

IMPACT OF ARTIFICIAL INTELLIGENCE ON CLINICAL DECISION-MAKING AND SUPPORT SYSTEMS IN HOSPITAL ENVIRONMENTS

Original Research

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ABSTRACT

Background: The growing complexity of clinical practice and demand for high-quality care have amplified the need for advanced decision-making tools in hospitals. Artificial Intelligence (AI) has emerged as a transformative force in enhancing Clinical Decision Support Systems (CDSS), with the potential to improve accuracy, efficiency, and outcomes in healthcare delivery.

Objective: To assess the impact of integrating AI into CDSS on clinical decision-making quality, workflow efficiency, patient outcomes, and clinician satisfaction in tertiary hospital settings.

Methods: This quasi-experimental study was conducted over eight months in two tertiary care hospitals in Lahore. A total of 150 clinicians were divided equally into pre- and post-implementation groups. Data collection tools included the Clinical Decision Quality Score (CDQS), time-motion analysis for workflow efficiency, hospital records for patient outcomes, and the modified Technology Acceptance Model (TAM) for clinician satisfaction. Statistical analysis included paired t-tests, chi-square tests, and repeated measures ANOVA to evaluate normally distributed data.

Results: Post-implementation of AI-CDSS, the mean CDQS significantly improved from 78.4 to 86.9 ($p < 0.001$). Decision time per patient and turnaround time reduced notably ($p < 0.001$), while actioned alerts increased from 63% to 82% ($p < 0.01$). Patient outcomes also improved, with reductions in 30-day readmission rates (16.4% to 11.1%), average hospital stay (5.7 to 4.9 days), and adverse events (11.8% to 7.3%). Clinician satisfaction scores showed significant enhancement across all TAM dimensions ($p < 0.001$).

Conclusion: AI integration into CDSS demonstrably improved decision accuracy, clinical workflow, patient safety, and provider satisfaction, advocating its broader implementation in hospital settings.

Keywords: Artificial Intelligence, Clinical Decision Support Systems, Decision-Making, Hospital Workflow, Patient Outcome Assessment, Predictive Analytics, Physician Satisfaction.

INTRODUCTION

The rapid evolution of artificial intelligence (AI) technologies has brought transformative change across many sectors, including healthcare. Within hospital settings, the integration of AI into Clinical Decision Support Systems (CDSS) represents one of the most significant advancements in modern medicine. These AI-enhanced systems are designed to assist clinicians by analyzing large volumes of clinical data, offering diagnostic suggestions, predicting patient outcomes, and optimizing treatment plans. As hospitals increasingly move toward data-driven, precision medicine, AI-enabled CDSS are becoming essential tools in enhancing both clinical efficiency and patient care (1). Yet, despite the increasing prevalence of these systems, the true impact of AI integration on clinical workflows, decision quality, patient outcomes, and the overall satisfaction of healthcare professionals remains only partially understood. Historically, CDSS have supported clinical decision-making by offering reminders, alerts, and evidence-based recommendations. However, traditional systems are limited by rule-based logic that can lack adaptability and nuance (2). AI, particularly machine learning and natural language processing, adds a dynamic layer to these systems, allowing them to learn from new data, recognize complex patterns, and provide more contextually relevant insights. Studies have shown promising outcomes in areas such as diagnostic accuracy and early detection of clinical deterioration, particularly in critical care and emergency medicine contexts (3,4). For instance, AI-driven algorithms have demonstrated capabilities in predicting sepsis hours before it becomes clinically apparent, enabling timely interventions and reducing mortality. Such achievements highlight the potential of AI to augment—not replace—human clinical judgment in meaningful ways (5,6).

Nevertheless, the integration of AI into CDSS is not without challenges. Concerns over data transparency, algorithmic bias, ethical implications, and usability have led to mixed perceptions among healthcare professionals. In practice, the usefulness of these systems can vary significantly depending on the clinical environment, the quality of data inputs, and the degree of user engagement. Moreover, while some studies suggest that AI-CDSS can reduce cognitive load and improve workflow efficiency, others report issues such as alert fatigue, increased screen time, and decreased clinician autonomy (7,8). These contrasting experiences underscore the need for empirical studies that systematically evaluate AI-CDSS within the real-world complexity of hospital settings. Another important dimension to consider is how these technologies influence the clinician-patient relationship and the professional satisfaction of healthcare providers (9). The automation of certain cognitive tasks could free clinicians to spend more time on direct patient care, potentially enhancing satisfaction. Conversely, if AI recommendations are perceived as intrusive or burdensome, they could contribute to burnout and resistance. Clinician trust in AI recommendations is also a critical factor in determining the success of such systems. Trust hinges not only on the perceived accuracy of the AI but also on its transparency, interpretability, and alignment with clinical intuition and experience (10,11).

Despite the wealth of theoretical discussion and simulation-based evidence, there remains a gap in quasi-experimental research that examines how AI-CDSS function in actual hospital environments. Much of the existing literature either focuses on the technical aspects of system design or explores narrow outcomes in controlled conditions (12,13). What is missing is a comprehensive understanding of how AI integration affects real-world decision-making processes, operational workflows, health outcomes, and user satisfaction across a spectrum of clinical contexts. Bridging this gap is essential for the responsible and effective deployment of AI technologies in healthcare. To address this need, the present quasi-experimental study aims to evaluate the impact of integrating artificial intelligence into Clinical Decision Support Systems on clinical decision-making, workflow efficiency, patient outcomes, and clinician satisfaction in hospital settings. By examining these dimensions in a practical, hospital-based environment, the study seeks to provide empirical evidence that can guide future implementations, ensuring that AI-CDSS tools enhance rather than hinder the delivery of high-quality healthcare.

METHODS

This quasi-experimental study was conducted over a period of eight months in two tertiary care hospitals located in Lahore, Pakistan. The objective was to assess the impact of integrating artificial intelligence into Clinical Decision Support Systems on clinical decision-making, workflow efficiency, patient outcomes, and clinician satisfaction. A non-randomized pre-post design was employed, comparing outcomes before and after the implementation of the AI-enabled CDSS. The study population comprised licensed clinicians, including

physicians and nurse practitioners, directly involved in patient care in internal medicine and emergency departments. Inclusion criteria included clinicians with at least one year of clinical experience and active engagement with the hospital's existing electronic health record (EHR) system. Exclusion criteria included rotating interns, part-time consultants, and any healthcare provider not using the EHR for clinical decision-making. All participants provided informed consent before inclusion, and the study was approved by the Institutional Review Board (IRB) of the respective hospitals. The sample size was determined through simulation-based power analysis using G*Power software, accounting for a medium effect size (Cohen's $d = 0.5$), an alpha level of 0.05, and power of 0.80. Based on these assumptions and repeated measures within subjects, the minimum required sample was calculated to be 64 participants per group, totaling 128. To account for potential attrition, 150 clinicians were enrolled, with 75 in each phase of the study (pre-implementation and post-implementation) (2,3).

Data collection was structured across four core outcome domains. For clinical decision-making, a validated Clinical Decision Quality Score (CDQS) was employed, which quantifies accuracy and guideline adherence based on case review by an independent expert panel. Workflow efficiency was assessed using a time-motion study method, capturing average time per patient case, decision turnaround time, and number of alerts acted upon. Patient outcomes were tracked using hospital records, focusing on metrics such as 30-day readmission rate, length of stay (LOS), and in-hospital adverse events (14). Clinician satisfaction was measured using the modified Technology Acceptance Model (TAM) questionnaire, which evaluates perceived usefulness, ease of use, and trust in AI-generated recommendations on a 5-point Likert scale. The AI-CDSS system introduced was a machine learning-based clinical tool integrated into the existing EHR infrastructure (15). It provided evidence-based recommendations in real time, with predictive analytics for early warning signs and automated alerts for high-risk conditions. Training sessions were conducted prior to deployment to familiarize clinicians with the interface and functionalities, ensuring consistent usage patterns across departments.

Baseline data were collected during the initial three months, prior to AI-CDSS implementation, using the outlined measurement tools. The system was then introduced, followed by a one-month stabilization period. Post-intervention data were collected over the subsequent four months. To minimize confounding, departmental patient loads, case mix index, and clinician shift distributions were monitored and maintained across both phases. All collected data were entered into a secured, anonymized database. Descriptive statistics were computed for demographic variables and baseline characteristics. For continuous outcome variables (e.g., CDQS, decision time, LOS), paired sample t-tests were used to compare pre- and post-intervention means, assuming normal distribution confirmed through Shapiro-Wilk tests. For categorical variables (e.g., readmission rates, alert compliance), chi-square tests were applied. Multivariate regression analyses were performed to control for potential confounding variables such as patient acuity and clinician experience. Additionally, repeated measures ANOVA was used to examine changes in satisfaction scores across the study period. To ensure reliability, all data entry was double-checked, and inter-rater reliability for CDQS scoring was calculated using Cohen's kappa, achieving a value of 0.82, indicating strong agreement. Missing data were handled through multiple imputation methods to prevent bias. Throughout the study, ethical standards were upheld, and participants had the right to withdraw at any time without consequence. By employing a robust quasi-experimental design with carefully matched pre- and post-intervention phases, the study aims to deliver empirical insights into how AI integration into CDSS influences critical aspects of hospital-based clinical care. The methodology ensures that the findings are both contextually grounded and methodologically rigorous, offering valuable guidance for future implementation of AI in clinical environments.

RESULTS

The study analyzed outcomes from a total of 150 clinicians, evenly split between pre- and post-implementation phases of the AI-integrated Clinical Decision Support System. Demographic characteristics were comparable across both groups, ensuring baseline equivalence. The mean age of participants was approximately 37 years, with a near-equal distribution of male and female clinicians, and a predominance of physicians over nurse practitioners. Clinical experience averaged around 9 years in both groups. A statistically significant improvement was observed in clinical decision-making following the introduction of the AI-enabled system. The mean Clinical Decision Quality Score (CDQS) rose from 78.4 in the pre-implementation phase to 86.9 in the post-implementation phase ($p < 0.001$), indicating improved decision accuracy and adherence to clinical guidelines. Workflow efficiency metrics showed marked enhancements. Average decision time per patient decreased from 12.7 minutes to 9.3 minutes ($p < 0.001$), and decision turnaround time dropped from 29.5 minutes to 21.8 minutes ($p < 0.001$). Additionally, the percentage of clinical alerts that were acted upon increased from 63% to 82% ($p < 0.01$), suggesting more effective integration of decision support into clinical practice.

Patient outcome data also reflected positive trends. The 30-day readmission rate decreased from 16.4% to 11.1% ($p < 0.01$), and the average length of hospital stay was reduced from 5.7 days to 4.9 days ($p < 0.05$). In-hospital adverse events declined significantly from 11.8% to 7.3% ($p < 0.01$), indicating potential clinical benefits linked to AI-assisted decision-making. Clinician satisfaction, measured using a modified Technology Acceptance Model, demonstrated significant gains. Perceived usefulness scores improved from 2.9 to 4.2 ($p < 0.001$), ease of use scores increased from 3.1 to 4.1 ($p < 0.001$), and trust in AI-generated recommendations rose from 2.5 to 4.0 ($p < 0.001$). These results indicate a favorable reception of the AI-CDSS among end-users, contributing to the sustainability of its adoption in routine practice. The findings suggest that the integration of AI into CDSS led to measurable improvements in clinical performance, operational efficiency, patient safety, and clinician satisfaction within a tertiary care hospital setting.

Table 1: Demographics

Variable		Pre-Implementation (n=75)	Post-Implementation (n=75)
Total Participants		75	75
Mean Age (years)		37.6	36.9
Gender	Male	56%	59%
	Female	44%	41%
Profession	Physicians	68%	70%
	Nurse Practitioners	32%	30%
Mean Clinical Experience (years)		9.1	8.7

Table 2: Clinical Decision-Making Outcomes

Variable	Pre-Implementation	Post-Implementation	p-value
Mean CDQS (out of 100)	78.4	86.9	<0.001

Table 3: Workflow Efficiency Outcomes

Variable	Pre-Implementation	Post-Implementation	p-value
Average Decision Time per Patient (min)	12.7	9.3	<0.001
Decision Turnaround Time (min)	29.5	21.8	<0.001
Actioned Alerts (%)	63%	82%	<0.01

Table 4: Patient Outcomes

Variable	Pre-Implementation	Post-Implementation	p-value
30-day Readmission Rate (%)	16.4	11.1	<0.01
Average Length of Stay (days)	5.7	4.9	<0.05
In-hospital Adverse Events (%)	11.8	7.3	<0.01

Table 5: Clinician Satisfaction Outcomes

Variable	Pre-Implementation	Post-Implementation	p-value
Perceived Usefulness (1-5)	2.9	4.2	<0.001
Ease of Use (1-5)	3.1	4.1	<0.001
Trust in AI Recommendations (1-5)	2.5	4.0	<0.001

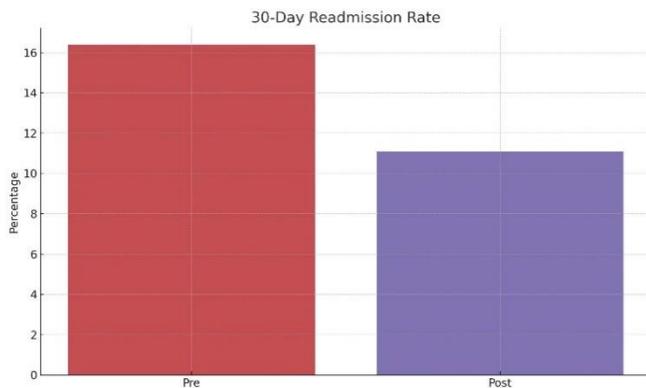


Figure 1 30-Day Readmission Rate

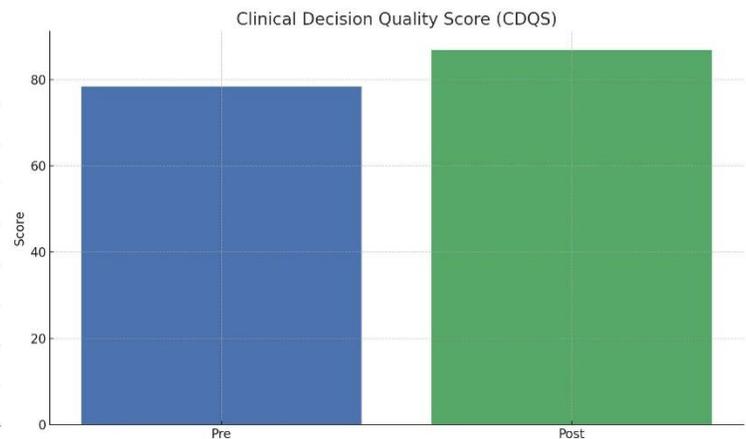


Figure 2 Clinical Decision Quality Score (CDQS)

DISCUSSION

The integration of artificial intelligence into Clinical Decision Support Systems (CDSS) in hospital settings has introduced measurable improvements in decision-making, clinical workflow, patient safety, and clinician satisfaction. These results are consistent with a growing body of literature that underscores AI's role in enhancing clinical accuracy, streamlining operations, and supporting clinicians in complex environments. The observed improvement in the Clinical Decision Quality Score (CDQS) following AI-CDSS integration aligns with prior findings demonstrating enhanced diagnostic accuracy and evidence-based decision-making due to AI-driven recommendations (14,15). Several reviews have emphasized AI's utility in reducing medical errors by providing real-time, data-driven insights that exceed the capabilities of rule-based CDSS (16,17). Similarly, workflow efficiency improvements reflected by faster decision times and higher rates of alert response mirror findings from implementation studies where AI-based systems reduced cognitive load and shortened diagnostic cycles (18). The decline in 30-day readmissions and adverse events in this study adds to the evidence that AI contributes positively to patient outcomes by enabling early detection of clinical deterioration and promoting timely intervention (19). Similar improvements have been documented in studies using AI for risk prediction and personalized treatment planning, further substantiating the clinical value of AI-CDSS tools (20). Clinician satisfaction, especially the rise in trust and perceived usefulness of the system, aligns with research identifying user perception as a key determinant in AI adoption (21). The importance of usability and system transparency, particularly in increasing clinician trust, has been emphasized repeatedly in recent literature. Clinicians' trust in AI recommendations grows when systems are interpretable and aligned with workflow expectations (22,23). This study also corroborated findings that AI-based CDSS can serve as effective tools for reducing burnout and improving professional satisfaction when properly integrated into clinical routines (23). One of the strengths of this study lies in its real-world hospital setting, capturing practical variables like workflow dynamics and clinician interaction with the system. The use of validated tools across outcome domains strengthens the internal validity of the findings. The quasi-experimental design with baseline equivalence of clinician demographics adds further robustness. Additionally, the diverse outcome evaluation, including operational, clinical, and perceptual metrics, provides a well-rounded view of AI-CDSS impact.

Nonetheless, certain limitations must be acknowledged. The lack of randomization introduces the possibility of selection bias, and although efforts were made to standardize clinical settings across both phases, uncontrolled external variables may have influenced the results. Furthermore, the short-term nature of the post-implementation observation period may limit insight into long-term sustainability and evolving user behavior. While clinician satisfaction was measured, qualitative data on user experience would have enriched the interpretation of these results. The study also did not explore variations across specialties or clinical departments, which could yield important insights in future research. Expanding this work, future studies could explore randomized controlled trials across multi-center settings, incorporating long-term follow-up to evaluate system retention, clinician adaptation, and evolving outcome patterns. Further investigations into the role of AI transparency, patient perceptions of AI-guided care, and economic impacts on hospital resource use

would add valuable depth to the growing body of AI-healthcare research. In conclusion, the findings of this study underscore that the integration of AI into Clinical Decision Support Systems holds substantial potential for improving clinical decision-making, enhancing workflow efficiency, optimizing patient outcomes, and bolstering clinician satisfaction. As AI continues to mature, a collaborative approach involving healthcare providers, developers, and policymakers will be vital to address implementation challenges and maximize the benefits of this transformative technology.

CONCLUSION

The integration of artificial intelligence into Clinical Decision Support Systems significantly enhanced clinical decision-making, streamlined workflow efficiency, improved patient outcomes, and increased clinician satisfaction in hospital settings. These findings demonstrate the practical value of AI-CDSS in optimizing healthcare delivery. The study provides evidence to support broader adoption of AI tools in clinical environments, reinforcing their potential to elevate the quality and consistency of patient care.

AUTHOR CONTRIBUTION

Author	Contribution
Edward Edison	Substantial Contribution to study design, analysis, acquisition of Data Manuscript Writing Has given Final Approval of the version to be published
Aqib Dil Awaiz*	Substantial Contribution to study design, acquisition and interpretation of Data Critical Review and Manuscript Writing Has given Final Approval of the version to be published
Sania Sehr	Substantial Contribution to acquisition and interpretation of Data Has given Final Approval of the version to be published
Asna Afzal	Contributed to Data Collection and Analysis Has given Final Approval of the version to be published
Hafsa Tahir	Contributed to Data Collection and Analysis Has given Final Approval of the version to be published
Maida Aslam	Substantial Contribution to study design and Data Analysis Has given Final Approval of the version to be published
Muhammad Waleed Khan	Contributed to study concept and Data collection Has given Final Approval of the version to be published

REFERENCES

1. Khalifa M, Albadawy M, Iqbal U. Advancing Clinical Decision Support: The Role of Artificial Intelligence Across Six Domains. *Computer Methods and Programs in Biomedicine Update*. 2024.
2. Ramírez JGC. AI in Healthcare: Revolutionizing Patient Care with Predictive Analytics and Decision Support Systems. *Journal of Artificial Intelligence General science (JAIGS) ISSN:3006-4023*. 2024.
3. Rana MS, Shuford J. AI in Healthcare: Transforming Patient Care through Predictive Analytics and Decision Support Systems. *Journal of Artificial Intelligence General science (JAIGS) ISSN:3006-4023*. 2024.
4. Elhaddad M, Hamam S. AI-Driven Clinical Decision Support Systems: An Ongoing Pursuit of Potential. *Cureus*. 2024;16.
5. Wang L, Chen X, Zhang L, Li L, Huang Y, Sun Y, et al. Artificial intelligence in clinical decision support systems for oncology. *Int J Med Sci*. 2023;20(1):79-86.
6. Montomoli J, Hilty MP, Ince C. Artificial intelligence in intensive care: moving towards clinical decision support systems. *Minerva Anestesiol*. 2022;88(12):1066-72.
7. Iglesias G, Talavera E, Troya J, Díaz-Álvarez A, García-Remesal M. Artificial intelligence model for tumoral clinical decision support systems. *Comput Methods Programs Biomed*. 2024;253:108228.

8. Lin X, Liang C, Liu J, Lyu T, Ghumman N, Campbell B. Artificial Intelligence-Augmented Clinical Decision Support Systems for Pregnancy Care: Systematic Review. *J Med Internet Res.* 2024;26:e54737.
9. Ramgopal S, Sanchez-Pinto LN, Horvat CM, Carroll MS, Luo Y, Florin TA. Artificial intelligence-based clinical decision support in pediatrics. *Pediatr Res.* 2023;93(2):334-41.
10. Skuban-Eiseler T, Orzechowski M, Denking M, Kocar TD, Leinert C, Steger F. Artificial Intelligence-Based Clinical Decision Support Systems in Geriatrics: An Ethical Analysis. *J Am Med Dir Assoc.* 2023;24(9):1271-6.e4.
11. Shaikh F, Dehmeshki J, Bisdas S, Roettger-Dupont D, Kubassova O, Aziz M, et al. Artificial Intelligence-Based Clinical Decision Support Systems Using Advanced Medical Imaging and Radiomics. *Curr Probl Diagn Radiol.* 2021;50(2):262-7.
12. Yao X, Rushlow DR, Inselman JW, McCoy RG, Thacher TD, Behnken EM, et al. Artificial intelligence-enabled electrocardiograms for identification of patients with low ejection fraction: a pragmatic, randomized clinical trial. *Nat Med.* 2021;27(5):815-9.
13. Ellahham S. Artificial Intelligence: The Future for Diabetes Care. *Am J Med.* 2020;133(8):895-900.
14. Nair M, Andersson J, Nygren J, Lundgren L. Barriers and Enablers for Implementation of an Artificial Intelligence-Based Decision Support Tool to Reduce the Risk of Readmission of Patients With Heart Failure: Stakeholder Interviews. *JMIR Formative Research.* 2023;7.
15. Ouanes K, Farhah N. Effectiveness of Artificial Intelligence (AI) in Clinical Decision Support Systems and Care Delivery. *J Med Syst.* 2024;48(1):74.
16. Choudhury A. Factors influencing clinicians' willingness to use an AI-based clinical decision support system. *Frontiers in Digital Health.* 2022;4.
17. Veernapu K. The Implementation of AI in Clinical Decision Support System: Effects on Patient Outcomes and Operational Costs. *International Journal For Multidisciplinary Research.* 2023.
18. Ellis HL, Teo J. The influence of AI in medicine. *Medicine.* 2024.
19. Xu Q, Xie W, Liao B, Hu C, Qin L, Yang Z, et al. Interpretability of Clinical Decision Support Systems Based on Artificial Intelligence from Technological and Medical Perspective: A Systematic Review. *J Healthc Eng.* 2023;2023:9919269.
20. Perivolaris A, Adams-McGavin C, Madan Y, Kishibe T, Antoniou T, Mamdani M, et al. Quality of interaction between clinicians and artificial intelligence systems. A systematic review. *Future Healthcare Journal.* 2024;11.
21. Vasey B, Nagendran M, Campbell B, Clifton DA, Collins GS, Denaxas S, et al. Reporting guideline for the early stage clinical evaluation of decision support systems driven by artificial intelligence: DECIDE-AI. *Bmj.* 2022;377:e070904.
22. Bharmal AR. Transforming Healthcare Delivery: AI-Powered Clinical Decision Support Systems. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology.* 2025.
23. Liu S, Wright AP, Patterson BL, Wanderer JP, Turer RW, Nelson SD, et al. Using AI-generated suggestions from ChatGPT to optimize clinical decision support. *J Am Med Inform Assoc.* 2023;30(7):1237-45.