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Identifying Barriers and Enablers to the Adoption of AI-Based Triage Tools in Emergency Departments

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A B S T R A C T

This study aimed to explore the perceived barriers and enablers influencing the adoption of artificial intelligence (AI)-based triage tools in emergency departments (EDs) from the perspective of frontline healthcare professionals. A qualitative research design was employed, utilizing semi-structured interviews with 19 participants—including emergency physicians, triage nurses, department managers, clinical administrators, and health informatics experts—working in emergency departments across Canada. Participants were selected using purposive sampling to ensure diversity in professional roles and institutional settings. Data collection continued until theoretical saturation was reached. Interviews were transcribed verbatim and analyzed using grounded theory methodology. Open, axial, and selective coding were conducted with the assistance of NVivo software to identify emerging themes and construct a conceptual model of AI adoption dynamics. The analysis revealed five core categories shaping AI-based triage adoption: (1) perceived risk and uncertainty, including lack of trust in AI outputs and concerns over legal liability; (2) institutional and organizational readiness, such as infrastructure limitations and workflow misalignment; (3) human capital and knowledge systems, including digital literacy gaps and lack of training; (4) system-level support and governance, highlighting the role of managerial commitment and national policy frameworks; and (5) value proposition and practical benefits, including efficiency gains, clinical decision support, and user-friendly integration. These categories reflected the interplay of technical, organizational, and human factors that either hindered or enabled AI integration in emergency care settings. Adopting AI-based triage tools in emergency departments requires addressing a complex ecosystem of trust, readiness, training, infrastructure, and systemic support. The findings underscore the importance of clinician engagement, targeted education, transparent design, and multi-level policy alignment to ensure effective and sustainable implementation.

Keywords: *Artificial intelligence, triage tools, emergency department, adoption barriers, enablers, qualitative study, clinical decision support, healthcare technology integration.*

1. Introduction

Emergency departments (EDs) are pivotal entry points to healthcare systems, where rapid decision-making can significantly influence patient outcomes. Triage, the process of prioritizing patients based on the urgency of their condition, remains one of the most critical functions in this setting. As EDs across the globe face mounting pressures from overcrowding, resource constraints, and increasing patient acuity, the need for efficient and reliable triage systems has never been more urgent. In response to these challenges, artificial intelligence (AI) has emerged as a promising solution to augment traditional triage models by offering automated, data-driven decision support systems that can improve accuracy, consistency, and speed in clinical assessments (1, 2).

AI-based triage tools, ranging from predictive algorithms to language models and machine learning applications, have been shown to enhance the identification of critical conditions, reduce errors, and optimize resource allocation (3, 4). These technologies can analyze a multitude of variables—such as vital signs, patient history, and presenting symptoms—at a speed and scale far beyond human capability (5, 6). Studies have demonstrated that AI-enhanced triage systems can reduce door-to-needle time for stroke patients, improve risk stratification, and predict adverse events with greater accuracy than conventional methods (7, 8). Moreover, in crisis contexts such as pandemics, AI can facilitate scalable triage solutions that adapt in real-time to shifting epidemiological patterns (9, 10).

Despite their potential, the integration of AI-based triage tools into clinical practice remains uneven, hindered by a variety of technological, organizational, and sociocultural barriers. Trust remains a significant concern. Health professionals often question the transparency and reliability of AI outputs, especially when clinical decisions carry life-or-death consequences (11, 12). The issue of algorithmic bias, arising from training data that may not represent diverse populations, further complicates trust-building and ethical acceptability (12, 13). Moreover, legal and regulatory frameworks lag behind technological advancements, leaving institutions uncertain about liability in the event of AI-related clinical errors (14, 15).

Another significant challenge is organizational readiness. The successful adoption of AI systems requires interoperability with existing electronic health records (EHRs), reliable IT infrastructure, and adequate technical support—all of which may be lacking, especially in smaller or underfunded hospitals (16, 17). Resistance to change, both at the administrative and clinical levels, often emerges from a perceived threat to professional autonomy, job security, and established workflows (18, 19). Moreover, without visible managerial commitment and a clearly articulated implementation roadmap, even promising technologies may fail to move beyond pilot phases (20, 21).

Knowledge and training gaps compound these difficulties. Many frontline clinicians report limited understanding of how AI tools function, their underlying assumptions, and their limitations (4, 22). This lack of digital literacy can foster dependence on—or conversely, rejection of—AI outputs, both of which compromise safe clinical decision-making (23, 24). Although studies highlight the benefits of integrating AI modules into medical education and continuous professional development, such integration remains sporadic and poorly institutionalized (15, 25).

Conversely, several enablers have been identified that can facilitate AI adoption in emergency settings. When AI tools are designed with clinician input, they are more likely to be perceived as useful, user-friendly, and aligned with actual clinical needs (2, 26). Pilot projects that demonstrate tangible improvements in workflow efficiency, diagnostic accuracy, or patient satisfaction can also generate internal momentum for broader adoption (8, 11). Moreover, clinical champions—individuals who advocate for and model the use of AI tools—can play a vital role in overcoming resistance and fostering peer learning (1, 3). Policy-level supports, such as funding incentives, accreditation requirements, and AI-specific clinical governance guidelines, can provide a macro-level framework for sustainable implementation (13, 14).

As AI systems grow more sophisticated, there is a growing need to explore their integration within real-world clinical settings. Much of the existing literature focuses on technical performance metrics or hypothetical models rather than actual implementation dynamics (4, 20). Few studies have systematically investigated the perceptions, experiences, and concerns of end-users—namely physicians,

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nurses, administrators, and IT personnel—who must interact with these tools daily and often under high-pressure conditions. This lack of qualitative insight limits the ability of developers, policymakers, and health system leaders to design context-sensitive AI solutions that are both effective and acceptable to those on the frontline (11, 12).

Furthermore, geographical and institutional variability must be considered. Most empirical studies have been conducted in highly resourced health systems with advanced IT infrastructure and strong institutional support (5, 10). This raises important questions about generalizability and equity in AI diffusion. In settings where emergency departments are understaffed, overburdened, or disconnected from national innovation agendas, the adoption of AI tools may face more profound constraints or require different strategies (17, 19).

Given this context, the present study aims to explore the barriers and enablers influencing the adoption of AI-based triage tools in emergency departments through a qualitative lens.

2. Methods and Materials

2.1. Study Design and Participants

This study employed a qualitative research design using a constructivist paradigm to explore the barriers and enablers influencing the adoption of AI-based triage tools in emergency departments. The aim was to gather rich, in-depth perspectives from key stakeholders involved in emergency healthcare delivery and health technology implementation. Participants were recruited from various emergency departments across Canada, including urban teaching hospitals and community-based settings.

A total of 19 participants were purposively selected based on their professional roles and relevance to the research topic. The sample included emergency physicians, triage nurses, department managers, health informatics experts, and clinical administrators with direct experience or involvement in AI tool evaluation, implementation, or usage. Maximum variation sampling was used to capture a broad range of views across different institutional contexts. Recruitment continued until theoretical saturation was achieved, meaning no new significant themes emerged from subsequent interviews.

2.2. Data Collection

An interview guide was developed based on a review of literature and expert consultation, focusing on themes such as perceived usefulness of AI-based triage, integration challenges, ethical and legal concerns, and organizational readiness. Each interview lasted between 45 and 75 minutes and was conducted either in person or via secure video conferencing, depending on participant preference and public health guidelines.

All interviews were audio-recorded with informed consent and subsequently transcribed verbatim. Field notes were also taken during and immediately after each interview to capture contextual observations and researcher reflections.

2.3. Data Analysis

The data were analyzed using thematic analysis, following Braun and Clarke's six-phase approach. NVivo software (version 14) was employed to assist with data organization, coding, and retrieval of emergent themes. Transcripts were independently reviewed by two researchers to ensure coding consistency and to enhance analytical rigor. An iterative process of constant comparison was used to refine categories and sub-themes, allowing patterns and relationships to emerge organically from the data. Discrepancies in coding were resolved through discussion until consensus was reached.

Trustworthiness of the findings was ensured through strategies such as member checking, peer debriefing, and maintaining an audit trail of analytical decisions.

3. Findings and Results

A total of 19 participants took part in this qualitative study. Participants were selected from various emergency departments across Canada and represented a range of professional backgrounds. The sample included 6 emergency physicians, 5 triage nurses, 3 clinical administrators, 3 health informatics specialists, and 2 department managers. In terms of gender, there were 11 female and 8 male participants. The participants' years of professional experience ranged from 7 to 28 years, with a mean of 15.3 years. Eleven participants were from urban

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academic hospitals, while 8 worked in community-based emergency departments.

The open coding phase involved a line-by-line examination of the interview transcripts to break down the data into discrete concepts and categories. Using an inductive approach, initial codes were assigned to meaningful units of text, reflecting participants' explicit statements or implied meanings. This stage generated a rich array of 76 open codes, capturing both the barriers and enablers to AI-based triage adoption in emergency departments. Codes were labeled to represent participants' language as closely as possible while ensuring conceptual clarity. Each code was tagged with the interview identifiers (e.g., P1–P19) to indicate which participants mentioned each concept. NVivo software facilitated the coding and ensured traceability across the dataset. The table below summarizes the open codes and the interview participants who contributed to each theme.

Table 1

Open Coding

Open Code	Interview Codes
Lack of trust in AI outputs	P1, P3, P6, P9, P14, P16
Fear of legal liability	P2, P7, P11, P18
Unclear ethical boundaries	P3, P4, P12
Lack of clinical validation	P1, P6, P8, P10, P13
Resistance to change	P2, P5, P7, P9, P17
Concerns about patient safety	P1, P6, P10, P12, P15, P19
Overreliance on algorithms	P4, P7, P11
Algorithmic bias	P3, P8, P14, P15, P17
Lack of training programs	P2, P5, P6, P13, P18
Fear of job displacement	P4, P6, P9, P12
Lack of interoperability with EHRs	P1, P2, P8, P10
Limited understanding of AI functionality	P5, P7, P11, P13
Budgetary constraints	P3, P6, P14, P19
Administrative inertia	P2, P7, P17
Fragmented IT infrastructure	P1, P10, P16, P19
Shortage of technical support staff	P5, P8, P13
Lack of physician buy-in	P3, P7, P11
Preference for human judgment	P2, P4, P6, P12
Inconsistent triage protocols	P9, P14, P18
No clear implementation roadmap	P5, P8, P15
Concern about data privacy	P1, P6, P10, P17
Lack of national guidelines	P3, P4, P11
Misalignment with hospital workflow	P2, P7, P13, P16
Insufficient pilot testing	P8, P10, P14
Cultural skepticism about AI	P3, P6, P12
Limited feedback mechanisms	P5, P9, P15
Positive outcomes in early pilots	P4, P8, P11
Improved triage efficiency	P2, P5, P14, P18
Faster patient routing	P1, P7, P13, P17
Increased diagnostic support	P6, P9, P12, P16
Enhanced situational awareness	P3, P8, P15
Reduction in triage errors	P5, P11, P14
Improved patient satisfaction	P4, P6, P13
Easier decision-making for nurses	P2, P9, P12
Decreased cognitive load	P1, P7, P10
Supports resource allocation	P3, P5, P14
Better time management	P6, P8, P11
Integration with clinical dashboards	P1, P10, P17
Encourages data-driven practice	P4, P6, P9
Transparent algorithm design	P3, P8, P13
Availability of technical training	P5, P11, P18
Managerial support for AI tools	P2, P7, P12
National interest in AI health innovation	P3, P14, P16

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Willingness to experiment	P1, P5, P13
Confidence in AI developers	P6, P8, P10
Data sharing infrastructure	P4, P9, P17
Involvement of clinicians in development	P2, P3, P11
User-friendly interface design	P5, P7, P16
Improved workflow documentation	P6, P10, P15
Inclusion in hospital policy	P1, P4, P13
Alignment with accreditation standards	P2, P6, P12
Incentives for early adopters	P3, P8, P14
Continuous algorithm improvement	P5, P10, P17
Customizability for local needs	P4, P7, P13
Clinical champions advocating adoption	P1, P6, P11
Peer learning among departments	P2, P5, P9
Benchmarking success across sites	P3, P8, P15
Triage tool updates based on feedback	P6, P10, P14
Clarity of AI role in decision-making	P1, P3, P7
Reduction of manual data entry	P4, P9, P16
Encouragement by provincial health bodies	P2, P6, P12
Collaboration with AI companies	P5, P8, P11
Public trust in digital health	P3, P7, P13
Evidence-based policy interest	P1, P4, P10
Onboarding programs for new staff	P6, P9, P15
Defined accountability structures	P2, P5, P17
Clear metrics for performance evaluation	P3, P8, P14
Regular audit and feedback cycles	P4, P6, P11
Training aligned with real-time use	P1, P7, P13

In the axial coding phase, the open codes were grouped into higher-order conceptual categories by identifying relationships between codes, examining causal conditions, context, intervening conditions, and consequences. This step involved reassembling the data by linking related open codes to form more abstract and integrated axial codes that could explain broader themes underlying the participants' perspectives. Using the constant comparative method within NVivo, relationships were identified between conditions (e.g., organizational, technological, cultural) and actions/interactions (e.g., adoption behaviors, resistance, support strategies). Through this process, 20 axial codes were developed, each comprising a cluster of related open codes from the previous phase.

Table 2

Axial Coding

Axial Code	Related Open Codes
Trust and Reliability Concerns	Lack of trust in AI outputs; Algorithmic bias; Overreliance on algorithms; Fear of legal liability; Concern about data privacy; Unclear ethical boundaries
Clinical Validation Gaps	Lack of clinical validation; Inconsistent triage protocols; Insufficient pilot testing
Organizational Resistance to Change	Resistance to change; Administrative inertia; Lack of physician buy-in; Fear of job displacement; Cultural skepticism about AI
Technological Infrastructure Barriers	Lack of interoperability with EHRs; Fragmented IT infrastructure; Shortage of technical support staff; Limited feedback mechanisms
Knowledge and Skill Deficits	Limited understanding of AI functionality; Lack of training programs; Lack of national guidelines
Workflow Misalignment	Misalignment with hospital workflow; No clear implementation roadmap; Preference for human judgment
Resource Constraints	Budgetary constraints; Shortage of technical support staff; Lack of incentives
Legal and Ethical Uncertainty	Unclear ethical boundaries; Concern about data privacy; Fear of legal liability
Positive Pilot Outcomes	Positive outcomes in early pilots; Reduction in triage errors; Improved patient satisfaction
Efficiency and Time Gains	Improved triage efficiency; Faster patient routing; Better time management; Decreased cognitive load
Clinical Decision Support	Increased diagnostic support; Easier decision-making for nurses; Enhanced situational awareness
Integration Capabilities	Integration with clinical dashboards; Transparent algorithm design; Customizability for local needs
Institutional Support	Managerial support for AI tools; Inclusion in hospital policy; Defined accountability structures
External Stakeholder Encouragement	National interest in AI health innovation; Encouragement by provincial health bodies; Evidence-based policy interest

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Training and Onboarding Infrastructure	Availability of technical training; Training aligned with real-time use; Onboarding programs for new staff
Clinician Involvement in Development	Involvement of clinicians in development; Peer learning among departments; Clinical champions advocating adoption
User Experience and Interface Design	User-friendly interface design; Clear metrics for performance evaluation; Clarity of AI role in decision-making
Continuous Improvement Mechanisms	Continuous algorithm improvement; Triage tool updates based on feedback; Regular audit and feedback cycles
Interdepartmental Knowledge Exchange	Peer learning among departments; Benchmarking success across sites; Collaboration with AI companies
Alignment with Policy and Accreditation	Alignment with accreditation standards; Inclusion in hospital policy; Evidence-based policy interest

This phase revealed 20 interrelated axial categories that synthesized the fragmented open codes into core conceptual areas, providing a structured foundation for the development of a theoretical framework in the subsequent phase. Codes such as *Trust and Reliability Concerns* and *Organizational Resistance to Change* emerged as dominant barriers, while themes like *Efficiency and Time Gains*, *Institutional Support*, and *Clinical Decision Support* reflected significant enablers. These axial categories not only organized the complexity of stakeholder perceptions but also clarified the interplay between contextual barriers, enablers, and institutional readiness for AI adoption in emergency care settings.

In the selective coding phase, the core categories (selective codes) were developed by integrating and refining the axial codes around central themes that represented the overarching structure of the study. This stage involved identifying the main phenomena that connected multiple axial codes and constructing a cohesive narrative about the conditions influencing the adoption of AI-based triage tools in emergency departments. The process focused on developing theoretical coherence by linking axial codes back to the research question and contextual conditions. Through this integrative process, five selective codes were identified, representing the principal dimensions of both barriers and enablers in the adoption landscape.

Table 3

Selective Coding

Selective Code (Core Category)	Related Axial Codes
Perceived Risk and Uncertainty	Trust and Reliability Concerns; Legal and Ethical Uncertainty; Clinical Validation Gaps
Institutional and Organizational Readiness	Organizational Resistance to Change; Resource Constraints; Technological Infrastructure Barriers; Workflow Misalignment
Human Capital and Knowledge Systems	Knowledge and Skill Deficits; Training and Onboarding Infrastructure; Clinician Involvement in Development
System-Level Support and Governance	Institutional Support; External Stakeholder Encouragement; Alignment with Policy and Accreditation
Value Proposition and Practical Benefits	Efficiency and Time Gains; Clinical Decision Support; Positive Pilot Outcomes; Integration Capabilities; Continuous Improvement Mechanisms; User Experience and Interface Design; Interdepartmental Knowledge Exchange

This phase distilled the complex web of participant experiences and perceptions into five core themes that constitute the foundation of a theoretical model for AI triage adoption. The category *Perceived Risk and Uncertainty* captured the psychological, legal, and ethical hesitations that limit acceptance, whereas *Institutional and Organizational Readiness* reflected structural and cultural resistance to change. *Human Capital and Knowledge Systems* emphasized the need for training, clinician participation, and skill development to enable adoption. At a broader level, *System-Level Support and Governance* addressed how national, provincial, and institutional bodies could enable or constrain implementation. Finally, *Value Proposition and Practical Benefits* unified participants' descriptions of efficiency, decision support, integration, and workflow alignment as key motivators for adoption. These core categories serve as the scaffolding for understanding how to effectively design, introduce, and sustain AI-based triage tools within emergency department systems.

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4. Discussion and Conclusion

This study explored the barriers and enablers to adopting AI-based triage tools in emergency departments (EDs) by analyzing the insights of 19 emergency care professionals in Canada. The findings revealed five central categories that influence AI integration: perceived risk and uncertainty, institutional and organizational readiness, human capital and knowledge systems, system-level support and governance, and value proposition and practical benefits. These categories underscore that AI adoption in high-stakes clinical settings is not merely a technical issue but a complex socio-technical transformation requiring systemic alignment across multiple dimensions.

One of the most significant barriers identified was the widespread perception of risk and uncertainty associated with AI triage tools. Many participants expressed concerns about the reliability and transparency of AI outputs, fearing that algorithmic decisions might lack contextual sensitivity or reflect hidden biases. This aligns with prior findings emphasizing clinician discomfort with "black box" models and the opacity of machine learning reasoning (12). Studies have highlighted that distrust in AI is particularly acute in emergency settings, where decisions often have immediate and life-threatening implications (11). Moreover, unresolved questions regarding liability in the event of AI-induced harm contribute to this anxiety, echoing concerns in the broader literature about the legal and ethical landscape of AI in medicine (14, 15).

Another major obstacle was institutional and organizational readiness, particularly regarding infrastructure and workflow integration. Participants noted the lack of interoperability between AI systems and existing electronic health record platforms as a recurrent problem. This aligns with previous research showing that many hospitals still operate in silos, where new AI modules must be manually interfaced with fragmented digital systems, slowing down their practical utility (16, 17). Resource limitations—such as outdated hardware, insufficient IT support, and absence of internal expertise—further complicate adoption efforts, especially in smaller or non-academic centers. These findings are consistent with large-scale reviews that identified technological capacity and administrative inertia as critical bottlenecks for AI integration (13, 21).

The study also uncovered gaps in human capital and knowledge systems. Many clinicians reported limited understanding of AI functionality, leading to either overreliance or outright rejection. These sentiments mirror observations from other contexts where frontline staff are asked to work with technologies they were neither trained for nor consulted about during development (4, 22). This issue is particularly acute in emergency care, where high-paced environments leave little time for exploratory learning or in-depth training. As others have argued, without a foundational understanding of how AI tools work, users cannot be expected to trust or correctly interpret their outputs (23, 25). The literature supports the notion that digital literacy and AI training should be embedded in clinical education to bridge this confidence gap (24).

In contrast to these barriers, the findings also highlighted several enabling factors that support AI adoption. Participants identified improved efficiency, faster triage decisions, and enhanced diagnostic support as key benefits. These practical gains are well-documented in empirical studies, which report shorter door-to-needle times, better risk stratification, and increased throughput in AI-augmented EDs (7, 8). The ability of AI tools to relieve clinicians of routine cognitive burdens and provide real-time alerts for critical deterioration was also valued, especially in understaffed departments. This corroborates earlier work indicating that well-designed AI systems can reduce cognitive load and improve clinical decision-making (1, 20).

Another significant enabler was the presence of system-level support and governance mechanisms. Participants pointed to managerial backing, involvement of health informatics teams, and alignment with national innovation priorities as crucial to successful implementation. Prior literature has emphasized that AI integration is far more likely to succeed when it is embedded in broader institutional strategies and not approached as a stand-alone innovation (5, 10). Governmental and regulatory bodies can also play a pivotal role by issuing guidelines, offering funding, and promoting standardized protocols, as observed in regions where AI integration has advanced more rapidly (2, 19).

The findings further underscored the importance of co-design and clinician involvement in the development and rollout of AI tools. Participants noted that tools created

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without user input often failed to match real-world clinical workflows, leading to resistance or misuse. On the contrary, when clinicians were engaged from the early stages, tools were more intuitive, accepted, and adaptable to local needs. This aligns with participatory design principles advocated in the literature, which argue that clinician engagement leads to better usability, trust, and long-term sustainability of AI systems (18, 26).

Finally, the study suggests that clinical champions and peer learning structures play a critical role in AI normalization. Participants highlighted how support from respected colleagues and visible success stories across departments helped demystify AI and accelerate its uptake. These social mechanisms of diffusion are consistent with prior research showing that peer endorsement and modeling behaviors significantly shape attitudes toward innovation in healthcare environments (1, 3).

While this study offers in-depth qualitative insights, it is subject to several limitations. First, the sample consisted exclusively of professionals from emergency departments in Canada, which may limit the generalizability of findings to other geographic or institutional contexts. Second, although the sample included a range of roles (physicians, nurses, administrators, and informatics specialists), the size was relatively small (n=19), which, while appropriate for qualitative saturation, may not capture all perspectives across the national emergency care landscape. Third, the dynamic and evolving nature of AI technology means that participant views may change over time, especially as systems are updated or new regulatory frameworks emerge. Lastly, the study relied on self-reported data, which may be influenced by recall bias or social desirability, particularly in interviews concerning technological adoption and workplace dynamics.

Future studies could expand the sample to include diverse geographic regions, institutional types, and countries with varying levels of digital maturity to compare adoption patterns. Mixed-methods research designs could also be employed to triangulate qualitative findings with quantitative data, such as usage statistics or patient outcomes associated with AI triage systems. Longitudinal studies would be especially valuable in tracking how perceptions and adoption evolve over time as new AI tools are piloted, refined, and embedded in clinical routines. Additionally, future research could explore patient perspectives on AI-driven triage, a topic rarely addressed but essential for ethical and trust considerations. Comparative studies between AI tools developed with versus without clinician co-design could also yield actionable insights for developers and implementers.

For successful integration of AI-based triage tools, healthcare institutions should prioritize building trust through transparent algorithm design, robust validation, and clinician engagement. Investment in training programs to improve AI literacy among all emergency department staff is essential. Institutions should also ensure technical infrastructure is prepared to support AI implementation, including interoperability with EHR systems and ongoing IT support. Establishing multidisciplinary teams—including clinical champions—to guide the implementation process can improve acceptance and adaptation. Finally, collaboration with policymakers to create clear regulatory guidelines and support frameworks will be key to facilitating sustainable and ethically grounded adoption of AI in emergency medicine.

Authors' Contributions

All authors equally contributed to this study.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethics Considerations

The study placed a high emphasis on ethical considerations. Informed consent obtained from all participants, ensuring they are fully aware of the nature of the study and their role in it. Confidentiality strictly maintained, with data anonymized to protect individual privacy. The study adhered to the ethical guidelines for research with human subjects as outlined in the Declaration of Helsinki.

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