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AI-Assisted Clinical Decision Support in Emergency Departments: Effects on Diagnostic Accuracy, Patient Throughput, and Allied Health Workflow

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Abstract
Emergency Departments (EDs) face rising patient volumes, diagnostic complexity, and workflow strain challenges amplified in low- and middle-income countries. AI-assisted clinical decision support systems (AI-CDSS) have been promoted as tools to improve diagnostic accuracy, reduce delays, and enhance team efficiency, including the work of radiographers, laboratory technologists, and triage personnel. To examine how AI-CDSS integration affects diagnostic accuracy, patient throughput, and allied health workflow efficiency in emergency departments. This review synthesizes quantitative findings from 2019–2025 empirical studies evaluating AI-CDSS in ED settings. Databases searched included PubMed, Scopus, and IEEE Xplore. Outcome measures included diagnostic accuracy, turnaround time (TAT), triage precision, and workflow performance indicators. AI-CDSS increased diagnostic accuracy for acute conditions by 8–22% across studies, particularly in sepsis, stroke, and trauma imaging. Several implementations reported 12–35% reductions in ED length-of-stay, mainly attributable to faster decision-making and reduced repeat testing. Allied health workflow improved through automated alerts, structured reporting, and prioritization algorithms, reducing technologist workload by 15–28%. Concerns included algorithm bias, over-reliance, and reduced professional autonomy. Evidence suggests AI-CDSS substantively improves ED diagnostic performance and patient flow while moderately reducing allied health burden. However, ethical risks and dependency concerns require robust training, oversight, and governance frameworks, especially in resource-constrained systems.

Keywords: *Emergency Departments, AI-CDSS, ED, Operational Efficiency, Diagnostic Complexity Workflow Strain*

Introduction

Emergency Departments (EDs) are high-stakes, high-pressure clinical environments where timely and accurate decision-making is critical. EDs worldwide face rising patient volumes, increasingly complex cases, and constrained human and technological resources. In low- and middle-income countries (LMICs) such as Pakistan, chronic understaffing, outdated diagnostic equipment, and inconsistent triage practices exacerbate delays, misdiagnoses, and patient morbidity (1). AI-assisted clinical decision support systems (AI-CDSS) have emerged as potential tools to mitigate these challenges by leveraging predictive analytics, machine learning, and pattern recognition to assist clinicians and allied health professionals in real-time decision-making (2–4).

AI-CDSS applications in EDs include automated triage, risk scoring for sepsis or myocardial infarction, AI-assisted interpretation of imaging, laboratory prioritization, and early detection of acute conditions. Quantitative studies show AI-CDSS improves diagnostic accuracy by 7–20%, reduces emergency length-of-stay by 12–35%, and improves workflow efficiency for allied health staff including radiographers, laboratory technologists, and triage nurses (5–8). These systems not only augment human decision-making but also help prioritize scarce resources in busy EDs.

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Problem Statement

Despite the growing adoption of AI-CDSS in high-income countries, evidence from LMICs remains limited. The unique challenges in low-resource EDs—variable documentation quality, unreliable network infrastructure, inconsistent triage protocols, and equipment limitations—may reduce the effectiveness of AI-CDSS. Moreover, the integration of AI impacts allied health workflow and professional autonomy, potentially introducing ethical dilemmas, overreliance, or bias (9,10). There is a critical need for empirical studies quantifying the effectiveness and workflow impact of AI-CDSS in such settings.

Research Questions

- **RQ1:** How does AI-assisted clinical decision support influence diagnostic accuracy in emergency departments?
- **RQ2:** To what extent does AI-CDSS improve patient throughput, including triage time, diagnostic turnaround, and ED length-of-stay?
- **RQ3:** How does AI-CDSS affect allied health workflow, including radiographers, laboratory technologists, and triage nurses?
- **RQ4:** What operational or ethical challenges emerge when implementing AI-CDSS in low-resource EDs, particularly in Pakistan?

Hypotheses

- **H1:** AI-assisted CDSS significantly increases diagnostic accuracy for acute emergency conditions compared with standard practice.
- **H2:** AI-CDSS reduces patient throughput time, including triage time, diagnostic turnaround, and overall ED length-of-stay.
- **H3:** AI-CDSS improves allied health workflow efficiency, measured by reduced task load, fewer repeat tests, and faster diagnostic processing.
- **H4:** Operational and ethical challenges, including algorithmic bias, inconsistent data quality, and workflow misalignment, moderate the effectiveness of AI-CDSS in low-resource EDs.

Study Significance

Integrating AI-CDSS into EDs in Pakistan has the potential to improve diagnostic precision, optimize patient flow, and enhance allied health workflow. Quantifying these impacts provides evidence for policymakers, hospital administrators, and healthcare professionals considering AI adoption in resource-constrained settings. Additionally, this study addresses gaps in operational research for LMIC emergency care, providing a model for ethical and effective AI integration that balances technological efficiency with human professional autonomy.

Literature Review

AI in Emergency Medicine

Artificial intelligence has increasingly been applied in emergency medicine to support clinical decision-making. AI-CDSS tools use machine learning, deep learning, and predictive analytics to assist in triage, diagnosis, and risk stratification. Kim et al. reported that AI-based triage models improved high-risk patient identification by 12–18% compared with conventional nurse-led triage in high-volume EDs (1). Xu et al. demonstrated that deep learning-based triage support reduced misclassification of sepsis patients by 15%, significantly improving early intervention rates (2). AI-CDSS systems have also been shown to reduce errors in trauma assessment, with diagnostic accuracy improvements of 8–22% in multi-center studies (3).

Diagnostic Accuracy and Clinical Outcomes

AI-enhanced imaging interpretation has been a major focus in emergency diagnostics. Lindsey et al. demonstrated that deep neural networks detected fractures with 95% sensitivity and 92% specificity, outperforming junior radiologists (4). Similarly, Lee et al. reported that AI-assisted CT brain analysis identified acute strokes 20% faster than conventional workflow, reducing door-to-needle times in EDs (5). Systematic reviews indicate that AI-CDSS improves early detection of critical conditions such as sepsis, pulmonary embolism, and myocardial infarction, translating into reduced morbidity and mortality (6–8).

Patient Throughput and Workflow Efficiency

Time efficiency is a critical metric in ED performance. AI-CDSS has been associated with measurable reductions in patient length-of-stay (LOS) and diagnostic turnaround times. Zhang et al. found that AI-assisted lab prioritization reduced biomarker turnaround time by 12–25%, facilitating quicker treatment decisions (9). Sterling et al. showed that predictive analytics in EDs reduced LOS by an average of 18% and decreased time-to-first-intervention by 22% (10). These improvements are particularly impactful in high-volume, low-resource settings, where workflow bottlenecks directly affect patient outcomes.

Impact on Allied Health Professionals

Allied health staff including radiographers, laboratory technologists, and triage nurses—are directly affected by AI-CDSS integration. Automated alerts and structured reporting reduce repetitive manual tasks, enhancing workflow efficiency. In a study by Patel et al., radiographers using AI-assisted detection tools reported a 15–28% reduction in redundant imaging and improved prioritization of urgent cases (11). Similarly, laboratory technologists experienced decreased sample processing delays and improved error detection with AI-driven systems (12). While efficiency gains are evident, some studies report concerns about deskilling and dependence on automated outputs, particularly among junior staff (13).

The adoption of AI-CDSS raises ethical and operational concerns. Algorithmic bias, often resulting from non-representative training datasets, can lead to inequitable care (14). Transparency and explainability are crucial, as clinicians must understand AI recommendations to make informed decisions (15). Morley et al. emphasized that AI could undermine professional autonomy if systems are used prescriptively rather than supportively (16). In low-resource settings, additional challenges include unreliable IT infrastructure, intermittent power supply, and limited staff training (17).

Gaps in Low-Resource Settings

Most empirical studies originate from high-income countries with robust health IT infrastructure. Limited research exists on the quantitative impact of AI-CDSS in LMICs, where EDs face chronic resource limitations. Evidence on allied health workflow, ethical compliance, and system adaptation in these contexts is sparse. This gap underscores the need for empirical investigations in countries such as Pakistan, where AI implementation could have significant operational and clinical impact but must be adapted to local resource constraints (18–20).

Methodology

Research Design

This study employed a cross-sectional quantitative research design to assess the impact of AI-assisted clinical decision support systems (AI-CDSS) on diagnostic accuracy, patient throughput, and allied health workflow efficiency in low-resource emergency departments (EDs) in Pakistan. The study integrates primary survey data from healthcare professionals with quantitative measures of workflow efficiency and patient outcomes. This design allows for hypothesis testing using structural equation modeling (PLS-SEM)

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to examine relationships among AI-CDSS implementation, workflow efficiency, diagnostic accuracy, and potential moderating variables such as operational challenges.

Study Setting and Population

The study was conducted across four major tertiary hospitals in Pakistan representing low-resource ED environments with high patient volume. The target population included:

- **Emergency physicians** responsible for diagnostic decisions
- **Allied health professionals** (radiographers, laboratory technologists, triage nurses)
- **Administrative personnel** overseeing ED workflow

Eligibility criteria required at least 1 year of ED experience and direct exposure to diagnostic procedures or workflow processes influenced by AI-CDSS.

Sampling Strategy

A stratified random sampling method was employed to ensure representation across professional groups. Based on power analysis for PLS-SEM (effect size $f^2 = 0.15$, $\alpha = 0.05$, power = 0.80), the minimum required sample size was 150 (1). To improve generalizability and account for non-response, 400 participants were recruited, distributed as follows: 100 physicians, 180 allied health professionals, and 120 administrative staff.

Data Collection Instrument

A structured survey instrument was developed and validated in two phases:

1. **Content validity:** Expert panel of five senior emergency physicians and health informatics specialists reviewed the instrument.
2. **Pilot testing:** Conducted with 30 participants to assess clarity, reliability, and construct validity.

The survey included Likert-scale items (1 = strongly disagree to 5 = strongly agree) covering:

- Diagnostic accuracy improvement
- Patient throughput and time efficiency
- Workflow efficiency for allied health staff
- Operational and ethical challenges
- Perceived professional autonomy

Clinical data (e.g., diagnostic error rates, length-of-stay) were collected anonymously from hospital records over a 6-month period.

Variables and Measurement

Variable	Measurement	Source
Diagnostic Accuracy	% correct diagnosis before vs after AI-CDSS	Hospital records, physician logs
Patient Throughput	ED length-of-stay (minutes), triage-to-treatment interval	Hospital electronic records
Allied Health Workflow Efficiency	Self-reported efficiency scores; task completion time	Survey instrument, time-motion studies
Operational Challenges	Likert-scale items on bias, infrastructure, workflow mismatch	Survey instrument
Professional Autonomy	Likert-scale items on clinical decision independence	Survey instrument

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Conceptual Framework
The study's conceptual model hypothesizes that AI-CDSS implementation influences diagnostic accuracy, patient throughput, and allied health workflow efficiency, with operational challenges acting as a moderator on these relationships.

Figure 1. Conceptual Framework

[AI-CDSS Implementation] ---> [Diagnostic Accuracy]
---> [Patient Throughput]
---> [Allied Health Workflow Efficiency]
[Operational Challenges] ------> moderates all above relationship

Data Analysis Techniques
Data analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS 4.0. Analyses included:

1. **Measurement Model Assessment:** Reliability (Cronbach $\alpha \geq 0.70$), convergent validity (AVE $\geq$ 0.50), discriminant validity (HTMT < 0.85)
2. **Structural Model Assessment:** Path coefficients (β), effect sizes (f^2), and significance (bootstrapping with 5000 resamples)
3. **Moderation Analysis:** Interaction terms for operational challenges on AI-CDSS effectiveness
4. **Descriptive Statistics:** Means, SDs, and frequency distributions for demographic variables

Ethical Considerations

- Ethical approval was obtained from Pakistan Health Research Ethics Committee (PHREC/2025/ED01).
- Written informed consent was obtained from all participants.
- Patient data were anonymized, and confidentiality was strictly maintained.
- Participation was voluntary, with the right to withdraw at any time.

Results and Interpretation
Descriptive Statistics
A total of 400 participants were recruited, with a response rate of 95% (n = 380). The sample consisted of:

- **Physicians:** 95 (25%)
- **Allied health professionals:** 170 (44.7%)
- **Administrative staff:** 115 (30.3%)

Mean participant age was **33.6 ± 6.2 years**, with **55% male** and **45% female**. Participants reported an average of **6.2 ± 3.1 years of ED experience**.

Table 1. Participant Demographics

Variable	n (%)	Mean ± SD
Gender	Male	209 (55%)
	Female	171 (45%)
Age (years)	–	33.6 ± 6.2
Profession	Physician	95 (25%)
	Allied Health	170 (44.7%)
	Administrative	115 (30.3%)

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Diagnostic Accuracy Outcomes

Before AI-CDSS implementation, the average diagnostic accuracy for critical conditions (stroke, sepsis, fractures) was 78.3 ± 5.4%**.** After AI-CDSS integration, accuracy increased to 91.2 ± 4.7%**,** a statistically significant improvement **(**$t = 12.54$, $p < 0.001$**)** (1,2).

Figure 1. Diagnostic Accuracy Pre- and Post-AI-CDSS Implementation

Bar chart showing:
- Pre-AI: 78.3%
- Post-AI: 91.2%

Physicians reported higher confidence in diagnostic decisions, while allied health staff observed fewer repeat imaging orders.

Patient Throughput Metrics

The mean ED length-of-stay (LOS) decreased from 246 ± 38 minutes to 201 ± 31 minutes post-AI integration (**$p < 0.001$**)**.** Time from triage to diagnostic decision reduced from 58 ± 12 minutes to 41 ± 9 minutes**.**

Table 2. Patient Throughput Pre- and Post-AI Implementation

Metric	Pre-AI	Post-AI	% Change	p-value
ED LOS (min)	246 ± 38	201 ± 31	-18.3%	<0.001
Triage to Diagnosis (min)	58 ± 12	41 ± 9	-29.3%	<0.001
Time to Lab Results (min)	74 ± 15	53 ± 10	-28.4%	<0.001

These findings align with prior studies reporting 15–30% reductions in ED throughput times after AI-CDSS adoption (3–5).

Allied Health Workflow Analysis

Allied health professionals reported significant improvements in workflow efficiency:

- **Task completion time:** reduced by 22%
- **Redundant testing:** decreased by 18%
- **Perceived workload:** Likert-scale mean decreased from 3.9 ± 0.8 to 2.8 ± 0.7 ($p < 0.001$)

Figure 2. Allied Health Workflow Efficiency Scores

Line chart showing:
- Pre-AI: 3.9
- Post-AI: 2.8

These results suggest AI-CDSS streamlined workflow, allowing radiographers and laboratory staff to prioritize critical cases effectively (6,7).

PLS-SEM Results

The structural model assessed the hypothesized relationships between AI-CDSS implementation and outcomes (diagnostic accuracy, patient throughput, allied health workflow), moderated by operational challenges.

- **Diagnostic accuracy:** $\beta = 0.48$, $t = 6.21$, $p < 0.001$
- **Patient throughput:** $\beta = 0.52$, $t = 7.34$, $p < 0.001$
- **Allied health workflow efficiency:** $\beta = 0.44$, $t = 5.88$, $p < 0.001$
- **Moderating effect of operational challenges:** significant for all relationships ($p < 0.05$)

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Figure 3. PLS-SEM Path Model

[AI-CDSS Implementation] ---> Diagnostic Accuracy (β=0.48**)
---> Patient Throughput (β=0.52**)
---> Allied Health Workflow (β=0.44**)
[Operational Challenges] --> Moderates all paths

Model fit metrics indicated satisfactory predictive relevance ($Q^2 > 0.35$) and explanatory power (R^2 diagnostic accuracy = 0.52, patient throughput = 0.54, workflow = 0.48).hgInterpretation

1. **Diagnostic accuracy:** Integration of AI-CDSS significantly improved correct diagnoses, particularly for stroke, sepsis, and fractures, corroborating findings from high-resource settings (1,2,4).
2. **Patient throughput:** Reductions in ED LOS and triage-to-diagnosis times indicate improved efficiency, supporting prior evidence of AI-driven predictive analytics in emergency care (3–5).
3. **Allied health workflow:** Task prioritization and reduced repetitive work indicate enhanced operational efficiency. Improvements in workload perception suggest that AI-CDSS may reduce cognitive and administrative burden (6,7).
4. **Moderating effect:** Operational challenges, including data quality and system reliability, partially moderated outcomes, highlighting the importance of infrastructure and staff training in low-resource EDs (8,9).

Discussion

Diagnostic Accuracy

The study demonstrated a significant improvement in diagnostic accuracy following AI-CDSS integration, with mean accuracy increasing from 78.3% to 91.2%. This aligns with prior studies showing AI-assisted imaging and triage tools improve detection rates for critical conditions such as stroke, fractures, and sepsis (1,2). The findings indicate that AI-CDSS can serve as a reliable support system for emergency physicians, reducing diagnostic errors, particularly in high-pressure, high-volume ED environments (3).

These improvements are particularly relevant for **low-resource settings**, such as Pakistan, where staffing shortages and limited access to specialized radiologists can delay accurate diagnoses. By providing decision support, AI systems can partially mitigate the limitations imposed by human resource constraints, consistent with evidence from similar LMIC contexts (4,5).

Patient Throughput

The integration of AI-CDSS led to a significant reduction in ED length-of-stay (−18.3%) and triage-to-diagnosis times (−29.3%). These results are in line with prior quantitative studies reporting improved throughput following AI implementation, particularly through predictive triage and optimized workflow scheduling (6,7).

Improved throughput has direct clinical implications: faster diagnosis facilitates timely treatment initiation, reduces crowding, and enhances patient safety. In resource-constrained EDs, these efficiency gains may translate into better allocation of limited human and material resources, reducing the risk of treatment delays for critically ill patients (8).

Allied Health Workflow Efficiency

Allied health professionals reported measurable improvements in workflow efficiency, including reductions in redundant imaging, shorter task completion times, and decreased perceived workload. These

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findings are consistent with prior literature highlighting AI's role in automating repetitive tasks, prioritizing urgent cases, and enabling staff to focus on higher-order clinical tasks (9,10).
However, some caution is warranted. Previous research notes the potential for deskilling among staff who over-rely on AI recommendations, particularly in diagnostic imaging and laboratory work (11). Continuous training and supervision are therefore critical to ensure that AI serves as a support tool rather than replacing professional judgment.

Operational Challenges as Moderators
Operational challenges including system reliability, data quality, and staff familiarity moderated the effectiveness of AI-CDSS across outcomes. These findings echo prior research emphasizing that AI implementation in low-resource settings is contingent upon infrastructure readiness, robust data systems, and continuous professional training (12,13). Hospitals with reliable IT infrastructure and structured workflow protocols reported greater improvements in both diagnostic accuracy and throughput. This highlights that technology adoption alone is insufficient; supportive organizational systems are essential to realize AI's full potential (14).

Ethical and Professional Considerations
The study also identified potential ethical implications. Although AI improved workflow and accuracy, staff emphasized the importance of maintaining clinical autonomy. Over-reliance on algorithmic recommendations could undermine decision-making authority, raising questions about responsibility and accountability in clinical outcomes (15,16).

These concerns are consistent with global discussions on the ethical integration of AI in healthcare, which recommend that AI should augment rather than replace human judgment, ensure transparency of decision logic, and safeguard patient confidentiality (17,18).

Implications for LMIC Contexts
The study provides strong evidence that AI-CDSS can enhance emergency care in low-resource settings, offering both operational and clinical benefits. However, contextual factors such as staff training, infrastructure quality, and local patient population characteristics must be addressed to maximize effectiveness (19,20).
Specifically, hospitals in Pakistan and similar LMICs should consider phased AI deployment, structured staff training, and ongoing performance monitoring to optimize both workflow efficiency and patient outcomes.

Policy Implications
Based on the findings, the following policy recommendations are proposed for healthcare administrators, policymakers, and hospital management:

1. **Infrastructure Investment:** Allocate resources to ensure robust IT infrastructure, reliable network connectivity, and access to electronic health records to maximize AI-CDSS effectiveness (8,9).
2. **Staff Training and Capacity Building:** Implement structured training programs for physicians, nurses, and allied health professionals to build AI literacy and ensure safe integration into clinical workflows (6,7).
3. **Clinical Governance and Oversight:** Develop clear guidelines to maintain **professional autonomy** and accountability, including decision review processes and AI audit mechanisms (10,11).

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4. **Phased Deployment:** Introduce AI-CDSS gradually in EDs to allow workflow adaptation, performance monitoring, and identification of operational bottlenecks (12,13).
5. **Ethical and Legal Frameworks:** Establish national policies and regulatory frameworks that address data privacy, algorithm transparency, and liability for AI-assisted clinical decisions (14).
6. **Integration with National Health Priorities:** Align AI-CDSS implementation with broader health system goals, such as reducing diagnostic delays, optimizing emergency care, and enhancing equitable access to quality healthcare (15,16).

These policy measures are critical to sustainably integrate AI technologies in emergency departments, particularly in low-resource settings, ensuring measurable improvements in patient outcomes and operational efficiency.

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