

# Practical and Legal Aspects of Applying Artificial Intelligence in Emergency Medicine

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## Abstract

This narrative review explores current applications of artificial intelligence (AI) in emergency medicine, critically evaluates the supporting evidence, and discusses the ethical, legal, and regulatory challenges surrounding its integration into clinical practice. Peer-reviewed literature and recent systematic reviews on AI applications in emergency medicine were analyzed using a structured narrative approach. AI-driven operational forecasting, predictive modeling for patient outcomes, diagnostic support, and AI-assisted triage systems are among the domains evaluated. AI models, such as neural networks and gradient boosting machines, have demonstrated superiority over traditional triage tools in forecasting outcomes like in-hospital mortality and intensive care unit admission. AI in diagnostics has enhanced point-of-care ultrasound analysis, sepsis detection, and electrocardiogram interpretation. Operationally, AI makes it possible to predict patient volume, emergency department crowding, and resource allocation in real time. Despite these developments, there are still few prospective clinical trials confirming better patient outcomes. Algorithmic bias, a lack of transparency, automation bias, and restrictions on generalizability across clinical settings are among the main issues. Emerging regulatory frameworks like the European Union AI act and ethical and legal frameworks like the General Data Protection Regulation and Health Insurance Portability and Accountability Act are essential for directing the responsible use of AI. AI has significant potential to improve the provision of emergency care. However, ethical protections, legal compliance, integration with clinical workflows, and thorough external validation are necessary for responsible implementation. To guarantee the safe and fair implementation of AI in emergency medicine, future initiatives must concentrate on explainable AI, multicenter prospective research, and stakeholder collaboration.

**Keywords:** Artificial intelligence, emergency medicine, clinical decision support, triage systems, machine learning, ethical issues, legal regulation, prognostic models, diagnostic accuracy

## Introduction

Emergency medicine is a high-stakes profession with inherent resource limitations, complicated patient flow, and time-sensitive decision-making. Chronic emergency department (ED) overcrowding and the Coronavirus disease-2019 pandemic have brought attention to systemic issues like long wait times, employee

burnout, and poor patient outcomes (1). Artificial intelligence (AI) has become a promising tool to supplement emergency care in this context. AI systems can help with quick triage, diagnostic support, outcome prediction, and operational decision-making thanks to developments in machine learning (ML) and data analytics. In fact, AI methods have already shown potential in enhancing



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**Cite this article as:** Buczek T, Szwedziak I, Vişneci EF, Pruc M, Xavier Duchateau F, Lepetit A. Practical and legal aspects of applying artificial intelligence in emergency medicine. Eurasian J Emerg Med. 2026;25: 20-8.

**Received:** 17.06.2025

**Accepted:** 25.07.2025

**Published:** 26.01.2026



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clinical decision support, medical imaging interpretation, and ED triage accuracy (1,2). From prehospital evaluation to in-hospital diagnostics, prognostication, and resource management, AI technologies are being used increasingly throughout the emergency care spectrum. AI-enabled symptom checkers can be used by patients before they arrive, and dispatch centers can use AI to streamline response logistics and triage. AI models assist in clinical decision-making during hospitalization by predicting results, analyzing diagnostics, and classifying risk. Predictive algorithms are used administratively to guide strategies for crowding mitigation, bed distribution, and staffing.

It is still difficult to integrate AI advancements into standard emergency care, despite this promise. Relatively few prospective trials have shown better patient outcomes in real-world settings, and the majority of AI applications in emergency medicine to date have come from retrospective studies or proof-of-concept models (1,2). For example, a 2020 scoping review identified 150 studies of AI in emergency care, over 82% of which were retrospective and only 2% were prospective controlled trials (2). The overall body of evidence is still small, even though about 25% of these interventions sought to improve diagnosis (particularly in imaging), and some algorithms even beat physicians in particular tasks. Before AI tools are widely used, thorough validation and an evaluation of their effects on patient-oriented outcomes are still required. This narrative review explores the main ethical, legal, and regulatory concerns related to the use of AI in emergency medicine while acknowledging both the potential and the gaps. The methodological approach, major application domains (triage, diagnostics, prognostication, resource management), ethical considerations (fairness, transparency, oversight, consent), and the legal/regulatory landscape [liability, data protection, and governance frameworks in the United States (US) and European Union (EU)] are all covered.

## Triage

An important advancement in digital health is the growing availability of AI-based symptom checkers on web and mobile platforms, which provide users with real-time triage recommendations (3). These tools interpret user-provided symptoms by utilizing natural language processing (NLP) and pattern recognition algorithms recommend appropriate care-seeking actions based on perceived urgency (4). The scientific community continues to have concerns about their accuracy and safety, despite their promising potential to empower patients and manage healthcare demand (3).

Variability in these systems' performance has been brought to light by systematic reviews and comparative studies. For example,

a 2020 study that looked at 22 different symptom checkers found significant variations in triage recommendations and diagnostic accuracy (3). Interestingly, the study found that both under- and over-triage rates were high, especially for conditions that require immediate attention, like myocardial infarction or stroke (3). While over-triage can unnecessarily strain emergency services, under-triage can result in delayed care for critical conditions, potentially worsening outcomes (5).

The proprietary nature of many underlying algorithms, sometimes referred to as "black boxes", presents a significant challenge in assessing and enhancing these tools (3). These algorithms might use antiquated medical guidelines or heuristics that haven't been thoroughly tested (3). It is challenging to evaluate their internal reasoning and spot any biases or limitations because of this lack of transparency.

Experts emphasize the importance of extensive validation studies and external benchmarking to ensure clinical reliability before public health initiatives or emergency medical care triage systems are widely implemented (3). Recalibration and prospective testing using patient data are ideal for this validation to preserve accuracy over time. Using ML and NLP to improve emergency room triage precision and consistency is still being studied (5). Frameworks are also being developed to reflect real-world patient circumstances in symptom assessment tool case vignettes (6). AI is being studied for clinical decision support systems, patient triage, and diagnostic support in emergency care (7). ML algorithms are also being used to predict inpatient admissions using ED triage data to improve patient flow management (8). Development of interpretable ML models for triage that address class imbalance is also underway to improve accuracy and clinical judgment (9).

More advanced AI applications are appearing in emergency dispatch. The Corti platform helps emergency call operators identify cardiac arrest-related clinical phrases, tone, and metadata using ML and real-time speech recognition. In retrospective tests, such technologies detected out-of-hospital cardiac arrest faster than human dispatchers, enabling advanced life support (10). AI simplifies triage decision-making and automatically extracts demographics and geography. Few prospective trials exist, and further study is needed to address false alarm rates, dispatcher over-reliance, and system latency before widespread adoption.

Studying the specific developments, difficulties, and factors surrounding AI-assisted triage systems is important to build on the analysis of the traditional Emergency Severity index (ESI) and the potential of AI models (like gradient boosting machines and neural networks) to improve triage accuracy.

Gradient boosting machines and neural networks can predict important outcomes such as intensive care unit (ICU) admission and in-hospital mortality better than the ESI. Studies have shown that ML models outperform the ESI in AUROC scores (11). One study using data from over 189,000 emergency patients created and validated interpretable ML models for ICU admission by comparing models based on ESI, vital signs, and a mix of vital signs, demographics, and medical history (12). Another study examined feed-forward neural networks, regularized regression, random forests, and gradient-boosted trees for predicting ICU versus non-ICU care after 24 hours of admission using 41,654 ED visits (12). These findings show that AI models can manage complex interactions between several variables, which could lead to more nuanced risk categorization than rule-based systems. The effectiveness of gradient boosting machines is demonstrated by increased research into specific ML methodologies. A study that used a gradient boosting ML model to predict early mortality in ED triage showed how useful it is of the model for enhancing patient classification (13). Extreme-Gradient-Boosting-based interpretable ML models have been used to forecast extended wait times in the ED, enabling the assessment of equity among various patient groups (14). For clinical adoption, this emphasis on interpretability is essential because it helps medical professionals comprehend the logic behind an AI's recommendation.

Even with little information available, deep-learning techniques, particularly neural networks, have demonstrated promise in identifying critically ill patients during triage (15). In time-sensitive triage situations where only preliminary information is available, deep learning's capacity to automatically extract complex features from raw data may be especially helpful. The efficiency of various ML models, such as artificial neural networks, for predicting ESI levels has also been compared (16).

The generalizability of AI models is still a major obstacle, despite the encouraging outcomes. Numerous models are trained and validated using datasets from individual institutions, which might not account for the differences in patient demographics, clinical procedures, and data gathering techniques among various emergency rooms (11). Before deployment, thorough local validation is required due to this limitation. A crucial area of study is the significance of external validation and the possibility of performance deterioration in unfamiliar settings.

Ensuring demographic fairness in AI-assisted triage is another significant challenge. Models that consistently under- or over-triage particular demographic groups, like minority populations, may result from bias in training data (14). This issue is brought to light by studies that examine differences in ED prioritization according to demographic traits even when triage acuity scores are comparable (17). When developing, assessing, and

implementing models, demographic fairness must be carefully taken into account. Building equitable AI systems requires methods for assessing fairness, like those employed in the study looking at ethnic differences in wait time prediction models (14).

A number of tactics are suggested to lessen these difficulties and make it easier for AI to be used responsibly in triage. To guarantee performance and dependability, local validation of AI models within the particular context of the implementing institution is crucial (14). Incorporating human-in-the-loop supervision is also crucial. Clinical judgment should not be replaced by AI; rather, it should be seen as an aid. When needed, medical professionals should be able to override AI recommendations and offer input, to help the system improve over time.

Beyond demographic data and vital signs, multimodal data integration offers additional promise for improving AI triage accuracy. A more complete picture of a patient's condition can be obtained by using NLP to incorporate unstructured data from electronic health records (EHR), such as doctor notes and past medical information (18). In addition to data gathered at the triage point, studies have investigated the use of ML predict hospital admission at triage based on patient history (19).

Building interpretable AI models is also essential to encouraging adoption and trust among medical professionals. Clinicians can validate a recommendation based on their medical expertise when they understand why a model makes a specific prediction. There is still research being done on interpretable ML models for triage prediction (12).

### **Diagnostics**

Advances in medical imaging, data synthesis, deep learning, and specialist tools like electrocardiogram (ECG) and sepsis tools affect pre-hospital and ED emergency diagnosis. Emergency medicine's high stakes and time limits demand fast and accurate diagnosis to improve patient outcomes (20). ED triage and outcome prediction using ML and AI are major areas of focus. ML models are being created to predict hospital admission and mortality using triage data as such as patient history, vital signs, and nursing notes (21). To reduce subjectivity in conventional systems like the ESI, a deep learning approach that uses electronic medical records (EMRs) has been proposed to improve ED triage accuracy (22). Comparisons of ML models with classical ESI show promising clinical outcome prediction (11). NLP is essential for extracting meaningful information from unstructured text data in triage notes and improving prediction accuracy (23).

Emergency diagnosis requires medical imaging. In hemodynamically unstable patients who may not be candidates

for computed tomography pulmonary angiography, point-of-care ultrasound is increasingly employed to diagnose large pulmonary embolism (24). AI models are also being studied for real-time ultrasound picture interpretation in emergency settings like the extended focused assessment with sonography in trauma test to improve diagnostic precision and decision-making (25). Multimodal AI systems that use metadata and ocular images, for primary diagnosis and eye emergency triage, show the potential of combining data sources for diagnostic efficiency (25).

Emergency cardiac diagnosis requires ECG analysis. AI and deep learning models, notably convolutional neural networks (CNNs), are revolutionizing ECG analysis by automating high-precision arrhythmia identification (25). ML algorithms using 12-lead ECGs are being developed to predict acute mortality in ED patients (25). Acute coronary syndrome patients need quick ECG acquisition at triage, and clinical prediction methods in tablet apps are being studied to accelerate this process (26). Bedside assays for high-sensitivity troponin I are also being compared to central laboratory analysis to determine if they can quickly diagnose acute myocardial infarction (27). Sepsis is life-threatening, and delayed treatment increases mortality; therefore, ED triage must discover it early (28). ML improves sepsis triage detection before lab results (28).

Data synthesis, which integrates multimodal data from physiological signals, EMRs, and medical imaging, is boosting diagnostic accuracy (29). Hybrid deep learning architectures using CNNs, recurrent neural networks, and transformer models are being studied for multimodal data fusion in healthcare diagnostics (29). To reduce ED overcrowding and improve resource allocation, deep learning is being used to analyze heterogeneous medical data to predict patient criticality and identify the appropriate clinical departments (30).

Despite advances, emergency AI-driven diagnostic tools are still challenging to implement. These include addressing the medicolegal implications of deploying AI in high-risk scenarios, ensuring AI model interpretability and fairness, and undertaking clinical validation studies (31). To ensure successful incorporation into healthcare workflows, clinician views on AI in emergency triage must be considered (31). Multidisciplinary panels must be used to investigate diagnostic errors in EDs to improve patient safety (32).

### **Prognostication**

Emergency medicine uses AI for prognostication, or patient outcome prediction from structured data. In high-acuity, fast-paced settings like the ED, AI-driven predictive models can help

doctors identify patients at risk of deterioration, ICU admission, protracted hospitalization, or death. These techniques improve early risk categorization for faster interventions, triage, and resource allocation.

ML algorithms can predict clinical worsening using preliminary ED data including vital signs, lab results, and patient demographics. Algorithms can predict in-hospital cardiac arrest, mechanical ventilation, major trauma transfusions, and infection, or septic shock. AI techniques for early sepsis identification that combine lab measurements and dynamic vital sign trajectories to provide real-time risk scores have garnered attention. Some models outperform rule-based systems in retrospective validations with AUROC values close to 0.90 (33). A meta-analysis of prognostic AI in emergency settings found that ML models outperformed conventional risk stratification methods in predicting hospital admission and short-term death (34). Many of these models are “early warning systems” that detect clinically stable patients who could decompensate in hours. Several health organizations are using AI-based early warning capabilities in their ED information systems to flag high-risk patients for clinical reassessment or escalation.

Translation into clinical practice is problematic. The generalizability of predictive AI models is often limited by their training setting. One often reported proprietary sepsis prediction system utilized in numerous hospitals performed worse than earlier reports, exhibiting low sensitivity and inappropriate calibration in external validation cohorts (35). This mismatch emphasizes the need for external validation and post-deployment monitoring. Audits, recalibrations, and impact analyses should be done regularly to detect performance drift and maintain clinical relevance.

Another issue is automation bias—physicians may overuse algorithmic risk rankings instead of clinical judgment. AI results should be considered as supporting data, not as final instructions. The doctor must interpret prognostic AI by combining contextual knowledge of the patient’s presentation with the algorithm’s detection of subtle, data-driven risk patterns.

Despite these shortcomings, prognostic AI could transform emergency treatment. Due to their ability to assess high-dimensional, temporally linked data, models can detect early signs of deterioration as such as hemodynamic microtrends or subtle laboratory abnormalities that humans cannot. These insights can reduce unnecessary outcomes, personalize monitoring intensity, and improve patient disposition decisions (ED discharge vs. observation vs. ICU stay). Future efforts should

focus on explainable AI (XAI) frameworks that integrate easily into ED procedures and provide interpretable risk estimates. Research priorities include prospective, multicenter trials to determine how AI-informed prognostication influences clinician judgment, patient outcomes, and health system performance.

AI is increasingly employed to improve clinical decision-making and operational efficiency in EDs, which often have congestion, resource constraints, and unpredictable patient surges. Dynamic capacity planning using AI-based forecasting, scheduling, and logistics systems may improve patient flow, reduce waits, and employee burnout for emergency medicine administrators.

### **Predictive Forecasting and Capacity Planning**

AI demand forecasting is among its most advanced operational uses. ML models trained on historical ED data, including chief complaints, patient arrival times, seasonal trends, weather data, and public event calendars, can effectively anticipate hourly or daily patient loads. These short-term estimates enable proactive personnel, space, and bed modifications. If an AI tool predicts a high-volume day after a major athletic or meteorological event, clinical directors can plan extra staff or pre-open surge capacity units. A recent study shows that AI-based ED crowding forecasts improve throughput and reduce left without being seen (36). Heuristic-based models do not.

Triage vitals, presenting complaint, first labs, and imaging can also be used by AI to predict patient-level length of stay (LOS). This aids downstream bed planning, transfer prioritization, and real-time patient streaming. In high-occupancy settings, LOS prediction helps estimate discharge rates more precisely, which helps manage bed turnover (37).

### **Staff Scheduling and Workload Balancing**

AI can help schedule staff by recognizing demand trends and matching staffing to expected acuity and volume. Dynamic scheduling algorithms can identify understaffed periods, optimize shift timing, and ensure the right skill mix of attending physicians, residents, and nurses during peak hours. In one application, AI-driven dashboards predicted ED crowding eight hours in advance and recommended real-time staffing adjustments, enhancing throughput and employee satisfaction (38).

AI is being studied for real-time ambulance dispatch optimization. AI algorithms can use prior EMS data, traffic patterns, and projected ED congestion to route ambulances to facilities with the correct acuity and capacity. This could reduce ED offload and transport delays, which cause system bottlenecks (39).

### **Inventory and Supply Chain Optimization**

AI helps with supply forecasting and logistics in emergency care, in addition to managing staff and beds. Based on historical and current data, algorithms can forecast trends in resource consumption, such as the use of tPA in stroke or the need for transfusions in trauma. By using these insights, hospitals can better stock equipment, drugs, and blood products, minimizing shortages during surges and cutting waste during lulls. This type of predictive logistics is particularly useful in high-stakes situations like disaster response or mass casualty incidents (40).

### **Implementation Considerations**

Even with promising pilot results, a number of crucial elements must come together for AI to be successfully implemented in ED operations:

**Data integration:** In order to access real-time data feeds, AI systems must easily interface with current hospital command centers, admission-discharge-transfer systems, and EHR.

**Interpretability:** The results of operational AI must be clear and intelligible. To trust and follow predictions and recommendations, clinicians and administrators must comprehend the reasoning behind these predictions and recommendations.

**Stakeholder buy-in:** Frontline employees' and administrative leadership's participation is crucial. To prevent resistance or unintentional disruption, tools must be co-designed with users in mind and customized to local workflows.

Small but significant gains in ED LOS, patient satisfaction, and clinician workload distribution have been shown in early trials of AI-supported operational systems (41). Scalable and validated AI tools for capacity management are set to become just as important as clinical algorithms in promoting patient-centered, resilient emergency care, as the demand on emergency services continues to increase.

### **Ethical Considerations in the Use of AI in Emergency Medicine**

AI in emergency medicine could boost efficiency and outcomes, but ethical issues must be addressed to ensure patient safety. AI ethics must be built on fairness, openness, human monitoring, and informed consent. This is because EDs treat vulnerable patients under time and budget constraints.

Fairness and bias are fundamental ethical dilemmas. If trained on unrepresentative datasets or structural inequities, AI models may unintentionally exacerbate care disparities. If training data show that women have historically underreported cardiac symptoms, a triage algorithm may continually underestimate

risk in female patients. In rural or resource-constrained contexts, algorithms based on metropolitan university hospital data may perform poorly. Variable measurement, algorithm design, and data sampling biases might worsen healthcare inequities and discriminatory treatment. To solve this problem, datasets must be representative and diversified, and models must use fairness requirements or employ bias correction methods, such as resampling or reweighting, to ensure fairness. After deployment, institutions should evaluate demographic subgroup AI performance and establish redress processes for inequalities. Finally, equitable results for all groups served are as crucial as technical performance. Transparency matters too. Many powerful AI models, especially deep learning-based ones, are “black boxes” that predict without explanation. Emergency clinicians must understand, contextualize, and question AI-generated recommendations to make rapid choices based on limited data. XAI provides a partial solution by producing interpretable outputs such as feature attribution scores or visual explanations like diagnostic image heatmaps. These arguments improve clinician trust, accountability, and decision-making. The EU General Data Protection Regulation (GDPR) and the impending AI act require individuals to have access to relevant information about automated judgments, making explainability in high-risk AI systems increasingly critical. Clarity and usability must be balanced in practice; too comprehensive an explanation can overwhelm doctors, while an explanation that is too simple will not impart meaningful information. Understanding that hypotension and altered mental status triggered a triage signal can help make care decisions in the high-pressure ED without delaying action.

Clinician autonomy and oversight are also ethical requirements. AI should complement human decision-making, not replace it. Doctors may overuse AI results and trust AI advice without adequate critical thinking, raising concerns about automated bias. This can be troublesome if the model is used outside its intended scope or if AI recommendations clash with clinical intuition. Over time, uncritical AI use can cause “moral deskilling,” leading to medical practitioners losing confidence in their judgment. AI systems reduce this risk by incorporating human-in-the-loop protections that let doctors change or question outcomes. Clinicians should have final-say over high-stakes care decisions per institutional policy. Certain AI platforms require clinicians to disclose their reasoning for rejecting or approving algorithmic advice to encourage reflection and discourage mindless acceptance. Regulators are codifying these expectations as the EU AI act requires human oversight for high-risk medical AI systems. Emergency medicine regulations may require human

providers to verify AI triage scores or diagnostic signals before acting.

AI complicates informed consent, which has long been a cornerstone of moral medical practice. AI in treatment should be explained to patients, especially if it affects their decision-making. AI tool discussions in the ED are often infeasible due to time constraints, unconscious patients, and possibly lethal scenarios. These instances fall under emergency informed consent exceptions in US and European law. We should be transparent about AI’s contribution wherever possible. Hospitals may employ signage, general consent forms, or institutional regulations to disclose AI systems for clinical decision-making. Hospitals should notify patients after AI significantly affects a diagnosis or treatment plan, especially without human review. Hospitals might adopt a strategy of “ongoing informed transparency” to ensure that patients are aware of AI use, even if particular disclosures are not possible during an urgent visit. Transparency is crucial when AI programs are experimental or make judgments without human input, such as EMS routing. Formal study methods or separate permission may be ethical in certain cases, although clarity on the context of ‘separate permission’ is advised.

### **Legal and Regulatory Issues**

A thorough grasp of current frameworks and new regulations is necessary to navigate the substantial legal and regulatory challenges associated with the integration of AI into emergency medicine. Although AI has the potential to improve productivity and patient care, its application is limited by a complicated framework that includes liability, data protection, and regulatory supervision (42).

Laws pertaining to privacy and data protection are a major concern (43,44). The Health Insurance Portability and Accountability Act (HIPAA) in the US establishes guidelines for safeguarding private patient health data (44). Regarding the use and disclosure of protected health information, HIPAA places duties on covered entities (healthcare clearinghouses, health plans, and providers) and their business associates. HIPAA compliance is crucial when AI systems handle patient data, necessitating strong administrative and technical safeguards to guarantee data security and privacy (45).

Even more stringent regulations are enforced by the GDPR of the EU (46) which gives people broad control over their personal data, including the ability to access, amend, and remove data as well as the ability to object to processing (47). Strict adherence to the principles of data minimization, purpose limitation, and transparency in algorithmic processing is required for the

GDPRs application to AI in healthcare (46). Obtaining appropriate patient consent for data usage, establishing clear data governance policies, and ensuring adequate anonymization or pseudonymization of data used for AI training and deployment are among the legal challenges in this area (48).

Another crucial legal issue is liability, and another is accountability (49,50). The advent of AI complicates traditional medical malpractice law, which holds healthcare organizations and individual practitioners accountable for careless acts (50). Determining who is at fault—the doctor, the healthcare facility, or the AI developer—when an AI system causes a negative outcome is a complex legal matter (49). The “learned intermediary” doctrine, which holds that AI is a decision-support tool and that the doctor is ultimately in charge of assessing AI recommendations and reaching clinical conclusions, is frequently invoked in current legal viewpoints (50). Physicians are required by this doctrine to use their own clinical judgment and evaluate AI systems’ output critically (50).

However, product liability law becomes more important as AI systems in emergency medicine become more self-sufficient and require less human intervention (51). The AI developer or manufacturer may be held accountable if damage is caused by an error in the warnings, design, or manufacturing of the AI system. This puts the AI product itself front and center instead of the doctor’s actions. There are particular legal difficulties in establishing a flaw in a sophisticated, self-learning AI system, such as establishing causation and pinpointing the precise part or algorithm that caused the damage (49). Globally, the legal frameworks pertaining to liability protection and AI service businesses are changing, with various jurisdictions investigating potential solutions (52).

The US Food and Drug Administration (FDA) and the US, through the proposed AI act, are playing important roles in the ongoing development of regulatory pathways for AI in healthcare. In recognition of the need for frameworks that can adjust to the iterative nature of AI development and learning, the FDA has started to develop regulatory approaches for medical devices that use AI. High-risk AI applications in healthcare are subject to strict requirements for conformance assessment, risk management, data governance, and human oversight (53,54). The EU AI act, a comprehensive regulatory framework for AI, classifies AI systems according to their risk level. The goal of these regulatory initiatives is to guarantee the ethical, safe, and efficient use of AI in clinical settings; however, developers and healthcare providers face compliance challenges as a result of these changing regulations (50).

Additional legal factors include the possibility of algorithmic bias producing discriminatory results, the need for transparency and explainability in AI decision-making to foster trust and support legal scrutiny, and intellectual property rights pertaining to AI algorithms and datasets (53). For AI to improve patient care in emergency medicine while reducing potential risks, legal and regulatory frameworks must change to keep up with the technology’s advancements. These frameworks must address concerns of safety, ethics, and accountability (43)

### Conclusions and Implications

AI, with its innovative capabilities to support triage, diagnosis, prognostication, and operational management, is rapidly transforming emergency medicine. AI tools are already being used in various ways, from clinical decision support systems and predictive analytics platforms to AI-supported emergency dispatch systems and patient-facing symptom checkers. According to preliminary assessments, these technologies have the potential to improve patient flow in emergency rooms, decrease the time it takes to treat critical conditions, and increase diagnostic accuracy, all of which can help address enduring issues like overcrowding, a lack of resources, and a heavy clinical burden. Although encouraging, the current body of evidence is still inconclusive. There have been little prospective validation or randomized clinical trials that verify improvements in patient outcomes, and the majority of published studies to date are retrospective. Premature or careless adoption of AI systems, if not thoroughly evaluated, risks unforeseen consequences, like missed diagnoses, skewed decision-making, or a decline in patient trust. If AI is to be used in emergency situations in a way that is both safe and moral, then key issues like algorithmic bias, lack of explanation, and variable integration with clinical workflows need to be carefully considered. Stakeholders in the clinical, research, ethical, and regulatory domains must consider several implications. First, to evaluate the practical effects of AI tools, there is an urgent need for thorough and methodologically sound research, especially multicenter prospective studies. Meaningful outcomes such as mortality, complication rates, patient satisfaction, and system-level efficiency should be included in these studies in addition to accuracy metrics. To identify deterioration over time and guarantee continued safety and relevance, systems for continuous performance monitoring and model recalibration should be put in place concurrently. Second, the deployment of AI must continue to revolve around ethical implementation. This means creating inclusive, equitable, and transparent systems with datasets that reflect a range of demographics and use cases. When implementing AI, hospitals should make sure that emergency personnel are properly trained in AI literacy and

that system design incorporates human oversight. Before new tools are put into use, institutional review boards or AI ethics committees may be crucial in ensuring that they are in line with ethical requirements and clinical needs. Third, it's crucial to navigate the constantly changing legal and policy landscape. Precise liability standards are required to maintain clinician trust and establish accountability in the event of AI-related harm. GDPR and HIPAA compliance, among other privacy laws, must be proactively incorporated into system architecture rather than being an afterthought. Crucially, legal frameworks ought to develop in tandem with technological advancements, providing safeguards without impeding responsible advancement. Last but not least, successful AI integration in emergency medicine will require interdisciplinary collaboration. To guarantee that AI systems are not only technically sound but also clinically beneficial, morally sound, and socially acceptable, clinicians, data scientists, engineers, ethicists, and legislators must collaborate from the very beginning of development. While working with legal experts can help anticipate and mitigate risks related to consent, bias, and accountability, involving frontline users in the design process can help ensure that tools are in line with the complex realities of the ED.

## Conclusion

Considering all factors, AI holds immense potential to improve the promptness, precision, and fairness of emergency care. However, achieving this potential will require more than just technological advancement; it will also require our shared dedication to evidence-based development, ethical responsibility, and operational and legal preparedness. When used carefully, AI can be a strong ally of emergency physicians, complementing human knowledge rather than taking its place and ultimately helping to create a more secure, responsive, and compassionate emergency care system.

## Ethics

**Acknowledgement:** The study was supported by the World Academic Council of Emergency Medicine (WACEM).

## Footnotes

### Author Contributions

Concept: T.B., I.S., L.S., Design: T.B., I.S., E.F.V., L.S., Data Collection or Processing: I.S., M.P., L.S., Analysis or Interpretation: T.B. I.S., E.F.V., M.P., F-X.D., A.L., L.S., Literature Search: T.B. I.S., M.P., F-X.D., A.L., L.S., Writing: T.B. I.S., E.F.V., M.P., F-X.D., A.L., L.S.

**Conflict of Interest:** No conflict of interest was declared by the authors.

**Financial Disclosure:** The authors declared that this study received no financial support.

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