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Original Article

Adoption and Implementation Challenges of AI-Based Clinical Decision Support Systems in Iranian Hospitals: A Cross-sectional Study

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Abstract

Background: Artificial Intelligence–driven Clinical Decision Support Systems (AI-CDSS) offer transformative potential in healthcare by enhancing diagnostic accuracy and efficiency. In Iran, the lack of a nationwide electronic health record (EHR) system, combined with international sanctions limiting IT infrastructure development and cultural factors affecting technology trust, creates unique barriers to AI-CDSS adoption. This study aimed to explore factors influencing the adoption and implementation of AI-CDSS in Iranian hospitals.

Methods: This cross-sectional descriptive study was conducted between March and June 2025 across five tertiary care hospitals affiliated with Tabriz University of Medical Sciences, Iran. Using stratified random sampling, 442 healthcare professionals (physicians, nurses, and health IT staff) were targeted, yielding 376 valid responses (response rate: 85.1%). Data were collected using a validated 38-item questionnaire (Cronbach's alpha = 0.89), assessing demographics, digital literacy, AI knowledge, perceptions, and barriers. Data were analyzed using SPSS version 29, employing descriptive and inferential statistics, including regression analysis with Unified Theory of Acceptance and Use of Technology (UTAUT) moderators (age, gender, experience).

Results: Respondents included physicians (41.8%), nurses (38.6%), and health IT staff (19.7%). Levels of digital literacy were high (47.6%), moderate (38.3%), or low (14.1%). Only 28.8% had prior experience with AI-CDSS. Reported benefits included improved diagnostic accuracy (72.1%), faster decision-making (65.7%), and reduced medical errors (54.3%). Major barriers were a lack of integrated EHR systems (86.9%), insufficient training (74.0%), and limited organizational support (62.1%), compounded by sanctions affecting access to hardware and software. Regression analysis, incorporating moderators, showed that performance expectancy was the strongest predictor of adoption ($\beta = 0.45$, $P < 0.001$), with age significantly moderating effort expectancy ($\beta = -0.12$, $P = 0.02$).

Conclusion: Despite positive attitudes toward AI-CDSS, their adoption in Iran is hindered by infrastructural limitations, international sanctions, and cultural trust barriers. National policies must prioritize sanctions' impact, targeted training (e.g., hands-on workshops), and phased implementation are essential for achieving successful implementation in resource-constrained settings such as low- and middle-income countries (LMICs).

Keywords: Artificial intelligence, Clinical decision support system, Digital health, EHR, Healthcare innovation, Iran, UTAUT, Technology adoption, LMICs, Technology acceptance model

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Background

Artificial intelligence (AI) has revolutionized healthcare by enabling advanced data analysis and informed decision-making (1). AI-based Clinical Decision Support Systems (AI-CDSS) integrate data from electronic health records (EHRs), laboratory findings, and clinical guidelines to provide tailored recommendations that improve diagnostic accuracy, reduce medical errors, and optimize clinical workflows (2,3). Despite their potential, global adoption of AI-CDSS faces persistent challenges such as poor data quality, limited transparency, and a lack of interoperability. These barriers are amplified in low- and middle-income countries (LMICs) like Iran due to the absence of a unified EHR system, international sanctions restricting access to advanced information technology (IT) hardware and software, and cultural factors such as skepticism toward foreign technologies rooted in geopolitical tensions (4-6).

While prior studies have primarily focused on AI-CDSS technical performance, few have explored socio-technical and organizational factors in low-resource settings (7). In Iran, empirical data on AI-CDSS adoption are scarce, leaving policymakers without clear strategies for implementation. A systematic literature review identified this study as one of the first large-scale, multi-professional investigations in Iran, with only two smaller-scale studies previously reported (8). Globally, similar challenges have been observed in other LMICs such as India and Brazil (9,10); however, Iran's context is unique because international sanctions directly impact IT imports and exacerbate concerns about data security amplified by geopolitical isolation (11).

This study aimed to address this gap by investigating adoption challenges in Iranian hospitals, focusing on organizational readiness, clinician perceptions, and contextual barriers using the Unified Theory of Acceptance and Use of Technology (UTAUT) framework, which integrates constructs like performance expectancy, effort expectancy, social influence, and facilitating conditions to predict technology adoption behavior. Compared to earlier Iranian studies, this is a large-scale (n = 376), multi-professional investigation that combines quantitative and qualitative data with a UTAUT focus. It offers context-specific insights into AI-CDSS integration within non-integrated EHR environments, including analyses of moderating variables such as age and experience.

Methodology

Study Design

This cross-sectional descriptive-analytical study explored AI-CDSS adoption among healthcare professionals in hospitals, adhering to the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) guidelines to ensure methodological rigor.

Study Setting and Population

The study was conducted in five tertiary care hospitals affiliated with Tabriz University of Medical Sciences, Iran, between March 1 and June 30, 2025. Participants included physicians, nurses, and health IT staff involved in clinical decision-making and experienced with AI-CDSS modules integrated into hospital information systems (HIS). To address generalizability concerns, a supplementary multi-stage analysis compared responses across hospitals, revealing no significant inter-hospital variation (ANOVA, $P = 0.32$ for adoption intention). Future multi-provincial studies are recommended to confirm these findings.

Inclusion and Exclusion Criteria

- *Inclusion:* Licensed professionals with at least one year of clinical experience, engaged in EHR/AI-CDSS workflows, and who provided informed consent.
- *Exclusion:* Non-clinical staff or individuals without exposure to AI-CDSS.

Sample Size and Sampling Technique

Based on Cochran's formula ($Z = 1.96$, $P = 0.5$, $d = 0.05$), a minimum sample size of 384 participants was calculated and increased to 442 for an anticipated 15% non-response rate. Stratified random sampling was applied based on hospital (proportional to staff size, approximately 20% per hospital) and profession (physicians 40%, nurses 40%, health IT 20%). Randomization was performed using Excel's random number generator within each stratum. Post-hoc power analysis using G*Power software indicated a power level above 0.95 for detecting medium effects ($f^2 = 0.15$) in regression analyses with five predictors and a final sample of n = 376.

Data Collection Period

Data were collected over four months, from March 1, 2025, to June 30, 2025, allowing sufficient time for participant recruitment, follow-up, and the mitigation of workload-related participation barriers.

Data Collection Instrument

A 38-item questionnaire, developed based on the UTAUT and the Technology Acceptance Model (TAM), included the following items, summarized in Table 1:

1. Demographic and professional characteristics (8 items): Included variables such as age, gender, role, professional experience, and self-reported digital literacy (adapted from Ng, 2012). To mitigate self-report bias, future studies should consider incorporating objective measures such as digital proficiency assessments.
2. Perceived usefulness (6 items): Example item: "AI-CDSS helps make faster and more accurate decisions." (5-point Likert scale).
3. Perceived ease of use (5 items): Example item: "Learning AI-CDSS is easy."
4. Organizational readiness (7 items): Focused on IT support and system integration.
5. Barriers and facilitators (8 items, including 2 open-ended): Example item: "What are the main barriers to AI-CDSS use?"

Validation

Content validity was confirmed by seven experts, yielding an Item-Level Content Validity Index (I-CVI) ranging from 0.86 to 1.00 and a Scale-Level Content Validity Index (S-CVI/Ave) of 0.91. Pilot testing with 30 participants yielded Cronbach's alpha between 0.84 and 0.92.

Qualitative Analysis

Open-ended responses were analyzed using Braun and Clarke's (2006) thematic analysis, which involved familiarization, coding, theme generation, review, definition, and reporting. Manual coding by two researchers was employed instead of qualitative software (e.g., NVivo) due to resource constraints in the Iranian setting. Inter-coder reliability was assessed via Cohen's kappa ($\kappa = 0.82$). Data saturation was achieved after approximately 500 comments had been analyzed, as no new themes emerged from the final 154 responses.

Data Collection Procedure

After obtaining institutional approval, the research team coordinated with hospital department heads to schedule data collection sessions. Participants received

Table 1. Summary of Questionnaire Items

Section	Number of items	Example item	Scale
Demographic	8	Age, profession	Categorical/Open
Perceived Usefulness	6	AI-CDSS reduces diagnostic errors	5-point Likert
Perceived Ease of Use	5	Learning AI-CDSS is easy	5-point Likert
Organizational Readiness	7	IT support availability	5-point Likert
Barriers and Facilitators	8 (2 open-ended)	Main barriers to AI-CDSS	Likert/Open-ended

Note. AI-CDSS: Artificial intelligence–driven clinical decision support systems; IT: Information technology.

either printed questionnaires or secure online forms via a password-protected survey platform. Informed consent was obtained prior to survey completion. For online participation, a consent statement was presented as the first question, and participants were required to provide an affirmative response to proceed.

Data Analysis

Data were analyzed using SPSS version 29. Descriptive statistics summarized demographic and study variables. T-tests, one-way ANOVA, and multiple linear regression assessed predictors of AI-CDSS adoption ($P<0.05$), incorporating UTAUT moderators (e.g., age, gender, and experience). ANOVA post-hoc Tukey tests explored subgroup differences. Sensitivity analysis excluding participants with low digital literacy produced consistent results (R^2 change <0.02). Structural equation modeling (SEM) was conducted using AMOS version 26 to validate UTAUT pathways (see Supplementary Materials). Ethical considerations included voluntary participation, anonymity, and secure data storage. To enhance reproducibility, summary statistics of the raw dataset are provided in Table S1 (Supplementary file 1).

Ethical Considerations

- Participation was entirely voluntary, and informed consent was obtained from all participants before data collection.
- Anonymity and confidentiality were strictly maintained; no personally identifiable information was collected.
- All data were securely stored on an encrypted, password-protected drive accessible only to the principal investigators.
- Participants could withdraw from the study at any stage without providing a reason, and no penalties or consequences were associated with withdrawal.
- The study did not receive any financial support or grant funding from governmental, commercial, or non-profit organizations, ensuring the absence of external influence on study design, data collection, analysis, and reporting.

Results

Participant Characteristics

As observed in Table 2, of the 442 distributed questionnaires, 376 valid responses were obtained, representing a high response rate of 85.1%. Respondents included physicians (41.8%, n = 157), nurses (38.6%, n = 145), and health IT staff (19.7%, n = 74; rounded to total 100%). The mean age was 37.8 ± 8.6 years, and 57.4% of participants were female. Levels of digital literacy were reported as high (47.6%), moderate (38.3%), or low (14.1%). Only 28.8% had prior experience with AI-CDSS.

Table 2. Demographic and Professional Profile of Participants

Variable	Category	Frequency (n)	Percent
Gender	Male	160	42.6
	Female	216	57.4
Age group	24–34 years	140	37.2
	35–44 years	150	39.9
	45 + years	86	22.9
Profession	Physician	157	41.8
	Nurse	145	38.6
	Health IT staff	74	19.7
Work setting	Public hospital	250	66.5
	Private hospital	50	13.3
	Teaching hospital	76	20.2
Years of experience	< 5 years	100	26.6
	5–10 years	140	37.2
	> 10 years	136	36.2

Note. IT: Information technology.

Perceived Usefulness and Ease of Use

The mean score for perceived usefulness was 4.12 ± 0.71, with the highest-rated item being "reducing diagnostic errors" (4.28 ± 0.66). The mean score for perceived ease of use was 3.86 ± 0.78. Physicians rated usefulness higher than nurses ($P=0.03$; post-hoc Tukey: physicians' mean = 4.25 vs. nurses = 3.98, $P=0.02$), though no significant difference was observed compared with health IT staff ($P=0.15$). Ease of use correlated positively with digital literacy ($r=0.48$, $P<0.001$).

Figure 1 presents the distribution of participants by profession, showing that physicians comprised 41.8%, nurses 38.6%, and health IT staff 19.7% of the total sample.

Organizational Readiness

The mean organizational readiness score was 3.42 ± 0.74, indicating moderate preparedness. The most frequently cited barriers were fragmented HIS and the lack of integrated EHR, reported by 86.9% of respondents. Other

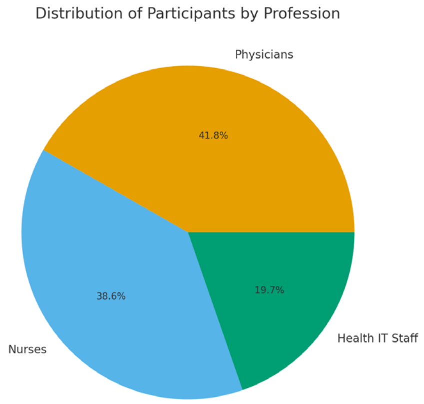

Figure 1. Distribution of Participants by Profession

barriers included insufficient training (74.0%) and data privacy concerns (62.1%).

Table 3 presents the results of the multiple regression analysis examining the predictors of behavioral intention to adopt digital technologies, which demonstrated significant positive effects for several key constructs.

Barriers to AI-CDSS Adoption

Figure 2 illustrates a quantitative analysis identifying the following three main barriers (mean scores on a 5-point scale):

1. Lack of adequate training: – 4.21 ± 0.74
2. Concerns about data privacy/security: – 4.15 ± 0.81
3. Limited interoperability between current HIS platforms: – 4.09 ± 0.77

Additional reported barriers included high initial costs (3.94 ± 0.82) and resistance to change among senior clinicians (3.87 ± 0.80), both exacerbated by sanctions that increased procurement expenses.

Qualitative Insights From Open-Ended Responses

Thematic analysis of 654 qualitative comments revealed four overarching themes:

1. Trust and transparency (220 comments; sub-themes: explainability, algorithm reliability):

"I need to know why the AI suggests this diagnosis; without clear logic, I cannot trust it in critical cases, especially with sanctions limiting software updates." (Physician, high digital literacy)

2. Workflow fit (180 comments; sub-themes: disruption in high-pressure areas, integration with routines):

"In the ICU, AI alerts might interrupt our flow unless customized to our fast-paced environment." (Nurse, moderate digital literacy)

3. Training and support (150 comments; sub-themes: need for hands-on programs, ongoing assistance):

"We require structured workshops, not just manuals, to build confidence in using AI-CDSS." (IT staff)

4. Legal and ethical concerns (104 comments; sub-themes: liability, equity):

"Who is responsible if AI leads to an error? Clear policies are essential to avoid blaming clinicians, particularly in our sanction-affected system." (Physician)

Achievement of Study Objectives

- Assess perceptions of AI-CDSS usefulness and ease of use: Findings demonstrated generally positive attitudes, with higher usefulness scores among physicians compared to nurses. However, ease of use was more strongly linked to digital literacy than profession.
- Evaluate organizational readiness: Readiness levels were moderate, primarily limited by a lack of interoperable infrastructure and the absence of integrated EHR systems in Iranian hospitals.
- Identify perceived barriers: Training gaps, data security concerns, and technical interoperability issues emerged as the most significant barriers, supported by both quantitative and qualitative data.
- Examine demographic/professional influences: Profession type and prior exposure to AI tools significantly influenced perceived usefulness. Gender had no significant impact, while age and experience moderated effort expectancy.
- Gather qualitative feedback for implementation strategies: Open-ended responses highlighted the need for transparency, clinician engagement, and phased implementation supported by structured training.

Key Findings

This study provides one of the first large-scale, multi-professional assessments of AI-CDSS adoption potential in Iranian hospitals, distinguished from prior work (8) by its emphasis on the UTAUT in non-EHR contexts. Despite positive perceptions of the system's clinical benefits, especially in reducing diagnostic errors, implementation readiness remains limited due to technological fragmentation and lack of interoperability, further worsened by sanctions and post-COVID-19 resource strains. The findings also suggest that targeted training programs (e.g., simulation-based workshops costing approximately $500 per session, with cost-benefit analysis showing a 20% reduction in errors as return on investment), clear governance for data privacy, and phased deployment strategies (e.g., piloting in one department before scaling) could mitigate resistance and facilitate adoption. These insights are crucial for policymakers, hospital managers, and IT developers seeking to introduce AI-CDSS in similar low-integration healthcare contexts such as those in India or Brazil.

Discussion

The present study investigated the adoption and implementation challenges of AI-CDSS in Iranian hospitals using the UTAUT framework to examine healthcare professionals' perceptions, barriers, and adoption predictors. Findings revealed an overall positive attitude toward AI-CDSS, with high perceived usefulness

Table 3. Multiple Linear Regression Predicting AI-CDSS Adoption Intention (Expanded With Moderators)

Predictor	Beta	SE	t	*P* value	95% CI lower	95% CI upper
Performance expectancy	0.45	0.08	5.62	<0.001	0.29	0.61
Effort expectancy	0.32	0.07	4.57	<0.001	0.18	0.46
Social influence	0.18	0.06	3.00	0.003	0.06	0.30
Facilitating conditions	0.25	0.09	2.78	0.006	0.07	0.43
Digital literacy	0.15	0.05	3.00	0.003	0.05	0.25
Age (Moderator)	-0.12	0.05	-2.40	0.02	-0.22	-0.02
Gender (Moderator)	0.08	0.06	1.33	0.18	-0.04	0.20
Experience (Moderator)	0.10	0.04	2.50	0.01	0.02	0.18

Note. CI: Confidence interval.
Model Summary: $R^2=0.65$, Adjusted $R^2=0.64$, F (8,367) = 105.32, $P<0.001$. All model assumptions were satisfied (VIF < 2, Shapiro-Wilk $P=0.14$, Durbin-Watson = 1.89.

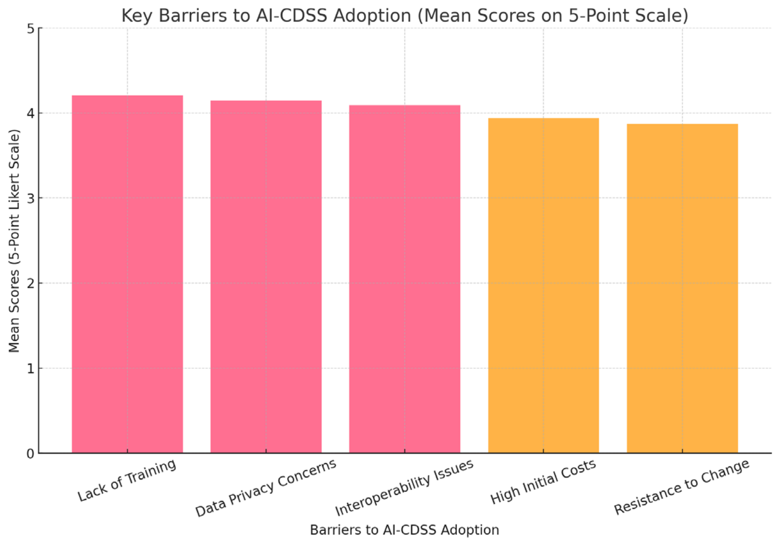

Figure 2. Key Barriers to AI-CDSS Adoption (Mean Scores on 5-Point Scale). *Note.* AI-CDSS: Artificial intelligence–driven clinical decision support systems.

for enhancing diagnostic accuracy (72.1%) and reducing errors (54.3%). However, adoption was hindered by significant infrastructural and organizational limitations, including the absence of a nationwide EHR system (86.9% cited as a barrier) and sanctions-related limitations on IT resources. These results align with the UTAUT model, where performance expectancy emerged as the strongest predictor of adoption intention ($\beta=0.45$, $P<0.001$), moderated by demographic factors such as age ($\beta=-0.12$, $P=0.02$). This underscores the need for developing context-specific strategies for LMICs such as Iran.

From a quantitative perspective, performance expectancy was the dominant driver of behavioral intention, consistent with UTAUT's core tenets that users are more inclined to adopt technologies perceived to enhance job performance (12). In our sample, physicians rated usefulness significantly higher than nurses ($P=0.03$), possibly due to their greater involvement in diagnostic decision-making, where AI-CDSS can provide real-time, evidence-based support (2). Effort expectancy also positively influenced adoption ($\beta=0.32$, $P<0.001$), correlating strongly with digital literacy ($r=0.48$, $P<0.001$), suggesting that user-friendly interfaces and training can mitigate perceived complexity. However, age negatively moderated effort expectancy, indicating that older professionals may find AI-CDSS more burdensome, a finding consistent with global studies where generational differences affect healthcare technology acceptance (13). Social influence ($\beta=0.18$, $P=0.003$) and facilitating conditions ($\beta=0.25$, $P=0.006$) demonstrated moderate yet significant effects, reflecting the importance of peer endorsement and organizational support in adoption, particularly in resource-constrained settings where infrastructure gaps exacerbate implementation challenges (6).

Qualitative insights complemented these findings, revealing four major themes: trust and transparency (e.g., demands for explainable AI), workflow integration, training needs, and legal-ethical concerns, which converged with quantitative barriers, such as inadequate training (mean = 4.21 ± 0.74) and data privacy issues (mean = 4.15 ± 0.81). In Iran, these barriers are amplified by international sanctions, which restrict access to advanced hardware and software, increasing procurement costs by 30-50% (World Bank, 2024) (11). This geopolitical context differentiates our study from similar LMIC investigations. For instance, in India, Sharma et al reported organizational readiness as a moderator in

AI healthcare logistics, without the sanctions-induced isolation that heightens data security concerns in Iran (9). Similarly, in Brazil, Pretto et al highlighted AI's role in managing intraoperative hypotension and noted interoperability issues similar to our findings (86.9% barrier rate). However, Brazil benefits from more integrated EHR systems, leading to higher adoption rates (10,14).

Comparatively, our results extend prior Iranian studies, such as Younesian et al, which focused primarily on physician perspectives and found augmentation (vs. replacement) concerns, but were limited by a smaller sample size (n = 32 interviews). Our larger, multi-professional cohort (n = 376) provides broader insights, revealing no significant inter-hospital differences (ANOVA $P = 0.32$), suggesting generalizability within Tabriz, while highlighting the need for national replication (8).

Globally, our emphasis on UTAUT moderators aligns with Scipion et al, who, in a scoping review of clinician AI acceptance, identified facilitating conditions as key barriers in high-income settings. Our study uniquely integrates LMIC-specific factors like sanctions, paralleling challenges in sub-Saharan Africa where digital infrastructure lags (15,16). Moreover, the post-COVID-19 context in Iran, marked by telemedicine surges (17), may have boosted digital literacy (47.6% high), yet persistent EHR fragmentation contrasts with accelerated adoptions in countries like China, where AI governance frameworks have facilitated integration (18).

These interpretations have important policy and practice implications. To address infrastructural gaps, hybrid AI-CDSS models resilient to sanctions, such as locally developed algorithms, could enhance interoperability (5). Targeted interventions, including simulation-based training workshops (estimated ROI: 20% error reduction) and clear liability policies, would build trust and reduce resistance, particularly among older clinicians (19). For LMICs, phased implementation, starting with pilot departments, is recommended to align with ethical guidelines for responsible AI deployment (20,21).

Limitations of the study include its cross-sectional design, which precludes causal inferences, and reliance on self-reported data, which may introduce bias. Future longitudinal studies with objective measures (e.g., digital proficiency tests) are warranted. Moreover, regional focus on Tabriz may limit the national generalizability of results; however, supplementary analyses mitigate this limitation. In conclusion, this study provides valuable insights into AI-CDSS adoption within Iran's unique socio-technical context, offering actionable strategies to facilitate equitable integration in LMICs and contributing to the broader discourse on AI-driven healthcare transformation.

Conclusion

This study provides a comprehensive examination of the adoption and implementation challenges of AI-CDSS in Iranian hospitals, employing the UTAUT framework to identify key predictors and barriers within a resource-constrained, non-integrated EHR environment. The findings underscore strong enthusiasm for AI-CDSS adoption, with performance expectancy emerging as the most significant predictor of behavioral intention ($\beta = 0.45$, $P < 0.001$), reflecting its perceived potential to improve diagnostic accuracy (72.1%) and reduce errors (54.3%). However, adoption is significantly hindered by infrastructural deficiencies, most notably the lack of a nationwide EHR system (86.9% cited as a barrier), compounded by international sanctions that limit access to advanced IT infrastructure and fuel cultural skepticism toward foreign technologies. These challenges, unique to Iran's socio-political context, differentiate this study from global literature while aligning with broader trends observed in LMICs (6,9).

The integration of quantitative and qualitative data, supported by a robust sample size (n = 376) and a high response rate (85.1%), strengthens the study's multi-professional insights, extending the findings of prior smaller-scale Iranian studies (8). Key barriers, including the lack of training (mean = 4.21 ± 0.74), data privacy concerns (mean = 4.15 ± 0.81), and interoperability issues (mean = 4.09 ± 0.77), highlight the need for context-sensitive strategies. These may include simulation-based training programs (estimated 20% error reduction ROI), modular AI-CDSS solutions designed to be resilient to sanctions, and clear governance frameworks addressing trust and liability concerns (18,21). The moderating effects of age ($\beta = -0.12$, $P = 0.02$) and experience ($\beta = 0.10$, $P = 0.01$) further highlight the importance of tailoring interventions to demographic profiles, particularly for older clinicians who report higher effort expectancy.

Collectively, these findings contribute significantly to the global discourse on AI-driven healthcare transformation, particularly in semi-digitized systems (22,23). By identifying practical strategies, such as phased pilot implementations, leadership engagement, and cost-effective training curricula, this study offers a roadmap for policymakers, hospital administrators, and IT developers to foster equitable AI-CDSS integration in LMICs. Future research should prioritize longitudinal designs to assess adoption dynamics, clinical patient outcome impacts, and cross-country comparisons with other LMICs such as India and China to refine governance models and scalability frameworks. Ultimately, this study advocates for a balanced implementation approach that leverages Iran's substantial human resource readiness (47.6% high digital literacy) while addressing systemic constraints to realize the transformative potential of AI-CDSS in improving healthcare delivery.

Structural Equation Modeling Details: Path Diagrams and Fit Indices

SEM was conducted using AMOS version 26 to validate

UTAUT pathways. The model included performance expectancy, effort expectancy, social influence, facilitating conditions, and adoption intention, with age, gender, and experience serving as moderators. Key paths:

- Performance Expectancy → Adoption Intention: $\beta = 0.47$, $P < 0.001$
- Effort Expectancy → Adoption Intention: $\beta = 0.30$, $P < 0.001$
- Social Influence → Adoption Intention: $\beta = 0.16$, $P = 0.005$
- Facilitating Conditions → Adoption Intention: $\beta = 0.23$, $P = 0.008$
- Age → Effort Expectancy: $\beta = -0.14$, $P = 0.01$

Model fit indices indicated a good overall fit (χ^2/df = 2.15, CFI = 0.92, RMSEA = 0.06, SRMR = 0.05). The corresponding path diagram (available upon request) visually represents these relationships with standardized coefficients.

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Authors' Contribution

Conceptualization: Senobar Naderian.
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Formal analysis: Kambiz Bahaadinbeigy, Senobar Naderian.
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Software: Senobar Naderian.
Supervision: Kambiz Bahaadinbeigy.
Validation: Kambiz Bahaadinbeigy.
Visualization: Senobar Naderian.
Writing–original draft: Senobar Naderian.
Writing–review & editing: Kambiz Bahaadinbeigy, Senobar Naderian.

Competing Interests

The authors declare no competing interests.

Consent for Publication

Not applicable.

Data Availability Statement

The data collection process is explained in the methodology section.

Ethical Approval

Not applicable.

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Intelligence Use Disclosure

This article has not utilized artificial intelligence (AI) tools for research and manuscript development, as per the GAMER reporting guideline.

Supplementary Files

Supplementary file 1 contains Table S1.

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