International Journal of Medical Informatics 197 (2025) 105838

Contents lists available at ScienceDirect

International Journal of Medical Informatics

journal homepage: www.elsevier.com/locate/ijmedinf

AI-driven triage in emergency departments: A review of benefits, challenges, and future directions

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ARTICLE INFO

Keywords:
AI-driven triage
Emergency Department
Patient prioritization
Machine learning
Healthcare innovation

ABSTRACT

Background: Emergency Departments (EDs) are critical in providing immediate care, often under pressure from overcrowding, resource constraints, and variability in patient prioritization. Traditional triage systems, while structured, rely on subjective assessments, which can lack consistency during peak hours or mass casualty events. AI-driven triage systems present a promising solution, automating patient prioritization by analyzing real-time data, such as vital signs, medical history, and presenting symptoms. This narrative review examines the key components, benefits, limitations, and future directions of AI-driven triage systems in EDs.
Method: This narrative review analyzed peer-reviewed articles published between 2015 and 2024, identified through searches in PubMed, Scopus, IEEE Xplore, and Google Scholar. Findings were synthesized to provide a comprehensive overview of their potential and limitations.
Results: The review identifies substantial benefits of AI-driven triage, including improved patient prioritization, reduced wait times, and optimized resource allocation. However, challenges such as data quality issues, algorithmic bias, clinician trust, and ethical concerns are significant barriers to widespread adoption. Future directions emphasize the need for algorithm refinement, integration with wearable technology, clinician education, and ethical framework development to address these challenges and ensure equitable implementation.
Conclusion: AI-driven triage systems have the potential to transform ED operations by enhancing efficiency, improving patient outcomes, and supporting healthcare professionals in high-pressure environments. As healthcare demands continue to grow, these systems represent a vital innovation for advancing emergency care and addressing longstanding challenges in triage.

1. Introduction

Emergency Departments (EDs) are fundamental to modern healthcare systems, offering critical care to patients presenting with a wide range of health conditions, from minor injuries to severe, life-threatening emergencies. EDs must provide timely, efficient care, often as the frontline response for individuals who may not have other immediate access to healthcare [1,2]. However, the increasing demand for emergency services, coupled with limited resources, has created a significant challenge of overcrowding in EDs worldwide. This overcrowding can compromise patient care, resulting in delayed treatment, increased morbidity, and prolonged suffering for patients awaiting attention. The strain also impacts healthcare providers, leading to higher stress levels, burnout, and decreased job satisfaction, further

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https://doi.org/10.1016/j.ijmedinf.2025.105838
Received 9 January 2025; Received in revised form 11 February 2025; Accepted 13 February 2025
Available online 15 February 2025
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affecting the quality of care delivered [3].

In response to this, EDs have traditionally used structured triage systems, such as the Emergency Severity Index (ESI) and the Manchester Triage System (MTS), to prioritize patients based on urgency [2,4]. The goal of these systems is to quickly assess each patient's condition and categorize them according to the severity of their symptoms. This prioritization is essential for ensuring that critically ill patients receive prompt attention, while those with less severe conditions wait longer. However, these traditional triage systems, despite being widely used and standardized, rely significantly on subjective clinical judgment, which may vary among practitioners [2,5]. Although clinicians are trained in triage protocols, inconsistencies and biases can occur, especially during periods of high patient volumes, such as peak hours or in the context of mass casualty events. Additionally, these systems can be time-consuming, particularly when EDs are experiencing severe overload, which further delays the provision of timely care to those in need.

The limitations of traditional triage have led to the exploration of innovative solutions to improve efficiency and consistency in EDs, with AI-driven triage systems emerging as a promising advancement. Recent years have seen considerable developments in artificial intelligence (AI) and machine learning (ML), fields that enable computers to analyze large datasets, recognize patterns, and make decisions that closely mimic human reasoning [6] These advancements offer new possibilities for EDs, where AI can assist in streamlining triage by processing vast amounts of patient data—including vital signs, symptoms, medical history, and demographics—to assess and categorize patients more objectively and quickly. Unlike traditional systems, AI-driven triage does not depend solely on real-time clinician evaluation; instead, it applies standardized algorithms to data inputs, reducing subjectivity and aiming to deliver more consistent results.

The potential benefits of AI-driven triage in the ED setting are significant. First, these systems have the capacity to evaluate multiple variables in a matter of seconds, a task that would be difficult and time-consuming for clinicians to perform, especially under pressure. With AI, the triage process can prioritize patients not only based on their presenting symptoms but also by considering historical data, which may indicate a higher risk of complications in certain cases. For instance, a patient with a history of cardiovascular disease who presents with chest pain might be triaged as a higher priority than a patient with similar symptoms but no significant medical history, thereby improving the accuracy and relevance of triage outcomes [7]. Furthermore, AI-driven triage systems offer EDs a way to manage resources more effectively, particularly during high-volume periods. By automatically adjusting patient prioritization based on real-time conditions and resource availability, AI systems can help ensure that ED resources, such as staff, beds, and diagnostic tools, are allocated more efficiently. This resource optimization is crucial not only for enhancing patient outcomes but also for maintaining the overall workflow of the ED and reducing the stress on healthcare providers [8,9].

This narrative review seeks to explore the recent advancements in AI-driven triage systems, focusing on their operational impact in EDs and their potential to improve patient outcomes. By examining current research, case studies, and applications of AI in triage, this review aims to provide an in-depth understanding of how these technologies can enhance ED efficiency, address the limitations of traditional triage methods, and potentially revolutionize emergency care. Ultimately, this review also discusses the challenges and ethical considerations that come with AI integration in healthcare, acknowledging that while the potential is considerable, successful implementation will require careful planning, rigorous validation, and sustained commitment to quality care in the face of advancing technology.

2. Methods

A systematic search of relevant literature was performed using electronic databases, including PubMed, Scopus, IEEE Xplore, and Google Scholar, to identify studies on AI-driven triage systems in Emergency Departments (EDs). The search terms applied included "AI-driven triage," "machine learning in emergency medicine," "natural language processing in healthcare," "real-time analytics in triage," and "ethical considerations in AI triage." The search was restricted to peer-reviewed articles published in English between 2014 and 2024 to ensure the inclusion of recent advancements in the field.

The article selection process followed a structured approach to enhance transparency and reproducibility. Inclusion criteria required that studies focus on the application of artificial intelligence or machine learning in ED triage, describe key components such as algorithms, natural language processing, and real-time analytics, or address challenges like bias, data quality, and ethical considerations. Additionally, studies presenting empirical evidence on the benefits, limitations, or implementation of AI-driven systems in emergency care were included. Exclusion criteria filtered out articles not directly related to AI in emergency settings, studies lacking methodological rigor, and papers focused solely on non-emergency healthcare applications.

After identifying eligible studies, data extraction was conducted using a structured approach to capture relevant information. Extracted data included descriptions of AI components in triage, reported benefits such as improved patient prioritization and resource optimization, identified limitations including data integration and algorithmic bias, and recommendations for future research and implementation strategies. The extracted findings were synthesized thematically to provide a comprehensive and evidence-based discussion, ensuring a balanced representation of the potential and challenges of AI-driven triage in emergency care.

3. Key components of AI-Driven triage systems

AI-driven triage systems represent a convergence of multiple advanced technologies, each designed to enhance the efficiency and accuracy of patient assessment in Emergency Departments – Eds [6]. These systems rely on several critical components—namely, data collection and processing, algorithmic models, real-time analytics and feedback, and natural language processing (NLP) for unstructured data. Recent studies highlight the effectiveness of AI-driven triage systems in enhancing triage speed and accuracy, with many systems demonstrating improved predictive power compared to traditional methods [10]. In a comparative study on sepsis detection, AI-driven triage algorithms outperformed standard ESI protocols, reducing the time to intervention and demonstrating better accuracy in identifying high-risk patients [11]. Another study found that implementing NLP within AI-driven triage systems significantly enhanced clinicians' ability to detect early signs of respiratory complications, underscoring NLP's role in managing unstructured clinical data [10].

Moreover, real-world applications of AI-driven triage have shown positive results in reducing patient wait times and improving resource allocation. For instance, one ED reported a 30 % reduction in average patient wait time after integrating a real-time AI triage system that automatically adjusted prioritization based on patient vitals and ED capacity [10]. Together, these key components—data collection and processing, algorithmic models, real-time analytics, and NLP for unstructured data—are foundational to AI-driven triage systems and represent significant advancements in ED triage technology. Fig. 1 illustrates the fundamental components and process flow of AI-driven triage systems implemented in Emergency Departments (EDs). Current evidence supports their potential to streamline patient prioritization, reduce overcrowding, and improve ED outcomes, ultimately contributing to a more responsive and effective healthcare system [1,12].

3.1. Data collection and processing

A primary component of AI-driven triage is the collection and processing of extensive patient data, a process that forms the foundation for

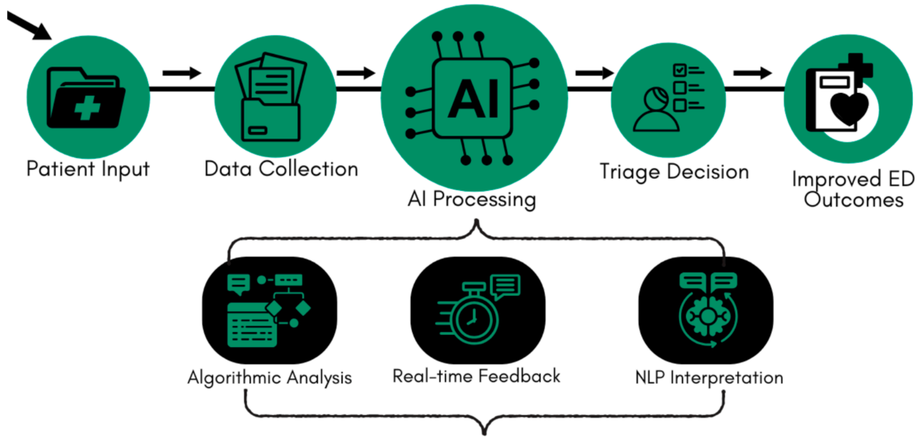

Fig. 1. Schematic representation of the key components and workflow in AI-driven triage systems for Emergency Departments. The diagram delineates sequential progression from initial patient data input to the ultimate triage decision and resultant outcomes. The process initiates with patient data acquisition, followed by systematic data collection and processing. The core of the system comprises AI processing, which integrates three critical elements: algorithmic analysis, real-time feedback mechanisms, and natural language processing (NLP) for unstructured data interpretation.

any predictive or decision-making AI model. Data inputs for these systems typically include vital signs, symptoms, medical history, and demographic information, all of which can provide nuanced insights into a patient's clinical condition [13]. For example, wearable devices can capture heart rate, respiratory rate, and oxygen saturation, data points that are critical in identifying patients at risk of deterioration [14].

Furthermore, studies indicate that the integration of EHR data with real-time inputs enables AI-driven triage systems to adapt to a wide array of patient presentations more effectively. In particular, combining historical health data with present clinical observations has been shown to enhance predictive accuracy, as patients with certain chronic conditions or past medical histories may be at increased risk even with mild presentations. By compiling and processing these data types, AI-driven systems can form a more comprehensive profile of each patient, setting the stage for accurate risk categorization.

3.2. Algorithmic models

At the core of AI-driven triage are machine learning (ML) algorithms capable of analyzing and categorizing patient risk levels based on complex data patterns. Various models are used in AI-driven triage systems, including decision trees, neural networks, and regression models. These models are trained on extensive historical datasets, which provide the foundation for AI systems to recognize clinical patterns associated with critical conditions. For instance, neural networks—a type of deep learning model—have been found particularly effective in recognizing subtle, non-linear patterns in patient data, leading to more accurate prioritization in triage [15].

One example of an effective application is the use of decision tree algorithms in fast-paced triage environments. Decision trees provide interpretable pathways, enabling clinicians to understand why certain patients are prioritized over others.

3.3. Real-Time analytics and feedback

AI-driven triage systems enhance Emergency Department (ED) efficiency by providing real-time analytics and feedback, enabling clinicians to make swift, informed decisions, especially during peak hours or mass casualty incidents. Studies indicate that instant feedback mechanisms help prioritize patients effectively, reducing treatment delays even in high-stress environments [16]. For example, AI can detect sudden spikes in vital signs indicative of sepsis, prompting immediate evaluation and intervention. Additionally, real-time analytics optimize resource management, dynamically adjusting prioritization based on patient load, bed availability, and on-call specialists. This adaptability improves patient throughput, preventing bottlenecks that could lead to deterioration [16]. By reducing clinician cognitive load, AI-driven triage allows providers to focus on critical decision-making rather than continuously monitoring for sudden patient status changes.

3.4. Natural language processing (NLP) for unstructured data

In the realm of healthcare, vast amounts of critical information are often embedded within unstructured data sources like patient complaints, clinician notes, and medical histories. Natural Language Processing (NLP) enables AI systems to process and interpret this unstructured data, adding a layer of depth to the triage process. By leveraging NLP, AI-driven triage systems can analyze textual inputs from EHRs, allowing them to capture nuances that might be overlooked in structured data alone. For instance, a patient's self-reported symptoms or a physician's observations might hint at subtle risk factors that are not readily apparent through quantitative measures alone.

Current evidence underscores the value of NLP in extracting and interpreting relevant clinical details from large amounts of unstructured data, which can improve triage accuracy. For example, studies show that NLP can detect early warning signs of conditions like sepsis or stroke based on textual descriptions in clinical notes, allowing the AI system to flag these cases for immediate attention [17]. Additionally, NLP can assist in standardizing patient descriptions, making it easier to compare cases and identify patterns that suggest critical conditions. This capacity to handle unstructured data ensures that AI-driven triage systems maintain a holistic understanding of each patient, improving the reliability and thoroughness of the triage process.

4. Benefits of AI-Driven triage systems in emergency Departments

AI-driven triage systems are transforming Emergency Departments (EDs) by addressing overcrowding, inconsistent prioritization, and resource allocation challenges. Studies and real-world applications highlight their benefits, including reduced patient wait times and improved outcomes, particularly in time-sensitive cases [9]. One study reported a 30 % decrease in wait times and a notable reduction in adverse outcomes among high-risk patients after implementing an AI-driven triage system. During mass casualty events, AI also optimized resource distribution, enabling EDs to manage high patient volumes more efficiently [17].

Beyond patient outcomes, AI-driven triage systems positively impact clinician workload and decision-making [18]. By automating initial assessments and generating objective risk scores, these systems reduce cognitive load, allowing clinicians to focus on complex cases and critical decisions. This support helps alleviate burnout and enhances job satisfaction, ultimately benefiting patient care [10]. Fig. 2 provides a concise visual representation of the transformative potential of AI technologies in emergency healthcare settings.

4.1. Enhanced patient prioritization and reduced wait times

One of the most significant benefits of AI-driven triage systems is their ability to rapidly assess and prioritize patients according to urgency, thus reducing wait times, particularly for critically ill patients. AI algorithms analyze multiple data points in real time—such as vital signs, symptoms, and medical history—allowing them to recognize high-risk cases within seconds. This expedited assessment is especially valuable for acute conditions, like strokes or heart attacks, where minutes can make a substantial difference in patient outcomes [19]. Current evidence supports the effectiveness of AI-driven triage in reducing treatment delays. For instance, studies show that AI-based triage systems can reduce time-to-treatment by up to 20 %, a considerable improvement that translates to faster intervention and better prognoses in critical cases [6,10]. By minimizing the time patients wait for necessary treatment, AI-driven triage systems enhance the overall quality of emergency care and improve patient satisfaction.

4.2. Consistency and Objectivity in triage decisions

Traditional triage processes depend on subjective clinical assessments, which can vary between clinicians and are influenced by factors such as experience, workload, and cognitive biases. This variability in decision-making can result in inconsistent prioritization, with some patients potentially receiving delayed care due to human error [20,21]. AI-driven triage systems address this issue by providing consistent, data-driven evaluations based on objective criteria, minimizing the influence of subjective judgment. AI algorithms are designed to follow standardized prioritization protocols, ensuring that each patient is assessed according to established risk factors rather than individual discretion. Research shows that AI-driven systems reduce triage variability and human error, which can lead to more accurate and fair patient prioritization [6]. This consistency not only enhances patient safety but also supports clinicians by offering a reliable tool that aligns with evidence-based practices, thereby improving overall decision-making in the ED.

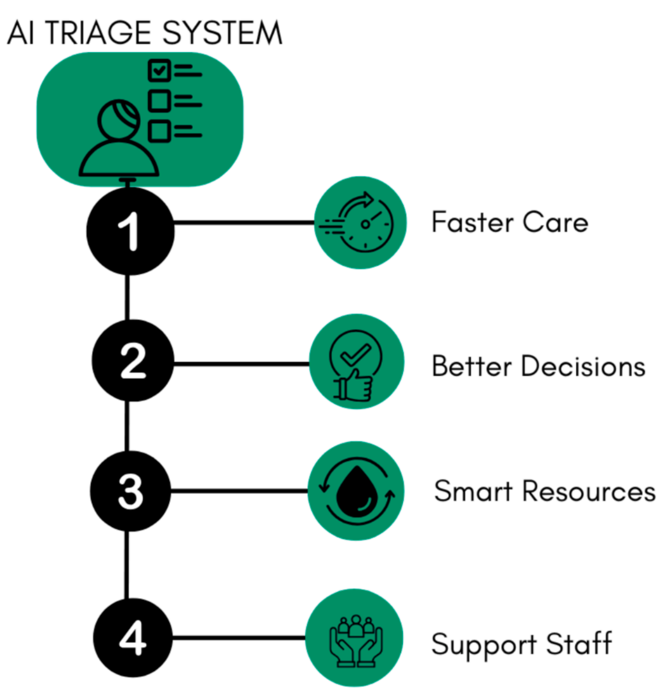

Fig. 2. Core benefits of AI-driven triage systems in Emergency Departments. The diagram is structured with "AI Triage System" as the central element, from which four key benefit categories emanate. These categories are represented as: (1) "Faster Care," indicating reduced wait times and improved efficiency; (2) "Better Decisions," reflecting enhanced clinical decision-making and risk assessment; (3) "Smart Resources," representing optimized resource allocation and utilization; and (4) "Support Staff," denoting reduced cognitive load and enhanced support for clinical personnel.

4.3. Adaptability in mass casualty events

In mass casualty incidents (MCIs), such as natural disasters, pandemics, or large-scale accidents, EDs often face an overwhelming influx of patients that exceeds their resources. Under such circumstances, traditional triage methods may be insufficient, as they lack the capacity to adjust dynamically to the sudden surge in patient volume and limited resources. AI-driven triage systems offer adaptive capabilities that are crucial in these high-demand scenarios, enabling real-time prioritization adjustments based on patient volume, severity, and resource availability. AI-driven systems can dynamically modify their criteria to match the ED's current capacity and the urgency of each case. For example, during a natural disaster, an AI system may prioritize patients with survivable but critical injuries for immediate intervention, while delaying care for minor injuries until resources are available [22].

This adaptability has been shown to be highly effective in optimizing ED workflows and improving patient outcomes during MCIs, as it ensures that resources are allocated where they are most needed. This flexibility also provides support to ED staff, reducing the cognitive and emotional stress associated with managing a high volume of patients under extreme conditions.

4.4. Efficient resource allocation

Efficient resource management is critical in Emergency Departments (EDs), where demand fluctuates unpredictably and resources—such as beds, diagnostic tools, and staff—are often constrained. AI-driven triage systems improve resource allocation by predicting ED demand and patient outcomes, allowing for optimized staff schedules, bed management, and surge preparation [23]. By analyzing historical data and real-time conditions, AI forecasts patient flow and adjusts resources accordingly. These predictions are particularly valuable during peak periods or seasonal outbreaks, such as flu season. For instance, if AI anticipates a surge in patient volume, ED managers can proactively adjust staffing levels or allocate additional treatment areas to prevent overcrowding. This proactive resource management enhances patient throughput, reduces bottlenecks, and ensures a more efficient, responsive emergency care environment [12].

5. Future directions and recommendations

To maximize the potential of AI-driven triage systems and ensure their responsible, effective use in Emergency Departments (EDs), several key steps are needed. These include refining algorithms, integrating wearable technology, prioritizing clinician education, developing ethical frameworks, and supporting ongoing research. Together, these strategies can address current limitations, improve system accuracy, and build clinician trust in AI-based triage, ultimately enhancing patient outcomes in emergency care settings.

5.1. Refinement of algorithms

For AI-driven triage systems to accurately assess patient risk across diverse populations, continuous refinement and validation of algorithms are crucial. Current AI systems are often trained on datasets that may not fully represent the diversity of patient demographics or conditions seen in EDs. By developing algorithms with data from a wide range of sources—including data reflecting different ethnicities, age groups, and socioeconomic backgrounds—developers can enhance the reliability and fairness of AI-driven triage [24]. Refining algorithms also involves regular testing and updates to keep pace with advances in medical knowledge and changes in patient demographics. For example, an algorithm initially trained on data from one population may require revalidation to perform accurately in different clinical settings. Research has shown that using diverse and representative datasets helps reduce bias in AI models, thus leading to more equitable healthcare delivery [25]. Regular validation with varied datasets can ensure that AI-driven triage systems maintain high levels of accuracy, fairness, and adaptability across EDs.

5.2. Integration with wearable technology

Integrating AI-driven triage systems with wearable health technology could significantly improve real-time monitoring and responsiveness, enabling more dynamic and accurate triage decisions. Wearable devices, such as smartwatches or portable ECG monitors, can continuously capture patient vitals, including heart rate, respiratory rate, oxygen saturation, and activity levels. This real-time data can provide a constant stream of updates to AI triage systems, offering a more comprehensive view of a patient's evolving condition, especially in situations where symptoms may change rapidly. For instance, in cases of acute heart failure or respiratory distress, wearables can detect subtle changes in vitals and notify clinicians through the AI system, allowing for proactive intervention. This integration is particularly valuable in high-acuity settings, where rapid condition changes could otherwise go unnoticed. Research in wearable technology and emergency medicine suggests that using wearables to feed data into AI systems can improve early detection and intervention, as well as reduce the need for repeated manual assessments [26]. Fig. 3 shows the key elements of the integration process, highlighting the potential for improved real-time monitoring and responsiveness in emergency care settings. Future AI-driven triage systems should prioritize compatibility with wearable devices, which can further enhance ED efficiency and patient safety.

5.3. Education and training for clinicians

The successful adoption of AI-driven triage systems hinges on clinician understanding and trust. To foster acceptance, healthcare institutions should implement comprehensive training programs that equip clinicians with the knowledge needed to work alongside AI. Training should include information on how the system functions, the types of data it uses, and the factors it considers when making triage recommendations. Additionally, providing real-world examples of how AI-driven triage has improved patient outcomes can help demonstrate its value in clinical practice. Educating clinicians on the limitations and potential biases of AI systems is equally important, as it allows them to critically assess the system's output and override AI recommendations if necessary. Studies indicate that clinicians are more likely to trust and utilize AI when they understand its processes and limitations. Transparent, evidence-based training can help build confidence in AI systems and foster collaborative human-AI workflows in ED settings [27,28].

5.4. Ethical frameworks and Policy development

The integration of AI in healthcare requires clear ethical guidelines and policies that address critical issues such as algorithmic bias, data privacy, and accountability. Ethical frameworks should clearly define the roles and responsibilities of AI developers, healthcare providers, and institutions, ensuring structured protocols for data security, patient consent, and AI decision-making. Given that AI systems rely on vast amounts of sensitive patient data, strict adherence to regulatory standards like HIPAA in the U.S. and GDPR in Europe is essential to safeguard patient confidentiality and prevent unauthorized data access. Ensuring compliance with these regulations is particularly important in Emergency Departments (EDs), where rapid patient triage involves real-time data processing and AI-based risk assessment. If not properly managed, these processes could increase the risk of data breaches, unauthorized access, or misuse of sensitive patient information, ultimately compromising patient trust and legal compliance [29].

Algorithmic bias remains a significant ethical challenge, as AI models trained on historical healthcare data can perpetuate disparities in triage decisions. For example, studies have shown that some AI-driven healthcare systems have exhibited racial and gender biases in patient risk assessment, leading to inequitable prioritization of care. A well-documented case involved an AI model used in emergency settings that systematically underestimated the severity of illness in Black patients compared to White patients, resulting in delayed care and poorer outcomes. This highlights the urgent need for bias detection mechanisms and algorithmic transparency to prevent unintended discrimination. To mitigate such risks, institutions should implement bias audits, fairness metrics, and algorithmic transparency measures, such as requiring AI developers to conduct regular bias testing and ensuring that models are trained on diverse, representative datasets [30]. Additionally, explainability techniques like interpretable machine learning models can help clinicians understand AI recommendations, fostering trust and reducing reliance on opaque "black-box" algorithms.

Another ethical concern is accountability in cases of AI-driven triage errors. Policies must clearly outline who is responsible—whether it be AI developers, healthcare institutions, or individual clinicians—when AI-generated recommendations contribute to adverse patient outcomes. Real-world examples, such as the misclassification of critically ill patients in AI-driven triage systems, underscore the need for human oversight in AI decision-making. For instance, a hospital in Europe piloting an AI triage system found that patients presenting with atypical symptoms of sepsis were consistently downgraded in priority due to incomplete pattern recognition by the AI model, leading to delayed intervention and increased mortality rates. This case reinforces the necessity of establishing legal and ethical frameworks that ensure clinicians remain the final authority in patient care decisions. Ethical guidelines should establish AI-human collaboration protocols, ensuring that AI serves as a decision-support tool rather than an autonomous decision-maker. Institutions can adopt governance models like the

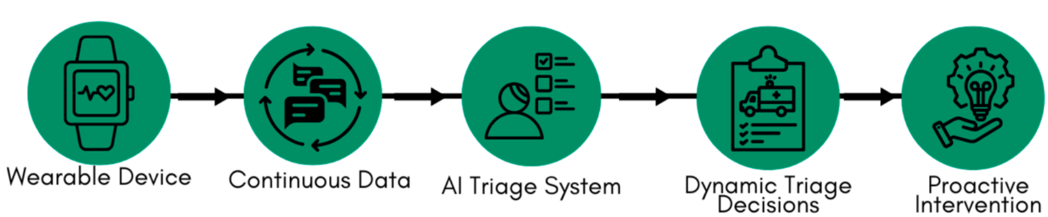

Fig. 3. Schematic representation of AI-driven triage system integration with wearable technology in Emergency Departments. The diagram depicts a simplified flow of data from wearable devices to the AI triage system, culminating in enhanced triage decisions. This visual representation emphasizes the continuous nature of patient monitoring and the potential for rapid response to changes in patient condition.

"Human-in-the-Loop" framework, which mandates clinician validation of AI-generated triage decisions before implementation. Moreover, institutional AI ethics committees should be involved in regular audits and assessments to review AI system performance and adjust protocols accordingly.

Finally, as AI technology evolves, ethical and regulatory frameworks must be adaptable to emerging challenges. AI systems that perform well in controlled research environments may fail in real-world settings due to the dynamic nature of emergency care, where patient presentations can vary widely. Continuous evaluation through AI ethics committees, third-party audits, and adaptive governance structures can help refine ethical standards as AI applications in healthcare expand. Governments and regulatory bodies must also establish legally binding guidelines on AI accountability, liability distribution, and malpractice considerations to protect both patients and healthcare providers. Additionally, as AI expands into global healthcare settings, frameworks must address cross-border regulatory inconsistencies to ensure ethical AI use in diverse healthcare systems. By establishing enforceable policies on bias detection, privacy safeguards, and human oversight, healthcare organizations can ensure that AI-driven triage systems are deployed responsibly, equitably, and transparently, ultimately benefiting both patients and providers [29].

5.5. Ongoing research and clinical trials

To build robust evidence on the efficacy and safety of AI-driven triage systems, ongoing research and clinical trials are essential. Future studies should include randomized controlled trials (RCTs) and multi-center studies that test these systems in varied clinical settings and patient populations. Such research will help determine the generalizability of AI-driven triage systems, revealing insights into their performance across different demographics, hospital capacities, and ED workflows. RCTs can provide high-quality evidence on the impact of AI-driven triage on patient outcomes, wait times, and ED efficiency. Multi-center studies, on the other hand, can assess how well AI-driven triage systems perform across different healthcare environments, providing critical data on their adaptability and reliability. Furthermore, ongoing research should focus on long-term impacts of AI-driven triage on healthcare costs, clinician workload, and patient satisfaction, as these factors contribute to the sustainability of AI in emergency care. Collaboration between AI developers, healthcare institutions, and academic researchers will be crucial for designing comprehensive studies and interpreting results. Continued research can refine AI algorithms, validate them against clinical outcomes, and build an evidence base that supports safe, effective implementation in EDs.

6. Limitations of the review

This narrative review provides a comprehensive exploration of AI-driven triage systems in Emergency Departments (EDs), but it is important to acknowledge its limitations. First, the review is narrative in nature, which inherently lacks the methodological rigour of systematic reviews or *meta*-analyses. As a result, while it provides a broad synthesis of the existing literature, it does not quantitatively evaluate the strength of evidence or statistical relationships. Another limitation is the restriction to peer-reviewed articles published in English between 2014 and 2024. This criterion excludes potentially valuable insights from older studies, grey literature, and non-English publications, which may contain relevant findings about AI applications in healthcare. Consequently, the review's scope may be narrower than what a more inclusive approach could achieve.

Additionally, the review relies on the available literature, which may itself be limited by publication bias. Studies reporting positive outcomes for AI-driven triage systems are more likely to be published, potentially leading to an overrepresentation of their benefits and underreporting of challenges or negative findings. This bias could skew the interpretation of the feasibility and effectiveness of AI systems in EDs. Lastly, this review does not address region-specific variations in healthcare systems and infrastructure, which may influence the applicability of AI-driven triage systems in different settings. Future research should consider regional disparities to better contextualize findings and support more targeted implementation strategies.

Despite these limitations, this review serves as a foundational discussion of the potential, challenges, and future directions of AI-driven triage in emergency care. It highlights areas requiring further research, particularly through systematic methodologies and diverse datasets, to validate and expand upon its conclusions.

7. Conclusion

AI-driven triage systems represent a transformative solution to some of the most persistent challenges facing emergency departments (EDs), including overcrowding, inconsistent prioritization, and resource limitations. These systems leverage advanced algorithms and vast data inputs to improve patient assessment, enabling faster and more accurate prioritization of cases. The benefits—such as enhanced patient prioritization, reduced wait times, and improved decision-making—highlight the potential of AI to optimize ED operations and improve overall patient outcomes. However, to fully realize these benefits, it is essential to address the associated challenges. Issues such as data quality, algorithmic bias, clinician trust, and ethical considerations require ongoing attention. By continuously refining algorithms, incorporating diverse datasets, and establishing clear ethical frameworks, healthcare systems can ensure that AI-driven triage systems are both effective and equitable. In a time when healthcare demands are rapidly increasing, AI-driven triage offers a promising innovation for emergency medicine. As research and development progress, these systems have the potential to revolutionize emergency care by optimizing resource allocation, supporting healthcare professionals, and ultimately enabling the delivery of timely, efficient, and high-quality care to patients in need.

CRediT authorship contribution statement

Adebayo Da'Costa: Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Conceptualization. **Jennifer Teke:** Writing – review & editing, Writing – original draft, Methodology, Investigation. **Joseph E. Origbo:** Writing – review & editing, Writing – original draft, Investigation, Formal analysis. **Ayokunle Osonuga:** Writing – review & editing, Writing – original draft. **Eghosasere Egbon:** Writing – review & editing, Writing – original draft, Visualization. **David B. Olawade:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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