Artificial Intelligence Applications in Prehospital Emergency Care, Epidemiology, Health Information Management, Paramedic Practice, and Health Assistant Services

Ahmed Abdullah Mohammed Salami[1], Khaled Hamad Salem Al-Anazi[2], Mohammed Mahal Salem Al-Anazi[3], Fahad Naif Mahmas Al-Otaibi[4], Ahmed Yahya Jaber Haqawi[5], Khaled Nashi Bajad Al-Otaibi[6], Sami Mohammed Naqi Al-Anzi[7], Adel Mohammed Aljabri[8], Turki Awad Alharbi[9], Naif Khalaf Al-Anazi[10], Abdullah Mohammed Al-Shammari[11], Abdulaziz Ismail Masmali[12], Munawir Zinaf M. Alqahtani[13], Muqbil Saad Ahmed Al-Anazi[14], Talal F. Alharbi[15]

[1] Ministry of National Guard, Riyadh, Saudi Arabia
[2] Ministry of National Guard, Riyadh, Saudi Arabia
[3] Field Hospital, Turaif, Saudi Arabia
[4] Ministry of National Guard, Riyadh, Saudi Arabia
[5] Ministry of National Guard, Riyadh, Saudi Arabia
[6] Ministry of National Guard, Riyadh, Saudi Arabia
[7] Ministry of National Guard, Saudi Arabia
[8] Field Medicine, Jeddah, Saudi Arabia
[9] Ministry of National Guard, Al Ahsa, Saudi Arabia
[10] Prince Turki Bin Abdulaziz I Mechanized Brigade, Riyadh, Ministry of National Guard, Saudi Arabia
[11] Ministry of National Guard Health Affairs (MNGHA), Saudi Arabia
[12] Saqr Al Jazeera Hospital, Riyadh, Ministry of National Guard, Saudi Arabia
[13] King Abdulaziz Medical City, Ministry of National Guard, Saudi Arabia
[14] Ministry of National Guard, Saudi Arabia
[15] Military Field Medicine, Riyadh, Ministry of National Guard, Saudi Arabia

Abstract

Background: Artificial intelligence (AI) has emerged as a transformative technology in prehospital Emergency Medical Services (EMS), addressing growing demands associated with increasing emergency call volumes, aging populations, mass casualty incidents, and healthcare resource limitations. Advanced AI technologies, including machine learning, deep learning, natural language processing, and large language models, have demonstrated considerable potential to improve emergency response efficiency, clinical decision-making, and patient outcomes.

Aim: This review aims to examine the applications of artificial intelligence in prehospital emergency care, highlighting its role in emergency call triage, clinical decision support, ambulance dispatch, predictive analytics, resource optimization, and multidisciplinary healthcare practice.

Methods: A narrative review of recent peer-reviewed literature was conducted to evaluate current AI methodologies and their applications in EMS. The review synthesizes evidence regarding machine learning algorithms, deep learning models, reinforcement learning, natural language processing, and large language models, while examining their integration into emergency medical workflows and the roles of health assistants, informatics professionals, emergency personnel, and paramedics.

Results: Artificial intelligence consistently demonstrated improvements in emergency call classification, patient risk prediction, diagnostic accuracy, ambulance deployment, and operational efficiency. Predictive algorithms enhanced identification of high-risk patients and optimized resource allocation through real-time data analysis. AI-assisted decision-support systems strengthened emergency triage, while natural language processing and large language models improved clinical documentation and communication. Successful implementation depended on high-quality healthcare data, multidisciplinary collaboration, cybersecurity, ethical governance, regulatory compliance, and continuous professional oversight.

Conclusion: Artificial intelligence has substantial potential to transform prehospital emergency care by supporting timely clinical decision-making, improving operational performance, and enhancing patient safety. Continued research, prospective validation, and responsible implementation are essential to ensure safe, ethical, and effective integration into emergency medical practice.

Keywords: Artificial intelligence; Emergency medical services; Prehospital care; Machine learning; Deep learning; Natural language processing; Large language models; Emergency medical technicians; Paramedics; Health informatics.

Introduction

Emergency Medical Services (EMS) constitute a critical component of healthcare systems by delivering rapid assessment, stabilization, and transportation of patients experiencing acute medical emergencies. The effectiveness of prehospital emergency care directly influences patient survival, functional recovery, and healthcare outcomes, particularly in cases of trauma, cardiac arrest, stroke, respiratory failure, and other time-sensitive conditions. However, EMS organizations worldwide are currently facing unprecedented operational challenges due to increasing service demands, growing population density, aging societies, expanding urbanization, and the rising prevalence of chronic diseases. These demographic changes have substantially increased the volume of emergency calls received by dispatch centers, placing considerable pressure on emergency communication systems, ambulance services, and healthcare personnel. Furthermore, the emergence of global pandemics, including Coronavirus Disease 2019 (COVID-19), together with the increasing frequency of natural disasters such as floods, earthquakes, hurricanes, and wildfires, has further intensified the complexity of emergency response operations and highlighted the limitations of conventional emergency management systems [1,2]. The growing burden on emergency healthcare systems has created an urgent need for innovative technological solutions capable of improving operational efficiency while maintaining high-quality patient care. For example, emergency service activity in France has increased by approximately 42% during the past decade, reflecting a substantial escalation in emergency healthcare demand. Similar trends have been observed across North America, Europe, and many developing countries, where emergency dispatch centers must rapidly process large numbers of emergency calls while accurately determining case severity, prioritizing ambulance deployment, and coordinating healthcare resources. Telephone-based triage remains one of the most important components of prehospital care because dispatch decisions significantly influence ambulance response times, resource utilization, and patient outcomes. Under these increasingly complex conditions, emergency response systems require modernization through intelligent technologies capable of supporting rapid clinical decision-making, improving dispatch accuracy, and enhancing communication among emergency healthcare providers.

Artificial intelligence (AI) has emerged as one of the most transformative technologies for modernizing prehospital emergency care. AI encompasses computational techniques that enable computer systems to simulate aspects of human intelligence, including learning, reasoning, pattern recognition, prediction, and decision-making. By integrating AI into EMS operations, healthcare organizations can automate repetitive processes, analyze large volumes of clinical and operational data in real time, predict emergency events, optimize ambulance allocation, and support healthcare professionals during critical decision-making. These capabilities have the potential to improve emergency response efficiency while reducing operational costs and enhancing patient safety. Consequently, AI is increasingly recognized as a strategic technology capable of transforming emergency medical services from reactive systems into intelligent, predictive, and data-driven healthcare networks. Emergency management is inherently multidisciplinary and requires continuous coordination among emergency medical dispatchers, paramedics, emergency physicians, nurses, firefighters, police services, hospital emergency departments, and public health authorities. The emergency management process can generally be divided into three interconnected phases: emergency call reception and triage, ambulance dispatch and on-scene patient management, and post-event documentation, analysis, and quality improvement. Each stage involves numerous complex decisions that directly affect the effectiveness of emergency care delivery. During call reception, dispatch personnel must rapidly evaluate symptom descriptions, determine the urgency of the incident, identify potential life-threatening conditions, and allocate appropriate emergency resources. Following dispatch, emergency teams must continuously assess patients, make critical treatment decisions, determine transport priorities, and communicate efficiently with receiving hospitals. After patient transfer, operational data are analyzed to evaluate system performance, identify areas for improvement, and support evidence-based quality assurance initiatives. Artificial intelligence technologies have demonstrated considerable potential to improve each of these operational phases through intelligent decision support, predictive analytics, workflow automation, and continuous performance monitoring [2,3].

Several countries have already begun integrating AI into various aspects of emergency medical services. In North America, artificial intelligence supports emergency call triage through intelligent decision-support systems capable of analyzing caller information and prioritizing emergency responses according to predicted clinical severity [3]. Machine learning algorithms are also employed for predictive analytics, allowing EMS organizations to forecast emergency demand, optimize ambulance deployment, and allocate personnel more efficiently. Real-time decision support systems provide emergency medical technicians and paramedics with clinical recommendations based on continuously updated patient information, enabling more consistent and evidence-based prehospital care [4]. These intelligent technologies contribute to shorter response times, improved operational efficiency, optimized resource utilization, and enhanced patient outcomes. In contrast, the implementation of artificial intelligence within EMS remains relatively limited in several European countries, including France and parts of Germany. Differences in healthcare infrastructure, regulatory frameworks, legal considerations, organizational culture, financial investment, and digital maturity contribute to the variable adoption of AI technologies across different healthcare systems. Among the various branches of artificial intelligence, machine learning (ML), deep learning (DL), and natural language processing (NLP) have attracted particular attention within healthcare applications. Machine learning enables computational systems to identify complex patterns from large datasets without explicit programming, allowing predictive models to improve continuously as additional data become available. Deep learning, a specialized subset of machine learning based on multilayer artificial neural networks, has demonstrated remarkable capabilities for solving highly complex healthcare problems involving image analysis, signal processing, and predictive modeling. Natural language processing complements these approaches by extracting clinically meaningful information from unstructured textual data, including ambulance reports, physician documentation, emergency dispatch records, electronic health records (EHRs), and clinical narratives [5].

The application of deep learning has produced substantial improvements across numerous healthcare domains. AI-powered diagnostic systems have demonstrated excellent performance in medical imaging interpretation, including automated detection of diabetic retinopathy, pulmonary diseases, fractures, intracranial hemorrhage, and malignant tumors [6-8]. Predictive algorithms have also improved early identification of patients at risk for chronic diseases, cardiovascular complications, sepsis, and heart failure, allowing earlier clinical intervention and improved disease management [9]. Within medication management, deep learning models analyze longitudinal electronic health records containing patient diagnoses, laboratory findings, previous medications, and clinical procedures to generate individualized medication recommendations that enhance therapeutic effectiveness while reducing medication errors and adverse drug events [10]. These successful applications illustrate the considerable potential of artificial intelligence to improve both clinical decision-making and healthcare quality. The integration of artificial intelligence into prehospital emergency care presents unique opportunities because EMS environments generate diverse forms of real-time clinical information, including physiological monitoring, electrocardiograms, voice communications, geospatial information, dispatch records, wearable sensor data, and electronic patient care reports. However, effective AI implementation also requires overcoming several important challenges. Healthcare data collected during emergency situations are often fragmented across multiple healthcare organizations, making data integration and interoperability particularly complex. Privacy protection, secure information sharing, standardized documentation, and compliance with healthcare regulations remain essential considerations during AI implementation. Furthermore, emergency datasets frequently include multimodal information consisting of structured clinical variables, free-text documentation, medical images, physiological signals, geographic coordinates, and audio recordings, requiring sophisticated methods for multimodal data representation and analysis. Developing robust big-data infrastructures capable of integrating these heterogeneous information sources is therefore fundamental for achieving reliable AI-supported emergency healthcare systems [5].

Recent advances in large language models (LLMs) have introduced additional opportunities for enhancing prehospital emergency care. These advanced artificial intelligence models possess powerful natural language understanding and generation capabilities that enable automated clinical documentation, intelligent communication support, medical information retrieval, emergency decision assistance, and summarization of complex patient information. LLMs may also facilitate communication between emergency dispatch centers, ambulance personnel, and hospital emergency departments by rapidly processing large volumes of textual information while supporting real-time clinical decision-making. Nevertheless, concerns regarding model reliability, explainability, patient privacy, ethical considerations, regulatory compliance, and clinical validation must be carefully addressed before widespread implementation within emergency medical services.

An Overview of Artificial Intelligence

Artificial intelligence (AI) has emerged as one of the most influential technological innovations in modern healthcare, transforming the way clinical information is collected, analyzed, and utilized to support patient care. AI refers to the capability of computer systems to perform tasks that traditionally require human intelligence, including learning from experience, recognizing patterns, solving complex problems, interpreting language, and making informed decisions. Within Emergency Medical Services (EMS), AI is increasingly recognized as a transformative technology capable of improving every stage of prehospital emergency care, from emergency call reception and ambulance dispatch to patient assessment, clinical intervention, transportation, and communication with receiving healthcare facilities. As emergency healthcare systems continue to face increasing operational demands, AI offers innovative solutions that enhance efficiency, accuracy, and responsiveness while supporting healthcare professionals in delivering timely, evidence-based care. The rapid expansion of electronic health records, wearable medical devices, Internet of Medical Things (IoMT) technologies, telemedicine platforms, and mobile health applications has generated unprecedented volumes of healthcare data. These datasets contain valuable clinical information but are often too large and complex for traditional analytical methods. Artificial intelligence provides the computational capacity to analyze structured and unstructured healthcare data rapidly, identify clinically relevant patterns, and generate actionable insights that support emergency healthcare professionals during time-critical situations. By integrating AI into EMS workflows, healthcare organizations can improve operational efficiency, optimize resource allocation, reduce unnecessary delays, and enhance the quality and safety of patient care [4,5].

One of the most significant advantages of artificial intelligence in prehospital emergency care is its ability to enhance clinical decision-making. Emergency medical personnel frequently operate under considerable time constraints while managing critically ill or injured patients with incomplete clinical information. AI-powered decision-support systems can analyze multiple patient variables simultaneously, including vital signs, symptoms, medical history, laboratory findings, electrocardiographic data, geographic location, and previous healthcare utilization, to generate real-time clinical recommendations. These systems assist emergency physicians, paramedics, nurses, and dispatch personnel by identifying high-risk patients, prioritizing emergency responses, suggesting appropriate interventions, and predicting potential clinical deterioration. Consequently, AI contributes to faster diagnosis, earlier treatment initiation, and improved patient outcomes. Artificial intelligence also plays a central role in optimizing emergency dispatch operations. Emergency communication centers receive large numbers of calls that vary considerably in urgency and complexity. Machine learning algorithms can rapidly analyze caller information, identify critical symptoms, assess emergency severity, and recommend appropriate ambulance dispatch priorities. Intelligent dispatch systems also optimize ambulance allocation by considering real-time traffic conditions, ambulance availability, hospital capacity, geographical distance, and predicted emergency demand. These capabilities improve response times, maximize resource utilization, and reduce operational inefficiencies while ensuring that emergency resources are directed toward patients with the greatest clinical need [5].

Another important application of AI involves patient trajectory prediction and risk stratification. Predictive analytics utilizes historical and real-time healthcare data to estimate future clinical events, enabling emergency healthcare providers to anticipate complications before they occur. Machine learning models can predict outcomes such as cardiac arrest, respiratory failure, sepsis, stroke progression, traumatic deterioration, or hospital admission requirements based on continuously updated patient information. These predictive capabilities support proactive clinical management, allowing emergency teams to initiate timely interventions, mobilize specialized resources, and prepare receiving hospitals before patient arrival. Early recognition of clinical deterioration ultimately improves survival rates and reduces preventable complications. Artificial intelligence additionally contributes to improving diagnostic accuracy during prehospital care. Advanced algorithms can analyze electrocardiograms, medical images, physiological waveforms, laboratory values, and other diagnostic information with remarkable speed and precision. For example, AI-assisted electrocardiographic interpretation facilitates rapid identification of acute myocardial infarction, cardiac arrhythmias, and other life-threatening cardiovascular conditions, enabling earlier activation of specialized cardiac care pathways. Similarly, AI-supported image analysis assists healthcare professionals in identifying fractures, intracranial hemorrhage, pulmonary abnormalities, and traumatic injuries. These capabilities enhance diagnostic confidence while reducing variability among clinicians, particularly in resource-limited or remote environments. The successful implementation of AI in healthcare has been closely linked to advances in Big Data analytics. Modern healthcare systems generate massive volumes of heterogeneous information originating from electronic health records, emergency dispatch databases, ambulance documentation systems, wearable sensors, imaging technologies, laboratory information systems, and mobile health devices. Artificial intelligence algorithms process these complex datasets to identify hidden clinical relationships that would be difficult or impossible to detect using conventional statistical approaches. These analyses facilitate evidence-based decision-making by providing healthcare professionals with comprehensive insights into patient conditions, disease progression, operational performance, and healthcare utilization patterns [6,7].

Machine learning represents one of the most widely utilized branches of artificial intelligence in healthcare. Machine learning algorithms automatically learn from historical data, continuously improving predictive performance without explicit programming. Supervised learning models, including support vector machines, decision trees, random forests, and artificial neural networks, are commonly applied to structured healthcare datasets for disease prediction, outcome classification, and risk assessment. Unsupervised learning techniques identify hidden relationships and patient subgroups within large clinical datasets, supporting personalized healthcare and operational planning. Reinforcement learning approaches further enable adaptive decision-making by optimizing sequential clinical actions based on continuous environmental feedback. Deep learning, a specialized subset of machine learning based on multilayer artificial neural networks, has demonstrated exceptional performance across numerous healthcare applications. Deep learning models excel in processing complex data types, including medical images, physiological signals, speech recordings, and sequential clinical information. Their ability to automatically extract hierarchical features from raw data has significantly improved diagnostic accuracy in radiology, cardiology, pathology, ophthalmology, and emergency medicine. Within prehospital care, deep learning algorithms facilitate automated electrocardiogram interpretation, trauma assessment, respiratory monitoring, and prediction of adverse clinical events, providing emergency healthcare professionals with valuable decision support during critical situations. Natural Language Processing (NLP) represents another important AI technology that enables computers to understand, interpret, and generate human language. Emergency healthcare systems routinely generate extensive unstructured textual information, including dispatch notes, ambulance reports, physician documentation, nursing assessments, discharge summaries, and clinical narratives. NLP algorithms transform these unstructured documents into structured clinical data suitable for analysis, allowing healthcare organizations to extract meaningful information efficiently. Applications include automated documentation, symptom recognition, clinical coding, quality monitoring, adverse event detection, and decision support. In emergency medical services, NLP improves communication efficiency while reducing administrative workload and documentation burden. More recently, Large Language Models (LLMs) have emerged as one of the most promising developments in artificial intelligence for healthcare applications. These advanced language models possess remarkable capabilities for understanding complex clinical language, summarizing patient information, answering medical questions, generating documentation, and supporting clinical reasoning. Within prehospital emergency care, LLMs can assist emergency dispatchers by interpreting emergency calls, supporting symptom assessment, generating structured clinical reports, and facilitating communication between ambulance personnel and hospital teams. They also provide rapid access to evidence-based clinical knowledge, enabling healthcare professionals to make informed decisions during emergency situations. Although LLMs offer substantial opportunities for improving emergency healthcare delivery, concerns regarding accuracy, explainability, patient privacy, regulatory compliance, and ethical implementation require careful consideration before widespread clinical adoption [6-10].

Artificial intelligence also contributes significantly to preventive healthcare by identifying early warning signs of disease progression before clinical deterioration becomes apparent. Predictive AI systems continuously analyze patient data to detect subtle physiological changes associated with developing illness, allowing earlier intervention and potentially preventing emergency events altogether [11,12]. These capabilities support population health management by identifying high-risk individuals who may benefit from preventive care, chronic disease monitoring, or early therapeutic intervention. Such proactive approaches reduce emergency department overcrowding, improve long-term patient outcomes, and enhance healthcare system sustainability. Despite its considerable potential, successful implementation of artificial intelligence within emergency medical services requires addressing several important challenges. Healthcare data quality, interoperability, algorithm transparency, model bias, cybersecurity, patient privacy, ethical governance, workforce training, and regulatory compliance remain critical considerations. AI systems should complement rather than replace healthcare professionals, serving as intelligent decision-support tools that enhance human expertise while preserving clinical judgment and patient-centered care. Establishing standardized evaluation frameworks, ensuring rigorous clinical validation, and promoting interdisciplinary collaboration among clinicians, engineers, informaticians, policymakers, and healthcare administrators will be essential for maximizing the benefits of AI while minimizing associated risks.

Artificial Intelligence Methodologies in Prehospital Emergency Medical Services

Artificial intelligence (AI) encompasses a diverse collection of computational methodologies that enable healthcare systems to analyze complex data, generate accurate predictions, automate decision-making, and continuously improve operational performance. Within prehospital Emergency Medical Services (EMS), AI methodologies have become essential tools for enhancing emergency call management, ambulance deployment, patient assessment, clinical decision support, and healthcare resource optimization. Advances in machine learning, deep learning, natural language processing, large language models, and reinforcement learning have substantially expanded the capabilities of emergency healthcare systems by allowing intelligent analysis of heterogeneous datasets generated during emergency response activities. Collectively, these technologies provide a comprehensive framework for improving both operational efficiency and patient outcomes throughout the continuum of prehospital emergency care. Machine learning (ML) represents one of the most extensively applied branches of artificial intelligence in emergency medicine. ML algorithms learn predictive patterns directly from historical healthcare data without requiring explicit programming for every possible scenario. These algorithms continuously improve their predictive accuracy as additional clinical information becomes available, making them particularly suitable for dynamic EMS environments characterized by uncertainty and rapidly changing patient conditions. Supervised machine learning approaches have demonstrated considerable success in solving classification and regression problems encountered during emergency care. Common supervised algorithms include Support Vector Machines (SVMs), Random Forests, Logistic Regression, Decision Trees, Gradient Boosting Machines, and Artificial Neural Networks. These techniques are widely employed to automate emergency call classification, estimate patient acuity, predict hospital admission requirements, identify patients at high risk of clinical deterioration, and support emergency dispatcher decision-making. By rapidly analyzing demographic information, presenting symptoms, physiological parameters, and historical medical records, supervised learning models assist dispatch personnel in prioritizing emergency responses while improving the accuracy and consistency of triage decisions [11,12].

In addition to supervised learning, unsupervised machine learning techniques have demonstrated substantial value for exploratory analysis of complex EMS datasets. Unlike supervised methods, unsupervised learning does not require predefined outcome labels but instead identifies hidden structures and relationships within data. Principal Component Analysis (PCA) is frequently used to reduce the dimensionality of large healthcare datasets while preserving clinically relevant information, thereby improving computational efficiency and facilitating visualization of complex data patterns. Clustering algorithms, including K-means clustering, hierarchical clustering, and density-based clustering methods, enable healthcare organizations to identify groups of patients with similar clinical characteristics, recognize temporal clusters of emergency incidents, detect seasonal variations in emergency demand, and identify geographic regions with increased emergency call density. These analytical capabilities support strategic planning, resource allocation, epidemiological surveillance, and emergency preparedness by providing healthcare administrators with valuable operational insights. Ensemble learning techniques further improve machine learning performance by combining predictions generated by multiple individual models. Methods such as bagging, boosting, Random Forests, AdaBoost, Extreme Gradient Boosting (XGBoost), and Light Gradient Boosting Machine (LightGBM) consistently outperform individual predictive models by reducing variance, minimizing prediction errors, and enhancing generalization capability. Within EMS, ensemble algorithms improve prediction accuracy for ambulance demand forecasting, patient outcome prediction, emergency severity assessment, and clinical risk stratification. Their robustness makes them particularly suitable for healthcare applications where high predictive reliability is essential for patient safety and operational decision-making. Deep learning (DL), an advanced subset of machine learning based on multilayer artificial neural networks, has revolutionized healthcare analytics through its remarkable ability to process large-scale, high-dimensional, and heterogeneous datasets. Unlike conventional machine learning algorithms that often require manual feature engineering, deep learning models automatically extract complex hierarchical features directly from raw healthcare data. This capability enables superior performance across numerous emergency medicine applications involving images, physiological signals, sequential clinical information, speech, and unstructured healthcare documentation [12,13].

Among deep learning architectures, Convolutional Neural Networks (CNNs) have become the dominant approach for image-based healthcare applications. CNNs automatically identify complex visual features within medical images, enabling rapid and accurate interpretation of diagnostic information. In prehospital emergency care, CNNs are increasingly investigated for evaluating traumatic injuries using photographs acquired at accident scenes, identifying fractures, estimating burn severity, assessing wound characteristics, detecting hemorrhage, and supporting remote consultation with hospital specialists. Integration of CNN-based image analysis into mobile emergency applications enables paramedics to receive immediate decision support during field assessments, improving diagnostic confidence while facilitating earlier treatment decisions. Sequential deep learning models play an equally important role in emergency medical services because many healthcare processes involve continuously evolving patient information. Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Gated Recurrent Units (GRUs) have demonstrated exceptional capability for analyzing time-dependent healthcare data, including continuous physiological monitoring, electrocardiographic recordings, respiratory waveforms, blood pressure trends, oxygen saturation measurements, and ambulance telemetry data. These architectures capture temporal relationships within sequential information, allowing prediction of patient deterioration, cardiac arrest, respiratory failure, or hemodynamic instability before clinical symptoms become apparent. Such predictive capabilities support proactive intervention by emergency healthcare professionals, thereby improving patient safety and clinical outcomes. More recently, advanced deep learning architectures including autoencoders and Transformer-based models have expanded the analytical capabilities of emergency healthcare systems. Autoencoders provide powerful tools for anomaly detection by learning compressed representations of normal operational patterns and identifying deviations associated with unusual clinical events or system abnormalities. Within EMS, these models facilitate detection of unexpected dispatcher communication patterns, equipment malfunctions, unusual ambulance utilization, and rare clinical presentations. Transformer architectures, originally developed for natural language processing, have demonstrated remarkable performance across numerous healthcare applications because of their ability to model long-range dependencies within sequential data. These models increasingly support automated incident report summarization, emergency documentation, multimodal healthcare data integration, and intelligent analysis of dispatcher–caller conversations. Their capacity to process large volumes of heterogeneous information simultaneously significantly enhances situational awareness and accelerates emergency decision-making [13].

Natural Language Processing (NLP) has become one of the most valuable AI technologies for analyzing the extensive unstructured textual information generated throughout emergency medical services. Ambulance reports, emergency call transcripts, physician documentation, nursing notes, electronic health records, discharge summaries, and clinical narratives collectively contain substantial amounts of clinically meaningful information that traditional analytical methods cannot efficiently process. Early NLP approaches relied primarily on frequency-based statistical techniques. The Bag-of-Words model represented textual documents by counting word frequencies while disregarding word order and contextual relationships, providing a simple but limited representation of language [13]. Subsequently, Term Frequency–Inverse Document Frequency (TF-IDF) introduced statistical weighting mechanisms that assigned greater importance to informative terms occurring less frequently across documents while reducing emphasis on commonly occurring words. Although these methods improved information retrieval performance, they remained incapable of capturing semantic meaning or contextual relationships among words. Recent advances in deep learning have fundamentally transformed natural language processing through distributed word embedding techniques such as Word2Vec and Global Vectors for Word Representation (GloVe). These models learn semantic representations by analyzing large corpora of text, enabling computational systems to recognize linguistic similarities, contextual meaning, and syntactic relationships among words [14]. The emergence of Transformer architectures has further revolutionized NLP by enabling efficient parallel processing of sequential information while capturing long-range contextual dependencies within language. Transformer-based models leverage attention mechanisms that selectively emphasize relevant contextual information during language understanding and generation, resulting in unprecedented improvements across numerous healthcare applications [13,14].

Large Language Models (LLMs) represent the latest generation of natural language processing technologies and have demonstrated remarkable capabilities for understanding, generating, and reasoning with complex clinical language. State-of-the-art models including GPT-4 [15] and LLaMA [16] have been adapted to support numerous EMS applications, including intelligent virtual assistants, automated clinical documentation, dispatcher education, medical knowledge retrieval, patient communication, and real-time clinical question answering. These models assist emergency personnel by summarizing lengthy patient histories, generating structured clinical reports, explaining evidence-based treatment recommendations, and facilitating communication between ambulance teams and receiving hospitals. Their ability to synthesize complex medical information substantially reduces documentation burden while improving information accessibility during emergency situations. Several complementary techniques have further enhanced the performance of large language models in healthcare. Prompt engineering optimizes model outputs by carefully designing input instructions that guide clinical reasoning toward specific objectives. Agentic AI extends LLM capabilities by enabling autonomous planning, reasoning, and execution of complex healthcare workflows involving multiple sequential tasks [17]. Retrieval-Augmented Generation (RAG) combines large language models with external medical knowledge repositories, allowing AI systems to retrieve current clinical guidelines, scientific literature, and institutional protocols before generating responses. This hybrid approach significantly improves factual accuracy, contextual relevance, and evidence-based decision support while reducing the likelihood of inaccurate or fabricated information. Despite these considerable advantages, integrating LLMs into EMS workflows requires careful attention to patient privacy, cybersecurity, algorithm transparency, ethical governance, regulatory compliance, and clinical validation. Reinforcement Learning (RL) represents another rapidly evolving branch of artificial intelligence that is particularly well suited for optimizing dynamic decision-making within emergency medical services. Unlike supervised learning, reinforcement learning enables computational agents to learn optimal decision strategies through continuous interaction with complex environments while maximizing cumulative rewards. This learning paradigm closely resembles many operational challenges encountered within EMS, where decisions must be continuously adapted according to changing patient conditions, resource availability, traffic patterns, weather conditions, and healthcare system capacity.

Model-free reinforcement learning algorithms, including Q-Learning, Proximal Policy Optimization (PPO), Deep Q Networks (DQN), and Actor-Critic architectures such as Asynchronous Advantage Actor-Critic (A3C), have demonstrated substantial value for optimizing ambulance routing, vehicle positioning, dispatch scheduling, and emergency resource allocation. These algorithms continuously learn optimal operational policies through repeated interaction with simulated or real healthcare environments without requiring explicit mathematical models of system dynamics. Conversely, model-based reinforcement learning approaches, including MuZero and World Models, construct internal representations of healthcare environments that enable simulation of future operational scenarios before actual implementation. These predictive capabilities facilitate proactive decision-making under uncertainty while reducing operational risks associated with emergency response planning. Hybrid Actor-Critic methods combine value estimation with policy optimization, balancing efficient exploration of alternative strategies against reliable exploitation of established decision policies. Such algorithms are particularly valuable in resource-constrained emergency environments where rapid adaptation and efficient utilization of limited healthcare resources are essential. More recently, Reinforcement Learning from Human Feedback (RLHF) has gained considerable importance, particularly for training large language models used within healthcare applications [18]. RLHF incorporates expert demonstrations, clinician preferences, and human evaluations into the learning process, ensuring that AI-generated recommendations align with ethical principles, professional standards, and evidence-based clinical practice. This human-centered learning approach substantially improves the reliability, safety, and acceptability of AI-supported decision-making in emergency medical services.

Benefits of Artificial Intelligence in Emergency Medical Services

Artificial intelligence (AI) is transforming Emergency Medical Services (EMS) by improving clinical decision-making, optimizing emergency response operations, enhancing diagnostic accuracy, and supporting efficient resource utilization throughout the prehospital care pathway [1-18]. Recent advances in machine learning (ML), deep learning (DL), natural language processing (NLP), reinforcement learning (RL), and large language models (LLMs) enable EMS systems to analyze large volumes of heterogeneous clinical and operational data, resulting in faster response times, improved patient outcomes, and more efficient emergency management [5,6]. One of the most important applications of AI in EMS is predictive modeling for emergency care. Machine learning algorithms have substantially improved emergency call triage by accurately classifying patient complaints and identifying patients requiring immediate intervention. Supervised learning models, including support vector machines, random forests, logistic regression, multilayer perceptrons, and extreme gradient boosting (XGBoost), have demonstrated excellent predictive performance for identifying stroke, cardiac arrest, traumatic injuries, cerebral hemorrhage, and other time-critical emergencies [3,4]. Deep learning approaches, particularly bidirectional long short-term memory (Bi-LSTM) networks and recurrent neural networks (RNNs), have further improved the prediction of neurological outcomes following out-of-hospital cardiac arrest and other severe emergencies [6]. These predictive models enable emergency dispatchers and paramedics to prioritize patients more effectively, initiate earlier interventions, and reduce undertriage while facilitating transportation to the most appropriate healthcare facility [3,4]. Artificial intelligence has also enhanced prehospital diagnosis by integrating multiple clinical data sources. Machine learning algorithms successfully identify anaphylaxis, distinguish stroke from stroke mimics, estimate trauma severity, and predict patient deterioration using information obtained during emergency calls and ambulance assessments [5,6]. Convolutional neural networks (CNNs) have demonstrated promising applications in image-based clinical decision support, including injury assessment and interpretation of field-acquired medical images [6]. Simultaneously, sequential deep learning models such as long short-term memory (LSTM) and gated recurrent unit (GRU) networks analyze continuously evolving physiological parameters, including electrocardiographic signals, blood pressure, oxygen saturation, and respiratory patterns, enabling earlier recognition of clinical deterioration before obvious symptoms develop [6].

Resource allocation represents another major area in which AI significantly improves EMS performance. Intelligent algorithms combine historical emergency demand, geographic information systems (GIS), Global Positioning System (GPS) data, weather conditions, traffic patterns, and ambulance availability to predict future emergency demand and optimize ambulance deployment [3,4]. Reinforcement learning algorithms dynamically adjust ambulance positioning, routing strategies, and dispatch decisions according to continuously changing operational conditions, thereby reducing response times and improving resource utilization [18]. These technologies support healthcare administrators in planning emergency services while increasing operational efficiency and reducing unnecessary expenditures. Artificial intelligence also strengthens emergency triage and dispatcher decision support. Deep learning systems process multimodal information, including structured clinical variables, dispatcher observations, physiological measurements, and free-text documentation, to classify emergency calls according to urgency and required response priority [5]. AI-assisted triage systems have demonstrated superior predictive accuracy compared with several traditional rule-based dispatch protocols, improving consistency in emergency prioritization and supporting evidence-based clinical decision-making [3,4]. Continuous model updating further enhances predictive performance as new operational and clinical data become available. Natural language processing has become increasingly valuable for analyzing the large volume of unstructured information generated during emergency care. Ambulance reports, emergency call transcripts, physician documentation, nursing notes, and electronic health records contain clinically relevant information that can be automatically extracted using NLP techniques [5]. Early methods such as Bag-of-Words and Term Frequency–Inverse Document Frequency (TF-IDF) provided statistical analysis of textual information, while modern embedding techniques including Word2Vec and GloVe capture semantic relationships among medical concepts [13,14]. Transformer-based architectures have substantially improved language understanding through contextual attention mechanisms, enabling more accurate processing of emergency documentation and communication [14].

Large language models, including GPT-4 and LLaMA, have further expanded AI applications within EMS by supporting automated documentation, emergency dispatcher education, clinical question answering, medical summarization, and virtual decision-support systems [15,16]. These models assist healthcare professionals by rapidly synthesizing patient histories, generating structured clinical reports, summarizing emergency incidents, and retrieving evidence-based recommendations. Advanced techniques such as prompt engineering, Retrieval-Augmented Generation (RAG), and agentic AI further improve factual accuracy and contextual relevance by integrating verified medical knowledge into AI-generated responses [17]. Nevertheless, successful implementation requires careful attention to patient privacy, cybersecurity, regulatory compliance, and continuous clinical validation to minimize inaccurate or fabricated outputs. Ethical and legal considerations remain fundamental to AI implementation in EMS. Healthcare organizations must ensure compliance with regulations governing patient confidentiality while maintaining algorithm transparency, fairness, explainability, and accountability [5]. AI systems should function as clinical decision-support tools that complement rather than replace the expertise of physicians, nurses, paramedics, emergency medical technicians, and dispatch personnel. Human oversight remains essential for high-risk clinical decisions, particularly in complex emergency situations requiring individualized patient assessment [5,17]. Overall, AI technologies have demonstrated substantial benefits across all phases of prehospital emergency care. Machine learning, deep learning, reinforcement learning, natural language processing, and large language models collectively improve emergency call triage, diagnostic accuracy, ambulance deployment, resource allocation, clinical documentation, operational efficiency, and patient outcomes [3-18]. Continued research focusing on explainable AI, multimodal learning, secure data integration, federated learning, and prospective clinical validation will further strengthen the safe implementation of AI within EMS while supporting healthcare professionals in delivering faster, more accurate, and patient-centered emergency care [5,17,18-27].

Role of Health Assistants, Informatics Professionals, Emergency Personnel, and Paramedics:

The successful integration of artificial intelligence (AI) into prehospital emergency care depends not only on technological innovation but also on the coordinated efforts of healthcare professionals who utilize these technologies in clinical practice. Health assistants, health informatics professionals, emergency personnel, and paramedics each contribute distinct yet complementary roles in ensuring that AI-driven systems improve patient care, operational efficiency, and emergency response while maintaining patient safety and ethical standards. Health assistants play a fundamental role in supporting frontline emergency services by assisting with patient assessment, monitoring vital signs, documenting clinical observations, and facilitating communication between patients and multidisciplinary healthcare teams. AI-enabled mobile applications and electronic patient care record systems assist health assistants in accurately documenting patient information, identifying abnormal physiological parameters, and ensuring timely transfer of essential clinical data to receiving healthcare facilities. Their active participation in data collection contributes to the quality and reliability of AI algorithms, which rely on accurate and standardized clinical information for effective decision support. Health informatics professionals are central to the implementation, management, and continuous improvement of AI technologies within Emergency Medical Services (EMS). They oversee the integration of electronic health records, ambulance information systems, dispatch platforms, clinical databases, and communication networks to ensure secure and interoperable data exchange. Informatics specialists are also responsible for maintaining data quality, protecting patient privacy, ensuring compliance with healthcare regulations, and evaluating AI system performance. Furthermore, they collaborate with clinicians, software developers, and healthcare administrators to optimize AI algorithms, improve interoperability, and support evidence-based decision-making through advanced analytics, predictive modeling, and real-time clinical dashboards. Emergency personnel, including emergency physicians, nurses, and dispatch officers, utilize AI-powered decision-support systems to enhance emergency call triage, prioritize resource allocation, and facilitate rapid clinical decision-making. AI technologies assist emergency professionals by analyzing patient symptoms, predicting clinical deterioration, recommending priority levels, and identifying appropriate treatment pathways. Despite these technological advances, emergency personnel remain responsible for interpreting AI-generated recommendations within the context of each patient's unique clinical presentation. Their professional judgment ensures that automated recommendations are integrated safely with established clinical guidelines and individual patient needs. Paramedics represent the primary users of AI technologies during prehospital patient care. Working in highly dynamic and time-sensitive environments, paramedics use AI-supported clinical decision systems to perform rapid patient assessments, interpret physiological monitoring data, identify high-risk conditions, and determine appropriate treatment strategies before hospital arrival. AI-assisted diagnostic tools, predictive algorithms, and mobile decision-support applications enable paramedics to recognize life-threatening conditions earlier, optimize treatment decisions, and communicate comprehensive clinical information to receiving emergency departments. Additionally, AI-enhanced navigation systems improve ambulance routing by incorporating real-time traffic conditions, hospital capacity, and geographical information, thereby reducing transport times and improving access to definitive care. Effective collaboration among health assistants, informatics professionals, emergency personnel, and paramedics is essential for maximizing the benefits of AI in prehospital emergency care. Through multidisciplinary cooperation, continuous professional education, standardized data management, and responsible implementation of AI technologies, these healthcare professionals collectively enhance emergency response efficiency, improve patient safety, strengthen clinical decision-making, and support the delivery of high-quality, patient-centered emergency medical services.

Conclusion

Artificial intelligence is reshaping prehospital emergency care by providing intelligent solutions that improve emergency response, clinical decision-making, and operational efficiency. Technologies including machine learning, deep learning, natural language processing, reinforcement learning, and large language models enable more accurate emergency call triage, earlier identification of critically ill patients, optimized ambulance deployment, and enhanced communication throughout the emergency care continuum. These innovations support healthcare professionals by transforming large volumes of clinical and operational data into actionable information while reducing delays in patient assessment and treatment. Nevertheless, successful implementation extends beyond technological advancement and requires multidisciplinary collaboration among paramedics, emergency personnel, health assistants, health informatics professionals, clinicians, and healthcare administrators. Equally important are robust cybersecurity measures, high-quality data management, ethical governance, regulatory compliance, and continuous clinical validation to ensure patient safety and maintain public trust. Future research should emphasize explainable and trustworthy AI, multimodal data integration, prospective clinical evaluation, and seamless interoperability with healthcare information systems. Collectively, these developments will strengthen the resilience, efficiency, and quality of prehospital emergency medical services while promoting safer, faster, and more patient-centered emergency care.

References

1. Gil-Jardiné, C.; Chenais, G.; Pradeau, C.; Tentillier, E.; Revel, P.; Combes, X.; Galinski, M.; Tellier, E.; Lagarde, E. Trends in reasons for emergency calls during the COVID-19 crisis in the department of Gironde, France using artificial neural network for natural language classification. *Scand. J. Trauma Resusc. Emerg. Med.* **2021**, *29*, 1–9.
2. Linardos, V.; Drakaki, M.; Tzionas, P.; Karnavas, Y.L. Machine learning in disaster management: Recent developments in methods and applications. *Mach. Learn. Knowl. Extr.* **2022**, *4*, 446–473.
3. Sterling, N.W.; Patzer, R.E.; Di, M.; Schrager, J.D. Prediction of emergency department patient disposition based on natural language processing of triage notes. *Int. J. Med Inform.* **2019**, *129*, 184–188.
4. Harford, S.; Del Rios, M.; Heinert, S.; Weber, J.; Markul, E.; Tataris, K.; Campbell, T.; Vanden Hoek, T.; Darabi, H. A machine learning approach for modeling decisions in the out of hospital cardiac arrest care workflow. *BMC Med Inform. Decis. Mak.* **2022**, *22*, 21.
5. Ahmed, Z.; Mohamed, K.; Zeeshan, S.; Dong, X. Artificial intelligence with multi-functional machine learning platform development for better healthcare and precision medicine. *Database* **2020**, *2020*, baaa010.
6. Alom, M.Z.; Taha, T.M.; Yakopcic, C.; Westberg, S.; Sidike, P.; Nasrin, M.S.; Hasan, M.; Van Essen, B.C.; Awwal, A.A.; Asari, V.K. A state-of-the-art survey on deep learning theory and architectures. *Electronics* **2019**, *8*, 292.
7. Willemink, M.J.; Koszek, W.A.; Hardell, C.; Wu, J.; Fleischmann, D.; Harvey, H.; Folio, L.R.; Summers, R.M.; Rubin, D.L.; Lungren, M.P. Preparing medical imaging data for machine learning. *Radiology* **2020**, *295*, 4–15.
8. Gulshan, V.; Peng, L.; Coram, M.; Stumpe, M.C.; Wu, D.; Narayanaswamy, A.; Venugopalan, S.; Widner, K.; Madams, T.; Cuadros, J.; et al. Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. *JAMA* **2016**, *316*, 2402–2410.
9. Choi, E.; Schuetz, A.; Stewart, W.F.; Sun, J. Using recurrent neural network models for early detection of heart failure onset. *J. Am. Med Inform. Assoc.* **2017**, *24*, 361–370.
10. Gong, F.; Wang, M.; Wang, H.; Wang, S.; Liu, M. SMR: Medical knowledge graph embedding for safe medicine recommendation. *Big Data Res.* **2021**, *23*, 100174.
11. Kang, D.Y.; Cho, K.J.; Kwon, O.; Kwon, J.m.; Jeon, K.H.; Park, H.; Lee, Y.; Park, J.; Oh, B.H. Artificial intelligence algorithm to predict the need for critical care in prehospital emergency medical services. *Scand. J. Trauma Resusc. Emerg. Med.* **2020**, *28*, 17.
12. Rafi, S.; Gangloff, C.; Paulhet, E.; Grimault, O.; Soulat, L.; Bouzillé, G.; Cuggia, M. Out-of-hospital cardiac arrest detection by machine learning based on the phonetic characteristics of the caller's voice. In *Challenges of Trustable AI and Added-Value on Health*; IOS Press: Amsterdam, The Netherlands, 2022; pp. 445–449.

13. Stewart, J.; Lu, J.; Goudie, A.; Arendts, G.; Meka, S.A.; Freeman, S.; Walker, K.; Sprivulis, P.; Sanfilippo, F.; Bennamoun, M.; et al. Applications of natural language processing at emergency department triage: A narrative review. *PLoS ONE* **2023**, *18*, e0279953.
14. Pennington, J.; Socher, R.; Manning, C.D. Glove: Global vectors for word representation. In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), Doha, Qatar, 25–29 October 2014; pp. 1532–1543.
15. Achiam, J.; Adler, S.; Agarwal, S.; Ahmad, L.; Akkaya, I.; Aleman, F.L.; Almeida, D.; Altenschmidt, J.; Altman, S.; Anadkat, S.; et al. Gpt-4 technical report. *arXiv* **2023**, arXiv:2303.08774.
16. Touvron, H.; Lavril, T.; Izacard, G.; Martinet, X.; Lachaux, M.A.; Lacroix, T.; Rozière, B.; Goyal, N.; Hambro, E.; Azhar, F.; et al. Llama: Open and efficient foundation language models. *arXiv* **2023**, arXiv:2302.13971.
17. Qiu, J.; Lam, K.; Li, G.; Acharya, A.; Wong, T.Y.; Darzi, A.; Yuan, W.; Topol, E.J. LLM-based agentic systems in medicine and healthcare. *Nat. Mach. Intell.* **2024**, *6*, 1418–1420.
18. Bai, Y.; Jones, A.; Ndousse, K.; Askell, A.; Chen, A.; DasSarma, N.; Drain, D.; Fort, S.; Ganguli, D.; Henighan, T.; et al. Training a helpful and harmless assistant with reinforcement learning from human feedback. *arXiv* **2022**, arXiv:2204.05862.
19. 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.; et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ* **2021**, *372*, n71.
20. Shi, J.; Ye, M.; Chen, H.; Lu, Y.; Tan, Z.; Fan, Z.; Zhao, J. Enhancing efficiency and capacity of telehealth services with intelligent triage: A bidirectional LSTM neural network model employing character embedding. *BMC Med Inform. Decis. Mak.* **2023**, *23*, 269
21. Ceklic, E.; Ball, S.; Finn, J.; Brown, E.; Brink, D.; Bailey, P.; Whiteside, A.; Brits, R.; Tohira, H. Ambulance dispatch prioritisation for traffic crashes using machine learning: A natural language approach. *Int. J. Med Inform.* **2022**, *168*, 104886.
22. Inokuchi, R.; Iwagami, M.; Sun, Y.; Sakamoto, A.; Tamiya, N. Machine learning models predicting undertriage in telephone triage. *Ann. Med.* **2022**, *54*, 2989–2996.
23. Rojas, A.; Calcín, K.; Casta neda, P. A Whisper and BETO-Bert Based Web Application for Classification of Emergency Calls. In Proceedings of the 2025 8th International Conference on Information and Computer Technologies (ICICT), Honolulu, HI, USA, 14–16 March 2025; pp. 236–241.
24. Brossard, C.; Goetz, C.; Catoire, P.; Cipolat, L.; Guyeux, C.; Gil Jardine, C.; Akplogan, M.; Abensur Vuillaume, L. Predicting emergency department admissions using a machine-learning algorithm: A proof of concept with retrospective study. *BMC Emerg. Med.* **2025**, *25*, 3.
25. Ferri, P.; Sáez, C.; Félix-De Castro, A.; Juan-Albarracín, J.; Blanes-Selva, V.; Sánchez-Cuesta, P.; García-Gómez, J.M. Deep ensemble multitask classification of emergency medical call incidents combining multimodal data improves emergency medical dispatch. *Artif. Intell. Med.* **2021**, *117*, 102088.
26. Abi Kanaan, M.; Couchot, J.F.; Guyeux, C.; Laiymani, D.; Atechian, T.; Darazi, R. Combining a multi-feature neural network with multi-task learning for emergency calls severity prediction. *Array* **2024**, *21*, 100333.
27. Chin, K.C.; Hsieh, T.C.; Chiang, W.C.; Chien, Y.C.; Sun, J.T.; Lin, H.Y.; Hsieh, M.J.; Yang, C.W.; Chen, A.Y.; Ma, M.H.M. Early recognition of a caller's emotion in out-of-hospital cardiac arrest dispatching: An artificial intelligence approach. *Resuscitation* **2021**, *167*, 144–150