Spatial Assessment of Emergency Medical Service Access for Elderly Drivers in Rural Areas

A Technical Report Submitted to the Rural Safe Efficient Advanced Transportation (R-SEAT) Center and United States Department of Transportation

FINAL REPORT

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METRIC CONVERSION CHART

When You Know	Multiply by	To Find
Length		
inches (in)	25.4	millimeters (mm)
feet (ft)	0.305	meters (m)
yards (yd)	0.914	meters (m)
miles (mi)	1.61	kilometers (km)
Volume		
fluid ounces (fl oz)	29.57	milliliters (mL)
gallons (gal)	3.785	liters (L)
cubic feet (ft^3)	0.028	meters cubed (m^3)
cubic yards (yd^3)	0.765	meters cubed (m^3)
Area		
square inches (in^2)	645.1	millimeters squared (mm^2)
square feet (ft^2)	0.093	meters squared (m^2)
square yards (yd^2)	0.836	meters squared (m^2)
acres	0.405	hectares (ha)
square miles (mi^2)	2.59	kilometers squared (km^2)

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16. Abstract

Elderly drivers in rural areas face heightened risks in roadway crashes due to age-related impairments, prolonged emergency medical service (EMS) response times, and limited healthcare. This study examines the differences in EMS coverage and their impact on injury severity among elderly rural drivers using the Enhanced Two-Stage Floating Catchment Area (E2FCA) method and Bayesian Ordinal Logistic Regression. By integrating crash data from the Fatality Analysis Reporting System (FARS) with socio-economic and geographic information, the research identifies key predictors of EMS availability and injury severity. Findings reveal significant spatial variations in EMS access, with rural regions farther from urban centers exhibiting reduced service availability and longer response times. Additionally, adverse roadway conditions, seating position, and EMS transport type emerged as critical factors influencing injury severity. While alcohol use and speed limits showed modest effects, EMS response time remained a dominant predictor of severe injuries. The study underscores the need for targeted policy interventions, including improved EMS infrastructure, strategic resource allocation, and roadway safety enhancements to mitigate injury severity and fatality risks for elderly rural drivers. These findings contribute to transportation safety research by providing data-driven insights for enhancing emergency response efficiency and post-crash care outcomes in rural communities.

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Elderly Drivers, Rural Areas, Injury Severity, Spatial Access.	No restrictions

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EXECUTIVE SUMMARY

Roadway crashes remain a significant public safety concern, with elderly drivers particularly vulnerable due to age-related impairments and increased fragility. This project investigates the coverage of emergency medical services (EMS) in rural areas, where longer response times and limited healthcare infrastructure contribute to adverse post-crash outcomes. Using the Enhanced Two-Stage Floating Catchment Area (E2FCA) method and data from the Fatality Analysis Reporting System (FARS), this research provides a comprehensive analysis of EMS availability and its impact on injury severity among elderly rural drivers.

The findings reveal substantial differences in EMS access across rural Ohio, with central rural regions experiencing the lowest service availability levels. At the same time, areas near urban centers benefit from higher service availability. A key contribution of this study is the identification of critical factors influencing EMS response efficiency and injury severity in rural crashes. Longer EMS response times, adverse roadway conditions such as icy surfaces and curved roads, and individual characteristics like seating position significantly increase the likelihood of severe injuries. While alcohol involvement and speed limits had a relatively modest impact on injury severity, EMS transport type emerged as a strong predictor of worse crash outcomes. Additionally, socio-economic attributes such as network density and insurance coverage were positively associated with EMS coverage, while higher education levels were unexpectedly linked to lower access.

This research highlights the urgent need for targeted policy interventions and infrastructure improvements to enhance EMS response times and improve post-crash care for elderly drivers in rural communities. Addressing these difficulties requires a multifaceted approach, including better roadway maintenance, improved EMS station placement, and strategies to reduce response times in regions with limited EMS coverage. The findings also underscore the importance of future research into broader social determinants, driving habits, and vehicle safety features that may further influence injury severity among elderly rural drivers. By providing data-driven insights, this study aims to inform transportation and public health policies that enhance emergency response efficiency, improve roadway safety, and ultimately reduce fatality risks for vulnerable populations in rural settings.

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1. INTRODUCTION

This section offers background information and context for the current research project on assessing the availability of Emergency Medical Services (EMS) for elderly populations in rural areas. This section is organized as follows: (1) an overview of elderly drivers and rural roadway crashes; (2) service provision challenges in rural areas; (3) challenges of providing EMS in rural settings; (4) objectives of this research project; (6) relevance of this project to the Rural Safe Efficient Advanced Transportation (R-SEAT) Center themes and USDOT Strategic Plan and structure of this technical report.

1.1. Elderly Groups and Rural Roadway Crashes

The "elderly" is a term that has been conventionally used to define a chronological age of 65 years and above (Orimo et al., 2006). In this context, we focused on elderly drivers, as they are a particularly vulnerable group due to several factors that will be mentioned later in this section. Roadway crashes have long been a major safety concern, with approximately 370,000 fatalities reported between 2011 and 2020 according to the National Roadway Safety Strategy (NRSS), including 38,680 deaths in 2020 alone (USDOT, 2022). Furthermore, the USDOT's National Highway Traffic Safety Administration (NHTSA) reports that there is a 6.8% increase in fatal crashes and a fatality rate of 1.34 per 100 million vehicle miles traveled, the highest since 2007 (NHTSA, 2022). Figure 1 shows a yearly breakdown of traffic crashes involving drivers 65 years and older. Older individuals have a disproportionately high rate of motor vehicle fatalities compared to other age groups (Lyman et al., 2000; Skyving et al., 2009; Zwerling et al., 2005). Crash patterns of fatal crashes involving older drivers and found that fragility of older drivers, fast-moving traffic, maneuvering difficulties at intersections, and crash type (single, head-on, etc.) are the key factors leading to over-representation of traffic fatalities of the older drivers compared to younger drivers (Skyving et al., 2009). Furthermore, older drivers are more likely to be involved in fatal crashes because of their reduced ability to select an adequate gap (Oxley et al., 2006). Substance use (alcohol and/or drug usage) has also been found to increase crash injury severity to older drivers in rural areas (Adeyemi, Bukur, et al., 2023).

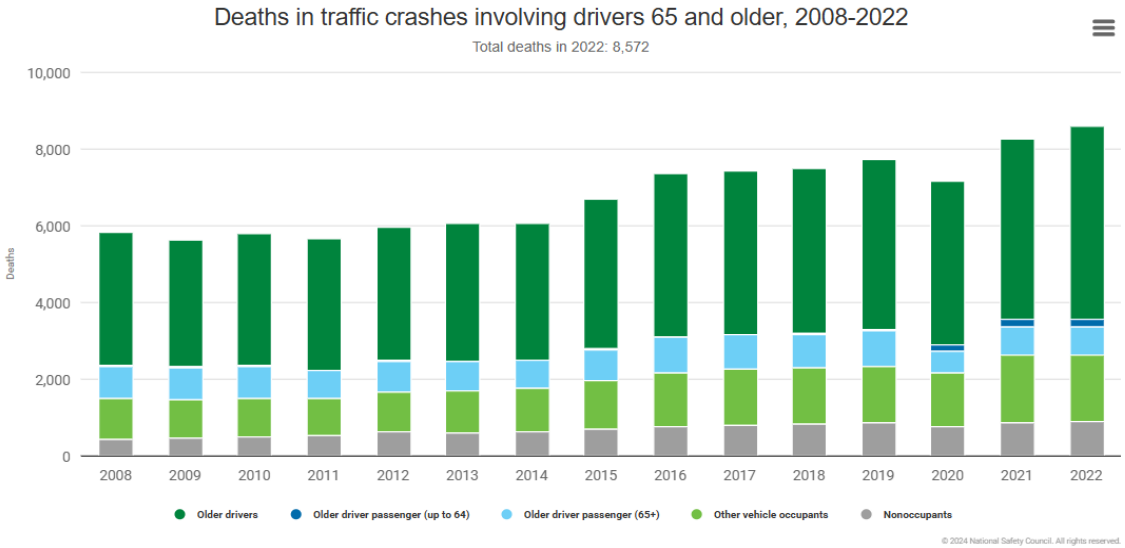

Figure 1: Annual Distribution of traffic crash fatalities involving drivers 65 years and older (Source: NSC)

1.2. Service Provision Challenges in Rural Areas

Service availability for elderly groups in relation to EMS (soon after the crash occurs) is of high importance to save the lives of those disadvantaged populations, especially in rural settings. Access to services is a crucial metric for evaluating EMS response performance and is defined variably across fields like transportation, urban planning, and geography. (Penchansky & Thomas, 1981) outlined five dimensions of health care access: affordability, acceptability, availability, accommodation, and geographic access. Among these, geographic access, which refers to the proximity and availability of health care services, is particularly emphasized in health and transport geography studies.

Researchers have also explored the availability of healthcare facilities to elderly populations. Findings show that rural elderly populations have poor access to healthcare services (Hassler & Ceccato, 2021a). Almost 15% of the US rural population is the elderly group (age > 65 years), who face geographic difficulties in terms of access to healthcare facilities (Rosenthal & Fox, 2000). Moreover, the rural elderly may face even greater challenges in accessing quality health care services (Hutchison & Hawes, 2010). A study by (Love & Lindquist, 1995) points out that 80% of rural elderly were more than 11.3 miles (18.2 km) from the medical facility compared to their counterparts in urban areas, who were within 6.7 miles (10.8 km). Moreover, there are rural-urban/social-spatial difficulties in terms of service access for the elderly to health care facilities (Hassler & Ceccato, 2021a; Lopes et al., 2019a).

Access to health services is crucial for social inclusion. This ensures that all individuals, regardless of their location, can access timely and essential medical care, reducing differences in health outcomes and fostering equitable community well-being. Research shows that the potential of Geographic Information Systems (GIS) and service access measures to support effective planning their full capabilities have not yet been leveraged in decision-making (Lopes et al., 2019b). Application of these strategies can improve access for vulnerable groups and reduce social exclusion. The availability of emergency medical services (EMS) is a critical aspect of healthcare, especially for vulnerable populations such as elderly drivers in rural areas. Spatial access significantly influences health-seeking behaviors, with studies highlighting the importance of proximity and availability of services (Shen & Tao, 2022). For instance, (Cui, Boisjoly, et al., 2019) demonstrates how improved spatial service access can lead to higher consultation rates, enhancing the realization of healthcare services. This is particularly crucial in rural areas where geographic barriers and limited healthcare infrastructure pose significant challenges (Arcury et al., 2005).

1.3. Challenges in Providing EMS in Rural Areas

Emergency Medical Services are vital in providing timely medical care after these crashes. Specifically, in rural areas where geographic and infrastructural challenges can hinder immediate medical attention (Gonzalez et al., 2009). These areas often face shortages in healthcare resources, contributing to longer EMS response times compared to urban settings.
Figure 2 shows a sequence of events following a traffic crash from the notification to arrival at the scene and provision of pre-hospital treatment. If more is needed, the victims will be taken to health-care facilities.

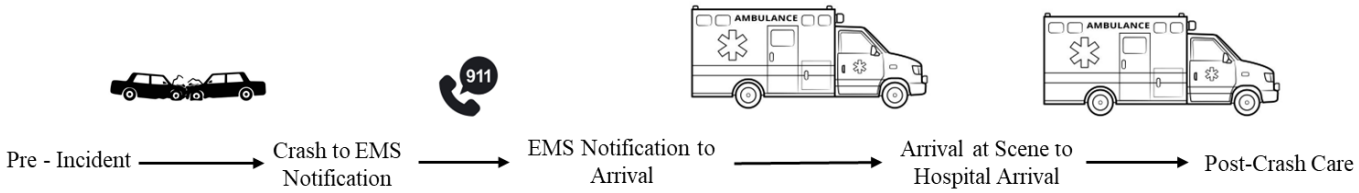

Figure 2: Emergency Response Sequence adopted from (National Academies of Sciences, 2013)

Research from rural areas worldwide offers insights into how local factors like population density, resources, and infrastructure uniquely have an association with EMS service access. A study by (Luo et al., 2022) shows that rural EMS stations improve access but may reduce total population coverage in urban areas, a trade-off that may be less significant in sparsely populated rural regions elsewhere, where service gaps are more severe. Rural areas are characterized by lower survival rates and prolonged response times in low-income countries areas (Alanazy et al., 2019). This highlights the critical impact of resource shortages and suggests that effective solutions in wealthier rural areas may need modification to fit low-resource environments. These studies echo that EMS planning must be tailored to each context's unique demographic, geographic, and resource conditions to avoid inefficiencies and adapt proven strategies effectively.

1.4. Project Objectives

The objectives of this research reflect the critical need to address safety and service access challenges for elderly drivers in rural areas. Rural communities often face significant difficulties in emergency medical service (EMS) response, which can exacerbate injury outcomes for vulnerable populations. By focusing on elderly drivers, this study highlights the intersection of healthcare access and transportation safety. The following section outlines the specific goals of this research and its alignment with broader transportation and public health priorities.

- Evaluate service availability for rural disadvantaged populations, particularly aging residents, to emergency medical services (EMS) and identify critical locations. This will involve estimating EMS service coverage for elderly drivers involved in crash incidents in rural areas.
- Determine socio-economic characteristics that influence the access to EMS of the aging population in rural areas.
- Investigate the influence of EMS response time and other contextual factors on injury severity among elderly drivers involved in rural crashes.

1.5. Project Relevance to R-SEAT Research Thrust and USDOT Strategic Plan

This project aligns with the R-SEAT Center thrust areas and directly contributes to the following themes:

Service Availability: The project addresses access by evaluating differences in Emergency Medical Services (EMS) availability for elderly populations in rural areas. It highlights the challenges faced by vulnerable groups, such as longer response times and limited EMS resources, which can exacerbate injury outcomes. By identifying critical areas with limited EMS service coverage, the study aims to inform strategies to bridge gaps in emergency care for underserved rural communities. The research emphasizes equitable healthcare delivery by focusing on the unique needs of elderly drivers, who are often at greater risk of severe injuries.

Ultimately, the project seeks to enhance the fairness and effectiveness of EMS systems, ensuring timely medical attention for all, regardless of geographic location.

Safety of Vulnerable Road Users: The project contributes to the theme of safety for vulnerable road users by addressing the unique risks faced by elderly drivers in rural areas. Rural regions experience disproportionately higher fatal crash rates, and elderly individuals are particularly vulnerable due to age-related challenges like diminished gap selection abilities and increased fragility. By evaluating EMS service availability and response times, the project directly tackles the critical need for timely post-crash care, a key component of the USDOT's Safe System Approach. Identifying areas with limited EMS coverage will help prioritize interventions to improve safety and reduce severe injury outcomes for aging populations. Ultimately, the findings will guide transportation planners and policymakers in implementing innovative solutions and technologies to enhance the safety and mobility of elderly road users in rural communities.

Resilience: The project contributes to transportation resilience by focusing on the timely delivery of emergency medical services (EMS) to elderly drivers in rural areas, a critical aspect of post-crash care. By identifying gaps in EMS access and response times and response times, it enhances the ability of rural transportation systems to adapt and respond effectively to emergencies. This research strengthens the system's capacity to minimize injury severity and fatalities, ensuring that vulnerable populations receive equitable and efficient care. Ultimately, the findings will support the development of a more robust and responsive transportation network that prioritizes safety for all users. Furthermore, the proposed project is expected to assist with meeting some of the major goals outlined in the USDOT 2022-2026 strategic plan, including the following: (1) improve safety of transportation systems and their users; (2) facilitate improved access to transportation systems and the communities they affect; (3) develop purpose-driven innovative decision support systems that can serve transportation users today and in the years to come; and (4) establish new policies and procedures (mainly focusing on emergency evacuation planning) to satisfy the critical needs of communities.

1.6. Report Structure

The report is structured to guide the reader through steps in achieving the objective of evaluating the assessment of EMS service availability of Elderly Groups to Emergency Medical Services (EMS) in Rural Areas. Specifically, the main sections of the report are organized as follows. Section 1 provides the background information of the research project. The section provides an overview of elderly drivers and rural roadway crashes, explores service access and EMS challenges in rural areas, outlines the research objectives, and highlights the project's alignment with REAT themes, the USDOT Strategic Plan, and the structure of the report. Section 2 reviews the efforts made related to the project. Various methodologies in evaluating service coverage of emergency medical services and health care facilities. Furthermore, forming a realization that there is a significant gap in the current literature is the consideration of roadway crashes as uncertain events impacting EMS access. The role of post-crash care on patient outcomes, socio-demographic factors on how they influence service availability, and the impact of EMS response time on injury severity. Section 3 goes into detail on the data sources and the definition of variables used from those sources. Section 4 is about methodologies used in achieving the mentioned objectives. Sections 6 and 7 are about results, findings, and conclusions, respectively.

2. LITERATURE REVIEW

In this section, the project focuses on a comprehensive review of existing research related to the availability of emergency medical services in rural areas. The study focused on geographic differences in EMS response times, their impact on patient outcomes, and existing methods used to evaluate EMS service access. Additionally, the role of post-crash care in reducing injury severity and mortality rates, challenges elderly individuals face in receiving timely medical attention, and the USDOT's Safe System Approach and its emphasis on post-crash care are discussed. Influence of income levels, healthcare infrastructure, and insurance coverage on EMS access. Moreover, studies have researched the relationship between EMS response times and crash survival rates. This review aids in identifying limitations in existing methodologies, particularly the consideration of roadway crashes as uncertain events impacting EMS service availability for elderly drivers.

2.1. Availability of Emergency Medical Services in Rural Areas

EMS in rural areas face significant challenges, primarily due to longer response times caused by geographic difficulties and limited resources (Newton et al., 2024). Spatial access to health services is crucial for social inclusion. This ensures that all individuals, regardless of location, can access timely and essential medical care, reducing difficulties in health outcomes and fostering equitable community well-being. Research from rural areas worldwide offers insights into how local factors like population density, resources, and infrastructure uniquely have an association with EMS access. A study by (Luo et al., 2022) shows that rural EMS stations improve service coverage but may reduce total population coverage in urban areas, a trade-off that may be less significant in sparsely populated rural regions elsewhere, where service gaps are more severe. Rural areas are characterized by lower survival rates and prolonged response times in low-income countries areas (Alanazy et al., 2019). This highlights the critical impact of resource shortages and suggests that effective solutions in wealthier rural areas may need modification to fit low-resource environments. These studies highlight that EMS planning must be tailored to each context's unique demographic, geographic, and resource conditions to avoid inefficiencies and adapt proven strategies effectively.

The relationship between distance, transportation, and healthcare utilization is well-documented in the literature. (Goodman et al., 1976) findings show that distance to hospitals exerts an important influence on hospitalization rates that is unlikely to be explained by illness rates, a finding echoed by (Stentzel et al., 2018) in their study on outpatient care access. The critical role of transportation in facilitating healthcare access is further emphasized by (Arcury et al., 2005), who examine the association between transportation access and healthcare visits. Additionally, research by (Al-Taiar et al., 2010; Fishman et al., 2018) explores how spatial access impacts preventive healthcare and emergency department utilization, respectively. These studies collectively highlight the importance of addressing both spatial and aspatial factors to improve EMS access in different geographical contexts. Research shows that the potential of Geographic Information Systems (GIS) and service access measures to support effective planning their full capabilities, has not yet been leveraged in decision-making (Lopes et al., 2019b).

Application of these strategies can improve access for vulnerable groups and reduce social exclusion. The availability of emergency medical services (EMS) is a critical aspect of healthcare, especially for vulnerable populations such as elderly drivers in rural areas. Spatial

service access significantly influences health-seeking behaviors, with studies highlighting the importance of proximity and availability of services (Shen & Tao, 2022). For instance, (Cui, Boisjoly, et al., 2019) demonstrates how improving healthcare service availability can lead to higher consultation rates, enhancing the realization of healthcare services. This is particularly crucial in rural areas where geographic barriers and limited healthcare infrastructure pose significant challenges (Arcury et al., 2005). The variability in physician-to-population ratios, as noted by Luo, (2004), underscores the need for fine-grained spatial data to accurately assess and address service access issues.

Several methodological advancements have been proposed to measure and improve healthcare service availability. (McGrail & Humphreys, 2009) critically reviews the two-step floating catchment area (2SFCA) method, identifying its strengths and limitations. This review supports the development of more sophisticated methods, such as the Enhanced Two-Stage Floating Catchment Area (E2FCA) method, which aims to improve the accuracy and reliability of service access assessments. With its many applications, such as how (Li et al., 2021) investigated how uncertain contextual factors in urban areas, such as time-varying population and traffic in a 100-year pluvial flood scenario, can influence EMS service coverage. Studies have suggested methods for measuring difficulties in physical access and spatial access, and explored the SPAR method, respectively (Joseph & Bantock, 1982; Khakh et al., 2019) . The Spatial Access Ratio (SPAR) model, an E2FCA model, integrates hospital capacity, patient demand, and travel time, offering a more sophisticated measure of healthcare access (McCrum et al., 2022). These methods provide valuable insights into how service access can be quantified and visualized. For instance, findings by (McCrum et al., 2022) revealed that nearly 10% of the U.S. population has low access to hospitals with emergency surgical services, with a higher prevalence of limited access among uninsured, publicly insured, and racial minority communities, especially in rural areas, using SPAR. SPAR effectively highlights these differences; its complexity requires detailed spatial and population data, making it more resource-intensive than simpler models, though potentially more impactful in guiding targeted healthcare improvements in underserved areas.

Access to healthcare and emergency services is a critical determinant of public health outcomes. Table 1 provides a summary of key studies on health care availability and EMS, and various methodologies used to achieve that. However, a significant gap in the current literature is the consideration of roadway crashes as uncertain events impacting EMS availability. While numerous studies have evaluated general spatial access and its effects on healthcare utilization, the specific challenges posed by emergencies such as traffic accidents involving elderly drivers in rural areas remain underexplored. This present project aims to address this gap by estimating EMS service coverage using the Enhanced Two-Stage Floating Catchment Area (E2FCA) method, particularly focusing on the context of crash incidents and determining socio-economic characteristics that influence the access of the aging population in rural areas. By integrating dynamic and uncertain factors such as the occurrence of roadway crashes, this research seeks to provide a more comprehensive understanding of EMS service provision challenges and potential solutions for elderly drivers in rural settings.

Table 1: Summary of research on access to healthcare and emergency medical services

Authors	Objective	Methodology used
1. Cui, Boisjoly, et al., 2019	Assess spatial access impact on healthcare utilization, especially consultations.	2SFCA to estimate hospital access; multilevel regression models consultation likelihood.
2. Joseph & Bantock, 1982	Assess rural healthcare access difficulties for General Practitioners	Utilization analysis to measure actual access; spatial methods assess potential access.
3. McGrail & Humphreys, 2009	Measuring primary care spatial access.	2SFCA to compute population-to-provider ratios within a set distance.
4. Goodman et al., 1976	Analyze the distance to healthcare facilities and their impact on hospitalization.	Calculated travel times; used Poisson regression to analyze hospitalization likelihood.
5. Boisjoly & El-Geneidy, 2016	Evaluate time-sensitive measures' effectiveness versus traditional constant access measures.	Compare three access measures using transit mode share model assessments.
6. Cui, Grisé, et al., 2019	Compare three access measures: static departure, variable departures, and the conventional approach at the census-tract level.	Multilevel mixed effects to model commute duration; linear regression for the percentage of commuters using public transport.
7. Luo, 2004	Evaluate the greatest variability in physician-to-population ratios occurring at local scales.	The floating catchment method (FCM) is used to address the internal spatial distribution problem by deriving population data from census tracts.
8. Bissonnette et al., 2012	Explore natural neighborhood boundaries and aspatial factors in healthcare access.	Modified 2SFCA to measure spatial and social dimensions of healthcare access.
9. Khakh et al., 2019	Evaluate access to primary health care facilities at the community level by simulating travel on walking, multimodal, and driving-oriented networks	SPAR (Spatial Access Ratio) is used, which takes into consideration the provider-to-population status of the population.
10. Shah et al., 2016	Understand access to healthcare at the national and provincial levels in Canada	3SFCA method to identify neighborhoods with poor geographical access to health-care services
11. Arcury et al., 2005	Examine the association of individual transport access links to healthcare visit frequency for chronic and checkup care	Multivariate modeling to compare chronic and checkup visits

12. Al-Taiar et al., 2010	Investigate the relationships between different measures of geographical access, namely straight-line distances, driving distances, and driving time to vaccination centers.	Pearson's correlation coefficients for log-transformed (distances and time) and the Kruskal-Wallis test for non-normal distributed data
13. Stentzel et al., 2018	Examine service coverage by car Public transport is associated with the utilization of outpatient general practitioners and specialized physicians.	Multivariate logistic regression were conducted to identify determinants for the utilization of gynecologists and GPs.
14. Fishman et al., 2018	Examine contributions of individual- and neighborhood-level spatial access to care to the utilization of emergency departments (EDs).	Multilevel logit regression was used to model the relationship between individual- and neighborhood-level attributes and preventable ED use.
15. Y. Huang et al., 2018	Explore neighborhood income, ethnicity, healthcare access, and elderly emergency services visits.	Multivariate Ordinary Least Squares (OLS) was used to examine their relationships with the rate of ACSC ED visits.
16. (Carr-Hill et al.,1996.)	Identify the socioeconomic determinants of consultation rates in general practice	Multilevel modelling techniques were used to take account of both individual patient data and small area statistics
17. (He et al., 2019)	Measure timely service, service coverage, and identify factors affecting EMS performance.	Spatial econometric model and geographically weighted regression (GWR) model were developed and then compared to the linear regression model to help identify response time factors.
18. (Price, 2006)	Examine paramedics' accounts of the effects on patient care and on their own health and safety of attempts to meet the 8-minute target.	In-depth semi-structured interview
19. (Li et al., 2021)	Measure EMS availability with the effect of a regular uncertain context and an irregular uncertain context.	Enhanced two-step floating catchment area (E2SFCA) method

2.2. Role of Post-Crash Care

Wall J P. (2013) defines post-crash care as activities that include emergency rescue, pre-hospital medical treatment, and transport services provided immediately after a crash. Post-crash care plays a crucial role in reducing injury severity and mortality rates, particularly for elderly individuals involved in roadway crashes. Timely and appropriate medical care is crucial to improving survival outcomes. Research shows 40% of crash victims succumb to their injuries

after the initial impact (NHTSA, 2022). Studies show that delayed EMS response time was associated with increased odds of fatal injuries among older adults (Adeyemi, DiMaggio, et al., 2023). In different settings, post-crash care has proven to be effective in reducing mortality rates. For instance, a study in Sub-Saharan Africa showed that effective post-crash care, including ambulance transport, emergency access telephone services, and medical training for doctors, was associated with lower mortality rates. Given the higher likelihood of severe outcomes among elderly drivers, ensuring equitable access to EMS is essential for enhancing rural roadway safety.

Despite its critical importance, elderly individuals in rural areas face significant challenges in receiving timely medical attention after a crash. Geographic isolation, limited availability of EMS resources, and prolonged response times often hinder access to immediate care (GAO, 2023). Difficulties in healthcare infrastructure, particularly in remote regions, exacerbate these challenges, leaving older adults at a greater risk of adverse outcomes (Mseke et al., 2024). Additionally, aging-related factors, such as cognitive decline and mobility limitations (Fraade-Blanar et al., 2018), may further complicate post-crash response and recovery. Addressing these barriers requires targeted policies and infrastructure improvements to ensure that emergency medical services can effectively reach and treat elderly crash victims in rural communities. Recognizing the importance of post-crash care, the USDOT's Safe System Approach emphasizes immediate and effective emergency response as a key strategy for reducing roadway fatalities and severe injuries (USDOT, 2025). This framework highlights the need for a comprehensive transportation safety system that prioritizes timely medical intervention, particularly for vulnerable populations such as elderly drivers. By integrating post-crash care into broader transportation planning efforts, policymakers can enhance EMS availability and reduce fatality rates in rural areas. Strengthening EMS networks, investing in advanced response technologies, and improving coordination between transportation and healthcare systems are critical steps toward achieving safer roadways for aging populations. Ultimately, prioritizing post-crash care aligns with national safety goals and promotes service coverage in emergency medical response for rural elderly drivers.

2.3. Socio-Demographic Factors and Impact of EMS Response Time on Injury Severity

Socio-economic factors play a critical role in determining access to emergency medical services (EMS), particularly in rural areas where healthcare infrastructure is often limited. Income levels influence an individual's ability to afford medical care, including transportation to healthcare facilities and follow-up treatments after an emergency. Lower-income populations experience delays in EMS response due to fewer available ambulance services and longer transport distances to hospitals (Fernandez, 2018). Insurance coverage significantly affects EMS coverage, as uninsured or underinsured individuals may hesitate to seek emergency care due to financial concerns. A study by (Ostermayer et al., 2017) reveals that changes in insurance coverage impacted EMS by influencing transport volumes, reimbursement rates, and the development of cost-effective prehospital care models. These economic barriers create difficulties in timely medical intervention, disproportionately impacting elderly individuals who may already face financial constraints due to fixed incomes or increased healthcare needs.

Demographic factors such as age, gender, and disability status further shape EMS availability and outcomes. Elderly individuals experience mobility limitations, cognitive impairments, and preexisting health conditions that can complicate emergency response and treatment (Bell et al.,

2021). Lower socioeconomic status (SES) is associated with a higher likelihood of repeated EMS calls and unplanned hospital visits after initial treatment or release, suggesting differences in the adequacy of prehospital care (Frydenlund et al., 2022). Addressing these demographic differences is essential to ensuring equitable EMS access and improving health outcomes for all rural residents, particularly vulnerable aging populations. Rural healthcare differences exacerbate challenges in EMS coverage, leaving residents at a heightened risk of delayed or inadequate post-crash care. Many rural areas suffer from hospital closures, a shortage of healthcare professionals, and long travel distances to trauma centers, all of which contribute to limited EMS availability (Lilley et al., 2024). These difficulties place crash victims at a significant disadvantage, as they are more likely to experience severe injuries and require immediate medical attention.

EMS response time is a critical factor in determining crash survival rates and injury severity, particularly in rural areas. Studies have consistently shown that shorter response times are associated with improved survival outcomes and reduced long-term health consequences (Bürger et al., 2018). Conversely, prolonged EMS response times increase the likelihood of fatal or severe injuries among crash victims (Gonzalez et al., 2009). Given the high fatality rates in rural areas, understanding the impact of EMS response time is crucial for developing strategies to enhance post-crash care and reduce preventable deaths. To analyze the effectiveness of EMS response and its impact on injury severity, researchers utilize various statistical models and methodologies. Survival analysis, Bayesian networks, and regression models are commonly employed to assess the relationship between response time and patient outcomes (P. Huang et al., 2024; Wilde, 2013; Wu et al., 2013). Geographic Information Systems (GIS) have also been widely used to map EMS coverage areas and identify critical locations with high response delays (P. Huang et al., 2024).

(Wu et al., 2013) employed survival analysis techniques, including Kaplan-Meier estimators, Weibull modeling, and Cox proportional hazard models, to assess the relationship between EMS response time and patient outcomes. Findings showed that earlier automatic collision notification (ACN) and EMS arrival significantly improve survival probabilities and reduce traffic crash fatalities. Machine learning techniques are being applied to predict EMS arrival times and optimize resource distribution in rural settings (Martin et al., 2021). A study by Nicoletta et al., (2022), used a generalized linear mixed effects model with Markov chain Monte Carlo simulation was applied to predict emergency call volumes across spatial and temporal distributions. This enabled more accurate ambulance service planning to reduce response times and improve patient outcomes. Generally, these analytical approaches provide valuable insights into the difficulties in EMS coverage and inform policy decisions aimed at improving emergency response efficiency. By leveraging data-driven methodologies, transportation and healthcare planners can implement targeted interventions to enhance EMS effectiveness and reduce injury severity in rural crashes.

3. STUDY AREA & DATA

In this section, the project focuses on a comprehensive review of databases used to achieve the objectives related to service coverage of emergency medical services.

3.1. Study Area

This study focused on the state of Ohio, with particular attention to rural areas. A map delineating rural areas across Ohio is shown in Figure 3. Crash incidents were then filtered to

include only those entries where the household density was less than 425 households per square mile. This threshold aligns with the U.S. Census Bureau's criteria for delineating rural areas from urban areas, as urban areas are typically defined by higher household densities. The incidents' coordinates were first converted into shapely point objects, used to create a GeoDataFrame. This GeoDataFrame, which represented the geographical locations of crash incidents involving elderly drivers, was spatially joined with a GeoDataFrame containing census tract data from a geodatabase. The spatial join operation matched each point to its corresponding census tract, adding the GEOID (census tract identifier) to the original dataset.

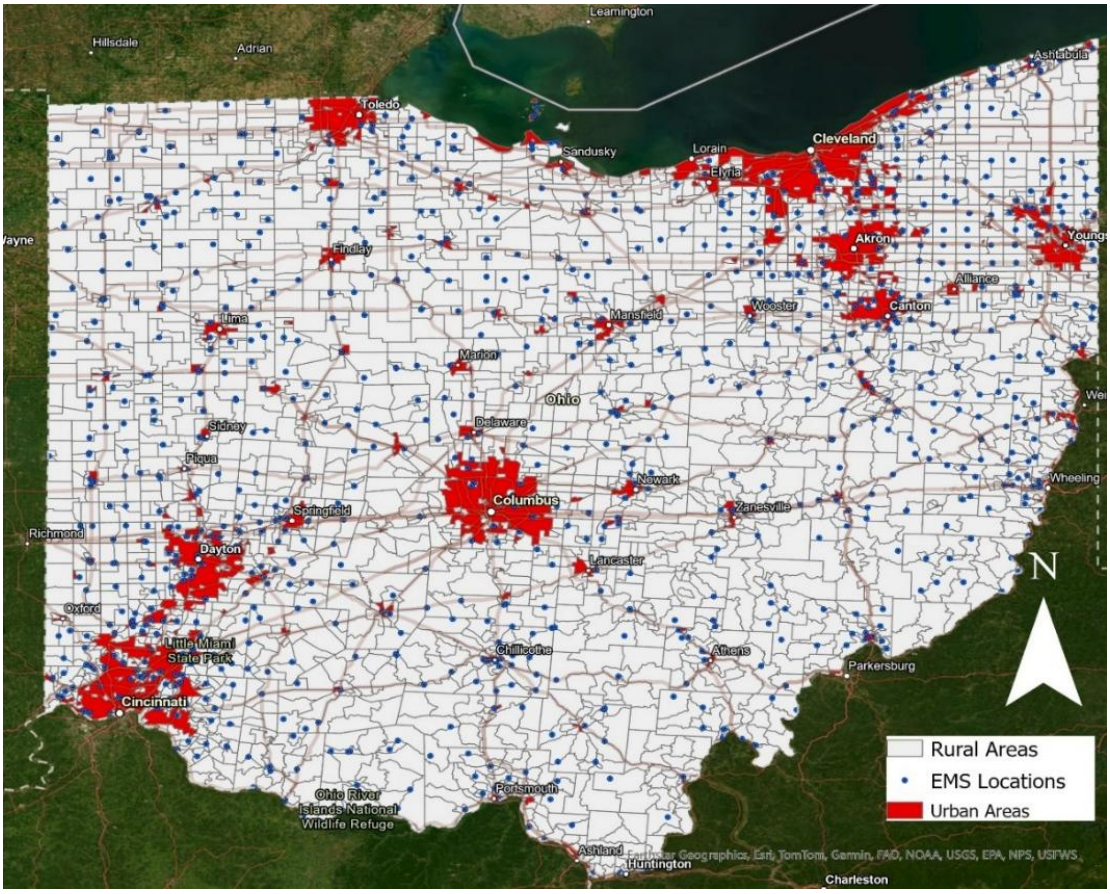

Figure 3: Study Area

3.2. Ohio Department of Public Safety

The Ohio Department of Public Safety (ODPS) provides detailed records of crash incidents through Electronic Crash Submission. Crash incidents involving elderly drivers (aged 65 years and older) for 6 years (2017-2022) were obtained. This dataset was critical for identifying the geographic coordinates (latitudes and longitudes) of crash incidents and understanding the spatial distribution of severe and fatal injuries in rural areas.

3.3. Homeland Infrastructure Foundation-Level Data (HIFLD)

EMS location data was obtained from the Homeland Infrastructure Foundation-Level Data (HIFLD). This dataset provided comprehensive information (including the geographical coordinates) on the geographic locations of EMS facilities, which served as the origins for the

service coverage analysis. The crash incident locations, derived from the ODPS dataset, were used as the destinations in this study for the Network Analysis (Closest Facility Analysis).

3.4. Socio-Demographic Data - Census Bureau Data and Smart Location Database

Furthermore, socio-economic data from the Census Bureau Data (2017-2022) with attributes such as insurance coverage, employment status, educational level, race, and population in each census block group were integrated into the analysis using a spatial join tool. Network density attribute was also included in the analysis obtained from the Smart Location Database (SLD). This integration allowed for a comprehensive assessment of how socio-economic factors may influence EMS service coverage and healthcare outcomes in rural areas.

3.5. Fatality Analysis Reporting System

This project also utilized data from the Fatality Analysis Reporting System (FARS) from the year 2016 to 2022, a nationwide database managed by the National Highway Traffic Safety Administration (NHTSA) that compiles data on fatal motor vehicle crashes in the United States. FARS data includes extensive information about crash circumstances, vehicle conditions, and individuals involved, making it a valuable source for analyzing crash injury severity across different demographics and environments. Any case that has missing data on the selected variables will be removed. The target population is elderly drivers (age 65+) involved in rural motor vehicle crashes, with a particular focus on those who have suffered injuries requiring EMS intervention. FARS, maintained by the National Highway Traffic Safety Administration (NHTSA), is an annual census of traffic crashes resulting in a fatality within 30 days of the event. In this context, the scope of this study was associative (examined relationships or correlations (not causation) between variables and observational (means analyzing existing, non-experimental data without manipulating the conditions or variables), aiming to evaluate how EMS response times influence injury severity among elderly drivers in rural crashes, while exploring the moderating effects of vehicle, roadway, and crash characteristics using existing data from the Fatality Analysis Reporting System (FARS). Table 2 shows variable descriptions.

Table 2: Description of data from the FARS Data

Variables	**Description**	**Variables**	**Description**
Injury Severity (**Response Variable**)	This data element describes the severity of the injury to this person in the crash using the KABCO scale.	Alcohol Usage	These data records whether alcohol was involved for this person and reflect the judgment of law enforcement.
EMS Response Time	Time from crash occurrence to EMS arrival. This is measured in minutes.	Speed Limit	These data identify the attribute that best represents the speed limit just prior to this vehicle's critical precrash event.
Gender	This data element identifies the sex or gender of the person involved in the crash.	Roadway Alignment	These data identify the attribute that best represents the roadway alignment before this vehicle's critical precrash event.

Type of EMS Transport	These data identify the mode of transportation to a hospital or medical facility provided for this person.	Roadway Grade	This data element identifies the attribute that best represents the roadway grade before this vehicle's critical precrash event.
Seating Position	These data identify the location of this person in or on the vehicle.	Roadway Surface Condition	This data element identifies the attribute that best represents the roadway surface condition before this vehicle's critical event.

4. METHODOLOGY

To enable spatial integration with the output of the closest facility analysis, all crash incident and EMS facility records were first geocoded using latitude and longitude coordinates. Using Python's Shapely and GeoPandas libraries, these coordinates were converted into spatial point geometries and projected onto a consistent coordinate reference system. This step ensured alignment with the Ohio road network dataset and supported accurate spatial operations in ArcGIS Pro. Next, each geocoded point was spatially joined to 2021 American Community Survey (ACS) census tract boundaries using their corresponding GEOIDs. This spatial linkage was essential for merging the travel time and distance outputs from the closest facility analysis with contextual population characteristics at the census block group level. By associating each incident location with a GEOID, the results of the network-based EMS response time analysis could be directly combined with population density and other contextual attributes. A summary of the data preparation and analysis workflow is presented in Figure 4.

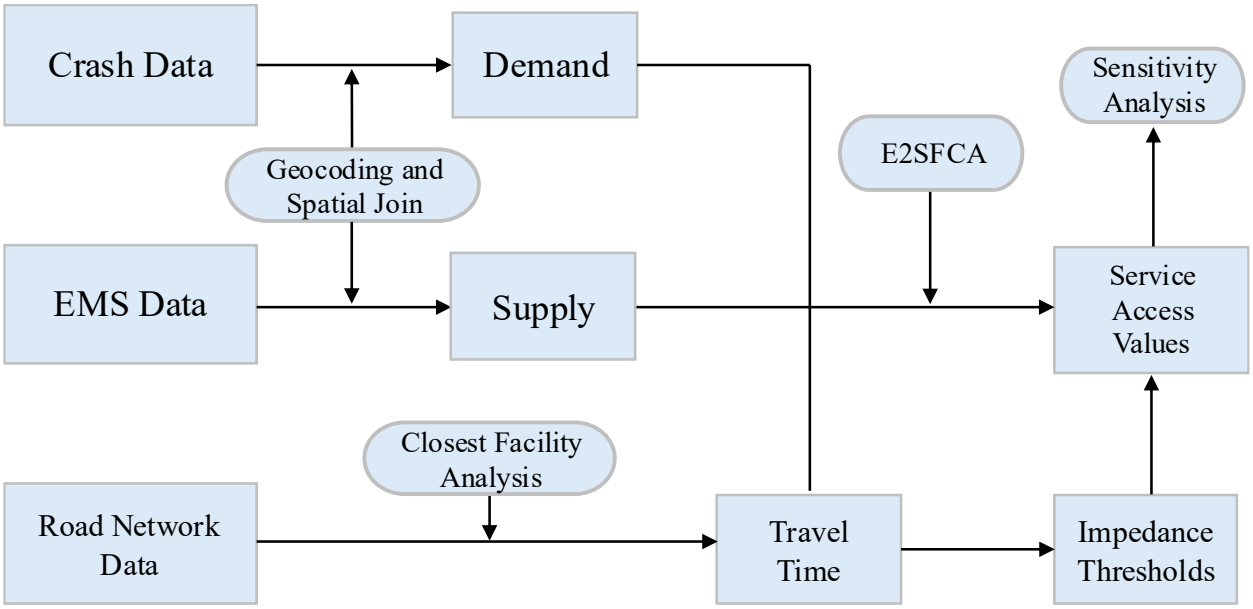

Figure 4: Study Design Flowchart for obtaining the EMS Access Scores

4.1. Closest Facility Analysis

A key component of the analysis involves creating a cost matrix through a Closest Facility Analysis. This step involved the calculation of the nearest travel distance and travel time between EMS locations and crash incident sites, providing a foundational understanding of spatial access. The E2SFCA method is then applied to these data points to generate service coverage values, offering a refined measure of EMS service coverage by considering both

distance and facility capacity. Ultimately, the results of this analysis will be examined to provide insights into the availability of EMS for elderly drivers in rural areas, particularly in the context of crash incidents. This project aims to inform policy decisions and strategic planning to enhance EMS response times and healthcare outcomes for vulnerable populations in rural settings.

Closest facility analysis was conducted in ArcGIS Pro software. We first prepared the necessary data, including a network dataset of the entire Ohio State and the locations of both facilities (i.e., EMS Locations) and incidents (i.e., crashes). A closest facility analysis layer was created, and the analysis settings. A maximum impedance cut-off of 8 minutes was assigned to clearly define the extent of coverage of all the crash locations. Running the analysis resulted in routes connecting incidents to their closest facilities appearing on the map and in the Routes sublayer of the Closest Facility group layer, as shown in the 3 counties of Medina, Cuyahoga, and Summit in Figure 5. This process provided a clear visualization of the most accessible facilities relative to each incident site.

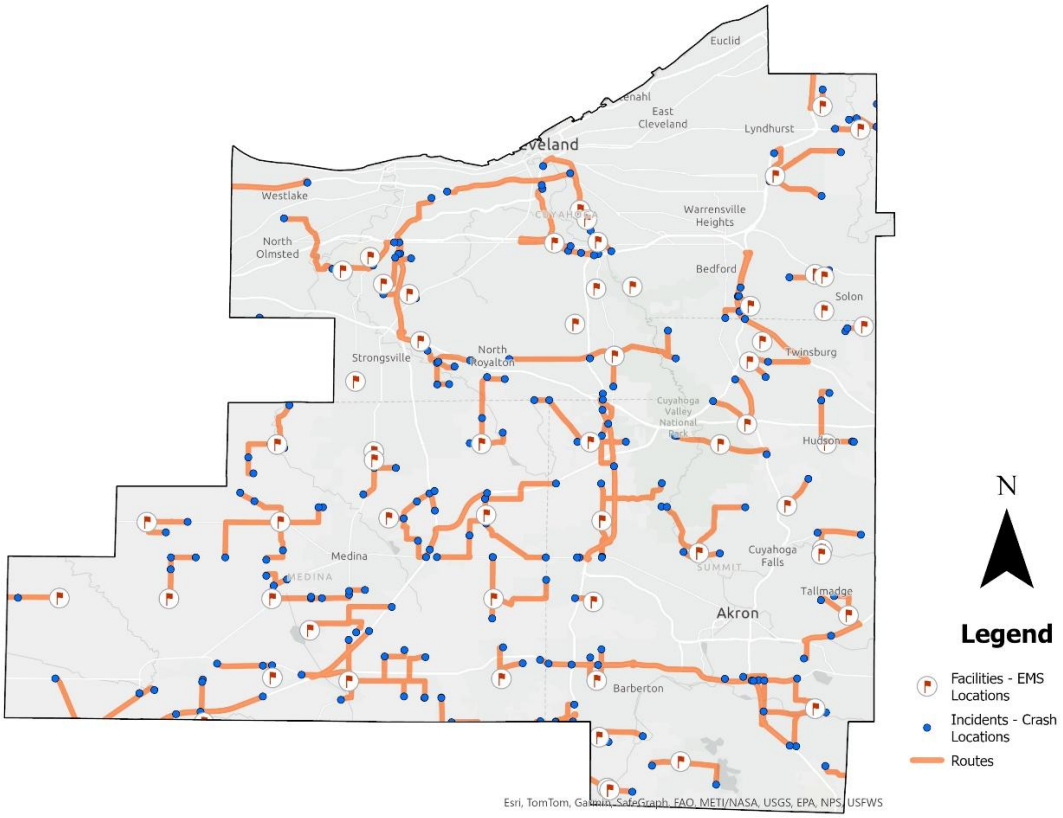

Figure 5: Closest Facility Analysis – 3 Counties (Medina, Cuyahoga, and Summit)

4.2. Enhanced Two-Stage Floating Catchment Area (E2SFCA)

This present project utilized the E2SFCA method to assess EMS access. The spatial access analysis began by merging the crash data with the distance matrix, linking each crash location to its corresponding travel times to various EMS stations. The first step, each census block group was assigned a supply to demand ratio. The supply to demand ratio was computed as shown in Equation 1.

$$R_j = \frac{S_j}{\sum_{i=1}^{n} D_i \cdot f_{t(ij)}} \quad (1)$$

Given R_j as the supply to demand ratio, where S_j represents the supply value at EMS station j within a specific census block group and D_i signifies the demand value, which in this case corresponds to crash incidents. The study area contained 1,020 EMS stations located in rural regions and recorded 3,548 crash incidents involving elderly drivers (focusing only on fatal and serious injury crashes). Each demand location was represented by a census block group. t(ij) denotes the access time between i and j ($t(ij) \leq t_0$) and $f_{t(ij)}$ is the distance decay function. The second step involves identifying all EMS stations that are reachable within the threshold time t_0 from the census block group crash incidents and summing the initial supply-to-demand ratios (R_j, j = 1,2, 3,..,m) as the service access score of location i at time T:

$$A_i = \sum_{j=1}^{m} R_j \, f_{t(ij)} \tag{2}$$

A_i is the EMS service availability index value of the EMS stations per the CBG population. Note that $f_{t(ij)}$ takes the form of a modified Gaussian function ($e^{-t(ij)2/\alpha}$) as shown in Equation 2. A study by (Kwan, 1998) indicates that the parameter α determines its rate of decline and the point where it approaches zero. The maximum mandatory EMS response time is 8 minutes (t_0) in rural areas, based on a study by (Rhodes et al., 2023), then $f_{t(ij)}$ approaches zero when t(ij) approaches 8 minutes, based on which α can be computed.

4.3. Generalized Linear Model: Regression Analysis

A generalized linear model with an inverse power function and a Gamma family was used because the response variable (EMS service access values) was continuous and skewed to the right and had outliers. To improve the interpretability of the model, estimates were obtained by multiplying the raw coefficients by 100 (Semi-elasticity). Semi-elasticity measures the percentage change in the outcome resulting from a one-unit change in the explanatory variable (Verma et al., 2023).

4.4. Bayesian Ordinal Logistic Regression

A Bayesian approach was applied to investigate how EMS response time and other factors affect injury severity among elderly drivers in rural crashes. This approach offers several advantages compared to the traditional frequentist methods commonly used for parameter estimation. Unlike the frequentist approach, which provides a single point estimate for each parameter (Kruschke, 2014). The Bayesian method treats model parameters as random variables. It estimates their posterior distributions, enabling more comprehensive inference and capturing uncertainty more effectively. Bayesian Ordinal Logistic Regression model was employed as it was suitable for handling ordinal response data, where the outcome variable represents categorized levels of injury severity (from No injury, Possible Injury, Minor Injury, Serious Injury, and Fatal Injury).

$$\pi_{ij} = f(\alpha_j + X_i'\tilde{\beta}) \tag{3}$$

Where:

π_{ij} is the probability that observation i falls into j^{th} category of injury severity, X_i' are the vector covariates for observation i that influence injury severity, $\tilde{\beta}$ is a vector of regression coefficients associated with the covariates X_i', α_j is the threshold parameter for category j (for j=1,2

corresponding to the boundaries between the three injury categories), *f*() = is a typical inverse-link function, which is equivalent to that adopted from (Kruschke, 2014),

$$\mu_k = \Phi\left(\frac{(\theta_k - lin(x)}{\sigma}\right) - \Phi\left(\frac{(\theta_{k-1} - lin(x)}{\sigma}\right) \quad (4)$$

Where: μ is the central tendency of the predicted data, *x* is the predictor variable, and lin(*x*) is a linear function of *x.*
Given the parameters α_j (thresholds) and $\tilde{\beta}$ (regression coefficients)(intercepts and regression coefficients), the likelihood L(Y| θ) represents the probability of observing the given data Y.

$$L(Y|\alpha_j, \tilde{\beta}) = \prod_{i=1}^{n} \prod_{j=1}^{J} \pi_{ij}(\alpha_j, \tilde{\beta})^{y_{ij}} \quad (5)$$

Where: J = number of categories, n = number of observations, π_{ij} = probability that the response for observation i is in category j or below.
Numerous studies have used non-informative priors to preserve objectivity in modeling associated with insufficient available information to develop informative priors. Moreover, such kind of priors minimize influence on the posterior, allowing the flexibility of the data to dominate (Kruschke, 2014). To ensure model flexibility and minimize prior influence, normal vague priors were applied with a normal distribution, using large variances such as 100^2 for threshold parameters (a_j) and 1000^2 for covariates (β). These vague priors allow the data to dominate the posterior estimation while accommodating empirical variability (Rezapour et al., 2021). The posterior distribution $P(\alpha_j, \tilde{\beta})|Y)$, was a multivariate distribution of the threshold parameters a_j and regression coefficients β given the data Y, influenced by the likelihood of the observed data and the specified priors. According to (Gelman et al., 2014) the posterior distribution can be expressed as.

$$P(\alpha_j, \tilde{\beta})|Y) \propto L(Y|\alpha_j, \tilde{\beta}).P(\alpha_j, \tilde{\beta}) \quad (6)$$

The Markov Chain Monte Carlo (MCMC) algorithm was employed to draw samples from the posterior distribution of model parameters. Analyses were conducted using the MCMC procedure in R and JAGS (JAGS, 2023). A total of 200,000 samples were obtained after a burn-in period of 1,000 steps to ensure convergence of the chains. To reduce autocorrelation between successive samples, thinning was applied at an interval of 10, resulting in effectively independent samples for posterior inference. Convergence diagnostics, such as trace plots, autocorrelation, and effective sample size (ESS), were employed.

5. DISCUSSION OF RESULTS

5.1. Results of Enhanced Two-Step Floating Catchment Area (E2SFCA) method.

Figure 6 displays the spatial distribution of EMS service access scores across Ohio at the CBG level. The map reveals substantial regional variation in service access, with lower scores (in dark and medium blue) concentrated in many rural portions of southern, southeastern, and western Ohio. These areas likely suffer from sparse EMS facility coverage, longer distances between incident locations and EMS stations, and limited roadway infrastructure. Conversely, higher service access scores (in red) are clustered around major urban centers such as Columbus,

Cleveland, and Cincinnati, where EMS facilities are denser, and more roadways support rapid emergency response. The mid-range service access scores (beige to light red) dominate central and northwestern parts of the state, indicating moderate reachability to EMS services within the 8-minute threshold. Addressing these differences is essential for improving EMS access and ensuring timely EMS response throughout the state.

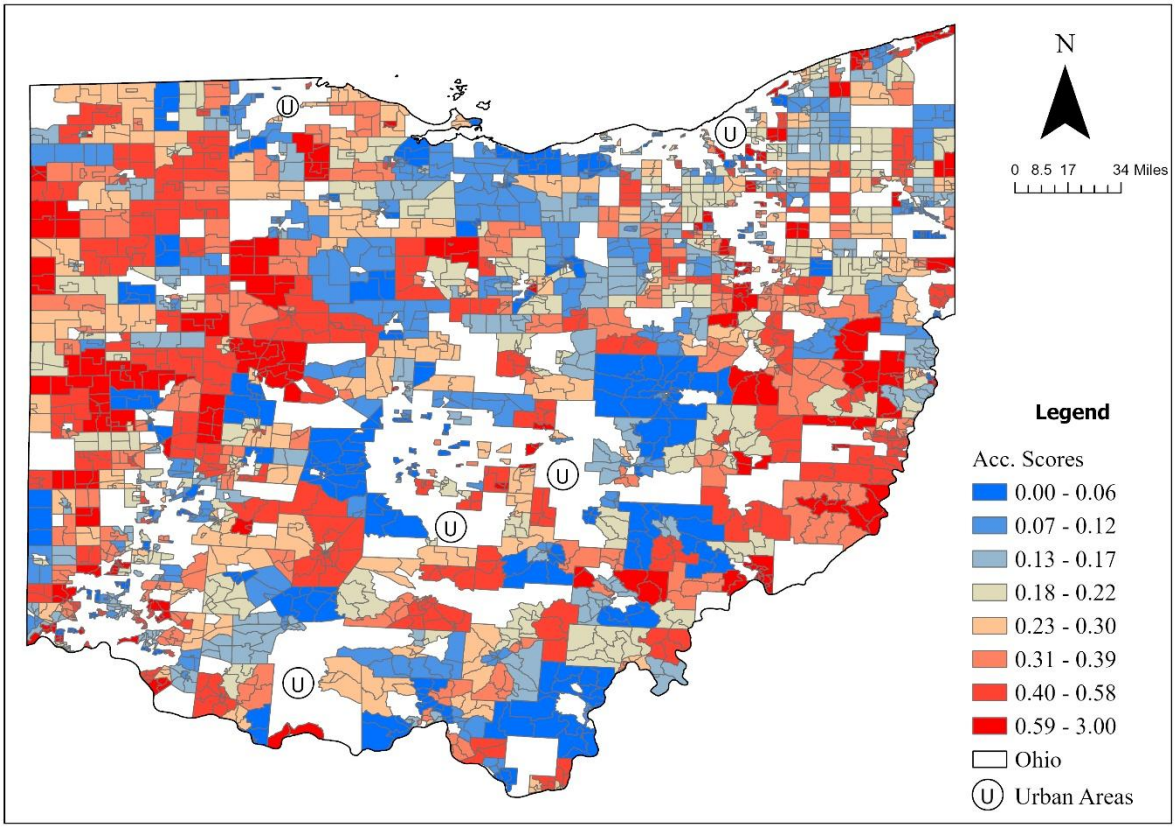

Figure 6: CBG-level EMS access scores across Ohio

Sensitivity Analysis

To evaluate the robustness of EMS service access outcomes, a sensitivity analysis was conducted using multiple threshold travel times. This approach recognizes the clinical significance of rapid emergency response, particularly within critical time windows such as the "Platinum Ten" and the "Golden Hour." The former refers to the first 10 minutes following a traumatic incident, during which prehospital care and stabilization can significantly influence survival outcomes. The latter first hour post-injury has long been used in emergency medicine as the benchmark for delivering definitive care (33,34). In this study, EMS service access was assessed under three different time thresholds: 10, 30, and 60 minutes to capture a range of response scenarios and to understand how variations in permissible travel time affect spatial service access patterns across

Ohio.

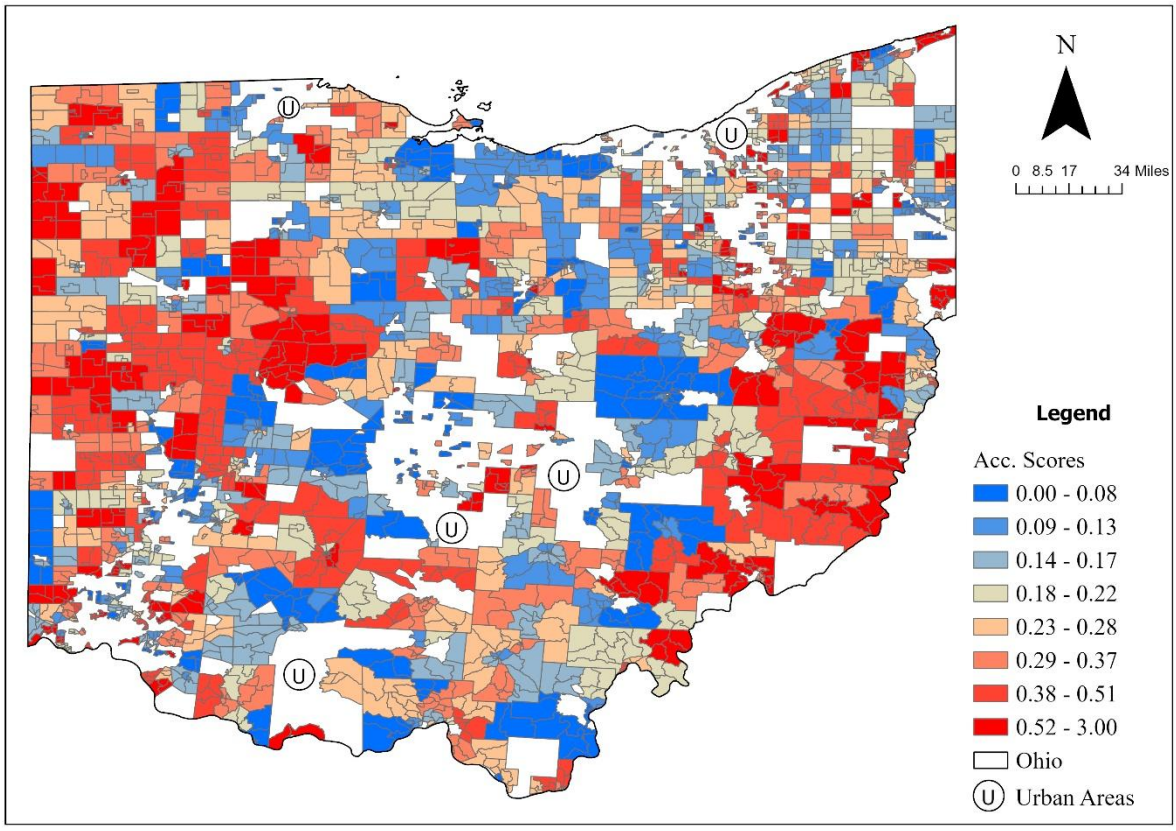

Figure 7: Results of the sensitivity analysis showing service access scores under a 10-minute travel time threshold scenario

When the time threshold was set to 10 minutes, EMS service access scores across Ohio revealed a relatively balanced spatial distribution. As shown in Table 3, most CBGs fell in the middle classification bands. Specifically, 444 CBGs (13.63%) were categorized within the 0.09–0.13 range, while 437 CBGs (13.42%) were classified in the 0.14–0.17 range. Combined, these groups represented more than a quarter of the state, reflecting moderate access to emergency services within the 10-minute window. However, a considerable number of CBGs remained in the lowest access tier (0.00–0.08), accounting for 390 CBGs or 11.97% of the total. These low-access areas are likely reflective of challenged regions with limited EMS infrastructure. Conversely, high-access scores above 0.52 were observed in only 369 CBGs (11.33%), suggesting that under stricter response-time expectations, only a limited portion of the population benefits from excellent EMS reach.

When the time threshold was extended to 60 minutes, the distribution of EMS service access scores became more concentrated in the mid-range categories, but without a significant increase in the maximum score values. The largest share of CBGs (19.25%) was recorded in the 0.20–0.27 range, followed by 16.45% and 15.14% in the 0.10–0.14 and 0.15–0.19 brackets, respectively. Notably, only 3.69% of CBGs reached the highest classification range (0.77–1.00), indicating that very few areas achieved optimal service access despite the extended travel window. Additionally, 374 CBGs (11.39%) remained in the lowest access range (0.00–0.09),

reinforcing that even under more generous time thresholds, challenges in service access remain.

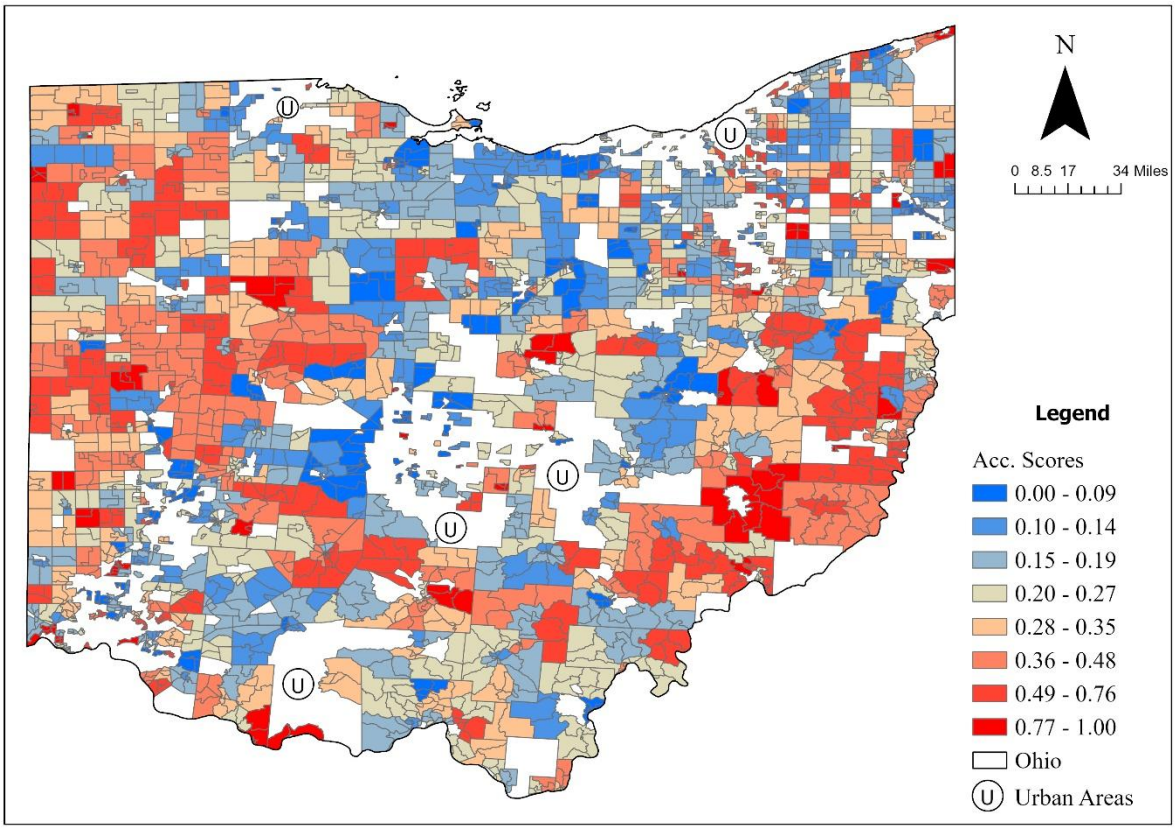

Figure 8: Results of the sensitivity analysis showing service access scores under a 60-minute travel time threshold scenario

Table 3: Classification of EMS service access values across CBGs under 10-minute and 60-minute travel time thresholds

Time Threshold	Service Acc Scores	Number of CBGs	Proportion of CBGs (%)
10 min	0.00 – 0.08	390	11.97
	0.09 – 0.13	444	13.63
	0.14 – 0.17	437	13.42
	0.18 – 0.22	371	11.39
	0.23 – 0.28	399	12.25
	0.29 – 0.37	435	13.36
	0.38 – 0.51	412	12.65
	0.52 – 3.00	369	11.33
60 min	0.00 – 0.09	374	11.39
	0.10 – 0.14	540	16.45
	0.15 – 0.19	497	15.14
	0.20 – 0.27	632	19.25
	0.28 – 0.35	372	11.33
	0.36 – 0.48	398	12.12
	0.49 – 0.76	349	10.63
	0.77 – 1.00	121	3.69

5.2. Socioeconomic Factors that Affect Service Availability

For the census block groups in Ohio, several demographic and socioeconomic variables from the Census Bureau database were defined and incorporated into the model. Race was categorized into three groups: White, African American, and Other (American Indian, Asian, Native Hawaiian, Other). Population refers to the total number of individuals residing in each block group. Insurance coverage was defined as the proportion of the population with health insurance. Employment status was measured by the employment rate, indicating the percentage of the working-age population 16 years and over that was employed. Education level was determined by the percentage of individuals with at least a bachelor's degree or a high school diploma. Network density was calculated by dividing the sum of link lengths by the covered areas in a census block group from the Smart Location Database. These variables were essential to account for differences in EMS service availability across diverse communities, providing a comprehensive understanding of how various demographic and socioeconomic characteristics influence EMS access in different census block groups.

Table 4: Descriptive statistics of the socio-economic attributes per CBG

Attribute	**Mean**	**Std**	**Min**	**Max**
Network Density	4.054	3.162	1.157	4.829
Race				
White	1210	529	0	1494
African American	29	121	0	2816
Other	23	61	0	1307
Population	1304	582	0	6598
Insurance Coverage	249	133	0	1175
Employment Status	641	317	0	4187
Educational Level	216	205	0	1703

The analysis of EMS service availability values, measured as the number of EMS stations per CBG population, reveals several significant relationships between service access and various demographic and socioeconomic attributes as depicted in Table 4. Network density emerges as a strong positive predictor of EMS service availability, with a high coefficient of 19.960, indicating that areas with higher network density are significantly associated with greater EMS access. This is an established finding that is underscored by the importance of robust infrastructure and connectivity in ensuring social services (Peng & Jin, 2023). Furthermore, the strong positive correlation between network density and EMS service access could be influenced by the strategic placement of EMS stations and hospitals in urban centers, where higher population densities justify more concentrated infrastructure. This urban bias can limit EMS service provision for rural areas with lower network density, as these communities are often farther from centrally located EMS services.

Table 5: Generalized Linear Regression Results

Attributes	coef	std err	z	p>|z|	0.025	0.975
Network Density	19.960	0.02	9.847	**0.000**	16.000	23.900
Race						
White	-0.050	0.001	-0.424	0.671	-0.300	0.200
African American	-0.040	0.001	-0.273	0.785	-0.300	0.200
Other	-0.210	0.001	-1.446	0.148	-0.500	0.100
Population	0.130	0.001	1.177	0.239	-0.100	0.300
Insurance Coverage	0.240	0.001	4.323	**0.000**	0.100	0.300
Employment Status	0.100	0.000	2.012	**0.044**	0.000	0.200
Education Level	-0.090	0.000	-2.218	**0.027**	-0.200	-0.100

Insurance coverage and employment status both exhibit positive and statistically significant associations with EMS service availability. Specifically, a higher percentage of insured individuals ($\beta = 0.240$) and employment status ($\beta = 0.100$) in a CBG are linked to improved EMS access, highlighting the role of socioeconomic stability in facilitating access to emergency medical services. These findings are consistent with (Meisel et al., 2011) where people with high insurance coverage are associated with high use of EMS. Additionally, because the healthcare system in the U.S., areas with higher insurance coverage are more likely to enjoy greater EMS availability due to the interconnected nature of healthcare funding (CDC, 2024). Conversely, education level shows a negative and significant relationship ($\beta = -0.090$), suggesting that areas with higher education levels may experience lower EMS service access. This finding is counterintuitive to the previous studies, as highly educated populations, who generally have lower healthcare needs, enjoy better access (Hassler & Ceccato, 2021b). Among racial demographics, the coefficients for White, African American, and other populations are negative, though none are statistically significant at conventional levels, suggesting that racial composition alone does not have a substantial direct impact on EMS access. Population size shows a positive but non-significant relationship with EMS service availability.

Based on the study's findings, the following policy recommendations aim to enhance EMS service availability and address difficulties in emergency healthcare access across different communities. Policy makers should prioritize enhancing network infrastructure and increasing EMS stations in areas with lower service access, particularly in socioeconomically disadvantaged or rural regions where network density is limited. Additionally, there should be a focus on improving EMS coverage in underserved areas, particularly those with low insurance coverage and employment rates, which could help address differences in access by ensuring that EMS stations are more strategically located to serve vulnerable populations. Policymakers might also consider reallocating resources to underserved areas, balancing investments between urban and rural regions, and employing data-driven planning methods to identify critical zones for new EMS facilities. Drawing on best practices from emergency healthcare management, such as establishing minimum service access thresholds or employing mobile EMS units, could further help mitigate urban-rural health differences and improve response times.

5.3. Injury Severity Analysis Findings

Regarding EMS response time, show a mode of 1.05 and an HDI ranging from 0.74 to 1.48, suggesting that delays in EMS response might slightly increase the odds of higher injury severity. This is an established finding as (Hosseinzadeh & Kluger, 2021) suggests that while faster EMS response times alone did not reduce injury severity, a combination of quicker response times and slower on-scene times was linked to less severe injuries, particularly those involving the whole body. This result suggests that improving EMS response times could be a key factor in reducing injury severity, especially for elderly drivers in rural settings.

Table 6: Descriptive Statistics

Variable	**Categories**	**Count (%)**
Injury Severity	No Injury	137(15.4)
	Possible Injury	42(4.7)
	Minor Injury	93(10.4)
	Serious Injury	84(9.4)
	Fatal Injury	534(60)
Gender	Male	532(59.8)
	Female	358(40.2)
Type of EMS Transport	EMS Ground	645(72.5)
	Air	25(2.8)
	Not Transported	220(24.7)
Alcohol Usage	Yes (Involved)	27(3)
	No (Not Involved)	281(31.6)
	Not Reported	582(65.4)
Seating Position	Front Seat	751(84.4)
	Second Seat	29(3)
	Non-Occupant	110(12.3)
Speed Limit	<35	120(13.5)
	35-45	347(39)
	>45	423(47.5)
Roadway Alignment	Straight	795(89.3)
	Curve	95(10.7)
Road Surface Condition	Dry	717(80.6)
	Wet	143(16.1)
	Snow	20(2.2)
	Ice (Frost)	10(1.1)

The analysis of the model coefficients, as shown in Table 8**,** offers significant insight into various factors contributing to injury severity among elderly rural drivers. The intercept has a mode of 45.84 with a wide HDI, indicating that, in the absence of other predictors, there is a high baseline probability of severe injuries for individuals in the reference group. Furthermore, the posterior distributions for the predictors, including gender, type of EMS transportation, seating position, alcohol involvement, vehicle speed limit, roadway alignment, EMS response time, and

road surface conditions, reveal varying levels of influence on injury severity, as evidenced by their respective modes and HDI ranges. Complementing this, Figure 9 shows the distribution of odds ratios for the beta coefficients, illustrating the magnitude and direction of the effects within the 95% HDI. The odds ratio provides a more interpretable framework for assessing the relative impact of each predictor, with credible intervals indicating the extent of uncertainty in the estimates.

Table 7: Posterior modes, lower and Upper HDI, and MCSE

Variables	**Mode**	**Lower HDI**	**Upper HDI**	**MCSE**
Intercept	4.180	3.000	5.340	0.004
Gender	0.255	-0.223	0.740	0.002
EMS Transport used	2.300	1.990	2.630	0.001
Seating Position	-2.510	-3.430	-1.780	0.003
Alcohol Involvement	0.037	-0.279	0.223	0.001
Speed Limit	-0.009	-0.022	0.008	0.000
Roadway Alignment	0.820	0.093	1.640	0.003
EMS Response Time	0.070	-0.277	0.409	0.001
Roadway Surface Condition	0.073	-0.285	0.512	0.001

Table 8: Odd ratios for Beta Coefficients, in terms of mode within the HDI 95%

Variables	**Mode**	**Lower HDI**	**Upper HDI**
Intercept	45.840	11.670	173.330
Gender	1.190	0.740	1.980
EMS Transport used	9.730	7.030	13.530
Seating Position	0.070	0.020	0.150
Alcohol Involvement	0.960	0.750	1.230
Speed Limit	0.990	0.980	1.010
Roadway Alignment	2.130	0.880	4.690
EMS Response Time	1.050	0.740	1.480
Roadway Surface Condition	1.060	0.700	1.580

5.3.1. Gender

Posterior mode odds for gender are 1.19 with a 95% HDI of 0.74 to 1.98, suggesting that being female may slightly increase the odds of higher injury severity compared to males. While it might seem like females are at a greater risk of severe injuries in crashes, research has long shown that they tend to be more likely to suffer injuries that lead to hospitalization (Cullen et al., 2021). This highlights the need for a deeper understanding of how gender affects crash risks and injuries as people age and gain more driving experience.

5.3.2. Type of EMS transport used

The EMS transport variable shows a strong association with injury severity. The mode of 9.73 and the narrow HDI suggest that being transported by EMS, particularly air transport, is significantly associated with higher injury severity compared to those not transported. This suggests that severe injuries are likely identified quickly in these individuals, necessitating EMS intervention. This finding is well established, according to (Galvagno et al., 2012) EMS by air transportation is associated with improved odds of survival and post-discharge outcomes compared to ground transport.

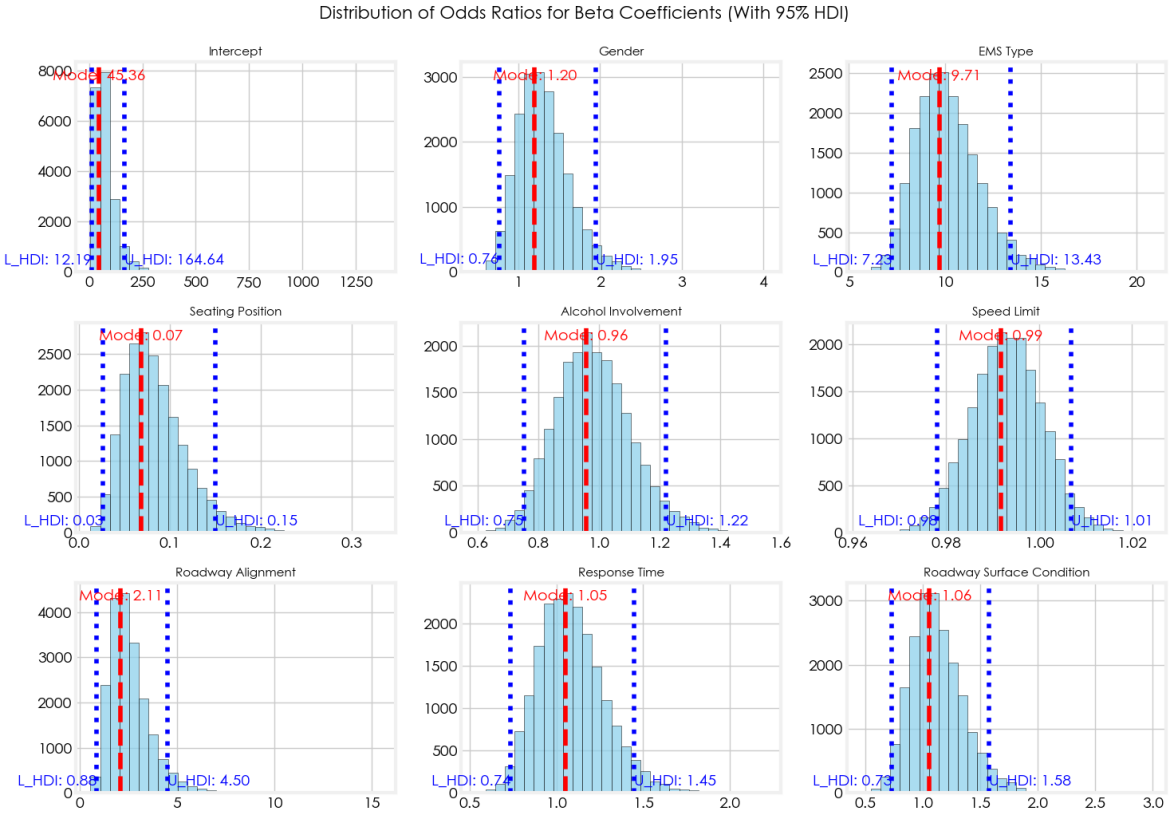

Figure 9: Distribution of odd ratios for Beta Coefficients, within the HDI 95% and mode

5.3.3. Seating Position

The findings for seating position are noteworthy, with the mode of 0.07 and a narrow HDI indicating that being in the front seat or other passenger seats is associated with significantly lower odds of severe injury compared to being in the second seat, which this consistent with existing studies (Steps Jermakian et al., 2008). This suggests that the seating position within the vehicle may offer some protective benefit, possibly due to better safety features in the front seats, like airbags. This result implies that improving safety measures for those in less protected seating positions (e.g., second seats) could potentially reduce injury severity, especially in older vehicles that may lack modern safety features.

5.3.4. Roadway Alignment

The roadway alignment and EMS response time variables also exhibit moderate effects. With a mode of 2.13 and an HDI range from 0.88 to 4.69, roadway alignment, particularly curved roads, increases the odds of higher injury severity. It is an established finding that crashes that occur on curved roadways are often more severe than straight road accidents (Zhu et al., 2019). Uncertainty, however, suggests that this effect could vary across different scenarios. This highlights the need for road design improvements, particularly in rural areas where winding or poorly marked roads may pose increased risks.

5.3.5. EMS Response Time

Regarding EMS response time, show a mode of 1.05 and an HDI ranging from 0.74 to 1.48, suggesting that delays in EMS response might slightly increase the odds of higher injury severity. This is an established finding as (Hosseinzadeh & Kluger, 2021) suggests that while faster EMS response times alone did not reduce injury severity, a combination of quicker response times and slower on-scene times was linked to less severe injuries, particularly those involving the whole body. This result suggests that improving EMS response times could be a key factor in reducing injury severity, especially for elderly drivers in rural settings.

5.3.6. Roadway Surface Conditions

Lastly, roadway surface conditions exhibit a similar effect with a mode of 1.06 and an HDI range from 0.7 to 1.58. While the effect is modest, the findings suggest that wet, snowy, or icy conditions could slightly increase the odds of higher injury severity. As snow and ice on pavements significantly increase the risk of crashes by decreasing pavement friction (Walker et al., 2024). Alcohol involvement and speed limit appeared to have minimal effects on injury severity. The uncertainty in the results, indicated by the high-density intervals (HDI) for both alcohol involvement (0.75 to 1.23) and speed limit (mode of 0.99 with a narrow HDI), suggests that these factors may not significantly impact injury severity.

6. CONCLUSIONS

Roadway crashes remain a critical public safety issue, with older drivers disproportionately affected due to their increased fragility and challenges in navigating high-speed traffic and complex intersections. Research indicates that age-related factors, such as reduced gap selection ability and maneuvering difficulties, contribute to the higher fatality rates among elderly drivers. Additionally, substance use has been shown to exacerbate crash injury severity among older individuals, particularly in rural areas. While service access to emergency medical services (EMS) is vital for ensuring timely post-crash care, elderly individuals in rural communities often face significant barriers due to geographic isolation and inadequate healthcare infrastructure. Limited EMS availability and prolonged response times further increase the risk of adverse health outcomes for older crash victims. Although Geographic Information Systems (GIS) and spatial access measures have the potential to enhance emergency response planning, their full capabilities remain underutilized. Addressing these difficulties requires targeted policies and infrastructure improvements to improve EMS access for aging populations in rural areas. Ensuring timely medical intervention is essential to reducing fatality rates and improving post-crash recovery outcomes among elderly drivers.

However, a significant gap in existing research is the consideration of roadway crashes as unpredictable events that impact EMS service availability, particularly for elderly drivers in rural

areas. While general spatial access to healthcare has been extensively studied, the unique challenges posed by emergencies remain underexplored. This project seeks to bridge this gap by employing the Enhanced Two-Stage Floating Catchment Area (E2FCA) method to estimate EMS service access in the context of crash incidents. A key focus is identifying socio-economic factors that influence access to emergency services for aging populations in rural communities. Additionally, the study examines how EMS response time and other contextual factors contribute to injury severity among elderly crash victims. Using Bayesian Ordinal Logistic Regression and data from the Fatality Analysis Reporting System (FARS), this research aims to provide a detailed understanding of the variables influencing post-crash outcomes. The hypothesis suggests that prolonged EMS response times, combined with factors such as alcohol use, roadway conditions, and driver unfamiliarity, exacerbate injury severity and fatality risks. The findings will support the development of targeted policy interventions and infrastructure improvements to enhance EMS response efficiency and improve post-crash care for elderly rural drivers.

This project utilized detailed crash incident data from the Ohio Department of Public Safety and EMS location data from the Homeland Infrastructure Foundation-Level Data to analyze EMS service availability for elderly drivers in rural Ohio. By incorporating socio-economic data from the Census Bureau and network density attributes from the Smart Location Database, the analysis employed the Enhanced Two-Step Floating Catchment Area (E2SFCA) method to assess EMS service access. A generalized linear model with an inverse power function and the Gamma family was used to examine the relationship between EMS service availability and various demographic and socio-economic factors.

The findings reveal significant variability in EMS service access across rural Ohio, with extensive rural regions marked by the lowest levels of service availability and rural regions adjacent to urban areas benefiting from higher service availability. Network density emerged as a strong positive predictor of EMS service access, while higher insurance coverage and employment status were also positively associated with improved service availability. Conversely, higher education levels were unexpectedly linked to lower EMS service availability, and racial composition did not show a significant direct impact. These insights highlight the need for targeted interventions to improve EMS response times and healthcare outcomes, particularly in central rural areas with the lowest service access levels. Addressing these difficulties is crucial for enhancing emergency medical services and ensuring timely responses for vulnerable populations in rural settings.

Moreover, the findings of this project highlight the significant factors that contribute to injury severity among elderly rural drivers, with particular focus on EMS response times, roadway conditions, and individual characteristics. The findings suggest that longer EMS response times, coupled with adverse roadway conditions, such as icy or snowy surfaces and curved roadways, significantly increase the likelihood of severe injuries. Additionally, certain factors like gender and seating position offer insight into how vehicle dynamics and personal attributes can affect crash outcomes. While the results suggest that factors such as alcohol involvement and speed limit have a relatively modest impact on injury severity, they still underscore the need to focus on more impactful variables, such as EMS transport, which showed a strong association with higher injury severity. This study's findings emphasize the vulnerability of elderly drivers in rural settings and the importance of improving emergency response times and roadway safety

measures to reduce injury severity in this population. The implications of these findings are crucial for informing policy and safety interventions aimed at reducing injury severity among elderly rural drivers, particularly in the context of EMS response efficiency and roadway safety.

This research also raises important questions about how other contextual factors, such as the experience and driving habits of elderly drivers, might influence injury outcomes in rural crashes. While EMS response times and roadway conditions play a significant role, further investigation is needed to explore the effects of road maintenance practices, vehicle safety features, and broader social determinants on injury severity. Additionally, the role of alcohol and speed limits in elderly driver crashes warrants further exploration to determine whether their modest effects could be compounded by other risk factors. Ultimately, this study opens the door to continued research that can drive improvements in both emergency response systems and rural infrastructure, to enhance safety and reduce injury severity among elderly drivers in vulnerable rural areas.

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