

Enhancing Paramedic Decision-Making Through Artificial Intelligence-Based Triage Systems In Prehospital Emergency Care

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Abstract

Background:

Paramedics operate in complex, high-pressure environments where rapid and accurate triage decisions are essential to patient survival. Traditional triage systems often rely on subjective clinical judgment, which can lead to inconsistency and delayed intervention. Advances in artificial intelligence (AI) have introduced data-driven triage tools designed to augment paramedic decision-making and improve patient outcomes in prehospital emergency care (PEC).

Objective:

This systematic review aimed to evaluate the effectiveness of AI-based triage systems in enhancing paramedic decision-making, improving triage accuracy, and optimizing response efficiency in prehospital settings.

Methods:

A systematic search was conducted across PubMed, Scopus, Web of Science, IEEE Xplore, and ScienceDirect for studies published between 2020 and 2025. Following PRISMA 2020 guidelines, 24 studies met the inclusion criteria. Data were extracted on AI model types, study design, triage outcomes, and clinical effectiveness. Quality appraisal was performed using the Newcastle–Ottawa Scale and the Joanna Briggs Institute checklist.

Results:

AI-based triage tools consistently outperformed conventional triage systems, demonstrating higher predictive accuracy (AUC range: 0.82–0.93) and reduced under-triage rates. Integrating AI decision support improved paramedic confidence, reduced cognitive load, and enhanced communication with receiving hospitals. Moreover, system-level outcomes such as response time reduction (8–21 seconds) and optimized resource allocation were reported.

However, challenges remain regarding algorithm transparency, data interoperability, and ethical oversight.

Conclusion:

AI-based triage systems represent a paradigm shift in prehospital emergency medicine. When appropriately implemented, they enhance clinical decision-making, strengthen patient safety, and support data-informed EMS management. Nevertheless, responsible integration requires ethical frameworks, explainable AI models, and structured training for paramedics to ensure human-centered and trustworthy application.

Keywords: Artificial intelligence, Paramedic decision-making, Prehospital care, Triage systems, Emergency medical services, Machine learning.

Introduction

Prehospital emergency care (PEC) represents one of the most complex environments in healthcare, where clinical decisions must be made rapidly and often under conditions of uncertainty and resource limitation. Paramedics play a pivotal role in early assessment, stabilization, and triage of critically ill or injured patients. However, conventional triage systems, which rely heavily on subjective clinical judgment, can be prone to variability and human error (McCallum et al., 2022). In recent years, the integration of artificial intelligence (AI) into PEC has emerged as a transformative innovation, aiming to enhance paramedic decision-making, improve triage accuracy, and optimize patient outcomes (Matsuo et al., 2020).

Artificial intelligence–based triage systems utilize algorithms trained on large datasets to assist EMS personnel in predicting patient severity, prioritizing care, and allocating resources effectively. These systems incorporate real-time physiological data, electronic patient care records, and environmental variables to generate risk predictions and clinical recommendations (Choi et al., 2023). For instance, AI models have demonstrated superior predictive accuracy compared to traditional triage tools, achieving higher area-under-the-curve (AUC) scores in identifying patients requiring critical care interventions (Liu et al., 2020). Moreover, AI-driven decision-support tools can reduce cognitive load for paramedics, facilitate standardized assessments, and enhance communication between prehospital and hospital teams (Ong et al., 2022).

Despite these advancements, integrating AI-based triage into prehospital workflows presents several challenges. Concerns include algorithm transparency, data quality, contextual adaptability, and potential overreliance on machine outputs (Price et al., 2023). Furthermore, the prehospital environment—characterized by unpredictable field conditions, limited connectivity, and time-critical operations—poses unique barriers to AI deployment (Lundgren et al., 2024). A recent scoping review found that most existing AI applications in PEC remain at early stages of development, with limited external validation and scarce prospective trials (McCallum et al., 2022). These findings underscore the necessity for rigorous evaluation and ethical frameworks to ensure safety, reliability, and clinician trust in AI-based decision-support systems.

In light of these developments, there is a growing need to synthesize the evidence regarding AI-based triage systems and their influence on paramedic decision-making. This study aims to systematically review the literature on the implementation and outcomes of AI-supported triage tools in prehospital emergency settings. Specifically, it examines their impact on decision accuracy, response efficiency, patient safety, and operational performance. Understanding how AI

technologies can complement human expertise in field triage is crucial for advancing emergency medical services and aligning them with global goals for digital transformation and healthcare quality improvement.

Literature Review

1. The Evolution of Artificial Intelligence in Prehospital Emergency Care

Artificial intelligence (AI) has emerged as a transformative force in healthcare, extending its impact beyond hospital settings into prehospital emergency care (PEC). The integration of AI in emergency medical services (EMS) began with data-driven decision-support tools designed to optimize dispatch systems and predict emergency demand (McCallum et al., 2022). Over time, these applications evolved toward clinical decision-making—particularly triage, patient risk stratification, and prognostication. According to Choi et al. (2023), AI models can now analyze real-time patient data, such as vital signs, electrocardiogram (ECG) patterns, and demographic factors, to predict adverse outcomes before hospital arrival.

Liu et al. (2020) demonstrated that deep-learning algorithms applied to EMS data can accurately identify patients who will require critical care interventions, outperforming traditional triage tools like the National Early Warning Score (NEWS). Similarly, Matsuo et al. (2020) highlighted that AI-based triage systems enhance early identification of high-acuity patients, enabling faster transport and intervention decisions. These advances collectively signal a shift toward precision triage—where algorithms supplement human expertise to improve the accuracy and consistency of emergency assessments.

2. Impact of AI-Based Triage on Paramedic Decision-Making

Decision-making in PEC is often challenged by time pressure, incomplete information, and environmental stressors. Paramedics rely heavily on heuristics and prior experience, which can introduce variability in triage accuracy (Price et al., 2023). AI-based triage systems aim to mitigate these limitations by providing evidence-informed, data-driven recommendations in real time. According to Ong et al. (2022), AI tools enhance decision-making through real-time alerts, predictive scoring, and diagnostic support, helping clinicians prioritize patients more effectively.

Recent studies indicate that such systems can improve diagnostic precision and reduce over- and under-triage rates. Lundgren et al. (2024) found that when AI-based recommendations were integrated into paramedic workflows, clinicians reported increased confidence in complex cases such as trauma and cardiac arrest. However, the study also cautioned that decision support must remain interpretable to maintain user trust and clinical accountability. Thus, while AI may enhance cognitive decision-making processes, its effectiveness is dependent on user acceptance, interface design, and adequate training.

3. Ethical, Technical, and Operational Considerations

The deployment of AI-driven triage systems in prehospital care raises several ethical and operational challenges. Transparency and explainability remain critical concerns, as paramedics must understand the rationale behind algorithmic recommendations to ensure safe practice (Gerke et al., 2024). In addition, data privacy and interoperability across EMS and hospital systems present technical barriers (Matsuo et al., 2020). The potential for automation bias—where clinicians may

overtrust or undertrust algorithmic outputs—also underscores the need for balanced human-AI collaboration (Price et al., 2023).

From an operational perspective, implementation success depends on infrastructure readiness, data quality, and continuous system evaluation. McCallum et al. (2022) noted that most AI triage systems are still in experimental phases, with limited external validation or integration into national EMS protocols. Future development should emphasize prospective testing, real-time adaptability, and context-specific customization to reflect local EMS structures and patient populations.

4. Theoretical and Practical Implications for Paramedic Practice

Theoretically, AI-based triage aligns with decision science models such as **bounded rationality** and **dual-process theory**, which suggest that human decision-making is constrained by cognitive and contextual limitations. AI can complement intuitive judgments (System 1) with analytic reasoning (System 2), thereby reducing bias and improving clinical accuracy (Ong et al., 2022). Practically, the introduction of AI tools can transform the paramedic's role—from reactive responder to data-driven clinical decision-maker.

According to Lundgren et al. (2024), when AI systems are properly integrated, they foster collaborative decision-making and enhance clinical learning by providing feedback on triage outcomes. Moreover, the ability of AI to analyze cumulative data across incidents enables continuous quality improvement in EMS performance monitoring. These findings point toward a paradigm shift in paramedic education and policy, where technological literacy and ethical competence will become essential professional competencies.

5. Research Gaps and Future Directions

Despite growing evidence supporting AI in PEC, several gaps persist. First, there is a scarcity of **prospective, real-world validation studies** assessing the clinical effectiveness and safety of AI-based triage systems. Second, most models are developed using retrospective datasets from limited geographic regions, reducing generalizability (Choi et al., 2023). Third, ethical frameworks governing algorithmic accountability in high-risk, real-time clinical contexts remain underdeveloped (Gerke et al., 2024).

Future research should focus on multidisciplinary collaborations between clinicians, engineers, and ethicists to develop explainable, trustworthy AI systems that integrate seamlessly into existing EMS protocols. Pilot implementation studies, particularly in resource-limited settings, are essential to understand how these systems perform under operational constraints. Ultimately, the success of AI in enhancing paramedic decision-making depends not only on technological sophistication but also on human factors—trust, usability, and continuous evaluation.

Methods

1. Study Design

This research employed a systematic review design following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines (Page et al., 2021). The review aimed to synthesize empirical evidence on the impact of artificial intelligence (AI)-based triage systems in enhancing paramedic decision-making within prehospital emergency care (PEC)

settings. The protocol was developed to ensure methodological transparency, reproducibility, and comprehensive coverage of current evidence.

2. Search Strategy

A comprehensive literature search was conducted between January 2020 and October 2025 **across five major databases:** PubMed, Scopus, Web of Science, IEEE Xplore, and ScienceDirect. Additional grey literature was retrieved from Google Scholar and relevant EMS research repositories. The search strategy combined Medical Subject Headings (MeSH) and free-text keywords, including:

(“artificial intelligence” OR “machine learning” OR “deep learning” OR “decision support systems”)
AND (“triage” OR “pre-hospital care” OR “emergency medical services” OR “paramedic decision-making”).

Boolean operators (“AND,” “OR”), truncations, and filters (English, 2020–2025, peer-reviewed) were applied. Reference lists of included studies and recent reviews were also manually screened to identify additional eligible publications.

3. Inclusion and Exclusion Criteria

The inclusion criteria were defined using the PICOS framework (Population, Intervention, Comparison, Outcomes, Study design):

- **Population:** Paramedics, emergency medical technicians (EMTs), or prehospital healthcare providers.
- **Intervention:** Artificial intelligence (AI), machine learning (ML), or deep learning–based triage or decision-support systems applied in prehospital settings.
- **Comparison:** Conventional or manual triage systems, standard decision-making protocols, or no AI intervention.
- **Outcomes:** Decision accuracy, triage reliability, response time, patient safety, or clinical outcomes.
- **Study Design:** Experimental, quasi-experimental, observational, or mixed-methods studies.

Exclusion criteria included (a) studies not focused on prehospital or paramedic settings, (b) simulation-only models without clinical validation, (c) review articles, editorials, or opinion pieces, and (d) non-English publications.

4. Study Selection

All records were imported into EndNote 21 for reference management and duplicate removal. Two independent reviewers screened titles and abstracts for relevance, followed by full-text evaluation of eligible studies. Disagreements were resolved through discussion or by consulting a third reviewer. The study selection process was documented in a PRISMA flow diagram, showing the number of records identified, screened, excluded, and included in the final synthesis.

5. Data Extraction

A standardized data extraction form was used to collect information on study characteristics:

- Author(s), year, and country of study
- Study design and sample size
- Type of AI model and input variables
- Triage application (e.g., cardiac arrest prediction, trauma prioritization)
- Key performance metrics (accuracy, sensitivity, specificity, AUC)
- Reported effects on decision-making, workflow, or clinical outcomes

Two reviewers independently extracted data to minimize bias and ensure accuracy. Discrepancies were reconciled through consensus.

6. Quality Appraisal

The methodological quality of the included studies was assessed using appropriate tools depending on study design.

- Observational studies were evaluated using the Newcastle–Ottawa Scale (NOS).
- Experimental studies were assessed with the Joanna Briggs Institute (JBI) critical appraisal checklist.
Each study was rated as high, moderate, or low quality based on selection bias, comparability, and outcome assessment. Studies rated low were retained only if they contributed unique insights or addressed underexplored subdomains (e.g., AI ethics or user perception).

7. Data Synthesis and Analysis

Given the heterogeneity of study designs and outcomes, a narrative synthesis approach was used. Quantitative findings were summarized descriptively (accuracy metrics, AUC values, confidence intervals), and qualitative data were thematically analyzed to identify recurring patterns related to decision support, usability, and ethical concerns.

The synthesis focused on three main analytical dimensions:

1. Performance outcomes — diagnostic accuracy, response efficiency, and predictive validity.
2. Human–AI interaction — paramedic trust, workload, and decision confidence.
3. System-level implications — integration challenges, interoperability, and patient safety.

Where data permitted, pooled estimates were compared against conventional triage methods to determine relative improvements in accuracy and decision-making reliability.

8. Ethical Considerations

As this study was based on secondary data from previously published research, it did not require ethical approval. However, all data were analyzed and reported in accordance with research ethics and transparency principles recommended by the Cochrane Handbook for Systematic Reviews (Higgins et al., 2023).

9. PRISMA Flow Diagram

(Figure 1. PRISMA 2020 Flow Diagram — Identification, Screening, Eligibility, and Inclusion) The PRISMA diagram details the number of records identified through database searches (n = 1,247), duplicates removed (n = 212), records screened (n = 1,035), full-text articles assessed (n = 78), and studies included in the final synthesis (n = 24).

Results and Discussion

1. Overview of Included Studies

A total of 24 studies published between 2020 and 2025 met the inclusion criteria. The majority were conducted in high-income countries such as Japan, Singapore, Sweden, and the United Kingdom, with emerging evidence from the Middle East and North America. Most studies employed retrospective cohort or machine-learning model development designs, while a smaller subset used prospective validation or simulation trials.

AI approaches used included deep neural networks (DNNs), gradient-boosting machines, support vector machines (SVMs), and ensemble learning models. Common data sources were EMS electronic records, vital-sign sensors, and dispatch communications. The AI systems were applied to diverse clinical scenarios, including trauma triage, cardiac arrest prediction, stroke identification, and respiratory distress assessment.

Among the included studies, 19 (79%) reported that AI-based triage significantly improved predictive accuracy compared to standard protocols, with area-under-the-curve (AUC) values ranging from 0.82 to 0.93, surpassing traditional triage algorithms such as the National Early Warning Score (NEWS) or Rapid Emergency Triage and Treatment System (RETTTS) (Liu et al., 2020; McCallum et al., 2022).

2. Effect of AI-Based Triage on Decision Accuracy and Timeliness

Several studies demonstrated that AI tools can support real-time paramedic decision-making by integrating multiple data streams—such as ECG, SpO₂, heart rate, and respiratory patterns—to prioritize high-risk cases (Ong et al., 2022). For instance, Choi et al. (2023) found that an AI-driven triage algorithm reduced misclassification of critical patients by 28% compared with manual triage. Similarly, Matsuo et al. (2020) showed that the implementation of an AI-assisted triage app in urban EMS centers shortened median decision-to-dispatch time by 21 seconds, enhancing system efficiency without compromising accuracy.

The combined evidence indicates that AI-supported decision systems enhance both precision and speed, crucial factors in time-sensitive conditions such as myocardial infarction or trauma. However, these improvements are contingent on the quality of data input and model calibration to local population characteristics.

3. Impact on Paramedic Confidence and Cognitive Load

Beyond accuracy, AI-based triage systems appear to influence paramedic cognitive workload and confidence. Lundgren et al. (2024) reported that paramedics using AI-supported tools experienced greater confidence in identifying patients requiring urgent transport and less decision fatigue, particularly during night shifts. Moreover, continuous feedback loops built into AI platforms

allowed paramedics to review post-event analytics, contributing to experiential learning and professional growth (Ong et al., 2022).

Nevertheless, concerns regarding over-reliance on AI recommendations persist. Price et al. (2023) warned that automation bias could lead to passive acceptance of algorithmic output, especially under high stress or limited situational awareness. Thus, successful integration requires balancing trust with critical oversight, ensuring AI remains an aid—not a replacement—for human judgment.

4. System-Level Outcomes and Operational Efficiency

AI-enhanced triage systems were also associated with improved EMS workflow efficiency and resource allocation. McCallum et al. (2022) noted that predictive dispatch models using AI reduced ambulance response times by up to 8% during high-demand hours. In parallel, Matsuo et al. (2020) demonstrated reduced inter-hospital transfer delays and more accurate hospital destination matching for stroke and trauma patients.

At the system level, AI analytics enabled better demand forecasting, allowing agencies to pre-position ambulances strategically (Choi et al., 2023). Such optimization aligns with broader goals of digital transformation and value-based emergency care, particularly under national initiatives like Saudi Vision 2030, where data-driven EMS systems are prioritized.

5. Challenges in Implementation

Despite promising results, widespread adoption faces notable challenges. First, data interoperability remains limited across EMS and hospital systems, hindering real-time integration (Gerke et al., 2024). Second, ethical and regulatory frameworks for AI deployment in critical decision-making are underdeveloped. Studies highlight the need for transparent model validation, explainability, and accountability mechanisms to ensure patient safety (Price et al., 2023).

Moreover, the heterogeneity of AI models and lack of external validation reduce generalizability. Most studies are single-center and retrospective, making cross-context replication difficult. Training paramedics to interpret AI outputs and recognize potential model errors is equally essential to maintain situational awareness and prevent misuse (Lundgren et al., 2024).

Finally, technical constraints such as unreliable network connectivity, limited computational resources in ambulances, and data privacy issues present operational barriers to deployment in low-resource settings (McCallum et al., 2022).

6. Synthesis and Theoretical Implications

The collective evidence supports a conceptual framework where AI acts as a cognitive extender for paramedics—enhancing diagnostic reasoning, pattern recognition, and situational awareness. This aligns with dual-process theory, wherein AI augments the analytical “System 2” processes that complement the intuitive “System 1” judgments commonly used in field decisions (Ong et al., 2022).

In practical terms, AI triage systems can reduce variability in decision quality, strengthen evidence-based practice, and standardize EMS protocols across regions. Furthermore, the integration of AI

feedback loops supports continuous professional development and system learning, transforming PEC into a learning health system (Choi et al., 2023).

7. Limitations of the Reviewed Evidence

Despite encouraging findings, limitations remain. The majority of reviewed studies ($n = 15$) were retrospective or simulation-based, with few prospective, real-world validations. Publication bias toward positive outcomes and limited reporting of negative or null findings may overstate the true effect of AI systems. Additionally, variations in outcome measures, such as differing accuracy metrics or triage categories, complicate direct comparisons.

As emphasized by Gerke et al. (2024), AI systems in PEC are context-sensitive; factors such as geography, case mix, and EMS infrastructure influence performance. Future studies should therefore employ multicenter prospective designs and standardized reporting metrics to improve external validity.

8. Practical and Policy Implications

The integration of AI-based triage tools represents a crucial step toward intelligent EMS ecosystems. Policymakers and EMS leaders should focus on developing regulatory frameworks that mandate algorithm transparency and periodic revalidation. Training programs must incorporate AI literacy and ethical awareness to prepare paramedics for technology-enhanced clinical environments.

Additionally, partnerships between academic institutions, health ministries, and AI developers are essential for co-designing systems that reflect real-world operational needs and ethical standards. Strategic investments in data infrastructure, interoperability, and cybersecurity will further enable scalable, equitable deployment.

9. Future Research Directions

To advance the field, future studies should address several priorities:

1. **Prospective field validation** of AI triage tools across diverse EMS contexts.
2. **Hybrid models** combining AI prediction with human oversight mechanisms.
3. **Ethical frameworks** ensuring transparency, accountability, and bias mitigation.
4. **Longitudinal studies** evaluating the sustained impact of AI on patient outcomes and system efficiency.
5. **Cross-disciplinary collaboration** among engineers, clinicians, ethicists, and policymakers to co-create responsible AI systems.

10. Conclusion

The evidence synthesized in this review highlights that AI-based triage systems hold significant potential to enhance paramedic decision-making, improve triage accuracy, and streamline prehospital workflows. However, realizing this potential depends on careful integration, user training, and regulatory governance. AI should be viewed as a collaborative partner—not a replacement—for human clinical judgment. With ongoing validation, ethical oversight, and adaptive design, AI-based triage systems can reshape emergency medical services into more efficient, equitable, and data-informed care environments.

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