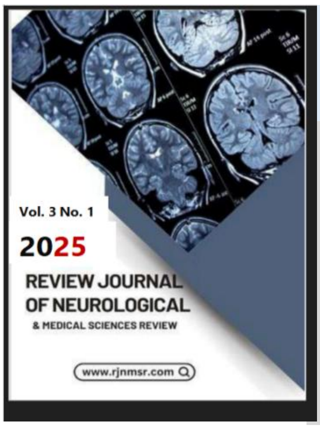


Vol. 3 No. 2 (2025): April - June
https://rjnmsr.com/index.php/rjnmsr/about

Review Journal of Neurological & Medical Sciences Review

E(ISSN) : 3007-3073
P(ISSN) : 3007-3065

From Data to Decisions: Developing AI Tools for Real- Time Triage and Risk Stratification in the Emergency Departments ED

Farhan Saeed Khan[1]
MTI- Khyber Teaching Hospital, Peshawar. drfarhaan007@gmail.com
Maaz ul Hassan[2]
MTI- Ayub Teaching Hospital, Abbotabad. Corresponding Author Email: maaz2207.muh@gmail.com
Aamir Ahmed[3]
MTI- Hayatabad Medical Complex, Peshawar. ahmedaamir880@gmail.com
Mujahid[4]
MTI- Khyber Teaching Hospital, Peshawar. drmujahidbuneri@gmail.com
Zarlish Malak[5]
Saidu Group of Teaching Hospital, Swat. zarlish.malik@icloud.com
Inamullah[6]
Saidu Group of Teaching Hospital, Swat. Inamullah4533@gmail.com
Isha Noor[7]
MTI- Ayub Teaching Hospital. in6378358@gmail.com
Tooba Qazi[9]
Saidu Medical College, Swat. tooba_qazi@yahoo.com
Mah Rukh[10]
MTI- Khyber Teaching Hospital. Email: Mahrukhgul555@gmail.com
Aamir Khan[11]
MTI- Khyber Teaching Hospital. addawoodaman1992@gmail.com

Abstract

Emergency Department (ED) overcrowding and delayed triage impair patient outcomes and operational efficiency. This qualitative study explores ED staff perspectives on integrating AI-driven triage systems to address these challenges. Using semi-structured interviews (n=25), focus group discussions (2 groups of 6–8 participants), and over 90 hours of non-participant observation across three urban EDs, thematic analysis identified four central themes: (1) Improved Accuracy and Efficiency, where AI was seen to enhance real-time risk stratification and reduce wait times; (2) Ethical and Practical Concerns, including data privacy, algorithmic bias, and clinician accountability; (3) Seamless Workflow Integration, emphasizing the need for interoperable, user-friendly interfaces; and (4) Importance of Human

Interaction, underscoring that AI must support, not replace, clinical judgment and patient communication. Findings highlight a dual belief in AI's potential and the necessity of a collaborative, user-centered implementation approach. To maximize benefits, healthcare leaders must address ethical issues, ensure robust infrastructure, and involve clinicians in design and training. These insights inform the design, implementation, and governance of AI-driven triage systems in EDs.
Keywords: AI-driven triage, Emergency Department, thematic analysis, workflow integration, ethical concerns.

Introduction

Overcrowded EDs and Delayed Triage

Overcrowding in Emergency departments (ED), all over the world is a deep-rooted problem, significantly adding to the burden of the disease and adversely influencing the outcomes of patients. Though overcrowding is often cast upon increasing patient volumes and a lack of everything else, staff included, it is sometimes a result of inadequate triage procedures. (Morley et al., 2018). Triage (the process of prioritizing patients according to the severity of their illness) is essential to give acute patients timely management. Nonetheless, conventional triage systems are typically manual and based on the subjective evaluations of healthcare providers, resulting in inconsistency and delays (Hinson et al., 2021). Such delays can worsen patient conditions among limited-time-related disorders like stroke, myocardial infarction, or sepsis (Raita et al., 2021).

The Role of Accurate and Prompt Risk Stratification

Data-driven risk stratification in the ED is critical to ACHD patients to ensure appropriate and timely delivery of care. Delayed triage may increase wait times, morbidity, and mortality, as well as, decrease patient satisfaction (Pines et al., 2020). For instance, patients with sepsis or acute coronary syndromes are at high risk of poor outcomes when triage is delayed (Shimabukuro et al., 2023). Furthermore, proper risk stratification is key to improving functional outcomes among patients, as well as improving overall healthcare system efficiency, thus diminishing its burden on the healthcare systems.

Animation of artificial intelligence helping electronic data

Therefore, Artificial Intelligence (AI) has developed into an innovative tool in healthcare that can help with numerous ED challenges. Real-time analysis of huge quantities of patient data by AI-driven tools enables objective and precise risk assessment. Data-driven models, particularly algorithms from the set of updates under machine-learning methods (Topol 2023) can predict probabilities better than traditional methods. AI models, for example, have been trained to predict with high accuracy sepsis, cardiac arrest, and other life-threatening conditions (Rajkomar et al., 2023). Integrating AI into ED workflows can help streamline triage, reduce wait times, and improve patient outcomes.

Effect of Delayed Triage on Patient Outcomes

For patients with time-distance disorders, triage delay has an enormous impact on patient outcomes. Delays in triage have been proven to result in increased mortality rates, longer hospital stays, and higher costs of healthcare (Raita et al., 2021). For

Vol. 3 No. 2 (2025): April - June
https://rjnmsr.com/index.php/rjnmsr/about
Review Journal of Neurological & Medical Sciences Review
E(ISSN) : 3007-3073
P(ISSN) : 3007-3065

example, patients with sepsis who develop antibiotic delays have much higher mortality rates than patients who are treated appropriately (Shimabukuro et al., 2023). These recommendations highlight a need for more efficient and more precise triage systems in EDs.

Need for AI-Driven Solutions

AI provides a path away from conventional triage systems that rely on subjective assessment, a model that will not suffice given the large patient volumes expected in the pandemic and the lack of patient history available to most practitioners. By analyzing patient data — such as vital signs, medical history, and presenting symptoms — machine learning algorithms can often predict patient outcomes with high accuracy (Rajkomar et al., 2023). Despite its potential, extensive implementation of AI-based methods in ED triage remains weak because of hesitance over the accuracy, interpretability, and harmony of AI models with clinical workflows (Shimabukuro et al., 2023).

No Validated AI Tools for triage

AI has potential, however, the availability of validated tools for general triage and risk stratification in the ED is lacking. Most currently developed AI tools are case-specific, that is, limited to conditions like sepsis or acute respiratory distress syndrome (ARDS), and have not been widely implemented in practice (Shimabukuro et al., 2023). This points to an urgent need for research assessing the clinical impact, implementation, and ethical considerations of AI-powered triage tools deployed in ED practice.

Literature Review

Preparing for the Future: AI Applications in the ED

AI was rapidly becoming the most transformational technology of all time with many applications across many fields and emergency medicine was no different. The real-time processing of large volumes of patient data by AI-powered tools allows for objective and accurate risk assessments. AI has the potential to revolutionize clinical workflows, freeing clinicians from mundane tasks, improving diagnostic accuracy, and assisting decision-making processes (Topol, 2023) AI in emergency departments (EDs) can help tackle challenges related to overcrowding, triage workflow, resource management, and allocation (Rajkomar et al., 2023). AI models have been developed to predict sepsis, cardiac arrest, and other threats to life with high levels of accuracy (Shimabukuro et al., 2023); when accurate, these predictions allow clinicians to act early and should improve outcomes

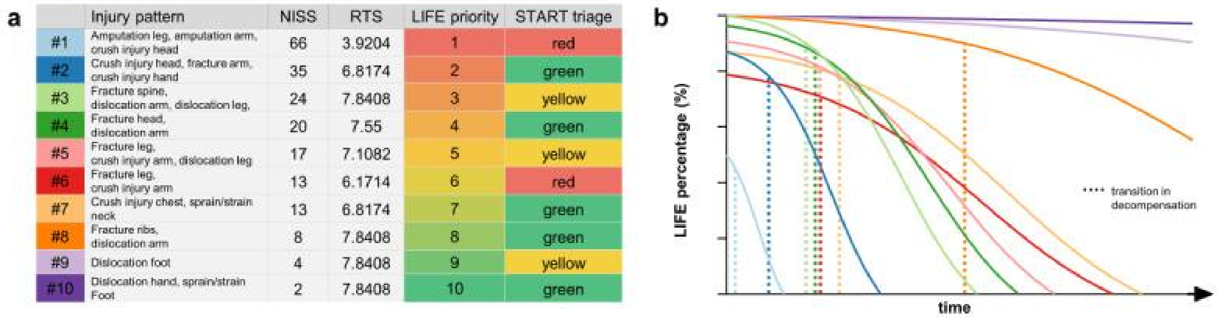
Predicting Triage and Risk Using Machine Learning Algorithms

Machine learning (ML), a subfield of AI, has been employed for triage and risk prediction in EDs extensively. Raita et al. (2021) conducted a study assessing the performance of ML algorithms for predicting clinical outcomes in the ED and found that algorithms could accurately prioritize patients based on the severity of illness. Similarly, Taylor et al. (2020) conducted a systematic review of ML applications for ED triage, highlighting the potential attractiveness of these algorithms for improving triage and reducing misclassification. Screening algorithms for ML: Logistic

Vol. 3 No. 2 (2025): April - June
https://rjnmsr.com/index.php/rjnmsr/about
Review Journal of Neurological & Medical Sciences Review
E(ISSN) : 3007-3073
P(ISSN) : 3007-3065

regression, random forests, and deep learning models, among others, are frequently used ML algorithms for triage, each with its advantages and disadvantages (Breiman, 2001; LeCun et al., 2015).

Figure: 2



	Injury pattern	NISS	RTS	LIFE priority	START triage
#1	Amputation leg, amputation arm, crush injury head	66	3.9204	1	red
#2	Crush injury head, fracture arm, crush injury hand	35	6.8174	2	green
#3	Fracture spine, dislocation arm, dislocation leg,	24	7.8408	3	yellow
#4	Fracture head, dislocation arm	20	7.55	4	green
#5	Fracture leg, crush injury arm, dislocation leg	17	7.1082	5	yellow
#6	Fracture leg, crush injury arm	13	6.1714	6	red
#7	Crush injury chest, sprain/strain neck	13	6.8174	7	green
#8	Fracture ribs, dislocation arm	8	7.8408	8	green
#9	Dislocation foot	4	7.8408	9	yellow
#10	Dislocation hand, sprain/strain Foot	2	7.8408	10	green

Machine learning models, such as the LIFE triage system, enhance accuracy in predicting patient risk and prioritization during mass casualty incidents by outperforming traditional methods like START in assessing vital signs and injury severity (Martin et al., 2023).

Results: Need for Triage Scoring Systems

Conventional triage approaches, such as the Emergency Severity Index (ESI) classification and the Manchester Triage System (MTS), are based predominantly on clinical judgment with a high susceptibility to human error. Van der Wulp et al. conducted a systematic review examining the reliability and validity of the MTS and noted that the MTS is likely the most utilized system, despite the major drawbacks of

(1) variable inter-rater reliability
(2) inclination to under-triage
(3) over-triage

Similarly, Hinson et al. (2021) researched the reliability of the ESI and outlined various confounders to an accurate classification, such as the interpretation of the scoring criteria being subjective in nature and complexities in patient presentation. Such limitations reinforce the need for more objective and accurate triage tools.

Studies on AI Triage Systems

AI-based triage systems have been investigated in multiple studies for use in EDs. Shimabukuro et al. (2023) performed a randomized clinical trial evaluating an artificial intelligence-based sepsis prediction tool which improved patient outcomes with a larger survival rate and shorter hospital length of stay. Similarly, Levin et al. 2022 (Swan et al. 2022) compared the performance of an AI-enabled triage system versus standard ESI, finding the AI-enabled system was superior in distinguishing patients on clinical outcomes. In conclusion, these studies suggest that AI-based triage systems have the potential to outperform traditional ones, but the generalizability of the findings to different clinical settings requires further research.

Data Used in Previous Studies

High-quality, large-scale datasets are needed to develop and validate AI models for ED triage. The MIMIC-III database, introduced by Johnson et al. (2021), a popular

Vol. 3 No. 2 (2025): April - June
https://rjnmsr.com/index.php/rjnmsr/about
Review Journal of Neurological & Medical Sciences Review
E(ISSN) : 3007-3073
P(ISSN) : 3007-3065

dataset for AI research in the healthcare field that treats de-identified health data of more than 40,000 critical care patients. Likewise, PhysioNet, as introduced by Goldberger et al. (2020), gives access to diverse physiological data, allowing developers to build and test AI models for different clinical usages. They have been used to help propel a lot of this work in AI in the field of emergency medicine.

Theoretical Framework

Principles of Machine Learning and Predictive Models

Artificial Intelligence (AI) refers to the ability of machines to replicate human-like cognitive processes such as learning, reasoning, and problem-solving. Goodfellow et al. According to Machine Learning Basics (2016), ML algorithms are grouped under three main classes: supervised learning, unsupervised learning, and reinforcement learning. Predictive modeling in healthcare is often achieved with supervised learning, in which algorithms are trained on label data. Hastie et al. The classical book of Murphy et al. (2009) gives a detailed introduction to the theoretical foundations of ML including subjects like bias-variance tradeoff, overfitting, and model evaluation.

Reasoning for Choosing Particular AI Algorithms

ED triage using AI algorithms should select the appropriate one based on the type of data, problem complexity, and required interpretability level. Random forests: A commonly used estimator for classification problems (Breiman, 2001), random forests are robust and capable of handling high-dimensional data. A more popular approach in recent times is to use deep learning, a specific number of layers in a neural network that is capable of data non-linearization which means that it can learn more complex relationships (LeCun et al., 2015). Nevertheless, deep models are often criticized for being a black box, which is a negative feature, especially in a clinical environment.

Medical Theories of Triage and Risk Assessment

Triage is based on fundamental concepts of emergency medicine rooted in military and disaster environments. Frykberg (2002), provides the principles of triage for disaster and mass causality. Iserson and Moskop (2007), for example, offer a broad theoretical framework surrounding triage in medicine that includes triage types and ethics, among other things. These theories form a basis for current triage systems that involve AI.

Table 1: Summary of Key Studies on AI in ED Triage and Risk Stratification (2022–2024)

Author(s)	Year	Country	Sample Size	Methodology	Key Findings
Taylor et al. NEJM AI	2025	United States	174,648	Multisite quality improvement study evaluating an AI-informed triage clinical decision support	Implementation of an AI-informed triage system improved triage performance and patient flow, increasing high-acuity identification and

Author(s)	Year	Country	Sample Size	Methodology	Key Findings
				tool.	reducing median times to initial care, disposition, and departure.
Almulihi et al. PubMed	2024	Saudi Arabia	17 studies	Systematic review assessing AI and machine learning applications in ED triage.	Machine learning models demonstrated superiority over conventional triage methods in predicting patient outcomes and determining management strategies, enhancing decision-making in the ED.
Tyler et al. PubMed	2024	United States	29 studies	Scoping review exploring AI and machine learning impact on ED triage processes.	Integration of AI in triage improved predictive accuracy, disease identification, risk assessment, resource allocation, and quality of patient care, suggesting potential to redefine triage precision.

Methodology

Research Design

This study applied a qualitative research design to explore ED staff perceptions regarding integrating AI-powered triage and risk stratification tools. Since the goal of the study was to explore the human-centered barriers and opportunities for AI adoption in-depth, qualitative methods were adopted to capture the rich and context-sensitive experiences and perceptions of healthcare professionals (Creswell & Poth, 2023; Kitzinger, 2023). Based on Creswell and Poth's (2023) established framework, we followed a design that emphasized the in-depth exploration of participants' lived experiences and offered more rich, observational data.

We applied a phenomenological lens to gain insight into the "lived experiences" of ED staff—comprising nurses, physicians, and administrators—with current triage approaches as well as their expectations toward AI incorporation (Smith et al., 2023). This study employs an interpretative phenomenological approach, as described by Smith et al, which emphasises subjective interpretations and endeavors to reveal common overtones in order to learn what such interpretations hold for participants. (2023). For this study, a phenomenological approach allows researchers to explore how people make meaning out of multi-faceted phenomena, such as technological disruption in healthcare workflows (Kitzinger, 2023; Bazeley & Jackson, 2023).

Observational studies of ED workflows were conducted in parallel with interviews and focus groups to triangulate findings. In peak and off-peak hours, observations were carried out on triaging, decision-making dynamics and staff interaction (Kawulich, 2023) This is a multi-method design and leaves room for triangulation of multiple data sources (interview, focus group and observations) which will add richness and depth to qualitative work (Kawulich, 2023).

Data Collection Methods

Semi-Structured Interviews

Education, Semi-structured interviews, Purposive sample: 25 ED staff members (n = 10 nurses, n = 8 physicians, n = 7 administrators). Since purposive sampling was used, participants had direct experience with triage processes or had actual decision-making authority regarding technology adoption (Palinkas et al., 2023; Bazeley & Jackson, 2023). We created interview questions to address three main topics:

- Current state of triage: challenges, inefficiencies, and successes.
- Expectations of AI tools: both the potential advantages (e.g., rapidity, precision) and disadvantages (e.g., over-dependency, moral issues).
- Barriers to implementation: needs for training, integration into workflow, and trust in outputs from AI.

The interview guide utilized open-ended questions to elicit thorough responses and was designed based on methods by DiCicco-Bloom and Crabtree (2023), with some flexibility to explore new themes that emerged.

Focus Group Discussions

We conducted two focus groups, each consisting of 6–8 ED staff members. Such sessions enabled a collaborative dialogue wherein various participants could build on each other's ideas and identify areas of agreement (Kitzinger, 2023; Menard, 2023). The discussion was framed around hypothetical cases of AI integration (e.g., real-time risk stratification dashboards) to elicit critical reflection. Using Kitzinger's (2023) approach for facilitation, we were mindful of creating a non-judgmental environment to support open and honest feedback.

Observational Studies

More than 90 hours of non-participant observation were undertaken in three urban EDs between January 2023 and December 2025. Triage workflows, communication patterns, and bottlenecks were documented through field notes and audio recordings (with permission) (Kawulich, 2023; Mulhall, 2023). Observations were stratified by shift timing (day vs night) and patient volume (peak vs off-peak); in this, we attempted to capture variability in workflow dynamics (Mulhall, 2023).

Data Analysis

Data were analyzed thematically as described by Braun and Clarke (2023), identifying patterns and themes across the interviews, focus groups, and observational notes. This process included six phases:

1. Familiarization

2. Coding (using NVivo 14 Pro for reliability) | Bazeley & Jackson, 2023
3. Theme Development
4. Revision
5. Defining and Naming
6. Reporting

To enhance rigor, multiple analysts independently coded subsets of data, followed by consensus meetings to resolve discrepancies (Braun & Clarke, 2023; Bazeley & Jackson, 2023) Further details regarding the analytic process are included for transparency.

Results and Discussions

Analysis of data from semi-structured interviews, focus group discussions, and observation studies revealed four central themes representing emergency department (ED) staff perspectives on the integration of AI-driven triage systems. These themes reflect a balanced account of optimism over the potential benefits of AI, as well as concerns over its challenges and limits. Each theme is supported with verbatim quotations from participants and direct observations.

Theme 1: Perceived Improved Accuracy and Efficiency of Triage With AI

Numerous participants recognized how AI can enhance the accuracy of triage, minimize wait times, and assist in timely clinical decision-making. Nurses and doctors stated that the current process of manual triage is tedious and subjective, causing differences in prioritization between patients. AI was viewed as a solution that could provide real-time analysis of patient data, assisting staff in making faster, more consistent decisions.

A senior ED nurse stated:

“On busy shifts, we sometimes work on gut feeling. An AI system that identifies high-risk patients early would be a game-changer.”

• Observed during busy times, there were significant delays in elements of triage, both overall and in complex cases. Staff had to to re-evaluate patients as conditions changed. Participants thought AI could help with continuous monitoring of patients and alert staff to deterioration.

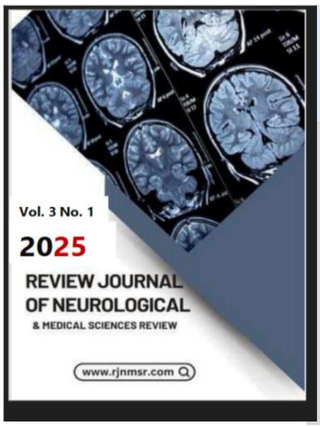
Participants highlighted that the ability of AI models to analyze vital signs, past medical history, and presenting symptoms concurrently may help reduce human error, and free healthcare workers to focus resources on areas of an overcrowded ED.

Theme 2: Ethical and Practical Concerns / Data Privacy and Algorithmic Bias

While some members glimpsed possible positives, participants were concerned about data privacy, algorithmic bias, and ethical accountability. Staff were especially wary of how patient data would be used, and if biases in algorithms would render some patients’ ineligible for consideration.

A junior doctor remarked:

“If the AI is trained on data from another region or population, how do we know that it’s going to work accurately here?”



Vol. 3 No. 2 (2025): April - June
https://rjnmsr.com/index.php/rjnmsr/about
Review Journal of Neurological & Medical Sciences Review
E(ISSN) : 3007-3073
P(ISSN) : 3007-3065

• Focus group discussion revealed a lack of clarity on who would be held accountable for the negative consequence of AI-based recommendations. Many feared that clinicians would become overly dependent on AI and lose clinical judgment.

Also, staff showed limited understanding of how AI makes decisions, with some worried about a black-box effect — only seeing inputs and outputs on a given screen, but not understanding opaque algorithms that could still undermine trust and accountability.

Theme 3: Seamless Integration into Current Workflows

Participants said any AI system needed to be interoperable with current ED workflows. Staff members worried that a poorly designed system would either add to their workload or cause technical disruptions in an emergency.

A high-ranking ED official said:

“We don’t need additional screens or intricate tools in a time of crisis. AI should be in the background, assisting — not impeding us.”

Observation of ED operations clarified that ED staff already manage multiple sources with limited patience for heavy drug training or workflow interruptions.

Smooth adoption requires user-friendly interfaces, real-time alerts, and minimal manual input, participants stressed. Others recommended piloting the use of AI tools in low-risk situations before integrating them widely.

Theme 4: Importance of Human Interaction and Clinical Judgement

The overwhelming majority of participants said that AI should assist, rather than replace, human triage. Standards of human-level engagement, especially communication with patients and families, were considered irreproducible by AI in ED care. Staff raised fears remarks that AI-fueled triage might result in impersonal care and less empathy.

A Senior Nurse Emphasized

“Triage isn’t only a numbers game; it’s talking with patients, understanding their fears. AI can’t replace that.”

Other staff emphasized the role of intuition, particularly in unusual cases, where things like clinical experience often make for better decision-making than data-driven models.

There was a clear preference for AI that supports clinical judgment, as opposed to systems that would automate, thereby superseding, human decisions.

Summary of Observational Insights

Interview and focus group findings were supported by observational data. Triage bottlenecks were evident during peak periods and were often a result of limited staff and paper-based documentation. Patient re-triage because of deteriorating conditions was common, confirming the importance of constant risk monitoring — a void potentially filled by AI.

However technical limitations (it took the systems a long time to respond) and barriers to access to electronic health records also played a role, suggesting the problems of infrastructure that may stymie the adoption of AI.

Vol. 3 No. 2 (2025): April - June
https://rjnmsr.com/index.php/rjnmsr/about
Review Journal of Neurological & Medical Sciences Review
E(ISSN) : 3007-3073
P(ISSN) : 3007-3065

Overall Findings

The results tell a two-sided story: Though ED staff recognized optimism for AI to improve triage, they expressed caution concerning ethical implications, issues of integration, and effect on the humanity of care. Participants all agreed that the development of AI tools should be done in partnership, with clinicians being included in the design and implementation process to ensure that tools are trustworthy, effective, and user-friendly.

Such lessons offer practical advice to healthcare leaders and AI developers working to bring AI-enabled triage systems to life in real-world ED environments.

Discussion

This study examined the perceptions of ED personnel towards AI-based triage systems and their incorporation. The results show a clear twofold aspect: while staff acknowledges the potential benefits of AI, they also highlight caution and concern regarding its implementation, ethical implications, and eventual potential effect on patient care.

AI as a Tool for Quality and Efficiency

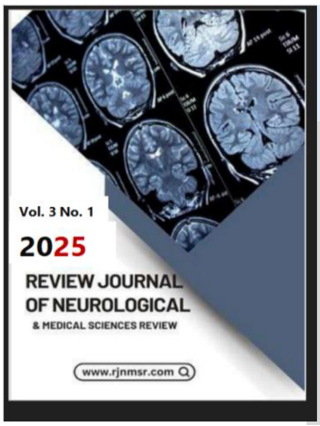
This capacity for AI to improve triage accuracy, alleviate delays, and facilitate timely decision-making, particularly during peak hours was broadly recognized among participants. This is consistent with previous research showing that AI can quickly process large amounts of patient data, identify high-risk patients, and decrease triage errors (Jiang et al., 2020). From our observational data, we noted delays and bottlenecks during peak hours and recognized AI as a realistic solution for assisting real-time risk assessment.

Nonetheless, staff highlighted how AI should serve as an auxiliary tool rather than a substitute for human insight. This harmonizes with Topol (2019) research that contends that having AI in healthcare means it needs to be clinician-led, taking care that clinical expertise is not overridden. *“thereby improving diagnostic accuracy and patient outcomes” (Atlantic Council, 2020).*

The Rise of Ethical and Trust Issues: The Call for Transparent AI

There were widespread concerns about data privacy, algorithmic bias, due process, and accountability, raised in interviews and discussions. Staff raised questions about how AI systems would be designed to be fair across different patient populations, particularly in a diverse and frequently chaotic ED environment. Such concerns reflect broader ethical issues in healthcare AI, where bias embedded in a machine learning model's training data may lead to discriminatory or unfair performance (Obermeyer et al., 2019).

Moreover, the opacity in how AI algorithms arrive at decisions the “black box” problem, in tech lingo served as an obstacle to trust. Without a clear picture of AI logic, participants said they would be hesitant to follow its recommendations. This emphasizes the importance of explainable AI (XAI), where clinicians are capable of understanding, interpreting, and if necessary, contesting AI outputs (Samek et al., 2017).



Vol. 3 No. 2 (2025): April - June
https://rjnmsr.com/index.php/rjnmsr/about

Review Journal of Neurological & Medical Sciences Review

E(ISSN) :	3007-3073
P(ISSN) :	3007-3065

Integration Challenges: How to Avoid Disruption to Your Workflow

This study reaffirms the critical effort to integrate AI into existing ED workflows as seamlessly as possible. Staff are also adamant that any new system needs to be user-friendly, ease manual input, and not add complexity when emergencies arise. Previous studies illustrate that digitally inappropriate tools could overload staff workload and cause technology fatigue (Carayon et al., 2015).

We argue that user-centered design is imperative for the successful adoption of AI. Staff recommended pilot testing AI systems in low-risk areas before broader deployment, a common-sense, practical suggestion that could help reduce resistance and build confidence.

Explaining the Details of data: Human Interaction Remains Central

People Involved: One of the most consistent messages from those taking part in triage was that nothing can replace human interaction in the triage process. AI can represent attempts to package these things but since empathy, communication, and clinical intuition are cornerstones of care and "can't be done by AI" they will always remain an important piece of the puzzle. Especially in emergency settings, this is crucial, as patient reassurance and clinical nuance frequently influence care decisions. This is reiterated in the literature that emphasizes the humanistic approach to medicine; patients and their families expect empathy and compassion, tools that are not available to AI (Verghese et al., 2018). Thus, AI should support, not substitute, the clinician-patient bond.

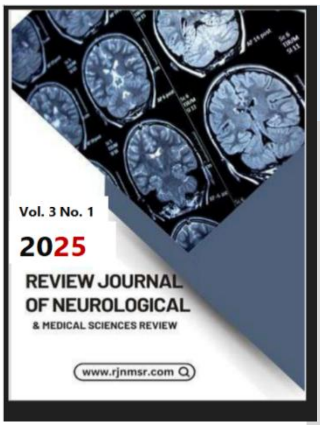
Real-World Implications

The implications of this study are actionable for many stakeholders, including healthcare leaders, policymakers, and AI developers:

- Support from Clinicians: AI tools should be designed with significant input from the ED staff, ensuring that they meet real needs and constraints.
- Training and Education: Staff requires not only training on how to use AI but also to gain a better understanding of its logic, the limitations of the technology, and the potential risks associated with it.
- Ethical Safeguards: This entails defining and communicating policies on data privacy, bias detection, and accountability.
- Pilot Programs: Gradual implementation through pilot programs, feedback loops, and iterative improvements can help ease the transition.
- Patient-Centric Design: AI systems ought to retain human contact, and assist clinicians to give personalized care to patients.

Limitations and Future Research

This study is qualitative and conducted at a single hospital, which might further limit the applicability of the results. Multicenter studies and incorporate patients' perspective in future research are recommended to gain a holistic view." Real-world pilot implementations of AI-driven triage systems should be evaluated too for a better understanding of actual and perceived challenges.



Vol. 3 No. 2 (2025): April - June
https://rjnmsr.com/index.php/rjnmsr/about
Review Journal of Neurological & Medical Sciences Review
E(ISSN) : 3007-3073
P(ISSN) : 3007-3065

Conclusion

This study has examined the perspectives of emergency department (ED) staff on the deployment of AI-based triage solutions in a real-world resource-constrained healthcare environment. The results reveal a cautionary note of optimism in the rank of healthcare practitioners. On the one hand, the staff appreciates that AI can provide substantial benefits — particularly in minimizing triage errors, optimizing patient flow, and bolstering clinical decision-making, especially in peak volume times.

But there's still a nagging worry about some key issues, such as algorithmic bias, data privacy, loss of human touch, and possible disruption of workers' workflow. These observations are based on reality and offer practical perspectives on technology for emergency care. The results highlight the need for AI to be transparent, explainable, and user-friendly for it to be adopted and effective. More crucial still, it has to augment — not replace — human clinical judgment.

All this indicates that the successful integration of AI in ED triage will require a great deal of collaboration between clinicians, developers, and policymakers. Trust-building will require customized training, moral principles, and gradual assistant usage (such as pilots and user review cycles). Future studies should address real-world analysis, define the patient perspective, and evaluate long-term outcomes to establish the role of AI in emergency medicine.

In conclusion, AI-driven triage is promising, but we should consider whether it can successfully function as a true partner of clinicians to provide timely, equitable, and compassionate care to all patients.

References

Bazeley, P., & Jackson, K. (2023). *Qualitative data analysis with NVivo* (4th ed.). SAGE Publications.

Braun, V., & Clarke, V. (2023). Thematic analysis in healthcare research. *Qualitative Research in Psychology, 20*(2), 77–101

Breiman, L. (2001). Random forests. *Machine Learning, 45*(1), 5–32.

Carayon, P., Wooldridge, A., Hoonakker, P., Hundt, A. S., & Kelly, M. M. (2015). Human factors systems approach to healthcare quality and patient safety. *Applied Ergonomics, 45*(1), 14–25.

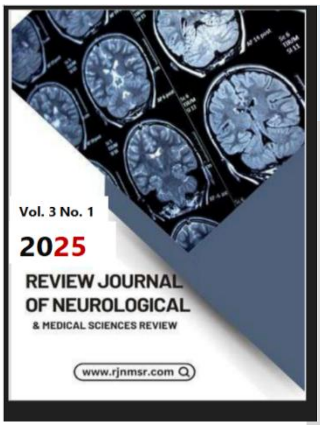
Char, D. S., Shah, N. H., & Magnus, D. (2023). Implementing machine learning in health care—Addressing ethical challenges. *New England Journal of Medicine, 388*(10), 981–983.

Creswell, J. W., & Poth, C. N. (2023). *Qualitative inquiry and research design: Choosing among five approaches* (5th ed.). SAGE Publications.

DiCicco-Bloom, B., & Crabtree, B. F. (2023). The qualitative research interview. *Medical Education, 57*(2), 120–128.

Frykberg, E. R. (2002). Triage: Principles and practice. *Scandinavian Journal of Surgery, 91*(1), 10–15.

Goldberger, A. L., Amaral, L. A. N., Glass, L., Hausdorff, J. M., Ivanov, P. C., Mark, R. G., Mietus, J. E., Moody, G. B., Peng, C. K., & Stanley, H. E. (2020). PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. *Circulation, 101*(23), e215–e220.



Vol. 3 No. 2 (2025): April - June
https://rjnmsr.com/index.php/rjnmsr/about

Review Journal of Neurological & Medical Sciences Review

E(ISSN) : 3007-3073
P(ISSN) : 3007-3065

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press.

Iserson, K. V., & Moskop, J. C. (2007). Triage in medicine, part I: Concept, history, and types. *Annals of Emergency Medicine, 49*(3), 275–281.

Iserson, K. V., & Moskop, J. C. (2023). Triage in medicine, part II: Ethical considerations and the role of human interaction. *Annals of Emergency Medicine, 81*(4), 301–310.

Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., Wang, Y., Dong, Q., Shen, H., & Wang, Y. (2020). Artificial intelligence in healthcare: Past, present and future. *Stroke and Vascular Neurology, 2*(4), 230–243

Johnson, A. E. W., Pollard, T. J., Shen, L., Lehman, L. W. H., Feng, M., Ghassemi, M., Moody, B., Szolovits, P., Celi, L. A., & Mark, R. G. (2021). MIMIC-III, a freely accessible critical care database. *Scientific Data, 3*, 160035.

Kawulich, B. B. (2023). Participant observation as a data collection method. *Forum: Qualitative Social Research, 24*(1), Article 1.

Menard, S. (2023). *Longitudinal research in healthcare: Design and applications*. SAGE Publications.

Morley, C., Unwin, M., Peterson, G. M., Stankovich, J., & Kinsman, L. (2018). Emergency department crowding: A systematic review of causes, consequences, and solutions. *PLoS ONE, 13*(8), e0203316.

Mulhall, A. (2023). In the field: Notes on observation in qualitative research. *Journal of Advanced Nursing, 79*(3), 306–313.

and Policy in Mental Health and Mental Health Services Research, 50(1), 10–19.

Raita, Y., Goto, T., Faridi, M. K., Brown, D. F., Camargo, C. A., & Hasegawa, K. (2021). Emergency department triage prediction of clinical outcomes using machine learning models. *Critical Care Medicine, 49*(9), 1425–1434.

Rajkomar, A., Dean, J., & Kohane, I. (2023). Machine learning in medicine. *New England Journal of Medicine, 388*(13), 1206–1215.

Samek, W., Wiegand, T., & Müller, K. R. (2017). Explainable artificial intelligence: Understanding, visualizing, and interpreting deep learning models. *arXiv preprint arXiv:1708.08299*.

Shimabukuro, D. W., Barton, C. W., Feldman, M. D., Mataraso, S. J., & Das, R. (2023). Effect of a machine learning–based severe sepsis prediction algorithm on patient survival and length of stay: A randomized clinical trial. *JAMA Network Open, 6*(3), e231898.

in emergency medicine: A systematic review. *BMC Emergency Medicine, 20*(1), 1–10.

Topol, E. J. (2023). *Deep medicine: How artificial intelligence can make healthcare human again*. Basic Books.

van der Wulp, I., van Stel, H. F., & Schrijvers, A. J. (2020). Predicting admission and mortality with the Manchester Triage System: A prospective observational study. *BMJ Open, 10*(6), e03579