. Percentage of Crashes within 20 miles of Trauma Center

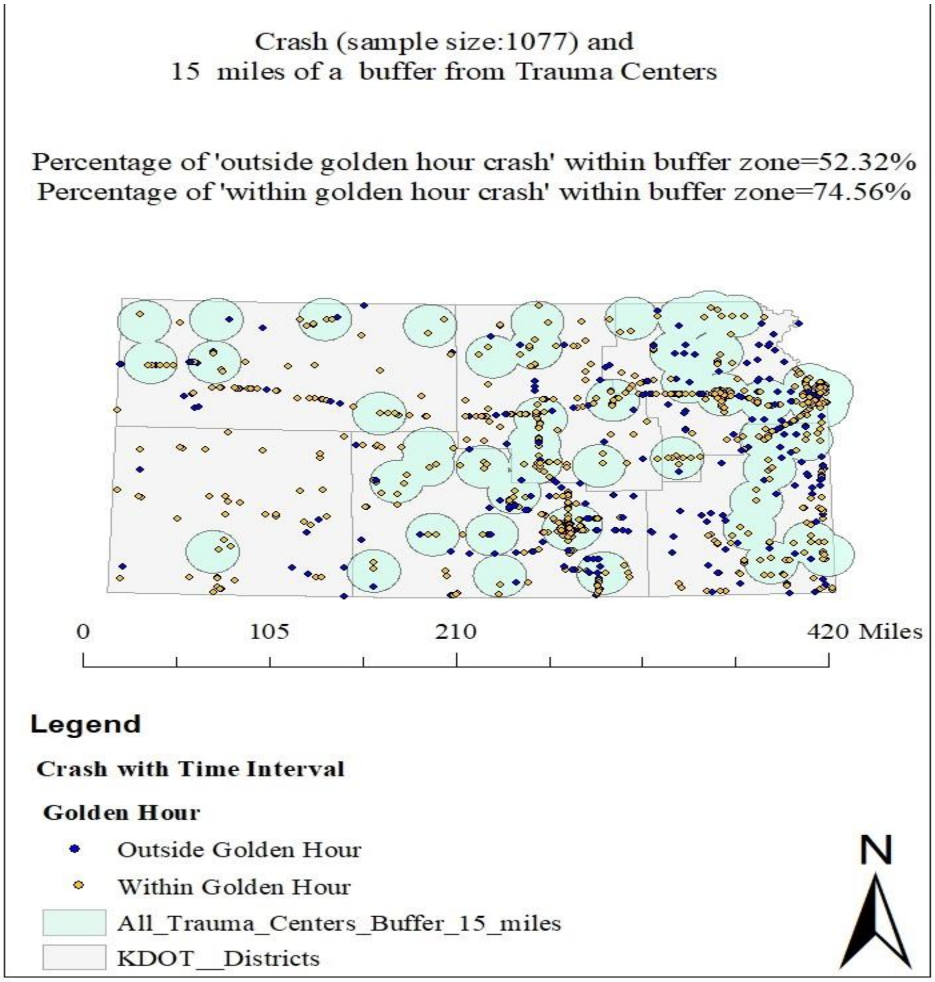

Figure 9. Percentage of Crashes within 15 miles of Trauma Center

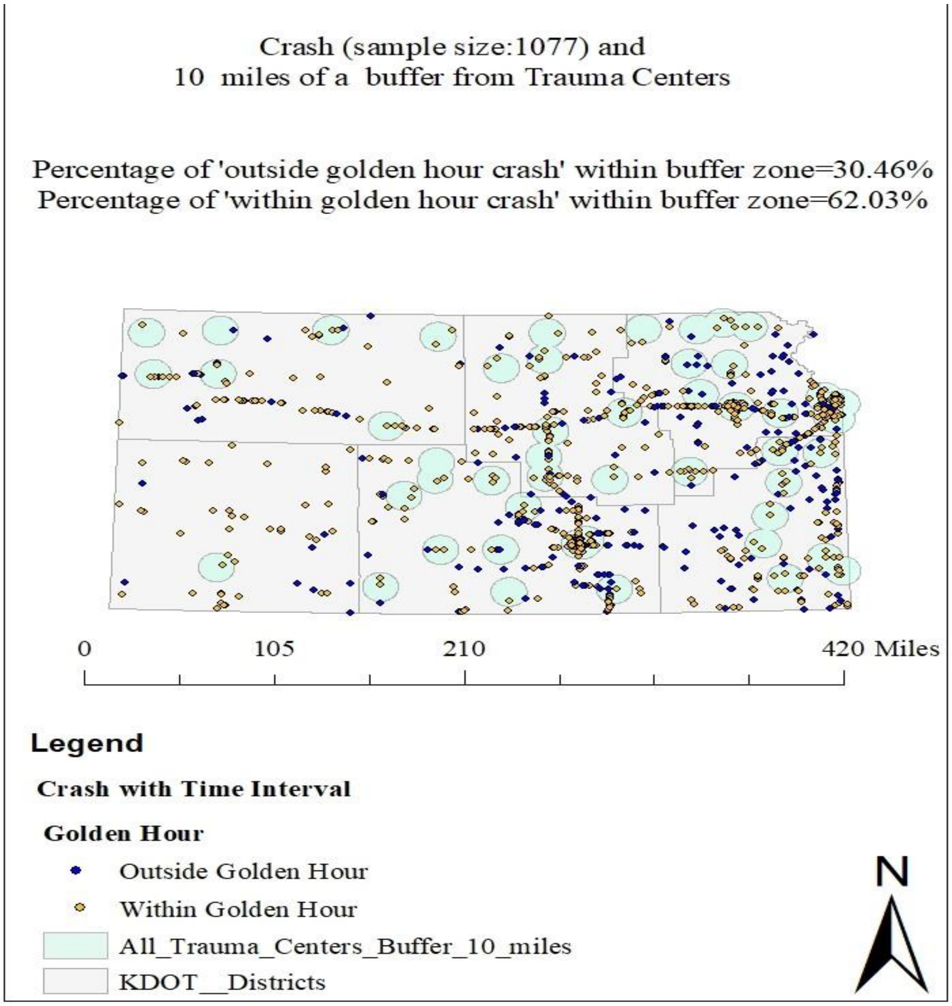

Figure 10. Percentage of Crashes within 10 miles of Trauma Center

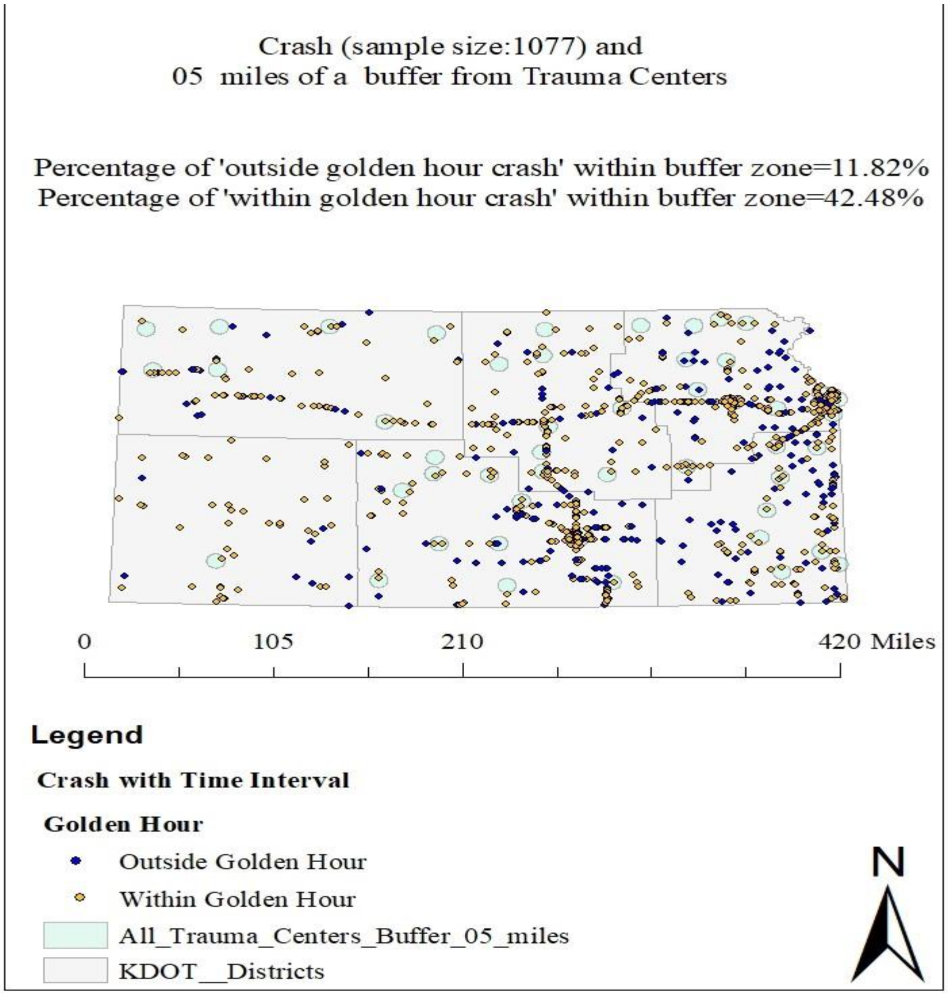

Figure 11. Percentage of Crashes within 05 miles of Trauma Center

- **Case 02**: Percentage of crashes within 20 miles of a trauma center.

Number of ‘outside Golden Hour’ crashes within 20 miles of a buffer from all trauma centers= 191

Percentage of ‘outside Golden Hour’ crashes within 20 miles of a buffer from all trauma centers= $\frac{191}{279} * 100 = 68.45\%$

Number of ‘within Golden Hour’ crashes within 20 miles of a buffer from all trauma centers= 643

Percentage of 'within Golden Hour' crashes within 20 miles of a buffer from all trauma centers= $\frac{643}{798} * 100 = 80.57\%$

- **Case 03**: Percentage of crashes within 15 miles of a trauma center

Number of 'outside Golden Hour' crashes within 15 miles of a buffer from all trauma centers= 146

Percentage of 'outside Golden Hour' crashes within 15 miles of a buffer from all trauma centers= $\frac{146}{279} * 100 = 52.32\%$

Number of 'within Golden Hour' crashes within 15 miles of a buffer from all trauma centers= 595

Percentage of 'within Golden Hour' crashes within 15 miles of a buffer from all trauma centers= $\frac{595}{798} * 100 = 74.56\%$

- **Case 04**: Percentage of crashes within 10 miles of a trauma center.

Number of 'outside Golden Hour' crashes within 10 miles of a buffer from all trauma centers= 85

Percentage of 'outside Golden Hour' crashes within 10 miles of a buffer from all trauma centers= $\frac{85}{279} * 100 = 30.46\%$

Number of 'within Golden Hour' crashes within 10 miles of a buffer from all trauma centers= 495

Percentage of 'within Golden Hour' crashes within 10 miles of a buffer from all trauma centers= $\frac{495}{798} * 100 = 62.03\%$

➢ **Case 05**: Percentage of crashes within 5 miles of a trauma center.

Number of 'outside Golden Hour' crashes within 5 miles of a buffer from all trauma centers= 33

Percentage of 'outside Golden Hour' crashes within 5 miles of a buffer from all trauma centers=

$\frac{33}{279} * 100 = 11.82\%$

Number of 'within Golden Hour' crashes within 5 miles of a buffer from all trauma centers= 339

Percentage of 'within Golden Hour' crashes within 5 miles of a buffer from all trauma centers=

$\frac{339}{798} * 100 = 42.48\%$

The above figures (from Figure 7 to Figure 11) showed that a significant percentage of 'outside Golden Hour' crashes occurred within the 30, 20, 15, 10, and 5 miles of a buffer from all trauma centers. Compared to the 'outside Golden Hour' crashes, a higher percentage of 'within Golden Hour' crashes occurred within the 30, 20, 15, 10, and 5 miles of a buffer from all trauma centers. In addition, with the decrease in buffer distance, the percentage of 'outside Golden Hour' crashes within the buffer zone decreased faster than the 'within Golden Hour' crashes. For example, 90.68% of 'outside Golden Hour' crashes occurred within 30 miles buffer distance, while this percentage was 92.68% for 'within Golden Hour' crashes within the same buffer zone. But for a buffer distance of 5 miles, this percentage decreased to 11.82% for 'outside Golden Hour' crashes and 42.48% for 'within Golden Hour' crashes. Table 32 shows the results of test of proportion (z-score and p-value). For buffer distance 5 miles, p-value less than 0.05 indicates that the proportion of crashes between two groups were significantly different. These indicate that a higher percentage of 'within golden hour' crashes occurred at a closer distance (buffer distance) from the trauma centers, and a lower percentage of ‘outside Golden Hour’ crashes occurred within a closer distance. This implies that distance was a significant factor affecting the TTI and TTT, but it was not necessarily the only determining factor. Because analysis showed that 11.82% (case 5) and 30.46% (case 4) of ‘outside Golden Hour’ crashes occurred within the 5 and 10 miles of buffer distances, respectively. Therefore, the distance between the hospitals (local hospitals and trauma centers) and the crash location was not the only determining factor for a crash to be within or outside the Golden Hour. Other factors, such as increased notification time and distance between the crash location and ambulance centers, could be significant factors. Because the location of emergency vehicle centers (such as ambulance location away from hospital) was unknown, the study could not estimate the influence of this distance (distance between an emergency vehicle center and crash location).

Table 32. Test of Proportion of Crashes Occurring within a Buffer Distance

	‘Within Golden Hour’		‘Outside Golden Hour'			
Buffer Distance	Frequency	Percentage	Frequency	Percentage	Z-score	P-value
30 miles	741	0.93	253	0.91	-1.03	1.70
20 miles	643	0.81	191	0.68	-3.52	2.00
15 miles	595	0.75	146	0.52	-5.80	2.00
10 miles	495	0.62	85	0.30	-3.37	2.00
5 miles	339	0.42	33	0.12	2.76	0.01*

*Indicates statistically significant at $\alpha = 0.05$ level of significance.

These figures also showed that many ‘within Golden Hour’ and ‘outside Golden Hour’ crashes occurred in the same or closer location. This indicates that crashes occurring at the same location might not be in the same group (e.g., ‘within Golden Hour’). Practically, crashes occurring at the same location could experience the same ATI and TTI unless other factors were involved. Other factors could be nighttime (2300-0659), adverse weather conditions, higher traffic volume, and road geometry. For example, crashes occurring at nighttime (2300-0659) might have longer NTI, and crashes occurring at peak hours might experience delay in travel time (TTI or ATI) due to higher traffic volume. The effect of roadway geometry was not analyzed in the research.

4.5 Crash and Road Coverage by Trauma Centers and Hospitals

Analysis was conducted on the crashes for which time intervals were available, and these decreased the sample size to 1112 (without outliers, the sample size was 1103), and the total number of fatal and severe crashes between 2018-2021 was 3397. Because time intervals were not available for all the 3397 crashes, it was not possible to investigate what factors affected the time intervals of these crashes.

Section 4.4 discussed the percentage of crashes within a certain distance from the trauma centers. Practically, if a higher percentage of crashes occurred within a lower distance (e.g., 25 miles) from the trauma centers, this would result in a lower TTI, and eventually, a lower TTT because a shorter distance would take less time to travel. Hence, an estimate of all crashes (sample size 3397) occurring at certain distances can provide a visual idea of whether the crashes are more likely to be within the Golden Hour. In addition, similar estimation of road networks could help future planning of trauma center recognition. The following scenarios describe this.

- **Case 01**: Coverage-area by 30-mile buffer from all hospitals

The total length of the road network was 19307.38 miles.

A total number of crashes=3319 (Because among 3397 crashes, 75 crashes had no information on latitude and longitude. Therefore, 75 crashes were not possible to include in the ArcGIS analysis).

The road network that falls within the 30-mile radius of all trauma centers= 19290.43 miles.

Percentage of road network coverage= $\frac{19290.433}{19307.381} * 100\% = 99.91\%$

Crashes that fall within a 30 miles radius of all trauma centers= 3309

Percentage of crash coverage= $\frac{3309}{3319} * 100\% = 99.69\%$

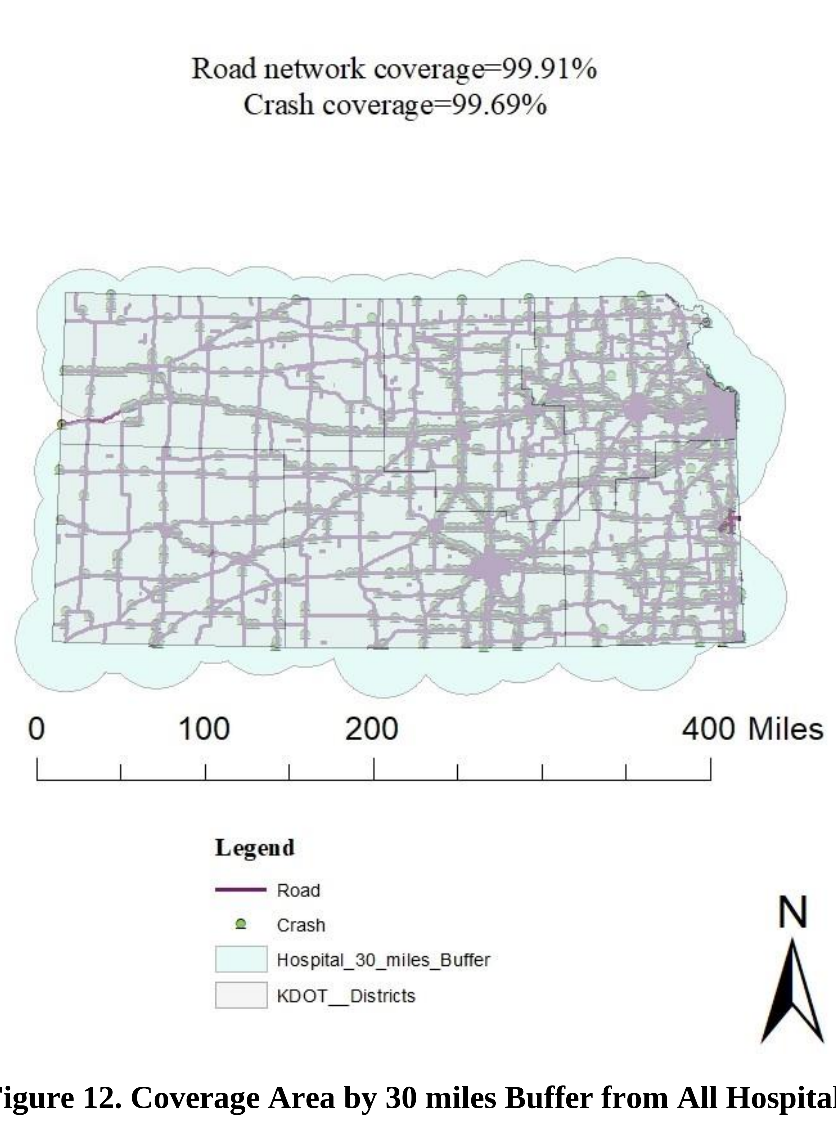

Figure 12. Coverage Area by 30 miles Buffer from All Hospitals

➢ **Case 02**: Coverage-area by 30-mile buffer from all trauma centers

The road network that falls within the 30 miles of a buffer from all trauma centers= 17310.31 miles

Percentage of road network coverage= $\frac{17310.311}{19307.381} * 100\% = 89.65\%$

Crashes that fall within the 30 miles of a buffer from all trauma centers= 3176

Percentage of crash coverage= $\frac{3176}{3319} * 100\% = 95.69\%$

From section 4.4, the number of 'outside Golden Hour' and 'within Golden Hour' crashes within 30 miles of a buffer from all trauma centers were 253 and 741, respectively.

Therefore, the percentage of crashes within the 30 miles of a buffer from all trauma enters=

$\frac{253+741}{\text{total number of crashes}} = \frac{253+741}{1077} = 92.29\%$

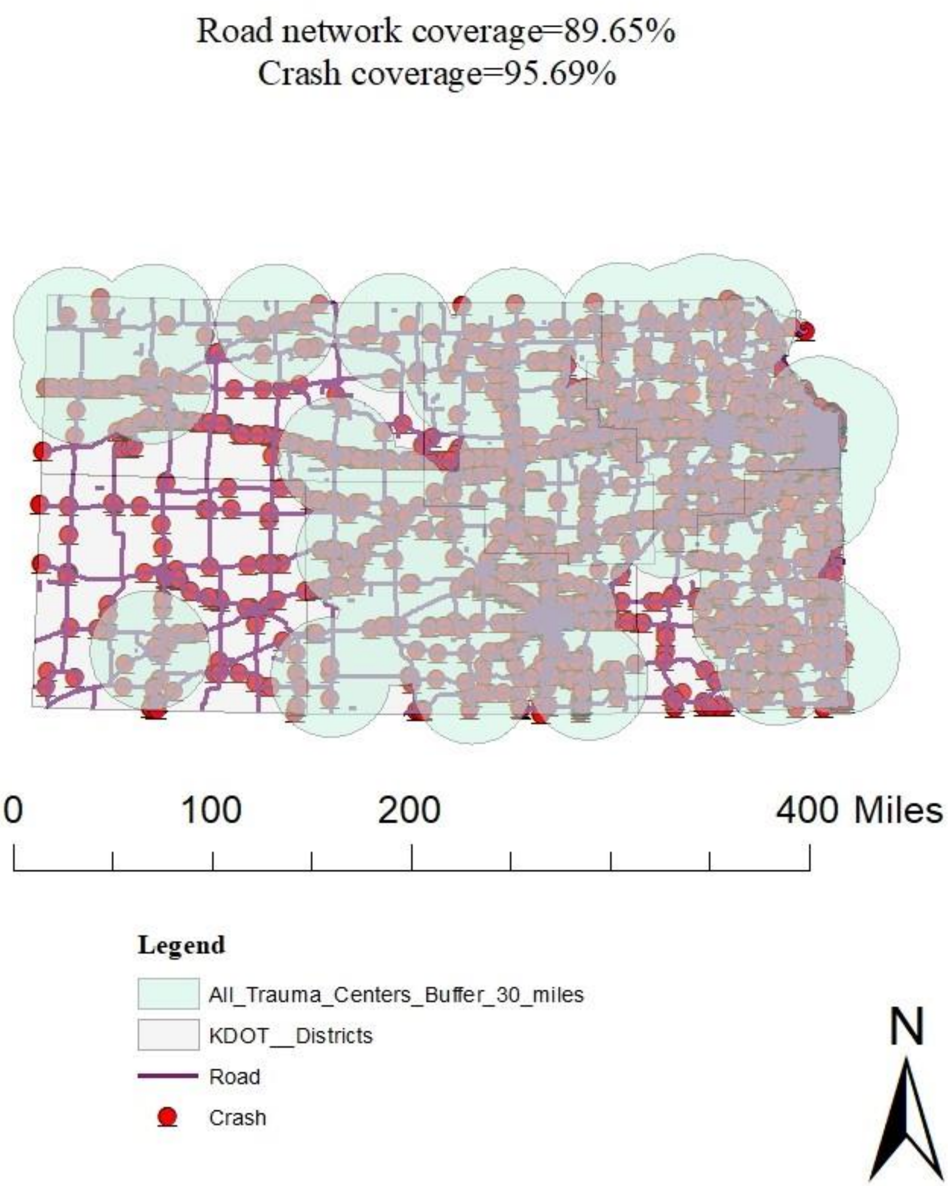

Figure 13. Coverage Area by 30 miles Buffer from All Trauma Centers

- **Case 03**: Coverage area by 25 miles buffer from all trauma centers

The road network that falls within the 25 miles of a buffer from all trauma centers= 16304.67 miles

Percentage of road network coverage= $\frac{16304.673}{19307.381} * 100\% = 84.44\%$

Crashes that fall within the 25 miles of a buffer from all trauma centers= 3058

Percentage of crash coverage= $\frac{3294}{3319} * 100\% = 92.13\%$

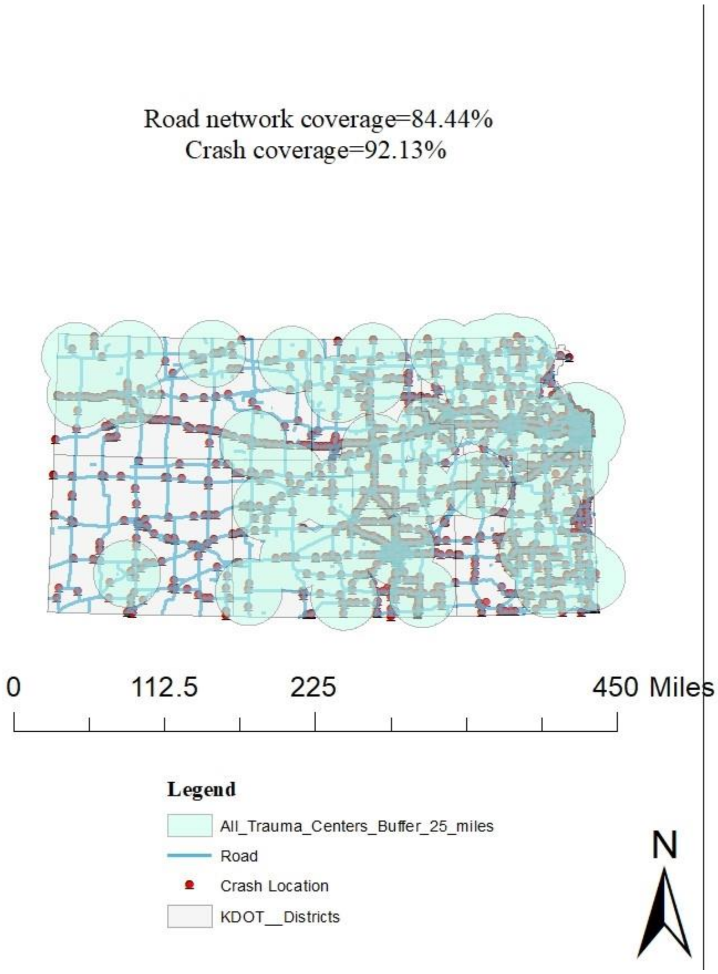

Figure 14. Coverage Area by 25 miles Buffer from All Trauma Centers

Section 4.2.8 discussed that patients were often taken to the local hospital instead of a state-designated trauma center, which indicates that local hospitals were helpful in supporting those patients involved in fatal and severe crashes. Therefore, Figure 12 estimated the crash and road network coverage by 30 miles buffer all hospitals, including trauma centers (sample size=124).

According to Figure 12, 99.91% of the total road network in Kansas and 99.69% of total crashes were within the 30 miles buffer from all local hospitals.

Figure 13 shows that 89.65% of road networks fall within 30 miles of a trauma center. In addition, among 3319 crashes, 95.69% of crashes occurred within 30 miles of all trauma centers (Figure 13). Estimation (section 4.5, case 2) also shows that among 1077 crashes, 92.29% of crashes occurred within the 30 miles buffer from all trauma centers.

Figure 13 and Figure 14 show that most of the road networks not within the buffer zone are located in District 6 and District 1 (For the district map, see Figure 4). Many crashes in District 6 are located outside the buffer zone. Therefore, District 6 could be a potential location to increase the number of hospitals or trauma centers. Section 4.2.8 and Appendix C also support that District 6 would be the best location for the new trauma center development. However, because District 6 had the lowest TTT (Table 21), District 1 could also be another location for a new trauma center.

Although Section 4.5 does not provide defining conclusions about the factors affecting the time intervals, this section is worthy of discussion. Findings from Section 4.5, combined with previous sections, can be used in selecting a location of new trauma centers (and/or upgrade existing hospitals) from the perspective of traffic crashes. More figures showing crashes and road networks within a buffer zone are shown in Appendix D, which can help identify possible new locations for trauma centers.

In addition, Section 4.5 paves the way for future research to investigate the crashes occurring in different districts. Although most of the road networks not within the 30- or 25-mile buffer from all trauma centers occurred in District 6, District 6 had the lowest TTT compared to other districts. This scope of future research was also discussed in Section 4.2.8.

4.6 Results of Binary Logistic Regression

This research applied logistic regression to see what factors influence a crash to be within the 'Golden Hour' or outside the Golden Hour. The Golden Hour indicator was the dependent variable, whereas 'outside Golden Hour' crashes were coded as 1 and 'within Golden Hour' crashes were coded as 0. The dependent variables were weather conditions, on-road speed limit, time of the crash, day of the week, KDOT districts, and crash severity. Lighting condition was not selected because lighting conditions are represented by the time of the day, and the two factors are correlated.

The estimation of the logistic regression in SPSS showed that Nagelkerke R-square and Cox & Snell R-square were too small (<0.05) to consider the model as a good-fitted model. Therefore, the results from the logistic regression model are not worth discussing here, but can be found in Appendix E.

4.7 Summary

The findings of the analysis are discussed in Section 4.2 through 4.5 can be summarized as follows:

- Adverse weather conditions (snow and strong winds) increased the TTT.
- NTI and TTT did not vary between weekends and weekdays.
- TTT exceeded the Golden Hour during dark lighting conditions with no streetlights. TTT was not higher than the Golden Hour in other factors analyzed in this research.

- The yearly average of the TTT remained the same during the study period (2018-2021).
- Both for the injury and fatal crashes, the average TTT was lower than the Golden Hour by approximately seven to nine minutes.
- Crashes occurring on roads with a speed limit of more than 45 mph experienced nearly seven to nine minutes higher TTT than crashes occurring on roads with a speed limit lower than 45 mph.
- Among the different times of the crash, crashes occurring between 2300 to 0659 had the highest NTI and TTT. The average NTI was nearly three minutes higher than the other times of the day.
- Among the six districts, NTI and TTT were the lowest in District 6, despite one trauma center in District 6. Further analysis showed that among 50 crashes in District 6, 49 were taken to the local hospitals (not a trauma center). Appendix C discusses that developing a new trauma center may result in the highest decrease in TTI in District 6 and District 2.
- Outside Golden Hour' crashes had two times more NTI and TTT than the NTI and TTT of 'within Golden Hour' crashes. Among many factors, the time of the day of crash occurrence might play the most crucial role in determining a crash to be within or outside the Golden Hour.
- The distance between the location of a crash and the trauma center was not necessarily the most critical factor. Although TTI increases with the increase of distance, the analysis showed that a significant percentage of 'outside Golden Hour' crashes occurred within 10 miles of trauma centers. Despite occurring at the same location, some crashes had TTT lower than the Golden Hour while others had TTT higher than the Golden Hour. This indicates that distance was not the most critical factor.

- Although most road network and crashes in District 6 were not within 30 or 20 miles of the trauma centers and hospitals, District 6 had the lowest TTT. Future research should investigate this and compare the crashes from other districts with District 6.
- Selecting a new trauma center or hospital location should estimate the percentage of the road network (and traffic volume) within a certain threshold (e.g., 15 miles) from the trauma center or local hospital. Analysis showed that District 2 or District 1 would be the good potential location to develop a new trauma center.

Chapter 5: Conclusions and Recommendations

This chapter discusses the key findings and possible implications of these findings. In addition, based on the findings, recommendations for future research are discussed.

5.1 Key Findings and Recommendations

Previous studies in the U.S. (Hu et al., 2018; Hu et al., 2020; Plevin et al., 2017) were primarily conducted based on fatal crashes to evaluate the effect of distance, time intervals, and other factors on prehospital mortality and emergency response times. However, this research investigated the impact of different factors on the time intervals (such as NTI, and TTT). This study also considered injury crashes. Therefore, this study fills the gap by analyzing the factors that affect the response time intervals. An understanding of the factors that affect the time intervals would help take action to improve the response time of emergency centers and ambulances.

In total, this research analyzed eight factors. Among these, the time of the crash occurrence and lighting conditions were the most critical factors affecting the NTI and TTT. For example, crashes occurring in the dark with no streetlights and at 2300-0659 (11 p.m. – 6:59 AM) experienced the longest NTI.

An increased NTI will increase the TTT and the risk of prehospital mortality (Plevin et al., 2017). Therefore, steps should be taken to reduce the NTI. Automatic crash notification features of vehicles that can send an automatic notification to EMS providers can help reduce NTI. After analyzing fatal crash data, a US-based study (Plevin et al., 2017) identified that vehicles equipped with advanced automatic collision notification (AACN) would be beneficial in scenarios with higher NTI.

Crashes on roads with low-speed limits experienced the lowest TTT. However, this research needed to be more certain about the reasons for this lowest TTT. This could be because crashes occurred in urban areas, and roads with low-speed limits are more likely located in the urban areas. Future research should investigate if the crashes occurring on low-speed roads occurred in urban areas and what was the distance between the hospital and the crash location.

Among the different weather conditions, crashes occurring during snow and strong winds had the longest TTT compared to the no adverse weather conditions. Other factors, such as the day of the week and injury severity, were not found to affect the time intervals.

Distance from the crash location to the trauma and EMS centers can be considered the most critical factor. Because the longer the distances are, the longer the TTT is. However, this research found that distance was not necessarily the determining factor for TTT longer than the Golden Hour. Analysis showed that many ‘outside Golden Hour’ crashes occurred within the 5 miles and 10 miles distance from the trauma centers. In addition, it was discussed that many ‘within Golden Hour’ and ‘outside Golden Hour’ crashes occurred nearly in the exact location (road segments). This indicates that distance was not the only factor. Crashes within 5 or 10 miles could experience TTT longer than the Golden Hour when NTI was more extended and/or a travel delay. Travel delays could be because of traffic congestion, adverse weather conditions, or other factors not usually discussed in the literature.

During estimating time intervals from the traffic crash data, this research investigated 39 crash reports. After reviewing the crash reports, the time of the EMS arrival at the scene and EMS arrival at the hospital were also found to have incorrect information. It was also found that sometimes the latitude and longitude of the crash location needed to be correctly reported. An accurate reporting of crash data is required for research.

The crash database records the hospital and trauma center names where the patients are taken. Crash data should also record that hospital's location (latitude and longitude) so that these hospitals can be used for spatial analysis. This would help to compare where the patients were taken and where the patients could be taken based on the nearest distance.

This research has two limitations. To estimate the distance to the closest facility from the location of the crash, it was assumed that the designation and total number of trauma centers and hospitals were unchanged during the study period. However, during the phone interviews with hospital staff for collecting local hospital data, it was found that one hospital lost its trauma designation. In addition, to be designated as a trauma center and to maintain the trauma designation, hospitals must apply every two years showing the facilities such availability of intensive care unit (ICU). Therefore, during the study period, it was not impossible that there was a change in the number of trauma centers. During the estimation of the network dataset and closest facility tool, it was also assumed that emergency vehicles could travel in any direction and no restrictions (e.g., left turn, right turn) were given. Practically, emergency vehicles cannot travel in any direction. For example, if a one-way road allows travel only eastbound, then traveling westbound on that road can be the reason for fatal traffic crashes.

5.2 Future Research

Analysis of additional factors and further research is recommended to best utilize these research findings. For example, this study has found that nighttime was the crucial time for an increased NTI and a crash resulting in TTT more than the A higher NTI indicates that there might not have been enough traffic who could notice the crash and notify the EMS. To be certain about this assumption, future research should investigate the traffic volume on the road where the crash occurred at the time of the crash. The KARS database does not record the traffic volume, and therefore, traffic volume needs to be collected from other sources and merged with traffic crash data.

A study in California (Brent and Beland, 2020) analyzed emergency response data after merging emergency response data with traffic volume data. The emergency response data for California were collected from the National Fire Incident Reporting System, which contained 2.7 million incidents. The traffic volume data were collected from the California Department of Transportation, which gathers traffic volume in 5-minute intervals. From 25,000 stations, nearly 21 billion observations were obtained. These 21 billion observations of traffic volume were merged with 2.7 million incidents by zip code. Hence, a combination of traffic volume and crash data can be combined with spatial location information. Spatial analysis toll such as ArcGIS and Python (e.g., GeoPandas) can help in this process. This type of combined database could help analyze impact of traffic volume data at the time of the crash and after the crash.

This research recommends analyzing the location of the crash in terms of urban or rural areas and investigating the time intervals based on this factor. This research found that crashes occurring at low-speed roads (less than or equal to 45 mph) had lower TTT. This could be because of the presence of low-speed roads in urban areas. In urban areas, NTI could be lower, and hospitals could be located in nearby areas resulting in shorter ATI and TTI. Analysis of the time intervals in terms of urban or rural areas will show if there was a difference. Besides, analyzing urban or rural areas is also important because a previous study (Plevin et al., 2017) reported that the percentage of fatal crashes was higher in rural areas than in urban areas when NTI was more than nine minutes.

Nighttime was found to be crucial because of increased NTI during the nighttime. Vehicles equipped with AACN could help solve this. However, not all cars will be equipped with AACN because everyone might not have a vehicle with the latest model. future research should investigate the influence of traffic volume on the NTI and identify a threshold of traffic volume below which NTI would be higher. Then the research should identify the specific time when some routes have traffic volume below the threshold.

Investigating the effect of factors such as the roadway geometry, presence of median barriers, and TC-HW distances could also reveal valuable insights that can be used in reducing the time to rescue a patient and travel time. A survey of EMS providers (Griffin and McGwin, 2013) reported that continuous median barriers increase the EMS response time. Therefore, analysis of the effect of geometric features will help to design the roadway geometry better to rescue a patient.

In addition, a questionnaire survey of the drivers of the emergency vehicles and EMS providers could help analyze the effect of traffic volume, roadway geometry, and other factors for which data are not available. The application of dynamically reallocating ambulances in Kansas and other states can also be researched, which could be a low-cost solution. Dynamically reallocating ambulances means what should be the best location of an ambulance at a specific time of the day and what should be the location of the same ambulance at other times of the day. A study in Singapore (Lam, Zhang, et al., 2015) tested two techniques of dynamically reallocating ambulances and showed the percentage of emergency calls coverage by the ambulance. These two techniques (Mathematical Programming-based models and GIS-based strategy) can be used to reallocate the ambulances and percentages of emergency call coverage by the two techniques. Comparing the results from both techniques, ambulances can be dynamically reallocated, considering other factors such as reallocation cost.

Chapter 6: References

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Appendix A

For Crash Key 20180024615, EMS was notified at 12:37 AM, but EMS arrived at 2326 (11:26 p.m.). The crash was a severe crash, and ArcGIS's closest facility analysis (see methodology) showed that the crash was located 14.71 miles away from the closest trauma center. It was more unlikely that EMS would take this long time to arrive at the scene for a severe crash. In addition, Police arrived at the crash scene at 2319 (11:19 p.m.). Therefore, it could be more reliable, the crash time is unreliable for the analysis.

For Crash Key 20190101304, the crash occurred at 0212; EMS was notified at 2113, while police were notified at 0212, and Police arrived at the scene at 0217. Therefore, Police could notify the EMS once they arrive at the scene because the crash was a severe crash. But EMS was notified at 2113 (9:13 PM). This EMS notification time is not reliable. Due to the same reason, EMS notification for crash key 20200124478 was unreliable.

As mentioned earlier, no discrepancy was found (see Chapter 4, section Estimating Time Intervals) between crash reports and the KARS database for time recording. Probably, the error was made during the crash report. For example, for crash key 20200124478, the crash occurred at 0014, and the Police were notified at 0014. But the time of EMS notification was 1219. What took a long time to notify EMS while the Police were notified instantly about a severe crash (incapacitating or non-incapacitating crash)? If the Police were notified, the EMS could be notified instantly because of a severe crash. Probably, the person who recorded the time made the mistakes. However, as the researcher was not certain where the error was, these three crashes with unreliable time records were excluded from the preliminary analysis.

Table 33. Three crashes with an unreliable record of the time interval

Crash Key	Time of Crash Occurrence	EMS Notification Time	EMS Arrival at Scene	EMS at Hospital	Crash Severity	Police Notification Time	Police Arrived	Distance to Closest Facility (miles)
20180024615	2305	0037	2326	0003	Severe Injury	2307	2319	14.711
20190101304	0212	2113	2117	0306	Severe Injury	0212	0217	5.918
20200124478	0014	1219	1228	1300	Severe Injury	0014	0031	32.039

Appendix B

Table 34. Average of time intervals during 24 Categories of the Time of the Crash

Time of Crash (One Hour Interval)	Sample Size	Notification Time Interval (minutes)	Arrival Time Interval (minutes)	Transport Time Interval (minutes)	Total Transport Time (minutes)
0000-0001	35	9.229	15.543	34.971	59.743
0100-0159	27	15.444	9.593	33.667	58.704
0200-0259	30	13.733	11.600	35.133	60.467
0300-0359	25	7.960	11.400	35.400	54.760
0400-0459	32	8.969	11.688	35.156	55.813
0500-0559	42	11.643	12.190	30.500	54.333
0600-0659	61	8.000	13.344	32.459	53.803
0700-0759	66	6.030	10.848	34.136	51.015
0800-0859	45	6.911	11.311	29.556	47.778
0900-0959	38	4.289	12.132	33.132	49.553
1000-1059	46	6.783	9.109	30.522	46.413
1100-1159	57	6.439	10.596	34.070	51.105
1200-1259	59	6.305	10.492	31.915	48.712
1300-1359	53	7.491	10.642	36.887	55.019
1400-1459	54	5.648	8.815	33.222	47.685
1500-1559	74	5.676	9.378	29.649	44.703
1600-1659	61	5.098	10.344	31.492	46.934
1700-1759	64	5.609	10.625	34.609	50.844
1800-1859	51	7.843	10.922	34.608	53.373
1900-1959	41	5.268	10.512	31.024	46.805
2000-2059	36	10.444	9.000	31.722	51.167
2100-2159	40	6.650	11.950	39.100	57.700
2200-2259	39	5.308	11.154	32.256	48.718
2300-2359	27	7.000	9.704	40.444	57.148

Appendix C

Table 35 shows the average distances and time for crashes occurring at the six KDOT districts from the crash location to the nearest trauma center and hospitals. The table only shows the transport distance and time required to travel that distance which is TTI. Therefore, the time estimated in the table does not include the NTI and ATI. As a result, the result in this table does not match the TTT shown in Table 20 in section 4.2.8.

Table 35. Estimated Distances and Time from the Location of the Crash to the Closest Facility

KDOT Districts	Sample Size (1074) *	Time and distance from the crash location to the closest facility (Total 53 Trauma Centers)		Time and distance from crash locations to the closest facility (Total 124 Hospitals)	
		Distance (miles)	Time (minutes)	Distances (miles)	Time (minutes)
DISTRICT 1	371	10.59	12.56	7.71	9.58
DISTRICT 2	146	22.53	22.45	9.58	10.42
DISTRICT 3	82	24.98	22.70	11.47	10.89
DISTRICT 4	153	22.57	22.53	16.53	16.88
DISTRICT 5	275	13.01	14.83	7.66	9.02
DISTRICT 6	47	**52.00**	**50.37**	**10.99**	**11.35**

*The total number of crashes was 1074 because 29 crashes did not find the closest facility. Because 26 crashes had no information on latitude and longitude, and another three crashes were not located within the KDOT boundary when imported into the crash data. Those three crashes had latitudes and longitudes far away from the KDOT boundary.

Table 35 shows that transport time (TTI) for District 6 decreased significantly if patients were taken to hospitals instead of trauma centers. This indicates that increasing the number of trauma centers in District 6 will reduce the TTT and improve patients' access to trauma centers within the Golden Hour. District 2 will be another potential area to increase the number of trauma centers.

Appendix D

- **Case 04**: Coverage area of 30 miles radius from Level I and Level II trauma centers

The total length of the road network= 19307.38 miles.

The total number of crashes= 3319.

The road network that falls within the 30 miles buffer from all trauma centers= 7596.75 miles

Percentage of road network coverage= $\frac{7596.75}{19307.38} * 100\% = 39.35\%$

Crashes that fall within the 30 miles buffer from all trauma centers= 2169

Percentage of crash coverage= $\frac{2169}{3319} * 100\% = 65.35\%$

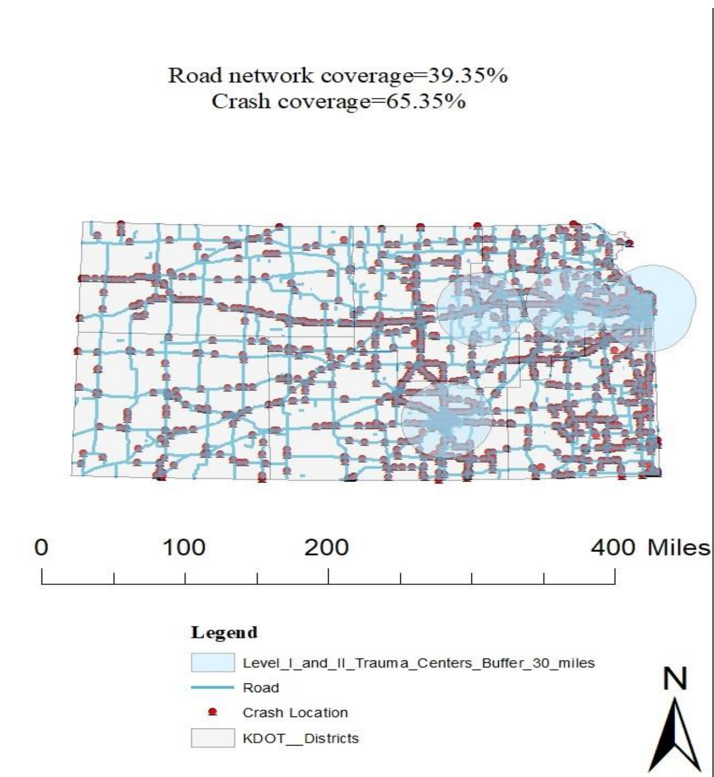

Figure 15. Coverage Area by 30 miles Buffer from Level I and II Trauma Centers

➢ **Case 05**: Coverage area of 50 miles radius from Level I and Level II trauma centers

The road network that falls within the 50 miles buffer from all trauma centers= 10507.01 miles.

Percentage of road network coverage= $\frac{10507.01}{19307.38} * 100\% = 54.41\%$

Crashes that fall within the 50 miles buffer from all trauma centers= 2601

Percentage of crash coverage= $\frac{3294}{3319} * 100\% = 78.36\%$

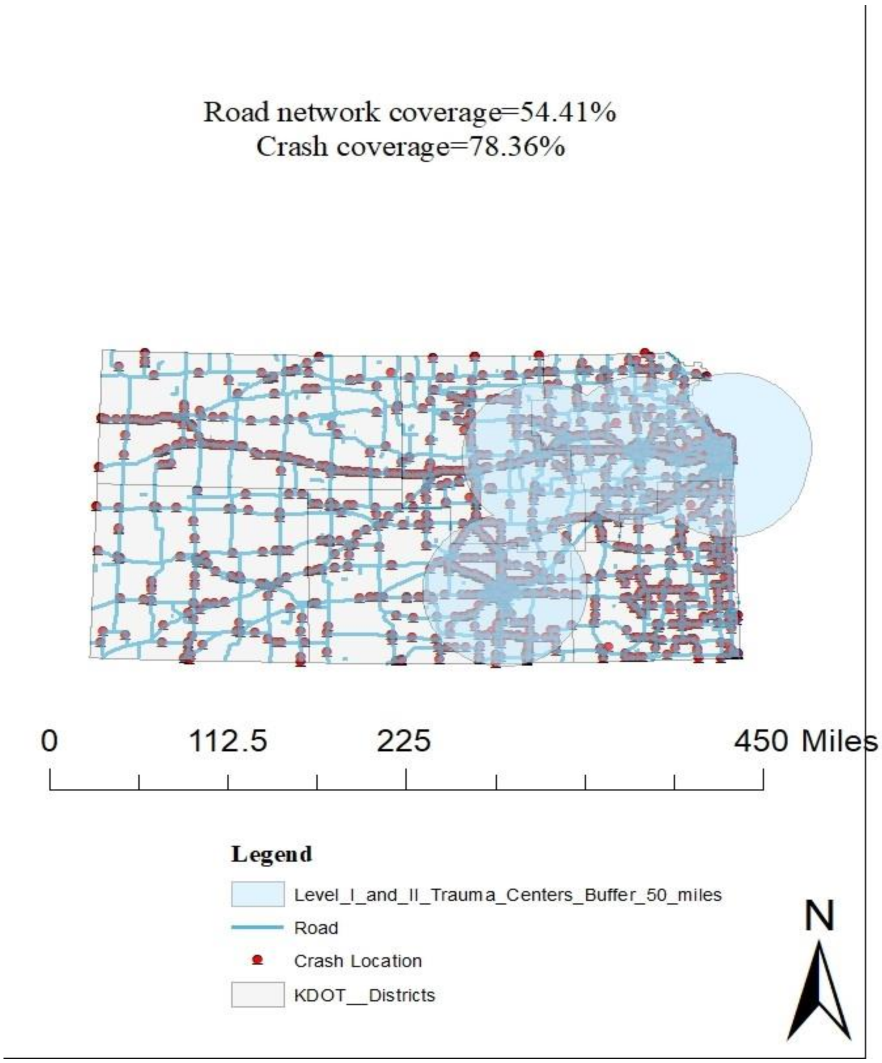

Figure 16. Coverage Area by 50 miles Buffer from Level I and II Trauma Centers

➢ **Case 06**: Coverage area of 60 miles radius from Level I and Level II trauma centers

The road network within the 60 miles buffer from all trauma centers= 11754.09 miles.

Percentage of road network coverage= $\frac{11754.09}{19307.38} * 100\% = 60.87\%$

Crashes that fall within the 60 miles buffer from all trauma centers= 2719

Percentage of crash coverage= $\frac{2719}{3319} * 100\% = 81.92\%$

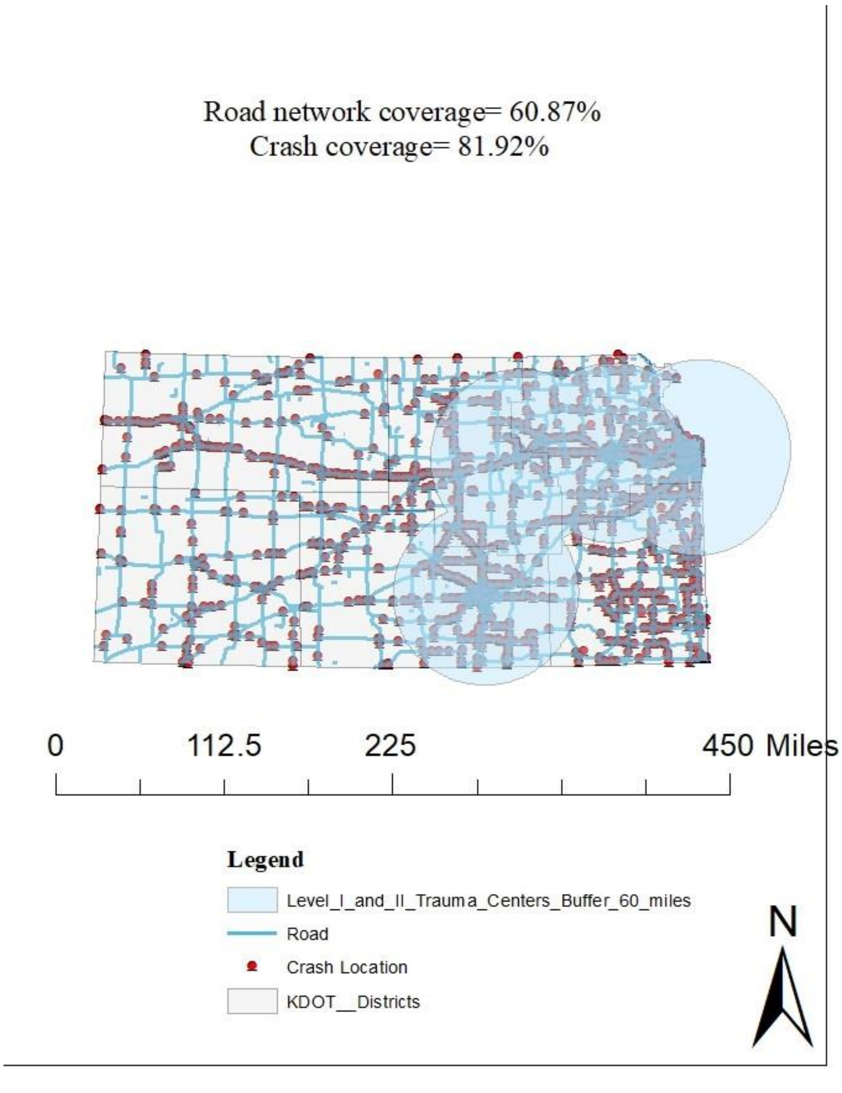

Figure 17. Coverage Area by 60 miles Buffer from Level I and II Trauma Centers

Appendix E

Table 36. Results of Binary Logistic Regression

Sample Size= 1103				Cos & Snell R Square= 0.022					
Dependent Variable: Yes (coded as 1) =820				Nagelkerke R Square= 0.032					
Dependent Variable: No (coded as 0) =283				The cutoff value for classification= 0.5					
Model Chi-square=24.243 & P-Value=0.001									
		Constant	Standard Errors	Wald Statistics	Degree of freedom	P-value	Odds Ratio	95% C.I. for odds ratio	
								Lower Bound	Upper Bound
On-road speed limit	Low Speed			9.318	2	0.009			
	High Speed	0.784	0.343	5.213	1	0.022	2.19	1.117	4.293
	Higher Speed	0.958	0.321	8.885	1	0.003	2.606	1.388	4.892
Weather Condition	Strong Wind			6.134	3	0.105			
	No adverse weather	-0.341	0.552	0.383	1	0.536	0.711	0.241	2.096
	Rain	-0.743	0.58	1.64	1	0.2	0.476	0.153	1.483
	Snow	-0.01	0.603	0	1	0.986	0.99	0.304	3.224
Time of the crash	2300-0659			6.944	2	0.031			
	0700-1759	-0.424	0.163	6.77	1	0.009	0.654	0.476	0.901
	1800-2259	-0.198	0.206	0.926	1	0.336	0.82	0.548	1.228
Constant		-1.281	0.644	3.96	1	0.047	0.278		
Variable(s) entered on step 1: On-road speed limit, Weather condition, Time of the Crash, Day of the week, Crash severity, KDOT Districts.									