Assessment of Knowledge, Attitudes, and Practices in Artificial Intelligence Among Healthcare Professionals in Mogadishu, Somalia

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Research Article

Keywords: Artificial Intelligence, Healthcare Professionals, Somalia

Posted Date: May 14th, 2024

DOI: https://doi.org/10.21203/rs.3.rs-4359643/v1

Additional Declarations: No competing interests reported.

Abstract

Background: The rapid advancement of artificial intelligence (AI) in various sectors has revolutionized problem-solving approaches, particularly in healthcare. Developed countries have invested significantly in AI research and applications in healthcare, while low-income countries such as Somalia lag due to various challenges. This study aimed to assess the knowledge, attitudes, and practices (KAP) of AI among healthcare professionals in Somalia and explore their familiarity with AI technologies and practices.

Methods: A cross-sectional study was conducted from January 1, 2024, to March 15, 2024, among 441 healthcare professionals in Somalia, using an online questionnaire. The questionnaire assessed the participants' sociodemographic information, knowledge of AI applications in healthcare, attitudes towards AI capabilities, and practical experience with AI in healthcare.

Results: Most participants demonstrated good knowledge of AI (67.6%) and a positive attitude towards its potential in healthcare (80.5%). However, a significant gap was observed in the practical application of AI, with 79.1% of the respondents reporting poor practice. The study also found that sociodemographic factors such as age, gender, and income level did not significantly influence knowledge or attitudes towards AI but did affect its practical use. Professionals in certain fields such as midwifery and public health are more likely to use AI in their work. Knowledge and attitude scores were also significant predictors of practice scores.

Conclusion: Healthcare professionals in Somalia demonstrate a good understanding and positive attitudes towards AI but encounter challenges in its practical application. This study emphasizes the necessity of an enhanced infrastructure, technical expertise, and data access to fully utilize AI's potential in healthcare. It also highlights the significance of addressing ethical considerations and implementing regulations to ensure responsible use of AI in healthcare. Efforts are needed to translate awareness and receptiveness into effective practice, which could result in a better healthcare system.

Background

The concept of Artificial Intelligence (AI) centers on machines, particularly computer systems, which mimic human thought processes. This broad field covers numerous technologies capable of performing tasks that typically require human intelligence, such as acquiring knowledge, critical thinking, problem-solving, and understanding verbal communication [1], [2]. These technologies include machine learning, in which algorithms are trained to make classifications or predictions, uncovering insights into data without being explicitly programmed; deep learning, which involves neural networks with many layers of processing units, taking advantage of advances in computing power and improved training techniques to learn complex patterns in large amounts of data; and natural language processing, which enables understanding, interpretation, and generation of human language by a computer [3], [4], [5]. AI is a broad field in computer science; however, its applications extend beyond computer science and cover a diverse range of fields, including health care. It is a fast-growing interdisciplinary area with the potential to revolutionize approaches to problem-solving in different fields [6]. In the healthcare domain, AI plays an important role in the treatment of diseases and significantly reduces errors in diagnosis and patient monitoring [7]. The use of AI has witnessed a recent surge, transitioning from theoretical research to practical applications in many industries [8].

Developed countries have allocated considerable financial resources to the advancement of AI research, particularly in healthcare. In lower-income countries, such as Somalia, there is an absence of strategies for the adoption of AI, in addition to a lack of research focused on this technology [9]. In the past decade, AI domains have witnessed significant expansion in technological advancements. Despite the long-standing history of AI development across various uses, the current wave of AI excitement sets itself apart from previous periods. The rapid progress of AI tools and approaches in the healthcare sector has been enabled by a combination of enhanced computational processing abilities, extensive data storage facilities, and a wealth of expertise in artificial intelligence [10], [11].

However, AI, especially machine learning (ML), is currently at an early stage of adoption in low-income countries owing to a range of challenges, including data gathering, infrastructure limitations, and ethical considerations [12]. ML is used across many medical sectors such as diabetes management, cancer detection and treatment, cardiological assessments, mental health interventions, and radiological imaging analysis, demonstrating its broad applicability and transformative potential in healthcare [13], [14]. Significant progress has been achieved in radiology and pathology through AI's capability to provide digitally encoded images for computational analysis. Pathologists are aided by AI with image-based diagnostic options and improved interpretation of microscopic slides using electronic slides and computer-aided diagnostic tools [15], [16]. Recent advancements in ML algorithms have significantly impacted cardiological practices, particularly the stratification of patients at elevated risk of coronary plaque progression [17], [18].

AI shows impressive ability to identify skin lesions and has the potential to improve primary care in dermatology. However, further validation is necessary prior to its clinical application in dermatology [19]. AI is transforming ophthalmology by enhancing disease detection and prognosis in conditions such as diabetic retinopathy, macular degeneration, and retinopathy of prematurity, with deep learning precision. Nonetheless, its clinical integration as a supportive tool is being actively researched [20], [21]. In nephrology, AI enhances patient care by refining diagnostic and prognostic accuracy, optimizing dialysis outcomes, and improving monitoring of transplant recipients [22]. The application of ML in drug discovery has transformed the field by automating the complex process of molecular design and streamlining the synthesis of new drugs, leading to faster and more efficient therapeutic innovations [23].

AI’s role in healthcare extends beyond that of its individual specialties; it is used to optimize hospital operations [24]. Globally, AI’s impact on healthcare is extensive, with its applications offering solutions for improving the delivery of healthcare services [25], capable of transcribing clinical notes and organizing patient data into electronic health records. This indicates the potential for improved efficiency, accuracy, and patient care [26], [27]. AI systems also offer reliable secondary opinions to healthcare professionals, thereby significantly reducing their time burden [28]. The use of AI systems can also be advantageous for patients by providing personalized medication management, enhancing patient engagement, and potentially improving adherence to treatment plans, thereby leading to improved clinical outcomes and overall quality of life. Additionally, AI systems can support and empower patients in their self-management and decision-making processes, contributing to better health outcomes [29]. AI enables distant patient diagnoses and expands healthcare access to underserved rural areas. Although challenges persist, the future of AI in healthcare is promising [30]. Despite the significant potential of AI in the healthcare industry, its implementation in Somalia has been disrupted by various obstacles including inadequate infrastructure, scarcity of technical expertise, and limited access to high-quality data. Overcoming these challenges is essential for the successful integration of AI into healthcare systems in the region. Moreover, there are concerns regarding privacy and transparency in the use of patient data, which are exacerbated by the absence of strong regulatory frameworks and data protection laws. The technological and regulatory difficulties faced in implementing AI-based services could hinder their adoption and limit the benefits that AI could bring to healthcare systems in Somalia [31]. This study aimed to investigate the level of knowledge, attitudes, and practices of AI among healthcare professionals in Somalia as well as their familiarity with different AI technologies and practices.

Methodology

Study Design

This cross-sectional study was conducted from January 1, 2024, to March 15, 2024, targeting healthcare professionals in Mogadishu, Somalia. The study used a questionnaire to assess the knowledge, attitudes, and practices concerning artificial intelligence (AI) among participants. The questionnaire was distributed online via social media platforms such as WhatsApp, Facebook, Messenger, and LinkedIn, and in person at hospitals and medical centers using tablets.

Study Population and Sampling Techniques

The study targeted healthcare professionals in Mogadishu, Somalia. Due to the absence of prior research in this area, the sample size was determined using a single population proportion formula. The formula used to calculate the sample size is as follows:

$$n = \frac{Z^2 * p * (1 - p)}{E^2}$$

Where:

n represents the sample size needed,

Z is the z-score associated with the desired confidence level (1.96 for a 95% confidence interval),

p is the estimated proportion of the attribute of interest, in this case, assumed to be a 50% probability of poor knowledge, practice, and attitude towards AI among healthcare professionals,

E is the margin of error, set at 5% (or 0.05).

A sample size of 384 healthcare professionals was initially calculated. The sample size was adjusted to 423 to adapt to a 10% nonresponse rate. Ultimately, a total of 441 participants were recruited for the study

Research Instruments and Measurements

A questionnaire was developed after a thorough review of the literature (S1). It includes sections gathering sociodemographic information, knowledge of AI in healthcare, attitudes towards AI capabilities, and practical experience with AI in healthcare. Each participant received scores for knowledge, attitude, and practice, based on their correct or appropriate responses. Knowledge was assessed through statements rewarding correct answers, with points ranging from 0 to 10. Using Bloom's cutoff, we dichotomized the scores into "poor knowledge" (0–5 points) and "good knowledge" (6–10 points). Attitudes were measured on a Likert scale, categorizing responses as "negative attitude" (< 60%) and "positive attitude" (≥ 60%). Similarly, practice scores based on correct actions followed this dichotomy: ‘poor practice’ (< 60%) and ‘good practice’ (≥ 60%). The reliability and credibility of the survey were validated through a pilot study with 30 participants. The internal consistency of the subscales was indicated by Cronbach's alpha values ranging from 0.7–0.8 (Knowledge = 0.76, Attitude = 0.74, and Practice = 0.73).

Statistical Analysis

Data was cleaned, coded, and analyzed using R programming software, using both descriptive and inferential statistics. Categorical data are summarized by frequency and percentage, whereas continuous data are represented as means and standard deviations. For inferential statistics, binary logistic regression was performed to calculate odds ratios and 95% confidence intervals, exploring the interrelations between KAP scores and sociodemographic characteristics. Variables were initially analyzed through bivariate logistic regression models to assess associations, and then through multivariable logistic regression models for adjusted odds ratios for potential confounders. Linear regression analyses were also performed to identify the predictors of practice scores.

Results

Table 1
Socio-demographic characteristics

Variables	Frequency	%
Age (Years)		
18–25	231	52.4
26 to 33	183	41.4
> 33	27	6.1
Age (Years)	Mean (SD) 25.7 ± 4.68	
Gender		
Male	216	49
Female	225	51
Marital Status		
Unmarried	329	74.6
Ever Married	112	25.4
Educational Level		
Bachelor’s degree	330	74.8
Postgraduate Degree	103	23.4
Doctoral Degree (PhD)	8	1.8
Professional Field		
Medicine	192	43.5
Nursing	121	27.4
Midwifery	15	3.4
Diagnostics	32	7.3
Public Health & Epidemiology	40	9.1
Pharmacy	9	2.0
Other	32	7.3
Monthly Income USD		
<100 $	140	31.7
101$ – 500$	167	37.9
501$ – 1000$	73	16.6

Variables	Frequency	%
>1000$	61	13.8

Table 2
Levels of Knowledge, Attitudes and Practices

Levels	Frequency n(%)	Mean (SD)
Knowledge		
Poor Knowledge (≤ 60%) (0 – 5 scores)	143 (32.4)	6.45 ± 2.36
Good Knowledge (> 60%) (6–10 scores)	298 (67.6)	
Attitude		
Negative Attitude (≤ 60%) (0–27 scores)	86 (19.5)	33.56 ± 7.62
Positive Attitude (> 60%) (28–47 scores)	355 (80.5)	
Practice		
Poor Practice (≤ 60%) (0 – 5 scores)	349 (79.1)	3.41 ± 2.59
Good Practice (> 60%) (6–10 scores)	92 (20.9)	

Table 3
Association between knowledge levels and socio-demographic characteristics

Variables	Knowledge Level		OR(95%CI)	P-Value	AOR(95%CI)
	Poor (%)	Good (%)			
Age (Years)					
18–25	64 (27.7%)	167 (72.3%)	1.00		1.00
26 to 33	67 (36.6%)	116 (63.4%)	0.66 (0.44–1.01)	0.054	0.81 (0.47–1.39)
> 33	12 (44.4%)	15 (55.6%)			
Age (Years)	Mean (SD) 25.7 ± 4.68				
Gender					
Male	78 (36.6%)	137 (63.4%)	1.00		1.00
Female	64 (28.4%)	161 (71.6%)	1.45 (0.97–2.17)	0.068	1.15 (0.71–1.84)
Marital Status					
Unmarried	106 (32.2%)	223 (67.8%)	1.00		1.00
Ever Married	37 (33.0%)	75 (67.0%)	0.96 (0.61–1.53)	0.873	1.53 (0.88–2.70)
Educational Level					
Bachelor’s degree	97 (29.4%)	223 (70.6%)	1.00		1.00
Postgraduate Degree	44 (42.7%)	59 (57.3%)	0.56 (0.35–0.88)	0.012*	0.65 (0.35–1.21)
Doctoral Degree (PhD)	2 (25.0%)	6 (75.0%)	1.25 (0.28–8.63)	0.787	1.17 (0.24–8.64)
Professional Field					
Medicine	67 (34.9%)	125 (65.1%)	1.00		1.00
Nursing	36 (29.8%)	85 (70.2%)	1.27 (0.78–2.08)	0.346	1.01 (0.59–1.74)
Midwifery	2 (13.3%)	13 (86.7%)	3.48 (0.93–22.7)	0.107	2.60 (0.66–17.39)

Variables	Knowledge Level		OR(95%CI)	P-Value	AOR(95%CI)
	Poor (%)	Good (%)			
Diagnostics	11 (34.5%)	21 (65.6%)	1.02 (0.47–2.32)	0.954	0.93 (0.42–2.15)
Public Health & Epidemiology	13 (32.5%)	27 (67.5%)	1.11 (0.55–2.36)	0.772	1.01 (0.52–2.39)
Pharmacy	2 (22.2%)	7 (77.8%)	1.88 (0.44–12.83)	0.441	1.78 (0.40–12.56)
Other	12 (37.5%)	20 (62.5%)	0.89 (0.42–1.99)	0.775	0.98 (0.44–1.27)
Monthly Income USD					
<100 $	36 (25.7%)	104 (74.3%)	1.00		1.00
101$ – 500$	56 (33.5%)	111 (66.5%)	0.69 (0.42–1.12)	0.137	0.75 (0.44–1.27)
501$ – 1000$	26 (34.2%)	48 (65.8%)	0.66 (0.36–1.23)	0.192	0.85 (0.41–178)
>1000$	26 (42.6%)	35 (57.4%)	0.47 (0.25–0.88)	0.018*	0.71 (0.31–1.63)

Table 4
Association between Attitude level and socio-demographic characteristics

Variables	Attitude Level		OR(95%CI)	P-value	AOR(95%CI)
	Negative (%)	Positive (%)			
Age (Years)					
18–25	40 (17.3%)	191 (82.7%)	1.00		1.00
26 to 33	40 (21.9%)	143 (78.1%)	0.73 (0.29–1.22)	0.246	0.67 (0.35–1.28)
> 33	6 (22.2%)	21 (77.8%)	0.73 (0.29–2.10)	0.530	0.70 (0.22–2.38)
Age (Years)	Mean (SD) 25.7 ± 4.68				
Gender					
Male	43 (19.9%)	173 (80.1%)	1.00		1.00
Female	43 (19.1%)	182 (80.9%)	1.05 (0.66–1.69)	0.833	1.06 (0.60–1.87)
Marital Status					
Unmarried	60 (18.2%)	269 (81.8%)	1.00		1.00
Ever Married	26 (23.2%)	86 (76.8%)	0.74 (0.44–1.26)	0.252	0.80 (0.43–1.51)
Educational Level					
Bachelor’s degree	64 (19.4%)	266 (80.6%)	1.00		1.00
Postgraduate Degree	20 (19.4%)	83 (80.6%)	1.00 (0.58–1.78)	0.996	1.40 (0.67–3.01)
Doctoral Degree (PhD)	2 (25.0%)	6 (75.0%)	0.72 (0.16–5.00)	0.694	1.08 (0.22–7.99)
Professional Field					
Medicine	35 (18.2%)	157 (81.8%)	1.00		1.00
Nursing	27 (22.3%)	95 (77.7%)	0.78 (0.44–1.37)	0.378	0.67 (0.36–1.25)
Midwifery	4 (26.7%)	11 (73.3%)	0.61 (0.20–	0.425	0.51 (0.15–

Variables	Attitude Level		OR(95%CI)	P-value	AOR(95%CI)
	Negative (%)	Positive (%)			
			2.31)		2.02)
Diagnostics	4 (12.5%)	28 (87.5%)	1.56 (0.57–5.52)	0.432	1.31 (0.46–4.73)
Public Health & Epidemiology	7 (17.5%)	33 (82.5%)	1.05 (0.45–2.76)	0.913	1.05 (0.43–2.83)
Pharmacy	2 (22.2%)	7 (77.8%)	0.78 (0.18–5.39)	0.763	0.73 (0.16–5.18)
Other	7 (21.9%)	25 (78.1%)	0.80 (0.33–2.12)	0.625	0.79 (0.32–2.16)
Monthly Income USD					
<100 $	30 (21.4%)	110 (78.6%)	1.00		1.00
101$ – 500$	25 (15.0%)	142 (85.0%)	1.55 (0.86–2.80)	0.143	1.75 (0.93–3.30)
501$ – 1000$	18 (24.7%)	55 (75.3%)	0.83 (0.43–1.65)	0.593	0.97 (0.43–2.21)
>1000$	13 (21.3%)	48 (78.7%)	1.01 (0.49–2.15)	0.985	1.07 (0.41–2.86)

Table 5
Association between Practice level and socio-demographic characteristics

Variables	Practice Level		OR(95%CI)	P-value	AOR(95%CI)	P-value
	Poor (%)	Good (%)				
Age (Years)						
18–25	180 (77.9%)	51 (22.1%)	1.00		1.00	
26 to 33	147 (80.3%)	36 (19.7%)	0.86 (0.53–1.39)	0.551	0.95 (0.49–1.80)	
> 33	22 (81.5%)	5 (18.5%)	0.80 (0.26–2.07)	0.672	0.76 (0.20–2.50)	
Age (Years)	Mean (SD) 25.7 ± 4.68					
Gender						
Male	174 (80.6%)	42 (19.4%)	1.00		1.00	
Female	175 (77.8%)	50 (22.2%)	1.18 (0.75–1.88)	0.473	0.95 (0.55–1.67)	
Marital Status						
Unmarried	262 (79.6%)	67 (20.4%	1.00		1.00	
Ever Married	87 (77.7%)	25 (22.3%)	1.12 (0.66–1.87)	0.666	1.27 (0.66–2.42)	
Educational Level						
Bachelor’s degree	258 (78.2)	72 (21.8%)	1.00		1.00	
Postgraduate Degree	85 (82.5%)	18 (17.5%)	0.76 (0.42–1.32)	0.344	0.62 (0.28–1.33)	
Doctoral Degree (PhD)	6 (75.0%)	2 (25.0%)	1.19 (0.17–5.31)	0.830	0.83 (0.10–4.48)	
Professional Field						
Medicine	165 (85.9%)	27 (14.1)	1.00		1.00	
Nursing	97 (80.2%)	24 (19.8%)	1.51 (0.82–2.77)	0.179	1.47 (0.77–2.84)	
Midwifery	6 (40.0%)	9	9.17 (3.07–	<	9.77 (3.07–	<

Variables	Practice Level		OR(95%CI)	P-value	AOR(95%CI)	P-value
	Poor (%)	Good (%)				
		(60.0%)	29.3)	0.001*	33.2)	0.001*
Diagnostics	22 (68.8%)	10 (31.2%)	2.78 (1.15–6.41)	0.086*	2.71 (1.10–6.43)	0.026*
Public Health & Epidemiology	27 (67.5%)	13 (32.5%)	2.94 (1.33–6.35)	0.006*	3.02 (1.33–6.72)	0.007*
Pharmacy	6 (66.7%)	3 (33.3%)	3.06 (0.62–12.4)	0.129	2.71 (1.10–6.43)	
Other	26 (81.2%)	6 (18.8%)	1.41 (0.49–3.56)	0.490	1.45 (0.49–3.78)	
Monthly Income USD						
<100 $	111 (79.3%)	29 (20.7%)	1.00		1.00	
101$ – 500$	132 (79.0%)	35 (21.0%)	1.01 (0.58–1.77)	0.958	1.03 (0.56–1.88)	
501$ – 1000$	55 (75.3%)	18 (24.7%)	1.25 (0.63–2.44)	0.511	1.48 (0.64–3.38)	
>1000$	51 (83.6%)	10 (16.4%)	0.75 (0.33–1.61)	0.477	1.26 (0.45–3.46)	

Table 6
Linear Regression of Knowledge and Attitude Scores Against Practice Score

Parameter Estimates				
Term	Estimate	Standard Error	t Value	Pr(>|t|)
Intercept	-0.1353	0.556	-0.243	0.807
Knowledge Score	0.3898	0.049	7.871	< 0.001*
Attitude Score	0.0306	0.015	1.999	0.0462 *

The results are presented based on data collected from 441 participants, including various demographics, knowledge levels, attitudes towards AI, and practical applications of AI in healthcare.

Demographic Characteristics

Most participants were aged 18–25 (52.4%) and 26–33 (41.4%). The study had an equal male (49%) and female (51%), with the majority being unmarried (74.6%) and holding a bachelor’s degree (74.8%).

Professionals from various fields, including medicine (43.5%), nursing (27.4%), midwifery, diagnostics, public health/epidemiology, and pharmacy, among others, also contributed to this study. In terms of monthly income distribution, most earned between $101 to $500 (37.9%), with smaller segments earning less than $100 or between $501–$1000 or over $1000.

Knowledge of AI in Healthcare

Most respondents showed good knowledge of AI, with 67.6% scoring above 60% on their knowledge assessment. The data also revealed good knowledge of how AI can improve diagnosis, treatment, research, education, and management, with over 74% recognizing its capabilities in these areas. However, there was a more varied awareness regarding the ethical considerations and limitations of AI among the respondents. For instance, only about half of the participants correctly identified ethical issues related to informed consent, accountability, responsibility, and transparency (66.7%) as well as limitations such as data quality, privacy, security, bias, and errors (69.8%).

Attitudes Towards AI in Healthcare

Most participants (80.5%) had a positive attitude towards AI in healthcare, agreeing that it could address complex issues, improve accessibility, reduce workloads, and optimize resources. A large percentage of professionals agreed that AI is a valuable problem-solving tool (63.8%) that enhances healthcare accessibility (65.3%). There were some concerns about the potential replacement of human doctors with AI, as only 8.6% strongly agreed and 22.2% agreed with this notion. The attitudes towards regulating and further researching AI in healthcare were largely positive at 65.3%, demonstrating an understanding of the need for the ethical use of these technologies.

Practice of AI in Healthcare

The majority of the respondents (79.1%) showed poor practices in the use of AI in healthcare, but were open to learning more about AI tools (56.7%) and actively sought information about new developments in healthcare (42.4%). The results highlighted challenges in adopting AI tools, including discomfort with sharing data with AI tools (72.8%), lack of trust in the outputs without validation (75.7%), and concerns over the reliability and dependability of AI tools without proper validation for practice (74%). However, a significant proportion of professionals expressed confidence in using approved AI tools in practice (30%) and verifying their accuracy before implementation (48%).

Association between knowledge levels and socio-demographic characteristics

Healthcare professionals under 33 years of age showed different probabilities of having higher AI knowledge. However, after adjustments, no specific age group demonstrated significantly greater knowledge than the other groups. While men appeared to have slightly higher knowledge of AI than women, this difference was not statistically significant ($P = 0.068$). Conversely, individuals earning over $1000 per month were less likely to have good AI knowledge, being about half as likely ($OR = 0.47$, $P = 0.018$) as their lower-earning counterparts. Additionally, participants with a postgraduate degree were approximately 0.56 times as likely to have strong AI knowledge compared to those with a bachelor's degree ($P = 0.012$). Despite these findings, there were no statistically significant differences in sociodemographic characteristics after adjusting for the multivariate analysis.

Association between Attitudes and socio-demographic characteristics

Bivariate analysis revealed that demographic factors, such as age, gender, and income level, did not significantly influence attitudes towards AI. Gender differences revealed that men were 0.67 times as likely to hold positive attitudes towards AI than women, although this difference did not reach statistical significance. Similarly, income levels, including those earning more than $1000 per month, showed no significant impact on attitudes towards AI. Educational level and professional field also did not significantly change the likelihood of holding positive attitudes towards AI compared to holding a bachelor's degree.

Association between practice and socio-demographic characteristics

In bivariate analysis, there were no significant differences in age, sex, or income. The analysis showed that men and women were equally likely to use AI in their practice, with no statistically significant sex disparity in AI application ($P > 0.05$). Income levels above $1000 per month do not influence the likelihood of AI practice. However, professionals in midwifery demonstrated a notably greater practice of AI, being over nine times more likely to use AI than their counterparts in medicine (OR: 9.17; CI: 3.07–29.3; $P < 0.001$). Similarly, those working in diagnostics (Laboratory Science and Radiology) were nearly three times more likely to practice AI (OR: 2.78; CI: 1.15 – 6 .41; P = 0 .026). Public Health & Epidemiology professionals also exhibited a notable tendency towards adopting AI practices after adjustments

Association of Knowledge and Attitude Scores with Practice Score

Bivariate linear regression analysis showed that both knowledge and attitude scores predicted practice scores for AI among healthcare professionals. An increase in the knowledge score for AI resulted in a notable increase in practice scores by 0.4112 units ($P < 0.0001$). Similarly, a positive attitude towards AI contributed to an increase in the practice score by 0.05677 units for every unit increase in the attitude score ($P = 0.000429$). In the multivariate linear regression analysis, each unit increase in knowledge score led to a 0.3898 unit increase in practice score ($P < 0.001$), and each unit increase in attitude score resulted in a 0.03069 unit increase in the practice score ($P = 0.0462$).

Discussion

This study assessed the knowledge, attitudes, and practices (KAP) related to artificial intelligence (AI) among healthcare professionals in Somalia, a critical exploration given the increasing intersection of AI with healthcare globally. Our study found that 67.6% of healthcare practitioners in Somalia had good knowledge of AI applications in healthcare, indicating a significant level of familiarity with AI technologies. This is not surprising considering that 93.8% (18–33 years) of the respondents were millennials whose adulthood coincided with technological advancements, including the popular use of social media, smartphones, and instant accessibility of information. This finding is consistent with results from more developed nations, where healthcare professionals have a high level of awareness and comprehension of AI due to extensive exposure and opportunities for training. For example, a study conducted in Germany highlighted good AI knowledge attributed to its advanced healthcare infrastructure and focus on technological education [32]. In contrast, a study conducted in Pakistan revealed varying levels of knowledge regarding AI among medical professionals and students, indicating increasing curiosity and recognition of the potential impact of AI on health care [33]. Our study found that 80.5% of the respondents had a positive attitude towards AI in healthcare, aligning with global trends. Healthcare professionals generally view AI as valuable for enhancing services, diagnostics, and patient care. Despite acknowledging the potential limitations and ethical concerns, positive attitudes suggest a good understanding of AI technology. This cautious optimism emphasizes the importance of ethical considerations and the responsible use of AI in healthcare globally [34].

With the rapidly evolving healthcare landscape, the integration of Artificial Intelligence (AI) has become essential to achieve efficiency and remain competitive, especially because of its potential application in precision medicine from predictive diagnosis to drug discovery. However, the potential risks and lack of monitoring and control of the epigenetic pace of this innovation in the healthcare field is a cause for concern.

Contrary to the high levels of knowledge and positive attitudes, our study identified a significant gap in the practical application of AI, with 79.1% of the respondents reporting poor practices regarding the use of AI in their healthcare profession.

This gap may be linked to the challenges faced by LMICs in adopting AI technologies, including lack of infrastructure, inadequate training, and financial constraints [35]. In addition, the lack of explainability due to its purely data-driven nature leads to apprehension about what exactly the algorithms learn and how they will behave in an environment like the lower middle-income countries that are different from the ones in which the technology was. Other important areas of concern are the lack of diversity in the electronic health records used to train the AI, irregular predictive performance due to confounding factors, domain shift usually associated with machine learning, and lack of universally applicable AI guidelines [36]. Aligning with our study, research has found that despite the high expectations of AI, its practical application is still evolving. Efforts are currently focused on ensuring that AI tools are reliable, ethical, and can enhance patient care without diminishing the value of human judgment [37], [38].

Furthermore, our study identified the sociodemographic factors that affect AI knowledge, attitudes, and practices. For example, individuals with postgraduate qualifications showed a lower likelihood of having greater AI knowledge than those with bachelor's degrees. This indicates that higher educational levels do not always result in improved understanding or use of AI technologies. Similar trends in generational differences in familiarity with AI have also been observed across different settings, suggesting a global phenomenon in which younger professionals are linked to technological advancements [38].

The association between professional field and AI practice is particularly notable in our study, with professionals in Midwifery, Diagnostics (Laboratory Science and Radiology), and Public Health & Epidemiology being significantly more likely to use AI in their work. This may reflect the specific applicability of AI tools in these fields, such as image analysis in diagnostics or data analysis in epidemiology, highlighting the role of professional context in AI adoption [39].

The lack of correlation between higher income or education levels and good AI knowledge calls for targeted educational and policy interventions aimed at democratizing AI knowledge across all professional demographics and ensuring equitable access to training resources, regardless of socioeconomic status. This includes tailored education programs for healthcare professionals that address their theoretical knowledge and practical skills. Improving data collection/storage capabilities, internet connectivity, and access to AI tools/software should address infrastructure limitations. Establishing clear ethical guidelines and collaborations among healthcare institutions, government agencies, academic institutions, and technology companies can facilitate knowledge exchange and drive innovation in AI applications.

This study has several limitations. While the structured questionnaire is effective for gathering data, it may not fully capture the complexities of the subject matter, potentially leading to a limited depth of information. Additionally, there was a risk of response bias, as participants might not have fully or accurately disclosed their views or experiences. To address these issues, further research is needed to explore these limitations in depth and to develop more comprehensive data collection methods.

Conclusion

The study revealed good knowledge and positive attitudes towards artificial intelligence (AI) in healthcare among healthcare professionals in Mogadishu, Somalia, despite significant challenges in its practical application. While 67.6% of participants demonstrated good knowledge of AI, 80.5% expressed positive attitudes towards its potential, and 79.1% showed poor practical application. This discrepancy highlights the need for an improved infrastructure, enhanced technical expertise, and better access to data to fully leverage AI in healthcare. In addition, addressing ethical considerations and implementing strong regulations are necessary to ensure AI usage. The findings suggest that while there is readiness to embrace AI among healthcare professionals in Somalia, translating this enthusiasm into effective practice is essential for optimizing healthcare delivery and patient outcomes. This study highlights the importance of targeted educational and policy interventions to bridge the gap between the knowledge and practice of AI in healthcare, ensuring that all professionals, regardless of socioeconomic status, have equitable access to AI resources and training.

Declarations

Author Contributions

MMA, NID, DELP III, Conceptualized the idea. The study's design was collaboratively developed by BG, MMH, HAA, FAHO, JH, SSM, JBO, DS, OJO, ZKO, AMM, and YAA. Material preparation, data collection, and analysis were specifically carried out by AKM, AAM, IA, ANA, FYM, SAM and ZOM. JHM analyzed and interpreted the data. The initial draft was composed by MMA. All authors contributed to the writing, reviewing, and editing of subsequent versions of the manuscript.

Conflicts of Interest: The authors declare no conflicts of interest.

Funding: The authors received no financial support for the research, authorship, or publication of this article.

Availability of Data and Materials: The Data supporting the findings of this study are available from the corresponding author upon reasonable request.

Ethical Approval and Consent to Participate

Ethical approval for this study was obtained from the Institutional Review Board (IRB) of SIMAD University, Mogadishu, Somalia, as per the approval letter dated December 30, 2023, with reference number 2023/SU-IRB/FMHS/P007.

In accordance with this approval, informed consent was obtained from all individual participants involved in the study. Participants were adequately informed about the study's objectives, their rights to confidentiality, and their right to withdraw consent at any time without repercussions.

Consent for Publication: Not applicable

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