Evaluating Post-Crash Care Availability of Emergency Medical Services (EMS) to Elderly Groups 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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DISCLAIMER

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 populations in rural areas face increased risks following motor vehicle crashes due to longer emergency medical services (EMS) response and limited access to hospital care. This study aimed to evaluate post-crash EMS care availability for older adults in rural Ohio, with a focus on identifying delays and testing strategies to improve timely access. We analyzed linked EMS and crash data, classifying incidents by rural and urban status using Rural-Urban Commuting Area (RUCA) codes. Hierarchical Bayesian survival models identified key factors contributing to EMS delays, such as distance to care, multi-patient incidents, adverse weather, and time of occurrence. Spatial optimization models, including joint EMS station and hospital siting, were applied to assess the impact of coordinated planning on service coverage. Results showed that joint coverage approaches increased the proportion of rural elderly residents reached within critical time thresholds, highlighting the benefits of integrated facility planning. The findings support recommendations for expanding EMS coverage, adopting joint planning models, and updating protocols to better serve older adults in rural communities.

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EXECUTIVE SUMMARY

This report evaluates the availability and effectiveness of Emergency Medical Services (EMS) for elderly populations in rural Ohio following motor vehicle crashes. The primary purpose is to identify gaps in EMS response and hospital access for older adults and to recommend strategies that can improve outcomes. As the elderly population grows, especially in rural areas, timely emergency care becomes increasingly critical. Existing EMS systems often fail to reach rural elderly patients within optimal timeframes, leading to higher risks of severe injury and mortality. The study's focus is on understanding the drivers of prehospital delays and testing solutions to reduce these delays. This work aims to guide EMS planners, policymakers, and public health leaders in making evidence-based improvements.

The problem addressed is the persistent delay in EMS response and hospital transport for elderly crash victims in rural communities. Factors such as long travel distances, limited EMS station coverage, complex patient needs, adverse weather, and multi-patient crashes contribute to these delays. Older adults experience the longest on-scene times, making them especially vulnerable. Disparities between rural and urban areas are clear, with rural residents facing consistently slower access to definitive care. These delays have significant consequences for survival and recovery. Without targeted interventions, gaps in rural emergency care for the elderly will likely widen as demographic trends continue.

To analyze the problem, the study used linked EMS and crash data from Ohio. We classified incidents by rural and urban status using Rural-Urban Commuting Area (RUCA) codes. Hierarchical Bayesian survival models identified key predictors of EMS delays, such as geographic proximity, environmental conditions, and timing of incidents. Spatial optimization models, including joint EMS station and hospital coverage scenarios, were applied to test how facility placement affects timely access to care. Results were evaluated by the share of elderly residents reached within critical time thresholds. The methods provided a comprehensive assessment of both operational and system-level factors affecting EMS performance.

Analysis revealed that coordinated planning of EMS stations and hospital locations significantly improved timely care for elderly crash victims in rural areas. Joint coverage strategies increased the proportion of elderly residents reached within key response and transport windows. The study recommends expanding EMS coverage in high-risk rural regions, adopting joint facility planning models, and updating protocols for elderly care. Agencies should invest in adaptive staffing and cross-agency coordination, especially for weekends and severe weather events. Continuous monitoring and data-driven adjustments are essential for maintaining high-quality EMS performance. Policymakers should act on these findings to reduce preventable delays and improve survival outcomes for older adults in rural communities.

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1. INTRODUCTION

This section sets the stage for the current research, which examines how Emergency Medical Services (EMS) deliver post-crash care to elderly populations in rural areas. The introduction is organized into the following subsections: (1) the role and challenges of rural EMS for elderly populations; (2) the impact of the golden hour and time-sensitive barriers to care; (3) EMS coverage constraints and service availability in rural regions; (4) project objectives; (5) the project's relevance to R-SEAT research thrusts and the USDOT Strategic Plan; and (6) an overview of the report structure.

1.1. Role and Challenge of Rural EMS for Elderly Populations

Emergency medical services (EMS) improve the survival and recovery of individuals sustaining injuries in road crashes, acting as the essential link between the incident scene and hospital care (Huabbangyang et al., 2021; Kitano et al., 2022). Geographic differences persist in EMS coverage and responsiveness. Rural residents often experience longer response and transport times than their urban counterparts (Alanazy et al., 2020; Alruwaili & Alanazy, 2022). These differences contribute to increased mortality and worse recovery for rural crash victims, underscoring the importance of rapid EMS intervention within the critical "golden hour" (Fatovich et al., 2011; Haider Khan et al., 2024; Lee et al., 2014; Lotfi et al., 2019; Newgard et al., 2010a). A combination of factors, including wide coverage areas, reliance on volunteer staff, resource limitations, and fragmented service networks, makes EMS delivery especially challenging in rural regions (Jonk et al., 2023; King et al., 2019; Nguyen & Shenoy, 2025).

While the need for timely emergency care is universal, there remains a limited understanding of the operational factors that cause delays and access barriers. Figure 1 shows that EMS incidents are concentrated in certain U.S. regions, with the South accounting for the largest share, followed by the Midwest, West, and Northeast. This pattern indicates heavier EMS workloads in specific regions of the country. These patterns highlight why understanding regional and age-based service demands is critical for evaluating EMS availability for elderly groups in rural areas. Rural areas have a larger share of older residents, and older adults experience a disproportionately higher fatal crash rate. As shown in Figure 2, drivers aged 65+ consistently have a higher fatality rate per 100,000 population compared to younger drivers. Moreover, they have significantly higher incidences of cardiac arrest and stroke compared to younger cohorts (L. Li et al., 2022). In fact, roughly one in three EMS calls in the United States now involves a patient over 65, underscoring the high baseline demand for urgent care among aging populations (Duong et al., 2018). As shown in Figure 3, the highest number of EMS calls involve adults aged 61 to 80, making older adults a major focus for emergency response systems nationwide.

Elderly adults face worse outcomes in road crashes than younger adults, due to age-related frailty and comorbidities (Cunha-Diniz et al., 2023; De Simone et al., 2024). One nationwide analysis revealed that advanced age is an independent predictor of mortality. Patients aged 65 or older in this study had over six times higher odds of death after injury than those under 18, even when controlling for injury severity (Jarman et al., 2016). The inherent vulnerability of older patients is compounded in resource-limited or remote regions that often lack timely EMS care. Furthermore, severe injuries in older patients present numerous challenges for prehospital providers, leading to high rates of undertriage and potential age bias in the field (Eichinger et al., 2021). A study found that older patients had significantly longer on-scene intervals than younger patients (Ordoobadi et al., 2022). This points to a potential issue where the assessment and stabilization of older patients in the field is time consuming**.**

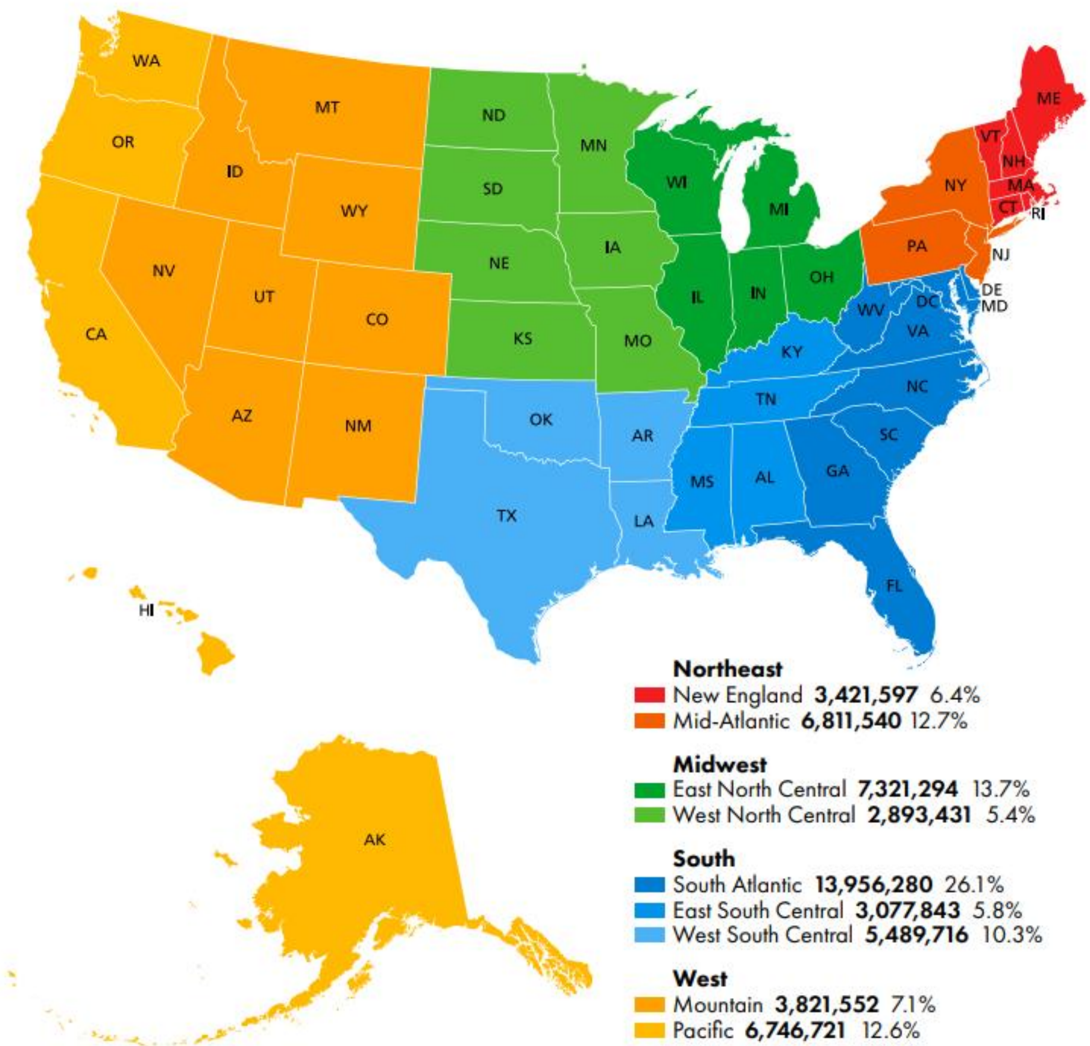

Figure 1: Share of EMS Incidents by U.S. Region (2022); Source - NEMSIS End of Year Report 2023

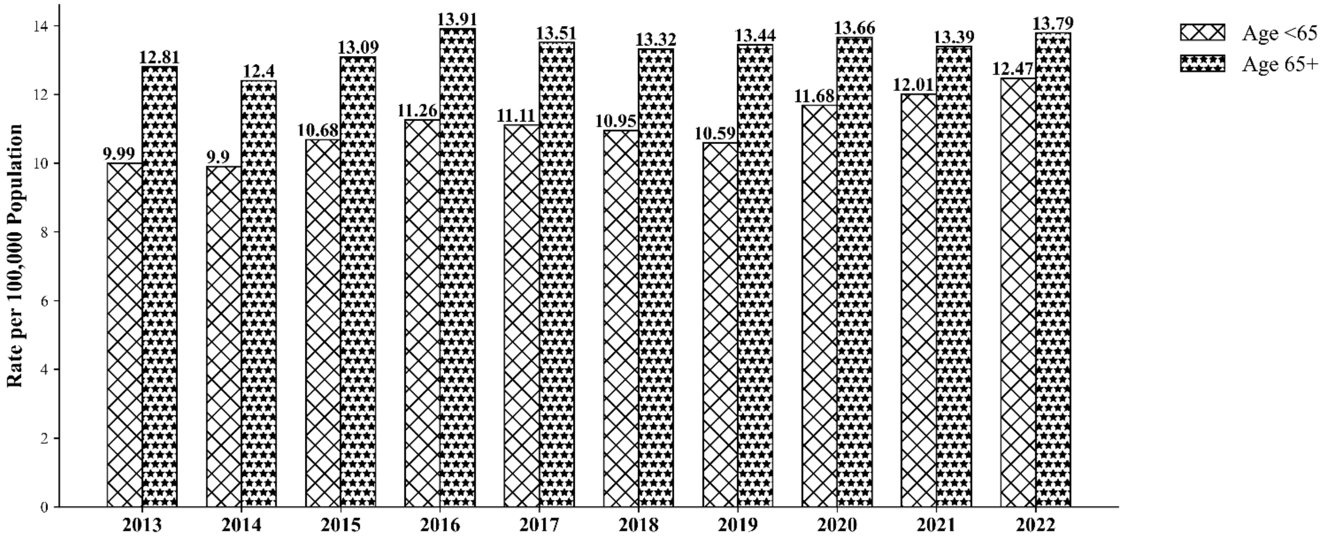

Figure 2: Fatality Rates per 100,000 Population, by Age Group, 2013–2022, Source: FARS 2013–2021 Final File, 2022 Annual Report File (ARF); Population – Census Bureau

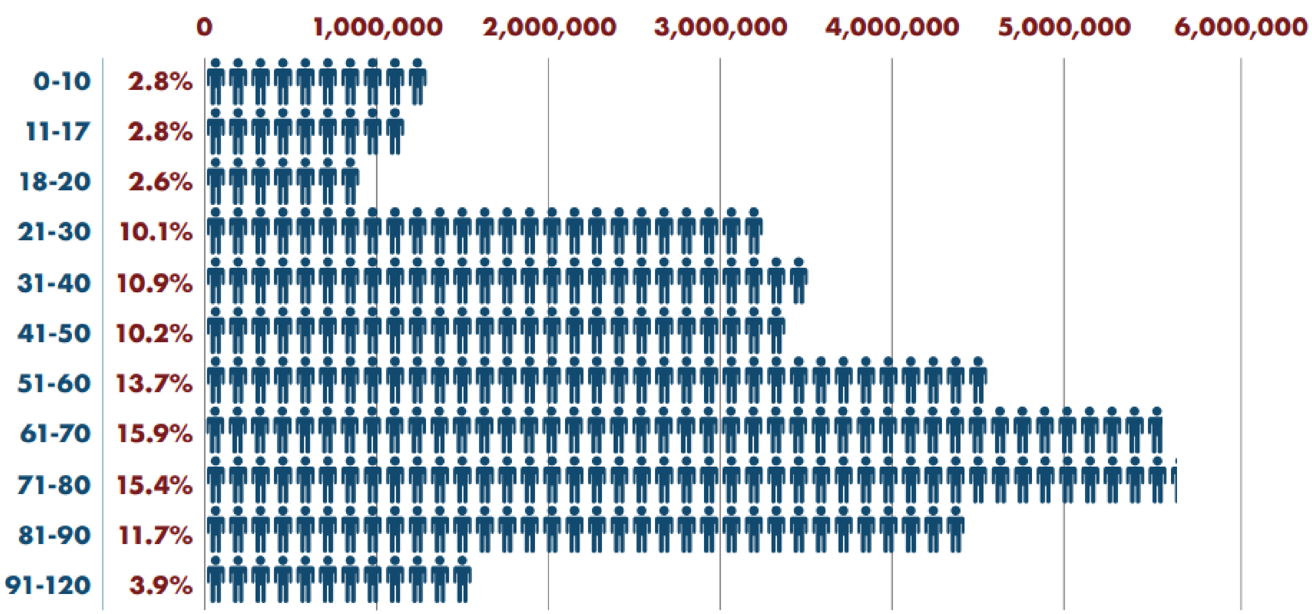

Figure 3: Number and Percentage of EMS Calls by Age Group in the U.S.; Source: NEMSIS End of Year Report 2023

1.2. Golden Hour and Time-Sensitive Barriers to Care

EMS are essential to the chain of survival, providing timely prehospital care and transport to patients with critical illnesses and injuries to definitive care. In this context, "definitive care" refers to treatment at a hospital or trauma center with the resources to fully manage and resolve the patient's emergency. Timely EMS response is widely recognized as a determinant of patient outcomes in time-sensitive emergencies such as trauma, cardiac arrest, and stroke (Bhattarai et al., 2023; Damdin et al., 2025). Around the world, health systems strive to ensure that EMS can reach patients quickly and transport them to appropriate hospitals within critical time frames.

National guidelines, such as those from the National Fire Protection Association (NFPA), set an 8-minute target for EMS response to life-threatening emergencies. The standard for reaching definitive care, often called the "Golden Hour," is to deliver the patient to a hospital within 60 minutes (Alanazy et al., 2019; Alshammari et al., 2024; Newgard et al., 2010b). Prehospital emergency care is now recognized as a crucial part of healthcare that directly affects outcomes for injuries and acute illnesses. Prior research has estimated that well-organized prehospital systems can reduce trauma mortality by about 25% (Delaney et al., 2024). Ensuring timely EMS access is a priority in both traffic engineering and health planning, making resource allocation and optimization essential.

1.3. Rural EMS Coverage Constraints and Service Availability

Despite its critical importance, timely EMS coverage is often inadequate across different regions and populations. In the United States (U.S.), for instance, approximately 29.7 million people (nearly 10% of the population) do not have access to a Level I or II trauma centre within one hour by road or air ambulance (Carr et al., 2017). These populations without timely trauma care are predominant in rural areas (Jonk et al., 2023; King et al., 2019; Nguyen & Shenoy, 2025). Research shows that longer emergency response times are associated with significantly higher mortality rates for critical conditions; a nationwide study in the U.S. found that in motor vehicle crashes, EMS responses of more than 12 minutes (vs. under 7 minutes) were associated with 46% increase in mortality risk (Byrne et al., 2019). Furthermore, an influential analysis showed that patients reached by EMS within 5 minutes had much better survival rates, beyond 5–8 minutes the probability of survival flattened at a lower level (Blackwell & Kaufman, 2002). Every minute of delay in treating life-threatening emergencies sharply reduces patient survival, yet delivering rapid EMS coverage everywhere is logistically and resource intensive. Rural areas are often outside standard response radii because ambulance stations and hospitals are few. Research shows that prehospital care timelines are longer in rural areas than in urban areas (Arcury et al., 2005; King et al., 2019; Mell et al., 2017).

1.4. Project Objectives

Ensuring timely and effective post-crash care for elderly individuals in rural areas is a growing challenge, as these populations face heightened risks and limited access to EMS following motor vehicle crashes. Geographic barriers, resource constraints, and evolving population patterns necessitate new approaches to understanding and improving EMS coverage and performance. This project addresses these challenges by integrating advanced modeling of EMS timelines and optimizing the spatial allocation of EMS and hospital resources to better serve elderly crash victims in rural settings. The following primary objectives guide this research:

Primary Objectives:

i. Evaluate differences in prehospital EMS timelines for elderly crash victims between rural and urban areas, focusing on response, on-scene, and transport phases of care.
ii. Identify key crash, environmental, and situational factors associated with prolonged EMS timelines for older adults, with particular attention to rural contexts.
iii. Assess how geographic proximity and community-level conditions influence the availability and effectiveness of post-crash EMS care for elderly populations.
iv. Examine whether coordinating EMS station placement and hospital access improves timely emergency response and transport for elderly residents in rural areas.
v. Evaluate the potential for joint EMS and hospital coverage strategies to reduce delays in post-crash care and increase the share of rural elderly populations receiving timely emergency services.
vi. Develop recommendations for EMS planners and policymakers aimed at optimizing base locations, refining prehospital protocols, and improving emergency care outcomes for older adults in rural areas.

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

This project directly supports R-SEAT Center research thrusts and advances several USDOT strategic goals through the following themes:

Service Availability: The project evaluates the availability and effectiveness of post-crash EMS care for elderly populations in rural areas, identifying where and why gaps persist in timely emergency response. By analyzing EMS response times, transport durations, and overall system coverage, the research provides actionable evidence on how limited EMS resources and geographic barriers impact critical care for older adults following motor vehicle crashes. The findings will inform strategies to improve EMS system planning, resource allocation, and deployment, ultimately supporting more reliable and equitable access to emergency care for rural communities.

Safety of Vulnerable Road Users: This research advances safety for vulnerable road users by focusing on elderly individuals involved in rural motor vehicle crashes. Older adults in these settings face higher fatality and injury risks due to frailty, slower emergency response, and fewer local medical resources. The project quantifies EMS response times and access barriers for elderly crash victims, offering insight into where timely care is most likely to fall short. It identifies specific gaps in both EMS and hospital coverage. These findings enable targeted improvements in station siting, route planning, and prehospital protocols. This approach supports the USDOT's Safe System Approach by reducing severe outcomes for aging populations. Policymakers and practitioners will gain actionable data to guide strategies that protect older adults 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, 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 several major goals outlined in the USDOT 2022–2026 Strategic Plan. These include: (1) improving the safety of transportation systems and their users through enhanced emergency response (2) expanding access to timely EMS and hospital care for vulnerable populations in rural communities (3) developing data-driven decision support tools for EMS planning and resource allocation and (4) informing new policies and procedures tailored to the needs of elderly crash victims, with a particular focus on post-crash care in low-density rural settings.

1.6. Report Structure

The report is organized as follows: Section 1 introduces the study by outlining the role and challenges of rural EMS for elderly populations, discussing the importance of the golden hour and time-sensitive barriers to care, describing coverage constraints, and presenting the project objectives and policy relevance to the R-SEAT research thrusts and the USDOT Strategic Plan. Section 2 presents the literature review, covering EMS operational time intervals and prehospital delays, rural–urban comparisons of EMS timelines, the evolution of EMS facility location and optimization models, and a synthesis of key findings and gaps in the literature. Section 3 describes the study area and data, including the selection of the study region, EMS and crash incident data, and the spatial, facility, and population datasets used for system optimization. Section 4 details the methods, beginning with the analytical framework for evaluating EMS timelines and contextual factors, followed by the spatial optimization framework for coordinated EMS and hospital coverage, candidate site selection, model specifications, variable definitions, and the formulations of the overall and joint coverage models. Section 5 presents and discusses the results, including rural–urban comparisons of EMS delays, the role of crash and environmental context, and the outcomes of spatial optimization analyses for improving EMS response and hospital access. Finally, Section 6 summarizes the main conclusions and implications of the study, followed by references and appendices.

2. LITERATURE REVIEW

The literature is organized into four subsections. The first subsection synthesizes evidence on EMS operational time intervals and their variation across geographic and demographic contexts, with a focus on elderly patients. The second subsection reviews studies that link crash characteristics and contextual factors to rural–urban differences in EMS performance and outcomes. The final subsection focuses on joint coverage spatial optimization models and identifies gaps in their application to rural, crash-prone environments, motivating the need for the present study.

2.1. EMS Operational Time Intervals and Prehospital Delays

Prompt EMS intervention improves outcomes in life-threatening emergencies such as highway crashes. EMS performance is often gauged by operational time intervals such as response time (911 call to EMS arrival), on-scene time (arrival to departure from scene), and transport time (scene departure to hospital arrival) (Alruwaili & Alanazy, 2022). Research suggests that a considerable percentage of prehospital deaths could be avoided with accelerated EMS response times (Beck et al., 2019; Eftekhari et al., 2019; Huang et al., 2024; Oliver et al., 2017). A growing body of evidence reveals that EMS time intervals are not uniform. Variations exist across different geographic and demographic contexts. For instance, national U.S. data show urban/suburban 911 response times average 7 minutes, versus over 14 minutes in rural areas, where nearly 10% of incidents wait almost 30 minutes (Mell et al., 2017). EMS timelines can also be influenced by patient population characteristics. Older patients tend to require longer on-scene assessment and management. Research consistently shows prolonged scene times for older trauma victims (Harthi et al., 2025; Ordoobadi et al., 2022).

Multiple studies have documented broad variations in EMS performance by geography and transport times. Multivariable analyses have been applied to evaluate the simultaneous effects of crash features and contextual factors on prehospital timelines (Hartka et al., 2021; Ngekeng et al., 2024; Verma et al., 2023). Existing research has identified several individual predictors of delayed EMS response or prolonged on-scene time. Advanced patient age, severe injuries, nighttime or weekend incidents, adverse weather, and rural locations have all been associated with slower EMS operational times and lower survival outcomes (Abdelrahman et al., 2021; Nwanna-Nzewunwa et al., 2022; Ueno et al., 2024; Vanga et al., 2022a). To gain a comprehensive understanding, studies have drawn on multiple data sources, linking EMS time metrics with crash characteristics

(Hosseinzadeh et al., 2022; Hosseinzadeh & Kluger, 2021a). Nevertheless, an examination centered on elderly adults in this context remains limited. Therefore, this study aims to evaluate factors influencing EMS prehospital time for older adults involved in crashes across various geographical settings.

2.2. Comparative Analysis of EMS Timelines in Rural and Urban Settings

Several studies have identified differences in EMS operational timelines between rural and urban areas as summarized in Table 1. Higher rates of prehospital mortality in rural regions compared to urban settings, particularly for elderly adults (Li et al., 2008). Similarly, they are reported to face a greater risk of severe injury and fatality rates due to delayed EMS response in rural areas (Adeyemi et al., 2022; Lee et al., 2018). The built environment plays a key role, with factors like distance to EMS facilities and road classifications significantly affecting response delays (Fu et al., 2022). Research also indicates that weather conditions, weekend incidents, and nighttime crashes significantly contribute to prolonged EMS times in rural areas (Vanga et al., 2022b). Age-related vulnerabilities thus compound the negative impacts of rural EMS delays. Furthermore, there are variations in EMS resource availability and dispatch challenges in remote areas.

Table 1: Summary of Studies Linking Crash and EMS Data on Rural-urban EMS Operational Timelines

Author (Year)	Contribution	Model	Findings
Li 2008 (Li et al., 2008)	Characterized geographic differences in accident factors and medical service use for traffic fatalities.	Log-linear analysis	Older age groups (60+) showed geographic interactions, but rural areas had more unrestrained victims and higher pre-hospital mortality, likely from delayed EMS.
Lee 2018 (Lee et al., 2018)	Examined the effects of EMS prehospital time intervals on injury severity across urban and rural areas.	Random effects ordered probit	Older adults (65+) in rural areas faced a compounded risk of severe injury due to delayed EMS.
Byrne 2019(Byrne et al., 2019)	Assessed the association between county-level EMS response times and motor vehicle crash mortality.	Hierarchical negative binomial regression model	Longer EMS times increased rural and crash mortality.
Hosseinzadeh 2021(Hosseinzadeh & Kluger, 2021b)	Investigated the impact of EMS times and crash-related variables on injury severity using linked police crash and EMS data.	Random effects ordered probit	Older individuals tended to have more severe injuries. Urban/suburban areas had relatively fast EMS response.
Li 2022(X. Li et al., 2022)	Examined how various EMS response	Parametric Survival Models	Older patients (>75 years) were significantly associated with longer on-scene delays.

	characteristics influence delays.		
Adeyemi 2022(Adeyemi et al., 2022)	Assessed rural-urban differences in crash response times and county-level crash fatalities.	Spatial negative binomial regression	Rural areas showed higher fatality rates despite lower crash counts, highlighting disparities in EMS access and outcomes.
Fu 2022(Fu et al., 2022)	Examined how built environment factors influence EMS response times to traffic crashes	Hierarchical ordered logit model	Rural crashes were more likely to experience EMS delays over 10 minutes.
Vanga 2022(Vanga et al., 2022b)	Investigated the influence of crash-related and environmental variables on EMS response time.	Geographically Weighted Regression (GWR)	EMS response times increased with longer travel times, worse weather, nighttime, and weekend crashes.
Ito 2022(Ito et al., 2022)	Examined factors influencing EMS on-scene time for road traffic injury patients.	Generalized linear mixed model (GLMM)	Elderly patients (≥65 years) experienced an additional 1.51 minutes on scene compared to younger patients.
Jung 2024(Jung & Qin, 2024)	Assessed and recommend EMS infrastructure expansion to reduce crash fatalities.	Random Forest & geographically weighted Binary Logit Regression	EMS response and transport times are significantly longer in rural
Babanezhad 2025(Babanezhad et al., 2025a)	Forecasted ambulance demand for traffic accident-related EMS calls	Time Series: Arima Models	Prehospital times were significantly longer on rural roads than in city locations

This research attempts to explore how crashes and contextual factors collectively influence prehospital EMS timelines for elderly drivers involved in crashes. We employ a hierarchical Bayesian survival modeling framework. We compare total prehospital EMS time, encompassing dispatch, response, on-scene stabilization, and transport to the hospital (see Figure 4), between rural and urban crash incidents involving older drivers. This approach allows for a nuanced examination of factors how EMS operations differ across geographic settings. Findings of this study aim to offer deeper insight into EMS timeline differences by explicitly modeling interactions among crash circumstances and contextual elements (e.g., temporal characteristics and environmental conditions). This research attempts to offer evidence to inform EMS operational policies and resource allocation strategies tailored to elderly crash victims. By applying advanced hierarchical Bayesian survival models, this study examines the combined duration of EMS response, on-scene, and transport times. The analysis focuses on both urban and rural crash locations to uncover key factors driving disparities. Findings from this work will support targeted interventions and more efficient resource allocation to improve EMS timeliness, especially for vulnerable older adults in rural areas.

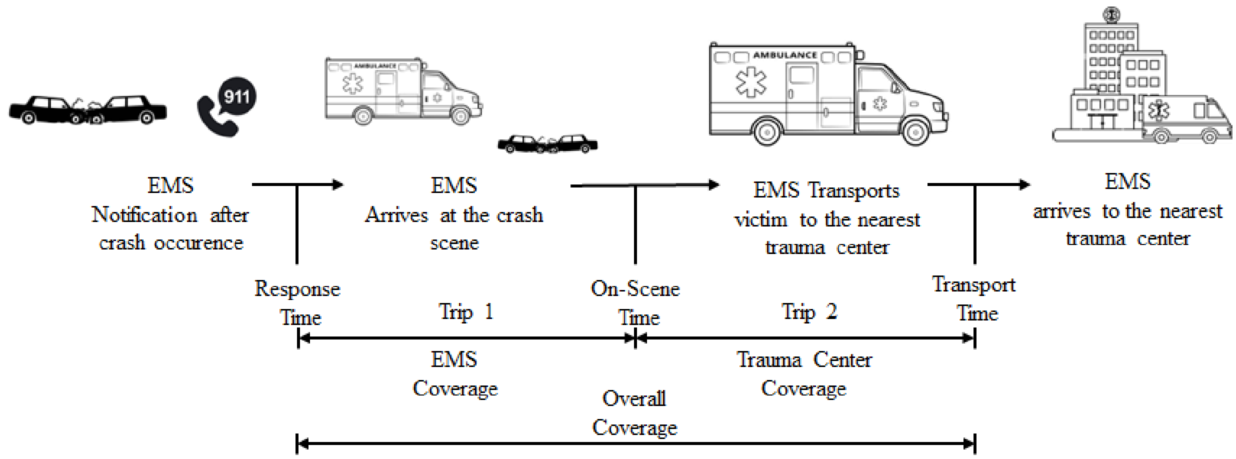

Figure 4: Breakdown of EMS and Trauma Centre/hospital Coverage Trips

2.3. Evolution of EMS Facility Location and Optimization Models

Addressing EMS coverage gaps is fundamentally a problem of optimal resource allocation. Classic covering models such as the Location Set Covering Problem (LSCP) and the Maximal Covering Location Problem (MCLP) were developed in the 1970s to guide the placement of emergency services and public facilities (Church & Revelle, 1974; Murray, 2016). Their goal is to achieve maximum coverage efficiency across a given area. MCLP locates a fixed number of service facilities such that the greatest possible demand (population) is covered within a given response distance or time. Over the decades, numerous studies around the world have applied MCLP and its variants to EMS planning from locating ambulance posts in rural Spanish provinces (Yin & Mu, 2012), to siting helicopter emergency medical bases in sparsely populated regions of Iceland and Norway (Gunnarsson et al., 2023; Røislien et al., 2017), to optimizing urban ambulance station locations in dense cities in China (Deng et al., 2021; Luo et al., 2025). These models usually focus on just one stage of service coverage. They either ensure an ambulance reaches the scene within a set response time or that patients are transported to a hospital within a total time limit.

Early EMS facility location models drew on classic facility location theory, including coverage and median-based formulations such as the LSCP, MCLP, and p-median problem. These frameworks have been widely used to optimize ambulance post or hospital siting separately, focusing either on covering demand points or on reducing response distances (Abdul Ghani & Ahmad, 2017; Church & Revelle, 1974; Ghani & Ruslim, 2006; Yin & Mu, 2012). This separation reflects the mathematical simplicity of optimizing one objective at a time, making these models easier to formulate and solve. Most early studies focused on single-stage objectives, such coverage or mean distance, without linking the full care pathway from incident to definitive care (Jang et al., 2021; Jánošíková et al., 2021; Newgard et al., 2010c). Traditional EMS location models generally optimize a single service leg, either ambulance response or patient transport without jointly modeling both stages of the prehospital care continuum (Khalilzadeh & Bahari, 2023; Shetab-Boushehri et al., 2022).

Recent advances have expanded the scope of EMS location modeling by integrating prehospital response with definitive care pathways. Emerging frameworks such as the Edge Maximal Covering Location Problem (EMCLP), hybrid DEA–MCLP models, multi-period capacitated formulations (EMSLSP), and joint coverage approaches reflect this methodological evolution (Luo et al., 2025; Mohri et al., 2020; Mohri & Haghshenas, 2021; Zhang et al., 2024). These models introduce severity weighting, backup coverage, facility capacity constraints, probabilistic demand, and dynamic travel times. Two-stage formulations, in particular, capture both the ambulance's response to the scene and the patient's subsequent transport to a hospital an essential linkage for time-critical conditions such as trauma and stroke (Gago-Carro et al., 2024; Zhang et al., 2019).

Among these, Luo et al., (2025) developed a joint coverage model (MCLP-JC) that simultaneously locates EMS bases and emergency centers to optimize both critical trips within the care continuum. In the Wuhan stroke care study, the MCLP-JC model increased the share of the population covered by both timely ambulance response (within 10 minutes) and overall delivery to definitive care within the "golden hour" from 83.3% (MCLP-OC) to 93.2%. This means the MCLP-JC covered nearly 10% more of the population with both rapid response and timely hospital arrival. The total population covered within 60 minutes remained similar between models (98.9% for MCLP-OC vs. 98.8% for MCLP-JC). Similar integrated formulations mark an important step toward system-level EMS planning. However, their applications remain largely confined to urban or high-density regions and generalized patient populations. Limited attention has been given to crash-prone or rural contexts, where sparse infrastructure and long transport times require specialized strategies (Amorim et al., 2017; Desai et al., 2023).

Generally, the progression of EMS facility location modeling demonstrates increasing sophistication in integrating multiple stages of emergency care and operational constraints. However, significant research gaps persist in adapting models to low-density rural environments with elevated emergency care needs, where traditional frameworks may not adequately address spatial risk heterogeneity or network sparsity. Advancing the field requires combining joint coverage optimization with empirically derived risk data and realistic travel time estimation to better represent rural EMS system demands. The present study addresses these needs by leveraging multi-criteria candidate site selection and systematically evaluating joint versus single-stage optimization in a rural context.

Recent spatial optimization models with Joint Coverage (MCLP-JC) and with Overall Coverage (MCLP-OC) have improved EMS planning by considering both ambulance and hospital locations together. These approaches aim to ensure timely prehospital response and patient transport by covering both stages in the emergency care process. However, relying solely on total prehospital travel time as a single measure risks overlooking critical delays in rapid on-scene response within the golden hour a gap highlighted in the literature as shown in Figure 4. To address this, we apply the two spatial optimization models MCLP-OC and MCLP-JC. Luo et al., (2025) applied a similar joint optimization approach for ambulances and emergency centers in urban Wuhan, China, demonstrating its benefits in densely populated areas. Yet, there remains limited understanding of how these approaches perform in rural settings with dispersed populations and elevated crash risk.

2.4. Literature Summary

The literature points to two essential themes guiding this project. First, a substantial body of research finds that EMS prehospital timelines covering dispatch, response, on-scene care, and transport to the hospital are shaped by geography, crash context, and patient characteristics. These timelines are not uniform. Elderly crash victims in rural areas routinely experience longer waits for care compared to their urban peers. Contributing factors include longer distances to emergency centers, more complex on-scene assessments, resource constraints, and challenging weather or roadway conditions. Such delays are linked to poorer outcomes, including higher rates of severe injury and fatality. While prior studies have documented these issues and outlined relevant risk factors, relatively few have examined how these factors interact for older adults, or modeled timelines in ways that support targeted EMS improvements for rural populations.

Second, advances in EMS system design show that traditional location models focused on either ambulance response or hospital transport alone may be insufficient for maximizing patient outcomes. Joint coverage models, which coordinate siting for both EMS stations and hospitals, have demonstrated improved access to timely care in some settings. These models account for both the initial EMS response and the transport leg to definitive care. However, most published applications are urban-focused or use generalized populations, leaving questions about how such models perform in the rural context. The literature highlights the need for spatial optimization frameworks that incorporate crash risk, realistic travel times, and the unique demands of elderly patients in low-density regions. Addressing these knowledge gaps will help inform practical strategies to improve post-crash care for vulnerable rural communities.

3. STUDY AREA & DATA

This section describes the geographic focus and data sources supporting the project's analysis of post-crash EMS care for elderly populations. We outline the criteria for selecting the study area and detail how rural and urban environments were classified. Key data sets used for evaluating crash risk, EMS coverage, and population characteristics are also introduced.

3.1. Study Area

For the first two primary objectives of the study all events were considered for the entire state of Ohio. Rural and urban status for each crash and EMS incident was classified using the Rural-Urban Commuting Area (RUCA) codes based on patient ZIP codes. RUCA codes provide a detailed geographic classification scheme that accounts for population density, urbanization, and daily commuting patterns, enabling a nuanced differentiation between rural, suburban, and urban areas. By linking ZIP codes to RUCA classifications, we were able to categorize incidents consistently and accurately within the Ohio study area.

For the optimization part of the study the study area was identified using a data-driven approach to pinpoint where EMS coverage most urgently lags behind the observed burden of crashes. We quantified this burden as the number of crashes involving drivers or occupants aged 65 and older, aggregated at the county level. A standardized mismatch score was calculated for all counties in Ohio as the difference between each county's z-score for elderly-involved crash counts and its z-score for EMS station density, as shown in Equations 1 and 2. Madison County had the highest mismatch score (1.43). Fayette and Pickaway counties, which are adjacent to Madison, were included due to their spatial proximity and similarly high imbalance values, as illustrated in Figure 5 for the top 15 counties.

$$\mathrm{Mismatch_i} = \mathrm{z(CrashCount_i)} - \mathrm{z(EMS_i)} \tag{1}$$

$$z(x) = \frac{x-\bar{x}}{s_x} \tag{2}$$

Madison, Pickaway, and Fayette counties are mostly rural areas in central Ohio as shown in Figure 6, with populations of about 44,000, 56,000, and 29,000, respectively (USA.COM, 2025). These counties have an appreciably aging demographic profile. For instance, according to the latest estimates, approximately 22.2% of Pickaway County's population is 65 or older compared with 17.7% nationwide (Neilsberg, 2025). The growing share of older adults since 2010 has increased healthcare pressures (Ogugua et al., 2024). An older population typically has higher medical needs, which strains local services and increases demand for timely EMS and hospital care. Geographically, the counties are traversed by major highways, and many residents live in dispersed communities, characterized by longer travel distances to medical facilities.

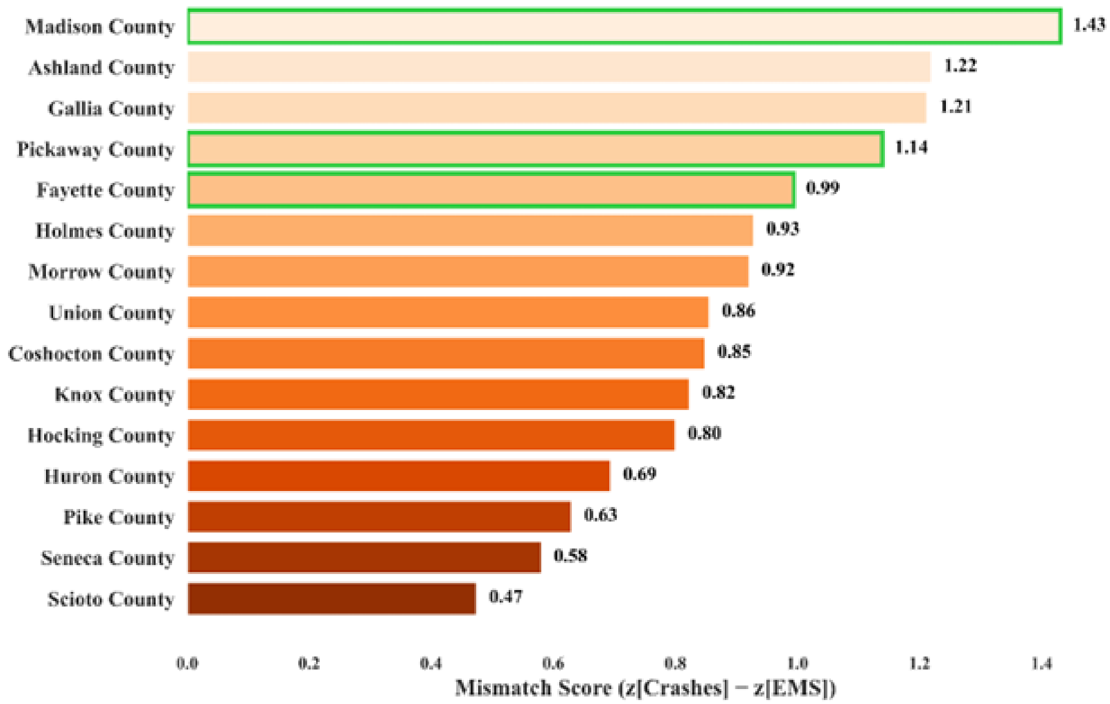

Figure 5: Z-Score Differential Between Crash Frequency and EMS Availability

EMS and hospital coverage in Madison, Pickaway, and Fayette counties are characterized by small-scale facilities and workforce limitations, with ongoing efforts to improve capacity. For example, a statewide assessment of rural EMS agencies highlighted difficulties recruiting and retaining personnel, with about 62% of agencies reporting unfilled positions for six months or more (Nudell et al., 2022). Madison County has two community hospitals, while Pickaway and Fayette each have one. These hospitals provide basic emergency care, but none is a designated trauma center (Colburn, 2021; Madison Health, 2016). Complex or high-acuity cases (multi-system trauma, stroke, cardiac events) often require transfer to tertiary centers in Columbus or Dayton. The EMS system is similarly stretched: services are delivered by a mix of county-run EMS districts, municipal fire/EMS departments, and volunteer squads. All three counties have 19 EMS stations in total as shown in Figure 6.

3.2. Data

This sub-section describes the main data sources used in the study. We detail how EMS incident records, crash reports, facility locations, population data, and road network files were collected and prepared for analysis. These datasets provide the foundation for examining EMS timelines and testing system optimization scenarios.

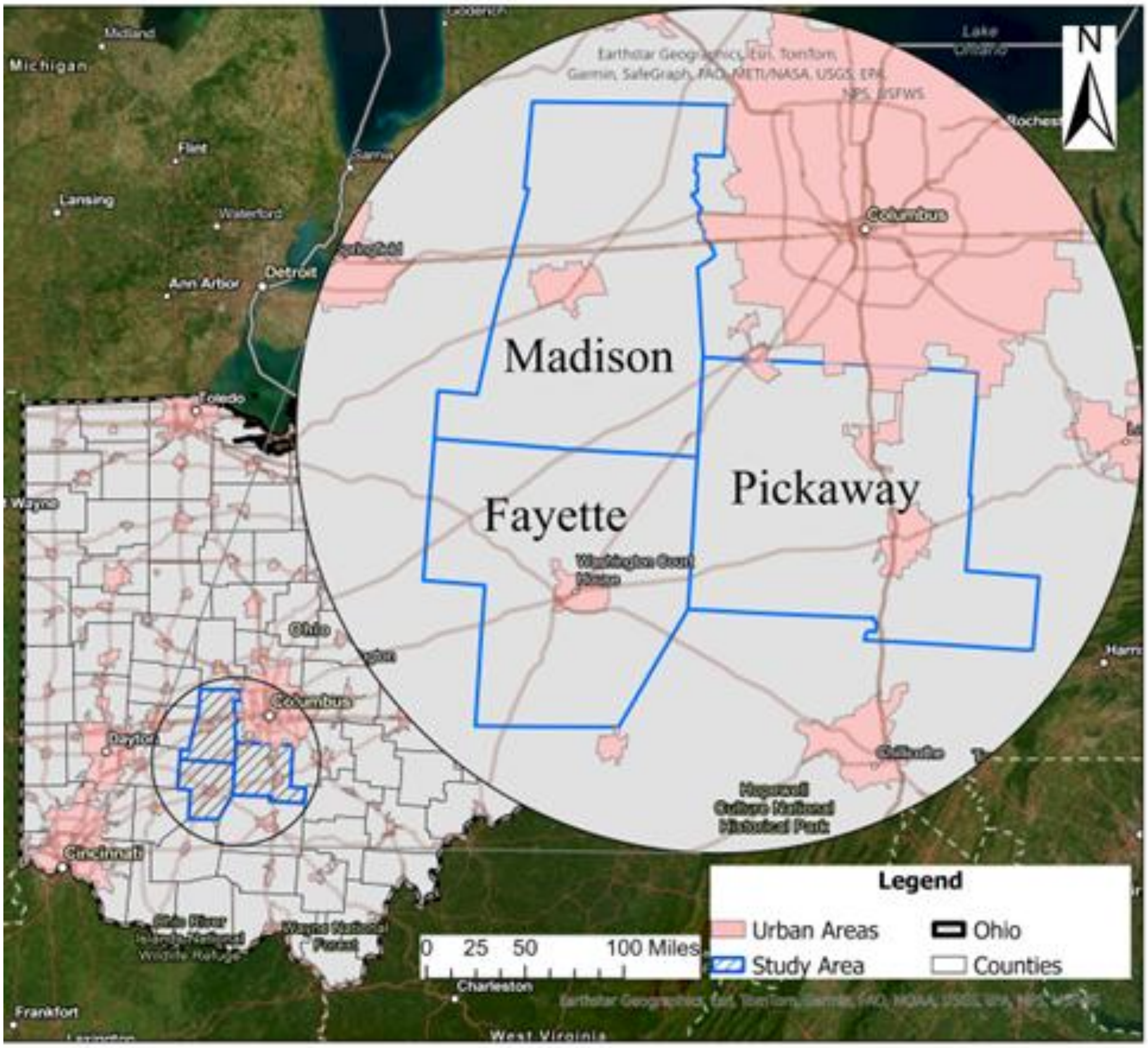

Figure 6: Study Area

3.2.1. EMS and Crash Incident Data

To analyze prehospital timelines for elderly crash victims, the study used EMS and crash data from across Ohio, spanning 2018 to 2023. EMS records were obtained from Ohio EMS Services, with each incident tracked using a unique submission ID across multiple linked files. These files provided comprehensive details including EMS agency characteristics, patient demographics, timestamps for all major EMS events, incident locations, and hospital destinations. Crash records were sourced from the Ohio Department of Public Safety's Electronic Submission System, offering statewide coverage of traffic incidents with complete details on crash circumstances, times, and all parties involved.

3.2.2. Spatial, Facility, and Population Data for System Optimization

For the joint optimization analysis of EMS and hospital locations, several additional datasets were integrated. Crash data from 2017-2023 were obtained from the Ohio Department of Public Safety, which granted access to the Electronic Submission System. This database provides reported traffic crashes across the state, including detailed information on crash location, time, vehicles, and individuals involved. EMS station and hospital locations were sourced from the Homeland Infrastructure Foundation-Level Data (HIFLD). HIFLD provides geospatial data to support critical homeland security functions, including emergency management, law enforcement, border protection, and infrastructure planning (Bradley et al., 2024; Schotten et al., 2024). Population data at the census tract level were obtained from the United States Census Bureau. Using census tract-level population data was a practical choice for this study, since smaller units like census block groups can have large, sparse, or even zero population counts in rural areas. Road network, travel speed, and amenities information were extracted using OSMnx. OSMnx is a Python toolkit that extracts and analyzes road networks, travel distances, and amenities attributes directly from OpenStreetMap (Boeing, 2017, 2025). Figure 5 presents the overall workflow used for data collection and analysis in this study.

4. METHODS

This section explains the analytical approaches used in the study. We describe how EMS timelines were measured and compared, outline the modeling techniques applied to identify factors affecting prehospital times, and present the spatial optimization methods used to assess EMS and hospital coverage. The methods are organized to reflect each objective of the project.

4.1. Analytical Framework for Evaluating EMS Timelines and Contextual Factors

This subsection describes the analytical approach used to address the study objectives related to prehospital EMS care for elderly crash victims. The framework evaluates differences in response, on-scene, and transport times between rural and urban settings and examines how crash characteristics, environmental conditions, and situational factors contribute to prolonged timelines. It also assesses how geographic proximity and community-level conditions shape the availability and effectiveness of post-crash EMS care for older adults.

Figure 7 illustrates the data integration workflow, showing the process of linking EMS records to crash data. A deterministic linkage approach was employed, in which EMS and crash records were matched using geographic proximity between the crash scene and the EMS arrival location. A ±15-minute threshold between crash and EMS dispatch/arrival times was applied, with patient age (≥65) and gender used to resolve cases where multiple candidate matches existed. This linkage allowed for a comprehensive dataset capturing both EMS operational timelines and crash characteristics following the algorithm established by (Hosseinzadeh et al., 2022b). After linking

EMS and crash records and restricting the dataset to patients treated and transported by EMS, only injury outcomes were present, with three categories remaining: minor injury, serious injury, and fatal injury. For the purposes of modeling, serious injury and fatal injury were combined into a "high-severity" category because both represent patients with critical physiological needs and are handled operationally under similar high-acuity EMS protocol.

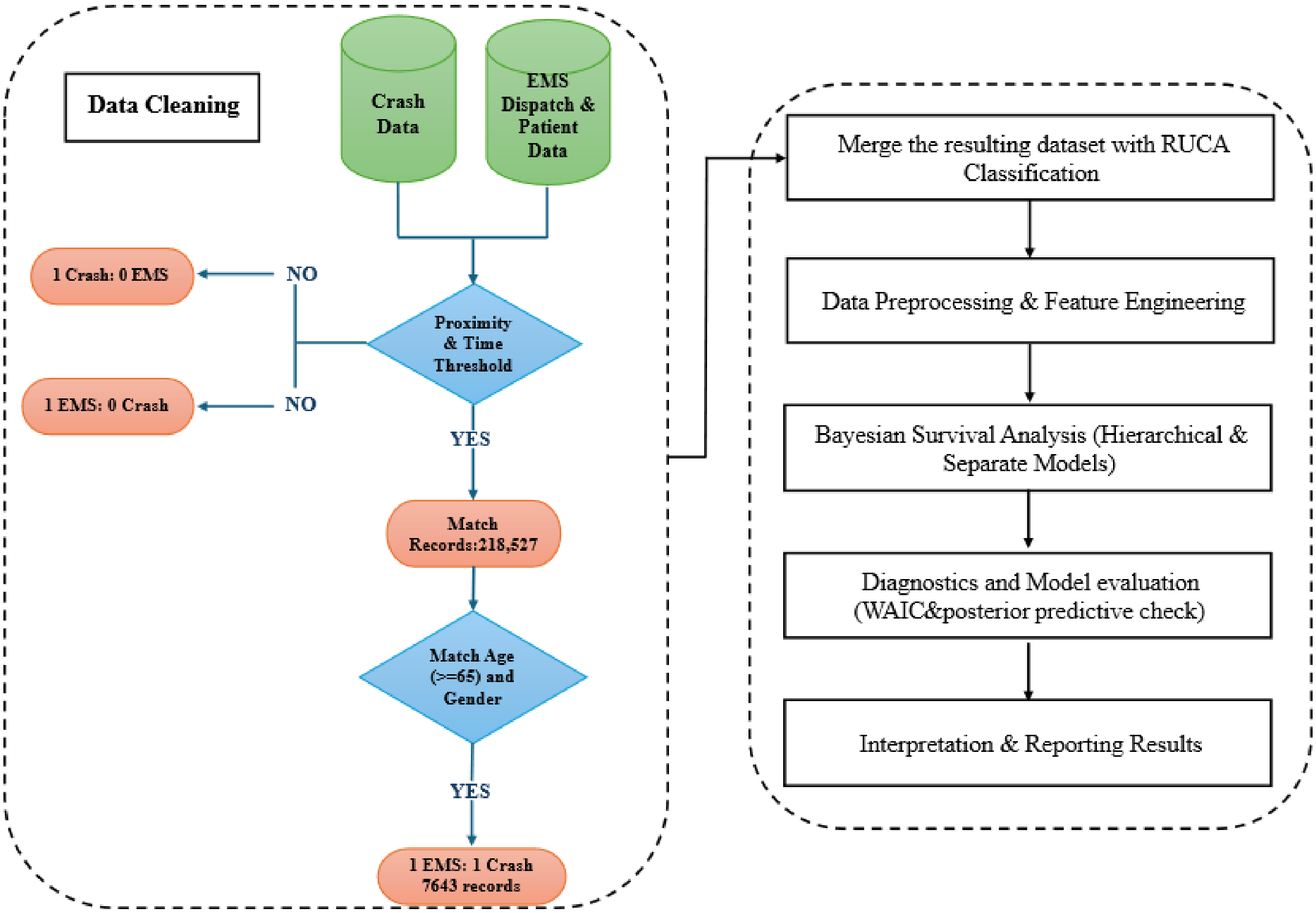

Figure 7: Data Integration and Analysis Workflow

Rural and urban status for each crash and EMS incident was classified using the Rural-Urban Commuting Area (RUCA) codes based on patient ZIP codes. RUCA codes provide a detailed geographic classification scheme that accounts for population density, urbanization, and daily commuting patterns, enabling a nuanced differentiation between rural, suburban, and urban areas. By linking ZIP codes to RUCA classifications, we were able to categorize incidents consistently and accurately within the Ohio study area. Ethical considerations were rigorously observed. All patient identifiers and EMS agency names were fully deidentified prior to analysis to ensure confidentiality and privacy. The research protocol adhered to institutional guidelines governing the use of human subjects' data and secured appropriate approvals for access and use of these datasets. Table 2 provides detailed variable descriptions and the corresponding coding structures applied for model specification.

Table 2: Variable Description

Variable	Description	Category
Distance	The linear distance, in miles, from the incident location to the nearest trauma center or designated hospital.	Continuous
Number of Patients	The total number of injured or affected people are present at the incident scene and requiring EMS assessment or intervention.	0 = Single, 1 = At least two patients
Number of Units	The count of distinct vehicles or operational units (e.g., cars, trucks, motorcycles) directly involved in the incident event.	0 = Single, 1 = At least two units
Crash Severity	Indicates the most severe outcome of the crash among all involved parties, based on crash report.	0 = Minor Injury, 1 = Fatal/Severe
Time of Day	The time in which the incident took place, assigned according to standardized intervals reflecting typical patterns of roadway activity and demand.	0 = Day, 1 = Night, 2 = Off-Peak, 3 = Peak
Day of the Week	Indicates whether the incident occurred on a weekday (Monday–Friday) or weekend (Saturday–Sunday), based on the incident report date.	0 = Weekday, 1 = Weekend
Weather Condition	Weather conditions observed or reported at the time and location of the incident, classified as either clear or inclement (e.g., rain, snow, fog).	0 = Clear, 1 = Inclement
WorkZone Related	Indicates if the incident occurred within or adjacent to a designated work zone, as identified in the incident or crash record.	0 = No, 1 = Yes
Area Type	Indicates the geographic setting where each EMS incident occurred.	0 = Urban, 1 = Rural
Total Prehospital time	Time elapsed, in minutes, from EMS notification by dispatch to patient arrival at the destination hospital.	Continuous

We adopted a Bayesian modeling framework for this study, given its distinct advantages over frequentist approaches. Bayesian methods offer a fundamentally different inference approach compared to frequentist analysis. Instead of viewing model parameters as fixed but unknown values, the Bayesian framework treats them as random variables with associated probability distributions (Kruschke, 2014; Van de Schoot et al., 2014). This approach also allows for a more intuitive understanding of uncertainty. For instance, a 95% Bayesian credible interval for a survival outcome directly signifies a 95% probability that the true effect falls within that range, given the observed data (Hespanhol et al., 2019; Kidando et al., 2019). Moreover, the Bayesian framework accommodates complex hierarchical structures and time-to-event models, allowing us to capture multiple levels of variability and uncertainty (Effati & Ramezanpoor, 2025; Salum et al., 2023).

A hierarchical Bayesian Weibull survival regression framework was employed to model total prehospital time, accounting for both group-level and individual-level variability. The model assumes that the operational time t_{ig} for each incident in group g follows a Weibull distribution parametrized by a common shape parameter α and a scale parameter η_{ig}. We employed the accelerated-failure-time (AFT) parameterization, in which the logarithm of the scale parameter is modeled as a linear combination of a group-specific intercept and covariates as shown in Equation 4. This hierarchical structure facilitates partial pooling, stabilizing parameter estimates for groups with sparse data and capturing unobserved heterogeneity. Under the Bayesian framework, priors encode initial uncertainty regarding model parameters and are formally updated by the likelihood informed by the observed data. For modeling total prehospital time, the Weibull distribution was selected as the likelihood function, providing a flexible parametric form for time-to-event outcomes.

$$t_{ig} \sim Weibull(\alpha, \eta_{ig}) \tag{3}$$

$$\log(\eta_{ig}) = \mu_{g[i]} + X_{ig}\beta_k \tag{4}$$

$$\beta_k \sim N(0, \sigma) \tag{5}$$

$$\mu_g = N(0, \sigma), \sigma \sim HalfCauchy(2.5), \alpha \sim HalfNormal(1.0) \tag{6}$$

Prior distributions were specified to be weakly informative, capturing uncertainty without imposing strong constraints on parameter estimates in the hierarchical regression model, as detailed in Eqns. (3) – (6). In this model, subscripts were defined as $i = 1, \dots, n$ indexes each individual crash–EMS record in the dataset; $g = 1,2$ denotes the two area types (urban and rural); and $k = 1, \dots, 8$ represents the set of covariates included in the regression model. Group intercepts µg we used normal priors centered at zero with their spread governed by a HalfCauchy (2.5) prior. The same weakly informative approach was applied to the covariate effects βk, we used normal priors centered at zero with their spread governed by a HalfCauchy (2.5) prior. The shape parameter was given a HalfNormal (1) prior. These weakly informative priors allow the data to drive inference, reflecting general uncertainty and avoiding strong prior assumptions. Figure 8 shows the representation of the hierarchical Weibull regression model structure

Markov Chain Monte Carlo (MCMC) simulations were performed using the NUTS (No-U-Turn Sampler) kernel, as implemented in the NumPyro statistical software package. A total of 30,000 iterations were run, consisting of 10,000 warm-up (or "burn-in") samples, which were discarded, and 20,000 main samples used for inference. These simulations were conducted with multiple chains to estimate the posterior distributions of the model parameters. To evaluate whether the multiple chains had converged, the Brooks-Gelman-Rubin (BGR) diagnostic statistic was employed. Convergence was determined when the BGR statistic for all parameters fell below a threshold of 1.05, indicating that the variability between chains was sufficiently similar to the variability within each chain. The effect of grouping data by area type was evaluated, comparing it against the baseline (urban) model. The analysis utilized the Widely Applicable Information Criterion (WAIC), a Bayesian metric that balances model accuracy and complexity (Vehtari et al., 2016).

$$WAIC = -2 * (P_{WAIC} + lppd) \tag{7}$$

Where P_{WAIC} is the estimated effective number of parameters and $lppd$ is the log pointwise predictive density.

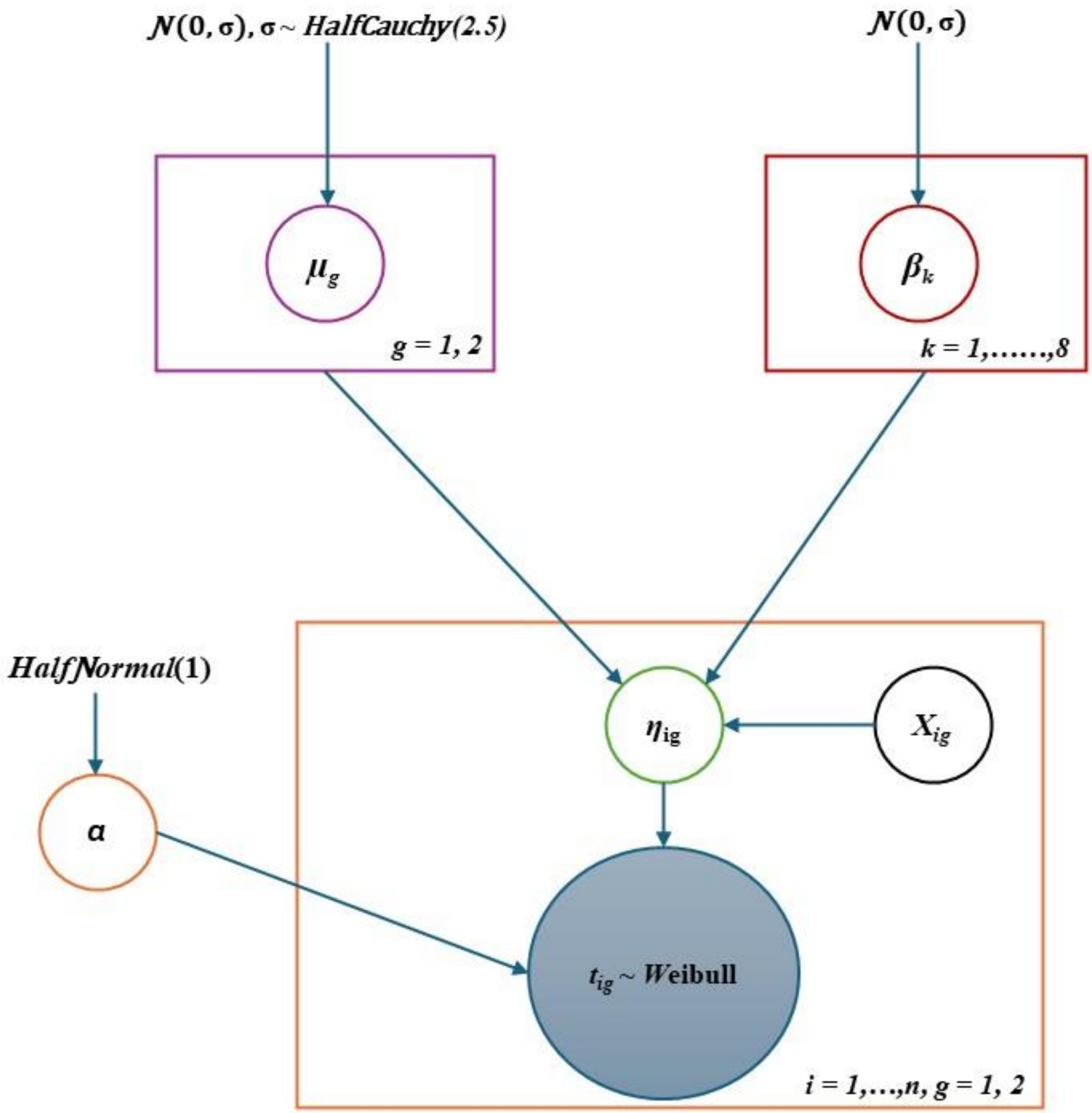

Figure 8: Representation of the Hierarchical Weibull Regression Model Structure

4.2. Spatial Optimization Framework for Coordinated EMS and Hospital Coverage

This subsection outlines the analytical framework used to evaluate coordinated EMS station and hospital placement in rural areas. The approach examines whether joint consideration of ambulance response and hospital access improves timely emergency response and transport for elderly residents. It further assesses the extent to which joint coverage strategies can reduce post-crash delays and increase the proportion of rural elderly populations receiving timely emergency services.

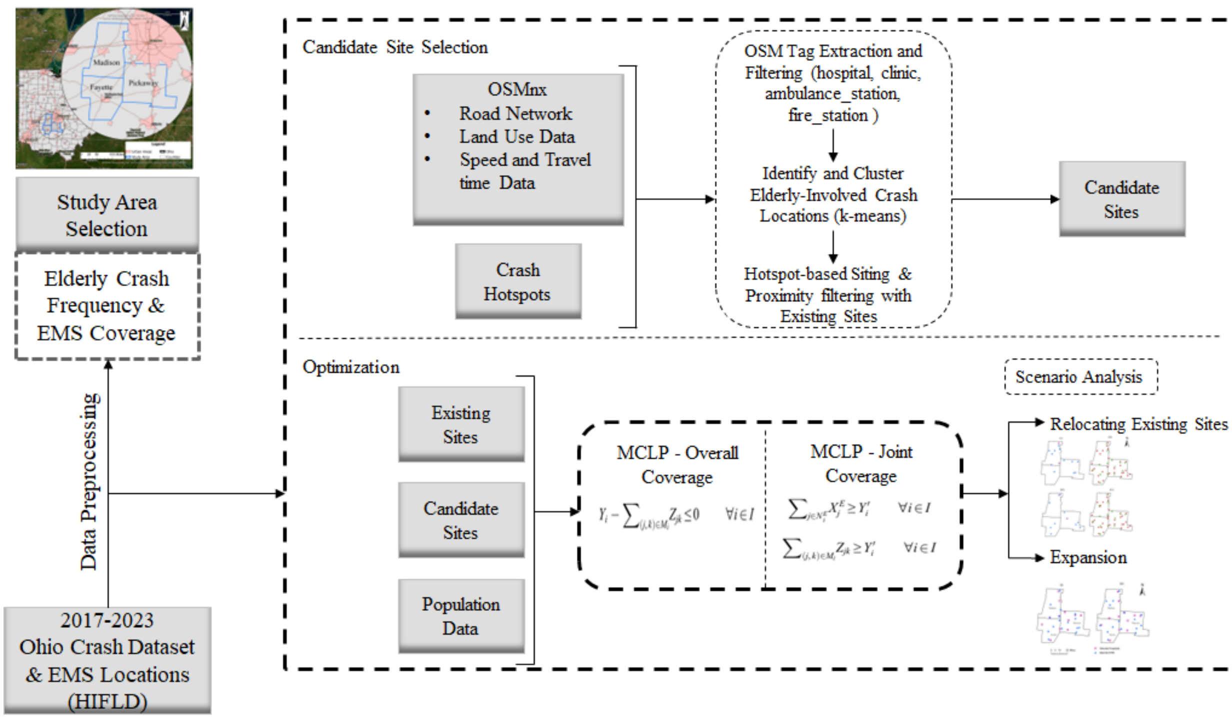

Figure 9: Workflow Summary

4.2.1. Candidate Site Selection

As indicated in Figure 9, candidate locations for new EMS and hospital sites were generated using spatial data integration and cluster analysis. First, OpenStreetMap (OSM) data for Madison, Pickaway, and Fayette counties were downloaded using the OSMnx Python toolkit. The counties' boundaries were geocoded and merged, and the drivable road network within this combined area was extracted. The drivable road network was modeled as a graph, with nodes representing all intersections and endpoints, and edges representing the road segments connecting them. Each node's geographic coordinates (latitude and longitude) were extracted from EMS and hospital locations. Edges were annotated with segment length, estimated speed, and travel time to enable realistic network distance analysis.

Candidate EMS and hospital facility locations were identified using standardized OSM tags (amenity = hospital, clinic; emergency = ambulance_stations and fire_station). OSM tags are widely used for mapping the locations of public facilities, including emergency and medical services (Feng et al., 2025; Genc et al., 2025). Facility locations were extracted as geospatial points and filtered by their tag category to distinguish between hospitals, clinics, and EMS-related infrastructure. This ensured that both existing ambulance stations and hospitals were fully represented in the candidate pool for site selection and relocation modelling as shown in Figure 10.

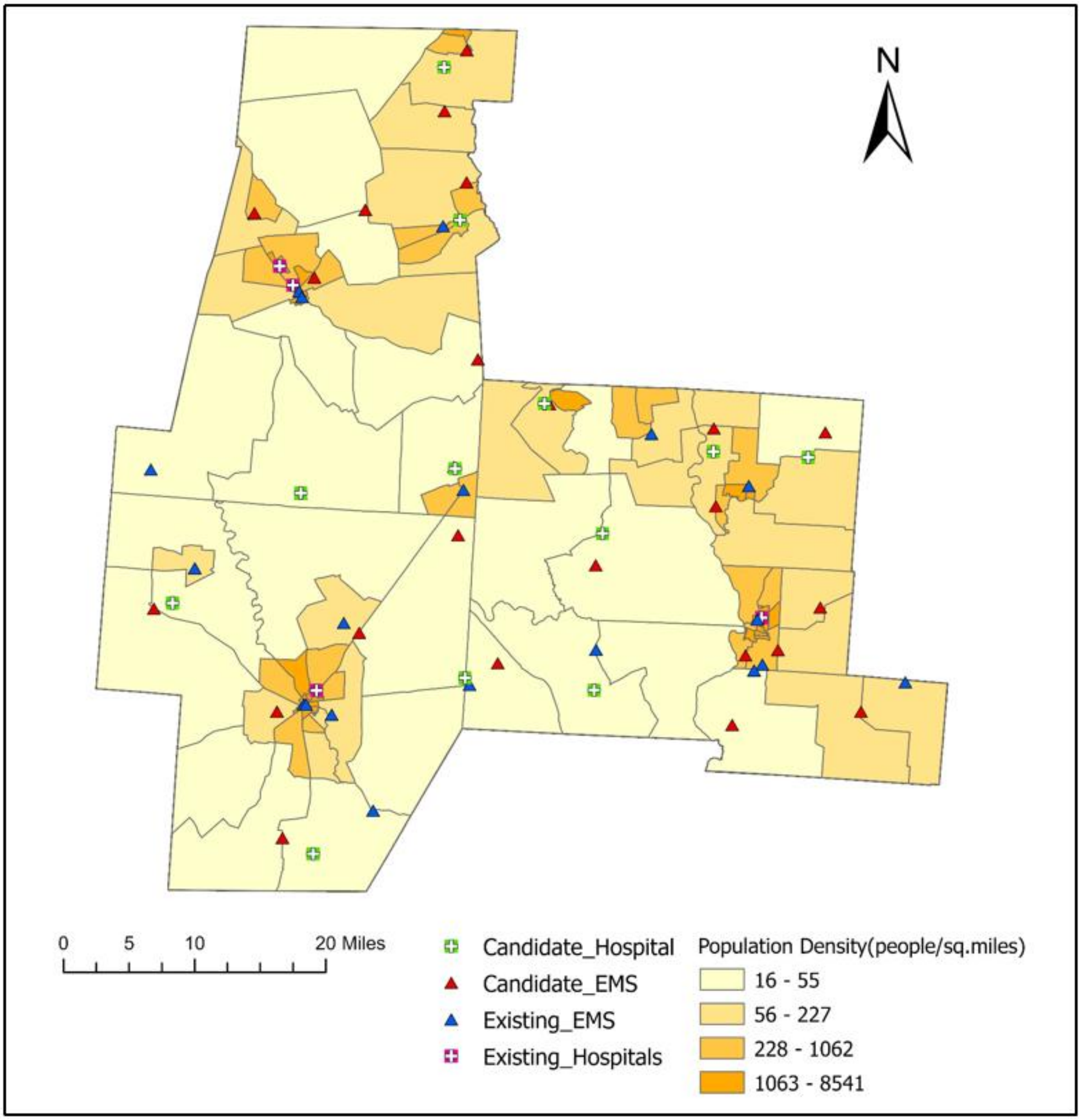

Figure 10: Spatial Distribution of Population, EMS Stations and Hospital Facilities in Madison, Fayette, and Pickaway Counties.

The target locations with the greatest impact, historical crash data were used to identify spatial clusters of elderly-involved crashes. A k-means clustering algorithm was applied to the crash locations to produce a user-defined number of crash “hotspot” centroids. These centroids then serve as candidate locations for EMS sites, making sure the selected points reflect real spatial patterns of crash risk. These centroids were then mapped to the nearest drivable road node using a BallTree nearest-neighbor search, ensuring that all candidate sites are feasible for EMS vehicle access. To avoid redundancy, candidate sites located within 1 mile of an existing EMS or hospital facility were excluded (Daskin & Stern, 1981; Schmid & Doerner, 2010). The final candidate site list thus included both existing EMS facilities and filtered crash-based hotspot locations. For validation, the number of elderly-involved crashes within a 1.5-mile radius of each candidate site was tallied to provide a measure of each site’s proximity to observed risk (Wolf, 2019). These spatial patterns of elderly crash risk are visualized in Figure 11, which displays the distribution of crash hotspots alongside existing EMS stations and hospitals in the study area.

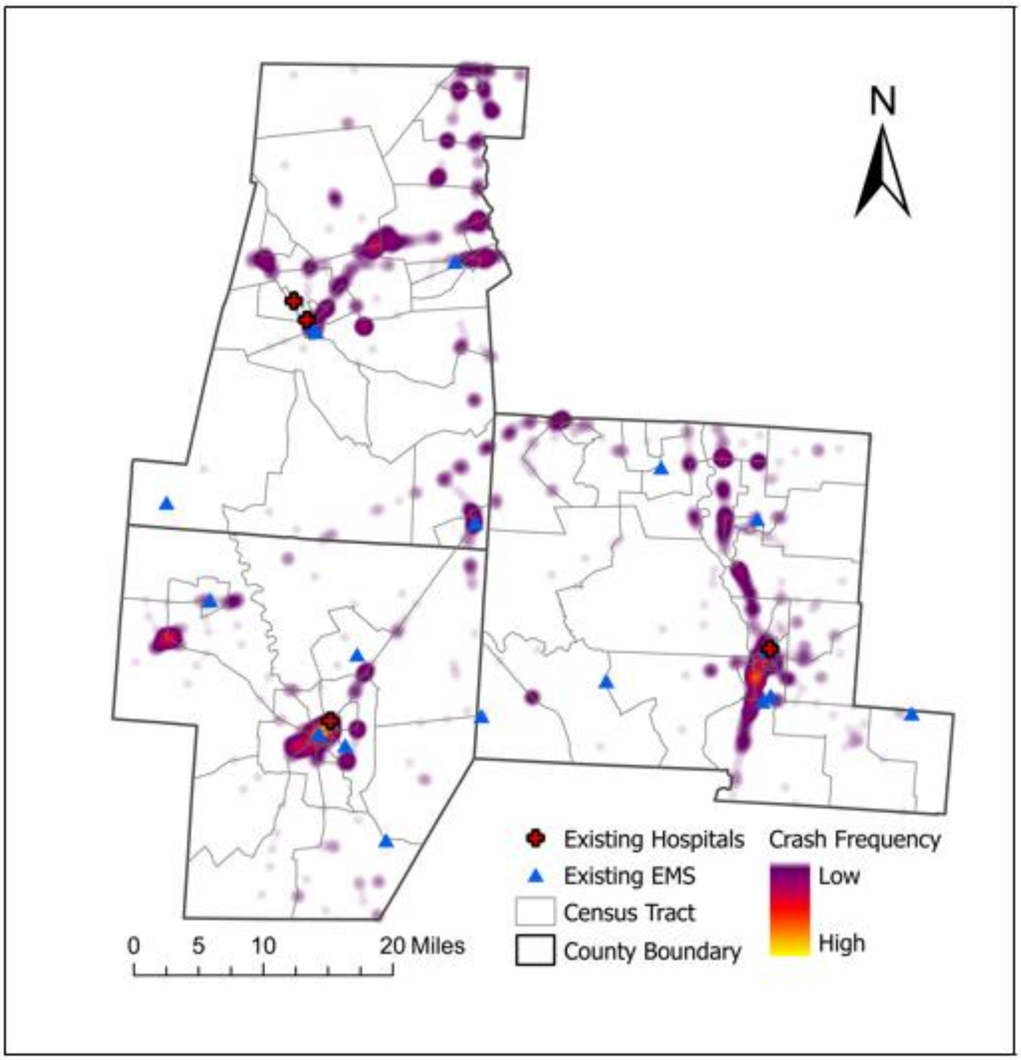

Figure 11: Spatial Distribution of Elderly-involved Crash Hotspots

4.2.2. Model Specifications

EMS planning requires models that can capture the urgency and sequence of real-world care delivery. This study applies two spatial optimization models formulated as a maximal covering location problem with overall and joint coverage MCLP-OC and MCLP-JC. This joint approach better reflects the realities of trauma care for older adults, where outcomes depend on both immediate intervention and prompt access to definitive treatment. Building on the work of (Church & Revelle, 1974; Luo et al., 2025), both models integrate both existing and potential EMS or hospital sites. These models make it possible to evaluate planning scenarios, such as building new stations, expanding capacity, or relocating existing facilities. Decision variables are specified whether an EMS or hospital facility is placed at each eligible candidate location. Coverage variables ensure that only demand points meeting the model's timely access standards are considered covered. Travel times between demand sites, EMS stations, and hospitals are calculated over the road network, incorporating localized speed and distance attributes. The complete mathematical structure including objective functions and constraints for both MCLP-OC and MCLP-JC are presented below.

4.2.3. Notations and Variable Definitions

i, j, k = index of demands, EMS Stations, and hospitals, respectively

I = set of demands

J, K = set of existing EMS stations and hospitals respectively,

J', K' = set of locations eligible for new EMS stations and hospitals, respectively,

a_i = amount of demand at location i,

S_o = standard of the overall service time,

p^E = total number of EMS stations to be sited,

p^H = total number of hospitals to be sited,

q^E = the maximum number of new EMS stations to be sited,

q^H = the maximum number of new hospitals to be sited,

t_{ji} = travel time between i and j,

t_{ik} = travel time between i and k,

$M = \{(j,k)|(t_{ji} + t_{ik}) \leq S_o\}$, set of pairs of EMS station $j(j \in JUJ')$ and hospital $k(k \in KUK')$ capable of jointly providing service to demand i within the standard of the overall service time,

$$X_j^E = \begin{cases} 1 \text{ if an EMS station is sited at location j} \\ 0 \text{ Otherwise} \end{cases}$$

$$X_k^H = \begin{cases} 1 \text{ if a hospital is sited at location k} \\ 0 \text{ Otherwise} \end{cases}$$

$$Y_i = \begin{cases} 1 \text{ if demand i is covered by overall service coverage} \\ 0 \text{ Otherwise} \end{cases}$$

$$Z_{jk} = \begin{cases} 1 \text{ if an EMS Station and a hospital is located at j and k respectively} \\ 0 \text{ Otherwise} \end{cases}$$

4.2.4. Maximal Covering Location Problem-Overall Coverage

The MCLP-OC extends the classic maximal covering location problem by using total prehospital travel time, rather than just ambulance response time, as its service benchmark. The mathematical formulation of the MCLP-OC is presented as follows:

Objective (8) below seeks to maximize the total demand served. Coverage is counted only if it meets the overall service time standard.

Maximize: $\sum_{i \in I} a_i Y_I$ (8)

Subject to

$\sum_{j \in J} X_j^E + \sum_{j \in J'} X_j^E = p^E$ (9)

$\sum_{k \in K'} X_k^H + \sum_{k \in K'} X_k^H = p^H$ (10)

Constraints (9) and (10) ensure that the total number of EMS stations and hospitals in the system equals the specified targets P^E and P^H, accounting for both existing and new sited facilities.

$\sum_{j \in J} X_j^E \leq q^E$ (11)

$\sum_{k \in K'} X_k^H \leq q^H$ (12)

Constraints (11) and (12) limit the number of new EMS stations and hospitals that can be established at q^E and q^H respectively. For example, these limits, combined with the total facility requirements in constraints (8) and (10), ensure that a minimum of (p^E- q^E) existing EMS stations and (p^H- q^H) existing hospitals must remain operational in the system.

$Y_i - \sum_{(j,k) \in M_i} Z_{jk} \leq 0 \qquad \forall i \in I$ (13)

Constraint (13) ensures that a demand point i is considered covered only if there exists at least one sited pair of EMS station j and hospital k such that the overall coverage provided by them $(t_{ji} + t_{ik})$ is within the standard of the overall service time S_o.

$Z_{jk} \leq X_j^E \qquad \forall j \in JUJ', k \in KUK'$ (14)

$Z_{jk} \leq X_k^H \qquad \forall j \in JUJ', k \in KUK'$ (15)

Constraints (14) and (15) guarantee that a demand can only be jointly covered by an EMS station at location j and a hospital at location k if both facilities are actually sited at those respective locations.

$X_j^E \in \{0,1\} \qquad \forall j \in JUJ'$ (16)

$X_k^H \in \{0,1\} \qquad \forall k \in KUK'$ (17)

$Y_i \in \{0,1\} \qquad \forall i \in I$ (18)

Constraints (16), (17), and (18) impose binary integer restrictions on the decision variables, requiring that EMS siting, hospital siting, and coverage indicators are each either 0 or 1.

4.2.5. Maximal Covering Location Problem-Joint Coverage

Unlike the MCLP-OC, the MCLP-JC model separately accounts for both ambulance response time (Trip 1) and patient transport time to a hospital (Trip 2), ensuring that each is met within their respective standards. This approach reflects the critical importance of timely on-scene intervention and rapid transfer to definitive care for emergency outcomes. The additional notation introduces the variables and parameters specific to the MCLP-JC formulation.

S_E = travel time standard for Trip 1 (e.g., EMS response time)

$N_i^E = \{j | t_{ji} \leq S_E\}$, the set of EMS stations $j (j \in JUJ')$ capable of providing service to demand i

$$\mathrm{Y}_\mathrm{i}' = \begin{cases} 1 & \text{if demand i is covered by both EMS and overall coverages} \\ & 0 \text{ otherwise} \end{cases}$$

Objective (19) maximizes the number of demand points that receive both timely EMS response at the scene and full coverage within the overall service time by EMS and hospitals.

Maximize: $\sum_{i \in I} a_i Y_i'$ (19)

$\sum_{j \in J} X_j^E + \sum_{j \in J'} X_j^E = p^E$ (20)

$\sum_{k \in K'} X_k^H + \sum_{k \in K'} X_k^H = p^H$ (21)

Constraints (20) and (21) establish the required totals for EMS stations and hospitals to be sited in the system.

$\sum_{j \in J} X_j^E \leq q^E$ (22)

$\sum_{k \in K'} X_k^H \leq q^H$ (23)

Constraints (22) and (23) limit the number of new EMS stations and hospitals that can be added to the system to q^E and q^H respectively.

$\sum_{j \in N_i^E} X_J^E \leq Y_i' \qquad \forall i \in I$ (24)

$\sum_{(j,k) \in M_i} Z_{jk} \leq Y_i' \qquad \forall i \in I$ (25)

Constraints (24) and (25) ensure that a demand point is only considered covered if it can be reached both by EMS from a sited station within the response time threshold (S_E), and by the nearest emergency center within the overall service time standard (S_o) after the call.

$Z_{jk} \leq X_j^E \qquad \forall j \in JUJ', k \in KUK'$ (26)

$Z_{jk} \leq X_k^H \qquad \forall j \in JUJ', k \in KUK'$ (27)

Constraints (26) and (27) require that a patient can only be transported from station j to emergency center k if both the EMS station at j and the hospital at k are actively sited in the solution.

$X_j^E \in \{0,1\} \qquad \forall j \in JUJ'$ (28)

$X_k^H \in \{0,1\} \qquad \forall k \in KUK'$ (29)

$Y_i' \in \{0,1\} \qquad \forall i \in I$ (30)

Lastly, constraints (28), (29), and (30) impose binary integer restrictions on all decision variables, ensuring they can only take values of 0 or 1.

4.2.6. Model Setup

The optimization models were implemented in Python 3.11 and solved using the spopt Python library for spatial optimization and solved with the open-source PuLP linear programming package (Feng et al., 2022; Mitchell, 2011). ArcGIS Pro (version 3.2.2) was used for spatial data processing and visualization. Two scenarios were constructed to explore the effects of relocation and system expansion. In Scenario 1, all 19 EMS stations and 4 hospitals could be freely relocated ($p^E = q^E = 19, p^H = q^H = 4$), with no requirement to retain any current sites. Scenario 2 required all existing EMS stations and hospitals to remain ($p^E = 19, p^H = 4$), while permitting the siting of up to 16 new EMS stations ($q^E = 16$) and 12 new hospitals ($q^H = 12$). Both scenarios applied a rural EMS response time standard of 14 minutes for Trip 1, for timely prehospital care in rural areas (Mell et al., 2017). The average on-scene care time was set at 15 minutes, resulting in a total prehospital service standard (S_0) of 49 minutes to achieve the "golden hour" target.

5. DISCUSSION OF RESULTS

This section presents the main findings of the study, organized around the project's key objectives. Results are reported for rural–urban differences in EMS prehospital timelines for elderly crash victims, factors linked to delays in EMS care, and the role of geographic and community characteristics in shaping emergency response. The section also covers the outcomes of spatial optimization analyses, evaluating how coordinated placement of EMS stations and hospitals can improve timely care for elderly residents in rural areas and expand overall service coverage.

5.1. Rural–Urban Comparisons and Determinants of EMS Delays in Elderly Care

In this study, we compared total prehospital EMS times between rural and urban areas to understand how location affects emergency response and patient transport. Table 3 presents summary statistics for both settings, showing that average prehospital times and transport distances were consistently higher in rural incidents. Rural cases had a mean total EMS time of 46.9 minutes compared to 40.8 minutes in urban settings, and the average distance traveled in rural areas (14.6 miles) was also notably greater than in urban areas (9.3 miles). To evaluate model performance and justify the use of hierarchical regression, we compared the WAIC values for the single (urban) and hierarchical models. The WAIC for the urban model was 218.35, while the hierarchical model achieved a lower value of 181.62. This substantial improvement indicates that the hierarchical model better captured key differences between groups and more accurately fit the data. Tables 6 and 7 are included for completeness to ensure full transparency on the standalone rural-only and urban-only models. They are not used for inference, because the hierarchical framework provides the final estimates.

Table 4 presents the posterior estimates from the hierarchical Weibull regression model. All variables were statistically significant at the 95% highest density interval (HDI). The table presents key summaries of each parameter's posterior distribution. It includes the mean, standard deviation, and the 95% Highest Density Interval (HDI). Monte Carlo standard errors (MCSE) are reported for both the mean and standard deviation. In our Weibull AFT specification, covariates enter on the log of the Weibull scale parameter, so positive coefficients increase the scale and are therefore associated with longer expected EMS times, whereas negative coefficients decrease the scale and are associated with shorter expected times. The percentage change column (% Change) offers a more intuitive interpretation of each coefficient's impact, its derivation is shown in Equation (31).

$$\%\, Change = \exp\big((\beta) - 1\big)\, X\ 100 \tag{31}$$

where β denotes the posterior mean of the corresponding parameter. This value represents the multiplicative change in the Weibull scale parameter. A positive % Change therefore indicates an increase in the scale (longer expected EMS duration), whereas a negative % Change reflects a decrease in the scale (shorter expected duration). It is important to note that, % Change does not represent the literal percent change in total prehospital time, but rather the proportional effect on the scale of the Weibull distribution from which expected duration is derived. These findings allow for direct comparison of the operational impact of each variable across urban and rural settings, as summarized in Table 4.

Table 3: Summary Statistics of the Data

Variable	Categories	Rural	Urban
		Count (Proportion(%))	Count (Proportion(%))
Number of Patients	Single	1953(95.27)	5227(93.46)
	Multiple	97(4.73)	366(6.54)
Number of Units	Single	319(15.56)	788(14.09)
	Multiple	1731(84.44)	4805(85.91)
Crash Severity	Minor Injury	1641(80.05)	4462(79.78)
	Fatal & Severe	409(19.95)	1131(20.22)
Time of Day	Day	990(48.29)	2765(49.44)
	Night	54(2.63)	136(2.43)
	Off-Peak	159(7.76)	412(7.37)
	Peak	847(41.32)	2280(40.77)
Day of the Week	Weekday	1585(77.32)	4421(79.05)
	Weekend	465(22.68)	1172(20.95)
Weather Condition	Clear	1238(60.39)	3491(62.42)
	Inclement	812(39.61)	2102(37.58)
WorkZone Related	Not Related	2014(98.24)	5481(98.00)
	Related	36(1.76)	112(2.00)

Total Prehospital time (minutes)	Mean	46.90	40.79
	Std	29.59	26.18
	Median	39.00	33.52
Distance (miles)	Mean	14.62	9.33
	Std	25.88	13.61
	Median	8.41	6.22

Figure 12 presents the posterior distributions of the baseline hazard by area type. The distributions show the posterior means and standard deviations of the baseline instantaneous probability of hospital arrival at time t, with other variables held constant. A higher value of the posterior mean reflects a high baseline hazard, whereas a lower value reflects a lower baseline hazard. The figure demonstrates that the intercept for rural incidents had a notably higher posterior mean (0.152) compared to urban incidents (0.065), indicating a higher baseline hazard. Although the rural baseline hazard is higher, this does not imply shorter total prehospital times in rural areas, because the baseline hazard reflects only the underlying probability of arrival before incorporating the effects of distance, weather, multiple patients, and other covariates.

Table 4: Posterior Results from the Hierarchical Weibull Regression Model

Variable	Categories	Mean	SD	HDI 3%	HDI 97%	MCSE Mean	MCSE SD	% Change
Intercept	Average	0.109	0.028	0.057	0.161	0.000	0.000	-
	Urban	0.065	0.025	0.018	0.113	0.000	0.000	-
	Rural	0.152	0.029	0.096	0.206	0.000	0.000	-
Distance	Continuous	0.015	0.003	0.010	0.020	0.000	0.000	1.51
Number of Patients	Single	-	-	-	-	-	-	-
	Multiple	0.056	0.028	0.002	0.108	0.000	0.000	5.76
Number of Units	Single	-	-	-	-	-	-	-
	Multiple	-0.171	0.022	-0.212	-0.128	0.000	0.000	-15.72
Crash Severity	Minor Injury	-	-	-	-	-	-	-
	Fatal & Severe	-0.035	0.016	-0.064	-0.005	0.000	0.000	-3.44
Time of Day	Day	-	-	-	-	-	-	-
	Night	0.358	0.047	0.267	0.442	0.000	0.000	43.05
	Off-Peak	0.090	0.027	0.041	0.141	0.000	0.000	9.42
	Peak	0.195	0.014	0.168	0.222	0.000	0.000	21.53
Day of the Week	Weekday	-	-	-	-	-	-	-
	Weekend	0.276	0.02	0.239	0.314	0.000	0.000	31.78
Weather Condition	Clear	-	-	-	-	-	-	-
	Inclement	0.294	0.014	0.268	0.320	0.000	0.000	34.18
WorkZone Related	Not Related	-	-	-	-	-	-	-
	Related	0.276	0.053	0.175	0.373	0.000	0.000	31.78

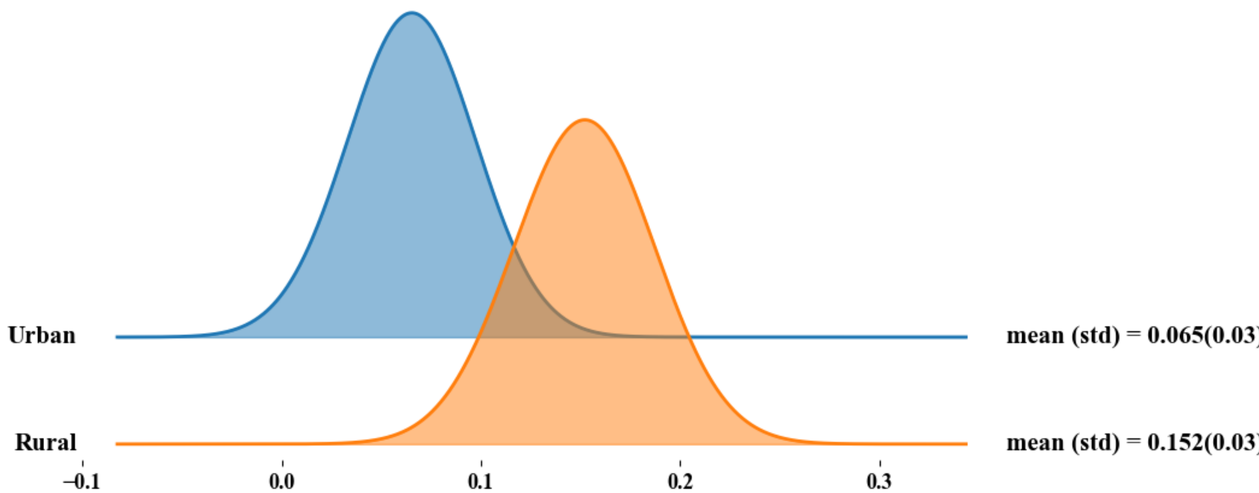

Figure 12: Posterior Mean Distributions of Total Prehospital Times by Area Type

5.2. Role of Crash and Environmental Context in EMS Performance

This section discusses the main contextual factors found to influence prehospital EMS timelines for elderly crash victims. Each factor, ranging from distance to care and number of patients, to time of day and weather, was examined for its specific impact on total prehospital duration. The following subsection presents detailed findings on how these variables shape delays and operational challenges for EMS response.

5.2.1. Distance to the Nearest Emergency Care Facility

Increasing distance to the nearest emergency care facility was associated with longer expected prehospital duration. Each additional mile increased total prehospital time by approximately 1.5%, meaning small increments accumulate quickly as distance grows. This effect becomes especially meaningful when considering that distance is not distributed equally across settings; for instance, a 10-mile difference corresponds to an estimated 16% longer prehospital duration. Rural crashes occurred much farther from emergency care facilities on average (Mean = 14.62 miles; Median = 8.41 miles) compared with urban crashes (Mean = 9.33 miles; Median = 6.22 miles). As a result, the cumulative effect of distance is substantially larger for rural incidents, even though the effect per mile is relatively small. This helps explain longer EMS timelines in rural settings once covariates are incorporated into the model, despite differences observed in baseline hazard. These findings are consistent with prior studies showing that greater distances to emergency care are linked to delayed hospital arrival and worse patient outcomes, particularly in rural areas (Dinh et al., 2023; Wiratama et al., 2021).

5.2.2. Number of Patients at the Scene

With single-patient incidents as the reference group, *multiple-patient* incidents were associated with a 5.76% increase in the Weibull scale parameter, indicating a longer expected prehospital duration under the AFT specification. This suggests that managing multiple patients simultaneously adds a significant burden to EMS operations. This is likely due to the increased time needed for patient assessment, treatment, and packaging, plus the potential for coordinating transport for multiple individuals. Consistent with prior findings in EMS and mass-casualty research, even modest multiplicative increases translate into appreciable operational delays when multiple victims are involved. From a practical standpoint, this highlights how resource-intensive mass-casualty or multi-patient incidents are (Gonzalez et al., 2009; Jankovič et al., 2025). Such incidents often require more EMS units and extended time spent at the scene (Apiratwarakul et al., 2025; Kao et al., 2015).

5.2.3. Number of Units involved in the Crash

Total prehospital time was estimated to decrease by 15.72% for incidents involving multiple EMS units relative to those with a single unit, indicating a substantial multiplicative reduction in overall duration under the AFT specification. This negative time ratio suggests that mobilizing more than one unit accelerates critical on-scene tasks, effectively shortening each stage of the prehospital process. Although this may seem counterintuitive since multi-unit responses are often triggered by more severe or complex incidents having more personnel and resources on scene allows key tasks to be performed in parallel. This often results in faster patient assessment, quicker stabilization, and more efficient scene clearance. Operationally, this finding highlights the benefit of coordinated multi-unit responses for reducing expected prehospital duration in situations where they are deemed necessary (Chen et al., 2020; Jin et al., 2023).

5.2.4. Crash Severity

When *minor injury* incidents served as the reference, *fatal and severe* crash incidents were associated with a 3.44% reduction in total prehospital time. This observation can be attributed to the "load and go" or "scoop and run" protocol often adopted for critically injured patients, where rapid transport to an emergency care facility takes precedence over extensive on-scene stabilization (Haas & Nathens, 2008; Taran, 2009). Practically, this demonstrates a prioritization of immediate transport for severe injury, reflecting established clinical guidelines aimed at improving patient outcomes (Breeding et al., 2024). This finding is associated with the severity of the patient's condition and established protocols.

5.2.5. Time of the Day

Using *day* as the reference category, *night* incidents show a substantial 43.05% increase in total prehospital time, *off-peak* hours result in a 9.42% increase, and *peak* hours are associated with a 21.53% increase. These percent changes indicate that EMS responses during night, peak, and even off-peak hours are systematically longer, consistent with the multiplicative effects captured by the AFT model. The significant increase during the *night* might be due to reduced visibility, lower staffing levels, or specific operational challenges during overnight hours (Basnawi, 2023; Khazaei et al., 2024). *Peak* hour increases are predictably linked to traffic congestion, while *off-peak* hours still sees an increase, possibly due to slightly lower speeds (Brent & Beland, 2020; Gorgens et al., 2024). These findings underscore that EMS faces fluctuating operational demands throughout the day, necessitating adaptable resource allocation and proactive strategic planning (Babanezhad et al., 2025b; Cantwell, Morgans, Smith, Livingston, Spelman, et al., 2015). These are associated with traffic patterns, staffing levels, and environmental factors.

5.2.6. Day of the Week

Weekend incidents showed a 31.78% increase in total prehospital time when contrasted with *weekday* incidents. This substantial increase could be due to several combined factors. These include higher recreational traffic and an increased occurrence of specific emergency types, such as trauma related to leisure activities (Al-Thani et al., 2021). Additionally, different hospital staffing patterns on weekends might affect patient offload times (Cantwell, Morgans, Smith, Livingston, & Dietze, 2015; Cantwell, Morgans, Smith, Livingston, Spelman, et al., 2015). This indicates that weekends pose distinct challenges that extend EMS incident durations. Therefore, specific planning for staffing and resource availability during weekends is warranted. This finding is associated with societal activity patterns and potential changes in traffic or resource availability.

5.2.7. Weather Conditions

Total prehospital time was estimated to be 34.18% longer during *inclement* weather, relative to *clear* conditions. This finding is intuitive. Adverse weather directly impedes travel speed, increases the complexity and caution needed for driving, makes on-scene operations more difficult and time-consuming (Ramgopal et al., 2019; Wong & Lin, 2020). From an EMS performance perspective, this highlights a significant external factor that consistently reduces efficiency. Therefore, heightened awareness and potentially adjusted response protocols are necessary during severe weather events.

5.2.8. Workzone Related

With *not related* as reference, incidents that are *related* to a work zone are associated with a 31.78% increase in total prehospital time. Work zones often introduce complex traffic patterns, including lane closures and reduced speed limits (Meng & Weng, 2013). They can also present physical obstacles that significantly impede EMS vehicle access, egress, and on-scene operations. This highlights particular challenges in navigating and managing incidents within construction or maintenance areas. Consequently, these factors can prolong the overall duration of EMS service.

5.3. Results of Spatial Optimization: Improving EMS Response and Hospital Access in Rural Areas

This section presents the findings of the optimization analysis. Results are compared for the MCLP-OC and MCLP-JC models in terms of optimal facility placement and population coverage. Figure 13 illustrates the optimal facility configurations for Scenario 1. For clarity, the results from each model are presented in two separate maps: one depicting the retained existing EMS stations and hospitals selected by the optimization, and the other highlighting the new sites identified for potential relocation. In this context, the optimal solution generated from MCLP-OC are shown in Figure 13 (i) and (ii), while the MCLP-JC solution is depicted in Figure 13 (iii) and (iv). Figure 13 (i) and (iii) show that both the MCLP-OC and MCLP-JC models retain a subset of existing facilities in their solutions, with 16 EMS stations and 12 hospitals selected to maximize coverage. Both models select a considerable number of hospitals outside the urban core as sites for EMS stations compared to the existing system, as shown in Figure 13 (ii) and (iv) and Figure 10.

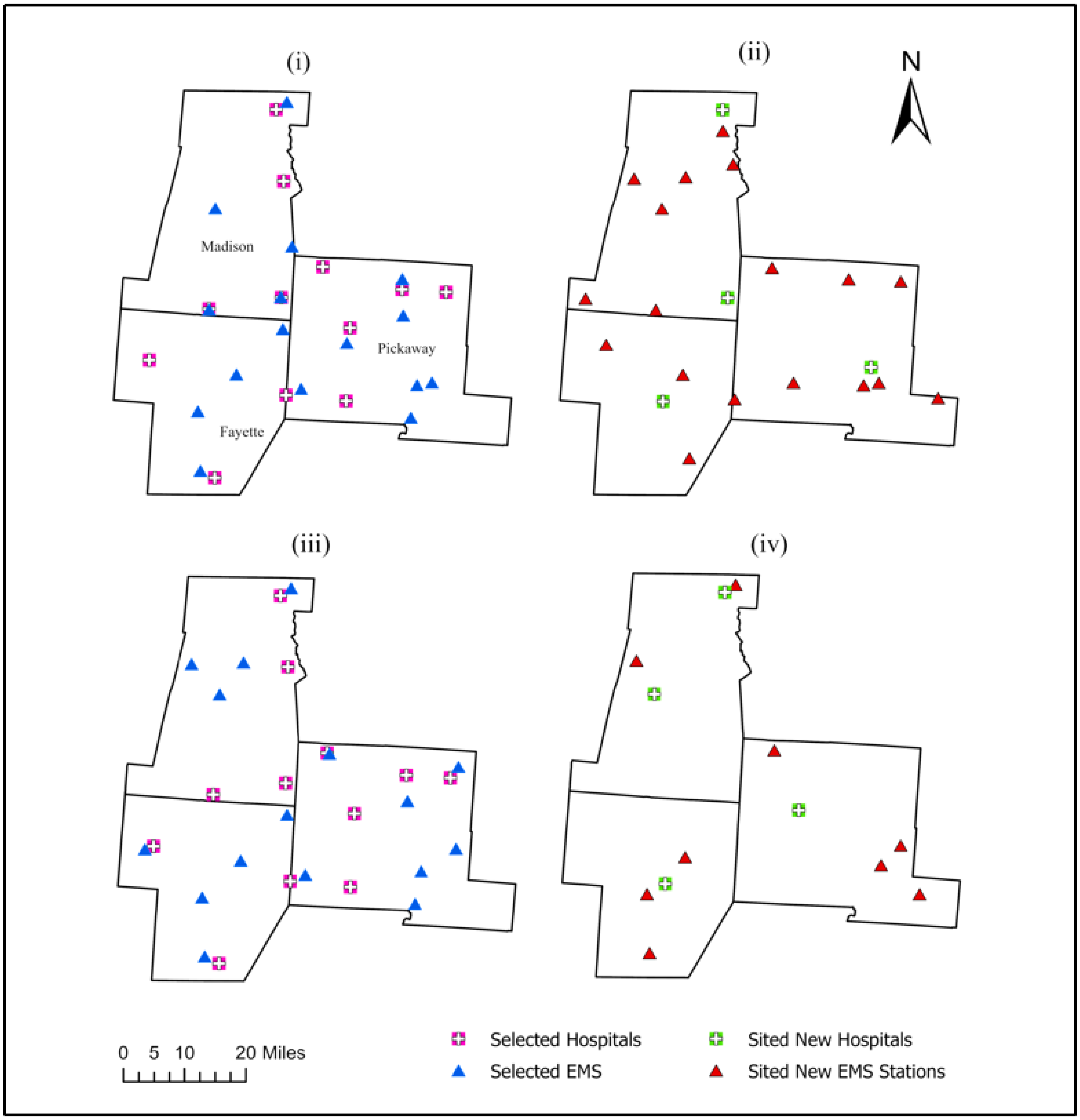

Figure 13: Scenario 1:MCLP-OC:(i) Selected Existing Facilities, (ii) Sited New Facilities; MCLP-JC:(iii) Selected Existing Facilities, and (iv) Sited New Facilities

For instance, in Pickaway County, the hospital is relocated out of the urban core, while in Madison County, hospitals move away from the central area under MCLP-OC, but one remains in the core with MCLP-JC. In this particular case, within the 3 counties the MCLP-OC relocates 18 EMS stations (2 from the pool of candidate sites) and 4 hospitals and MCLP-JC sites 9 EMS stations and 4 hospitals. In operational terms, out of the 18 EMS station sites selected under the MCLP-OC relocation scenario, 16 are retained from existing facilities while 2 are new locations chosen for optimal coverage. This means nearly 90% of selected EMS stations are existing sites, reflecting substantial overlap between current infrastructure and the optimal solution.

As shown in Table 5, both models substantially improve timely EMS coverage compared to the current system. Under the relocation scenario, the MCLP-OC covers 97.0% of the population within the overall trip time standard (≤ 60 min), while the MCLP-JC achieves a similar rate at 96.7%. When the response time requirement (Trip 1 ≤ 14 min) is included, 80.9% of the population is reached by ambulance and delivered within the golden hour using the MCLP-OC, whereas the MCLP-JC increases this to 91.9%. This means the joint coverage model ensures an additional 11% of residents receive both rapid ambulance response and timely transport compared to the overall coverage model. Notably, the gap between overall trip coverage and full response-plus-transport coverage is much smaller for the MCLP-JC, indicating more comprehensive service.

Table 5: Covered Population (%) by Trip 1 and Overall Trip

	Covered Population (%)			
	Scenario 1 (Relocation)		Scenario 2 (Expansion)	
Model	Overall trip (≤ 60 min)	Trip 1 (≤ 14 min) and overall trip (≤ 60 min)	Overall trip (≤ 60 min)	Trip 1 (≤ 14 min) and overall trip (≤ 60 min)
MCLP-OC	97.0	80.9	99.1	86.8
MCLP-JC	96.7	91.9	98.2	92.5

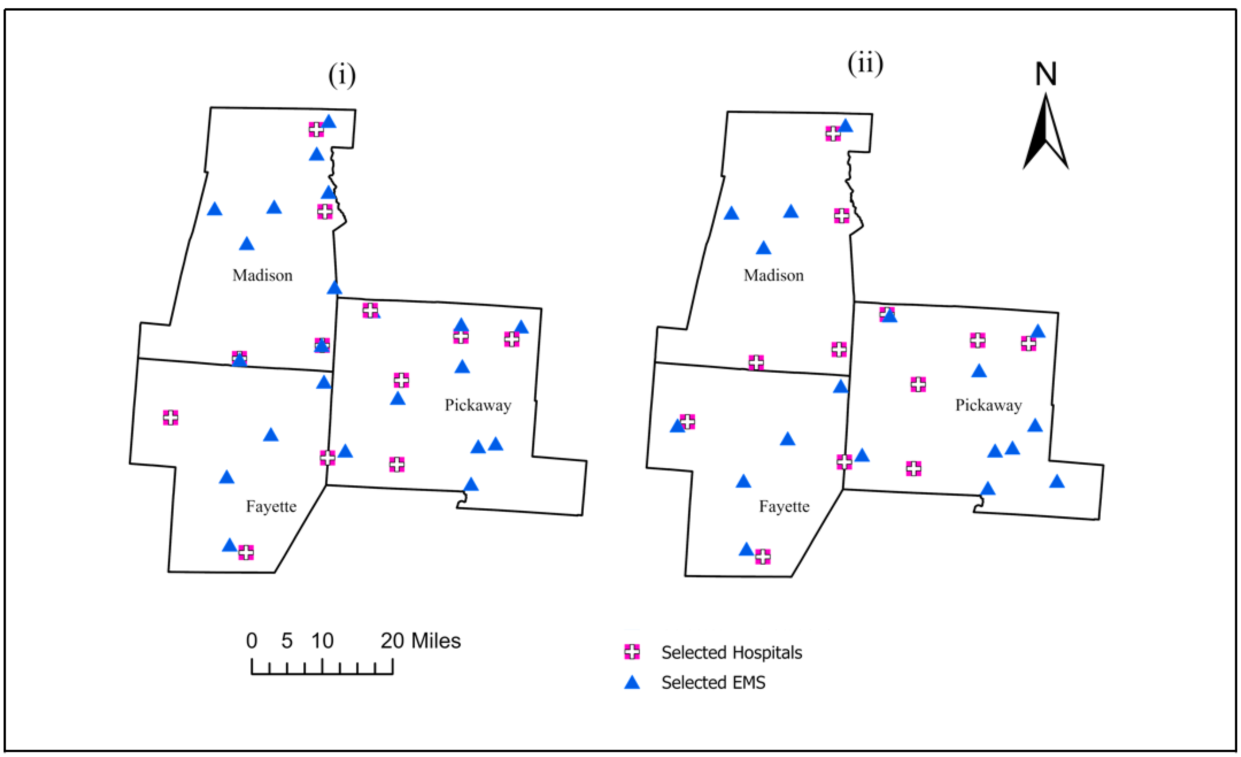

Figure 14: Scenario 2: Sited New Facilities: (i) MCLP-OC (ii) MCLP-JC

Figure 14 presents the optimal facility layouts for Scenario 2, which simulates the expansion of the EMS network. Here, the MCLP-OC solution (Figure 14(i)) identifies five additional EMS station sites, four in Madison County and one in Pickaway County while the MCLP-JC (Figure 14(ii)) adds just two new stations, both in Pickaway. In both models, the majority of EMS stations and hospitals selected for expansion overlap substantially with the existing network, demonstrating that most current facilities already occupy advantageous locations. Notably, the new sites chosen under MCLP-OC in Madison are dispersed across rural zones to maximize spatial coverage, while MCLP-JC's additions further concentrate in Pickaway, likely reflecting persistent service gaps identified in the joint coverage analysis.

Table 5 highlights the population coverage gains achieved by these expansions. Under MCLP-OC, 99.1% of the total population is covered within the 60-minute overall trip standard, with 86.8% receiving both timely ambulance response (≤ 14 min) and golden hour transport. The MCLP-JC achieves 98.2% and 92.5% on these same measures, respectively, surpassing the OC model for rapid response coverage. These results indicate that network expansion, especially when guided by joint coverage standards, narrows the gap between overall and full (response plus transport) coverage, ensuring that a larger share of residents benefit from both prompt EMS arrival and definitive hospital care.

The comparative results between MCLP-OC and MCLP-JC models highlight key differences in the spatial arrangement and effectiveness of EMS system planning. While both models retained most existing EMS stations in the relocation scenario, the MCLP-JC introduced a more balanced configuration by factoring in both EMS response and hospital transport. This resulted in hospital sites moving beyond urban cores and select EMS stations being retained in high demand locations, particularly in Madison County. In contrast, the MCLP-OC concentrated relocations and new site selections driven by a single-trip coverage objective. This approach often resulted in clusters of sites focused on reaching the largest possible number of demand points within a set response time. Approximately 90% of EMS stations selected by both models overlapped with existing sites, indicating that the current network is already well-optimized for station placement. However, both models identified specific gaps in hospital locations, highlighting opportunities to further improve system coverage.

Under the network expansion scenario, distinct patterns emerge between the two models in both site selection and system performance. The MCLP-OC recommends five additional EMS stations primarily dispersed across rural Madison County to broaden spatial coverage whereas the MCLP-JC identifies just two new sites, both targeted in Pickaway County. This difference highlights the strength of joint-coverage metrics: rather than distributing new stations broadly, the joint-coverage approach targets specific gaps in service. In both models, most new facilities overlap with existing high-value sites, indicating that the current network already capitalizes on many optimal locations. Allocating new EMS stations to rural areas is often necessary to improve coverage in less-served regions. However, this approach can lead to lower total population coverage and poses a trade-off between maximizing spatial access and overall network efficiency (Luo et al., 2022). Previous research has shown that in U.S. border communities, the reliance of federal agencies on local EMS resources can place additional demands on the system. This highlights the need to consider local operational contexts when planning EMS networks (Blackburn et al., 2024).

Performance metrics further underscore the value of a joint-coverage approach. Under the relocation scenario, the MCLP-JC ensures that 91.9% of the population receives both rapid EMS response (≤14 minutes) and hospital transport (within 60 minutes), an increase of over 11 percentage points compared to the 80.9% achieved under MCLP-OC. Even though the overall population coverage for the 60-minute standard is comparable between models (97.0% for MCLP-OC and 96.7% for MCLP-JC), the joint-coverage framework closes the gap between theoretical coverage and real-world access to definitive care. With network expansion, these gains become even more pronounced; the MCLP-JC delivers both higher rapid response and overall trip coverage than MCLP-OC (98.2% and 92.5%, respectively). These findings make a clear case that EMS system design guided by joint-coverage metrics offers a more complete and clinically relevant solution, ensuring timely intervention across the full EMS care continuum. Policy and funding barriers may delay or prevent the relocation or expansion of EMS stations recommended by the optimization models. Local governance structures, zoning laws, and public resistance can also influence implementation timelines. For practical planning, system-level interventions like reducing offload delays and addressing staffing gaps are essential to maximize the benefits of new facility placements and improve overall EMS response (Burke et al., 2013; Cooney et al., 2011).

6. CONCLUSION

This research evaluated the availability and effectiveness of post-crash EMS care for elderly populations in rural Ohio, addressing both operational timelines and system planning. We analyzed linked EMS and crash data from 2018 to 2023 to compare response, on-scene, and transport times for elderly crash victims in rural and urban settings. The study identified key crash, environmental, and situational factors such as distance to care, multiple-patient incidents, adverse weather, and off-peak periods that contributed to prolonged EMS timelines. Elderly patients consistently experienced longer on-scene times, underscoring the complexity of their assessment and management. By applying spatial optimization models, we examined whether coordinated EMS station and hospital siting could improve timely access to care. Results showed that joint coverage approaches increased the share of rural elderly residents reached within critical time thresholds, highlighting the benefits of data-driven facility planning.

These findings have important implications for EMS system design, policy, and workforce development. Agencies should prioritize expanding geographic coverage in rural regions where elderly crash risk is highest. The adoption of joint coverage optimization frameworks can help balance response and transport times, reducing preventable delays in both phases of prehospital care. EMS planners should tailor protocols and training to the specific needs of older adults and anticipate the impact of weekends, severe weather, and multi-patient events on operational performance. Policymakers are encouraged to invest in infrastructure, cross-agency coordination, and adaptive staffing models to improve overall system resilience. Regular evaluation and realignment of resource allocation using updated crash and EMS data will further support equitable, effective emergency care for aging rural populations.

There are several limitations and opportunities for future research. This study did not incorporate real-time operational factors, such as ambulance availability, staffing shortages, or system surges during major incidents, which may impact EMS timelines regardless of facility location. Our demand estimates were based on total population rather than risk-adjusted measures for elderly groups, and clinical outcome data were not available for direct linkage to prehospital delays. Future work should include dynamic operational data, risk-adjusted demand modeling, and patient outcome tracking to refine system optimization. Evaluating the effectiveness of interventions in actual EMS operations, especially for rural and elderly populations, will be essential for guiding policy and practice. Expanding the analysis to more regions and diverse EMS systems will help improve the generalizability of recommendations. Addressing these gaps will support continued progress toward reducing delays and improving survival for elderly crash victims in rural communities.

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8. APPENDICES

Table 6: Posterior Estimates of Hierarchical Weibull Regression Model for Urban Crashes

Variable	Categories	Mean	SD	HDI 3%	HDI 97%	MCSE Mean	MCSE SD	% Change
Intercept	Average	0.295	0.081	0.170	0.443	0.001	0.001	-
Distance	Continuous	-0.005	0.016	-0.035	0.023	<0.001	<0.000	0.50
Number of Patients	Single	-	-	-	-	-	-	-
	Multiple	0.206	0.036	0.138	0.273	<0.001	<0.001	22.88
Number of Units	Single	-	-	-	-	-	-	-
	Multiple	-0.167	0.012	-0.191	-0.145	<0.001	<0.001	-15.38
Crash Severity	Minor Injury	-	-	-	-	-	-	-
	Fatal & Severe	-0.025	0.019	-0.062	0.011	<0.001	<0.001	-2.47
Time of Day	Day	-	-	-	-	-	-	-
	Night	0.206	0.056	0.102	0.311	<0.001	<0.001	22.88
	Off-Peak	0.083	0.031	0.025	0.141	<0.001	<0.001	8.65
	Peak	0.291	0.016	0.261	0.321	<0.001	<0.001	33.78
Day of the Week	Weekday	-	-	-	-	-	-	-
	Weekend	0.471	0.023	0.426	0.513	<0.001	<0.001	60.16
Weather Condition	Clear	-	-	-	-	-	-	-
	Inclement	0.348	0.016	0.317	0.379	<0.001	<0.001	41.62
WorkZone Related	Not Related	-	-	-	-	-	-	-
	Related	0.312	0.065	0.188	0.432	0.001	0.001	36.62

Table 7: Posterior Estimates of Hierarchical Weibull Regression Model for Rural Crashes

Variable	Categories	Mean	SD	HDI 3%	HDI 97%	MCSE Mean	MCSE SD	% Change
Intercept	Average	0.244	0.073	0.130	0.376	<0.001	0.001	-
Distance	Continuous	-0.031	0.042	-0.111	0.043	<0.001	<0.001	-3.05
Number of Patients	Single	-	-	-	-	-	-	-
	Multiple	-0.088	0.067	-0.214	0.036	<0.001	<0.001	-8.42
Number of Units	Single	-	-	-	-	-	-	-
	Multiple	0.380	0.026	0.330	0.430	<0.001	<0.001	46.23
Crash Severity	Minor Injury	-	-	-	-	-	-	-
	Fatal & Severe	0.227	0.037	0.157	0.299	<0.001	<0.001	25.48
Time of Day	Day	-	-	-	-	-	-	-
	Night	0.337	0.113	0.130	0.556	0.001	0.001	40.07
	Off-Peak	0.076	0.056	-0.028	0.18	<0.001	<0.001	7.90
	Peak	0.039	0.030	-0.017	0.096	<0.001	<0.001	3.98
Day of the Week	Weekday	-	-	-	-	-	-	-
	Weekend	0.098	0.034	0.035	0.164	<0.001	<0.001	10.30
Weather Condition	Clear	-	-	-	-	-	-	-
	Inclement	0.062	0.030	0.006	0.119	<0.001	<0.001	6.40
WorkZone Related	Not Related	-	-	-	-	-	-	-
	Related	0.272	0.125	0.037	0.505	0.001	0.001	31.26