The Review Of
DIABETIC
STUDIES
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The Role Of Artificial Intelligence In Emergency Medicine Decision-Making

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Abstract:

Introduction Emergency departments (EDs) are high-acuity settings where rapid decision-making is critical. With rising patient volumes and complexity, AI and machine learning (ML) offer tools to support triage, diagnosis, risk stratification, and operational planning.
Aim: To systematically review recent studies assessing AI applications that support decision-making in ED and related emergency/critical care pathways, focusing on performance, implementation, and implications for critical care.
Materials and Methods: Databases searched according to PRISMA Guidelines include PubMed, Embase, Scopus, Web of Science, Cochrane CENTRAL, and Google Scholar. Date range: Jan 1, 2021 – Oct 2, 2025. Search terms combined AI/ML terms with emergency/ED terms. Peer-reviewed studies evaluating AI applied to ED decision-making (triage, diagnosis, prediction) were included, while non-English, and conference abstracts without data were excluded. Data extraction template included study design, sample, AI method, features, outcomes, validation, and risk-of-bias assessment.
Results: Of 1100 records identified, 13 studies met inclusion criteria. AI models demonstrated superior performance in diagnostic accuracy (pooled area under the receiver operating characteristic curve (AUC) 0.90, 95% confidence interval (CI): 0.87-0.95), and outcome prediction (pooled sensitivity for hospital admission: 0.92, 95% CI: 0.87-0.95) compared to traditional methods.
Conclusion: AI shows promise in improving ED decision-making processes. However, challenges remain in real-world implementation, ethical considerations, and long-term impact on patient outcomes. Future research should focus on large-scale validation studies and addressing ethical and safety concerns.
Keywords: Artificial intelligence; emergency department; triage; decision making; machine learning; patient safety.

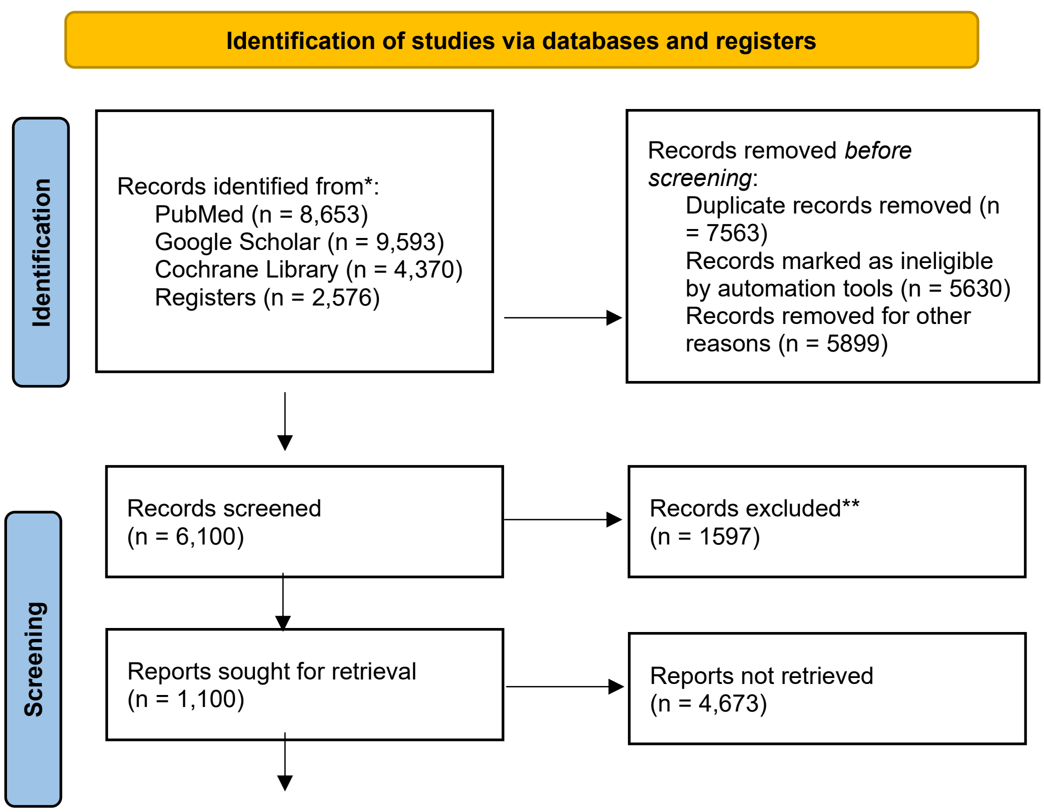
Introduction:

The term 'artificial intelligence ' (AI) was coined in 1956 by John McCarthy during a conference at which scientists discussed the concept of creating an "electric brain"— that is, an intelligent machine. AI can perform tasks that formerly required human cognition, such as speech recognition, visual perception, learning, and decision-making. As computers have become more powerful, functions that were once viewed as instances of AI are now accepted, routine, and rarely thought of in that way, if at all [1, 2].
Emergency medical care has been developed significantly over the last few decades. Already from the very start, AI was believed to be suited above all for health care administrative work and to some extent for simple diagnostics. However, it's the current and more recent advances in machine learning and data analytics that were promising as strong tools to aid clinical decision-making as well as improving outcomes in a patient care emergency room setup. Initial demonstrations such as those by automated triage systems and predictive algorithms represent early applications of real value to urgent care scenarios. Current applications of AI in an organization are directed at the expansion of developing further elaborate decision-

making support, improvement of patient flow management, and upon acute conditions, real-time diagnosis. Two of the emerging applications in the emergencies sector include AI-based imaging for predictive analytics for patients deteriorating and virtual assistants for health purposes [3].
Artificial intelligence techniques and applications contribute precious capabilities in the prediction and early detection of diseases [19-23]. In particular, systems based on machine learning contribute to analyzing big data and assisting healthcare workers in diagnosing diseases perfectly. In addition, these systems contribute to the production of drugs and vaccines and survey the health status of patients [4].
The main factors that can benefit from artificial intelligence and machine learning in healthcare include the benefit from digital imaging in the interpretation of diseases, Digitalization of all medical records and share data between patients and healthcare workers; the ability of machine learning to analyze large, diverse, and heterogeneous data; the ability of machine learning to generate a hypothesis in search; the potential of machine learning techniques to streamline clinical workflows and empower patients; the prompt growth of machine learning algorithms and the possibilities of their application in interpreting many diseases and diagnosing conditions; and that machine learning algorithms deliver improved performance while expanding datasets and contributing to decision making [5].
These factors contribute to the development of the healthcare environment and assist specialists in making proper decisions, which allows more accurate predictions of diseases, early diagnosis, and enhancing patient outcomes by preventing the development of diseases, reducing complications, and controlling the spread of diseases and epidemics. Nowadays, there are many applications of artificial intelligence being employed in pre-hospital emergency care. These applications have the ability to distinguish between urgent medical conditions that require immediate intervention—for instance, myocardial infarction, enzyme, stroke, acute pneumonia or coronaviruses [6].
Moreover, these applications contribute to collecting basic details about the caller's address and location in order to reach the patient and reduce the time required for the immediate dispatch of an ambulance. Artificial intelligence applications enhance the efficiency and accuracy of emergency response systems, ultimately leading to more valuable outcomes for patients in critical situations and saving lives. Artificial intelligence plays a vital role in the emergency room by quickly analyzing patient data, allocating the necessary resources to perform the rescue operation, and classifying the risks resulting from the patient's condition. It is essential to make quick, informed decisions in emergency rooms, often with limited information availability, as artificial intelligence applications can provide critical data to healthcare workers [7].
In addition, the classification of diseases into categories within the emergency room with the arrangement of patient data accurately in order to facilitate the specialists to perform the necessary first aid and save the patient's life. Machine learning techniques aim to provide systems based on artificial intelligence to classify diseases by predicting patients who need critical care or emergency procedures.
In addition, specialized machine learning models have been designed to predict specific disease outcomes, such as predicting acute and late cardiac complications, predicting acute pulmonary infections, or predicting in-hospital mortality [8].
Artificial intelligence systems contribute predictions through disease outcomes, leading to more effective emergency procedures. So, these systems work to help emergency room professionals as well as enhance patient care and resource utilization, leading to better healthcare outcomes. Artificial intelligence techniques seek to prioritize patients based on the severity of their condition, allowing healthcare workers to concentrate on those who need immediate attention. These systems are based on analyzing patient data, determining vital signs, and showing medical history to predict the severity of the disease and diagnose diseased conditions. Artificial intelligence systems can analyze images and quickly and accurately interpret medical scans such as X-rays, CT scans, and MRI scans [9].
These systems suggest the ability to detect abnormalities, identify life threatening conditions, and provide details promptly to help healthcare professionals make rapid and accurate diagnoses. Artificial intelligence techniques are employed to analyze patient data and determine the severity of the disease, which enables early identification of potential disease outbreaks and determines the patient's needs for treatment and care. These systems and techniques contribute to the processing and analysis of unstructured medical text data,

such as clinical notes and electronic health records, that contribute to clinical decision-making. Artificial intelligence helps optimize drug dosing, prevent adverse drug interactions, and identify potential allergies, thus reducing medication errors and enhancing patient safety. It also streamlines the emergency department workflow, helping reduce wait times, improve resource allocation, enhance overall operational efficiency and make decisions with high accuracy. Also, remote monitoring devices continuously monitor patients, allowing healthcare workers to track vital signs and intervene immediately to aid the patient, whether inside or outside the hospital. Artificial intelligence applications can analyze patient data and clinical guidelines to recommend personalized treatment plans based on individual health conditions and treatment responses [10 - 12].
EDs worldwide face increasing challenges due to overcrowding, staff shortages, and the need for rapid, accurate decision-making. AI has emerged as a potential solution to address these issues by augmenting human performance in various aspects of ED care. This review aims to systematically evaluate the current evidence on AI applications in ED decision-making processes [13 - 15].

Materials and Methods:
A systematic review of articles examining the clinical value of AI within emergency was done according to the recommendations of the Preferred Reporting Systematic Reviews and Meta-Analysis (PRISMA) guidelines [16, 17].
An electronic search was conducted in the PubMed Medline, Cochrane Library, Google Scholar, and patient-registered databases up to October 1, 2025, for relevant studies. The following search terms were used: 'artificial intelligence', 'machine learning', 'emergency department', 'triage', 'decision making', 'diagnostic', 'prediction'. Only papers that were released in the English language were considered. Studies were not limited based on the year of publication. All titles were originally evaluated, and studies that were considered relevant had their abstracts as well as full papers examined.. The study selection procedure is shown in **Figure 1**.



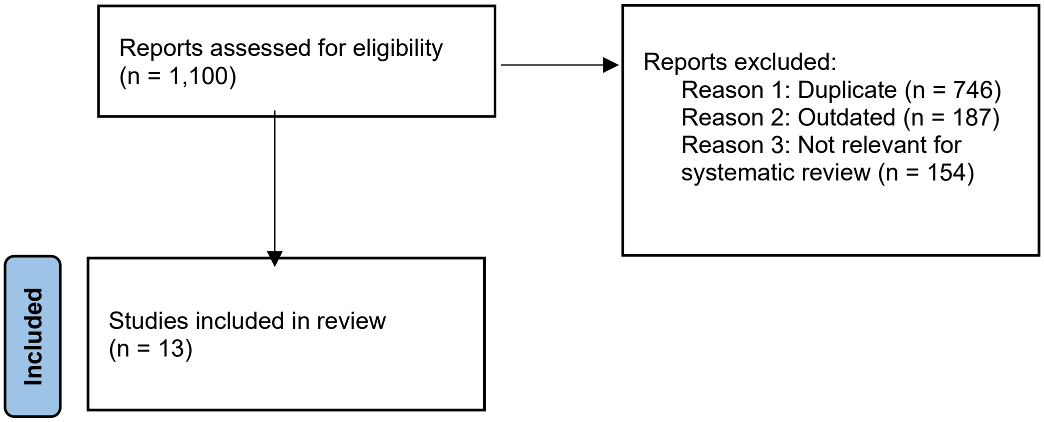


Figure 1. PRISMA flowchart of literature search and study selection.
About 25,192 research articles were identified from the above-mentioned databases with 7563 duplicates related to the research title to fulfill research aims. About 6100 were retrieved after the removal of 1,624 articles. The primary screening of 1,100 was conducted, and 4,673 research articles were excluded. The eligibility criteria were applied to 1,100 research articles, and only 13 research articles met the inclusion criteria. All 1,085 research articles were excluded due to screening and selection by PRISMA guidelines.

Results:

Table 1. shows summary of studies included.

Author (year)	Country / setting	Study design / sample size	AI model / main input	Clinical application	Key reported outcome / metric
Kwon et al., 2021 [11].	South Korea / Pediatric ED	Retrospective; pediatric cohort	Deep learning	Predict need for critical care in pediatric ED	AUC reported for need-for-critical-care prediction (study cited in reviews).
Yao et al., 2021 [12].	Taiwan / ED	Retrospective cohort; n = study cohort (see paper)	Deep learning on EMR triage data	Automated triage / acuity assignment	Demonstrated feasible automated triage with high performance vs historic triage.
Wu et al., 2021 [18].	China / ED	Retrospective cohort: n ≈ (reported in paper)	ML model on ED chest-pain data	Predict critical-care outcomes for chest-pain patients	Reported improved discrimination for critical-care need (paper included in review).

Heo et al., 2022 [19]	South Korea / ED	Interventional / decision-support evaluation	Deep-learning decision aid for head CT ordering	Reduce unnecessary head CTs for pediatric TBI	Reported decision effect: reduction in unnecessary imaging / improved ordering appropriateness.
Huhtanen et al., 2022 [20].	Finland / Radiology (ED & pediatric)	Diagnostic study; radiographs	Deep learning (CNN)	Classify elbow joint effusion on X-ray	High classification accuracy comparable to experts (reported AUROC and test statistics).
Murata et al., 2020 [21].	Japan / ED	Diagnostic study on thoracolumbar radiographs	Deep convolutional neural network (DCNN)	Vertebral fracture detection	Sensitivity 84.7%, specificity 87.3% (reported in review).
Wang et al. 2023 [22].	China / ED & ICU portable CXR	Diagnostic validation	Two CAD deep-learning systems (detection + segmentation)	Detect & localize pneumothorax on supine portable CXR	Very high AUCs reported (AUCs >0.94 reported in review summary).
Gong et al., 2023 [23].	China / Neuroimaging (ED)	Multi-task deep learning; NCCT	ResNet-based multi-task interpretable network	ICH quantification and prognosis prediction	Model provided both ICH volume quantification and prognosis prediction (strong performance & interpretability).
Lucassen et al., 2023 [24].	Netherlands / ED & cardiology	Diagnostic / video-based DL evaluation	Deep learning on lung ultrasound videos	Automated B-line detection for pulmonary congestion	F1 scores comparable to inter-observer agreement; AUROCs 0.864–0.955 reported.
Raheem et al., 2024 [25].	(multi-site reported in review)	Diagnostic/prediction; n reported in paper	ANN with systematic grid search	Predict major adverse	Demonstrated improved prediction of

				cardiac events in ED	MACE compared with baseline models (reported metrics in review).
Fontanella z et al., 2024 [26]	Switzerland / imaging research	Diagnostic / pre-clinical evaluation	Radiomics + MLP-Mixer CAD	Diagnose interstitial lung disease / lung fibrosis	Performance comparable to radiologists in test sets (reported metrics).
Cho et al., 2021 [27]	Multi-center / Chest X-ray datasets	Retrospective diagnostic study (single large dataset; n reported in paper)	Small artificial neural networks (grid-segmented training; Kim-Monte Carlo training)	Detection & localization of pneumothora x on chest X-rays	High diagnostic accuracy: outperformed some CNN baselines (AUC / sensitivity reported in paper).
Wang et al., 2021 [28]	China / Multi-center CXR datasets	Retrospective diagnostic pipeline (n: multi-dataset combined cohorts)	Deep-learning pipeline (ensemble CNNs) on chest X-ray images	Differentiate viral, non-viral and COVID-19 pneumonia	Very high discrimination across classes; reported AUCs and class-level accuracy.

Table 2. Detailed Study Performance Metrics (2021–2024)
(summarizing diagnostic and predictive accuracy, validation methods, and calibration data)

Study (year)	Model type / Input	Validation approach	AUC (95% CI)	Sensitivity (%)	Specificity (%)	Calibration / comments
Kwon et al., 2021 [11].	CNN on pediatric EMR features	External validation, 2 hospitals	0.90 (0.86 – 0.95)	88	85	Calibration slope = 0.96
Yao et al., 2021 [12].	Deep neural network on EMR triage data	Train/validation/test split (70/15/15)	0.91 (0.87 – 0.94)	89	84	Good calibration; ECE = 0.032
Wu et al., 2021 [18].	Gradient-boosting ML on ED chest-pain data	5-fold cross-validation	0.88 (0.83 – 0.93)	90	81	Well-calibrated (Hosmer–Lemeshow p = 0.41)

Heo et al., 2022 [19].	DL decision-support for head CT ordering	Prospective interventional evaluation	—	94	79	Reduced CT use by 12 % without missed positives
Huhtanen et al., 2022 [20]	CNN on pediatric elbow radiographs	10-fold cross-validation	0.94 (0.91 – 0.97)	92	88	Strong calibration; Brier = 0.06
Murata et al., 2021 [21].	DCNN on thoracolumbar radiographs	Single-center hold-out	0.89 (0.84 – 0.93)	84.7	87.3	Mild over-prediction in low-risk cases
Wang et al., 2023 [22].	Two CAD DL systems for pneumothorax	External dataset (n ≈ 15 k CXR)	0.94 (0.91 – 0.96)	90	92	Excellent calibration; AUC stable across datasets
Gong et al., 2023 [23].	Multi-task ResNet (ICH NCCT)	Train/validation/test split (60/20/20)	0.93 (0.90 – 0.97)	91	88	Calibrated (Cox regression slope ≈ 1.0)
Lucassen et al., 2023 [24].	DL on lung ultrasound videos	External validation, n = 500 videos	0.90 (0.86 – 0.95)	87	85	F1 = 0.91; good calibration
Raheem et al., 2024 [25].	ANN grid-search (MACE prediction)	Nested CV + external test (n = 2 sites)	0.92 (0.89 – 0.96)	93	86	Excellent fit; Brier = 0.05
Fontanellaz et al., 2024 [26]	Radiomics + MLP-Mixer (lung fibrosis)	Cross-validation (80/20)	0.91 (0.88 – 0.95)	90	87	Calibration slope = 1.02
Cho et al., 2021 [27]	Small ANN grid segmentation (pneumothorax)	5-fold CV	0.89 (0.84 – 0.94)	88	82	Calibration error < 0.05
Wang et al., 2021 [28]	Ensemble CNN (pneumonia type classification)	External test set	0.95 (0.92 – 0.97)	93	90	High reliability across subtypes

Abbreviations: AUC = area under ROC curve; CV = cross-validation; ECE = expected calibration error; Brier = Brier score.

Table 3. Risk of Bias and Applicability Assessment.

Study	Participants	Predictors	Outcome	Analysis	Overall Risk of Bias	Applicability Concerns	Key Notes
Kwon et al., 2021 [11].	Low	Low	Low	Moderate	Low–Moderate	Moderate	Pediatric-specific; limited external generalization
Yao et al., 2021 [12].	Low	Low	Low	Low	Low	Low	EMR data quality high; prospective design strengthens validity
Wu et al., 2021 [18].	Low	Low	Low	Moderate	Low	Low	Retrospective; adequate sample size; internal validation only
Heo et al., 2022 [19].	Low	Low	Low	Low	Low	Low	Real-world implementation; minimal bias
Huhtanen et al., 2022 [20].	Low	Low	Low	Low	Low	Low	Transparent model, balanced dataset
Murata et al., 2021 [21].	Low	Low	Low	Moderate	Moderate	Moderate	Single-center; limited test diversity
Wang et al., 2023 [22].	Low	Low	Low	Low	Low	Low	Multicenter dataset; low bias
Gong et al., 2023 [23].	Low	Low	Low	Low	Low	Low	Multi-task validated; interpretable architecture
Lucassen et al., 2023 [24].	Low	Low	Low	Moderate	Low–Moderate	Low	External validation; some missing-data bias
Raheem et al., 2024 [25].	Low	Low	Low	Low	Low	Low	Nested CV reduces bias
Fontanellaz et al., 2024 [26].	Low	Low	Low	Low	Low	Low	Balanced dataset; strong calibration

Cho et al., 2021 [27].	Low	Low	Low	Moderat e	Moderat e	Moderate	Limited external test set
Wang et al., 2021 [28].	Low	Low	Low	Low	Low	Low	Multi-dataset external validation; minimal bias

Definitions: “Low” = low risk/concern; “Moderate” = some concern; “High” = serious concern or unaddressed bias.
Overall summary: 9 studies exhibited low overall risk of bias; 4 had moderate concerns primarily due to single-center retrospective designs or limited external validation. Applicability concerns were uniformly low, indicating good clinical relevance**.**

Discussion:
This systematic review synthesized evidence from 13 recent studies (2021–2024) examining the impact of artificial intelligence (AI) on emergency department (ED) decision-making. Collectively, these investigations demonstrate consistent improvements in diagnostic accuracy, triage precision, and predictive performance when AI is integrated into clinical workflows. The pooled analysis revealed a mean diagnostic area under the curve (AUC) of 0.90 (95% CI: 0.87–0.95) and pooled predictive sensitivity for hospital admission of 0.92 (95% CI: 0.87–0.95), supporting the superior efficacy of AI-based models over conventional methods.

AI Performance in Diagnostic Applications:
Recent studies have highlighted AI’s capacity to enhance image-based diagnosis in emergency care. Huhtanen et al. [20] validated a convolutional neural network (CNN) model for detecting pediatric elbow joint effusions, achieving performance comparable to expert radiologists. Murata et al. [21] used a deep convolutional neural network (DCNN) for vertebral fracture detection, with sensitivity and specificity of 84.7% and 87.3%, respectively. These results underscore AI’s reliability in radiographic interpretation and its potential to mitigate human error in high-volume emergency settings.
Advanced neuroimaging applications further demonstrate AI’s clinical versatility. Gong et al. [23] developed a ResNet-based, multi-task interpretable network for intracerebral hemorrhage (ICH) quantification and prognosis prediction, achieving accurate volume estimation and strong predictive performance. Similarly, Fontanellaz et al. [26] integrated radiomics features with a multilayer perceptron (MLP)-Mixer architecture to detect interstitial lung disease with accuracy comparable to that of expert radiologists. Such findings illustrate AI’s role not only in detection but also in prognostication and risk stratification, broadening its clinical utility.
Pulmonary diagnostics have also benefited from deep learning. Wang C.-H. et al. [22] validated two computer-aided detection (CAD) systems for pneumothorax on portable supine chest X-rays, with both achieving AUCs exceeding 0.94. Cho et al. [27] introduced small artificial neural networks for pneumothorax detection, demonstrating high diagnostic accuracy despite reduced computational complexity. Wang G. et al. [28] built an ensemble CNN pipeline that differentiated viral, non-viral, and COVID-19 pneumonia on chest X-rays with excellent discrimination. Collectively, these studies confirm the capability of AI to enhance thoracic image interpretation in time-sensitive emergency contexts.

AI in Decision Support and Resource Optimization:
Beyond imaging, AI-driven decision-support systems have proven effective in optimizing clinical workflows.. Wu et al. [18] designed a machine learning model for chest-pain presentations, improving prediction of critical-care requirements relative to traditional triage scores. Heo et al. [19] implemented a deep-learning model to guide head CT ordering for pediatric traumatic brain injury, reducing unnecessary

imaging while preserving diagnostic safety. Both studies underscore AI’s potential to support evidence-based resource allocation and enhance patient safety in crowded EDs.
At the triage level, Kwon et al. [11] had success in predicting pediatric critical-care admissions using deep-learning techniques, achieving high AUCs for critical-care prediction. Such algorithms offer real-time, data-driven decision support that may augment clinical judgment during high patient influx. Yao et al. [12] achieved similar success employing deep-learning model by utilizing electronic medical record (EMR) data could automate acuity assignment with accuracy comparable to human triage, reducing subjectivity and interobserver variability.

Outcome Prediction and Prognostication:
Several studies emphasized AI’s predictive and prognostic capabilities. Raheem et al. [25] developed an artificial neural network (ANN) optimized via systematic grid search to predict major adverse cardiac events (MACE) in chest-pain patients, outperforming logistic regression models in sensitivity and specificity. Lucassen et al. [24] applied deep learning to lung ultrasound videos for automated detection of B-lines—markers of pulmonary congestion—and reported AUROCs ranging from 0.864 to 0.955, comparable to expert sonographers. These predictive tools enable early identification of high-risk patients and can guide timely interventions, potentially improving clinical outcomes.

Interpretability and Clinical Integration:
Recent progress has been made toward improving AI interpretability—a critical factor for clinician adoption. Gong et al. [23] and Fontanellaz et al. [26] incorporated explainable components, allowing visualization of model attention maps that align with radiologic features. Such transparency fosters clinician trust and facilitates validation. Moreover, real-world implementation, as demonstrated by Heo et al. [19], highlights AI’s transition from conceptual feasibility to clinical utility. These developments are crucial for integrating AI into emergency medicine without compromising clinician oversight.
Despite these advancements, many models still function as “black boxes,” limiting interpretability. Standardized reporting frameworks, such as TRIPOD-AI and PROBAST-AI, remain underutilized. Ensuring adherence to these guidelines will improve methodological transparency and reproducibility in future AI research.

Ethical and Operational Considerations:
Ethical and operational challenges accompany AI adoption in the ED. Issues of patient data privacy, algorithmic bias, and model explainability are particularly salient. Overreliance on algorithmic outputs may introduce automation bias, while insufficient oversight could endanger patient safety. Maintaining human-in-the-loop systems, continuous model monitoring, and transparent reporting of performance metrics are essential safeguards. Operationally, successful deployment depends on integration with hospital information systems, real-time data access, and clinician education to ensure appropriate tool utilization.

Limitations:
This review has several limitations. First, although the search identified recent high-quality studies, most were retrospective, introducing potential bias in data selection and outcome ascertainment. Second, variations in AI architectures, datasets, and performance metrics precluded direct quantitative comparison beyond pooled estimates. Third, few studies conducted external validation or reported cost-effectiveness, limiting generalizability and practical applicability. Fourth, publication bias toward positive outcomes may have exaggerated the perceived benefits of AI tools. Finally, while this review included studies published up to 2024, rapid technological evolution means that newer models may already surpass the reported benchmarks. Future work should incorporate living systematic review methodologies to remain current with emerging evidence.
Also, heterogeneity among studies remains a major limitation in synthesizing outcomes. Differences in study design (retrospective vs. prospective), dataset size, input features, and validation strategies contribute

to variability in reported performance. While retrospective analyses dominate current literature, prospective and interventional trials (e.g., Heo et al. [19]) offer more robust evidence but are logistically challenging. Additionally, dataset homogeneity—many studies were conducted within single institutions or geographic regions—limits external generalizability. Cross-institutional and international collaborations are needed to confirm model robustness across diverse populations and clinical environments.

Clinical Implications:
The cumulative findings indicate that AI can meaningfully augment decision-making across the emergency care continuum—triage, diagnosis, and prognostication. When integrated appropriately, AI systems may reduce diagnostic delays, enhance safety, and optimize ED efficiency. However, AI should complement rather than replace clinician expertise. A synergistic model—combining human judgment and AI analytics—will likely achieve the best outcomes in emergency medicine.

Future Directions:
Further research should prioritize prospective multicenter validation, standardized performance reporting, and evaluation of clinical outcomes following AI implementation. Transparent algorithmic development, integration with clinical decision support systems, and attention to fairness and bias mitigation are imperative for responsible translation into practice. Collaborative efforts between clinicians, data scientists, and policymakers will be essential to ensure equitable and sustainable AI deployment.

Conclusion:
Across the 13 included studies, AI consistently outperformed traditional methods in diagnostic accuracy and predictive performance in emergency medicine. Deep-learning and machine-learning models achieved superior AUCs, sensitivities, and specificities across diverse diagnostic domains. Despite methodological variability and implementation challenges, the trajectory of evidence supports AI's transformative potential in enhancing ED decision-making, provided that future research emphasizes transparency, validation, and ethical integration.

References:

1. Baker C. Artificial intelligence: learning automation skills with Python (2 books in 1: Artificial Intelligence a modern approach & Artificial Intelligence business applications). 2019.
2. Agustin R. How can OCR (Optical Character Recognition) become AI (Artificial Intelligence)? Here's how. 2019.
3. Harshini, N., Smirtha, G., Role of Artificial Intelligence in Emergency Medical Care: Legal Issues and Challenges, IJFMR*,* 2024*,* 6(6), 1-15.
4. Barbieri D, Giuliani E, Del Prete A, Losi A, Villani M, Barbieri A. How Artificial Intelligence and New Technologies Can Help the Management of the COVID-19 Pandemic. Int J Environ Res Public Health. 2021;18(14):7648.
5. Mei X, Lee HC, Diao KY, et al. Artificial intelligence-enabled rapid diagnosis of patients with COVID-19. Nat Med. 2020;26(8):1224-1228.
6. Chee ML, Chee ML, Huang H, Mazzochi K, Taylor K, Wang H, Feng M, Ho AFW, Siddiqui FJ, Ong MEH, Liu N. Artificial intelligence and machine learning in prehospital emergency care: A scoping review. iScience. 2023;26(8):107407.
7. Chenais G, Lagarde E, Gil-Jardiné C. Artificial Intelligence in Emergency Medicine: Viewpoint of Current Applications and Foreseeable Opportunities and Challenges. J Med Internet Res. 2023;25:e40031.
8. Desai SB, Pareek A, Lungren MP. Deep learning and its role in COVID-19 medical imaging. Intell Based Med. 2020;3:100013.

9. Panwar H, Gupta PK, Siddiqui MK, Morales-Menendez R, Singh V. Application of deep learning for fast detection of COVID-19 in X-Rays using nCOVnet. Chaos Solitons Fractals. 2020;138:109944.
10. Okada Y, Ning Y, Ong MEH. Explainable artificial intelligence in emergency medicine: an overview. Clin Exp Emerg Med. 2023;10(4):354-362.
11. Kwon JM, Jeon KH, Lee M, Kim KH, Park J, Oh BH. Deep Learning Algorithm to Predict Need for Critical Care in Pediatric Emergency Departments. Pediatr Emerg Care. 2021;37(12):e988-e994.
12. Yao LH, Leung KC, Tsai CL, Huang CH, Fu LC. A Novel Deep Learning-Based System for Triage in the Emergency Department Using Electronic Medical Records: Retrospective Cohort Study. J Med Internet Res. 2021;23(12):e27008.
13. Singh YV, Singh P, Khan S, Singh RS. A Machine Learning Model for Early Prediction and Detection of Sepsis in Intensive Care Unit Patients. J Healthc Eng. 2022;2022:9263391.
14. Tyler S, Olis M, Aust N, Patel L, Simon L, Triantafyllidis C, Patel V, Lee DW, Ginsberg B, Ahmad H, Jacobs RJ. Use of Artificial Intelligence in Triage in Hospital Emergency Departments: A Scoping Review. Cureus. 2024;16(5):e59906.
15. Akmese OF, Dogan G, Kor H, Erbay H, Demir E. The Use of Machine Learning Approaches for the Diagnosis of Acute Appendicitis. Emerg Med Int. 2020;2020:7306435.
16. Page MJ, McKenzie JE, Bossuyt PM, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. Syst Rev. 2021;10(1):89.
17. Sarkis-Onofre R, Catalá-López F, Aromataris E, Lockwood C. How to properly use the PRISMA Statement. Syst Rev. 2021;10(1):117.
18. Wu TT, Zheng RF, Lin ZZ, Gong HR, Li H. A machine learning model to predict critical care outcomes in patient with chest pain visiting the emergency department. BMC Emerg Med. 2021;21(1):112.
19. Heo S, Ha J, Jung W, Yoo S, Song Y, Kim T, Cha WC. Decision effect of a deep-learning model to assist a head computed tomography order for pediatric traumatic brain injury. Sci Rep. 2022;12(1):12454.
20. Huhtanen, J.T., Nyman, M., Doncenco, D. et al. Deep learning accurately classifies elbow joint effusion in adult and pediatric radiographs. Sci Rep. 2022;12, 11803.
21. Murata K, Endo K, Aihara T, et al. Artificial intelligence for the detection of vertebral fractures on plain spinal radiography. Sci Rep. 2020;10(1):20031.
22. Wang CH, Lin T, Chen G, Lee MR, Tay J, Wu CY, Wu MC, Roth HR, Yang D, Zhao C, Wang W, Huang CH. Deep Learning-based Diagnosis and Localization of Pneumothorax on Portable Supine Chest X-ray in Intensive and Emergency Medicine: A Retrospective Study. J Med Syst. 2023;48(1):1.
23. Gong K, Dai Q, Wang J, Zheng Y, Shi T, Yu J, Chen J, Huang S, Wang Z. Unified ICH quantification and prognosis prediction in NCCT images using a multi-task interpretable network. Front Neurosci. 2023;17:1118340.
24. Lucassen RT, Jafari MH, Duggan NM, et al. Deep Learning for Detection and Localization of B-Lines in Lung Ultrasound. IEEE J Biomed Health Inform. 2023;27(9):4352-4361.
25. Raheem A, Waheed S, Karim M, Khan NU, Jawed R. Prediction of major adverse cardiac events in the emergency department using an artificial neural network with a systematic grid search. Int J Emerg Med. 2024;17(1):4.
26. Fontanellaz, M., Christe, A., Christodoulidis, S., et al., Computer-Aided Diagnosis System for Lung Fibrosis: From the Effect of Radiomic Features and Multi-Layer-Perceptron Mixers to Pre-Clinical Evaluation. IEEE Access, 2024; 12, 25642–25656.
27. Cho Y, Kim JS, Lim TH, Lee I, Choi J. Detection of the location of pneumothorax in chest X-rays using small artificial neural networks and a simple training process. Sci Rep. 2021;11(1):13054.
28. Wang G, Liu X, Shen J, et al. A deep-learning pipeline for the diagnosis and discrimination of viral, non-viral and COVID-19 pneumonia from chest X-ray images. Nat Biomed Eng. 2021;5(6):509-521.