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Readiness and Associated Factors to Use AI-Based Clinical Decision Support System Among Healthcare Professionals at University of Gondar Comprehensive Specialized Hospital, Ethiopia, 2025.

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Research Article

Keywords: AI, CDSS, Health Care Professionals, Readiness, University of Gondar Comprehensive Specialized Hospital

Posted Date: August 13th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10296437/v1

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Additional Declarations: No competing interests reported.

Abstract

Introduction

The integration of artificial intelligence into healthcare is a significant promise for improving patient outcomes and enhancing the efficiency of clinical operations. However, the successful implementation of AI-based Clinical Decision Support System largely depends on the readiness and acceptance of healthcare professionals.

Objective

The aim of this study was to assess readiness and associated factors to use AI-based Clinical Decision Support System among Healthcare Professionals at the University of Gondar Comprehensive Specialized Hospital, Ethiopia, 2025.

Methods

An institution-based cross-sectional study supplemented with qualitative data was conducted. A total of 423 healthcare professionals were selected by a simple random sampling method for quantitative study, while 7 participants were selected for qualitative study using purposive sampling and key informant interviews were used. Bi-variable and multi-variable logistic regression analyses were used. To ascertain association, an odds ratio with a 95% confidence interval was used to declare statistical significance at a p-value of less than 0.05. Qualitative data were analyzed thematically.

Result

Out of 423 invited participants, 410 responded, yielding a 97% response rate. The overall readiness level for adopting AI-based CDSS was 50.5% (95% CI: 45.5%–55.4%). Profession, educational level, years of work experience, and ownership of a personal computer were significantly associated with readiness. Physicians, highly educated professionals, and those who owned computers were more likely to demonstrate higher readiness. Qualitative findings revealed facilitators such as perceived usefulness and potential to improve patient care. Barriers included limited digital literacy, inadequate infrastructure, and concerns about job displacement.

Conclusion

Approximately half of healthcare professionals demonstrated adequate readiness for AI-based CDSS adoption. Strengthening digital literacy, improving access to computers, enhancing self-efficacy,

promoting positive attitudes and raising awareness about AI benefits are essential to improve readiness for implementation in this setting.

Introduction

Technologies can now facilitate the accomplishment of activities that humans once considered impossible and are responsible for substantial social and public policy changes in health care (1). Clinical Decision Support Systems (CDSS), interpreted as the computer programs that assist healthcare professionals in making medical decisions, represent: a pivotal advancement in healthcare, integrating technological prowess with medical expertise to augment clinical decision-making processes. These systems are designed to provide healthcare professionals with actionable insights, evidence-based recommendations, and patient-specific information at the point of care, thereby enhancing diagnostic accuracy, treatment efficacy, and patient outcomes (2).

The integration of AI has significantly reshaped CDSS, offering innovative solutions that optimize patient care and streamline clinical workflows. Through the application of advanced algorithms and machine learning techniques, AI-driven CDSS empowers healthcare professionals by providing invaluable insights and assistance across various facets of medical practice. From diagnostic support to personalized treatment recommendations, proactive risk prediction, and the facilitation of clinical documentation, AI in CDSS revolutionizes traditional approaches, paving the way for a new era of precision medicine (4).

The University of Gondar Comprehensive Specialized Hospital (UoGCSH), one of Ethiopia's leading academic and referral hospitals, plays a vital role in medical education, research, and healthcare service delivery. Before implementing such systems in UoGCSH, the researchers of this study felt that it is important to assess the user's readiness and the essential metrics. In environments with limited resources, this study also will make it possible for policymakers to comprehend user needs prior to system deployment. Therefore, the objective of this study was to assess readiness and associated factors to use AI-based Clinical Decision Support System among Healthcare Professionals at the University of Gondar Hospital, Ethiopia.

Existing research suggests that healthcare professional's perception, trust, and willingness to use Artificial Intelligent Based Clinical Decision Support System (AI-CDSS) are key determinants of adoption (6). Studies in other settings have shown that perceived usefulness, ease of use, and prior exposure to AI technologies significantly influence readiness (7). Additionally, concerns about job displacement, ethical issues, and data security have been reported as major barriers to AI adoption in clinical practice (8).

AI has demonstrated remarkable capabilities for predicting and classifying diagnoses, as well as providing recommendations and insights (9). The increasing empirical evidence suggests that knowledge-based computerized decision support (CDS) and, in particular, knowledge-based clinical decision support systems have the potential to enhance practitioner performance (10). AI systems have been successful in multiple medical imaging use cases, such as detecting mitosis in breast cancer histology images(11), classifying skin cancer with dermatologist-level accuracy(12), diagnosing diabetic

retinopathy from retinal fundus photographs (13), and predicting cardiovascular risk factors from retinal fundus photographs (14).

AI-CDSS can assist healthcare professionals by providing real-time, evidence-based recommendations, reducing diagnostic errors, and improving efficiency. However, the successful implementation of AI-CDSS depends on the readiness of healthcare professionals to adopt and integrate these systems into their clinical workflows (17). Despite its potential, the adoption of AI-CDSS in low-resource settings such as Ethiopia remains limited due to various challenges, including lack of awareness, limited digital literacy, infrastructural constraints, ethical concerns, and resistance to AI-driven decision-making (18). Without assessing readiness factors, the introduction of AI-CDSS may face significant resistance and inefficiencies, ultimately impacting its effectiveness in improving healthcare outcomes. Therefore, this study aims to assess the readiness of healthcare professionals at the University of Gondar Hospital to use AI-CDSS, identify key enablers and barriers, and provide recommendations for successful implementation. The findings will contribute to informed policymaking, AI training programs, and tailored implementation strategies to facilitate AI-CDSS integration in Ethiopia's healthcare system.

Methods and materials

Study design, setting and period

An institution-based cross-sectional study supplemented with qualitative data was conducted to assess readiness to use AI-based Clinical Decision Support System among all Healthcare Professionals at the University of Gondar Specialized Hospital, Ethiopia. This study was conducted from July-August 2025.

Study population

The source population for the quantitative component included all health professionals working at the University of Gondar Specialized Hospital, while the source population for the qualitative component consisted of all key informants working at the same hospital. The study population for the quantitative part comprised licensed, registered, or certified health professionals who provide healthcare services at the hospital. For the qualitative component, the study population included key informants with relevant experience at the University of Gondar Specialized Hospital. The study units were randomly selected health professionals for the quantitative study and purposively selected key informants for the qualitative study.

Eligibility criteria

An institution-based cross-sectional study supplemented with qualitative methods was conducted among healthcare professionals at the University of Gondar Comprehensive Specialized Hospital from July to August 2025.

For the quantitative component, the sample size was determined using a single population proportion formula, assuming a 95% confidence level, 5% margin of error, and a proportion of 50% to obtain the maximum sample size. After adding a 10% non-response rate, the final sample size was 423 participants(Fig. 1).

A simple random sampling technique was applied to select study participants. For the qualitative component, key informants were selected purposively based on their experience and involvement in clinical and digital health activities, and interviews were conducted until data saturation was achieved.

Data were collected using a structured self-administered questionnaire adapted from previously validated studies, along with a semi-structured interview guide for the qualitative part.

Study variable

The dependent variable of the study was readiness to use AI-CDSS. The independent variables included socio-demographic factors (age, sex, educational status, occupation, and work experience), healthcare provider–related factors (computer skill, AI knowledge, perceived usefulness, trust in AI, and ethical concerns), and organizational factors (availability of a computer at the office, internet access at the office, and personal computer ownership).

Operational definitions

The **AI-CDSS** Using artificial intelligence algorithms and data analysis techniques to provide personalized recommendations and insights by healthcare professionals in making informed and evidence-based decisions in patient care (37).

Readiness to AI-CDSS

The preparedness of healthcare professionals to embrace changes brought by the introduction of AI based CDSS. In this study by using Likert scale data by analyzing Computer skill and innovation, cognitive, ability, vision, ethic and Perceived usefulness domains if the mean value is 50% and above respondents have readiness towards AI-CDSS (34).

Data collection procedures

For the quantitative part of this study, self-administered structured questionnaires were used. These questionnaires are adapted from Nata Pratama Hardjo Lugitos study and another related study. The questionnaires were first prepared in English, and then it was translated into Amharic for data collection purposes. Later, it was translated back from Amharic to English for analysis purposes. The study was included 42 questions covering the following domains: socio-demographic characteristics (Ten questions), Computer skill and innovation (Six questions), Respondents' readiness in the cognitive

domain (eight questions), Respondents' readiness in the ability domain (eight questions), Respondents' readiness in the vision domain (three questions), Respondents' readiness in the ethic domain (three questions) and Perceived usefulness of AI based CDSS (four questions). The data was collected by two health information technicians with diplomas and experience in data collection, and supervision was provided by one BSC health informatics professional. For the qualitative part, data was collected by the principal investigator through the use of open-ended questions. Several probes were used to obtain deep insight into health professional's readiness, and the guide was pretested to ensure relevance and appropriateness.

Data Quality management

Quantitative Data Quality management

Two days of training was given to the data collectors and supervisors based on the objective of the study, data collection procedures, data collection tools, respondents' approach, data confidentiality, and respondent rights before the data collection date. A pretest was conducted out of the study area at Tibebe Ghion Specialized Hospital using 5% (22) of the sample before actual data collection. The face validity of the tool was checked by 2 health informatics experts. The principal investigator and one supervisor were supervised the data collection technique and ensure the completeness of tools daily.

Trustworthiness (Qualitative Data Quality) management

The researcher spent prolonged time with the study and actively participated in the data collection process to ensure the study's credibility. Probing and paraphrasing techniques were employed to enhance the reliability of the findings. Confirmability was guaranteed through the use of bracketing, reflexivity, and triangulation. Detailed and descriptive data were provided to facilitate the transferability of the study's findings. Additionally, notes taken during discussions were carefully compared with audio recordings and transcribed word-by-word. The collected data was organized and categorized into themes manually.

Data processing and analysis

Quantitative Data process and analysis

Structured interviewer administered questionnaire facilitated by Kobo tool digital data collection software was used as a data collection tool. The collected data was thoroughly checked for completeness and consistency. Outliers were managed by winsorization technique (replacing the outlier with nearby values). Subsequently, the data was transferred to Stata version 16.0 for analysis. Descriptive statistics, such as frequencies and percentages, were computed and reported. Additionally, variables were explained using frequency tables, graphs, and summary statistics. Bi-variable and multi-variable logistic regression analyses were used to identify factors associated with readiness to AI-CDSS. Variables with a P-value < 0.25 in the bi-variable analysis was exported to the multi-variable analysis to

control the possible effect of confounders. The model was selected based on Log-likelihood (Log-LL) value that shows the higher number. Multi-co linearity was checked among selected independent variable using variance inflation factor (VIF) < 10 after fitting pseudo-linear regression. Additionally, goodness-of-fit-test statistics for logistic regression were checked using Hosmer-Lem show. Adjusted odds ratio (AOR) with 95% confidence interval (CI) and P-value < 0.05 was used to select significantly associated variables with readiness to AI-CDSS.

Qualitative Data process and analysis

Each interview was accompanied by comprehensive field notes. The audio recordings were undergone verbatim transcription and translation into English. Subsequently, the gathered data was organized through thematic analysis, and it was analyzed manually. The principal investigator conducted the data analysis thoroughly, reviewing the transcript to comprehend the concepts for further analysis.

Ethical consideration

Ethical clearance was taken from ethical clearance committee of UOGCSH college of Medicine and Health science, Approval was obtained from University of Gondar Specialized Hospital and written consent was obtained from the study subjects, following an explanation of purpose of the interview and observation. Written consent from the service provider was obtained, and issues related to client's confidentiality and any potential risk benefits from participation were discussed. In addition, participants were informed that participation is voluntary and that they can withdraw at any time without any precondition.

Results

Sociodemographic Characteristics

In this study, 410 study participants responded, yielding a response rate of 97%. More than to half were males 229 (55.85%). Most of the study participants were in the age group of 29–33(27.32%) years old. The majority, 263(68.1%) of the respondents were first-degree holders. This study revealed that the majority, 174(42.4%) of the respondents were nurses. Two hundred thirty-six (57.76%) of the respondents had more than five years of experience. Among the total respondents, 215(52.44%) did not have their own computer. Furthermore, 405(98.78%) of the study participants had their own smart phone (Table 1).

Table 1
Socio-demographic characteristics study participants for assessing Readiness and Associated Factors to Use AI-Based Clinical Decision Support System Among Healthcare Professionals at University of Gondar Comprehensive Specialized Hospital, Ethiopia, 2025.

Variable	Category	Frequency	Percentage
Age	24–28	87	21.22
	29–33	112	27.32
	34–38	108	26.34
	39+	103	25.12
Sex	Female	181	44.15
	Male	229	55.85
Profession	Anesthetists	11	2.68
	HO	6	1.46
	Lab-technologist	21	5.12
	Midwives	49	11.95
	Nurse	174	42.44
	Physiotherapist	26	6.34
	Pharmacy	20	4.88
	Physician	95	23.17
	Other	8	1.95
Educational level	Diploma	65	15.85
	BSc (1st degree)	258	62.93
	2nd degree and above	30	7.32
	GP	9	2.2
	Resident	28	6.83
	Specialist	20	4.88
Work Experience	Less than 2	19	4.63
	2–3 years	69	16.83
	4–5 years	86	20.98
	More than 5	236	57.56

Variable	Category	Frequency	Percentage
Own Computer	No	215	52.44
	Yes	195	47.56
Internet on Computer	No	10	3.91
	Yes	246	96.09
Own Smartphone	No	5	1.22
	Yes	405	98.78
Internet on Smartphone	No	0	0
	Yes	405	100

About Qualitative Data

A total of seven healthcare professionals were interviewed, representing diverse fields including Health Informatics, Nursing, Pharmacy, Physician, Laboratory Science, and Optometry. Their professional experience ranged from four to ten years.

Respondents Computer skill and innovation

Table 2 presents the frequency of computer use and innovation-related activities among respondents. More than half of the participants (56.1%) reported using a computer at work daily, while 10.98% used it weekly and 8.54% several times a day. At home, 36.83% of respondents used a computer daily, and 17.32% used it weekly, whereas 18.54% reported never using a computer at home (Table 2).

Table 2
:Respondent's computer skill for assessing Readiness and Associated Factors to Use AI-Based Clinical Decision Support System Among Healthcare Professionals at University of Gondar Comprehensive Specialized Hospital, Ethiopia, 2025.

Items	Never	Rarely	Weekly	Daily	Several times a day
How often do you use a computer at work?	25(6.10%)	75(18.29%)	45(10.98%)	230(56.10%)	35(8.54%)
How often do you use a computer at home?	76(18.54%)	98(23.90%)	71(17.32%)	151(36.83%)	14(3.41%)
How often do you search for health-related information online?	0(0.00%)	37(9.02%)	106(25.85%)	191(46.59%)	76(18.54%)
How often do you use e-mail to Communicate with healthcare providers?	44(10.73%)	181(44.15%)	122(29.76%)	59(14.39%)	4(0.98%)
Have you been questioned by patients about online means of contacting you?	94(22.93%)	220(53.66%)	61(14.88%)	32(7.80%)	3(0.73%)
How often do you download/ upload information through the internet?	0(0.00%)	45(10.98%)	135(32.93%)	215(52.44%)	15(3.66%)

Respondents Readiness in the cognitive domain

Table 3 illustrates respondent's cognitive readiness toward the use of Artificial Intelligence (AI) in healthcare. Most respondents demonstrated a good understanding of fundamental AI-related concepts. Specifically, 70.98% agreed and 3.66% strongly agreed that they could define the basic concepts of data science. Similarly, 54.63% agreed and 10.49% strongly agreed that they could define the basic concepts of statistics (Table 3).

Table 3
Cognitive Domain Readiness of Healthcare Professionals to Use AI-Based Clinical Decision Support Systems at the University of Gondar Comprehensive Specialized Hospital, Ethiopia, 2025

Items I Can	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Define the basic concepts of data science	14(3.41%)	20(4.88%)	70(17.07%)	291(70.98%)	15(3.66%)
Define the basic concepts of statistics	5(1.22%)	46(11.22%)	92(22.44%)	224(54.63%)	43(10.49%)
Explain how AI systems are trained	6(1.46%)	149(36.34%)	113(27.56%)	136(33.17%)	6(1.46%)
Define the basic concepts and terminology of AI	14(3.41%)	17(11.46%)	59(14.39%)	287(70%)	3(0.73%)
Properly analyze the data obtained by AI in healthcare	5(1.22%)	39(9.51%)	39(9.51%)	320(78.05%)	7(1.71%)
Differentiate between the functions and features of AI related tools and applications	6(1.46%)	47(11.46%)	40(9.76%)	313(76.34%)	4(0.98%)
Organize workflows in accordance with the logic of AI	3(0.73%)	44(10.73%)	47(11.46%)	307(74.88%)	9(2.20%)
Express the importance of data collections, analysis, evaluation and safety; for the development of AI in healthcare	2(0.49%)	16(3.90%)	28(6.83%)	308(75.12%)	56(13.66%)

Respondents Readiness in the ability domain

This table presents the respondent's readiness in terms of their ability to use artificial intelligence (AI) in healthcare related contexts. A large majority of respondents (73.9%) agreed, and 12.4% strongly agreed that they could use AI-based information in combination with their professional knowledge. Similarly, 77.8% agreed and 8.8% strongly agreed that they could use AI technologies effectively and efficiently in healthcare delivery (Table 4).

Table 4
Healthcare Professionals' Readiness in the Ability Domain at the University of Gondar Comprehensive Specialized Hospital, Ethiopia, 2025

I Can	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Use AI-based information in combination with my professional knowledge	6(1.46%)	26(6.34%	24(5.85%)	303(73.90%)	51(12.44%)
Use AI technologies effectively and efficiently in healthcare delivery	3(0.73%)	13(3.17%)	39(9.51%)	319(77.80%)	36(8.78%)
Use AI applications in accordance with its purpose	0(0%)	26(6.34%)	26(6.34%)	329(80.24%)	29(7.07%)
Access, evaluate, use, share and create new knowledge using information and communication technologies	3(0.73%)	12(2.93%)	36(8.78%)	312(76.10%)	47(11.46%)
Explain how AI applications in healthcare offer a solution to which problem	0(0.00%)	28(6.83%)	60(14.63%)	298(72.68%)	24(5.85%)
I find it valuable to use AI for education, service and research purposes	3(0.73%)	16(3.90%)	28(6.83%)	311(75.85%)	52(12.68%)
Explain the AI applications used in healthcare services to the patient	0(0.00%)	33(8.05%)	38(9.27%)	309(75.37%)	30(7.32%)
Choose the proper AI application for the problem encountered in healthcare	2(0.49%)	24(5.85%)	44(10.73%)	318(77.56%)	22(5.37%)

Respondents Readiness in the vision domain

This table presents the respondent's readiness in the vision domain, which reflects their ability to understand, evaluate, and anticipate the broader implications of artificial intelligence (AI) technologies in healthcare. A large proportion of respondents (69.0%) agreed and 11.0% strongly agreed that they could explain the limitations of AI technology, while only 8.3% disagreed and 0.5% strongly disagreed. Similarly, 72.2% agreed and 11.0% strongly agreed that they could explain both the strengths and weaknesses of AI technology, with only 8.3% expressing disagreement (Table 5).

Table 5
Healthcare Professionals' Readiness in the Vision Domain at the University of Gondar Comprehensive Specialized Hospital, Ethiopia, 2025

I Can	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Explain the limitations of AI technology	2(0.49%)	34(8.29%)	46(11.22%)	283(69.02%)	45(10.98%)
Explain the strengths and weaknesses of AI technology	0(0.00%)	34(8.29%)	35(8.54%)	296(72.20%)	45(10.98%)
Foresee the opportunities and threats that AI technology can create	0(0.00%)	35(8.54%)	32(7.80%)	302(73.66%)	41(10.00%)

Respondents Readiness in the ethic domain

This table presents the respondent's readiness in the ethics domain, which assesses their awareness and adherence to ethical principles, legal regulations, and data protection norms in the use of artificial intelligence (AI) technologies in healthcare. An overwhelming majority of respondents (90.0%) agreed and 0.5% strongly agreed that they act in accordance with ethical principles while using AI technologies, whereas only 5.9% disagreed and 3.7% remained neutral. Similarly, 86.3% of respondents agreed that they follow legal regulations regarding the use of AI technologies in healthcare, with 6.1% disagreeing and 7.6% remaining neutral (Table 6).

Table 6
Healthcare Professionals' Readiness in the Ethics Domain at the University of Gondar Comprehensive Specialized Hospital, Ethiopia, 2025

I Can	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Act in accordance with ethical principles while using AI technologies	0(0.00%)	24(5.85%)	15(3.66%)	369(90.00%)	2(0.49%)
Follow the legal regulations regarding the use of AI technologies in healthcare	0(0.00%)	25(6.10%)	31(7.56%)	354(86.34%)	0(0.00%)
Use health data in accordance with legal and ethical norms	0(0.00%)	10(2.44%)	23(5.61%)	374(91.22%)	3(0.73%)

Perceived Usefulness of AI based CDSS in healthcare practice among respondents

This table presents respondent's perceptions regarding the usefulness of AI-based Clinical Decision Support Systems (CDSS) in healthcare practice. The findings indicate a highly positive attitude toward

the benefits of AI-based CDSS for job performance, productivity, and effectiveness. A substantial proportion of respondents (68.3%) agreed and 20.7% strongly agreed that using AI-based CDSS would improve their job performance, while only 3.7% expressed disagreement and 7.3% remained neutral. Similarly, 74.6% agreed and 18.3% strongly agreed that the use of AI-based CDSS would increase their productivity, with very few respondents disagreeing (1.5%) or remaining neutral (5.1%) (Table 7).

Table 7
Perceived Usefulness of AI-Based Clinical Decision Support Systems in Healthcare Practice among Respondents at the University of Gondar Comprehensive Specialized Hospital, Ethiopia, 2025

I Can	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Using AI based CDSS would improve my job performance.	2(0.49%)	6(3.17%)	21(7.32%)	306(68.29%)	85(20.73%)
Using AI-based CDSS would improve my productivity.	2(0.49%)	6(1.46%)	21(5.12%)	306(74.63%)	75(18.29%)
Using AI based CDSS would enhance my effectiveness on the job.	5(1.22%)	9(2.20%)	18(4.39%)	274(66.83%)	104(25.37%)
I would find AI based CDSS useful in my job.	0(0.00%)	21(5.12%)	18(4.39%)	280(68.29%)	91(22.20%)

Determinants of AI based CDSS

After checking for assumptions of binary logistic regression such as, multi-collinearity, outliers, and observed/expected values in cross tab of each independent variables, bivariable logistic regression analysis was employed to select those variables that have association with readiness to AI based CDSS. Profession, Educational level, Work Experience, Own Computer and Own Smartphone were found to be associated with readiness to AI based CDSS with a P- value of less than 0.25 and were entered into the multivariable analysis to check for statistical significance of association. In multivariable logistic regression Profession, Educational level, Work Experience and Own Computer were significantly associated with readiness to AI based CDSS with a p- value less than 0.05 (Table 8).

Table 8
Multivariable Logistic Regression Analysis of Factors Associated with Healthcare Professionals' Readiness to Use AI-Based Clinical Decision Support Systems at at the University of Gondar Comprehensive Specialized Hospital, Ethiopia, 2025

Variable	Category	COR (95% CI)	AOR (95% CI)	P value
Profession	Anesthetists	1.00	1.00	
	HO	0.84 (0.53–1.26)	0.93 (0.61–1.42)	0.749
	Lab-technologist	1.15 (0.80–1.63)	1.19 (0.86–1.64)	0.307
	Midwives	0.97 (0.70–1.34)	1.06 (0.79–1.42)	0.675
	Nurse	1.01 (0.75–1.36)	1.04 (0.79–1.36)	0.762
	Physiotherapist	0.85 (0.61–1.21)	0.93 (0.68–1.28)	0.661
	Pharmacy	1.07 (0.75–1.54)	1.13 (0.82–1.57)	0.454
	Physician	1.26 (0.93–1.72)	1.42 (1.06–1.92)	0.020
	Other	1.05 (0.67–1.63)	1.12 (0.75–1.68)	0.578
Educational level	Diploma	1.00	1.00	
	BSc (1st degree)	1.16 (1.02–1.32)	1.13 (1.00-1.27)	0.046
	2nd degree and above	1.48 (1.20–1.81)	1.28 (1.06–1.55)	0.011
	GP	1.15 (0.85–1.57)	0.80 (0.59–1.08)	0.147
	Resident	1.25 (1.02–1.52)	0.90 (0.73–1.10)	0.311
	Specialist	1.19 (0.92–1.52)	0.84 (0.65–1.08)	0.174
Work Experience	Less than 2	1.00	1.00	
	2–3 years	1.28 (1.03–1.59)	1.25 (1.02–1.51)	0.032
	4–5 years	1.22 (0.98–1.52)	1.19 (0.97–1.44)	0.094
	More than 5	1.13 (0.92–1.36)	1.13 (0.95–1.35)	0.18
Own Computer	No	1.00	1.00	
	Yes	1.52 (1.39–1.65)	1.48 (1.35–1.60)	< 0.001

Qualitative Data Result

AI-CDSS are emerging technologies that use artificial intelligence to assist healthcare professionals in making clinical decisions. These systems provide quick, precise, and evidence-based information tailored to specific clinical needs and can deliver personalized recommendations. AI-CDSS can support healthcare providers similarly to consulting a senior professional by improving patient care, enhancing treatment decisions, supporting disease prevention, reducing medical errors, and shortening hospital

length of stay. However, several concerns exist, including potential reduction in human resource roles, unemployment fears, limited digital literacy, infrastructure challenges, and negative attitudes or perceptions toward AI. To effectively implement AI-CDSS, healthcare professionals require technical training, clinical integration training, and continuous support Table (9).

Table 9
:Qualitative Study Findings from the University of Gondar Comprehensive Specialized Hospital, Ethiopia, 2025

Tell me about AI-based Clinical Decision Support Systems (AI-CDSS)	AI is the recently arrived system
	AI is a platform that is creating an impact
	A system that we can get different evidence on short and precise way based on our requirements
	A system where we can get personalized answers.
Advantages	Developed it is like consulting senior health professional
	Useful for enhancement of patient care
	Quality improvement
	Treatment
	Disease prevention
	Timely care providing
	Different clinical activities
	Reducing medical errors
	Shortening hospital length of stay
Main Concerns	Individuals cannot dig out their ability
	It can reduce human resources
	Leads to unemployment
	Digital literacy
	Infrastructure
	Attitude and perception
What kind of training needed	Technical training
	Clinical integration training
	Ongoing support

Discussion

This study evaluated healthcare providers' readiness to use AI-based CDSS and found an overall readiness level of 50.5% [95% CI of 45.5% to 55.4%]. This is similar to findings from Saudi Arabia, where readiness was reported at 55% (38). In several Sub-Saharan African countries, including Kenya, South Africa, Uganda, Nigeria, and Ghana, readiness was lower (33–35%), which could be due to limited access to AI technologies, fewer training opportunities, and lower exposure to digital health initiatives (39). In contrast, higher readiness levels were observed in countries such as Australia (70%), Iran (88.9%), and China (83%), likely reflecting stronger technological infrastructure, more widespread integration of AI in healthcare, and higher digital literacy among healthcare professionals (29, 40, 41). These differences highlight how variations in resources, training, and institutional support can influence AI adoption in clinical practice across different settings.

This was supported by a key informant interview, where he responded that: -

"Several key concerns influence the readiness of healthcare professionals to adopt AI-CDSS. The first thing is digital literacy, the level of digital literacy among healthcare professionals is a critical factor. Evidence from various hospitals and health centers indicates that digital literacy among health workers remains relatively low, creating a significant gap in their ability to effectively utilize AI technologies. The second one infrastructure, adequate infrastructure is essential for the successful implementation of AI-CDSS. Reliable access to smartphones, computers, and stable internet connectivity within hospital wards and outpatient departments (OPDs) is necessary. The other concern is health professional's attitude on AI based CDSS. Because, when AI first introduced we were ignoring it. But now it has become our everything. Knowledge of how to use, search, digital literacy, attitude and perceptions are the general concerns."

. [27 years old, male, health informatics professional].

The integration of AI into healthcare also raises questions about acceptance. For instance, if AI provides the most recent literature and data, this may sometimes contradict the existing knowledge or practices of healthcare professionals, potentially creating resistance. However, the use of AI in healthcare is becoming increasingly necessary. As with any technological innovation, initial concerns and skepticism are common within communities. For example, when electricity was first introduced, there was widespread fear of job loss. Over time, however, electricity not only transformed daily life but also generated new forms of employment. Similarly, while AI may initially be met with apprehension, it has the potential to enhance healthcare delivery and open new opportunities for professional growth.

. [33 years old, male, pharmacy professional].

In this study, four key factors educational level, computer ownership, working experience and profession were found to be significantly associated with health professional's readiness to implement AI-CDSS. Health professionals with a bachelor's degree or higher were more likely to be ready to adopt AI-CDSS compared to those with diplomas. Specifically, those holding a first degree were over two times more

likely, and those with a second degree or above were nearly four times more likely to be ready. A systematic review on health students and academics showed that senior students and those with doctoral degrees exhibited more favorable outlooks compared with their less experienced counterpart's in terms of attitudes toward AI The potential explanation for this could be more education often includes exposure to technology, research methods, critical thinking, which helps people understand AI, its limitations and uses (42). Ethiopian studies on EMR and telemedicine readiness, also report that more educated health professionals tend to have more knowledge, skills, and more positive attitudes, which correlate with being ready (43)

The second strong factor of readiness was computer ownership. Professionals who owned a computer were nearly 1.5 times more likely to be ready to use AI-CDSS than those without. This result highlights the importance of digital access and infrastructure as prerequisites for successful AI adoption. The study that was done in China stressed that availability of digital tools is foundational for AI-based clinical practice (44). Likewise, the WHO's 2020–2025 Global strategy on digital health emphasize access to hardware (computers, tablets, smartphones) as a core determinant of readiness for AI integration in healthcare (45). These findings suggest that beyond individual attitudes, structural and infrastructural readiness is critical to the effective implementation of AI-CDSS. The potential explanation for this could be if someone already owns a computer; he/she is more familiar with its use, more likely to experiment, less constrained by access issues (46).

The third factor of readiness was the profession. Studies show that professionals in AI-intensive fields (like radiology, health informatics) tend to report higher readiness, familiarity, or positive attitudes towards AI (46). The BMC Health Services Research study "Healthcare workers' readiness for artificial intelligence and organizational change …" found that readiness was higher among doctors and internal sciences compared to other professions (47). The potential explanation for this could be the role of one's profession influences how relevant one perceives AI/CDSS to be. Some professions are more exposed to technology or research, so they may have more prior exposure

The last factor of readiness was working experience. In the Amhara Health professionals' telemedicine readiness at private hospitals, more work experience was significantly associated with greater readiness (43). However, some studies also show that younger professionals (or less experienced) are more digitally literate in certain contexts, so experience matters but how recent or how tech-oriented the experience is will modulate the effect (48). The potential explanation for this could be that experience gives exposure to many situations, maybe witnessing or using earlier versions of digital tools, which may reduce fear or uncertainty about new AI-based systems.

Strength and Limitation of the Study

Strength of the Study

The major strength of the study was that it triangulated qualitative findings.

Limitation of the Study

It didn’t incorporate other types of readiness, for instance organizational and technology readiness.

Conclusion

More than half of the respondents had a good level of overall healthcare professional’s readiness for the adoption of AI based CDSS. This finding suggests that a huge effort is required to improve readiness before the actual implementation of AI based CDSS. The finding implied that those who had their Own Computer were more ready for such technology which in turn implied; those who hadn’t their Own Computer one needs more concern. Enhancing computer literacy, confidence building to raise self-efficacy of such technology, addressing the issue of computer availability at health facilities, building a positive attitude, awareness campaign of AI based CDSS, and recognizing the usefulness of such systems were the necessary measures to improve AI based CDSS readiness in this setting. Additionally, further studies are recommended to encompass all types of AI based CDSS readiness such as organizational readiness, technology readiness, societal readiness, and so on.

Recommendations

To Ethiopian Ministry of Health Develop structured AI-CDSS training programs focusing on computer literacy, AI basics, and integration into clinical workflows, with continuous professional development.

To UoGCSH administrators Increase access to computers and ensure reliable internet connectivity across hospital wards, provide technical support staff for smooth AI-CDSS adoption. Integrate AI-readiness into hospital digital health strategy, establish ethical/legal guidelines, and allocate budget for AI-CDSS implementation. Conduct awareness campaigns and workshops to improve perceptions of AI-CDSS benefits, address concerns (e.g., job displacement, ethical issues), and promote success stories.

To Researchers Conduct additional studies on organizational, technological, and societal readiness, and employ longitudinal designs to capture changes in readiness over time

Declarations

Ethics approval and consent to participate

All methods were carried out in accordance with relevant guidelines and regulations, including the principles of the Declaration of Helsinki. This study used primary data analysis, hence direct participation from individuals was required. Ethical clearance was taken from ethical clearance committee of University of Gondar College of Medicine and Health science, Approval was obtained from University of Gondar Specialized Hospital and written consent was obtained from the study subjects, following an explanation of purpose of the interview and observation. This study used exclusively de-

identified information, ensuring full compliance with ethical standards for participant privacy and confidentiality.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

Funding

This study did not receive any funding.

Author Contribution

T.D.S. conceptualized and designed the study, led the data analysis, and drafted the manuscript. T.H., W.Z., and A.M.N. supervised the study, contributed to the study design, and critically reviewed the manuscript. T.A.A. and E.A.T. participated in data collection, data cleaning, and preliminary analysis. A.A.Y. contributed to qualitative data collection and analysis. All authors read, revised, and approved the final manuscript for publication.

Data Availability

The datasets generated and/or analyzed during the current study are not publicly available because they contain information that could compromise participant confidentiality. The data are available from the corresponding author on reasonable request, subject to approval by the relevant ethics committee and institutional requirements.

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Figures

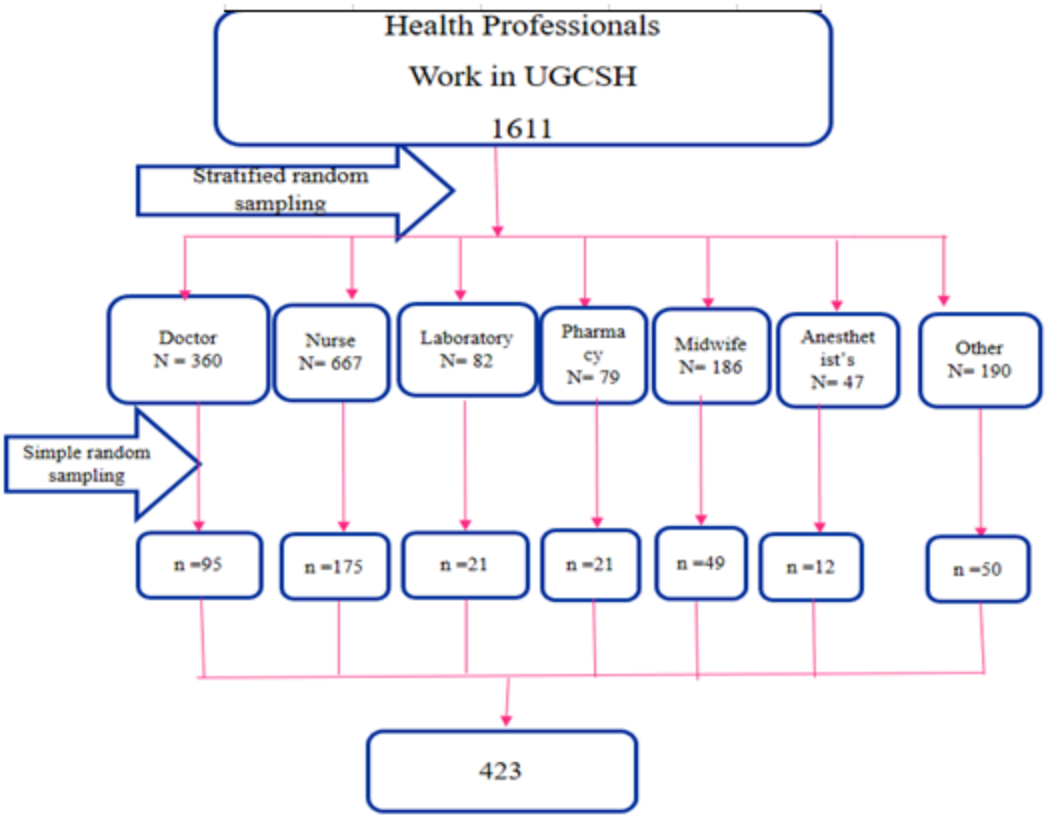


Figure 1

Sampling procedure for Readiness and associated factors to use AI-based Clinical Decision Support System among Healthcare Professionals at the University of Gondar Hospital, Ethiopia, 2025.