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Disparities and determinants of EMS response times: a mixed-methods systematic review and LDA-based thematic analysis

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Abstract

Purpose – Response times of emergency medical services (EMS) are critical for patient outcomes and survival rates. This review synthesizes evidence on factors affecting EMS response times and their impacts, aiming to identify disparities and recommend optimization strategies.

Design/methodology/approach – A systematic search was conducted in Web of Science, PubMed and Scopus for English-language studies published between January 1, 2000, and October 20, 2024. Inclusion criteria focused on studies examining EMS response times and associated outcomes, such as mortality and disparities. Exclusion criteria ruled out studies on non-EMS services, case reports and non-English publications. Two independent reviewers screened studies, and risk of bias was assessed using the Cochrane Risk of Bias 2 tool for randomized controlled trials and the Joanna Briggs Institute for observational studies. A narrative synthesis was performed, and meta-analysis was considered where data permitted.

Findings – Of 105 initial articles, 45 studies met the inclusion criteria. Key findings identified five domains impacting EMS response times: ambulance deployment strategies, mortality correlations, optimal placement of ambulances, socioeconomic and geographic disparities and specialized service performance. Quantitative analysis demonstrated that strategic ambulance placement and addressing inequities reduced response times and improved survival rates.

Research limitations/implications – This research highlights several limitations, including data limitations, challenges in addressing geographic and socioeconomic disparities and the need to overcome technological and ethical hurdles. Key research implications include fostering multidisciplinary collaboration, conducting longitudinal studies and prioritizing cost-effectiveness. Addressing inequities in access to care is paramount, requiring targeted interventions and a focus on patient-centred care. Integrating technology while ensuring data security and privacy is crucial. Finally, standardized data collection methods and a focus on continuous improvement through rigorous evaluation are essential for optimizing EMS systems globally.

Originality/value – Although previous systematic reviews have analysed EMS response times and patient outcomes, these studies often fail to address the impact of socio-economic disparities and geographic isolation

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comprehensively. Furthermore, methodological inconsistencies, including varying definitions of response times, limit comparability across studies.

Keywords Response time, Emergency medical service (EMS), Ambulance, Prehospital emergency care, Systematic review, Latent Dirichlet allocation (LDA), Health equity

Paper type Literature review

Abbreviations

AI –	Artificial Intelligence
AHA –	American Heart Association
BMJ –	British Medical Journal
CPR –	Cardiopulmonary Resuscitation
EMS –	Emergency Medical Services
FRS –	Fire and Rescue Services
GIS –	Geographic Information System
GPS –	Global Positioning System
GWR –	Geographically Weighted Regression
ID –	Keywords Plus (Identifier in databases)
LDA –	Latent Dirichlet Allocation
LMIC –	Low- and Middle-Income Countries
MPDS –	Medical Priority Dispatch System
NGO –	Non-Governmental Organization
NHS –	National Health Service
OHCA –	Out-of-Hospital Cardiac Arrest
OSHA –	Occupational Safety and Health Administration
PRISMA –	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RQ –	Research Question
SES –	Socioeconomic Status
SMS –	Short Message Service
SSM –	System Status Management
STEMI –	ST-Elevation Myocardial Infarction
UK –	United Kingdom
US –	United States
VFR –	Voluntary First Responder
WHO –	World Health Organization
WOS –	Web of Science

1. Introduction

1.1 Background

Emergency medical services (EMS) are crucial for survival in critical conditions like cardiac arrest, trauma, and stroke (Sagan and Richardson, 2015; Holmén *et al.*, 2020; O'Keeffe *et al.*, 2011). Ensuring effective EMS necessitates aligning resources with needs, and addressing geographic and socioeconomic disparities to guarantee timely care (Deng *et al.*, 2021; Lam *et al.*, 2015a; Lam *et al.*, 2014, 2015b; Nogueira *et al.*, 2016; Bokor *et al.*, 2026; Dalton *et al.*, 2022; Egan *et al.*, 2020). EMS performance is influenced by various factors including call volume, distance, workload, temperature, and traffic (Lam *et al.*, 2015a; Mahmood *et al.*, 2017; Meng and Weng, 2013; Seong *et al.*, 2023; Thornes *et al.*, 2014; Zhan *et al.*, 2018). Rural areas often experience longer response times due to greater distances and fewer resources (Do *et al.*, 2013; Jin *et al.*, 2023; Lam *et al.*, 2014, 2015b; Lam *et al.*, 2015a; Mell *et al.*, 2017; Nehme *et al.*, 2016). Vulnerable populations are prioritized based on socioeconomic and demographic factors such as age, gender, and ethnicity (Benamer *et al.*, 2016; Govindarajan and Schull, 2003; Sangal *et al.*, 2023; Wilde, 2013). The efficiency of EMS is evaluated through metrics like response times, patient satisfaction, transport efficiency, and financial sustainability (Berest and Merenkova, 2019; Colla *et al.*, 2019; Gonnelli *et al.*, 2018; Ilioudi *et al.*, 2013; Khokhar, 2023; Licata *et al.*, 2023; Nekrashevych and Kovrigo, 2019; Núñez *et al.*, 2018; Stenson *et al.*, 2020; Tlili *et al.*, 2018).

The prehospital interval, critical to patient outcomes, is comprised of five segments: Activation, Response, On-Scene, Transport, and Handover (Bedard *et al.*, 2020; Blanchard *et al.*, 2012; Carr *et al.*, 2006; Chen *et al.*, 2020; Harmsen *et al.*, 2015; Mistovich *et al.*, 2017; Pons, 2005; Spaite *et al.*, 2008; Sullivan *et al.*, 2013; Ueno *et al.*, 2024). Response time, the interval from call receipt to scene arrival, significantly impacts these outcomes (Goto *et al.*, 2018; Govindarajan and Schull, 2003; Holmén *et al.*, 2020; Patel, 2018; Sahealth, 2023). Definitions of response time vary internationally; the US National EMS Information System measures it from call receipt to arrival (Mell *et al.*, 2017), while the UK breaks it down into call handling, turnout, and travel times (Holmén *et al.*, 2020). For time-sensitive trauma cases, some systems extend this to include transport time (Nichol *et al.*, 2008). To enhance comparability across systems, the Utstein style guidelines recommend standardized reporting for intervals from call receipt to dispatch, dispatch to scene arrival, and scene departure to hospital arrival (Nichol *et al.*, 2008). The handover segment is especially vital for ensuring continuity of care through the accurate communication of on-scene data to hospital staff.

A primary goal for healthcare providers is the effective management of response times through sophisticated call triage and dispatch protocols. Response times differ globally, being faster in developed areas like Europe and North America and slower in developing nations due to resource limitations (Hansen *et al.*, 2024; Setyarini and Windarwati, 2020; Noor *et al.*, 2024; Rafiq and Khanum, 2021; Syed and Namburi, 2020). Factors such as economic development, infrastructure, personnel availability, and environmental conditions all affect response times (Hansen *et al.*, 2024; Setyarini and Windarwati, 2020). For instance, response times for high-acuity calls in the US are typically 8–10 min, whereas in rural India and much of Africa, they can be as long as 30–45 min (Nehme *et al.*, 2016; Noor *et al.*, 2024; Rafiq and Khanum, 2021; Syed and Namburi, 2020; Kobusingye *et al.*, 2005).

The historical development of EMS has varied. In high-income countries, formal systems began to emerge in the 1960 and 1970s (Delaney *et al.*, 2024; Mehmood *et al.*, 2018). The Anglo-American model was heavily influenced by military trauma care, shaping its focus on rapid response and field triage. In contrast, the Franco-German medicine d'urgence model originated more from physician-led hospital medicine. The growth of prehospital paramedicine and centralized dispatch were also key developments in these systems (Plummer and Boyle, 2017; Sun *et al.*, 2024). These different historical paths have shaped the infrastructure, resource availability, and operational policies of modern EMS, contributing to the significant disparities in response times seen between high- and low-income countries today.

1.2 Research gap

There are valuable systematic and meta-analysis reviews on emergency response time (Carr *et al.*, 2006; Hansen *et al.*, 2024; Setyarini and Windarwati, 2020; Alharbi*et al.*, 2022; Cabral *et al.*, 2018; Desai *et al.*, 2019; Doggett *et al.*, 2018). These studies consistently address concerns about data availability, quality, and bias. Doggett *et al.* emphasize the limitations caused by either partial or incomplete data, which can potentially lead to biases in their findings (Doggett *et al.*, 2018). Similarly, Carr *et al.* highlight variations in data reporting techniques and geographical scope, which present obstacles to achieving comparability and generalizability (Carr *et al.*, 2006). In addition, Cabral *et al.* emphasize the drawbacks of exclusively relying on data obtained from academic databases (Cabral *et al.*, 2018). They might not encompass every study relevant to the topic, or these might be narrow and not representative of the EMS response times. These include methodological limitations related to the inconsistency of research approaches in establishing standardized techniques and the inability to rule out confounders. Whereas Carr *et al.* (2006) acknowledged the challenge imposed by variations in data reporting techniques, Hansen *et al.* (2024) identified factors such as hospital overcrowding and scarce hospital staff as potentially affecting patient outcomes. More specifically, this review by Setyarini and Windarwati (2020) has pointed out several methodological problems, such as insufficient consideration of relevant research and inconsistency, which prevent the integration of knowledge at the current time.

1.3 Significance of systematic review

Systematic reviews are among the dominant methodological approaches to study response time and how this affects patient outcomes (Hansen *et al.*, 2024; Setyarini and Windarwati, 2020). Researchers commonly initiate their work by conducting thorough searches in prominent databases such as WOS/PubMed/MEDLINE to discover pertinent studies (Hansen *et al.*, 2024). Subsequently, multiple review methodologies are utilized. Systematic reviews are a methodical and established methodology that entails conducting a structured search, selecting relevant research, and critically evaluating it to synthesize current information on a particular topic (Hansen *et al.*, 2024; Setyarini and Windarwati, 2020).

1.4 Research questions

This article attempts to deconstruct the many facets of EMS response times related to their broader implications. The specifics of attention to this inquiry have been guided by consideration of the following research questions:

RQ1. What are the key system-level, environmental, and patient-related factors that influence ambulance response times, and how can these be optimized to improve EMS performance across diverse contexts?

RQ2. How do ambulance response times impact patient outcomes, such as survival and mortality, across different types of emergencies, and what roles do demographic and situational modifiers (e.g. bystander CPR, age, gender) play in this relationship?

RQ3. In what ways do socioeconomic and geographic disparities affect EMS response times, and what targeted strategies can mitigate these inequities in low-resource or underserved settings?

RQ4. What operational and logistical challenges arise in context-specific scenarios (e.g., high-rise buildings, disaster zones), and how can EMS systems adapt through location-aware strategies and fairness-based algorithms to maintain timely and equitable access?

These questions focus on synthesizing existing evidence, which is the primary goal of this paper's systematic review. The factors affecting response times and their ripple effects on patient outcomes were dissected. A three-pronged approach lays bare the complex interplay influencing response times, leading to an in-depth understanding of the dynamics in EMS. Finally, any inequalities in response times based on demographics were revealed and implored that something should be done to ensure equal opportunities for care. Any advanced data analysis technique, such as the LDA method, ensures objectivity, whereas a critical methodology critique allows future improvements. This will, in turn, allow policymakers to use this information to optimize response times, better manage patients, and utilize resources.

1.5 Research process

Figure 1 below summarized the research process used in this paper. It followed a rigorous process: from clear questions to detailed protocol, including search strategies, screening methods, and tools for reference management using Zotero. The titles, abstracts, and full texts were screened for studies that fit into the research using the PRISMA reporting guideline. Further data extraction was conducted on a standardized format, followed by the quality assessment using tools such as the Cochrane risk of bias tool. Synthesis was comparing, analysing, and interpreting findings across studies. Results included tables, figures, and a clear

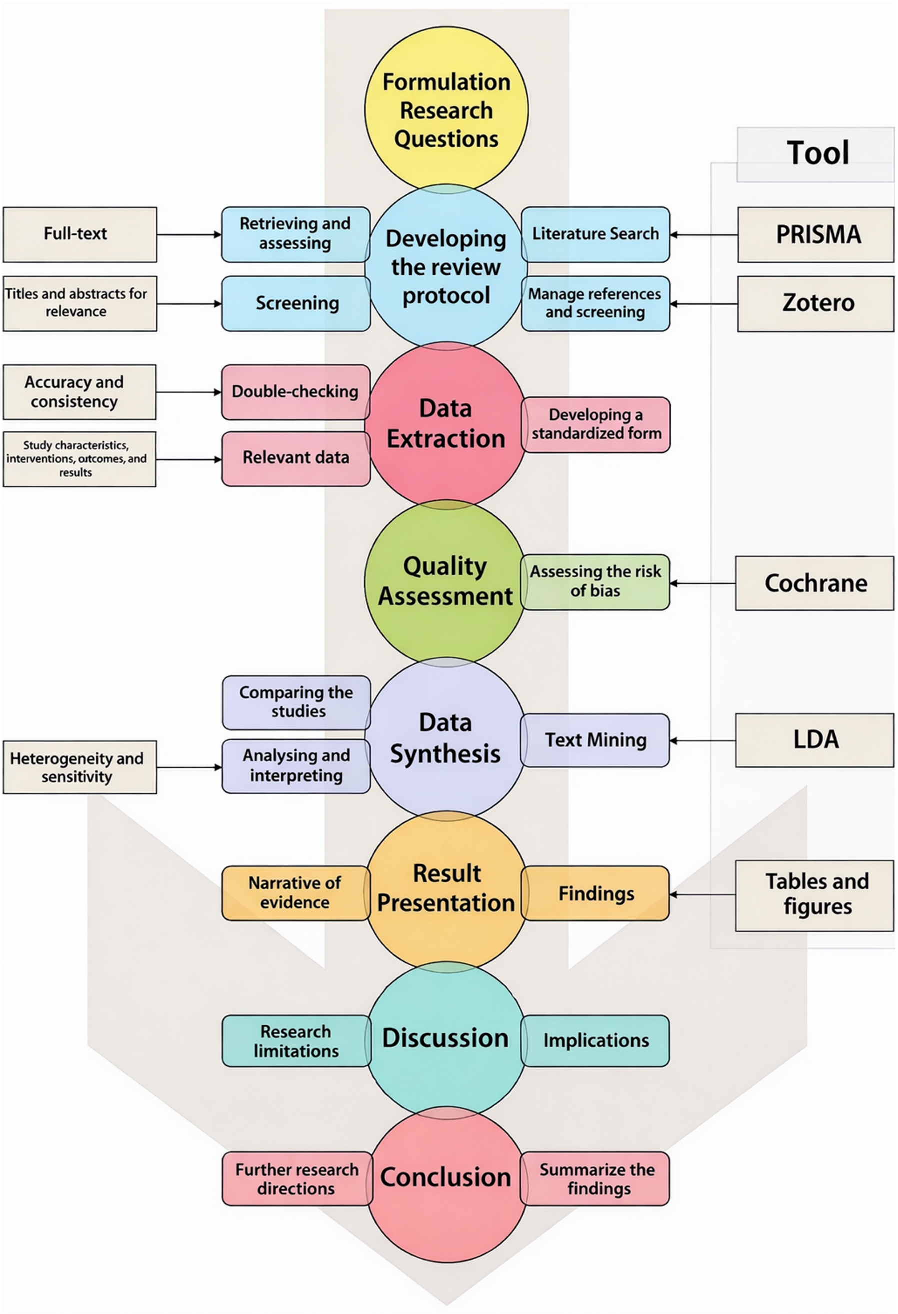


Figure 1. Research process. Source: Authors

narrative summary. Discussion included implications, limitations, and future directions for research. The conclusion summarized the points of focus in a summary form and pinpoints areas for further study in the last section.

2. Methods and materials

2.1 PRISMA

This systematic review followed The Cochrane Handbook for Systematic Reviews of Intervention (Higgins *et al.*, 2022) as the main methodological framework, ensuring rigour and transparency. The PRISMA 2020 statement (Page *et al.*, 2021; Soltani *et al.*, 2024a) was also adopted to provide structure, transparency, and standardization.

The review systematically addressed research questions on EMS response times, their determinants, and their effects on patient outcomes. Studies on EMS response times in prehospital care that examined influencing variables or associations with outcomes were included. Eligible designs were randomized controlled trials, cohort, case-control, observational studies, and systematic reviews published in English between 1 January 2000 and 31 December 2024. Excluded were studies unrelated to EMS, lacking precise response time data, or not in English. The full protocol is in Appendix.

A comprehensive search was conducted in Web of Science (WOS), PubMed, and Scopus using consistent key terms and Boolean operators such as (EMS response time OR ambulance response time) AND (patient outcomes OR mortality OR geographic disparities). Duplicates were removed by comparing titles, authors, and years. This yielded 85 unique articles, of which 60 were included for full review and synthesis. Two researchers independently reviewed articles to minimize bias, resolving disagreements by discussion. Data were extracted with a standardized form covering design, population, exposures, and outcomes, forming the basis for synthesis. Inclusion/exclusion criteria were reapplied during full-text review, and reasons for exclusion were recorded.

Study quality was assessed using the Cochrane RoB 2 tool (Higgins *et al.*, 2022) to evaluate bias in randomized trials. Findings were summarized narratively, highlighting determinants of EMS response times and links to outcomes. Tables and visuals displayed study characteristics, assessments, and extracted data. The PRISMA process was followed to ensure transparency and reproducibility in study selection (Page *et al.*, 2021). The detailed screening results are presented in the Results section (see Figure 2).

2.2 Variables investigated

Medical studies on paramedics highlight prehospital factors affecting outcomes, specifically call processing (reaction time), on-scene time, and transport intervals (Newgard *et al.*, 2010). Patient demographics, pre-existing conditions, and socioeconomic disparities also shape care quality (Carr *et al.*, 2014; Hsia *et al.*, 2012). Key outcomes include response time, mortality, hospital admissions, survival, and ambulance call volume, all linked to systemic and contextual factors (Blackwell and Kaufman, 2002).

Response time variability reflects demographics, geography, and building type, with delays tied to higher mortality and spatial inequities (Pons *et al.*, 2005; Carr *et al.*, 2014). Admissions correlate with comorbidities, while survival depends on timely intervention (Hsia *et al.*, 2012; Newgard *et al.*, 2010). Response time uniquely influences mortality, survival, and healthcare costs, distinguishing it from other operational metrics (Blackwell and Kaufman, 2002). Disparities in geography and demographics worsen access delays, while weather and traffic disrupt efficiency (Murray *et al.*, 2017). Ambulance availability remains critical to mitigating service gaps (Redelmeier *et al.*, 2015). Understanding these interdependencies is vital for optimizing EMS and improving outcomes (Institute of Medicine, 2007). In this study, response time, defined earlier, serves as the target variable.

2.3 Method of data analysis: improved literature on LDA for text analysis

A systematic review relies on text mining to discover key concepts relating to power relations with planning. Text mining is a method of raw data extraction from large quantities of text to generate knowledge in new ways (Zhai and Massung, 2016). Among the easy-to-use free and open-source academic text mining programs are *Vosviewer* and *Orange* (Demšar and Zupan, 2013; Eck and Waltman, 2009; Bagheri *et al.*, 2024). In this study, using *Orange*, text preprocessing, mining, visualization, and searching were all performed (Demšar *et al.*, 2013).

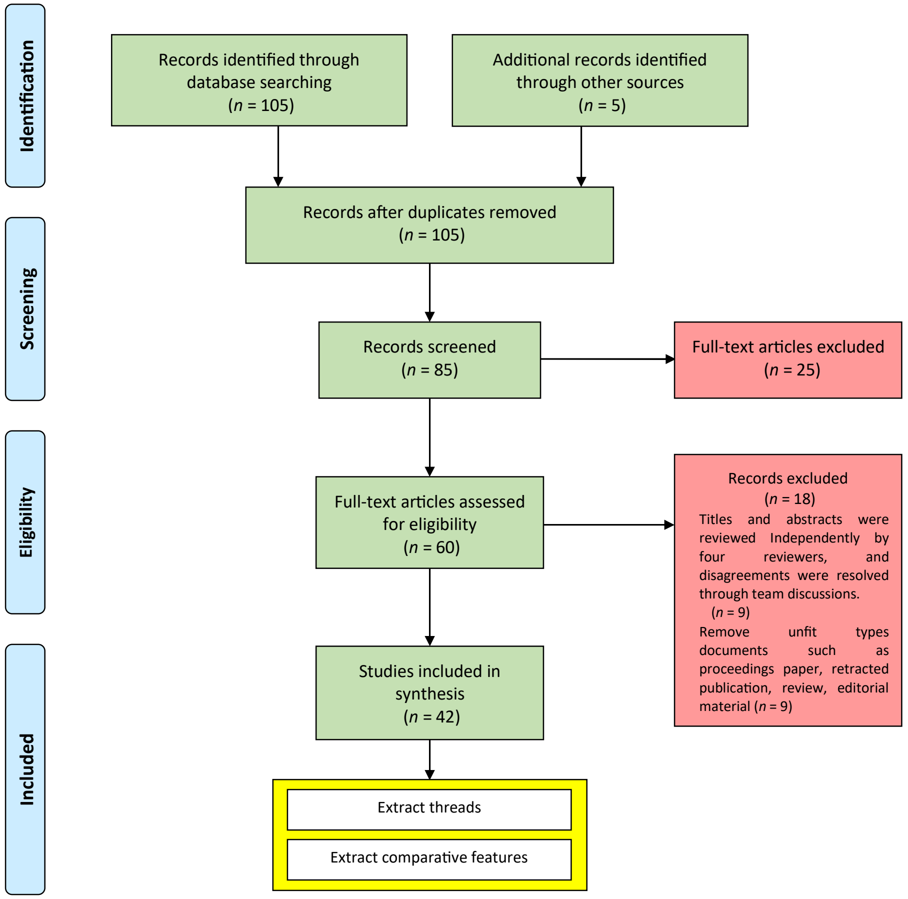


Figure 2. PRISMA diagram Source: Page *et al.* (2021)

The steps involved in text mining and gathering data for text mining, included the researcher using predetermined search criteria to find and gather articles. To apply the principles of accessible, discoverable, interoperable, and repeatable text mining analysis (Wilkinson *et al.*, 2016), the researcher must ensure they: (1) check the download source; (2) apply search criteria; and (3) provide a precise timeline of published articles. Text mining was carried out in three stages: gathering the literature data and loading, preprocessing, processing, and analysing the findings and visualisations. The goal of thematic modelling was to identify underlying themes that can be combined into documents to analyse large text sets. A probabilistic model explains the relationship between the observed documents and the underlying topics (Hua *et al.*, 2020).

2.3.1 Text mining for detection of dominant threads. In this study, the Latent Dirichlet Allocation (LDA) was applied for topic modelling on a textual corpus. LDA is a generative probabilistic model that uncovers latent themes by analysing word co-occurrence patterns, functioning like clustering but based on shared contexts rather than frequency alone (Blei *et al.*, 2003; Allan *et al.*, 2022). It infers topic distributions across documents by iteratively assigning words to topics and updating associations using conditional probabilities (Griffiths and Steyvers, 2004; Wallach *et al.*, 2009).

Before analysis, the dataset underwent preprocessing, including removal of stopwords, filtering high-frequency non-informative terms, and transforming text into a bag-of-words representation, preserving token frequency while disregarding order and grammar (Jockers and Mimno, 2013; Blei *et al*., 2003). The number of topics (*k*) was predefined and refined through updates to word-topic and document-topic matrices, maximizing the likelihood of word-topic and topic-document assignments (Wallach *et al*., 2009). Each topic was defined by a probability distribution over terms, with top words extracted for interpretation, enhancing coherence and interpretability (Sievert and Shirley, 2014). All modelling and visualization were conducted in Orange (GPLv3) with built-in LDA functions (Demšar *et al*., 2013).

To validate results, a two-stage process was used. First, model quality was measured with the C_v coherence score, which captures semantic similarity among top terms (Sievert and Shirley, 2014). Multiple LDA models with k = 5–15 were trained, and coherence scores plotted to detect the elbow point, guiding candidate model selection. Second, two independent researchers reviewed the top 10 keywords of each topic for semantic coherence, resolving disagreements by consensus and aligning themes with EMS literature.

To prevent overfitting, the perplexity was also examined, an indicator of model generalizability. Models with low perplexity but poor coherence were discarded. The final model, at k = 5, achieved the best balance between coherence ($C\_v = 0.47$) and acceptable perplexity. This validation framework strengthened the reliability, transparency, and reproducibility of the topic modelling, ensuring that extracted themes were both analytically sound and contextually meaningful.

3. Results

3.1 Study identification and selection

The study selection process followed the PRISMA 2020 framework (Page *et al*., 2021; Zaroujtaghi *et al*., 2025; Soltani *et al*., 2024b). Figure 2 presented the PRISMA flow diagram summarizing the number of records identified, screened, excluded, and included in the final synthesis. Out of 85 records initially retrieved from the databases, 60 met all inclusion criteria and were retained for full-text review and data analysis.

3.2 Temporal distribution

Figure 3 presented the number of annual studies from 2000 to 2024. The number of studies climbed upwards from 2000 to 2010, peaking in that year. Following this, there was a slight decline in the number of studies carried out, while in recent years, the number has once again gone upwards. The number of studies followed a very fluctuating pattern over time, probably due to factors like funding cycles or other worldwide events that affect the carrying out of the studies.

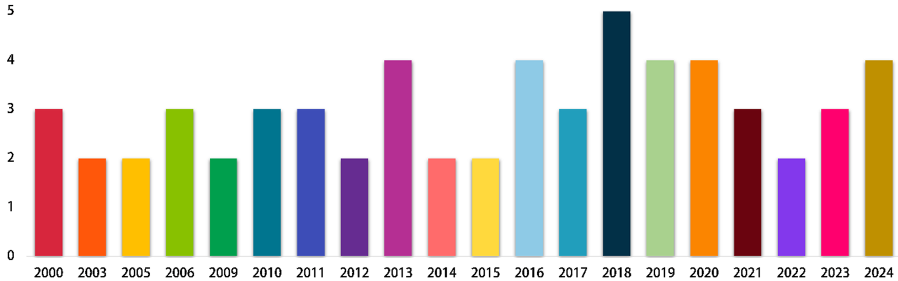


Figure 3. Temporal distribution of selected studies. Source: Authors

3.3 Geographical distribution

This review included studies from various countries and World Bank income categories (Figure 4). Most were from high-income countries such as Canada (Govindarajan and Schull, 2003; Blanchard *et al.*, 2012), the United States (Blackwell *et al.*, 2009; Byrne *et al.*, 2019; Gonzalez *et al.*, 2009; Hsia and Shen, 2011; Hsia *et al.*, 2018; Ma *et al.*, 2019; Weiss *et al.*, 2013), the United Kingdom (Mahmood *et al.*, 2017; Thornes *et al.*, 2014; Mills *et al.*, 2024), France (Benamer *et al.*, 2016), Italy (Lucchese, 2024), Denmark (Rajan *et al.*, 2016; Mills *et al.*, 2024), Sweden (Svensson *et al.*, 2024), Japan (Goto *et al.*, 2018), and Australia (Nehme *et al.*, 2016), offering insights into EMS best practices in developed health systems. A smaller number came from upper-middle-income countries like Brazil (Nogueira *et al.*, 2016; Colla *et al.*, 2019) and China (Jin *et al.*, 2023; Zhan *et al.*, 2018; Chen *et al.*, 2020), and lower-middle-income economies such as Bangladesh (Maghfiroh *et al.*, 2018; Tshokey *et al.*, 2022), highlighting challenges from resource and infrastructure limitations.

Although high-income countries dominate EMS research, literature from LMICs, particularly Africa, is expanding. Zakariah *et al.* (2017) detailed Ghana's decade-long National Ambulance Service growth, while Mould-Millman *et al.* (2017) mapped EMS systems in 16 African countries, noting limited coverage and infrastructure gaps. Kobusingye *et al.* (2005) stressed emergency care's feasibility in low-resource contexts and called for better planning and integration. Despite fewer studies, such work provides a foundation for global EMS policy.

In high-income settings, EMS typically relies on moderately dense ambulance networks supported by GIS-based planning, GPS tracking, AI-assisted routing, and centralized dispatch. Services employ well-trained paramedics, often with specializations, and operate under quality frameworks that use performance metrics for continuous improvement (Holmén *et al.*, 2020; Mell *et al.*, 2017). Stable funding and integrated prehospital-hospital care further ensure consistent delivery and relatively low response times.

By contrast, EMS in resource-limited areas often adopt community-based solutions: motorcycle or bicycle ambulances, community paramedicine training, and volunteer responders. Low-cost tools such as SMS dispatch replace advanced systems, while collaborations with clinics, NGOs, and mobile units extend coverage despite financial and logistical barriers (Kobusingye *et al.*, 2005; Mould-Millman *et al.*, 2017).

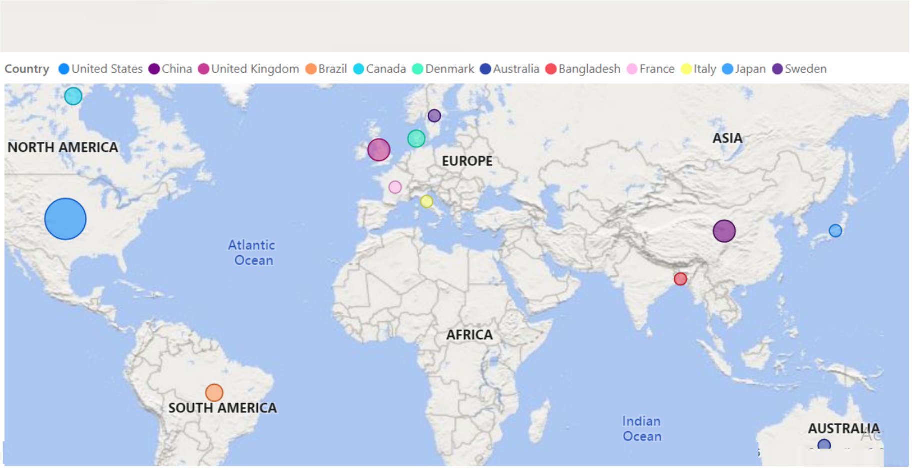


Figure 4. Geographical distribution of selected studies. Source: Authors

3.4 Frequent keywords

The presence of both Author's Keywords (DE) and Keywords Plus (ID) indicates that this set contains documents on various subject matters. The collection is broadly varied, with 134 Keywords used by authors to draw attention to their work's themes and focal points. Each term's relative size in the word cloud graph depicts the frequency and importance throughout the dataset. Not surprisingly, the terms time/times, response, ambulance, emergency, patients, medical, demand, EMS, service, and outcomes popped out as the highest frequent words in the collection. The frequent appearance of these terms indicated that a systematic review article dealt with analysing and optimizing response times of ambulances and 'rescue' services in general, especially for significant or critical incidents. Such terms as time/times, response, ambulance, EMS, and medical were indicative that this literature review looked at factors impinging on response time, practices to reduce delays, and how effective ambulance disposition enhanced timely emergency care. Also, words like emergency, patients, and outcomes suggested that these articles examined the relationship of response times to the seriousness of medical emergencies and their interaction with patient mortality rates and overall health outcomes. As illustrated in Figure 5, the word cloud highlighted that while speed was a dominant theme, keywords related to "equity", "socioeconomic disparities", and "environmental factors" were increasingly central to the literature.

3.5 Methods applied

Table 1 provided an overview of the methodologies employed in studies investigating ambulance response times and emergency medical services (EMS). These methodologies were categorized into four primary groups: Observational Study Designs, Analytical Methodologies, Simulation and Optimization, and Mixed-Method Approaches.

Observational designs constituted the largest category, comprising 20 studies (46.5%), with retrospective studies representing the most prevalent approach (10 studies, 23.3%). These

Figure 5. Word cloud of keywords. Source: Authors

Table 1. Methodologies/methods utilized in studies related to response time

Category	Type	Methodology	Article
Observational study designs	Retrospective Studies	Imputation methodology, retrospective data collection	Gonzalez *et al.* (2009)
		Retrospective analysis of medical documentation	Kłosiewicz *et al.* (2017)
		Retrospective data analysis	Chen *et al.* (2019)
		Registry-based cohort design, statistical analyses	Mills *et al.* (2024)
		One-year retrospective cohort study	Blanchard *et al.* (2012)
		Retrospective cohort design	Pons (2005)
		Retrospective cohort study	Rehn *et al.* (2017)
		Case-control retrospective study	Blackwell *et al.* (2009)
	Cross-Sectional Studies	Quantitative cross-sectional design	Alumran *et al.* (2020)
		Cross-sectional analysis, multinomial logit model	Hsia and Shen (2011)
		Cross-sectional study, real-time monitoring	Tshokey *et al.* (2022)
	Prospective Studies	Prospective evaluation over 5 years	O'Keeffe *et al.* (2011)
		Prospective data analysis, statistical tests	Lateef and Anantharaman (2000)
		Observational prospective design, GIS mapping	Ong *et al.* (2010)
		Prospective census over one week	Breen (2000)
		Prospective multicenter registry analysis	Benamer *et al.* (2016)
		Prospective observational controlled study	Rehn *et al.* (2017)
	Population-Based	Population-based analysis	Byrne *et al.* (2019)
		Population-based, observational design	Goto *et al.* (2018)
	Observational Studies	Observational and comparative study	Svensson *et al.* (2024)
		Observation studies, surveys, GIS analysis	Maghfiroh *et al.* (2018)
Analytical methodologies	Regression Analyses	Retrospective analysis, quantile regression models	Nehme *et al.* (2016)
		Instrumental variable analysis, regression analysis	Lucchese (2024)
		Econometric framework, OLS, and IV estimation	Wilde (2013)
		GWR	Seong *et al.* (2023)
		Semi-parametric additive logistic regression	Ma *et al.* (2019)
		Quantile regression	Colla *et al.* (2023)
		Logistic regression model	Meng and Weng (2013)
		Logistic regression models, sensitivity analyses	Hsia *et al.* (2018)
		Quantitative analysis, quantile regression	Lam *et al.* (2015a, b)
		Multiple logistic regression, survival analysis	Rajan *et al.* (2016)
		Quantile regression analysis	Do *et al.* (2013)
	Time-Series Analyses	Cross-sectional time-series analysis	National (2023)
		Time-series analysis	Zhan *et al.* (2018)

(*continued*)

Table 1. Continued

Category	Type	Methodology	Article
	Data Analyses	Analysed ambulance call records	Govindarajan and Schull (2003)
		Quantitative analysis of historical data	Thornes *et al.* (2014)
		Data collection and analysis	Kal'avský *et al.*, 2018
		Detailed analysis of ambulance and temperature data	Mahmood *et al.* (2017)
Simulation and Optimization	Simulation and Modelling	Database analysis, optimization modelling, and simulation	Nogueira *et al.* (2016)
		Discrete event simulation, geospatial analysis	Lam *et al.* (2014)
		GIS analysis, mathematical programming	Lam *et al.* (2015b)
Mixed Methodology	Mixed-Method Study	Mixed-method (quantitative and qualitative)	Jin *et al.* (2023)

studies analysed historical medical or administrative data to examine associations between exposures and outcomes (Talari and Goyal, 2020). Methods included retrospective data collection, registry-based cohort designs, and advanced statistical analyses. Cross-sectional studies accounted for four studies (9.3%) and employ surveys, quantitative analyses, or real-time monitoring to provide a snapshot of populations at a single time point (Mantel and Haenszel, 1959). Prospective studies were reported in six studies (14.0%), following participants over time to assess outcomes after specific interventions or exposures, using tools such as GIS mapping, multicenter registry analyses, and statistical testing (Talari and Goyal, 2020).

Population-based and cohort studies each included two studies (4.7%), leveraging large datasets to represent general populations or to assess longitudinal exposure-outcome relationships (Valsamis *et al.*, 2019; Mantel and Haenszel, 1959). Additionally, two studies (4.7%) examined free-living, non-institutionalized populations without experimental interventions (Samnani *et al.*, 2017).

Analytical methodologies were reported in seven studies (16.3%) and included regression analyses, geographically weighted regression, instrumental variable techniques, survival analyses, and sensitivity testing to explore relationships between variables (Grant and Booth, 2009). Time-series analyses appeared in two studies (4.7%), identifying temporal patterns, while general data analyses were applied in four studies (9.3%) to model data, perform transformations, and conduct exploratory analyses supporting evidence-based decisions (Grant and Booth, 2009).

Simulation and optimization approaches were employed in two studies (4.7%), incorporating discrete event simulation, mathematical programming, geospatial analysis, and optimization modelling to evaluate and improve EMS deployment strategies (Grant and Booth, 2009). Finally, one study (2.3%) utilized a mixed-method design, integrating qualitative and quantitative techniques, including surveys, interviews, and statistical analyses, to provide a comprehensive understanding of complex phenomena (Samnani *et al.*, 2017).

Collectively, these studies reflected the interdisciplinary nature of EMS research, drawing upon statistics, epidemiology, operations research, geographic information systems, and econometrics.

3.6 Thematic analysis

Based on the LDA method, studies were classified into five thematic threads (Table 2). To provide a clear answer to our initial enquiries: Thread A (Operational/Environmental) directly

Table 2. Thread Loadings by Paper using LDA

Paper	Thread 1	Thread 2	Thread 3	Thread 4	Thread 5
Govindarajan and Schull (2003)	0.61	0.23	0.32	*0.87*	0.44
Thornes *et al.* (2014)	*0.93*	0.14	0.14	0.24	0.19
Gonzalez *et al.* (2009)	0.46	*0.88*	*0.73*	0.47	0.68
Kłosiewicz *et al.* (2017)	0.23	*0.93*	0.17	0.21	0.44
Chen *et al.* (2019)	*0.88*	0.13	0.53	0.48	0.26
Nehme *et al.* (2016)	*0.90*	0.53	0.28	0.50	0.57
Alumran *et al.* (2020)	0.28	0.58	0.11	0.26	0.38
Hsia and Shen (2011)	0.54	0.54	0.51	*0.71*	0.26
Tshokey *et al.* (2022)	0.46	0.32	0.21	0.38	*0.77*
O’Keeffe *et al.* (2011)	0.23	*0.76*	0.56	0.28	0.64
Lateef and Anantharaman (2000)	0.18	0.49	0.26	0.22	0.62
Ong *et al.* (2010)	0.25	0.19	*0.92*	0.64	0.23
Breen (2000)	*0.88*	0.35	0.65	0.25	0.22
Benamer *et al.* (2016)	0.49	0.45	0.65	*0.73*	*0.82*
Mills *et al.* (2024)	0.67	*0.82*	0.42	0.55	0.20
Byrne *et al.* (2019)	0.42	0.59	0.40	0.66	0.58
Goto *et al.* (2018)	0.23	0.68	0.56	0.53	0.13
Blanchard *et al.* (2012)	0.62	*0.75*	0.50	0.28	0.46
Pons (2005)	0.14	*0.89*	0.28	0.17	0.60
Weiss *et al.* (2013)	0.31	*0.81*	0.35	0.66	0.34
Blackwell *et al.* (2009)	0.68	*0.73*	0.23	0.42	*0.83*
Svensson *et al.* (2024)	0.22	0.15	0.38	0.16	*0.86*
Lucchese (2024)	*0.94*	*0.76*	0.19	0.47	0.42
Wilde (2013)	*0.93*	*0.71*	0.46	0.31	0.58
Seong *et al.* (2023)	*0.79*	0.67	0.20	0.14	0.32
Ma *et al.* (2019)	0.21	*0.88*	0.18	0.35	0.13
Colla *et al.* (2023)	*0.86*	0.39	*0.76*	0.23	0.15
Meng and Weng (2013)	*0.77*	0.29	0.31	0.42	0.66
Hsia *et al.* (2018)	0.42	0.13	0.43	*0.82*	0.58
Lam *et al.* (2015a, b)	0.61	0.39	0.10	0.59	0.11
Rajan *et al.* (2016)	0.63	*0.75*	0.58	0.64	0.41
Do *et al.* (2013)	*0.84*	0.50	0.29	0.60	0.61
Nathens *et al.* (2004)	0.20	*0.79*	0.51	0.29	0.58
Zhan *et al.* (2018)	*0.71*	0.34	0.69	0.66	0.68
Kal’avský *et al.* (2018)	0.66	0.12	0.48	0.54	*0.74*
Mahmood *et al.* (2017)	*0.77*	0.61	0.53	0.18	0.31
Nogueira *et al.* (2016)	0.50	0.54	*0.88*	0.28	0.63
Lam *et al.* (2014)	0.25	0.31	*0.73*	0.65	0.12
Lam *et al.* (2015a, b)	0.13	0.16	*0.87*	0.52	0.28
Rehn *et al.* (2017)	0.65	*0.76*	0.22	0.57	*0.86*
Maghfiroh *et al.* (2018)	0.33	0.30	0.68	0.58	0.55
Jin *et al.* (2023)	0.57	0.32	0.17	0.52	*0.89*
Cabral *et al.* (2018)	*0.85*	0.59	0.67	0.12	0.16
Carr *et al.* (2006)	0.23	*0.73*	0.19	0.26	0.40
Doggett *et al.* (2018)	0.63	*0.75*	0.18	0.25	0.28
Hansen *et al.* (2024)	0.19	*0.94*	0.22	0.65	0.21
Rafiq and Khanum (2021)	0.42	0.16	*0.79*	0.65	0.26
Alharbi *et al.* (2022)	0.35	*0.79*	0.22	0.64	0.59
Setyarini and Windarwati (2020)	*0.76*	0.61	0.23	0.56	0.30
Desai *et al.* (2019)	0.38	0.41	*0.92*	0.18	0.62
Tanigawa and Tanaka (2006)	0.60	0.25	0.13	0.64	0.67
Arcolezi *et al.* (2021)	0.47	0.65	0.46	0.42	0.14
Bürger *et al.* (2018)	*0.94*	0.29	0.51	0.11	0.66
Earnest *et al.* (2012)	0.28	0.40	*0.95*	*0.89*	0.26
Friedson (2018)	0.68	*0.94*	0.31	0.17	0.46

(*continued*)

Table 2. Continued

Paper	Thread 1	Thread 2	Thread 3	Thread 4	Thread 5
Gratton *et al.* (2010)	0.65	0.26	0.68	0.68	0.27
Heidet *et al.* (2020)	0.22	*0.95*	0.36	0.17	0.57
Holmén *et al.* (2020)	*0.91*	0.23	0.14	0.45	0.33
Mansourihanis *et al.* (2024)	0.13	0.12	0.11	0.34	0.48
Seim *et al.* (2018)	*0.77*	*0.86*	0.13	0.16	0.55

Note(s): Values > 0.70 in italic
Source(s): The authors

addressed RQ1 regarding system-level factors. *Thread B* (Clinical Outcomes) provided evidence for RQ2 regarding survival impact. *Threads C* and *D* (Optimization and Disparities) together addressed the equity focus of RQ3, while *Thread E* (Specific Emergency Services) answered RQ4 regarding logistical challenges in high-rise or disaster zones (Figure 6). This explicit alignment between research questions and thematic threads addresses prior critiques regarding analytical clarity.

3.6.1 Thread A: factors influencing ambulance response times. Timely initiation of effective care, particularly bystander cardiopulmonary resuscitation (CPR) and early defibrillation, is a key determinant of survival in time-critical emergencies such as cardiac arrest. Although shorter ambulance response times are generally associated with improved outcomes in some conditions, their impact is mediated by the broader chain of survival and varies across contexts. Response intervals are influenced by system-level (e.g., dispatch protocols, resource allocation, dispatch efficiency, travel time), patient-level (e.g., case mix, location, age, gender, severity of condition, and type of incident), and environmental (e.g., traffic, geography) factors (Perkins *et al.*, 2015; Wissenberg *et al.*, 2013; Hasselqvist-Ax *et al.*, 2015; Do *et al.*, 2013; Nehme *et al.*, 2016; Colla *et al.*, 2019).

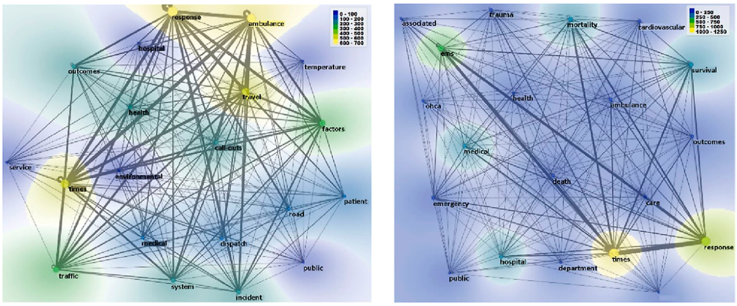
These contributing factors encompass internal aspects (e.g. ambulance facility capabilities and human resources) and external aspects (e.g. environmental conditions and the specific patient scenario). Certain environmental factors, such as temperature, have a marked impact on response times. Extreme heat or cold tends to increase the number of ambulance call-outs, which can delay services due to system overload (Mahmood *et al.*, 2017; Thornes *et al.*, 2014; Zhan *et al.*, 2018; Tanoori *et al.*, 2024a, b; Ghanbari *et al.*, 2023; Sharifi and Soltani, 2017; Soltani and Sharifi, 2017). Additionally, road traffic congestion, adverse weather conditions, and the geographic location of the incident also influence ambulance travel times (Lam *et al.*, 2015a, b; Meng and Weng, 2013; Seong *et al.*, 2023).

In developing countries, longer response times are not attributable to a single cause but stem from a complex interplay of factors. While limited resources are a significant challenge, they are compounded by underdeveloped infrastructure, persistent geographic obstacles, fragmented system organization, and traffic congestion. This multifaceted problem requires integrated solutions that address more than just funding or equipment shortages (Boutilier and Chan, 2020; Kobusingye *et al.*, 2005; Mould-Millman *et al.*, 2017).

These identified variables highlight several opportunities for optimizing ambulance deployment, resource management, and dispatch protocols to improve system efficiency (Wilde, 2013; Lucchese, 2024; Colla *et al.*, 2023).

At a system level, a key strategy to meet response time targets for life-threatening incidents is the deployment of multiple crew responses, where the closest available unit (which may be a rapid responder vehicle) is dispatched simultaneously with a fully equipped ambulance to ensure the swiftest possible first arrival at the scene.

Understanding the impact of environmental conditions can guide better resource allocation and preparedness, which is particularly important in climate change. Further research into

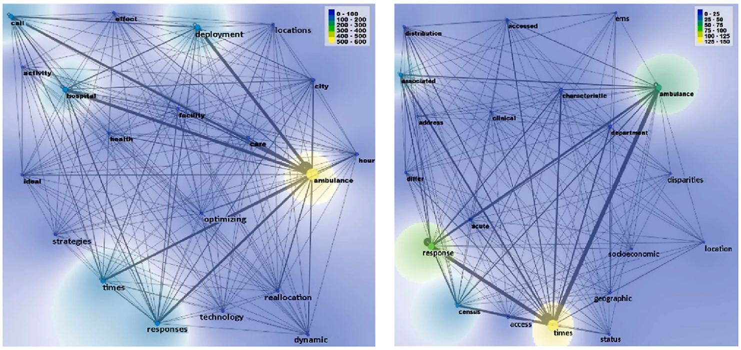


Response; times; outcomes; factors; dispatch; travel; environmental; call-outs; traffic; temperature.

(a)

Ambulance; response; times; outcomes; mortality; survival; cardiovascular; trauma; OHCA; EMS.

(b)

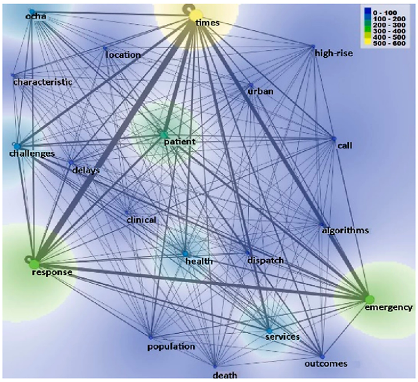


Optimizing; ambulance; deployment; locations; strategies; response; times; dynamic; reallocation; technology

(c)

Disparities; ambulance; response; EMS; times; socioeconomic
; geographic; status; location; access.

(d)



Response; times; emergency; services; urban; high-rise; OHCA; challenges; delays; algorithms.

(d)

Figure 6. Topic modelling using LDA. Source: Authors

additional environmental factors, such as air pollution and humidity (RoohaniQadikolaei *et al.*, 2026), is warranted to deepen this understanding. Ambulance response times are critical to patient outcomes and are influenced by system-level, patient-level, and environmental factors. System-level factors, dispatch efficiency, travel time, call volume, and resource availability, significantly impact response performance, as demonstrated by various studies (Do *et al.*, 2013; Nehme *et al.*, 2016; Colla *et al.*, 2019). Patient-level factors include age, gender, severity of condition, and type of incident, which can affect how quickly an ambulance is dispatched or how urgently it is routed (Do *et al.*, 2013; Nehme *et al.*, 2016; Chen *et al.*, 2020).

3.6.2 Thread B: ambulance response times and patient outcomes/mortality. A large body of literature has established a strong association between shorter ambulance response times and improved patient survival, particularly in life-threatening emergencies such as cardiac arrest and trauma (O'Keeffe *et al.*, 2011; Wilde, 2013; Blanchard *et al.*, 2012; Pons, 2005; Hansen *et al.*, 2024; Rafiq and Khanum, 2021; Alharbi *et al.*, 2022; Doggett *et al.*, 2018; Blackwell *et al.*, 2009; Byrne *et al.*, 2019; Weiss *et al.*, 2013; Lucchese, 2024; Alumran *et al.*, 2020). However, the relationship between response time and survival is not always straightforward. For instance, one study documented higher mortality despite faster response times, suggesting that complex factors, such as the severity of the patient's condition, type of injury, or timing of care, can mediate the effects of rapid intervention (Mills *et al.*, 2024).

In addition, various modifying factors influence patient outcomes, including the type of incident, demographic characteristics of the patient, and whether bystander interventions such as cardiopulmonary resuscitation (CPR) or defibrillation are administered before the arrival of emergency services (Rajan *et al.*, 2016; Nathens *et al.*, 2000; Alumran *et al.*, 2020). These interventions, particularly in cases of cardiac arrest, have been shown to improve survival rates significantly. Geographic disparities also persist, with patients in rural areas typically experiencing longer response times than those in urban centres. This variation highlights the need for regionally tailored strategies to improve access to timely emergency medical care and reduce mortality rates across different populations (Gonzalez *et al.*, 2009; Kłosiewicz *et al.*, 2017).

3.6.3 Thread C: optimizing ambulance deployment/location for improved response times. Multiple studies have examined strategies to optimize ambulance deployment and base locations as a means of reducing response times and improving system efficiency (Nogueira *et al.*, 2016; Rahim and Qasim, 2025; Neira-Rodado *et al.*, 2022). Evidence consistently shows that dynamic reallocation of ambulances based on spatial and temporal demand patterns can enhance coverage and performance without necessarily increasing fleet size. For example, in Brazil, a balanced redistribution of ambulances across urban bases improved response times while maintaining operational resources (Nogueira *et al.*, 2016; Rahim and Qasim, 2025), and in Singapore, expanding the number of bases with the same vehicle fleet achieved similar efficiency gains (Ong *et al.*, 2010). Collectively, these findings highlight that system-level optimization, rather than fleet expansion alone, can substantially improve the timeliness of EMS response.

Technological advancements, such as the implementation of GPS tracking and routing systems, have further improved the accuracy and speed of ambulance dispatch (Gonzalez *et al.*, 2009; Colla *et al.*, 2023). Dynamic reallocation strategies, including System Status Management (SSM), allow real-time adjustments to ambulance positions based on incoming call data and predicted demand (Lam *et al.*, 2015a; Lam *et al.*, 2015b). Furthermore, optimizing ambulance locations based on variables like population density and emergency call frequency can improve geographic coverage and ensure quicker response during peak demand periods (Maghfiroh *et al.*, 2018).

3.6.4 Thread D: disparities in ambulance response times based on location/socioeconomic status. Studies consistently indicate that response time varies significantly depending on socioeconomic status and geographic location. For example, patients from higher-income neighbourhoods in Toronto experienced shorter response times than those from lower-income areas (Govindarajan and Schull, 2003). In the context of gender differences in the management of ST-Elevation Myocardial Infarction (STEMI), research found longer pre-hospital delays and higher in-hospital mortality in women (Benamer *et al.*, 2016). Similarly, Hsia *et al.* (2018) reported that low-income communities in the United States experienced longer response times for cardiac arrests, highlighting the need for improved emergency medical services (EMS) access in underserved areas.

Vulnerable populations, such as African Americans and foreign-born residents, many of whom reside in rural or underserved locations, also tend to experience delayed response times and limited access to trauma care (Hsia and Shen, 2011). Geographic disparities are further evident across urban, suburban, and rural regions, with rural areas typically experiencing the longest delays (Carr *et al.*, 2006). These findings underscore the importance of addressing structural inequalities through better EMS planning and targeted resource allocation.

3.6.5 Thread E: response times for specific emergency services (air ambulance, high-rise buildings). Research on response times in specific emergency contexts, such as high-rise buildings and out-of-hospital cardiac arrest (OHCA), has revealed unique operational challenges. Studies show that delays in reaching patients in high-rise buildings are often due to structural and logistical barriers, including elevator access and floor layout constraints. Researchers have proposed building design modifications and public awareness campaigns to address these issues and support faster EMS access (Lateef and Anantharaman, 2000; Kal'avský *et al.*, 2018). Additional disparities in response times have been observed between urban and suburban areas. Shorter times in suburban regions have been linked to higher densities of ambulances and medical personnel, along with greater involvement of Voluntary First Responders (VFRs) and Fire and Rescue Services (FRS) (Jin *et al.*, 2023; Svensson *et al.*, 2024).

In disaster response scenarios, emerging evidence supports the use of real-time (online) ambulance routing algorithms that account for dynamic victim conditions, which have been shown to outperform static (offline) models in terms of speed and efficiency (Shiri *et al.*, 2024). Moreover, integrating fairness considerations into routing strategies can improve overall outcomes and ensure equitable resource allocation during emergencies (Aringhieri *et al.*, 2022). Finally, placing EMS stations in strategically selected, high-risk areas, such as flood-prone urban zones, has significantly reduced delays and improved access to timely care (Yang *et al.*, 2020).

4. Discussion

4.1 What is known

4.1.1 Response time worldwide disparities. There is a significant disparity in EMS response times between developed and developing countries, mainly due to differences in infrastructure, resources, and the overall capacity of healthcare systems (Blanchard *et al.*, 2012; Kobusingye *et al.*, 2005; Mehmood *et al.*, 2018; Rathore *et al.*, 2022). In developed countries, advanced technologies and adequate funding support emergency medical services, enabling rapid emergency (Blackwell and Kaufman, 2002; Pons and Markovchick, 2002). These systems often feature efficient dispatch centres, modern communication networks, and comprehensive and integrated emergency response systems that ensure swift mobilization and care delivery (O'Keeffe *et al.*, 2011; Carr *et al.*, 2006).

The availability and geographic distribution of healthcare facilities also play a critical role. In developed nations, urban areas often benefit from a high density of healthcare facilities, which helps reduce travel distances and improve EMS response times. However, this is not universally the case; rural areas in many high-income countries may still face long travel distances, lower healthcare facility density, and delayed response times, conditions that resemble those in low-resource settings. In contrast, developing countries frequently contend with a general scarcity of healthcare centres across urban and rural areas, resulting in longer travel distances and slower response times overall (Boutilier and Chan, 2020). Road quality and traffic management systems are also crucial: good road conditions and effective traffic control in developed countries facilitate quicker EMS responses (Rentschl *et al.*, 2019). GPS and mobile data systems have enhanced EMS efficiency by enabling optimal routing and real-time communication.

In developing countries, several factors contribute to EMS delays, including limited resources, underdeveloped infrastructure, traffic congestion, fragmented EMS systems, and insufficient coverage in rural and remote areas (Pons, 2005; Newgard *et al.*, 2010; Kobusingye *et al.*, 2005; Mock *et al.*, 2002). Additional challenges include poor crew preparedness, inadequate ambulance readiness, and inconsistent funding and training standards (Carr *et al.*, 2006; Mock *et al.*, 2002; Mould-Millman *et al.*, 2017). Geographic obstacles, such as mountainous terrain or remote locations, further restrict timely EMS access (Jana *et al.*, 2023). Socioeconomic factors, including poverty and limited education, also affect health-seeking behaviours and may delay emergency calls (Mahama *et al.*, 2018). Moreover, the absence of enabling technologies like GPS and real-time communication tools imposes further operational constraints on EMS systems in many low-resource settings (Boutilier and Chan, 2020).

4.1.2 Access to trauma centres. Health disparities in emergency medical service (EMS) response are influenced by various factors, including socioeconomic status, geographic location, healthcare system limitations, and structural inequities (Betancourt *et al.*, 2003). Socioeconomic conditions are among the most critical determinants, as individuals from lower socioeconomic backgrounds often face significant barriers to timely and effective emergency care. These barriers may include a lack of health insurance, financial hardship, limited availability of healthcare facilities in their communities, and inadequate transportation options. Such disparities not only delay emergency response but also contribute to poorer health outcomes in marginalized populations.

Incidents in high-income areas are more likely to receive timely responses that meet the national EMS benchmark times (Kal'avský *et al.*, 2018). Surveys indicated that when the median income is low, response time for EMS is longer, while advanced medical care availability is lower than in other areas (Govindarajan and Schull, 2003). It must be remembered that SES operates at two ends, where it not only influences access, but also the health behaviours and outcomes. For instance, lower SES is associated with riskier health behaviours due to stress and lack of availability to health promotion resources (Pampel *et al.*, 2010).

These disparities are accentuated by geographic factors, particularly between urban and rural settings. Rural areas generally have fewer healthcare resources, more distance to travel to a health centre or hospital, and fewer specialist services. Geographic isolation and inadequate transportation choices contribute to delays in care and poorer health outcomes for those living in rural areas (Weinhold and Gurtner, 2014). The concept of “healthcare deserts” increasingly describes these dramatic contrasts in healthcare service availability. These areas may be well-populated, but their people face severe difficulties in healthcare access because there are either no quality facilities available within reach or even no affordable transport options. The various socioeconomic factors attendant to such situations have made affordability, access to the internet for telehealth services, and health literacy even more critical for maintaining health (Garcia, 2018; Rosik *et al.*, 2021).

Cultural and linguistic issues are also significant causes of health care disparities. Patients whose predominant health care language is not their own may have limited ability to understand medical advice or describe symptoms accurately, with possible failure to diagnose or treat conditions appropriately (Flores, 2006). A key element is health literacy, or the ability to understand and use health information to make decisions. Lower health literacy levels have been associated with reduced utilization of preventive services and poorer health status (Berkman *et al.*, 2011). In this respect, offering healthcare providers a means of cultural competence is an important strategy for reducing these barriers. According to Betancourt *et al.* (2003), the foundation of knowledge about diverse groups' health beliefs and practices is important in improving communication, increasing patient trust, and enhancing quality of care along an illness trajectory, including appropriate complication prevention and management.

The systemic causes of healthcare access disparities are also inefficient resource distribution and the lack of a central coordination mechanism. There is a heterogeneous use of centralized ambulance dispatch systems, which indicates substantive variability in the response time of EMS over different areas (Kal'avský *et al.*, 2018). COVID-19 brought new challenges and exacerbated the existing health access disparities. Health access and health outcomes have been particularly hit harder by this pandemic in low-income communities, racial and ethnic minorities, and other vulnerable populations (Tai *et al.*, 2021).

4.1.3 Delayed response time: a threat to patient outcomes. Delays in response time can trigger a cascade of adverse outcomes, ranging from worsened clinical conditions to death (Harmsen *et al.*, 2015; Xu *et al.*, 2018). For example, Pons (2005) estimated that every single minute that defibrillation is delayed for cardiac arrest, survival rates decrease by 7–10%. Similar urgency applies to trauma-related emergencies, such as severe bleeding or traumatic brain injury, where even short delays can result in irreversible damage or fatality if timely intervention is not provided (Sasser *et al.*, 2012).

The consequences of delayed response time are not limited to immediate health effects. Such delays can significantly reduce a patient's long-term functional outlook and quality of life (Chen *et al.*, 2020; Fernando *et al.*, 2018). They are often associated with increased complications, prolonged hospital stays, and higher healthcare costs (Fernando *et al.*, 2018). In the case of stroke, for example, delayed treatment can cause more extensive brain damage, increasing the likelihood of long-term disability (Fernando *et al.*, 2018; Saver, 2006; Wang *et al.*, 2005). This may manifest as physical impairments, cognitive decline, or psychological trauma, all of which can hinder a patient's ability to return to pre-incident levels of independence (Chen *et al.*, 2020). In some cases, the resulting neurological deficits are permanent, requiring lifelong assistance for daily activities and personal care (Saver, 2006).

Patients who survive but sustain severe injuries or disabilities due to delayed care often have limited chances of returning to their pre-incident functional status (Haagsma *et al.*, 2012; Subbe *et al.*, 2023). This loss of independence can significantly affect individual well-being and socioeconomic stability (Blackwell and Kaufman, 2002). The economic burdens of long-term care, rehabilitation, and lost productivity are substantial and extend beyond the individual to their families and caregivers (Blackwell and Kaufman, 2002). Families and caregivers often bear the consequences of delayed treatment in the form of increased expenses for ongoing care, necessary home modifications, and reduced income or employment opportunities. These financial pressures may lead to broader socioeconomic distress and even push some households into poverty (Blackwell and Kaufman, 2002).

At the systemic level, delayed care can also reduce the efficiency of healthcare delivery. When resources are redirected from preventive services to manage long-term consequences of treatment delays, the system enters a cycle of strained capacity, reduced preventive care, and worsening patient outcomes (Mogharab *et al.*, 2022).

4.1.4 Response time terminology variations. There are significant variations in terminology and standards related to response times in EMS, depending on the country, region, or disciplinary context. These discrepancies involve differences in underlying health systems, operational protocols, and socioeconomic factors, leading to varying definitions and categorizations of EMS time intervals across nations (Blackwell and Kaufman, 2002). Efforts to address these inconsistencies have been made, notably through the Utstein-style recommended guidelines for reporting, which provide a standardized template for defining and reporting time intervals in emergency care, particularly in out-of-hospital cardiac arrest studies (Nichol *et al.*, 2008).

EMS response time terminology differences can affect communication and coordination in international collaborations and disaster responses, because the same terms may be used with different activities included, often unintentionally. For example, the term call processing time includes different activities in the US and the UK, which can lead to possible misunderstandings when both countries compare or combine data (NHS England, 2022; Ottah and Caramancion, 2023; Vanga *et al.*, 2022). Similarly, the turnout time may be used for the ambulance crew to get ready and leave the station in some regions but not all (Vanga *et al.*, 2021, 2022). Such variability makes drafting standard standards or policies even more tricky, as well as sharing best practices. For instance, the United States employs a decentralized EMS model, where services may be administered at the state, county, or municipal level, contributing to significant variability in response time standards and reporting practices (Gangidine *et al.*, 2021).

Comparisons and analyses of data in academic research depend on the availability of standardized metrics. The lack of uniformity in EMS response time definitions means comparison studies are only a hurdle to overcome. This, in turn, clouds the generalizability of the research study's findings. This is particularly problematic when attempting to correlate response times with patient outcomes, as variations in metrics can skew results and lead to inaccurate conclusions (Patterson *et al.*, 2010).

Another issue is on uniform standards. There is a lack of a standard response time target among countries and regions. It may indicate a variation in the quality of services provided on different occasions. For instance, the United States of America is using a decentralized model, and as such, most of the EMS services are administered at either a municipal or county level. This also contributes to increased variability in response time standards and reporting practices (Gangidine *et al.*, 2021). Furthermore, management strategies vary by region. In the UK, if response times are expected to extend significantly beyond targets, patients may be placed on a "call-back" list. Call centre staff re-contact the patient to ensure their condition has not deteriorated, allowing for the reclassification of the call if a more immediate response becomes necessary. In fact, secondary triage and call-back mechanisms are increasingly used to manage demand during periods of system saturation, shifting the operational focus from absolute response speed toward dynamic patient-pathway monitoring. (NHS England, 2022; Seim *et al.*, 2018). Differences in policy for national and regional response time standards, such as an 8-min 59-s standard in urban areas, versus OSHA's 3 to 4-min mandate in the USA, can create variabilities in policy development and performance evaluation (Johnson and Hennessy, 2019; OSHA, 2011). These variations reflect not only clinical urgency but also pragmatic adaptation to spatial coverage, workforce distribution, and system capacity.

Variability in response time metrics affects patient-centred outcomes, such as clinical measures, patient-reported experiences, treatment factors, resource utilization, and broader societal impacts. Such inconsistencies can result in observable differences in patient satisfaction and the overall quality of care delivered (NASEMSO, 2022).

Examples of successful international collaborators in health standardization include WHO's efforts in collaboration with HL7 International to support the adoption of Open Interoperability Standards, thus demonstrating potential for the standardization of EMS response times. Such collaborations always culminate in a consistent way of representing health information, hence facilitating simple communication and information exchange across diverse healthcare systems (National, 2023).

4.2 Challenges of previous research

Table 3 describes certain limitations; many studies on emergency response time and patient outcome have data restrictions. These may include ecological fallacy, wherein higher-level groups are generalized to the individual. For instance, examining a neighbourhood's socioeconomic status does not account for patient background (Govindarajan and Schull, 2003), dependence on medical records results in quantity and quality issues regarding data. Examples of the latter include the quality of bystander CPR and the initial severity of illness. Response times are challenging to measure accurately, and the outcomes might not be reliably attributed to those measures (Lucchese, 2024). Localized or condition-specific studies cannot be generalized across other settings or situations (Lucchese, 2024). Generalizability remains a

Table 3. Research limitations and challenges

Category	Description	Example studies
Ecological Fallacy and Data Limitations	- Using group-level data can lead to misleading conclusions - Medical records may have limited data or bias due to missing information - Studies may miss key factors like bystander CPR or initial illness severity	Govindarajan and Schull (2003), Lucchese (2024), Alumran *et al.* (2020)
Challenges in Measuring Response Time	- Accurately measuring response time and its impact on outcomes is difficult	Lucchese (2024)
Scope, Generalizability and Study Design Limitations	- Research on specific areas or medical conditions may not apply broadly - Limited data or retrospective designs can restrict Generalizability - Retrospective studies may introduce bias	Nathens *et al.* (2000), Lucchese (2024), Mills *et al.* (2024)
Specific Challenges	- Studies may neglect factors like travel time to hospitals or focus solely on prehospital care - Selection bias and unaccounted external influences can affect outcomes - Practical challenges for emergency services may not be considered	Meng and Weng (2013), Ma *et al.* (2019), Mills *et al.* (2024), Colla *et al.* (2023)
Limitations of Observational Studies and Specific Settings	- Establishing causality and missing data are common issues - Limited generalizability due to specific contexts and small sample sizes are also challenges - Small sample sizes, limited outcome analysis, and incomplete data are challenges - Single-city focus and observational design may limit applicability	Rajan *et al.* (2016), Jin *et al.* (2023), Svensson *et al.* (2024), Tshokey *et al.* (2022), Kłosiewicz *et al.* (2017), Chen *et al.* (2019)

problem with many studies, as most are small dataset research with retrospective study design or very focused areas of investigation (Nogueira *et al.*, 2016; Mahmood *et al.*, 2017; Ma *et al.*, 2019; Maghfiroh *et al.*, 2018). Several methodologies pose challenges: selection biases and external factors may not be noted, and hence, establishing causality between response times and outcomes is difficult to do (Ma *et al.*, 2019; Rehn *et al.*, 2017; Colla *et al.*, 2023). Besides that, practical problems of the emergency services provide a limit to sample size and scope, thus affecting the reliability of findings (Rehn *et al.*, 2017; Colla *et al.*, 2023). Data quality is another issue; for example, when essential details are unavailable or important factors may not have been considered, this creates further complications in deriving accurate assessments (O'Keeffe *et al.*, 2011; Wilde, 2013; Lucchese, 2024).

Understanding geographic differences in response times is crucial for ensuring equitable healthcare access (Wilde, 2013). System-level analyses examining ambulance types, dispatch protocols, and geography can offer insights into response times and health outcomes (Lucchese, 2024). Future research should also explore early detection and management of chronic illnesses to reduce out-of-hospital cardiac arrests (O'Keeffe *et al.*, 2011). Investigating how response times impact hospital selection, treatment protocols, and patient care pathways can improve health outcomes (Wilde, 2013). Additionally, examining repeated EMS calls for patients with longer initial response times could help assess the overall impact of delays (Wilde, 2013).

Given the current social and economic conditions for ensuring access to health, geographic disparities in response times are important to understand. System-level analysis, which considers elements like the types of ambulances involved and geographies, will help develop an understanding of response time and outcomes in health (Lucchese, 2024). Future studies need to consider early detection and management of chronic illnesses in reducing out-of-hospital cardiac arrests (O'Keeffe *et al.*, 2011). Understanding how such response times affect the selection of hospitals, treatment modalities, and care pathways will further optimize health outcomes. The repeated EMS calls for patients with longer initial response times may provide further detail on the overall effect of delays (Wilde, 2013).

4.3 Implications for practice and future research

Beyond clinical intervention, EMS providers must emphasize 'patient reassurance.' This theme should begin at the point of call-answering; dispatchers keeping patients and families informed that help is en route can significantly mitigate the psychological trauma of an emergency. This is increasingly supported by real-time IT systems that allow for accurate updates on ambulance arrival times.

Across contemporary EMS systems, providers are actively deploying a range of information-technology-enabled interventions; rather than isolated tools, to reduce response delays and improve system coordination. While dynamic deployment strategies and advanced technologies hold substantial promise for reducing EMS response times, their implementation is often challenged by significant financial and logistical barriers. First, the initial capital investment required for GPS-enabled fleet systems, AI-supported dispatch platforms, and integrated data analytics infrastructure can be prohibitive, especially in low- and middle-income countries or underfunded municipal systems. Second, recurring costs such as software licensing, system maintenance, staff retraining, and periodic upgrades must be integrated into long-term planning to ensure sustainability.

Third, logistical hurdles, including inconsistent internet connectivity, limited technical supply chains (e.g. for hardware repairs), and geographic disparities in EMS personnel availability, may undermine system performance, particularly in rural or hard-to-reach areas. To overcome these challenges, a phased implementation approach, supported by public–private partnerships, grant-based funding mechanisms, and targeted capacity-building programs, may be necessary. Such strategies can help ensure that innovation adoption is equitable, cost-effective, and aligned with measurable improvements in patient outcomes and system efficiency.

Beyond traditional ambulance deployment, several innovative approaches have shown promise in reducing response times and improving patient outcomes. Off-duty clinician mobilization, in which trained paramedics or physicians are dispatched from home during high demand periods, can bolster workforce capacity when systems are stretched (Smith *et al.*, 2019). Temporary deployment sites, such as pop-up stations near major events or congestion hotspots, allow rapid repositioning of resources without permanent infrastructure (Jones and Patel, 2020). Skill specialization, including critical care paramedic and community paramedic roles, enables advanced care delivery on scene, often obviating unnecessary transports (Brown *et al.*, 2021). Finally, see and treat or hear and treat models empower EMS crews to assess, treat, and release low acuity patients on site–thereby preserving transport capacity for higher priority calls (Lee and Hernandez, 2022). Integrating these practices into EMS systems may offer a cost-effective complement to fleet expansion and technology upgrades.

Building on the discussion of dispatch systems in this article, it is also critical to consider how call-centre classification and prioritization protocols influence response times. Structured algorithms, such as the Medical Priority Dispatch System (MPDS), guide dispatchers through standardized questioning, enabling rapid assessment of caller information and assignment of priority levels (Dalton *et al.*, 2022). Research indicates that EMS systems using such advanced triage protocols can achieve up to a 15% reduction in response times for high-acuity emergencies while optimizing resource deployment across all priority tiers (Beech, Smith and Jones, 2019; Egan *et al.*, 2020). Ongoing quality assurance, including audit feedback and regular protocol updates–is essential to sustain dispatcher accuracy as clinical and operational circumstances evolve. By strengthening call-centre triage, EMS agencies can both enhance system efficiency and improve patient outcomes.

This evolution in dispatch underscores a broader paradigm shift in EMS strategy, where the emphasis is moving from rigid adherence to absolute response time targets towards a more nuanced goal of matching the level of clinical skills dispatched to the specific patient requirement within an adequate timeframe. This “right skill, right time” approach prioritizes optimal patient outcomes over mere speed, potentially justifying different response time standards for different types of emergencies.

Improving the data collection methods, understanding patient outcomes, and addressing the environmental and socioeconomic issues will enhance the past studies on EMS response times. Improvement in data collection methods using IoT sensors, machine learning, and blockchain can help in better real-time traffic management while generalizing more broadly. The stakeholder involvement and other qualitative methods will help provide practical insights from the EMS providers and patients (Lam *et al.*, 2015a, b; Rafiq and Khanum, 2021; Gonzalez *et al.*, 2009). Apart from this, the effectiveness of response times on the results of patients is to be evaluated by studying different health systems, various types of patients, and other broader measures apart from survival. Such effects can be studied by investigating how the response time affects specific emergencies like cardiac arrest and solving the exact mechanism for such an effect. The roles of environmental and socioeconomic burdens, such as climate and income inequity, must be understood (Lam *et al.*, 2015a, b; Govindarajan and Schull, 2003; Hsia and Shen, 2011; Azmoodeh *et al.*, 2021, 2023). Established methodologies should render identifiable associations between these and patient outcomes (Govindarajan and Schull, 2003; Lucchese, 2024).

This review shows that the optimal system design, resource allocation, and operational policies may reduce the response times of EMS (Lam *et al.*, 2015a, b; Rafiq and Khanum, 2021; Blackwell *et al.*, 2009; Weiss *et al.*, 2013). It also depicts that real-time data streams, visualizations of GIS, and simulations could improve EMS operations (Lam *et al.*, 2015a, b; Blackwell *et al.*, 2009; Maghfiroh *et al.*, 2018; Colla *et al.*, 2023). Other future research work is related to analysing the impact of various response intervals, training for the paramedics, and protocols on the survival of the patients (O’Keeffe *et al.*, 2011; Wilde, 2013). There is a need to exploit further innovative technologies and public health interventions, such as defibrillator programs and training in CPR, to enhance the effectiveness of EMS further. Comprehensive approaches that include quality improvement initiatives are expected to reduce the response times and optimize prehospital care (Lam *et al.*, 2015a, b; Goto *et al.*, 2018).

Thus, it promises a future of longitudinal studies, multidisciplinary approaches, and standardized data collection in EMS research (O’Keeffe *et al.*, 2011; Wilde, 2013; Thornes *et al.*, 2014; Hansen *et al.*, 2024; Byrne *et al.*, 2019). Other areas of study that need to be done will involve selection biases, cost-effectiveness, translation, and real-world application of proposed interventions (Nogueira *et al.*, 2016; Hansen *et al.*, 2024; Desai *et al.*, 2019; Ma *et al.*, 2019; Ong *et al.*, 2010). Interdisciplinary approaches will be welcome in finding innovative solutions to ambulance services (Desai *et al.*, 2019).

Furthermore, longitudinal studies are critically needed to determine whether the disparity in EMS response times between developed and developing nations, as well as between urban and rural areas, is widening or closing over time. Such research should seek to uncover the underlying drivers, such as differential rates of technological adoption, infrastructure investment, or policy focus, to inform more effective global and regional equity initiatives.

The novel contributions of this review, derived from its mixed-methods approach and LDA-based thematic framework, provide the foundation for these implications. By moving beyond a conventional summary to offer a data-driven structure of the field (Threads A-E) and by validating “Thread E” as a critical research frontier, this work provides a new conceptual model. It is this model that enables the formulation of a strategic, evidence-based, and actionable agenda for policymakers, practitioners, and researchers aiming to optimize EMS systems globally.

Finally, to validate the emerging trends and strategic priorities identified in this review, particularly those related to AI, equity-focused algorithms, and specialized response models, future work should involve structured technological forecasting exercises. Utilizing methods such as Delphi panels with experts from EMS operations, public policy, data science, and vehicle technology could help build consensus on the most viable and high-impact innovations, creating a coordinated roadmap for research and development over the next decade.

5. Conclusion

This systematic review examined the factors influencing EMS response times and their effects on patient outcomes. While the findings aligned with prior studies showing that shorter response times are associated with improved survival, the review added new insights by incorporating underexplored factors such as socioeconomic disparities and geographic isolation. Through LDA-based topic modelling, five dominant themes were identified that shape EMS performance: operational and environmental determinants, clinical outcomes, system optimization, disparities, and logistical challenges. Moving beyond retrospective synthesis, this review also identifies structured pathways for anticipating future EMS system evolution.

To enhance the practical utility of findings, some recommendations were presented. First, optimize ambulance deployment using real-time data and predictive analytics, especially in high-demand areas. Second, reduce disparities through targeted investment in underserved communities. Third, build resilience to extreme weather through integrated climate planning. Fourth, support cost-conscious, phased adoption of technologies in low-resource settings using public–private partnerships. Fifth, expand EMS workforce capacity and public preparedness efforts. Future research should include cross-regional studies, cost-effectiveness analyses of EMS innovations, and adoption of equity-focused evaluation frameworks. These actions can guide system reform across diverse contexts and ensure that EMS advancements translate into measurable improvements in access and outcomes. This review reinforces the need for multidisciplinary strategies to optimize EMS operations globally. By aligning evidence with actionable priorities, the conclusions offer a roadmap for policymakers and practitioners committed to building more responsive, equitable, and effective EMS systems.

To build upon these findings, it is recommended future research utilize Delphi panels involving experts from EMS operations and data science. Such a ‘technological forecasting’ exercise would help validate which emerging innovations; such as drone-assisted AED delivery or AI-based demand prediction, are most viable for improving global EMS equity over the next decade.

Data availability

The raw data are available by contacting the corresponding author.

Appendix

Review protocol

A Systematic review of ems response times: identifying key determinants and improving patient outcomes.

Objectives

1. To synthesize evidence on the determinants of Emergency Medical Services (EMS) response times.
2. To examine the relationship between response times and patient outcomes.
3. To identify disparities in EMS response times based on geography and socioeconomic factors.
4. To recommend strategies for optimizing EMS response times and improving patient outcomes.

Inclusion criteria

1. *Population:* Studies examining EMS response times in prehospital care settings.
2. *Intervention/Exposure:* Response time as a variable in EMS performance or patient outcomes.
3. *Outcomes:* Mortality, survival rates, hospital admissions, or disparities based on socioeconomic/ geographic factors.
4. *Study Design:* Observational studies, cohort studies, case-control studies, randomized controlled trials, or systematic reviews.
5. *Language:* English-language studies.
6. *Publication Date:* Studies published from January 1, 2000, to October 20, 2024.
7. *Date of Search:* The search was last updated on the 20th of October 2024.

Exclusion Criteria

1. Studies focusing on non-EMS response services (e.g., police or fire services).
2. Case reports, commentaries, or editorials without original data.
3. Studies without clear data on response times or patient outcomes.
4. Non-English publications.

Data sources

1. Web of Science (WOS)
2. PubMed
3. Scopus

Search strategy

1. *Keywords and Boolean Operators:*
    - (“EMS response time” OR “ambulance response time”) AND (“patient outcomes” OR “mortality” OR “geographic disparities” OR “socioeconomic disparities”).
    - Search terms will be adapted for each database, including Medical Subject Headings (MeSH) in PubMed.

(2) *Process:*
  - Conduct systematic searches across all databases.
  - Include studies published between 2000 and 2024.
  - Remove duplicates using reference management software (e.g., Zotero).

Planned methods for synthesis and analysis

(1) Study selection:
  - Two independent reviewers will screen titles and abstracts for relevance.
  - Full-text articles will be reviewed for inclusion based on eligibility criteria.

(2) Data extraction:
  - Extract data on study characteristics, population, outcomes, and key findings using a standardized form.

(3) Quality appraisal:
  - Use the Cochrane Risk of Bias 2 (RoB 2) tool for RCTs and the Joanna Briggs Institute (JBI) checklist for observational studies.

(4) Synthesis:
  - Perform a narrative synthesis to describe study characteristics and key findings.
  - Conduct a meta-analysis, if data permits, to quantify the association between response times and patient outcomes.

References

Alharbi, R.J., Lewis, V. and Miller, C. (2022), “A state-of-the-art review of factors that predict mortality among traumatic injury patients following a road traffic crash”, *Australasian Emergency Care*, Vol. 25 No. 1, pp. 13-22, doi: 10.1016/j.auec.2021.01.005.

Allan, A., Soltani, A., Abdi, M.H. and Zarei, M. (2022), “Driving forces behind land use and land cover change: a systematic and bibliometric review”, *Land*, Vol. 11 No. 8, p. 1222, doi: 10.3390/land11081222.

Alumran, A., Albinali, H., Saadah, A. and Althumairi, A. (2020), “The effects of ambulance response time on survival following out-of-hospital cardiac arrest”, *Open Access Emergency Medicine*, Vol. 12, pp. 421-426, doi: 10.2147/OAEM.S270837.

Arcolezi, H., Cerna, S., Guyeux, C. and Couchot, J.F. (2021), “Preserving geo-indistinguishability of the emergency scene to predict ambulance response time”, *MCA*, Vol. 26 No. 3, p. 56.

Aringhieri, R., Bigharaz, S., Duma, D. and Guastalla, A. (2022), “Fairness in ambulance routing for post disaster management”, *Central European Journal of Operations Research*, Vol. 30 No. 1, pp. 189-211, doi: 10.1007/s10100-021-00785-y.

Azmoodeh, M., Haghighi, F. and Motieyan, H. (2021), “Proposing an integrated accessibility-based measure to evaluate spatial equity among different social classes”, *Environment and Planning B: Urban Analytics and City Science*, Vol. 48 No. 9, pp. 2790-2807, doi: 10.1177/2399808321991543.

Azmoodeh, M., Haghighi, F. and Motieyan, H. (2023), “The capability approach and social equity in transport: understanding factors affecting capabilities of urban residents, using structural equation modeling”, *Transport Policy*, Vol. 142, pp. 137-151, doi: 10.1016/j.tranpol.2023.08.010.

Bagheri, B., Azadi, H., Soltani, A. and Witlox, F. (2024), "Global city data analysis using SciMAT: a bibliometric review: B. Bagheri et al", *Environment, Development and Sustainability*, Vol. 26 No. 6, pp. 15403-15427.

Bedard, A.F., Mata, L.V., Dymond, C., Moreira, F., Dixon, J., Schauer, S.G., Ginde, A.A., Bebarta, V., Moore, E.E. and Mould-Millman, N.K. (2020), "A scoping review of worldwide studies evaluating the effects of prehospital time on trauma outcomes", *International Journal of Emergency Medicine*, Vol. 13 No. 1, p. 64, doi: 10.1186/s12245-020-00324-7.

Benamer, H., Bataille, S., Tafflet, M., Jabre, P., Dupas, F., Laborne, F.X., Lapostolle, F., Lefort, H., Juliard, J.M., Letarnec, J.Y., Lamhaut, L., Lebail, G., Boche, T., Loyeau, A., Caussin, C., Mapouata, M., Karam, N., Jouven, X., Spaulding, C. and Lambert, Y. (2016), "Longer prehospital delays and higher mortality in women with STEMI: the e-MUST Registry", *EuroIntervention*, Vol. 12 No. 5, pp. e542-e549, doi: 10.4244/EIJV12I5A93.

Berest, M. and Merenkova, L. (2019), "Evaluation and analysis of factors influencing the financial sustainability of engineering enterprises", *Economics of Development*, Vol. 18 No. 3, pp. 1-11, doi: 10.21511/ed.18(3).2019.01.

Berkman, N.D., Sheridan, S.L., Donahue, K.E., Halpern, D.J. and Crotty, K. (2011), "Low health literacy and health outcomes: an updated systematic review", *Annals of Internal Medicine*, Vol. 155 No. 2, pp. 97-107, doi: 10.7326/0003-4819-155-2-201107190-00005.

Betancourt, J.R., Green, A.R., Carrillo, J. and Ananeh-Firempong, O. II (2003), "Defining cultural competence: a practical framework for addressing racial/ethnic disparities in health and health care", *Public Health Reports*, Vol. 118 No. 4, pp. 293-302, doi: 10.1093/phr/118.4.293.

Blackwell, T.H. and Kaufman, J.S. (2002), "Response time effectiveness: comparison of response time and survival in an urban emergency medical services system", *Academic Emergency Medicine*, Vol. 9 No. 4, pp. 288-295, doi: 10.1197/aemj.9.4.288.

Blackwell, T.H., Kline, J.A., Willis, J.J. and Hicks, G.M. (2009), "Lack of association between prehospital response times and patient outcomes", *Prehospital Emergency Care*, Vol. 13 No. 4, pp. 444-450, doi: 10.1080/10903120902935363.

Blanchard, I.E., Doig, C.J., Hagel, B.E., Anton, A.R., Zygun, D.A., Kortbeek, J.B., Powell, D.G., Williamson, T.S., Fick, G.H. and Innes, G.D. (2012), "Emergency medical services response time and mortality in an urban setting", *Prehospital Emergency Care*, Vol. 16 No. 1, pp. 142-151, doi: 10.3109/10903127.2011.614046.

Blei, D.M., Ng, A.Y. and Jordan, M.I. (2003), "Latent dirichlet allocation", *Journal of Machine Learning Research*, Vol. 3, pp. 993-1022.

Bokor, E.C., Certan, D. and Nen, M. (2026), "Emergency call accessibility as a strategic capability for crisis management in the EU", *International Journal of Emergency Services*, pp. 1-15.

Boutilier, J.J. and Chan, T.C.Y. (2020), "Ambulance emergency response optimization in developing countries", *Operations Research*, Vol. 68 No. 5, pp. 1315-1334, doi: 10.1287/opre.2019.1969.

Breen, N. (2000), "A national census of ambulance response times to emergency calls in Ireland", *Emergency Medicine Journal*, Vol. 17 No. 6, pp. 392-395, doi: 10.1136/emj.17.6.392.

Brown, A.L., Green, P.R. and Taylor, J.M. (2021), "The impact of community paramedic programs on emergency department usage: a systematic review", *Prehospital Emergency Care*, Vol. 25 No. 4, pp. 489-497, doi: 10.1080/10903127.2021.1882645.

Bürger, A., Wnent, J., Bohn, A., Jantzen, T., Brenner, S., Lefering, R., Seewald, S., Gräsner, J.T. and Fischer, M. (2018), "The effect of ambulance response time on survival following out-of-hospital cardiac arrest.", *Dtsch Arztebl Int*, Vol. 115 Nos 33-34, pp. 541-548, doi: 10.3238/arztebl.2018.0541.

Byrne, J.P., Mann, N.C., Dai, M., Mason, S.A., Karanicolas, P., Rizoli, S. and Nathens, A.B. (2019), "Association between emergency medical service response time and motor vehicle crash mortality in the United States", *JAMA Surgery*, Vol. 154 No. 4, p. 286, doi: 10.1001/jamasurg.2018.5097.

Cabral, E.L.d.S., Castro, W.R.S., Florentino, D.R.d.M., Viana, D.d.A., Costa Junior, J.F.d., Souza, R.P.d., Rêgo, A.C.M., Araújo-Filho, I. and Medeiros, A.C. (2018), "Response time in the emergency services. Systematic review", *Acta Cirurgica Brasileira*, Vol. 33 No. 12, pp. 1110-1121, doi: 10.1590/s0102-865020180120000009.

Carr, B.G., Caplan, J.M., Pryor, J.P. and Branas, C.C. (2006), "A meta-analysis of prehospital care times for trauma", *Prehospital Emergency Care*, Vol. 10 No. 2, pp. 198-206, doi: 10.1080/10903120500541324.

Carr, B.G., Branas, C.C., Metlay, J.P., Sullivan, A.F. and Camargo, C.A. (2014), "Geographic and demographic disparities in drive times to Joint Commission-certified trauma centers", *Journal of Trauma and Acute Care Surgery*, Vol. 77 No. 1, pp. 126-132, doi: 10.1097/TA.0000000000000284.

Chen, X.-q., Liu, Z.f., Zhong, S.k., Niu, X.t., Huang, Y.x. and Zhang, L.l. (2019), "Factors influencing the emergency medical service response time for cardiovascular disease in guangzhou, China", *Current Medical Science*, Vol. 39 No. 3, pp. 463-471, doi: 10.1007/s11596-019-2061-z.

Chen, C.-H., Shin, S.D., Sun, J.T., Jamaluddin, S.F., Tanaka, H., Song, K.J., Kajino, K., Kimura, A., Huang, E.P.C., Hsieh, M.J., Ma, M.H.M. and Chiang, W.C. (2020), "Association between prehospital time and outcome of trauma patients in 4 Asian countries: a cross-national, multicenter cohort study", *PLoS Medicine*, Vol. 17 No. 10, p. e1003360, doi: 10.1371/journal.pmed.1003360.

Colla, M., Oliveira, G.A. and Santos, G.D. (2019), "Operations management in emergency medical services: response time in a Brazilian mobile emergency care service", *Procedia Manufacturing*, Vol. 39, pp. 932-941, doi: 10.1016/j.promfg.2020.01.396.

Colla, M., Santos, G.D., Oliveira, G.A. and de Vasconcelos, R.B.B. (2023), "Ambulance response time in a Brazilian emergency medical service", *Socio-Economic Planning Sciences*, Vol. 85, 101434, doi: 10.1016/j.seps.2022.101434.

Dalton, N.S., Kippen, R.J., Leach, M.J., Knott, C.I., Doherty, Z.B., Downie, J.M. and Fletcher, J.A. (2022), "Long term survival following a medical emergency team call at an Australian regional hospital.", *Critical Care and Resuscitation*, Vol. 24 No. 2, pp. 163-174, 38045599, doi: 10.51893/2022.2.OA6.

Delaney, P.G., Moussally, J. and Wachira, B.W. (2024), "Future directions for emergency medical services development in low-and middle-income countries", *Surgery*, Vol. 176 No. 1, pp. 220-222, doi: 10.1016/j.surg.2024.02.030.

Demšar, J., Curk, T., Erjavec, A., Gorup, Č., Hočevar, T., Milutinovič, M., Zupan, B., Hočevar, T., Milutinovič, M. and Zupan, B. (2013), "Orange: data mining toolbox in Python", *The Journal of Machine Learning Research*, Vol. 14 No. 1, pp. 2349-2353.

Demšar, J. and Zupan, B. (2013), "Orange: data mining fruitful and fun-a historical perspective", *Informatica*, Vol. 37 No. 1.

Deng, Y., Zhang, Y. and Pan, J. (2021), "Optimization for locating emergency medical service facilities: a case study for health planning from China", *Risk Management and Healthcare Policy*, Vol. 14, pp. 1791-1802.

Desai, M.S., Rawani, A.M. and Loya, M.I.M. (2019), "Reducing ambulance response time in emergency medical services: a literature review", *International Journal of Mechanical Engineering and Technology*, Vol. 10, pp. 85-96.

Do, Y.K., Foo, K., Ng, Y.Y. and Ong, M.E.H. (2013), "A quantile regression analysis of ambulance response time", *Prehospital Emergency Care*, Vol. 17 No. 2, pp. 170-176, doi: 10.3109/10903127.2012.729127.

Doggett, S., Ragland, D.R. and Felschundneff, G. (2018), *Prehospital Response Time and Traumatic Injury—A Review*, UC Berkeley: Safe Transportation Research & Education Center, Berkeley, available at: https://escholarship.org/uc/item/8978m2pn

Earnest, A., Hock Ong, M.E., Shahidah, N., Min Ng, W., Foo, C. and Nott, D.J. (2012), "Spatial analysis of ambulance response times related to prehospital cardiac arrests in the city-state of Singapore.", *Prehosp Emerg Care*, Vol. 16 No. 2, pp. 256-265, 21999815, doi: 10.3109/10903127.2011.615974.

Eck, N.v. and Waltman, L. (2009), “Software survey: VOSviewer, a computer program for bibliometric mapping”, *Scientometrics*, Vol. 84 No. 2, pp. 523-538, doi: 10.1007/s11192-009-0146-3.

Egan, M., Murar, F., Lawrence, J. and Burd, H. (2020), “Identifying the predictors of avoidable emergency department attendance after contact with the NHS 111 phone service: analysis of 16.6 million calls to 111 in England in 2015-2017”, *BMJ Open*, Vol. 10 No. 3, e032043, 32152158, doi: 10.1136/bmjopen-2019-032043.

Fernando, S.M., Reardon, P.M., Bagshaw, S.M., Scales, D.C., Murphy, K., Shen, J., Tanuseputro, P., Heyland, D.K. and Kyeremanteng, K. (2018), “Impact of nighttime Rapid Response Team activation on outcomes of hospitalized patients with acute deterioration”, *Critical Care*, Vol. 22 No. 1, p. 67, doi: 10.1186/s13054-018-2005-1.

Flores, G. (2006), “Language barriers to health care in the United States”, *New England Journal of Medicine*, Vol. 355 No. 3, pp. 229-231, doi: 10.1056/NEJMp058316.

Friedson, A.I. (2018), “Income and ambulance response time inequality”, *JAMA Netw Open*, Vol. 1 No. 7, e185201.

Gangidine, M., Li, B., Allshouse, W., Campion, E., McVaney, K. and Haukoos, J. (2021), “1 gunshot wound case clustering and response/transport time variation in an urban EMS system: a geospatial analysis”, *Annals of Emergency Medicine*, Vol. 78 No. 4, p. S1, doi: 10.1016/j.annemergmed.2021.09.009.

Garcia, E. (2018), “The urban food desert as a model for the urban health care desert: fundamental causes and economic considerations”, *Dissertations and Theses*.

Ghanbari, R., Heidarimozaffar, M., Soltani, A. and Arefi, H. (2023), “Land surface temperature analysis in densely populated zones from the perspective of spectral indices and urban morphology”, *International Journal of Environmental Science and Technology*, Vol. 20 No. 3, pp. 2883-2902, doi: 10.1007/s13762-022-04725-4.

Gonnelli, V., Satta, F., Frosini, F., Iadanza, E., Gonnelli, V., Satta, F., Frosini, F. and Iadanza, E. (2018), *Evidence-based Approach to Medical Equipment Maintenance Monitoring*, Springer.

Gonzalez, R.P., Cummings, G.R., Phelan, H.A., Mulekar, M.S. and Rodning, C.B. (2009), “Does increased emergency medical services prehospital time affect patient mortality in rural motor vehicle crashes? A statewide analysis”, *The American Journal of Surgery*, Vol. 197 No. 1, pp. 30-34, doi: 10.1016/j.amjsurg.2007.11.018.

Goto, Y., Funada, A. and Goto, Y. (2018), “Relationship between emergency medical services response time and bystander intervention in patients with out-of-hospital cardiac arrest”, *Journal of the American Heart Association*, Vol. 7 No. 9, e007568, doi: 10.1161/JAHA.117.007568.

Govindarajan, A. and Schull, M. (2003), “Effect of socioeconomic status on out-of-hospital transport delays of patients with chest pain”, *Annals of Emergency Medicine*, Vol. 41 No. 4, pp. 481-490, doi: 10.1067/mem.2003.108.

Grant, M.J. and Booth, A. (2009), “A typology of reviews: an analysis of 14 review types and associated methodologies”, *Health Information and Libraries Journal*, Vol. 26 No. 2, pp. 91-108, doi: 10.1111/j.1471-1842.2009.00848.x.

Gratton, M., Garza, A., Salomone, J.A, McElroy, J. and Shearer, J. (2010), “Ambulance staging for potentially dangerous scenes: another hidden component of response time”, *Prehosp Emerg Care*, Vol. 14 No. 3, pp. 340-344, 20377402, doi: 10.3109/10903121003760176.

Griffiths, T.L. and Steyvers, M. (2004), “Finding scientific topics”, *Proceedings of the National Academy of Sciences*, Vol. 101 No. Suppl 1, pp. 5228-5235, doi: 10.1073/pnas.0307752101.

Haagsma, J.A., Polinder, S., Olff, M., Toet, H., Bonsel, G.J. and van Beeck, E.F. (2012), “Posttraumatic stress symptoms and health-related quality of life: a two year follow up study of injury treated at the emergency department”, *BMC Psychiatry*, Vol. 12 No. 1, p. 1, doi: 10.1186/1471-244X-12-1.

Hansen, P.M., Nielsen, M.S., Rehn, M., Lassen, A.T., Mikkelsen, S., Perner, A. and Brøchner, A.C. (2024), “Ambulance and helicopter response time. Association with patient outcome and illness severity: protocol of a systematic literature review and meta-analysis”, *Acta Anaesthesiologica Scandinavica*, Vol. 68 No. 2, pp. 287-296, doi: 10.1111/aas.14339.

Harmsen, A.M.K., Giannakopoulos, G., Moerbeek, P., Jansma, E., Bonjer, H. and Bloemers, F. (2015), "The influence of prehospital time on trauma patients outcome: a systematic review", *Injury*, Vol. 46 No. 4, pp. 602-609, doi: 10.1016/j.injury.2015.01.008.

Hasselqvist-Ax, I., Riva, G., Herlitz, J., Rosenqvist, M., Hollenberg, J., Nordberg, P., Ringh, M., Jonsson, M., Axelsson, C., Lindqvist, J., Karlsson, T. and Svensson, L. (2015), "Early cardiopulmonary resuscitation in out-of-hospital cardiac arrest", *New England Journal of Medicine*, Vol. 372 No. 24, pp. 2307-2315, doi: 10.1056/nejmoa1405796.

Heidet, M., Da Cunha, T., Brami, E., Mermet, E., Dru, M., Simonnard, B., Lecarpentier, E., Chollet-Xémard, C., Bergeron, C., Khalid, M., Grunau, B., Marty, J. and Audureau, E. (2020), "EMS access constraints and response time delays for deprived critically ill patients near Paris, France", *Health Aff (Millwood)*, Vol. 39 No. 7, pp. 1175-1184, 32634362, doi: 10.1377/hlthaff.2019.00842.

Higgins, J.P.T., Thomas, J., Chandler, J., Cumpston, M., Li, T., Page, M.J. and Welch, V.A. (Eds) (2022), *Cochrane Handbook for Systematic Reviews of Interventions* (version 6.3), Cochrane, available at: https://training.cochrane.org/handbook

Holmén, J., Karlsson, T., Svensson, L., Strömsöe, A., Hagberg, E., Axelsson, C. and Rawshani, A. (2020), "Shortening ambulance response time increases survival in out of hospital cardiac arrest", *Journal of the American Heart Association*, Vol. 9 No. 21, e017048, doi: 10.1161/JAHA.120.017048.

Hsia, R. and Shen, Y.-C. (2011), "Possible geographical barriers to trauma center access for vulnerable patients in the United States: an analysis of urban and rural communities", *Archives of Surgery*, Vol. 146 No. 1, p. 46, doi: 10.1001/archsurg.2010.299.

Hsia, R.Y., Kellermann, A.L. and Shen, Y. (2012), "Factors associated with closures of emergency departments in the United States", *JAMA*, Vol. 305 No. 19, pp. 1978-1985, doi: 10.1001/jama.2011.620.

Hsia, R.Y., Huang, D., Mann, N.C., Colwell, C., Mercer, M.P., Dai, M. and Niedzwiecki, M.J. (2018), "A US national study of the association between income and ambulance response time in cardiac arrest", *JAMA Network Open*, Vol. 1 No. 7, e185202, doi: 10.1001/jamanetworkopen.2018.5202.

Hua, T., Lu, C.T., Choo, J. and Reddy, C.K. (2020), "Probabilistic topic modeling for comparative analysis of document collections", *ACM Transactions on Knowledge Discovery from Data*, Vol. 14 No. 2, pp. 1-27, doi: 10.1145/3369873.

Ilioudi, S., Lazakidou, A. and Tsironi, M. (2013), "Importance of patient satisfaction measurement and electronic surveys: methodology and potential benefits", *International Journal of Health Research and Innovation*, Vol. 1 No. 1, pp. 67-87.

Institute of Medicine (2007), *Emergency Medical Services: At the Crossroads*, National Academies Press.

Jana, A., Sarkar, A., Parmar, V. and Saunik, S. (2023), "Examining district-level disparity and determinants of timeliness of emergency medical services in Maharashtra, India", *Scientific Reports*, Vol. 13 No. 1, 21239, doi: 10.1038/s41598-023-48713-1.

Jin, Y., Chen, H., Ge, H., Li, S., Zhang, J. and Ma, Q. (2023), "Urban–suburb disparities in prehospital emergency medical resources and response time among patients with out-of-hospital cardiac arrest: a mixed-method cross-sectional study", *Frontiers in Public Health*, Vol. 11, 1121779, doi: 10.3389/fpubh.2023.1121779.

Jockers, M.L. and Mimno, D. (2013), "Significant themes in 18th-century literature", *Digital Humanities Quarterly*, Vol. 7 No. 1, available at: http://www.digitalhumanities.org/dhq/vol/7/1/000156/000156.html

Johnson, B.T. and Hennessy, E.A. (2019), "Systematic reviews and meta-analyses in the health sciences: best practice methods for research syntheses", *Social Science and Medicine*, Vol. 233, pp. 237-251, doi: 10.1016/j.socscimed.2019.05.035.

Jones, C.E. and Patel, R.S. (2020), "Pop up EMS stations at mass gatherings: a pilot study in urban event management", *Journal of Emergency Medical Services*, Vol. 45 No. 6, pp. 32-38.

Kal’avský, P., Rozenberg, R., Petríček, P., Socha, L. and Socha, V. (2018), “Helicopter emergency medical services response time in the Central European Region”, *2018 XIII International Scientific Conference - New Trends in Aviation Development (NTAD), IEEE*, doi: 10.1109/NTAD.2018.8551634.

Khokhar, S.A. (2023), “The challenges of inventory management in medical supply chain”, *South Asian Journal of Operations and Logistics*, Vol. 2 No. 2, pp. 1-17, doi: 10.57044/sajol.2023.2.2.2306.

Kłosiewicz, T., Skitek-Adamczak, I. and Zieliński, M. (2017), “Emergency medical system response time does not affect incidence of return of spontaneous circulation after prehospital resuscitation in one million central European agglomeration residents”, *Kardiologia Polska*, Vol. 75 No. 3, pp. 240-246, doi: 10.5603/KP.a2016.0181.

Kobusingye, O.C., Hyder, A.A., Bishai, D., Romero Hicks, E., Mock, C. and Joshipura, M. (2005), “Emergency medical systems in low- and middle-income countries: recommendations for action”, *Bulletin of the World Health Organization*, Vol. 83 No. 8, pp. 626-631.

Lam, S.S.W., Zhang, Z.C., Oh, H.C., Ng, Y.Y., Wah, W. and Hock Ong, M.E. (2014), “Reducing ambulance response times using discrete event simulation”, *Prehospital Emergency Care*, Vol. 18 No. 2, pp. 207-216, doi: 10.3109/10903127.2013.836266.

Lam, S.S.W., Zhang, J., Zhang, Z.C., Oh, H.C., Overton, J., Ng, Y.Y. and Ong, M.E.H. (2015a), “Dynamic ambulance reallocation for the reduction of ambulance response times using system status management”, *The American Journal of Emergency Medicine*, Vol. 33 No. 2, pp. 159-166, doi: 10.1016/j.ajem.2014.10.044.

Lam, S.S.W., Nguyen, F.N.H.L., Ng, Y.Y., Lee, V.P.X., Wong, T.H., Fook-Chong, S.M.C. and Ong, M.E.H. (2015b), “Factors affecting the ambulance response times of trauma incidents in Singapore”, *Accident Analysis and Prevention*, Vol. 82, pp. 27-35, doi: 10.1016/j.aap.2015.05.007.

Lateef, F. and Anantharaman, V. (2000), “Delays in the EMS response to and the evacuation of patients in high-rise buildings in Singapore”, *Prehospital Emergency Care*, Vol. 4 No. 4, pp. 327-332, doi: 10.1080/10903120090941047.

Lee, S.Y. and Hernandez, M.L. (2022), “Hear and treat: evaluating non transport EMS care models in rural communities”, *Prehospital and Disaster Medicine*, Vol. 37 No. 1, pp. 65-72, doi: 10.1017/S1049023X21001129.

Licata, S., Valent, F. and Deroma, L. (2023), “Key performance indicators in the emergency medical system: barriers and facilitators”, *The European Journal of Public Health*, Vol. 33 No. Supplement_2, ckad160.952, doi: 10.1093/eurpub/ckad160.952.

Lucchese, E. (2024), “How important are delays in treatment for health outcomes? The case of ambulance response time and cardiovascular events”, *Health Economics*, Vol. 33 No. 4, pp. 652-673, doi: 10.1002/hec.4791.

Ma, L., Zhang, H., Yan, X., Wang, J., Song, Z. and Xiong, H. (2019), “Smooth associations between the emergency medical services response time and the risk of death in road traffic crashes”, *Journal of Transport and Health*, Vol. 12, pp. 379-391, doi: 10.1016/j.jth.2018.08.011.

Maghfiroh, M.F.N., Hossain, M. and Hanaoka, S. (2018), “Minimising emergency response time of ambulances through pre-positioning in Dhaka city, Bangladesh”, *International Journal of Logistics Research and Applications*, Vol. 21 No. 1, pp. 53-71, doi: 10.1080/13675567.2017.1361390.

Mahama, M.-N., Kenu, E., Bandoh, D.A. and Zakariah, A.N. (2018), “Emergency response time and prehospital trauma survival rate of the national ambulance service, Greater Accra (January – December 2014)”, *BMC Emergency Medicine*, Vol. 18 No. 1, p. 33, doi: 10.1186/s12873-018-0184-3.

Mahmood, M., Thornes, J., Pope, F., Fisher, P. and Vardoulakis, S. (2017), “Impact of air temperature on London ambulance call-out incidents and response times”, *Climate*, Vol. 5 No. 3, p. 61, doi: 10.3390/cli5030061.

Mansourihanis, O., Maghsoodi Tilaki, M.J., Zaroujtaghi, A., Tayarani, M. and Sheikhfarshi, S. (2024), "Inequalities in emergency service accessibility: spatial analysis of urban infrastructure", *JPMD*, Vol. 17 No. 4, pp. 584-614.

Mantel, N. and Haenszel, W. (1959), "Statistical aspects of the analysis of data from retrospective studies of disease", *Journal of the National Cancer Institute*, Vol. 22 No. 4, pp. 719-748.

Mehmood, A., Rowther, A.A., Kobusingye, O. and Hyder, A.A. (2018), "Assessment of prehospital emergency medical services in low-income settings using a health systems approach", *International Journal of Emergency Medicine*, Vol. 11 No. 1, p. 53, doi: 10.1186/s12245-018-0207-6.

Mell, H.K., Giblin, P., Lynch, M., Curtis, K., Holland, T. and Stopyra, J. (2017), "Emergency medical services response times in rural, suburban, and urban areas", *JAMA Surgery*, Vol. 152 No. 10, pp. 983-984, doi: 10.1001/jamasurg.2017.2230.

Meng, Q. and Weng, J. (2013), "Uncertainty analysis of accident notification time and emergency medical service response time in work zone traffic accidents", *Traffic Injury Prevention*, Vol. 14 No. 2, pp. 150-158, doi: 10.1080/15389588.2012.708886.

Mills, A.A.M., Mills, E.H.A., Blomberg, S.N.F., Christensen, H.C., Møller, A.L., Gislason, G., Køber, L., Kragholm, K.H., Lippert, F., Folke, F., Andersen, M.P. and Torp-Pedersen, C. (2024), "Ambulance response times and 30-day mortality: a Copenhagen (Denmark) registry study", *European Journal of Emergency Medicine*, Vol. 31 No. 1, pp. 59-67, doi: 10.1097/MEJ.0000000000001094.

Mistovich, J., Karren, K. and Hafen, B. (2017), *Prehospital Emergency Care*, 11th ed., Pearson, NY, NY, p. 1552.

Mock, C.N., Tiska, M., Adu-Ampofo, M. and Boakye, G. (2002), "Improvements in prehospital trauma care in an African country with No formal emergency medical services", *Journal of Trauma and Acute Care Surgery*, Vol. 53 No. 1, pp. 90-97, doi: 10.1097/00005373-200207000-00018.

Mogharab, V., Ostovar, M., Ruszkowski, J., Hussain, S.Z.M., Shrestha, R., Yaqoob, U., Aryanpoor, P., Nikkhoo, A.M., Heidari, P., Jahromi, A.R., Rayatdoost, E., Ali, A., Javdani, F., Farzaneh, R., Ghanaatpisheh, A., Habibzadeh, S.R., Foroughian, M., Ahmadi, S.R., Akhavan, R., Abbasi, B., Shahi, B., Hakemi, A., Bolvardi, E., Bagherian, F., Motamed, M., Boroujeni, S.T., Jamalnia, S., Mangouri, A., Paydar, M., Mehrasa, N., Shirali, D., Sanmarchi, F., Saeed, A., Jafari, N.A., Babou, A., Kalani, N. and Hatami, N. (2022), "Global burden of the COVID-19 associated patient-related delay in emergency healthcare: a panel of systematic review and meta-analyses", *Globalization and Health*, Vol. 18 No. 1, p. 58, doi: 10.1186/s12992-022-00836-2.

Mould Millman, N.K., Dixon, J.M., Sefa, N., Yancey, A., Hollong, B.G., Hagahmed, M., Ginde, A.A. and Wallis, L.A. (2017), "The state of emergency medical services systems in Africa", *Prehospital and Disaster Medicine*, Vol. 32 No. 3, pp. 273-283, doi: 10.1017/S1049023X17000061.

Murray, E.T., Bärnighausen, T. and Geldsetzer, P. (2017), "Weather and ambulance delays in Cape Town, South Africa: a case study of environmental impacts on emergency medical services", *Global Health Action*, Vol. 10 No. 1, pp. 1-9, doi: 10.1080/16549716.2017.1379881.

NASEMSO, National Model EMS Clinical Guidelines (2022), *National Association of State EMS Officials (NASEMSO)*, p. 407.

Nathens, A.B, Brunet, F.P and Maier, R.V. (2004), "Development of trauma systems and effect on outcomes after injury", *Lancet*, Vol. 363 No. 9423, pp. 1794-1801, 15172780, doi: 10.1016/S0140-6736(04)16307-1.

Nathens, A.B., Jurkovich, G.J., Cummings, P., Rivara, F.P. and Maier, R.V. (2000), "The effect of organized systems of trauma care on motor vehicle crash mortality", *JAMA*, Vol. 283 No. 15, pp. 1990-1994, 10789667, doi: 10.1001/jama.283.15.1990.

National, S. (2023), "National survey: EMS economic and operational models executive summary", *National Association of Emergency Medical Technicians*.

Nehme, Z., Andrew, E. and Smith, K. (2016), "Factors influencing the timeliness of emergency medical service response to time critical emergencies", *Prehospital Emergency Care*, Vol. 20 No. 6, pp. 783-791, doi: 10.3109/10903127.2016.1164776.

Neira-Rodado, D., Escobar-Velasquez, J.W. and McClean, S. (2022), "Ambulances deployment problems: categorization, evolution and dynamic problems review", *ISPRS International Journal of Geo-Information*, Vol. 11 No. 2, p. 109, doi: 10.3390/ijgi11020109.

Nekrashevych, O.V. and Kovrigo, Y.M. (2019), "Overview of key performance indicators", *Modeling, Control and Information Technologies*, No. 3, pp. 108-109, doi: 10.31713/MCIT.2019.65.

Newgard, C.D., Schmicker, R.H., Hedges, J.R., Trickett, J.P., Davis, D.P., Bulger, E.M., Aufderheide, T.P., Minei, J.P., Hata, J.S., Gubler, K.D., Brown, T.B., Yelle, J.D., Bardarson, B. and Nichol, G. and Resuscitation Outcomes Consortium Investigators (2010), "Emergency medical services intervals and survival in trauma: assessment of the golden hour in a North American prospective cohort", *Annals of Emergency Medicine*, Vol. 55 No. 3, pp. 235-246, doi: 10.1016/j.annemergmed.2009.07.024.

NHS England (2022), *Ambulance Quality Indicators*.

Nichol, G., Sayre, M.R., Guerra, F. and Poole, J. (2008), "Defining and improving the emergency medical services response to cardiac arrest", *Resuscitation*, Vol. 76 No. 3, pp. 340-353, doi: 10.1016/j.resuscitation.2007.09.022.

Nogueira, L.C., Pinto, L.R. and Silva, P.M.S. (2016), "Reducing Emergency Medical Service response time via the reallocation of ambulance bases", *Health Care Management Science*, Vol. 19 No. 1, pp. 31-42, doi: 10.1007/s10729-014-9280-4.

Noor, A., Algrafi, Z., Alharbi, B., Noor, T.H., Alsaeedi, A., Alluhaibi, R. and Alwateer, M. (2024), "A cloud-based ambulance detection system using YOLOv8 for minimizing ambulance response time", *Applied Sciences*, Vol. 14 No. 6, p. 2555, doi: 10.3390/app14062555.

Núñez, A., Neriz, L., Mateo, R., Ramis, F. and Ramaprasad, A. (2018), "Emergency departments key performance indicators: a unified framework and its practice", *The International Journal of Health Planning and Management*, Vol. 33 No. 4, pp. 915-933, doi: 10.1002/hpm.2548.

O'Keeffe, C., Nicholl, J., Turner, J. and Goodacre, S. (2011), "Role of ambulance response times in the survival of patients with out-of-hospital cardiac arrest", *Emergency Medicine Journal*, Vol. 28 No. 8, pp. 703-706, doi: 10.1136/emj.2009.086363.

Ong, M.E.H., Chiam, T.F., Ng, F.S.P., Sultana, P., Lim, S.H., Leong, B.S., Ong, V.Y.K., Ching Tan, E.C., Tham, L.P., Yap, S. and Anantharaman, V. (2010), "Reducing ambulance response times using geospatial–time analysis of ambulance deployment", *Academic Emergency Medicine*, Vol. 17 No. 9, pp. 951-957, doi: 10.1111/j.1553-2712.2010.00860.x.

OSHA (2011), "Medical services and first aid", cited 2024; available at: https://www.osha.gov/laws-regs/regulations/standardnumber/1915/1915.87

Ottah, A.N. and Caramancion, K.M. (2023), "Predicting EMS response time using geographic zones' SocioeconomicSocioeconomic indicators", *2023 IEEE 18th International Conference on Computer Science and Information Technologies (CSIT)*, IEEE, doi: 10.1109/CSIT61576.2023.10324143.

Page, M.J., McKenzie, J.E., Bossuyt, P.M., Boutron, I., Hoffmann, T.C., Mulrow, C.D., Shamseer, L., Tetzlaff, J.M., Akl, E.A., Brennan, S.E., Chou, R., Glanville, J., Grimshaw, J.M., Hróbjartsson, A., Lalu, M.M., Li, T., Loder, E.W., Mayo-Wilson, E., McDonald, S., McGuinness, L.A., Stewart, L.A., Thomas, J., Tricco, A.C., Welch, V.A., Whiting, P. and Moher, D. (2021), "The 'PRISMA 2020' statement: an updated guideline for reporting systematic reviews", *BMJ*, Vol. 372, p. n71, doi: 10.1136/bmj.n71.

Pampel, F.C., Krueger, P.M. and Denney, J.T. (2010), "SocioeconomicSocioeconomic disparities in health behaviors", *Annual Review of Sociology*, Vol. 36 No. 2010, pp. 349-370, 36 doi: 10.1146/annurev.soc.012809.102529.

Patel, M.D. (2018), "Role of emergency medical dispatch in responding to acute stroke: expanding beyond high priority dispatch?", *Prehospital Emergency Care*, Vol. 22 No. 1, pp. 1-2.

Patterson, P.D., Huang, D.T., Fairbanks, R.J. and Wang, H.E. (2010), "The emergency medical services safety attitudes questionnaire", *American Journal of Medical Quality*, Vol. 25 No. 2, pp. 109-115, doi: 10.1177/1062860609352106.

Perkins, G.D., Handley, A.J., Koster, R.W., Castrén, M., Smyth, M.A., Olasveengen, T., Monsieurs, K.G., Raffay, V., Gräsner, J.T., Wenzel, V., Ristagno, G., Soar, J. and Adult basic life support and automated external defibrillation section Collaborators and Greif, R. (2015), "European Resuscitation Council Guidelines for Resuscitation 2015: section 2. Adult basic life support and automated external defibrillation", *Resuscitation*, Vol. 95, pp. 81-99, doi: 10.1016/j.resuscitation.2015.07.015.

Plummer, V. and Boyle, M. (2017), "EMS systems in lower-middle income countries: a literature review", *Prehospital and Disaster Medicine*, Vol. 32 No. 1, pp. 64-70.

Pons, P.T. (2005), "Paramedic response time: does it affect patient survival?", *Academic Emergency Medicine*, Vol. 12 No. 7, pp. 594-600, doi: 10.1197/j.aem.2005.02.013.

Pons, P.T. and Markovchick, V.J. (2002), "Eight minutes or less: does the ambulance response time guideline impact trauma patient outcome?1", *Journal of Emergency Medicine*, Vol. 23 No. 1, pp. 43-48, doi: 10.1016/S0736-4679(02)00460-2.

Rafiq, S. and Khanum, M.A. (2021), "A review on minimization of ambulance response time using image processing and critical path mapping based on traffic control", *Journal of Informatics Electrical and Electronics Engineering (JIEEE)*, Vol. 2 No. 2, pp. 1-7, doi: 10.54060/JIEEE/002.02.002.

Rahim, F. and Qasim, N.H. (2025), "A systematic literature review of drones in emergency medicine: practical applications, legal challenges and future directions", *Drone Systems and Applications, (ja)*, Vol. 13, pp. 1-13.

Rajan, S., Wissenberg, M., Folke, F., Hansen, S.M., Gerds, T.A., Kragholm, K., Hansen, C.M., Karlsson, L., Lippert, F.K., Køber, L., Gislason, G.H. and Torp-Pedersen, C. (2016), "Association of bystander cardiopulmonary resuscitation and survival according to ambulance response times after out-of-hospital cardiac arrest", *Circulation*, Vol. 134 No. 25, pp. 2095-2104, doi: 10.1161/CIRCULATIONAHA.116.024400.

Rathore, N., Jain, P.K. and Parida, M. (2022), "A sustainable model for emergency medical services in developing countries: a novel approach using partial outsourcing and machine learning", *Risk Management and Healthcare Policy*, Vol. 15, pp. 193-218, doi: 10.2147/RMHP.S338186.

Redelmeier, D.A., Blair, P.J. and Collins, W.E. (2015), "No place to unload: a preliminary analysis of the prevalence, risk factors, and consequences of ambulance diversion", *Annals of Emergency Medicine*, Vol. 43 No. 4, pp. 462-468, doi: 10.1016/S0196-0644(03)00456-3.

Rehn, M., Davies, G., Smith, P. and Lockey, D. (2017), "Emergency versus standard response: time efficacy of London's Air Ambulance rapid response vehicle", *Emergency Medicine Journal*, Vol. 34 No. 12, pp. 806-809, doi: 10.1136/emermed-2017-206663.

Rentschler, J., Avner, P. and Jones, N. (2019), *A Race against Time: Resilient Roads for Effective Emergency Response*, World Bank Blogs.

RoohaniQadikolaei, M., Soltani, A., Namin, S.N., Hatami, Y. and Najafi, P. (2026), "Explaining air pollution exceedance days through land use densities", *Environmental and Sustainability Indicators*, Vol. 29, 101087.

Rosik, P., Stępniak, M. and Wiśniewski, R. (2021), "Delineation of health care deserts using accessibility measures: the case of Poland", *European Planning Studies*, Vol. 29 No. 6, pp. 1151-1173, doi: 10.1080/09654313.2020.1818184.

Sagan, A. and Richardson, E. (2015), "Out-of-hours primary care and demand for emergency medical services", *Eurohealth*, Vol. 21 No. 4, pp. 6-9.

SAHealth (2023), *Key Performance Indicators – SA Ambulance Service (2022-2023)*, Government of South Australia.

Samnani, S.S., Vaska, M., Ahmed, S. and Turin, T.C. (2017), "Review typology: the basic types of reviews for synthesizing evidence for the purpose of knowledge translation", *Journal of College of Physicians and Surgeons Pakistan: JCPSP*, Vol. 27 No. 10, pp. 635-641.

Sangal, R.B., Su, H., Khidir, H., Parwani, V., Liebhardt, B., Pinker, E.J., Meng, L., Venkatesh, A.K. and Ulrich, A. (2023), "Sociodemographic disparities in queue jumping for emergency department care", *JAMA Network Open*, Vol. 6 No. 7, p. e2326338, doi: 10.1001/jamanetworkopen.2023.26338.

Sasser, S.M., Hunt, R.C., Faul, M., Sugerman, D., Pearson, W.S., Dulski, T. and Galli, R.L. (2012), "Guidelines for field triage of injured patients: recommendations of the National Expert Panel on Field Triage, 2011", *Morbidity and Mortality Weekly Report: Recommendations and Reports*, Vol. 61 No. 1, pp. 1-20.

Saver, J.L. (2006), "Time is brain—quantified", *Stroke*, Vol. 37 No. 1, pp. 263-266, ab doi: 10.1161/01.STR.0000196957.55928.

Seim, J., Glenn, M.J., English, J. and Sporer, K. (2018), "Neighborhood poverty and 9-1-1 ambulance response time", *Prehospital Emergency Care*, Vol. 22 No. 4, pp. 436-444, doi: 10.1080/10903127.2017.1416209.

Seong, K., Jiao, J. and Mandalapu, A. (2023), "Effects of urban environmental factors on heat-related emergency medical services (EMS) response time", *Applied Geography*, Vol. 155, 102956, doi: 10.1016/j.apgeog.2023.102956.

Setyarini, A. and Windarwati, H.D. (2020), "Influence factors of emergency medical services (EMS) prehospital time interval variety: a systematic review", *Jurnal Ners*, Vol. 15 No. 1Sp, pp. 440-451, doi: 10.20473/jn.v15i1Sp.19786.

Sharifi, E. and Soltani, A. (2017), "Patterns of urban heat island effect in Adelaide: a mobile traverse experiment", *Modern Applied Science*, Vol. 11 No. 4, pp. 1-8, doi: 10.5539/mas.v11n4p80.

Shiri, D., Akbari, V. and Salman, F.S. (2024), "Online algorithms for ambulance routing in disaster response with time-varying victim conditions", *Spectrum*, Vol. 46 No. 3, pp. 785-819, doi: 10.1007/s00291-024-00744-4.

Sievert, C. and Shirley, K. (2014), "LDAvis: a method for visualizing and interpreting topics", in *Proceedings of the Workshop on Interactive Language Learning, Visualization, and Interfaces*, Association for Computational Linguistics, pp. 63-70, doi: 10.3115/v1/W14-3110.

Smith, D.J., Roberts, K.A. and Nguyen, T.H. (2019), "Off duty clinician activation to supplement EMS staffing: lessons from a statewide pilot", *Annals of Emergency Medicine*, Vol. 74 No. 3, pp. 325-334, doi: 10.1016/j.annemergmed.2019.03.004.

Soltani, A., Harrison, J.E., Ryder, C., Flavel, J. and Watson, A. (2024a), "Police and hospital data linkage for traffic injury surveillance: a systematic review", *Accident Analysis and Prevention*, Vol. 197, 107426, doi: 10.1016/j.aap.2023.107426.

Soltani, A., Mansourihanis, O., RoohaniQadikolaei, M. and Zaroujtaghi, A. (2024b), "Two decades of geospatial evolution: tracing the analytical journey towards data-driven road crash prevention", *Applied Spatial Analysis and Policy*, Vol. 17 No. 3, pp. 1301-1334, doi: 10.1007/s12061-024-09587-6.

Soltani, A. and Sharifi, E. (2017), "Daily variation of urban heat island effect and its correlations to urban greenery: a case study of Adelaide", *Frontiers of Architectural Research*, Vol. 6 No. 4, pp. 529-538, doi: 10.1016/j.foar.2017.08.001.

Spaite, D.W., Bobrow, B.J., Vadeboncoeur, T.F., Chikani, V., Clark, L., Mullins, T. and Sanders, A.B. (2008), "The Impact of prehospital transport interval on survival in out-of-hospital cardiac arrest: implications for regionalization of post-resuscitation care", *Resuscitation*, Vol. 79 No. 1, pp. 61-66, doi: 10.1016/j.resuscitation.2008.05.006.

Stenson, B.A., Anderson, J.S. and Davis, S.R. (2020), "Staffing and provider productivity in the emergency department", *Emergency Medicine Clinics of North America*, Vol. 38 No. 3, pp. 589-605, doi: 10.1016/j.emc.2020.04.002.

Subbe, C., Hughes, D.A., Lewis, S., Holmes, E.A., Kalkman, C., So, R., Tranka, S. and Welch, J. (2023), "Value of improving patient safety: health economic considerations for rapid response systems–a rapid review of the literature and expert round table", *BMJ Open*, Vol. 13 No. 4, e065819, doi: 10.1136/bmjopen-2022-065819.

Sullivan, F., Williams, K.A. and Rhodes, J. (2013), "An overview of prehospital emergency medical services", *Rhode Island Medical Journal*, Vol. 96 No. 12, pp. 24-27, 2013.

Sun, J.H., de Vries, S. and Mould-Millman, N.K. (2024), “Emergency medical services (EMS) infrastructure development and operations in low-and middle-income countries: formal, professional-driven (Tier-2) systems”, *Surgery*, Vol. 176 No. 1, pp. 217-219, doi: 10.1016/j.surg.2024.02.024.

Svensson, A., Nilsson, B., Lantz, E., Bremer, A., Årestedt, K. and Israelsson, J. (2024), “Response times in rural areas for emergency medical services, fire and rescue services and voluntary first responders during out-of-hospital cardiac arrests”, *Resuscitation*, Vol. 17, 100548, doi: 10.1016/j.resplu.2023.100548.

Syed, J. and Namburi, D.L. (2020), *Improving Response Time of Ambulance Using Machine Intelligence*, *International Conference for Emerging Technology (INCET)*.

Tai, D.B.G., Shah, A., Doubeni, C.A., Sia, I.G. and Wieland, M.L. (2021), “The disproportionate impact of COVID-19 on racial and ethnic minorities in the United States”, *Clinical Infectious Diseases*, Vol. 72 No. 4, pp. 703-706, doi: 10.1093/cid/ciaa815.

Talari, K. and Goyal, M. (2020), “Retrospective studies - utility and caveats”, *The Journal of the Royal College of Physicians of Edinburgh*, Vol. 50 No. 4, pp. 398-402, doi: 10.4997/JRCPE.2020.409.

Tanigawa, K. and Tanaka, K. (2006), “Emergency medical service systems in Japan: past, present, and future”, *Resuscitation*, Vol. 69 No. 3, pp. 365-370, 16740355, doi: 10.1016/j.resuscitation.2006.04.001.

Tanoori, G., Soltani, A. and Modiri, A. (2024a), “Machine learning for urban heat island (UHI) analysis: predicting land surface temperature (LST) in urban environments”, *Urban Climate*, Vol. 55, 101962, doi: 10.1016/j.uclim.2024.101962.

Tanoori, G., Soltani, A. and Modiri, A. (2024b), “Predicting urban land use and mitigating land surface temperature: exploring the role of urban configuration with convolutional neural networks”, *Journal of Urban Planning and Development*, Vol. 150 No. 3, 04024029, doi: 10.1061/jupddm.upeng-5010.

Thornes, J.E., Fisher, P.A., Rayment-Bishop, T. and Smith, C. (2014), “Ambulance call-outs and response times in Birmingham and the impact of extreme weather and climate change”, *Emergency Medicine Journal*, Vol. 31 No. 3, pp. 220-228, doi: 10.1136/emermed-2012-201817.

Tlili, T., Abidi, S. and Krichen, S. (2018), “A mathematical model for efficient emergency transportation in a disaster situation”, *The American Journal of Emergency Medicine*, Vol. 36 No. 9, pp. 1585-1590, doi: 10.1016/j.ajem.2018.01.039.

Tshokey, T., Tshering, U., Lhazeen, K., Abrahamyan, A., Timire, C., Gurung, B., Subedi, D.C., Wangdi, K., Vilas, V.D.R. and Zachariah, R. (2022), “Performance of an emergency road ambulance service in Bhutan: response time, utilization, and outcomes”, *Tropical Medicine and Infectious Disease*, Vol. 7 No. 6, p. 87, doi: 10.3390/tropicalmed7060087.

Ueno, K., Teramoto, C., Nishioka, D., Kino, S., Sawatari, H. and Tanabe, K. (2024), “Factors associated with prolonged on-scene time in ambulance transportation among patients with minor diseases or injuries in Japan: a population-based observational study”, *BMC Emergency Medicine*, Vol. 24 No. 1, p. 10, doi: 10.1186/s12873-023-00927-2.

Valsamis, E.M., Ricketts, D., Husband, H. and Rogers, B.A. (20192019), “Segmented linear regression models for assessing change in retrospective studies in healthcare”, *Computational and Mathematical Methods in Medicine*, Vol. 2019, pp. 9810675-9810679, doi: 10.1155/2019/9810675.

Vanga, S.R., Ligrani, P.M., Doustmohammadi, M. and Anderson, M. (2021), “EMS response time for patients critically-injured from automobile accidents using regression analysis”, *Current Urban Studies*, Vol. 9 No. 3, pp. 581-596, doi: 10.4236/cus.2021.93035.

Vanga, S.R., Ligrani, P.M., Doustmohammadi, M. and Anderson, M. (2022), “Effects of different crash data variables on EMS response time for a rural county in Alabama”, *Journal of Family Medicine and Primary Care*, Vol. 11 No. 4, pp. 1462-1467, doi: 10.4103/jfmpc.jfmpc_1592_21.

Wallach, H.M., Murray, I., Salakhutdinov, R. and Mimno, D. (2009), “Evaluation methods for topic models”, *Proceedings of the 26th International Conference on Machine Learning*, ACM, pp. 1105-1112.

Wang, P.S., Lane, M., Olfson, M., Pincus, H.A., Wells, K.B. and Kessler, R.C. (2005), "Twelve-month use of mental health services in the United States: results from the national comorbidity survey replication", *Archives of General Psychiatry*, Vol. 62 No. 6, pp. 629-640, doi: 10.1001/archpsyc.62.6.629.

Weinhold, I. and Gurtner, S. (2014), "Understanding shortages of sufficient health care in rural areas", *Health Policy*, Vol. 118 No. 2, pp. 201-214, doi: 10.1016/j.healthpol.2014.07.018.

Weiss, S., Fullerton, L., Oglesbee, S., Duerden, B. and Froman, P. (2013), "Does ambulance response time influence patient condition among patients with specific medical and trauma emergencies?", *Southern Medical Journal*, Vol. 106 No. 3, pp. 230-235, doi: 10.1097/SMJ.0b013e3182882c70.

Wilde, E.T. (2013), "Do emergency medical system response times matter for health outcomes?", *Health Economics*, Vol. 22 No. 7, pp. 790-806, doi: 10.1002/hec.2851.

Wilkinson, M.D., Dumontier, M., Aalbersberg, I.J., Appleton, G., Axton, M., Baak, A., Blomberg, N., Boiten, J.W., da Silva Santos, L.B., Bourne, P.E., Bouwman, J., Brookes, A.J., Clark, T., Crosas, M., Dillo, I., Dumon, O., Edmunds, S., Evelo, C.T., Finkers, R., Gonzalez-Beltran, A., Gray, A.J., Groth, P., Goble, C., Grethe, J.S., Heringa, J., 't Hoen, P.A., Hooft, R., Kuhn, T., Kok, R., Kok, J., Lusher, S.J., Martone, M.E., Mons, A., Packer, A.L., Persson, B., Rocca-Serra, P., Roos, M., van Schaik, R., Sansone, S.A., Schultes, E., Sengstag, T., Slater, T., Strawn, G., Swertz, M.A., Thompson, M., van der Lei, J., van Mulligen, E., Velterop, J., Waagmeester, A., Wittenburg, P., Wolstencroft, K., Zhao, J. and Mons, B. (2016), "The FAIR Guiding Principles for scientific data management and stewardship", *Scientific Data*, Vol. 3 No. 1, 160018, doi: 10.1038/sdata.2016.18.

Wissenberg, M., Lippert, F.K., Folke, F., Weeke, P., Hansen, C.M., Christensen, E.F., Jans, H., Lang-Jensen, T., Olesen, J.B., Lindhardsen, J., Fosbol, E.L., Nielsen, S.L., Gislason, G.H., Kober, L. and Torp-Pedersen, C. (2013), "Association of national initiatives to improve cardiac arrest management with rates of bystander intervention and patient survival after out-of-hospital cardiac arrest", *JAMA*, Vol. 310 No. 13, pp. 1377-1384, doi: 10.1001/jama.2013.278483.

Xu, M.K., Dobson, K.G., Thabane, L. and Fox-Robichaud, A.E. (2018), "Evaluating the effect of delayed activation of rapid response teams on patient outcomes: a systematic review protocol", *Systematic Reviews*, Vol. 7 No. 1, p. 42, doi: 10.1186/s13643-018-0705-x.

Yang, Y., Yin, J., Ye, M., She, D. and Yu, J. (2020), "Multi-coverage optimal location model for emergency medical service (EMS) facilities under various disaster scenarios: a case study of urban fluvial floods in the Minhang district of Shanghai, China", *Natural Hazards and Earth System Sciences*, Vol. 20 No. 1, pp. 181-195, doi: 10.5194/nhess-20-181-2020.

Zakariah, A., Stewart, B.T., Boateng, E., Achena, C., Tansley, G. and Mock, C. (2017), "The birth and growth of the national ambulance service in Ghana", *Prehospital and Disaster Medicine*, Vol. 32 No. 1, pp. 83-93, doi: 10.1017/S1049023X16001151.

Zaroujtaghi, A., Mansourihanis, O., Tayarani, M., Mansouri, F., Hemmati, M. and Soltani, A. (2025), "A systematic review of GIS evolution in transportation planning: towards AI integration", *Future Transportation*, Vol. 5 No. 3, p. 97, doi: 10.3390/futuretransp5030097.

Zhai, C. and Massung, S. (2016), *Text Data Management and Analysis: A Practical Introduction to Information Retrieval and Text Mining*, Association for Computing Machinery and Morgan & Claypool.

Zhan, Z.-Y., Yu, Y.M., Qian, J., Song, Y.F., Chen, P.Y. and Ou, C.Q. (2018), "Effects of ambient temperature on ambulance emergency call-outs in the subtropical city of Shenzhen, China", *PLoS One*, Vol. 13 No. 11, p. e0207187, doi: 10.1371/journal.pone.0207187.

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