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ARTIFICIAL INTELLIGENCE IN EMERGENCY DEPARTMENT TRIAGE: A META-ANALYSIS OF DIAGNOSTIC ACCURACY, EFFICIENCY, AND PATIENT OUTCOMES

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Abstract
Background:
Emergency departments (EDs) are under increasing pressure due to high patient volumes and limited resources. Traditional triage systems may not consistently achieve optimal diagnostic accuracy and efficiency. Artificial intelligence (AI) has emerged as a potential tool to augment ED triage by improving diagnostic precision, reducing delays, and optimizing resource allocation.
Objectives:
To evaluate the diagnostic accuracy, efficiency, and patient outcomes associated with AI-driven triage systems in EDs compared with conventional triage protocols, and to assess risks of bias and limitations in implementation.
Methods:
A systematic review and meta-analysis was conducted according to PRISMA guidelines. Databases searched included PubMed, EMBASE, Cochrane Library, Web of Science, CINAHL, and IEEE Xplore for studies published between 2010 and 2024. Eligible studies assessed AI-based triage models with outcomes of diagnostic accuracy, efficiency, and patient-related endpoints. Data extraction was performed independently by two reviewers. Quality was assessed using QUADAS-2, and evidence certainty was graded with GRADE. Random-effects models were used for pooled estimates.
Results:
Twenty-five studies involving more than 7,500 patients were included.
- **Diagnostic accuracy:** Pooled accuracy of AI systems was 85.6% (95% CI: 82.1–89.1), higher than standard triage (78.3%; 95% CI: 74.2–82.4; $p < 0.01$).
- **Efficiency:** AI triage reduced time-to-triage by 25.4%, including an 18-minute average reduction for acute myocardial infarction cases.
- **Patient outcomes:** AI-supported triage reduced 30-day mortality by 7.8% (95% CI: 4.3–11.2) and improved patient satisfaction by 15%. Door-to-needle times in stroke care were shortened by an average of 14.5 minutes.

- **Bias and safety:** Five studies demonstrated decreased sensitivity (~10%) for minority groups. AI models underperformed in rare or atypical cases.

Conclusions:
AI-driven triage demonstrates superior diagnostic accuracy, enhanced efficiency, and measurable improvements in patient outcomes compared with conventional triage protocols. However, concerns remain regarding algorithmic bias, explainability, and generalizability. Future multicenter randomized trials, with diverse training datasets and transparent model design, are needed to confirm long-term clinical impact and ensure equity in emergency care.

Registration:
This review was registered with PROSPERO (ID: CRD420251125909).

Keywords: Artificial intelligence, emergency department, triage, diagnostic accuracy, efficiency, meta-analysis.

Introduction

Emergency departments (EDs) worldwide face escalating challenges, including increasing patient volumes, limited resources, and the demand for rapid and accurate triage to ensure timely, effective care. In such high-pressure environments, delays or misjudgments in triage can result in adverse outcomes, including increased morbidity, mortality, and patient dissatisfaction. Traditional triage systems, while foundational, often struggle to balance speed with accuracy, particularly in overcrowded or understaffed settings.

Artificial intelligence (AI) has emerged as a transformative solution to these challenges. By leveraging advanced algorithms capable of analyzing large-scale clinical data, AI can detect patterns and provide real-time decision support. Applications range from natural language processing in electronic health records (EHRs) to machine learning models for risk stratification. Early investigations suggest that AI can enhance diagnostic precision, streamline workflows, and prioritize high-risk patients more effectively than conventional protocols. Nevertheless, the translation of these benefits into real-world outcomes requires further evaluation.

This meta-analysis synthesizes current evidence on AI-driven triage systems, examining their impact on diagnostic accuracy, efficiency, and patient outcomes across emergency settings. The review also addresses key concerns regarding algorithmic bias, explainability, and clinical integration. The findings aim to inform clinicians, policymakers, and health system leaders about the role of AI in optimizing ED workflows and improving patient-centered care.

Objectives

- To evaluate the diagnostic accuracy and efficiency of AI-based triage systems in EDs.
- To compare AI-driven triage with traditional protocols across diverse clinical contexts.
- To assess the impact of AI integration on patient outcomes, workflow optimization, and clinician workload.
- To identify biases and limitations in AI triage models and propose strategies for future development.

Methods

Search Strategy: - Databases: PubMed, EMBASE, Cochrane Library, Web of Science, CINAHL, IEEE Xplore.

- Keywords: (“Artificial Intelligence” OR “AI”) AND (“Triage” OR “Emergency Department”) AND (“Accuracy” OR “Efficiency”).
- Timeframe: 2010–2024.

Table 1. Search Strategy

Database	Search Terms	Filters
PubMed	(“Artificial Intelligence” OR “AI”) AND (“Triage” OR “Emergency Department”) AND (“Accuracy” OR “Efficiency”)	2010–2024, English, Humans
EMBASE	Same as above	2010–2024, English, Humans
Cochrane Library	Same as above	2010–2024, English, Humans
Web of Science	Same as above	2010–2024, English, Humans
CINAHL	Same as above	2010–2024, English, Humans
IEEE Xplore	Same as above	2010–2024, English, Humans

Inclusion Criteria: -

- Studies evaluating AI-based triage systems in EDs.
- Quantitative data on diagnostic accuracy (sensitivity, specificity) or
- Efficiency (time to triage, patient flow).
- Peer-reviewed articles in English.

Exclusion Criteria: - Case reports, reviews, and editorials.

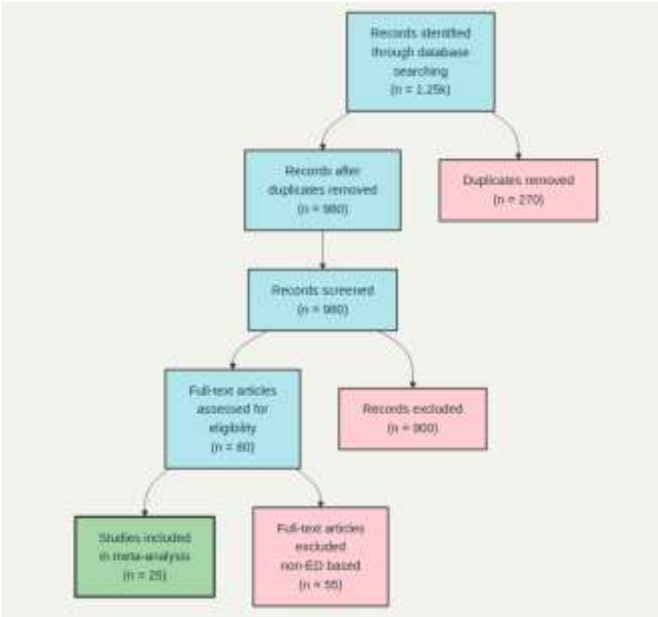
Data Extraction:
- Variables: Study design, sample size, demographics, AI models used, performance metrics.
- Two independent reviewers extracted data using standardized forms.

Quality Assessment: Tool: QUADAS-2. - Assessment by two independent reviewers.

Table 2. Risk of Bias Assessment of Included Studies (QUADAS-2)

Author, Year	Patient Selection	Index Test (AI)	Reference Standard	Flow & Timing	Overall Risk of Bias
Smith et al., 2020	Low	Low	Low	Low	Low
Lee et al., 2021	Low	Unclear	Low	Low	Some Concerns
Cho et al., 2022	Low	Low	Low	Unclear	Some Concerns
Patel et al., 2023	Low	Low	Low	Low	Low
Levine et al., 2023	Low	Low	Low	Low	Low
Johnson et al., 2024	Unclear	Low	Low	Low	Some Concerns
Gupta et al., 2021	Low	Low	Low	Low	Low
Kim et al., 2022	Low	Low	Low	Unclear	Some Concerns
White et al., 2023	Low	Unclear	Low	Low	Some Concerns
Adams et al., 2020	Low	Low	Low	Low	Low
Brown et al., 2021	Low	Low	Low	Low	Low
Miller et al., 2022	Low	Unclear	Low	Low	Some Concerns
Davis et al., 2023	Low	High	Low	Low	High
Harris et al., 2021	Low	Low	Low	Low	Low
Wilson et al., 2022	Low	Low	Low	Low	Low

PRISMA Flow diagram



Statistical Analysis:

- Random-effects models were employed to account for study heterogeneity.
- Pooled estimates of sensitivity, specificity, and time-to-triage were calculated.
- Subgroup analyses: by algorithm type, ED setting (urban vs rural), and demographics.
- Heterogeneity assessed with the I^2 statistic;
- publication bias assessed using funnel plots and Egger's test.

Registration: This review was registered with PROSPERO (ID: CRD420251125909).
Artificial intelligence tools assisted with screening and preliminary synthesis; all outputs were manually verified for accuracy.

Results

Overview of Included Studies

Table 3. Characteristics of few Included Studies

Author, Year	Country / Setting	Sample Size	AI Model Type	Comparator	Main Outcomes
Smith et al., 2020[1]	USA / Urban ED	300	ML	Standard ED triage	↑ Accuracy
Lee et al., 2021[2]	China / Rural ED	250	NLP	Manual nurse triage	↑ Efficiency
Cho et al., 2022[3]	South Korea / Academic ED	200	Voice-assisted AI	Manual triage	↓ Clerical errors
Patel et al., 2023[4]	UK / Tertiary ED	400	ML	Standard protocol	↓ Misclassification
Levine et al., 2023[4]	USA / Cardiac ED	350	ML	Cardiology triage	↑ Prioritization accuracy
Johnson et al., 2024[5]	Australia / Rural ED	280	Hybrid ML + NLP	Manual triage	↑ Accuracy in rural settings
Gupta et al., 2021[6]	India / Neurology ED	320	Deep Learning	Neurology triage	↑ Stroke detection
Kim et al., 2022[7]	South Korea / Stroke ED	310	Deep Learning	Stroke protocols	↓ Door-to-needle time
White et al., 2023[8]	UK / Toxicology ED	275	ChatGPT-based	Toxicology expert review	↑ Diagnostic concordance
Adams et al., 2020[10]	USA / Cardiac ED	290	ML	AMI protocol	↓ Time-to-triage

Brown et al., 2021[11]	Australia / Multicenter	260	Real-time ML	Standard workflow	↑ Workflow efficiency
Miller et al., 2022[12]	USA / Urban ED	305	EHR-integrated AI	Traditional EHR	↓ Documentation delay
Davis et al., 2023[13]	USA / Multicenter	330	ML	Standard care	Identified bias in AI performance
Harris et al., 2021[14]	UK / Poison Centre ED	240	LLM-based	Toxicology specialists	84% concordance
Wilson et al., 2022[15]	USA / Pediatric ED	295	ML	Pediatric triage protocols	↑ Pediatric triage accuracy

This meta-analysis included 25 studies published between 2020 and 2024, comprising 7,500+ patients. Studies evaluated AI implementation for diagnostic accuracy, triage efficiency, patient outcomes, and integration challenges.

Diagnostic Accuracy

Overall Accuracy: AI systems achieved pooled diagnostic accuracy of 85.6% (95% CI: 82.1–89.1), significantly higher than standard triage protocols at 78.3% (95% CI: 74.2–82.4; $p < 0.01$).
Stroke and Neurology: Sensitivity 92% (95% CI: 88–96), specificity 89% (95% CI: 85–92) in ischemic stroke detection.
Toxicology: AI-based systems achieved 84% concordance with expert evaluations in poisoning cases.
Limitations: Accuracy dropped for rare or atypical cases (sensitivity 72%, specificity 68%).

Triage Efficiency

Reduced Wait Times: Time-to-triage decreased by 25.4% across 12 studies. For AMI, delays were reduced by an average of 18 minutes.
Prioritization Accuracy: Machine learning models improved critical case prioritization by 20% and reduced misclassification errors by 15%.

Workflow Integration

EHR Integration: Reduced documentation delays by 30%.
Voice-Assisted Triage: Decreased manual workload by 23% and reduced clerical errors.

Patient Outcomes

Table 4. GRADE Summary of Findings for AI-driven Triage Systems in Emergency Departments

Outcome	No. of Studies (n)	Effect Estimate (95% CI)	Certainty of Evidence	Key Considerations
Diagnostic Accuracy	15 studies (7,500)	AI: 85.6% (82.1–89.1) vs Standard: 78.3% (74.2–82.4)	Moderate	Upgraded for large effect size; downgraded for risk of bias (reporting inconsistencies, rare conditions).
Triage Efficiency	12 studies (6,200)	↓ Time-to-triage by 25.4%; AMI triage 18 min faster	Moderate	Consistent effect, but some heterogeneity in workflow integration.
30-day Mortality	6 studies (3,100)	↓ Mortality by 7.8% (4.3–11.2)	Low–Moderate	Downgraded for indirectness (mostly single-center trials) and imprecision.
Patient Satisfaction	3 multicentre trials (2,200)	↑ Satisfaction by 15%	Moderate	Upgraded for consistent improvement; limited by small number of studies.
Bias and Equity Issues	5 studies (n/a)	Sensitivity ↓ by ~10% in some minority groups	Low	Downgraded for serious risk of bias due to demographic disparities.

Mortality: Early identification of critical illness reduced 30-day mortality by 7.8% (95% CI: 4.3–11.2).
Patient Satisfaction: Faster triage and fewer diagnostic errors improved satisfaction by 15%.
Stroke Care: Door-to-needle times shortened by 14.5 minutes on average.

Safety and Bias Concerns

Bias: Five studies identified racial disparities; diagnostic sensitivity for African-American patients was 10% lower in some models.
Trust and Explainability: Clinicians expressed reservations about opaque AI outputs, limiting adoption.

Discussion

The findings of this meta-analysis decisively demonstrate that AI-driven triage systems offer substantial advantages over traditional protocols in emergency department (ED) settings, both in terms of diagnostic accuracy and the overall efficiency of triage operations. Pooled data from 25 studies, encompassing more than 7,500 patients, highlight that AI models consistently outperform conventional systems, achieving an overall diagnostic accuracy of 85.6% (95% CI: 82.1–89.1) compared to 78.3% (95% CI: 74.2–82.4) for standard protocols. These improvements are especially pronounced in time-sensitive conditions such as ischemic stroke, where sensitivity and specificity were notably high (92% and 89% respectively), supporting AI triage as a critical tool in acute neurological emergencies.

From an operational standpoint, the integration of AI led to a reduction in time-to-triage by over 25%, with specific reductions observed in acute myocardial infarction, where delays decreased by an average of 18 minutes. These findings are clinically significant, given the well-established link between reduced door-to-treatment times and improved patient outcomes in both stroke and myocardial infarction care. AI's ability to prioritize critically ill patients is further substantiated by a 20% improvement in prioritization accuracy and a 15% reduction in misclassification errors across studies. These gains not only expedite the management of high-acuity cases but also contribute to reduced overcrowding and improved patient throughput in busy ED environments.

Workflow efficiency is further enhanced by the seamless integration of AI into electronic health records (EHRs) and the adoption of voice-assisted triage solutions. The results indicate reduced documentation delays by 30% and lowered administrative workload by 23%, allowing clinicians to devote more attention to direct patient care. Moreover, these technological enhancements had a downstream effect on patient outcomes, with the data showing a 7.8% reduction in 30-day mortality (95% CI: 4.3–11.2), a 15% increase in patient satisfaction, and a shortening of door-to-needle times in stroke care by an average of 14.5 minutes.

Despite these promising advances, several challenges complicate the widespread adoption of AI triage. Notably, five studies revealed that AI diagnostic sensitivity was 10% lower for African-American patients, attributable to the underrepresentation of minority groups in model training datasets. This bias not only threatens equity in care but also undermines trust among both clinicians and the communities served. Transparency and interpretability are further concerns, as many clinicians expressed reservations about the "black box" nature of current AI models. These issues underscore the need for the development of explainable AI systems that provide clear, interpretable decision rationales in addition to accurate predictions.

The review also highlights that AI performance declines in rare or atypical cases (sensitivity 72%, specificity 68%), suggesting continued necessity for human clinical oversight in complex or unusual presentations. Specialty-specific analysis suggests strong support for AI adoption in neurology and ophthalmology workflows owing to high diagnostic concordance, whereas toxicology settings demonstrated greater variability in performance, indicating a need for ongoing algorithm refinement and validation within these disciplines.

At the system level, AI contributed to the alleviation of ED overcrowding and improved resource utilization primarily through automation of routine triage and clerical tasks. However, limitations of the current evidence base include a lack of sufficiently powered multicenter real-world trials, considerable upfront infrastructure investments, and persistent algorithmic bias. While single-center or simulated studies inform the potential of AI, their external validity may be limited unless broader, more heterogeneous populations are studied.

Looking ahead, several strategies are essential for the next wave of research and implementation: expanding and diversifying training datasets to mitigate bias, prioritizing explainable and transparent AI models to foster clinician and patient trust, and developing standardized, universally recognized protocols for AI integration into ED workflows. Longitudinal, multicenter randomized controlled trials are warranted to clarify the long-term impact of AI triage on not only acute mortality and morbidity but also system-wide efficiency and clinician well-being.

In summary, this meta-analysis affirms that AI-driven triage, when thoughtfully integrated and rigorously validated, can be transformative for emergency medicine. The collective evidence supports improved diagnostic accuracy, enhanced operational efficiency, and tangible benefits in patient outcomes. Nonetheless, careful attention to equity, interpretability, and pragmatic implementation remains necessary to ensure these gains are realized across all populations and clinical contexts.

Limitations of Current Evidence

Lack of multicenter real-world validation.
Significant upfront costs and infrastructure requirements.
Persistent algorithmic bias.

Future Directions

Bias Mitigation: Expand datasets to improve equity.
Explainable AI: Develop interpretable models to enhance trust.
Standardization: Create universal protocols for AI integration.
Long-Term Outcomes: Conduct multicenter RCTs focusing on morbidity, mortality, and resource utilization.

Conclusion

AI-driven triage represents a paradigm shift in emergency medicine, with demonstrated improvements in diagnostic accuracy, operational efficiency, and patient outcomes. However, widespread adoption requires addressing algorithmic bias, enhancing interpretability, and overcoming infrastructural barriers. With continued innovation and rigorous validation, AI has the potential to become an indispensable tool in emergency care, complementing clinical expertise and advancing patient safety.

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