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Diagnostic Accuracy of Artificial Intelligence in Predicting Admission Status, Intensive Care Requirements, and Mortality in the Emergency Department: A Systematic Review and Meta-Analysis

Seyed Mohammad Hosseini Kasnavieh[1], Seyed Hossien Shaker[2], Maryam Milanifard[3], Roxana Hessam[4]*, Ali Saghandian Tousi[5], Marjan Ghadesi[6]

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Abstract

Background: Predicting patient outcomes in the emergency department is crucial for effective resource management and enhancing the quality of care. Recent advancements in artificial intelligence have facilitated accurate predictions of patient outcomes; however, consistent evidence regarding the diagnostic accuracy of these models in the emergency department remains limited. Therefore, the aim of the present study was to evaluate the diagnostic accuracy of artificial intelligence in predicting admission status, intensive care requirements, and in-hospital mortality in the emergency department.

Methods: In the present study, the PubMed, Embase, Cochrane Library, and Web of Science databases were searched from January 2020 to November 2025 using targeted keywords. A total of 34 relevant studies were included in the analysis. Meta-analysis was conducted using Stata v.17 software.

Results: The overall diagnostic sensitivity and specificity of the models for predicting admission were 0.77 (95% CI, 0.60-0.93) and 0.78 (95% CI, 0.62-0.95), respectively. For critical care, sensitivity was 0.85 (95% CI, 0.57-1.00) and specificity was 0.86 (95% CI, 0.57-1.00). For mortality, sensitivity was 0.83 (95% CI, 0.60-1.00) and specificity was 0.90 (95% CI, 0.67-1.00).

Conclusion: Artificial intelligence models, encompassing both machine learning and deep learning, serve as effective tools for predicting the conditions of emergency patients. The findings indicate that AI holds significant potential to enhance clinical decision-making within the emergency department.

Keywords: Artificial Intelligence, Machine Learning, Deep Learning, Emergency Department, Diagnostic Accuracy

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Introduction

Millions of visits to hospital emergency departments are recorded annually worldwide. With the increasing aging population, the rising prevalence of chronic diseases, and a significant growth in accidents and incidents, the emergency department is regarded as the most vital and busiest point of contact for patients within the healthcare system (1-3). Studies have shown that the number of emergency department visits has exceeded 300 million, and the proportion of patients with complex clinical conditions has also increased (4, 5). Consequently, rapid and accurate decisions regarding patient admission, the need for intensive care, and the probability of death play a crucial role in the quality of care, resource allocation, and prevention of adverse outcomes (6, 7). The use of the Emergency Severity Index (ESI), Canadian Triage and Acuity Scale (CTAS), and Manchester Triage System (MTS) tradition-

Corresponding author: Dr Roxana Hessam, hessam.r@iums.ac.ir

1. Department of Emergency Medicine, School of Medicine, Hazrat-e Rasool General Hospital, Iran University of Medical Sciences, Tehran, Iran
2. Department of Emergency Medicine, School of Medicine, Hazrat-e Rasool General Hospital, Iran University of Medical Sciences, Tehran, Iran
3. Trauma and Injury Research Center, Student Research Committee, Iran University of Medical Sciences, Tehran, Iran
4. Department of Emergency Medicine, School of Medicine, Iran University of Medical Sciences, Tehran, Iran
5. Department of Emergency Medicine, School of Medicine, Iran University of Medical Sciences, Tehran, Iran
6. Department of Emergency Medicine, School of Medicine, Iran University of Medical Sciences, Tehran, Iran

↑What is "already known" in this topic:
Predicting patient outcomes in the emergency department is essential for optimizing resources and enhancing the quality of care. Artificial intelligence models, including machine learning and deep learning, offer innovative tools for outcome prediction; however, consistent evidence regarding their diagnostic accuracy remains limited.

→What this article adds:
Artificial intelligence models, including machine learning and deep learning, exhibit high accuracy in predicting admissions, critical care needs, and mortality among patients in emergency departments. These findings underscore the potential of AI to enhance clinical decision-making and improve resource management in emergency care.

ally encounters several challenges, including disagreements among assessors, limited sensitivity in complex cases, and decreased efficiency in crowded conditions (8).

Timely admission, assessment of the need for intensive care unit (ICU) placement, and evaluation of mortality risk are critical components of emergency medicine that can influence clinical decision-making, bed management, human resource planning, and the prompt implementation of interventions. Conventional triage methods may result in errors or delays in patient diagnosis (9). Evidence indicates that approximately 15-20% of emergency admissions are preventable, and 10% of patients experience delays in ICU transfer, which can significantly elevate the risk of death by more than 30% (10, 11). This highlights the necessity for more accurate and reliable tools.

The emergence of artificial intelligence, particularly through machine learning (ML) and deep learning (DL) methods, has catalyzed a significant transformation in emergency medicine by enhancing prediction accuracy (12). Artificial intelligence-based models can analyze vast volumes of clinical data—including vital signs, tests, medical images, and electronic health record patterns—with improved precision (13). Research findings indicate that artificial intelligence outperforms traditional triage tools (14). However, the extent of this performance has been reported inconsistently across studies, influenced by factors such as data type, algorithm, validation method, and variations in patient populations. These heterogeneities have raised concerns regarding the generalizability and reliability of these models in actual emergency settings.

The rapid growth of AI-based research in emergency medicine has resulted in a highly diverse array of studies concerning design, input variables, performance indicators, and quality of reporting. This diversity complicates the generalization of results and poses challenges to the transfer of evidence into real clinical settings. Consequently, clinicians and policymakers continue to grapple with the question of which AI models possess high diagnostic accuracy and the stability of their performance across different hospital environments. Therefore, it is imperative to conduct a systematic review and comprehensive meta-analysis to accurately assess the performance of AI in predicting three critical outcomes: admission, ICU need, and death. Previous studies have predominantly concentrated on a specific outcome, a particular type of algorithm, or limited populations, thereby leaving a significant gap in the existing evidence. The present study aims to provide a clear and reliable picture of the diagnostic accuracy of AI models by integrating evidence from various settings and populations; this topic can serve as a crucial guide for clinical application, future model design, and evidence-based decision-making. The results of this study could facilitate the development of intelligent decision-making tools, enhance patient safety, and improve the operational efficiency of emergency departments worldwide. Thus, the aim of the present study is to evaluate the diagnostic accuracy of artificial intelligence in predicting admission status, intensive care needs, and mortality in the emergency department.

Methods

Study Design, Information Sources, and Search Strategy

The study design, implementation, and reporting process adhered to the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. A systematic search was performed across international electronic databases, including PubMed/MEDLINE, Embase, Web of Science, Scopus, and the Cochrane Library. The search period spanned from January 2020 to November 2025, with the last five years selected to capture evidence from more recent articles. To mitigate publication bias, searches for grey literature were also conducted, including those on Google Scholar. Additionally, the reference lists of included articles and related reviews were manually examined to ensure that no potential studies were overlooked.

The search strategy was designed using MeSH terms: ((((((((((((((("Artificial Intelligence"[Mesh]) OR "Artificial Intelligence/statistics and numerical data"[Mesh]) OR ("Machine Learning"[Mesh] OR "Machine Learning Algorithms"[Mesh])) OR ("Deep Learning"[Mesh] OR "Detection Algorithms"[Mesh])) AND ("Emergency Service, Hospital"[Mesh] OR "Emergency Room Visits"[Mesh])) OR ("Emergency Service, Hospital/standards"[Mesh] OR "Emergency Service, Hospital/statistics and numerical data"[Mesh])) AND "Patient Admission"[Mesh]) AND "Hospitalization"[Mesh]) AND "Critical Care"[Mesh]) AND "Intensive Care Units"[Mesh]) AND ("Mortality"[Mesh] OR "mortality" [Subheading] OR "Hospital Mortality"[Mesh])) OR "Death"[Mesh]) AND "Diagnosis"[Mesh]) OR "Data Accuracy"[Mesh]) OR ("Prediction Algorithms"[Mesh] OR "Prediction Methods, Machine"[Mesh])) OR "Nomograms"[Mesh].

Study inclusion and exclusion criteria

Studies were designed and selected based on the PICOS framework:

Population (P): Patients presenting to the hospital emergency department

Intervention (I): Any type of artificial intelligence model, including machine learning or deep learning methods.

Comparator (C): Reference Standard

Outcome (O): Sensitivity, specificity, area under the curve (AUC) / area under the receiver operating characteristic curve (AUROC), positive and negative likelihood ratios (LR+, LR–), and diagnostic odds ratio.

Studies (S): Observational studies, model development and/or validation studies, and studies utilizing an AI model to predict outcomes in the ED, where diagnostic accuracy was reported; studies published in English.

All review studies, letters to the editor, case reports, editorials, protocols, and conference abstracts that lacked complete data, studies unrelated to the emergency setting, and studies containing duplicate or overlapping data were excluded from the study.

Screening, study selection process, and data extraction.

All identified articles from the databases were consolidated, and duplicates were removed using EndNote X8 reference management software. Two researchers independently and blindly screened the titles and abstracts

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according to the established inclusion and exclusion criteria. Articles deemed eligible at this stage were obtained in full text and re-reviewed independently by two blinded researchers. Disagreements were resolved through discussion and, if necessary, with the input of a third researcher.

A standardized, pre-designed form was utilized to extract data. Two researchers independently extracted the following information from each included study: the first author's name, year of publication, country, design type, sample size, age and gender, patient type, and details of the artificial intelligence model. In instances of incomplete or ambiguous data, the authors of the articles were contacted, and any discrepancies in data extraction were resolved through discussion and consensus or by consulting a third researcher.

Quality assessment and risk of bias

The risk of bias in the included studies was assessed using the QUADAS-2 (Quality Assessment of Diagnostic Accuracy Studies) tool by two independent and blinded assessors. This tool evaluates four primary domains: participant selection, index test, reference standard, and flow and time. For each domain, the risk of bias is categorized as low, unclear, or high. In the present study, the results of the quality assessment are presented in tabular form and were considered in the interpretation of the meta-analysis results.

Statistical analysis and data synthesis

Meta-analysis of diagnostic accuracy in the present study was conducted for each outcome (Admission, Critical care, Mortality). Sensitivity and specificity were pooled using a bivariate random-effects model, which accounts for the correlation between sensitivity and specificity as well as the variability across studies, thereby providing reliable summary estimates. Confidence intervals for sensitivity and specificity were derived from this bivariate model. Heterogeneity between studies was assessed by examining the I^2 statistic, confidence intervals, and visual assessments of forest plots. Subgroup analyses were performed. All statistical analyses were conducted using STATA/MP.V17 software, with a significant level of less than 0.05 considered.

Results

Literature Search, and Characteristics included studies

The search strategy was conducted in accordance with the selected keywords and the PRISMA 2020 protocol. Initially, 2,856 articles were identified; after the removal of duplicates and screening of titles, the abstracts of 2,235 articles were reviewed. Subsequently, 2,085 articles that did not meet the inclusion criteria and were consistent with the exclusion criteria were eliminated at this stage. The full texts of 150 articles were then reviewed.

Articles characterized by scattered data, poor methodological quality, unclear sample sizes, absence of study grouping, lack of accurate result presentation, restricted access to full texts, contradictory findings, and biased data were excluded from the research. Ultimately, 34 articles that fulfilled the inclusion criteria for the present study were selected (Figure 1).

The total number of patients included in the preset studies was 12,895,728. In terms of algorithm type, the majority of studies utilized machine learning (ML) models, including Random Forest, XGBoost, LightGBM, and CatBoost. The sample size reflects the extensive application of AI across various clinical settings, thereby enhancing the generalizability of the results (Table 1).

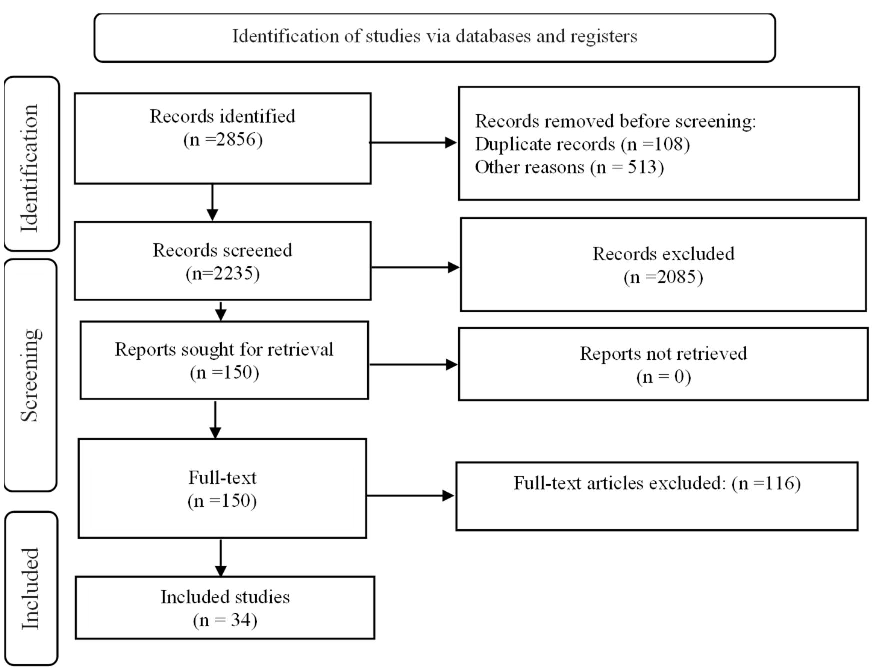

Figure 1. PRISMA 2020 Flow Diagram

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Table 1. Characteristics of the included RCT and observational cohort studies

No.	Study. Years	AI technique	Algorithm	Number of patients	Disposition	Positive cases (n)			Overall Risk
						Admission	Critical care	Mortality	
1	Menshawi et al., 2025 (15)	ML	RF	4399	Admission	4148	-	-	Low
2	Pandey et al., 2025 (16)	ML	RF	484094	Admission	323678	-	-	Low
3	Akhlaghi et al., 2024 (17)	DL	DNN	77125	Admission	12009	-	-	Moderate
4	Chang et al., 2024 (18)	ML	LightGBM	8274	Admission, Mortality	364	-	207	Low
5	Lee et al., 2023 (19)	ML	Stacking	6536260	Mortality	-	-	6351	Low
6	Elhaj et al., 2023 (18)	ML	RF	2688	Admission, Critical care, Mortality	862	1040	146	Low
7	Son et al., 2023 (20)	ML	CatBoost	1157	Mortality	-	-	19	Low
8	Mekkodathil et al., 2023 (21)	ML	SVM	922	Mortality	-	-	204	Moderate
9	Greco et al., 2023 (22)	ML	RF	425	Mortality	-	-	65	Moderate
10	Lee et al., 2023 (23)	ML	Stacking	172809	Critical care	-	6615	-	Low
11	Logaras et al., 2022 (24)	ML	RF	157	Admission	70	-	-	Low
12	Feretzakis et al., 2022 (25)	ML	RF	13991	Admission	6303	-	-	Low
13	Xie et al., 2022 (26)	DL	RNN	441437	Admission, Critical care	208976	26174	-	Low
14	Patel et al., 2022 (27)	ML	XGBoost	841825	Admission	201520	-	-	Low
15	Cusidó et al., 22 (28)	ML	GBM	3189204	Admission	351450	-	-	Low
16	Kim et al., 2022 (29)	ML	XGBoost	8325	Admission	1469	-	-	Low
17	Matsuo et al., 2022 (30)	ML	XGBoost	120	Mortality	-	-	9	Low
18	Calvillo-Batllés et al., 2022 (31)	ML	GBM	371	Mortality	-	-	69	Moderate
19	Di Napoli et al., 2022 (32)	DL	CNN	1031	Critical care, Mortality	-	125	296	Low
20	Duanmu et al., 2022 (33)	DL	DNN	186	Mortality	-	-	76	Low
21	Cheng et al., 2022 (34)	DL	CNN	214080	Mortality	-	-	19434	Low
22	Lee et al., 2022 (35)	DL	DNN	155623	Mortality	-	-	2752	Low
23	Fransvea et al., 2022 (36)	DL	DNN	2570	Mortality	-	-	238	Low
24	Dadabhoy et al., 2021 (37)	ML	RF	245548	Admission	14571	-	-	Moderate
25	Tahayori et al., 2021 (38)	DL	DNN	249532	Admission	28517	-	-	Low
26	Tan et al., 2021 (39)	ML	RF	5508	Admission, Mortality	606	-	121	Low

Bias Assessment

The QUADAS-2 evaluation indicated a generally low to moderate risk of bias among the included studies. Most studies demonstrated robust patient selection and reference standards, with only minor concerns related to index test blinding and timing reporting (Table 1).

Sensitivity

According to the subgroup meta-analysis, AI algorithms showed good sensitivity across all subgroups. The highest sensitivity was observed in intensive care, at 0.85 (95% CI, 0.57, 1.00), followed by mortality at 0.83 (95% CI, 0.60, 1.00), and admission at 0.77 (95% CI, 0.60, 0.93) (Figure 2). Very low heterogeneity ($I^2 = 0\%$) was noted across all subgroups, indicating that the sensitivity esti-

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Table 1. Continued

No.	Study. Years	AI technique	Algorithm	Number of patients	Disposition	Positive cases (n)			Overall Risk
						Admission	Critical care	Mortality	
27	Yun et al., 2021 (40)	ML	XGBoost	16087	Critical care	-	722	-	Low
28	Chen et al., 2021 (41)	ML	RF, LightGBM	52626	Admission, Critical care, Mortality	-	13157	4947	Moderate
29	Heldt et al., 2021 (42)	ML	XGBoost	879	Admission, Mortality	152	-	193	Moderate
30	Mowbray et al., 2021 (43)	ML	GBM	2274	Admission	632	-	-	Moderate
31	Roquette et al., 2020 (44)	ML	CatBoost	32282	Admission	24704	-	-	Low
32	Zhang et al., 2020 (45)	ML	RF	85254	Critical care	-	214	-	Low
33	Lee et al., 2020 (46)	ML	RF	2846	Critical care	-	129	-	Low
34	Hong et al., 2020 (47)	ML	RF	45819	Critical care	-	202	-	Low

mates were largely consistent between studies. We note, however, that an I^2 of 0% does not imply complete absence of clinical or methodological differences; rather, it reflects minimal variation in the effect estimates included in this analysis.

The test for differences between subgroups ($Q\_b = 0.34$, $P = 0.843$) indicates that there was no significant difference among the subgroups, and that the performance of AI in predicting admission, intensive care, and mortality is comparable (Figure 2).

Specificity

Based on the subgroup meta-analysis, AI demonstrated strong performance in detecting true negatives (specificity). The highest feature was associated with mortality, yielding a value of 0.90 (95% CI, 0.67, 1.00), followed by intensive care at 0.86 (95% CI, 0.57, 1.00), and admission at 0.78 (95% CI, 0.62, 0.95) (Figure 3). Very low heterogeneity ($I^2 = 0\%$) was observed across all subgroups, indicating consistent results among the studies.

The test of difference between subgroups ($Q\_b = 0.72$, $P = 0.70$) shows that there was no significant difference between subgroups (Figure 3).

A total of 29 studies employed machine learning, while 13 studies utilized deep learning. The difference test between the groups indicated that there was no significant difference between machine learning and deep learning ($P = 0.87$).

Discussion

The present meta-analysis demonstrated that AI models exhibited strong performance in predicting hospitalization, the need for intensive care, and mortality in emergency departments. The overall sensitivity of the models was 0.80, while the overall specificity was 0.83, indicating their capacity to accurately identify both positive and negative patients. The subgroup analyses based on AI type (ML and DL) and disposition type (Admission, Mortality, Critical Care) were homogeneous, with no significant heterogeneity observed. This finding underscores the reliability and stability of the models' performance across various clinical and hospital settings.

In comparison to previous meta-analyses, the present study reported similar findings. The meta-analysis conducted by Naemi et al. in 2021 exclusively examined the performance of machine learning (ML) in predicting mortality (48). The current results align with the findings of Kuo et al. in 2025, who reported the sensitivity and diagnostic specificity of artificial intelligence (AI) for predicting admission at 0.81 and 0.87, for critical care at 0.86 and 0.89, and for mortality at 0.85 and 0.94. This agreement underscores the consistency and reliability of the results derived from the pooling of multiple studies, thereby confirming the validity of AI predictions in emergency clinical settings (49). The primary distinction between the present study and the meta-analysis by Kuo et al. in 2025 lies in the inclusion criteria. Nevertheless, the performance trends of the algorithms and their predictive power were comparable in both meta-analyses, suggesting the generalizability of the results across different clinical populations. The present findings indicated low heterogeneity between groups, with the I^2 index reported to be close to zero, signifying high consistency of study results and acceptable data quality. This indicates that AI algorithms possess high reliability and reproducibility in predicting the status of emergency patients, even in varied environments with differing sample sizes.

One notable finding was the high discriminative properties of the models in predicting mortality and the need for critical care (0.903 and 0.855), indicating that the models rarely misidentify healthy patients as requiring intensive care. This characteristic could help reduce the workload in emergency departments, prevent the misallocation of resources, and optimize the performance of intensive care units. In examining the types of algorithms, no significant difference was observed between ML and DL models, suggesting that both categories of algorithms possess adequate predictive ability in clinical settings. Sreedharan et al. (2024) demonstrated that artificial intelligence algo-

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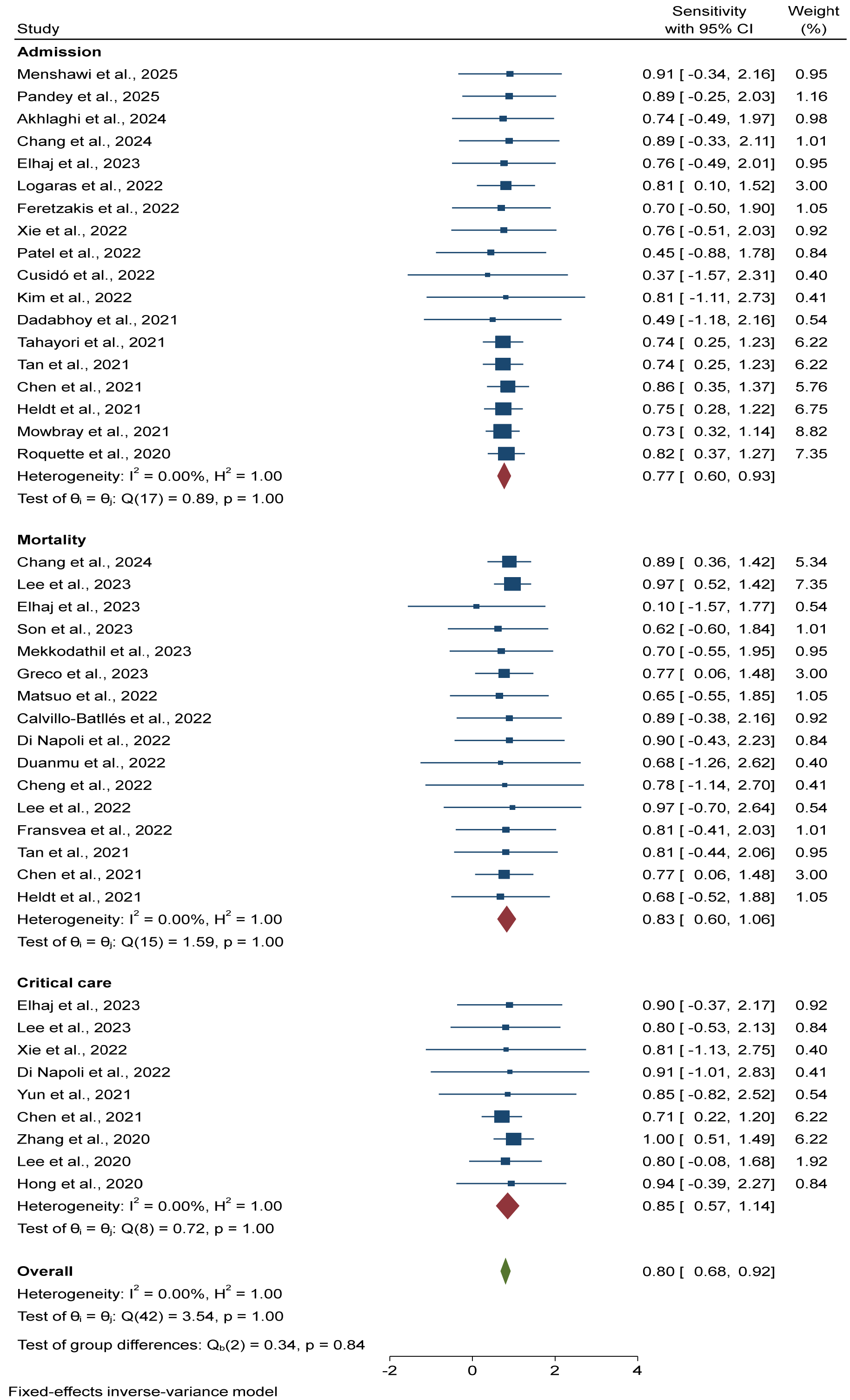

rithms exhibit good clinical performance in diagnosing diseases such as esophageal cancer, cardiac arrest, esophageal adenocarcinoma, sepsis, and gastrointestinal stromal tumors. The sensitivity, diagnostic specificity, positive and negative predictive values, and accuracy of the algorithms were reported, and all studies exhibited high heterogeneity with a *P*-value < 0.05, indicating significant variability in results and data (50). Furthermore, the previous study primarily focused on the diagnosis of specific diseases, whereas the current study examined the perfor-

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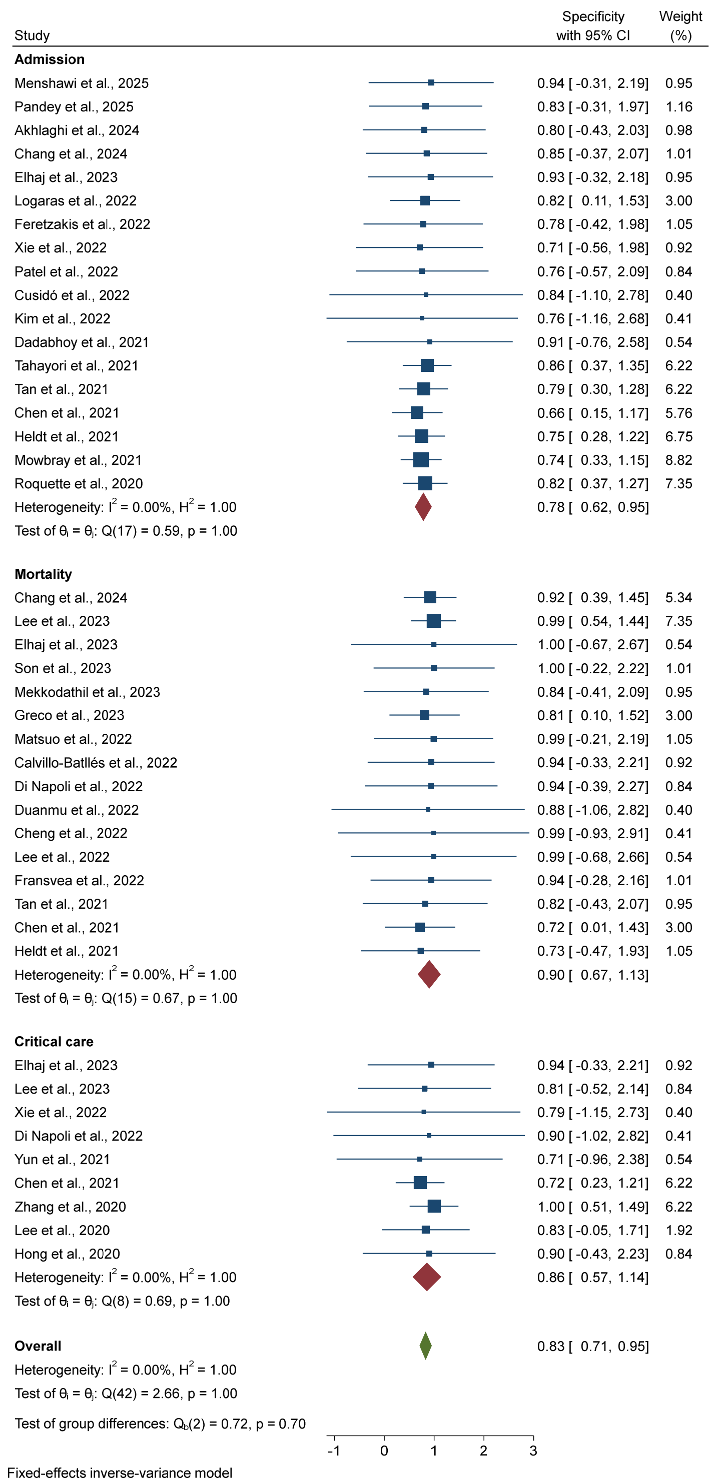

Figure 3. Forest plot illustrating the specificity of artificial intelligence in predicting outcomes in the emergency department.

mance of AI in predicting emergency clinical outcomes, including hospitalization, the need for intensive care, and death. This distinction reflects the expansion of AI applications from disease diagnosis to clinical management and rapid decision-making in the emergency department.

The limitations of the present study include very large sample sizes in some articles and small sample sizes in others. However, the lack of significant heterogeneity suggests that this variation did not have a substantial impact on the overall results, indicating that the findings are generalizable. Conversely, differences in the type of input data and clinical parameters utilized in the models may lead to slight variations in their performance. Future studies should prioritize data standardization, external validation, and the integration of models with clinical information systems. Additionally, evaluating models in real hospital settings and examining their impact on clinical decisions and patient outcomes could enhance the value of the research.

Conclusion

The findings of the present study indicate that artificial intelligence, whether utilizing machine learning (ML) or deep learning (DL) algorithms, serves as a potent tool for enhancing clinical decision-making in the emergency department. It has the potential to reduce mortality, improve patient management, and optimize emergency department resources. The results of this meta-analysis can facilitate the development of AI-based clinical decision support systems and contribute significantly to the digital transformation of emergency care.

Acknowledgment

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Conflict of Interests

The authors declare that they have no competing interests.

Authors' Contributions

S.M.H.K., S.H.S., M.M., R.H., A.S.T., M.G. contributed to the conception and design of the study. S.M.H.K., S.H.S., M.M., R.H. conducted the data collection. S.M.H.K., S.H.S., M.M., R.H. performed the analysis. S.M.H.K., S.H.S., M.M., R.H., A.S.T., M.G. contributed to drafting and revising the manuscript and approved the final version.

Ethical Considerations

As this study is a systematic review and meta-analysis based on previously published data, it did not involve direct interaction with human participants or access to identifiable personal data. Therefore, ethical approval and informed consent were not required. All included studies were conducted in accordance with relevant ethical standards, and the present study adhered to established guidelines for conducting and reporting systematic reviews.

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This research received no external funding.

Data Availability

All data analyzed in this study are derived from previously published articles, which are cited within the manuscript. Additional details are available from the corresponding author upon reasonable request.

AI Use Statement

Artificial intelligence tools were used to assist in language editing and improving the clarity of the manuscript. No AI tools were used for data analysis or generation of scientific results. All content was critically reviewed and approved by the authors, who take full responsibility for the integrity and accuracy of the work.

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