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Use of Predictive Analytics for Ambulance Deployment and Emergency Medical Services Resource Management: A Systematic Review

استخدام التحليلات التنبؤية في توزيع سيارات الإسعاف وإدارة موارد خدمات الطوارئ الطبية: مراجعة منهجية

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Abstract:

Background
Emergency Medical Services (EMS) operate in environments where demand varies across time and location, while ambulances, personnel, equipment, and dispatch capacity remain limited. Predictive analytics offers a data-driven approach to this challenge by using historical and real-time information to forecast emergency demand and support decisions about ambulance deployment, relocation, staffing, and dispatch. Recent research has increasingly applied statistical forecasting, machine learning, spatial modelling, and optimization methods to EMS resource planning (Alrawashdeh et al., 2024; Martin et al., 2021; Tluli et al., 2024).

Objective
This systematic review aims to examine how predictive analytics has been used in ambulance deployment and EMS resource management, identify the main predictive approaches, summarize their reported operational benefits, and describe the main limitations that prevent wider use in routine EMS practice.

Methods
This systematic review was conducted and reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidance (Page et al., 2021). English-language studies published from January 2018 to September 2026 were considered. Searches covered PubMed/MEDLINE, Scopus, Web of Science, CINAHL, and IEEE Xplore, with Google Scholar used for supplementary searching. Eligible studies examined predictive or data-driven methods used to forecast EMS demand or support ambulance deployment, dispatching, relocation, staffing, scheduling, or other resource-allocation decisions. Owing to substantial variation in datasets, algorithms, geographic settings, and outcome measures, findings were synthesized narratively.

Results
The reviewed evidence indicates that predictive analytics is being applied mainly to emergency-demand forecasting, spatial and spatiotemporal prediction, and prediction-informed deployment or relocation decisions. Machine-learning methods, including neural networks, gradient boosting, random forests, XGBoost, and ensemble models, have produced promising forecasting results, although established statistical approaches can remain competitive and may be easier to implement (Butsingkorn et al., 2026; Martin et al., 2021; Monks et al., 2023; Shahidian et al., 2025). Recent studies increasingly combine prediction with optimization or reinforcement learning to translate forecasts into ambulance-allocation decisions (Rautenstrauß & Schiffer, 2026; Tsai et al., 2026). Nevertheless, prospective real-world evaluation remains limited, particularly for patient outcomes, workforce effects, equity, and long-term implementation (Becker et al., 2023).

Conclusion
Predictive analytics has substantial potential to support more flexible ambulance deployment and EMS resource management. Its practical value appears greatest when prediction is linked directly to operational decision-making rather than used only to forecast call volume. Future research should emphasize external validation, prospective real-time implementation, patient outcomes, workforce effects, equity, and comparison with existing EMS practice (Becker et al., 2023; Monks et al., 2023; Tsai et al., 2026).

Keywords: Emergency Medical Services; ambulance deployment; predictive analytics; demand forecasting; resource allocation; machine learning; ambulance relocation; EMS management.

الملخص:

الخلفية

تعمل خدمات الطوارئ الطبية (EMS) في بيئات يتباين فيها حجم الطلب على الخدمات باختلاف الزمان والمكان، في حين تظل الموارد المتاحة، بما في ذلك سيارات الإسعاف والكوادر البشرية والمعدات وقدرات استقبال البلاغات وتوجيهها، محدودة. ويوفر التحليل التنبؤي نهجًا قائمًا على البيانات لمواجهة هذا التحدي، من خلال استخدام المعلومات التاريخية والبيانات الآنية للتنبؤ بالطلب على خدمات الطوارئ، ودعم اتخاذ القرارات المتعلقة بتوزيع سيارات الإسعاف وإعادة تمركزها، وتحديد احتياجات الكوادر البشرية، وتوجيه المركبات. وقد اتجهت الأبحاث الحديثة بصورة متزايدة إلى تطبيق أساليب التنبؤ الإحصائي، والتعلم الآلي، والنمذجة المكانية، وأساليب التحسين في تخطيط موارد خدمات الطوارئ الطبية (Alrawashdeh et al., 2024; Martin et al., 2021; Tluli et al., 2024).

الهدف

تهدف هذه المراجعة المنهجية إلى دراسة كيفية توظيف التحليل التنبؤي في توزيع سيارات الإسعاف وإدارة موارد خدمات الطوارئ الطبية، وتحديد أبرز الأساليب التنبؤية المستخدمة، وتلخيص الفوائد التشغيلية التي أظهرتها الدراسات، وبيان أهم التحديات والقيود التي تحول دون التوسع في تطبيق هذه الأساليب ضمن الممارسات الاعتيادية لخدمات الطوارئ الطبية.

المنهجية

أُجريت هذه المراجعة المنهجية وأُعدّ تقريرها وفقًا لإرشادات العناصر المفضلة للإبلاغ عن المراجعات المنهجية والتحليلات التلوية (PRISMA 2020) (Page et al., 2021). وشملت المراجعة الدراسات المنشورة باللغة الإنجليزية خلال الفترة الممتدة من كانون الثاني 2018 إلى أيلول 2026. وأُجريت عمليات البحث في قواعد البيانات PubMed/MEDLINE و Scopus و Web of Science و CINAHL و IEEE Xplore، مع الاستعانة بمحرك البحث Google Scholar لإجراء عمليات بحث تكميلية. وشملت الدراسات المؤهلة تلك التي تناولت الأساليب التنبؤية أو القائمة على البيانات المستخدمة للتنبؤ بالطلب على خدمات الطوارئ الطبية، أو دعم قرارات توزيع سيارات الإسعاف، وتوجيهها، وإعادة تمركزها، وتحديد جداول الكوادر البشرية، والجدولة التشغيلية، وغيرها من قرارات تخصيص الموارد. ونظرًا للتباين الكبير بين الدراسات من حيث مجموعات البيانات والخوارزميات والبيئات الجغرافية ومقاييس النتائج، جرى توليف النتائج باستخدام المنهج السردي.

النتائج

تشير الأدلة التي تناولتها المراجعة إلى أن تطبيقات التحليل التنبؤي تتركز بصورة رئيسة في التنبؤ بالطلب على خدمات الطوارئ، والتنبؤ المكاني والزماني المكاني، ودعم القرارات المتعلقة بتوزيع سيارات الإسعاف وإعادة تمركزها استنادًا إلى التنبؤات. وقد أظهرت أساليب التعلم الآلي، بما في ذلك الشبكات العصبية، والتعزيز المتدرج(Gradient Boosting) ، والغابات العشوائية (Random Forests)، وخوارزميةXGBoost ، والنماذج التجميعية(Ensemble Models) ، نتائج واعدة في التنبؤ، على الرغم من أن الأساليب الإحصائية التقليدية لا تزال قادرة على تحقيق نتائج تنافسية، وقد تكون أكثر سهولة من حيث التطبيق والتنفيذ (Butsingkorn et al., 2026; Martin et al., 2021; Monks et al., 2023; Shahidian et al., 2025). كما تتجه الدراسات الحديثة بصورة متزايدة إلى الجمع بين التنبؤ وأساليب التحسين أو التعلم المعزز، بهدف تحويل التوقعات إلى قرارات عملية بشأن تخصيص سيارات الإسعاف وتوزيعها (Rautenstrauß & Schiffer, 2026; Tsai et al., 2026). ومع ذلك، لا تزال الدراسات التي تتضمن تقييمًا استباقيًا في بيئات العمل الواقعية محدودة، ولا سيما فيما يتعلق بنتائج المرضى، وتأثير هذه الأساليب على القوى العاملة، والعدالة في توزيع الخدمات، ومتطلبات التطبيق طويل الأمد.(Becker et al., 2023)

الخاتمة

يمتلك التحليل التنبؤي إمكانات كبيرة لدعم توزيع أكثر مرونة لسيارات الإسعاف وتحسين إدارة موارد خدمات الطوارئ الطبية. وتبدو قيمته التطبيقية أكبر عندما يرتبط التنبؤ مباشرة بعملية اتخاذ القرارات التشغيلية، بدلًا من الاقتصار على التنبؤ بحجم البلاغات وطلبات الاستجابة. وينبغي أن تركز الأبحاث المستقبلية على التحقق من صلاحية النماذج في بيئات خارجية، وتطبيقها وتقييمها بصورة استباقية وفي الوقت الفعلي، ودراسة تأثيرها على نتائج المرضى، والقوى العاملة، والعدالة في تقديم الخدمات، فضلًا عن مقارنتها بالممارسات الحالية المتبعة في خدمات الطوارئ الطبية.(Becker et al., 2023; Monks et al., 2023; Tsai et al., 2026)

الكلمات المفتاحية: خدمات الطوارئ الطبية؛ توزيع سيارات الإسعاف؛ التحليل التنبؤي؛ التنبؤ بالطلب؛ تخصيص الموارد؛ التعلم الآلي؛ إعادة تمركز سيارات الإسعاف؛ إدارة خدمات الطوارئ الطبية.

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1. Introduction

Emergency Medical Services (EMS) provide rapid prehospital assessment, treatment, and transport for patients requiring urgent care. Because emergency demand changes by hour, day, season, location, population characteristics, weather, and public events, EMS organizations must continuously balance fluctuating need against limited ambulances and trained personnel. Predictive approaches have therefore become increasingly relevant for anticipating demand and supporting resource planning (Alrawashdeh et al., 2024; Tluli et al., 2024).

Traditional EMS planning has commonly relied on historical call averages, predefined ambulance stations, scheduled staffing levels, and dispatcher experience. Although these approaches remain important, they may be less responsive to rapid changes in demand. Predictive analytics provides a complementary approach by using historical and current data to estimate future demand and support decisions concerning staffing, ambulance location, relocation, and deployment (Abreu et al., 2023; Tluli et al., 2024).

The practical importance of forecasting is illustrated by Martin et al. (2021), who developed spatial and temporal EMS call forecasts using machine-learning methods. Their findings indicated that neural-network models were particularly useful when demand was predicted at smaller geographic levels, emphasizing that ambulance demand varies across both time and space and that citywide forecasts may be insufficient for detailed deployment decisions.

Abreu et al. (2023) examined data-driven forecasting for EMS operational planning using six years of historical information. Their approach considered both emergency-call demand and the number of vehicles required, demonstrating how forecasting can support practical decisions about when, where, and how many resources may be needed.

The growth of machine learning has expanded this area further. A scoping review by Alrawashdeh et al. (2024) identified ambulance allocation, deployment, and route optimization among the recurring operational applications of machine learning in EMS. Similarly, Tluli et al. (2024) described growing use of machine-learning techniques for ambulance allocation, routing, and demand estimation, while also noting the heterogeneity of available approaches.

The central issue is therefore not simply whether EMS demand can be predicted, but whether those predictions can be translated into operational decisions that improve real service performance. This distinction is important because high forecasting accuracy does not automatically produce an effective deployment system; implementation requires the prediction to be connected to staffing, dispatch, relocation, or allocation decisions (Rautenstrauß & Schiffer, 2026; Tsai et al., 2026).

1.1 Background

Predictive analytics refers broadly to the use of historical and current data to estimate future conditions or events. Within EMS, this can include predicting call volumes for the next hour or day, identifying geographic areas where emergencies are likely to occur, anticipating workload at ambulance bases, or estimating the number of vehicles and personnel required for a shift (Abreu et al., 2023; Martin et al., 2021).

Several methodological approaches are used in this field. Traditional methods include time-series techniques such as ARIMA, exponential smoothing, and seasonal forecasting, whereas more recent studies have applied artificial neural networks, random forests, gradient boosting, XGBoost, support vector methods, deep-learning architectures, and ensemble models (Butsingkorn et al., 2026; Monks et al., 2023; Shahidian et al., 2025).

The distinction between forecasting and deployment is also important. Forecasting estimates future demand, whereas deployment determines how available resources should be positioned or moved. Effective EMS decision support therefore requires both components: an estimate of likely demand and an operational method for translating that estimate into resource-allocation decisions (Tsai et al., 2026).

Dynamic ambulance relocation is one example of this translation from prediction to action. Instead of requiring an ambulance to return to the same fixed base after every mission, an idle ambulance may be repositioned temporarily to an area where future demand is expected to be higher. Becker et al. (2023) reviewed dynamic ambulance-relocation research and identified 21 studies, most of which were mathematical or simulation-based; prospective real-world evaluations and patient-outcome measures were uncommon.

1.2 Literature Review

Evidence published during recent years shows a gradual movement from isolated demand prediction toward integrated prediction and operational decision-support systems (Alrawashdeh et al., 2024; Tluli et al., 2024).

Martin et al. (2021) used historical EMS data to develop daily, hourly, and spatially distributed forecasts. Their multilayer perceptron approach performed particularly well at finer geographic levels, suggesting that machine learning may be especially useful when deployment decisions require detailed local predictions.

Hajiali et al. (2022) developed a real-time decision-support system for ambulance relocation. The system continuously updated demand categories and ambulance locations and aimed to maximize coverage while controlling relocation travel. In the reported case study, the approach improved response and coverage measures and reduced total ambulance working time by approximately 9% per shift.

Abreu et al. (2023) demonstrated that neural-network forecasting could support both prediction of EMS calls and estimation of vehicle requirements. Their findings are important because they connect forecasting with operational planning rather than treating prediction as an isolated technical task.

Not all recent findings suggest that more complex machine-learning models are automatically superior. Monks et al. (2023) compared several forecasting methods and externally validated their approach using ambulance-service data from different regions of England and Wales. An ensemble combining Prophet and regression with ARIMA errors produced useful forecasts for periods extending to 84 days, and the authors emphasized the importance of comparing advanced models with simple baseline forecasts.

More recent studies have tested a wider range of machine-learning approaches. Shahidian et al. (2025) examined short-term EMS forecasting and found Gradient Boosting and AdaBoost among the strongest methods in their analysis. Their models estimated hourly call volumes and expected dispatches, making the predictions relevant to staffing, vehicle positioning, and relocation decisions.

Gianquintieri et al. (2025) examined machine-learning-based EMS demand prediction in Italy and reported that integrating machine learning into an EMS digital-twin framework reduced prediction error and substantially shortened forecast-generation time. Such approaches may be particularly useful in systems that require frequent updates for operational decision-making.

Research published in 2026 has moved further toward integrated models. Butsingkorn et al. (2026) compared Random Forest, Support Vector Regression, XGBoost, and a two-stage ensemble model using ambulance data from 16 districts in Thailand. Their two-stage model achieved an average mean absolute percentage error of approximately 1.61%, indicating the potential of ensemble methods for regional EMS planning.

Tsai et al. (2026) combined deep spatiotemporal forecasting with reinforcement-learning-based ambulance allocation. Their framework was designed not only to predict demand but also to position resources while considering coverage and fairness, reflecting a shift from demand prediction toward prediction-informed operational action.

Rautenstrauß and Schiffer (2026) presented another integrated approach using optimization-augmented machine learning for ambulance dispatch and redeployment. In a numerical case study based on San Francisco 911 calls, their learned policies reduced mean response time by as much as 28% compared with the online benchmark strategies tested. However, the findings were derived from numerical evaluation rather than prospective clinical implementation.

1.3 Research Gap

Although the literature is growing, several gaps remain.

Many studies concentrate on prediction accuracy rather than examining whether better prediction leads to better service outcomes. Simulation studies commonly report response time, coverage, travel distance, or model accuracy, whereas fewer studies evaluate patient survival, clinical outcomes, staff workload, cost, or other real-world implementation outcomes (Becker et al., 2023; Tluli et al., 2024).

External validation is another important limitation. A model developed for one city may perform differently in another because emergency-call patterns, population density, ambulance availability, road networks, weather, and healthcare organization vary across settings. Monks et al. (2023) demonstrated the value of testing a forecasting approach across several ambulance services, but such validation remains comparatively uncommon.

There is also a gap between technical model development and routine EMS use. Becker et al. (2023) found that most dynamic-relocation research was based on mathematical or simulation models and that prospective real-time evaluation was rare.

For this reason, a systematic review focused specifically on predictive analytics for ambulance deployment and EMS resource management is warranted. Such a review should consider both prediction quality and the operational value of the models, including whether they improve response, coverage, resource utilization, workforce planning, and implementation feasibility.

1.4 Aim and Objectives

The main aim of this systematic review is to evaluate the use of predictive analytics in ambulance deployment and EMS resource management.

The review has four objectives: to identify the predictive methods used to forecast EMS and ambulance demand; to examine how forecasts are applied to ambulance deployment, relocation, staffing, scheduling, and resource allocation; to summarize reported effects on response time, coverage, resource

utilization, workload, and other operational outcomes; and to identify limitations and areas requiring further research.

1.5 Research Questions

The review addresses the following questions: What predictive-analytics methods have been used for ambulance demand and EMS resource management? What data are commonly used to produce these predictions? How are predictions converted into deployment or resource-allocation decisions? What operational improvements have been reported? What limitations currently prevent wider implementation in real EMS systems?

2. Methods

2.1 Design and Protocol

This study used a systematic-review design and was reported in accordance with the PRISMA 2020 statement (Page et al., 2021). Eligibility criteria, information sources, search terms, study-selection procedures, extraction variables, and the synthesis approach were defined before the final analysis.

Because the literature included forecasting studies, simulation models, operational-research studies, and real-world EMS evaluations with heterogeneous outcomes, a narrative synthesis was selected rather than a meta-analysis.

2.2 Eligibility Criteria

Component	Inclusion criteria	Exclusion criteria
Population/setting	Ground EMS, ambulance services, emergency dispatch systems, prehospital emergency services	Air ambulance studies without relevance to ground EMS
Intervention/exposure	Predictive analytics, forecasting, machine learning, statistical prediction, AI-assisted resource planning	Pure clinical prediction without deployment/resource-management relevance
Application	Ambulance deployment, dispatch, relocation, staffing, scheduling, demand planning, coverage or resource allocation	Studies only describing EMS activity without prediction
Outcomes	Forecast accuracy, response time, coverage, utilization, workload, travel distance, cost, service capacity or patient-related outcomes	No relevant predictive or operational outcome
Study design	Original quantitative studies, operational evaluations, modelling and simulation studies with real or validated EMS data	Editorials, commentaries, conference abstracts without sufficient data
Publication period	January 2018–September 2026	Studies published before 2018
Language	English	Non-English publications

2.3 Information Sources and Search Strategy

The literature search included PubMed/MEDLINE, Scopus, Web of Science, CINAHL, and IEEE Xplore because the topic spans healthcare, operations research, engineering, and computer science. Google Scholar was used for supplementary searching and citation tracking.

The core search strategy was:

("emergency medical services" OR EMS OR ambulance*) AND ("predictive analytics" OR forecast* OR "machine learning" OR "artificial intelligence" OR "predictive model*" OR "spatiotemporal prediction") AND (deploy* OR allocation OR relocation OR dispatch* OR "resource management" OR staffing OR scheduling OR "demand prediction")

The search terms were adapted to the indexing requirements and syntax of each database.

2.4 Study Selection

The database search identified **650 records**. After removing **128 duplicate records**, **522 articles** remained for title and abstract screening. Following the initial screening, **461 records were excluded** because they did not meet the review objectives or eligibility criteria. The full texts of **61 articles** were then assessed for eligibility. Of these, **48 studies were excluded** because they did not directly examine predictive analytics in relation to ambulance deployment, EMS demand forecasting, resource allocation, staffing, relocation, or other relevant operational outcomes. Finally, **13 studies** met the eligibility criteria and were included in the systematic review.

The study-selection process was summarized using the PRISMA 2020 flow diagram in accordance with Page et al. (2021).

The study-selection results were as follows:

- Records identified: n = 650
- Duplicates removed: n = 128
- Records screened by title and abstract: n = 522
- Records excluded after title/abstract screening: n = 461
- Full-text articles assessed for eligibility: n = 61
- Full-text articles excluded: n = 48
- Studies included in the systematic review: n = 13

2.5 Data Extraction

A standardized extraction form was used to record author and year, country, EMS setting, dataset size and period, prediction target, variables used, forecasting method, validation method, deployment or resource-management application, comparator, performance measures, operational outcomes, and reported study limitations.

Particular attention was given to whether each model was tested retrospectively, through simulation, or prospectively in routine EMS operations.

2.6 Quality Assessment

Quality assessment was tailored to study design. Observational evaluations were considered using principles from appropriate critical-appraisal frameworks, while modelling studies were examined for data-source quality, separation of training and testing data, handling of missing data, comparison with baseline models, external validation, risk of data leakage, and reporting of operational outcomes.

Quality findings were used to support interpretation of the evidence rather than to exclude studies solely because of methodological limitations.

2.7 Data Synthesis

Because substantial differences were present across models, datasets, forecasting horizons, and reported outcomes, the evidence was synthesized narratively.

The studies were grouped into five main areas: demand forecasting, spatial and spatiotemporal prediction, ambulance deployment and relocation, staffing and resource-capacity planning, and integrated prediction-optimization systems.

Where comparable information was available, forecasting measures such as MAE, RMSE, MAPE, and MASE were summarized alongside operational measures such as response time, coverage, resource utilization, and travel distance.

3. Results: Narrative Synthesis

3.1 Prediction of EMS Demand

Demand forecasting is one of the most established applications of predictive analytics in EMS resource management. Historical call records are typically the main input, although models may also incorporate time, location, holidays, weather, population characteristics, and special events (Martin et al., 2021; Tluli et al., 2024).

Recent studies suggest that no single forecasting method is best in every setting. Martin et al. (2021) reported advantages for neural-network models when forecasting EMS demand at detailed spatial levels. Abreu et al. (2023) also reported good performance from neural-network-based forecasting and extended prediction from call counts to vehicle requirements.

In contrast, Monks et al. (2023) showed that an ensemble of established forecasting methods performed well across several ambulance services in England and Wales and was externally validated. This finding is important because EMS organizations may not always require the most complex algorithm; reliability, interpretability, ease of use, and transferability can also influence practical value.

More recent work supports the use of ensemble machine learning. Shahidian et al. (2025) reported strong performance from boosting approaches for short-term demand prediction, while Butsingkorn et al. (2026) found that a two-stage ensemble improved accuracy compared with individual models in their dataset.

3.2 Spatial and Spatiotemporal Prediction

For deployment purposes, predicting only the total number of calls may be insufficient because managers also need to anticipate where emergencies are likely to occur. Spatially explicit forecasts can therefore provide information that is directly relevant to resource placement (Martin et al., 2021).

Spatial and spatiotemporal methods divide the EMS service area into zones and estimate demand within each location. Martin et al. (2021) combined clustering with neural-network prediction and showed that the value of machine learning became more evident at finer spatial resolutions.

Recent deep-learning approaches have expanded this concept by learning relationships between neighboring regions and changes over time. Tsai et al. (2026), for example, integrated spatiotemporal forecasting with ambulance-allocation decisions so that expected geographic demand could directly influence resource placement.

3.3 Predictive Analytics and Ambulance Relocation

Prediction becomes operationally useful when it affects where ambulances are placed.

Dynamic relocation systems move idle ambulances to temporary locations according to current system status or predicted future demand. Hajiali et al. (2022) developed a real-time decision-support approach that continuously updated demand and ambulance coverage. Their findings suggested that relocation could improve response and coverage measures, although relocation may also increase vehicle movement and staff burden.

The broader evidence remains less certain. Becker et al. (2023) found that, although mathematical relocation models are common, prospective real-world implementation remains limited. Their review also identified little evidence concerning patient outcomes or the effects of repeated relocation on EMS personnel.

3.4 Resource and Workforce Planning

Predictive analytics can also support decisions made several days or weeks before a shift begins.

Forecasting expected demand can help determine how many ambulances should be available, how many staff members should be scheduled, and which bases are expected to require greater capacity. Monks et al. (2023) developed forecasts suitable for workforce planning and demonstrated useful accuracy for horizons extending several weeks.

Abreu et al. (2023) similarly connected forecast outputs with vehicle requirements, showing that predictive models can support both temporal and geographic planning of EMS resources.

These applications may be easier to implement than fully automated real-time deployment because final decisions remain under the control of EMS managers.

3.5 Integration of Prediction and Optimization

One of the clearest recent trends is the integration of forecasting with optimization.

Instead of producing a forecast and leaving the dispatcher to interpret it independently, newer systems use predicted demand as an input to an allocation or optimization algorithm. Tsai et al. (2026) combined deep forecasting with reinforcement learning, while Rautenstrauß and Schiffer (2026) combined machine learning with combinatorial optimization for ambulance dispatch and redeployment.

This approach is promising because the final goal of EMS analytics is not simply to predict the next emergency. The goal is to use that information to make a better decision before or when the emergency occurs.

4. Discussion

The available literature shows considerable progress in predictive analytics for EMS. Demand can now be forecast across several time scales and geographic levels, and increasingly complex datasets can be incorporated into prediction models (Alrawashdeh et al., 2024; Martin et al., 2021; Tluli et al., 2024).

However, predictive accuracy should not be treated as the only measure of success. A model may estimate demand accurately but still fail to improve ambulance operations if it cannot be integrated into

dispatch systems, if recommendations are impractical, or if operational constraints are inadequately represented (Rautenstrauß & Schiffer, 2026; Tsai et al., 2026).

The comparison between machine learning and traditional forecasting is particularly important. Neural networks and ensemble methods may offer advantages for complex temporal or spatial patterns (Martin et al., 2021; Shahidian et al., 2025), whereas Monks et al. (2023) demonstrated that established forecasting techniques can also provide strong, externally validated performance. EMS organizations should therefore select models according to operational requirements rather than assume that the newest or most complex method will always provide the greatest benefit.

Another important finding concerns implementation. Evidence from simulation and retrospective validation is substantially stronger than evidence from prospective real-time operational use. Becker et al. (2023) identified very limited prospective evaluation in the dynamic-relocation literature and little evidence concerning patient outcomes.

This gap deserves greater attention because improvements observed in simulation do not necessarily demonstrate that patients receive better care, that geographic coverage remains equitable, or that repeated ambulance relocation is acceptable to personnel. Prospective implementation studies are therefore essential for evaluating both service and workforce effects (Becker et al., 2023).

Equity should also be considered in EMS predictive modelling. Optimization focused only on average response time may disadvantage lower-demand or rural communities. The inclusion of fairness considerations in newer allocation approaches, such as the framework described by Tsai et al. (2026), therefore represents an important methodological direction.

The most useful future systems are likely to combine reliable demand forecasting, operational optimization, and human decision support. Dispatchers and EMS managers should remain able to understand recommendations and override them when contextual information not represented in the model becomes important (Tluli et al., 2024).

4.1 Implications for EMS Practice

Predictive analytics can support EMS management at strategic, tactical, and operational levels by informing long-term planning, staffing, ambulance positioning, dispatch, and relocation decisions (Abreu et al., 2023; Tluli et al., 2024).

At the strategic level, long-term patterns may guide station planning and fleet requirements. At the tactical level, forecasts can support shift scheduling, staffing, and planned ambulance positioning. At

the operational level, near-real-time predictions can support dispatch and dynamic relocation (Hajiali et al., 2022; Monks et al., 2023).

Implementation should begin with a clearly defined operational problem. EMS organizations should determine which decision requires improvement—such as weekend staffing, night coverage, relocation during peak periods, or resource availability in high-demand zones—before selecting a predictive method. This problem-oriented approach can help ensure that analytics remains aligned with service needs rather than model complexity alone.

4.2 Strengths and Limitations

A strength of this review is that it connects forecasting research with practical ambulance and EMS resource management and integrates evidence from healthcare, operations research, and computer science. This broader perspective is useful because deployment decisions depend on both predictive performance and operational feasibility.

Several limitations should be acknowledged. The included studies differ substantially in datasets, forecasting horizons, geographic units, algorithms, validation approaches, and outcome measures, which limits direct statistical comparison. In addition, much of the available evidence is retrospective or simulation-based rather than prospectively implemented in routine EMS operations (Becker et al., 2023).

Publication bias is also possible because studies reporting successful predictive models may be more likely to be published than studies showing limited or no improvement. The restriction to English-language publications may additionally have excluded relevant evidence from some regions.

4.3 Future Research

Future studies should provide external validation using data from EMS systems other than those used to develop the models. Prospective real-time trials are also needed to determine whether predicted improvements are achieved during routine service (Becker et al., 2023; Monks et al., 2023).

Researchers should report both forecasting accuracy and operational outcomes. Response time, coverage, vehicle utilization, staff workload, relocation frequency, costs, patient outcomes, and equity should be examined together where possible so that technical gains can be interpreted in relation to service performance.

The recent move toward integrated prediction and optimization should continue, but models must remain understandable and usable by EMS professionals. The purpose of predictive analytics should be to support operational judgment rather than replace it (Rautenstrauß & Schiffer, 2026; Tsai et al., 2026).

5. Conclusion

Predictive analytics is becoming an important tool for ambulance deployment and EMS resource management. Current research shows that statistical forecasting, machine learning, neural networks, boosting models, and spatiotemporal methods can estimate emergency demand with useful levels of accuracy (Butsingkorn et al., 2026; Martin et al., 2021; Shahidian et al., 2025).

The strongest practical value appears when predictions are connected with resource decisions. Predictive information can help estimate how many ambulances are required, where they should be positioned, when relocation may be useful, and how staffing can be adjusted to expected demand (Abreu et al., 2023; Hajiali et al., 2022; Tsai et al., 2026).

Nevertheless, the evidence remains stronger for forecasting and simulation than for routine real-world implementation. More prospective studies are required to determine whether predictive systems consistently improve response time, patient care, workforce conditions, cost, and equitable access to EMS (Becker et al., 2023).

Predictive analytics should therefore be viewed as a decision-support tool rather than a replacement for EMS operational judgment. When reliable data, appropriate models, operational rules, and human expertise are combined, these methods may contribute to more responsive and efficient emergency medical services.

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