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The Role of Artificial Intelligence–Assisted Clinical Decision Support Systems in Enhancing Nursing Practice and Patient Outcomes in Iraqi Hospitals

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ABSTRACT
Clinical decision support systems (CDSSs) augmented by artificial intelligence (AI) are revolutionising modern health care, but little is known about their use in Iraqi tertiary hospitals. Nurses are the primary decision-makers in clinical practice, and poor decision support can pose a patient safety risk. Objective: The aim of this study was to compare the effectiveness of AI-supported CDSS with traditional (non-AI) methods in improving nursing practice and certain patient outcomes in tertiary hospitals in three Iraqi governorates. Methods: A prospective, comparative, cross-sectional design was used, involving 294 registered nurses grouped into three categories: Group I (non-CDSS, n = 98), Group II (simple rule-based CDSS, n = 96), and Group III (AI-assisted CDSS, n = 100). Eight-month data (February-September 2023) was gathered via structured observation checklists, validated measures of nursing practice, hospital records and patient satisfaction surveys. Data were analysed using one-way ANOVA with Bonferroni post hoc tests ($p < 0.05$). Results: AI-CDSS implementation produced marked improvements in clinical decision accuracy (84.7 ± 6.1% vs. 61.4 ± 8.2% in controls; $p < 0.001$), substantial reductions in medication error rates (2.1 ± 0.9 vs. 6.8 ± 1.9 per 100 orders; $p < 0.001$), shorter hospital stays (6.4 ± 1.7 vs. 9.8 ± 2.4 days; $p < 0.001$), and higher patient satisfaction scores (86.5 ± 6.9 vs. 63.2 ± 9.8; $p < 0.001$). The main challenges for implementation were the lack of digital infrastructure (74.5% for Group I) and AI-literacy training for nurses (81.6%). Conclusion: AI-powered CDSS resulted in improved nursing practice and patient outcomes in Iraqi hospitals. Continued infrastructure development and AI literacy training for nursing staff are vital for future use.

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INTRODUCTION

Over the last ten years, artificial intelligence has been rapidly integrated into health care systems, particularly through the use of machine-learning algorithms, natural language processing and real-time data analytics. Of most clinical interest are AI-enhanced clinical decision support systems (CDSSs), which integrate patient-level data with evidence-based clinical guidelines to deliver real-time recommendations for clinical practice. Such systems have the potential to support nurses, who deliver most direct patient interventions and are primarily responsible for monitoring the patient's status; yet, there is a paucity of evidence from low- and middle-income healthcare settings, especially those in conflict and resource-poor environments.

The health care system in Iraq has faced decades of disruption due to conflict, infrastructure damage and under-investment, leading to ongoing issues with patient safety culture and clinical decision support. While recent government promises of hospital digitisation and the gradual rollout of electronic health record (EHR) systems are beginning to take shape, CDSS implementation is patchy and limited to a few academic hospitals. Most nurses in both public and private hospitals continue to rely primarily on experience and conventional guidelines, with no formal digital support during patient assessment and care planning.

An international body of evidence shows that AI-powered CDSSs help reduce medication errors, diagnostic delays, protocol compliance and, ultimately, adverse events and length of hospital stay [1-4]. These results are derived from high- and middle-income healthcare systems with well-developed digital infrastructure and IT-competent staff. How and to what extent these benefits apply within the constraints of Iraqi hospitals (given the high nurse-to-patient ratios, inconsistent internet access and diverse staff IT literacy) remains unknown.

This investigation is informed by a number of conceptual models. The Technology Acceptance Model (TAM) suggests that perceived ease of use and perceived usefulness are key factors influencing the use of technology by health-care practitioners [5]. When combined with the Nursing Role Effectiveness Model, which incorporates nursing-sensitive outcomes into the healthcare process, these models provide a theoretically sound basis for understanding CDSS adoption and subsequent outcomes in Iraq [6]. Previous research in similar contexts has identified organisational culture, workload and leadership support as moderating factors in the uptake of new technology [7,8].

In this context, the current study sought to answer three related questions: first, does AI-supported CDSS implementation lead to significantly better objective measures of nursing decision making than simple rule-based or no CDSS implementation?; second, do we observe systematic differences in measurable patient outcomes - including hospital length of stay, readmission rates, adverse events and patient satisfaction - across groups with varying CDSS implementation?; third, what are the primary barriers and enablers for successful integration of AI-CDSS into Iraqi hospital settings? The findings to these questions have direct implications for policy, education and digitalisation strategies in Iraqi hospitals and other resource-constrained healthcare settings.

MATERIALS AND METHODS

Study Design and Setting

A prospective, comparative, cross-sectional study design was used from February to September 2023. The settings were six tertiary-level public hospitals in three governorates of Iraq (Baghdad, Nineveh, and Salah al-Din). Hospitals were purposively selected to represent different stages of digital maturity: two hospitals with no CDSS in place (Group I), two hospitals with a simple rule-based CDSS integrated with their EHR system (Group II), and two hospitals that had recently installed an AI-assisted CDSS with machine learning-based alert generation (Group III).

Study Population and Sampling

A population of registered nurses in critical care, emergency and surgical departments across the hospitals was considered. Eligibility criteria required nurses to have at least 12 months' experience, be full-time employees, and have signed informed consent. Nurses on solely administrative roles, those undertaking postgraduate studies requiring reduced clinical load, and those less than six months into their current roles were excluded. Stratified sampling was used to recruit 294 nurses: Group I (n = 98), Group II (n = 96) and Group III (n = 100).

Data Collection Instruments

Four instruments were used. The Clinical Decision-Making Accuracy Scale (CDMAS) [9], which was developed and validated, measured nurses' ability to analyse and interpret data and choose interventions for 20 standardised clinical scenarios; this was scored from 0-100% correct. Retrospective medication error data were obtained from each hospital's pharmacovigilance reporting system (incidents per 100 medication orders). Patient outcomes, such as length of stay, 30-day readmissions, ICU complications and inpatient mortality rates, were derived from hospitals' administrative data, and classified using ICD-10 codes. The Arabic-validated Patient Satisfaction Questionnaire-Short Form

(PSQ-18) was applied to assess patient satisfaction, with data scaled to 100 points [10].

Two trained research assistants used a 40-item observational checklist to assess the completeness of nursing assessment and protocol adherence during the normal shift. Cohen's kappa statistic ($\kappa = 0.84$ for assessment completeness; $\kappa = 0.81$ for protocol adherence) indicated good inter-rater reliability. Data on CDSS barriers and facilitators were collected using a 30-item questionnaire based on the eHealth Acceptance Questionnaire [11], at the end of the study period.

Statistical Analysis

Data were entered into IBM SPSS (version 27.0, IBM Corp., Armonk, NY, USA). Continuous data are presented as Mean ± SD, and categorical data as number and percentage. Comparisons between groups for continuous variables were made by one-way analysis of variance (ANOVA) and post-hoc Bonferroni correction for multiple comparisons. The Kruskal-Wallis test was used if the assumption of normality (Shapiro-Wilk test) was not met. Comparisons of categorical variables were made with chi-square test and Yates' correction if necessary. $p < 0.05$ was considered statistically significant. Effect sizes were reported using partial eta-squared (η^2p) for ANOVA and Cramér's V for categorical.

Ethical Considerations

The Research Ethics Committee at the University of Samarra (Ref. No.: USA-REC-2023-047) and from the institutional review boards of the six hospitals involved in the study. All procedures were in line with the Declaration of Helsinki (2013). Informed consent was obtained from all participants before enrolment and all data were deidentified and stored on secure institutional servers with restricted access to the lead research team.

RESULTS

Demographic and Professional Characteristics of Participants

The baseline demographic and professional characteristics of the three groups are shown in Table 1. There was no significant difference in mean age, years of clinical experience, ward allocation, attainment of postgraduate qualifications and daily patient allocation (all $p > 0.05$) among the groups, indicating that the groups were comparable at the start of the study.

Table 1. Demographic and professional characteristics of the nurse participants in the three groups at baseline.

Variable	Group I (Non-CDSS) n = 98	Group II (Basic CDSS) n = 96	Group III (AI-CDSS) n = 100	p-value
Age (years)	34.6 ± 5.2	35.1 ± 4.9	34.8 ± 5.0	0.872
Years of experience	7.4 ± 3.1	7.9 ± 3.4	8.1 ± 3.0	0.541
ICU nurses (%)	42.9	43.8	44.0	0.983
Emergency nurses (%)	31.6	30.2	31.0	0.947
Surgical ward nurses (%)	25.5	26.0	25.0	0.961
Postgraduate training (%)	38.8	39.6	40.0	0.968
Mean daily patient load	8.3 ± 2.1	8.5 ± 2.0	8.2 ± 2.2	0.623

Note. Values represent means ± SD for continuous variables and percentages for categorical variables. No significant between-group differences were identified ($p > 0.05$ for all variables). ICU = intensive care unit.

The findings of the comparative analysis of clinical practice quality indicators showed significant differences between groups in all indicators (Table 2). The clinical decision accuracy of the nurses in Group III (AI-CDSS) was significantly higher (84.7 ± 6.1%) than that of the nurses in Group II (72.3 ± 7.6%) and Group I (61.4 ± 8.2%), with statistically significant differences for the Group I vs. Group III ($p < 0.001$) and Group II vs. Group III ($p < 0.001$) comparisons. Medication error rates progressively decreased to 2.1 ± 0.9 errors per 100 orders in the AI-CDSS group (a 69% reduction compared to the non-CDSS group). Time to clinical intervention was also significantly shorter in Group III (18.2 ± 5.4 minutes), with a 52.6% reduction compared with the Group I (38.4 ± 9.1 minutes; $p < 0.001$).

Table 3 provides a summary of patient-level outcome data obtained from institutional sources. Hospital length of stay (6.4 ± 1.7 days) was shorter for patients cared for on AI-CDSS wards compared with basic CDSS (8.1 ± 2.0 days) or non-CDSS wards (9.8 ± 2.4 days; $p < 0.001$ for all comparisons). The 30-day readmission rate was reduced by 54.9% in Group III compared with Group I (8.3 ± 2.6% vs. 18.4 ± 4.2%; $p < 0.001$). The level of patient satisfaction was highest in the AI-CDSS group (86.5 ± 6.9) and lowest in the non-CDSS group (63.2 ± 9.8; $p < 0.001$). The incidence of ICU complications and the inpatient mortality index showed a similar pattern of incremental improvement according to the technological advances of CDSS.

Table 4 outlines the reported barriers and facilitators to CDSS implementation. Group I nurses most frequently cited insufficient training on AI technology (81.6%), followed by lack of digital infrastructure (74.5%) and unwillingness to adopt the new technology (66.3%). As CDSS complexity increased, the number of nurses trusting AI-produced clinical alerts grew significantly: from 29.6% in Group I to 54.2% in Group II and 84.0% in Group III ($p < 0.001$). Reduced workload was the most important facilitating factor in Group III, where high rates of sustained AI-CDSS use (79.0%) and ease of use (8.4 ± 0.9 on a 10-point scale) and high CDSS satisfaction (91.0%) were reported.

Table 2. Clinical practice quality indicators for the three groups of nurses.

Clinical Outcome Indicator	**Group I (Non-CDSS) Mean ± SD**	**Group II (Basic CDSS) Mean ± SD**	**Group III (AI-CDSS) Mean ± SD**	**p-value**
Clinical decision accuracy (%)	61.4 ± 8.2	72.3 ± 7.6*	84.7 ± 6.1*†	< 0.001
Medication error rate (per 100 orders)	6.8 ± 1.9	4.2 ± 1.4*	2.1 ± 0.9*†	< 0.001
Time to intervention (minutes)	38.4 ± 9.1	27.6 ± 7.3*	18.2 ± 5.4*†	< 0.001
Adverse event rate (%)	14.3 ± 3.7	9.4 ± 2.8*	5.1 ± 1.9*†	< 0.001
Nursing assessment completeness (%)	67.8 ± 9.4	78.9 ± 8.1*	91.2 ± 5.7*†	< 0.001
Adherence to clinical protocols (%)	59.2 ± 10.1	73.5 ± 8.9*	88.4 ± 6.3*†	< 0.001

*Note. Values are Mean ± SD. * $p < 0.05$ vs. Group I (Non-CDSS); † $p < 0.05$ vs. Group II (Basic CDSS), Bonferroni post-hoc test. CDSS = clinical decision support system.*

Table 3. Outcomes by CDSS group.

Patient Outcome Parameter	Group I (Non-CDSS) Mean ± SD	Group II (Basic CDSS) Mean ± SD	Group III (AI-CDSS) Mean ± SD	p-value
Hospital length of stay (days)	9.8 ± 2.4	8.1 ± 2.0*	6.4 ± 1.7*†	< 0.001
30-day readmission rate (%)	18.4 ± 4.2	13.6 ± 3.5*	8.3 ± 2.6*†	< 0.001
Patient satisfaction score (0–100)	63.2 ± 9.8	74.8 ± 8.3*	86.5 ± 6.9*†	< 0.001
ICU complication rate (%)	22.6 ± 5.1	16.4 ± 4.2*	9.7 ± 3.1*†	< 0.001
Mortality index (per 100 patients)	6.1 ± 1.8	4.3 ± 1.4*	2.8 ± 1.0*†	< 0.001
Nurse–patient communication score	58.4 ± 10.3	71.2 ± 9.0*	83.6 ± 7.4*†	< 0.001

*Note. Values are Mean ± SD for continuous variables. * p < 0.05 vs. Group I; † p < 0.05 vs. Group II, Bonferroni post-hoc test. ICU = intensive care unit; CDSS = clinical decision support system.*

Table 4. Nurses' reported barriers and facilitators of CDSS implementation.

Barrier / Facilitator	Group I (Non-CDSS) %	Group II (Basic CDSS) %	Group III (AI-CDSS) %	p-value
Infrastructure inadequacy	74.5	68.7*	52.0*†	< 0.001
Insufficient AI/digital training	81.6	70.8*	44.0*†	< 0.001
Resistance to technology adoption	66.3	54.2*	31.0*†	< 0.001
Trust in AI-generated alerts	29.6	54.2*	84.0*†	< 0.001
Perceived workload reduction (%)	22.4	46.9*	79.0*†	< 0.001
System ease-of-use rating (0–10)	3.8 ± 1.2	6.1 ± 1.4*	8.4 ± 0.9*†	< 0.001
Overall satisfaction with CDSS (%)	—	58.3	91.0*†	< 0.001

*Note. Barrier data expressed as percentage of nurses reporting that item as significant. Ease-of-use rating presented as Mean ± SD. * p < 0.05 vs. Group I; † p < 0.05 vs. Group II, chi-square test for proportions. CDSS = clinical decision support system; — = not applicable.*

DISCUSSION

This study's results offer strong empirical support that clinical decision support systems (CDSS) augmented by artificial intelligence (AI) can dramatically improve the technical quality of nursing care and the objective safety of patient care in Iraqi tertiary health care facilities, a setting that has seen little academic research despite its important public health implications. The step-wise improvement across Group I, Group II and Group III in almost every outcome variable examined is suggestive of a dose-response effect of CDSS technological complexity and clinical benefit, a finding consistent with mechanistic explanations based on the growing cognitive augmentation afforded by more advanced forms of AI.

The 23-percentage point increase in clinical decision accuracy for AI-CDSS users compared with the non-CDSS baseline is consistent with estimates from high-income settings. Sutton et al. [12] described an average 19-26% improvement in the accuracy of clinical decision making with AI-CDSS interventions across specialities, whereas a recent multicentre study in ICUs across Europe found that the use of machine learning-based alerts reduced critical assessment errors by 21.3% [13]. The consistency of effect sizes across such an ecologically diverse set of healthcare settings supports the generalisability of the benefits of AI-CDSS and suggests that the mechanism of action (real-time integration of clinical evidence with patient-level data) works effectively even in the absence of abundant healthcare resources.

Perhaps the most clinically significant finding is the AI-CDSS group's 69% reduction in medication error rates. Medication errors are one of the most common and avoidable causes of patient harm worldwide and the Iraqi healthcare system has previously lacked the necessary pharmacovigilance reporting to identify such errors [14]. Our finding that error rates decreased from 6.8 per 100 orders to 2.1 per 100 orders after AI-CDSS was deployed suggests that smart alerting (i.e. drug interactions, weight-based dosing, allergy cross-checking, renal/hepatic dose adjustments) can, at least in part, fill the gap left by the lack of strong pharmacist oversight in resource-poor settings. Similar improvements have been observed by Al-Dorzi et al. [15] in a Saudi ICU, although their report was confined to a single centre.

The individual patient-level data support clinical relevance of nursing practice improvement. An average hospital stay reduction of 3.4 days (6.4 vs. 9.8 days) for the AI-CDSS group has significant economic and operational implications for the heavily burdened public hospitals in Iraq, where occupancy rates are often 110% above capacity. Similar decreases in length of stay have been observed after AI-CDSS deployment in Jordanian teaching hospitals [16] and Egyptian university medical centres [17], suggesting a potentially consistent pattern across the region that should be of interest to health ministries in the Arab region.

The analysis of barriers to AI-CDSS adoption demonstrates an ironic conundrum that pervades technology adoption in resource-limited health care: a lack of infrastructure and training is most evident in areas where the benefit of advanced technology is potentially greatest. It is particularly noteworthy that 81.6% of nurses who reported insufficient AI training in non-CDSS hospitals is one of the major barriers, as it highlights the need to provide equipment without investing in competency-building. Alarmingly, this barrier was not alleviated in Group II hospitals, where 70.8% of nurses still expressed concerns about insufficient training, even though they had access to the simple CDSS. It was only in the AI-CDSS group that the barrier to insufficient training dropped to 44.0%, most likely due to the fact that the more recent AI-CDSS systems have been designed with a more intuitive interface and provide contextual support [18].

Trust in AI-system alerts is a complex predictor of CDSS use that has gained attention in the human factors and patient safety literature. That only 29.6% of nurses in the non-CDSS group trusted automated alerts (despite never having experienced them) probably reflects a broader distrust of algorithmic recommendations that is more pronounced in a population with low prior technology exposure [19]. The almost threefold increase in trust in Group III (84.0%) suggests that positive experience with AI-CDSS is a key factor in changing attitudes, in line with the experience-driven aspect of the Technology Acceptance Model and the broader research on algorithm aversion and appreciation [20]. Prior exposure, for example through AI-CDSS training in simulation environments prior to deployment, may help expedite this process in nurses in hospitals that plan to implement AI-CDSS in the future.

This study has some limitations. The cross-sectional nature of the study prevents inference about causation; while the allocation to groups was based on pre-existing hospital characteristics, rather than random, selection bias is possible. Nurse-level variability in computer self-efficacy was not considered, which may explain the relationship between CDSS exposure and quality of care. Further, patient outcomes were obtained from the hospital's administrative data, rather than prospective clinical follow-up, and coding practices may differ between hospitals. Future longitudinal follow-up studies using randomised or quasi-experimental designs, and patient-level variables, would considerably add to the evidence base for AI-CDSS policy in Iraq.

CONCLUSION

This research confirms, for the first time in Iraq's health sector, the benefit of AI-powered clinical decision support systems in producing both significant and statistically relevant improvements in quality of nursing clinical practice and patient care outcomes in critical care, emergency and surgical wards. The size of the benefit - in terms of clinical decision quality, medication safety, length of stay, readmission and patient satisfaction - aligns with global evidence and reinforces the need for rapid, policy-driven integration of AI-CDSS in Iraqi tertiary care facilities. However, realisation of these benefits for enhancing patient health will depend on concurrent investment in digital system infrastructure and training in AI literacy for nurses, as well as leadership cultures that prioritise the translation of evidence-based technology into clinical practice. Future studies should focus on multi-site randomised designs, cost benefit analysis of implementation and cost reduction, and strategies to optimise CDSS to the unique workflow patterns in Iraqi health care.

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