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Artificial intelligence readiness among healthcare students in Nigeria: A cross-sectional study assessing knowledge gaps, exposure, and adoption willingness

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ABSTRACT

Background: Artificial intelligence (AI) is rapidly transforming healthcare globally, yet its adoption in developing countries remains limited. As future practitioners, the readiness of healthcare students is crucial for successful AI integration, but this remains unexplored in the Nigerian context.

Objectives: This study aimed to assess AI readiness among healthcare students at a major Nigerian university by evaluating their foundational knowledge, practical exposure, and willingness to adopt AI technologies in clinical practice.

Methods: A cross-sectional study was conducted among 551 healthcare students at Obafemi Awolowo University using a semi-structured, validated questionnaire. The instrument utilized distinct sections with open-ended questions to objectively measure AI knowledge, assess exposure to AI applications, and gauge attitudes toward AI adoption. Data were analyzed using descriptive statistics and one-way ANOVA, with statistical significance set at $p < 0.05$.

Results: A significant knowledge-perception paradox emerged: while 60 % of students believed they had high AI knowledge; objective assessment showed 92 % had low knowledge levels. Foundational concepts were poorly understood, with only 12 % correctly defining machine learning. Despite this, students expressed overwhelmingly positive attitudes, with 90.8 % believing AI would improve workflow efficiency and 84.4 % willing to undertake AI training. Practical exposure to AI was minimal, with electronic record keeping being the most frequently encountered application (43.4 %). Knowledge levels were significantly associated with willingness to adopt AI ($p < 0.05$), as students with higher knowledge showed greater confidence but also a more critical awareness of AI's limitations.

Conclusion: Nigerian healthcare students show strong enthusiasm for AI adoption but have significant knowledge gaps and limited practical exposure. However, substantial concerns exist regarding the translation of expressed willingness into actual practice, particularly among early-year students who lack clinical exposure to understand AI limitations, bias, and real-world implementation challenges. These findings highlight an urgent need for AI curriculum integration and infrastructure development to prepare future healthcare professionals for an increasingly AI-driven healthcare landscape.

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1. Introduction

Artificial intelligence (AI) has rapidly emerged as a transformative force in healthcare delivery worldwide, with scholarly literature documenting its accelerated adoption and expanding applications across various medical domains [1]. The technology is projected to reach $187.69 billion by 2030, reflecting a compound annual growth rate of 38.62 % [2]. This rapid expansion has been driven by AI's proven capabilities in enhancing diagnostic accuracy, streamlining workflows, and improving patient outcomes across various healthcare domains, including radiology, pathology, and clinical decision support systems [3,4]. Organizations in developed countries are actively engaging with AI technologies. For instance, a study reported that 84 % of surveyed health systems had integrated AI-derived predictive models (AIDPM) into clinical practice [5]. These implementations primarily focus on enhancing clinical decision support, operational efficiency, and patient care.

Despite these global advances, the adoption of AI in healthcare across developing countries, particularly in sub-Saharan Africa, has been markedly slower and more fragmented [6]. African healthcare systems face unique challenges, including inadequate digital infrastructure, limited internet penetration (39 % across the continent), widespread inaccessibility to reliable electricity in approximately half of African health facilities, and substantial gaps in regulatory frameworks governing AI implementation [7,8]. These infrastructural limitations, combined with the absence of comprehensive national digital health policies in many African countries, have significantly hindered the integration of AI technologies into healthcare delivery systems [9,10]. Furthermore, the shortage of healthcare professionals and data scientists, coupled with limited financial resources and dependency on externally developed technologies that are often not adapted to local needs, has perpetuated technological inequalities and limited African countries' sovereignty in defining their own health strategies [11].

In Nigeria specifically, while innovative AI initiatives such as Ubenwa (a startup using machine learning for birth asphyxia diagnosis) and pharmaceutical authentication platforms have emerged, healthcare AI adoption remains largely confined to pilot projects and test cases [12]. The country's healthcare education system faces significant challenges, including outdated curricula, limited educational infrastructure, and chronic resource constraints that have not adequately prepared healthcare professionals for the evolving technological landscape [13,14]. Recent calls by global health advocates have emphasized the urgent need for comprehensive regulatory frameworks and capacity-building initiatives to ensure that Nigeria and other West African countries can effectively harness AI's potential while addressing associated risks related to privacy, data security, and ethical considerations [15].

Healthcare students are central to the successful integration of AI, yet international studies reveal a consistent and concerning gap in their preparedness. A systematic review found that while 76 % of students held positive attitudes toward AI, half had low knowledge levels, and 67 % reported no practical experience with AI technologies [16]. This knowledge-attitude-practice gap is particularly pronounced in developing nations, where curricula often lack AI-focused training [17,18]. However, a critical concern emerges regarding the depth of understanding among healthcare students, particularly early-year students who may lack sufficient exposure to real-world clinical environments to fully comprehend AI's practical applications, inherent limitations, potential for bias, and the complexity of training data requirements. This limited clinical exposure may result in overly optimistic attitudes that do not reflect the challenges of real-world AI implementation.

While the AI readiness of healthcare students has been examined globally, a significant research gap exists for students in SSA. Given Nigeria's position as Africa's most populous country and a regional leader in healthcare education, understanding the perspectives of its future practitioners is crucial for informing effective, location-specific educational policies. This study addresses this gap by providing the first comprehensive assessment of the knowledge, exposure, and willingness of Nigerian healthcare students to adopt AI. The findings offer essential evidence to guide curriculum development and establish a baseline for preparing the next generation of healthcare professionals for an AI-driven future.

Table 1 highlights this study's contributions to the field compared with previous knowledge on AI readiness among healthcare students.

2. Methods

2.1. Study design and setting

This cross-sectional study assessed the knowledge, exposure, and willingness of university students to adopt AI in healthcare. The study was conducted at Obafemi Awolowo University, which was strategically selected based on several criteria: the presence of well-established healthcare training programmes, availability of trained research assistants within the institution, and a diverse student population enrolled in various healthcare-related disciplines to ensure comprehensive insights into AI awareness and readiness among future healthcare professionals. Obafemi Awolowo University is among Nigeria's premier federal universities, established in 1962, with a comprehensive medical school that offers programs comparable to other leading Nigerian medical institutions, making it representative of high-quality healthcare education in the country.

2.2. Participants and sampling Technique

The study employed a probability sampling method using simple random sampling to select participants from the student population at Obafemi Awolowo University. The target population comprised all registered students enrolled in healthcare-related programmes within the university.

Eligibility criteria included: (1) being enrolled as a student at Obafemi Awolowo University, (2) being registered in a healthcare-related programme at any academic level, and (3) providing voluntary consent to participate. Students were selected through on-spot surveys using simple random sampling from available students in each class.

Exclusion criteria included: students who were on academic suspension or those who declined to participate after being informed about the study.

The final sample comprised 551 students across various healthcare programmes at the university. Also, 50 teaching staff members were enrolled in the study to compare their AI in healthcare knowledge with that of the students. To assess representativeness, we compared our sample demographics with the overall healthcare student population at the university. Our sample included 38.8 % second-year students and 31.8 % third-year students, which aligns with the typical distribution in Nigerian medical schools where these years have the highest enrollment due to attrition in later years [19]. The gender distribution and age ranges in our sample were consistent with national data on healthcare education demographics in Nigeria [20].

2.3. Data collection instrument

A structured, self-administered questionnaire was specifically developed for this study after extensive literature review and consultation with subject matter experts. The final questionnaire comprised 21 main questions with multiple sub-components, totaling 56 individual response items when accounting for all AI applications, terminologies, and attitude statements assessed. The questionnaire development process involved three phases: (1) initial item generation based on comprehensive literature review and expert consultation, (2) content validation by a panel of experts (including nursing educators, AI specialists, and healthcare administrators), and (3) pilot testing with 20

Table 1
Summary of Study Contributions Compared to Previous Knowledge.

Aspect	Previous Knowledge	This Study's Findings	Novel Contribution
Geographic Context	AI readiness studies predominantly from developed countries and select developing nations (Pakistan, Syria, China)	Novel comprehensive assessment among healthcare students in Nigeria and sub-Saharan Africa	Provides baseline data for Africa's most populous country and regional healthcare education leader
Knowledge-Perception Gap	Limited evidence of discrepancy between self-assessed and actual AI knowledge in healthcare students	60 % believed they had high AI knowledge, but 92 % demonstrated low knowledge levels objectively	Quantifies significant knowledge-perception paradox in resource-limited educational settings
Fundamental AI Concepts	Variable understanding of basic AI terminology across global studies, with gaps noted but not systematically quantified	Only 12 % correctly defined machine learning; 7.5 % understood supervised/ unsupervised learning; 10.2 % grasped IoT concepts	Demonstrates severe deficits in foundational AI literacy among African healthcare students
Attitude-Knowledge Relationship	Generally positive attitudes toward AI adoption (76 % globally), but limited correlation analysis with actual knowledge	90.8 % positive about workflow efficiency despite knowledge gaps; significant correlation between knowledge and adoption willingness ($p < 0.05$)	Establishes empirical link between knowledge levels and adoption readiness in sub-Saharan context
Practical Exposure	International studies show 67 % of students report no practical AI experience globally	Minimal exposure with electronic records highest at 43.4 %; advanced applications < 10 % exposure	Confirms and quantifies the practical experience gap in African healthcare education settings
Infrastructure Concerns	General awareness of implementation challenges in developing countries but limited student perspective data	54.2 % doubt infrastructure adequacy; 48.5 % concerned about privacy/ethics	Provides specific quantification of perceived barriers from future practitioners' perspective
Training Willingness	High willingness for AI training reported globally (variable percentages)	84.4 % willing to undertake AI training despite significant knowledge gaps	Demonstrates learning readiness that could inform targeted educational interventions
Curriculum Implications	Calls for AI integration in medical curricula primarily from developed country contexts	Identifies specific knowledge deficits requiring immediate curricular attention in African medical education	Provides evidence-based foundation for curriculum reform in resource-limited settings
Regional Policy Relevance	Limited policy guidance for AI education in sub-Saharan African healthcare systems	Establishes baseline metrics for measuring AI readiness improvement and policy effectiveness	Offers quantitative benchmarks for regional healthcare education policy development

students not included in the main study to assess clarity and comprehensibility.

Content validation: Face and content validity of the instrument were established through review by a panel of local healthcare specialists, nursing educators, and AI professionals. The questionnaire demonstrated good internal consistency with Cronbach's alpha values of 0.82 for the knowledge section and 0.79 for the willingness section.

The questionnaire design incorporated established frameworks from recent AI literacy assessments in healthcare education, adapting questions to the Nigerian context while maintaining comparability with international studies. The questionnaire was designed specifically to assess AI awareness among university students and comprised four main sections:

Section A: Sociodemographic Information (6 items) – including:

- Year of study (One to Six)
- Degree programme (ND, HND, BSc., MSc., PhD, Others)
- Programme of study (Nursing, Pharmacy, MBBS, Physiotherapy, Human Nutrition, Dentistry, Medical Laboratory Science, Public Health, Occupational Therapy, Physiology Therapy, Others)
- Age range (<16 years to > 30 years)
- Religion (Christianity, Islam, Traditionalist, Atheist, Others)
- Marital status (Single, Married, Separated/Divorced, Widow/ Widower)

Section B: Knowledge about AI Facilities in Healthcare (6 items) – assessing:

- Self-rated knowledge about AI implementation in healthcare (No knowledge to High knowledge)
- Familiarity with 13 specific AI applications in healthcare settings (from electronic record keeping to AI in monitoring chronic diseases)
- Knowledge of 13 AI-related terminologies (from Machine learning to Internet of Things)
- Three open-ended questions testing understanding of: (1) machine learning, (2) supervised and unsupervised learning, and (3) Internet of Things (IoT)

Section C: Exposure to AI Integration/Facilities in the Workplace (1 item) – evaluating practical experience with 13 specific AI technologies during clinical placements and academic training.

Section D: Willingness to Adopt New AI Technologies in Healthcare (8 items) – measuring attitudes, concerns, and readiness using a 3-point scale (Yes/Undecided/No) for eight specific statements about AI adoption, including willingness to take training courses, beliefs about workflow efficiency, confidence in adaptation, infrastructure concerns, trust issues, privacy concerns, and employment impact fears.

Knowledge scoring system: The knowledge assessment combined responses from multiple-choice questions about AI applications and terminologies, with additional points awarded for correct responses to open-ended questions. Open-ended responses about machine learning, supervised/unsupervised learning, and IoT were scored by two independent reviewers using predefined criteria, with disagreements resolved through discussion. These scores were incorporated into the overall knowledge assessment. Total knowledge scores were then recoded into three levels: low (0–16), average (17–24), and high (25–34) based on tertile distribution of scores and expert consensus on clinically meaningful cut-off points.

Specific examples from the questionnaire include:

- Knowledge section: "Which of these AI-driven facilities in the healthcare setting do you know about? Please select all that apply" (Multiple selection from 13 options including electronic record keeping, Diagnostic differentials, Robot-assisted procedures, etc.)

- Open-ended questions: "What do you understand by machine learning?" and "What do you understand by Internet of Things (IoT)?"
- Willingness section: "I am willing to take a training course to learn about the application of AI in healthcare settings" (Yes/Undecided/No response options)

2.4. Data collection process

Data collection was conducted between September 2024 and December 2024 at Obafemi Awolowo University. Trained research assistants, who were postgraduate students or junior faculty members at the institution, administered the questionnaires. Prior to data collection, a comprehensive two-day training workshop was conducted for all research assistants to ensure standardised data collection procedures.

The questionnaires were distributed during scheduled class sessions after obtaining permission from course instructors and relevant academic departments. Participants were provided with clear instructions emphasising the confidentiality of their responses and their right to withdraw at any time.

Participants were given adequate time to complete the questionnaire, with an average completion time of 25–30 min due to the inclusion of open-ended questions. The questionnaires were collected immediately upon completion to ensure high response rates and data quality. The response rate was 89.2 %, with 551 complete responses from 618 approached students.

2.5. Data management and analysis

Data were managed and analysed using Microsoft Excel and JASP 0.19.

Descriptive statistics: Frequencies, proportions, means, and standard deviations were used to summarise the data, presented in charts and tables.

Data quality measures: Data were checked for completeness and accuracy before analysis, with missing data handled using listwise deletion for cases with more than 10 % missing responses. Open-ended responses about machine learning, supervised/unsupervised learning, and IoT were scored by two independent reviewers using predefined criteria, with disagreements resolved through discussion.

Inferential statistics: Analyses were conducted at a 95 % confidence interval ($p < 0.05$). One-way ANOVA was used to assess the association between mean knowledge scores and sociodemographic characteristics, as well as willingness to adopt AI technologies. Effect sizes were calculated using eta-squared ($\eta 2$) to determine the practical significance of significant findings. In cases of unequal variances (significant Levene's test), Welch's ANOVA was used, and Games-Howell post hoc tests replaced Tukey's post hoc tests. Chi-square tests were used to identify associations between exposure to AI facilities and students' characteristics. Cramer's V was used to measure the effect size for significant associations. Confidence intervals (95 % CI) were calculated for all proportions and mean differences to provide additional context for the findings.

2.6. Ethical considerations

Ethical approval was obtained from BOWEN University Teaching Hospital Research Ethics Committee with the approval number "BUTH/REC-1134″. Written informed consent was obtained from all participants prior to their participation, with clear assurance that their information would be kept strictly confidential and no identifiable information would be recorded.

Participants were explicitly informed of their right to withdraw from the study at any point without any repercussions, ensuring they understood the study purpose, procedures, potential risks and benefits. The study introduction clearly stated: "We assure you that your information will be kept strictly confidential. No identifiable information will be recorded, ensuring your privacy throughout the study. You have the right to withdraw from participating at any point without any repercussions.".

Confidentiality was maintained throughout the study through the use of unique identifier codes instead of personal names, and secure data storage procedures. No undue compensation was provided to the participants to avoid coercion, though light refreshments were offered during data collection sessions to acknowledge their time and contribution.

3. Results

3.1. Respondents' sociodemographic characteristics

As shown in Table 2, the study sample comprised 551 students with distinct demographic profiles. Among staff, the majority (62 %) had 3–5 years of experience, while most were either 18–25 years (42 %) or 25–35 years (42 %) of age. Staff were predominantly Christian (86 %), single (64 %), and without children between 10 and 18 years (80 %). The student population featured mostly second-year (38.8 %) and third-year (31.8 %) undergraduates pursuing BSc degrees (79.7 %), aged 21–25 years (53.9 %), Christian (81.6 %), and overwhelmingly single (96.5 %). Details of the respondents' occupation (staff) and program of study are provided in Fig. 1.

3.2. Knowledge of respondents

3.2.1. Knowledge variables

The respondents had a mean knowledge score of 7.4 ± 5.2, with both students and academics having similar knowledge scores (7.4 ± 5.2 and 7.3 ± 5.3, respectively). While about 60 % of the respondents believed

Table 2
Sociodemographic information for student respondents.

Variable	Frequency (551)	Proportion (%)
Year of study		
1	62	11.3
2	214	38.8
3	175	31.8
4	58	10.5
5	34	6.2
6	8	1.5
Degree in view		
ND	13	2.4
HND	4	0.7
BSc.	439	79.7
PhD	2	0.4
BNSc	93	16.9
Age range		
<16 years	5	0.9
>16 to 20 years	225	41.0
21 to 25 years	296	53.9
26 to 30 years	19	3.5
>30 years	4	0.7
Religion		
Christianity	449	81.6
Islam	92	16.7
Traditionalist	5	0.9
Atheist	4	0.7
Marital Status		
Single	530	96.5
Married	18	3.3
Separated	1	0.2

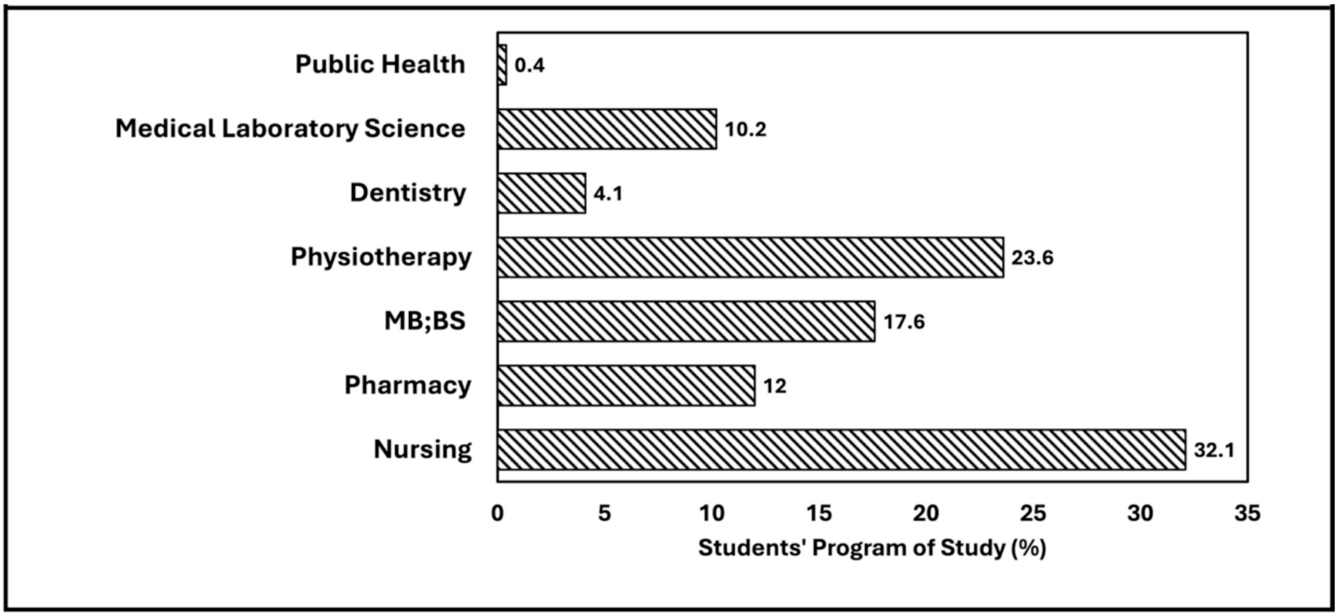

Fig. 1. Students' program of study.

they had a high level of knowledge of AI in healthcare, their responses to specific questions showed otherwise. In fact, the targeted questioning revealed that about 92 % of the respondents had low knowledge, while only 0.4 % had high knowledge. The disparities between knowledge categories based on self-assessment and questionnaire assessment can be seen in Fig. 2.

Table 3 reveals concerning gaps in AI healthcare knowledge among respondents. While just over half demonstrated awareness of AI in electronic record keeping (55.6 %) and disease detection from scans (51.2 %), knowledge was notably limited across most applications.

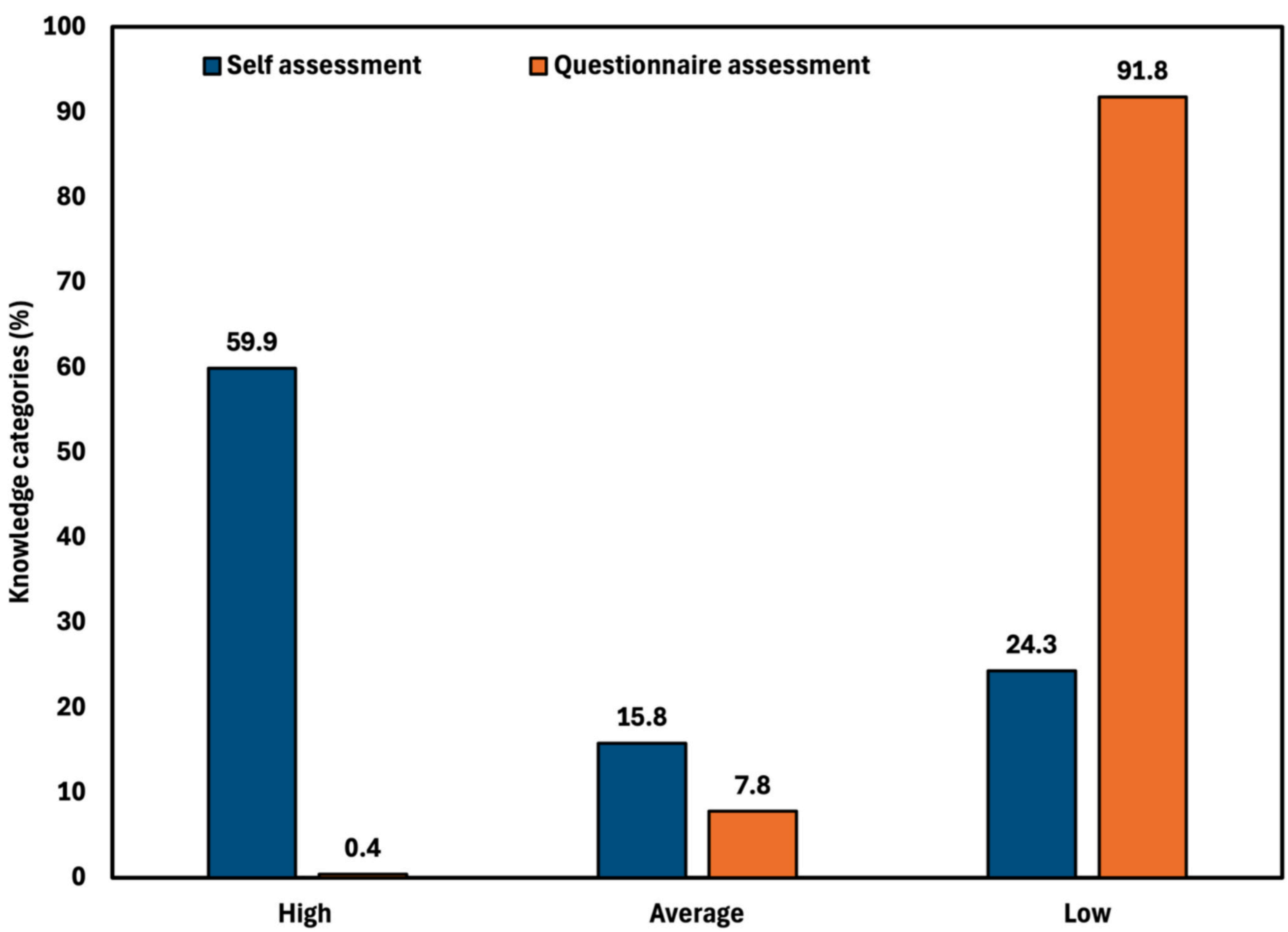

Fig. 2. Comparison between respondents' AI knowledge based on self-assessment and questionnaire assessment.

Particularly alarming was the low familiarity with AI for patient outcomes prediction (20.4 %), personalized treatment plans (19.5 %), and patient follow-up management (14.6 %). Even more worrying was respondents' poor grasp of fundamental AI terminology (Fig. 3), with only 12 % correctly defining machine learning, 7.5 % understanding supervised and unsupervised learning, and 10.2 % recognizing the Internet of Things concept, highlighting a critical need for education in these areas.

As highlighted in Table 4, there was a statistically significant association between the students' knowledge score and their degree in view ($p = 0.018$). Knowledge score was particularly very low among students working towards an ND degree (3.5 ± 2.1), which was the lowest learning category, while students working towards their HND (7.5 ± 6.2), BSc (7.8 ± 5.1), and PhD (7.0 ± 2.8) had higher knowledge scores. Based on their program of study, pharmacy (8.8 ± 4.6), dentistry (8.7 ± 6.2) and MBBS (8.5 ± 5.4) students had the highest knowledge scores, compared to physiology therapy (5.0 ± 2.8) and nursing (6.7 ± 5.6) students. Interestingly, the youngest respondents (<16 years) had the highest knowledge score (9.8 ± 6.1), while the oldest respondents had the lowest knowledge scores (26 to 30 years- 5.9 ± 5.2 and > 30 years- 6.5 ± 6.1). While there was no statistically significant difference between the knowledge scores among the respondents' religion, Christians (7.6 ± 5.3) and Muslims (7.0 ± 4.9) had the highest scores, while traditionalists (4.0 ± 3.2) and atheists (3.8 ± 2.9) had the lowest scores.

3.3. Willingness of respondents to adopt AI technologies in healthcare

Table 5 presents a remarkably positive outlook towards AI adoption in healthcare, with an overwhelming 90.8 % of respondents believing AI integration would improve workflow efficiency. Similarly encouraging, 86.7 % were confident it would enhance patient outcomes and increase healthcare professional productivity, whilst 84.4 % expressed willingness to undertake AI training. Despite this enthusiasm, significant concerns persist, 54.2 % doubted the adequacy of existing infrastructure to support AI implementation, 48.5 % worried about privacy and ethical issues, and 32.9 % expressed distrust in AI technologies. Notably, most respondents (58.4 %) rejected the notion that AI would primarily replace human jobs, suggesting a nuanced understanding of AI as an assistive rather than replacement technology.

The knowledge of respondents significantly ($p < 0.05$) impacted their willingness to adopt AI in healthcare (Table 6). Respondents willing to take a training course to learn about AI applications possessed significantly higher knowledge than those who were undecided/unwilling to take a training course. Thus, having basic AI training in secondary education and in the first year of tertiary education will enhance individuals' overall AI acceptance. Similarly, respondents who believed AI integration would enhance the efficiency of the workflow and that it would improve patient outcomes possessed significantly higher knowledge than others. Respondents' AI knowledge also significantly ($p < 0.001$) imparted their confidence in adapting to the AI introduction in healthcare, having one of the highest effect sizes (0.025). Furthermore, respondents without full trust in AI and who believed its integration should be limited had significantly higher knowledge. This implies that the higher the knowledge an individual possesses, the more sceptical they become about AI applications. Thus, future training models should emphasise safe boundaries of AI application in healthcare to guarantee wide acceptance. On the other hand, respondents with concerns over privacy and ethical issues had the least knowledge (6.8 ± 5.4), while those who were not concerned had the highest knowledge score (9.0 ± 5.4). Finally, respondents who believed that AI integration is designed to take over human jobs and increase unemployment had significantly ($p < 0.001$) lower knowledge scores (6.1 ± 4.8) compared to those who disagreed with the notion (8.4 ± 5.2), having the highest effect size (0.04).

Table 3
Knowledge of specific applications of AI in healthcare and associated terminologies.

Variable	Yes	No
Electronic record keeping	334 (55.6 %)	267 (44.4 %)
Diagnostic differentials	163 (27.1 %)	438 (72.9 %)
Robot-assisted procedures	236 (39.3 %)	365 (60.7 %)
Disease detection from scans	308 (51.2 %)	293 (48.8 %)
Predictive analytics for patient outcomes	123 (20.4 %)	478 (79.6 %)
Personalized treatment plans	117 (19.5 %)	483 (80.4 %)
Drug interaction analysis	141 (23.5 %)	460 (76.5 %)
Virtual health assistants	209 (34.8 %)	392 (65.2 %)
Telemedicine platforms	176 (29.3 %)	425 (70.7 %)
Medical research assistance	216 (35.9 %)	385 (64.1 %)
AI in managing patient follow-up and adherence	88 (14.6 %)	513 (85.4 %)
Automated administrative tasks	145 (24.1 %)	456 (75.9 %)
AI in monitoring and managing chronic diseases	149 (24.8 %)	452 (75.2 %)
Correct definition of terms		
Machine learning	72 (12.0 %)	529 (88.0 %)
Supervised & Unsupervised learning	45(7.5 %)	556 (92.5 %)
Internet of Things (IoT)	61 (10.2 %)	540 (89.8 %)

3.4. Exposure of respondents to AI integration/facilities

Table 7 reveals a striking disconnect between AI enthusiasm and actual exposure, with most respondents having minimal firsthand experience with healthcare AI applications. Electronic record keeping emerged as the most commonly encountered application (43.4 %), followed by disease detection from scans (29.3 %) and medical research assistance (20 %). However, exposure rates plummeted for more advanced applications, only 8.8 % had encountered predictive analytics for patient outcomes, 7.5 % had experience with personalized treatment plans, and a mere 7.3 % had seen AI used for patient follow-up management. These figures highlight a substantial gap between theoretical knowledge and practical implementation in healthcare settings, suggesting that despite positive attitudes, most respondents' understanding of AI remains largely conceptual rather than experiential.

4. Discussion

This study provides the first comprehensive assessment of artificial intelligence knowledge, exposure, and willingness to adopt AI technologies among healthcare students at a major Nigerian university. Our findings reveal a complex landscape characterised by significant knowledge gaps, overwhelmingly positive attitudes, limited practical exposure, and strong willingness to embrace AI in healthcare practice. These results have important implications for medical education policy and curriculum development in Nigeria and potentially across sub-Saharan Africa.

4.1. The knowledge-perception paradox and the intention-behavior gap

One of the most striking findings of this study is the substantial discrepancy between students' self-perceived and actual knowledge of AI in healthcare. While approximately 60 % of participants believed they possessed high levels of AI knowledge, objective assessment revealed that 92 % actually demonstrated low knowledge levels, with only 0.4 % achieving high knowledge scores. This knowledge-perception paradox is particularly concerning among early-year healthcare students who lack sufficient clinical exposure to understand the complexities of AI implementation in real-world healthcare settings [21]. Early-year students may form opinions about AI based on popular media representations or basic academic concepts without comprehending critical issues such as algorithmic bias, data quality requirements, model interpretability, and the limitations of AI decision-making in clinical contexts [22,23].

However, the knowledge-perception paradox aligns closely with findings from similar studies in developing countries, where Pakistani

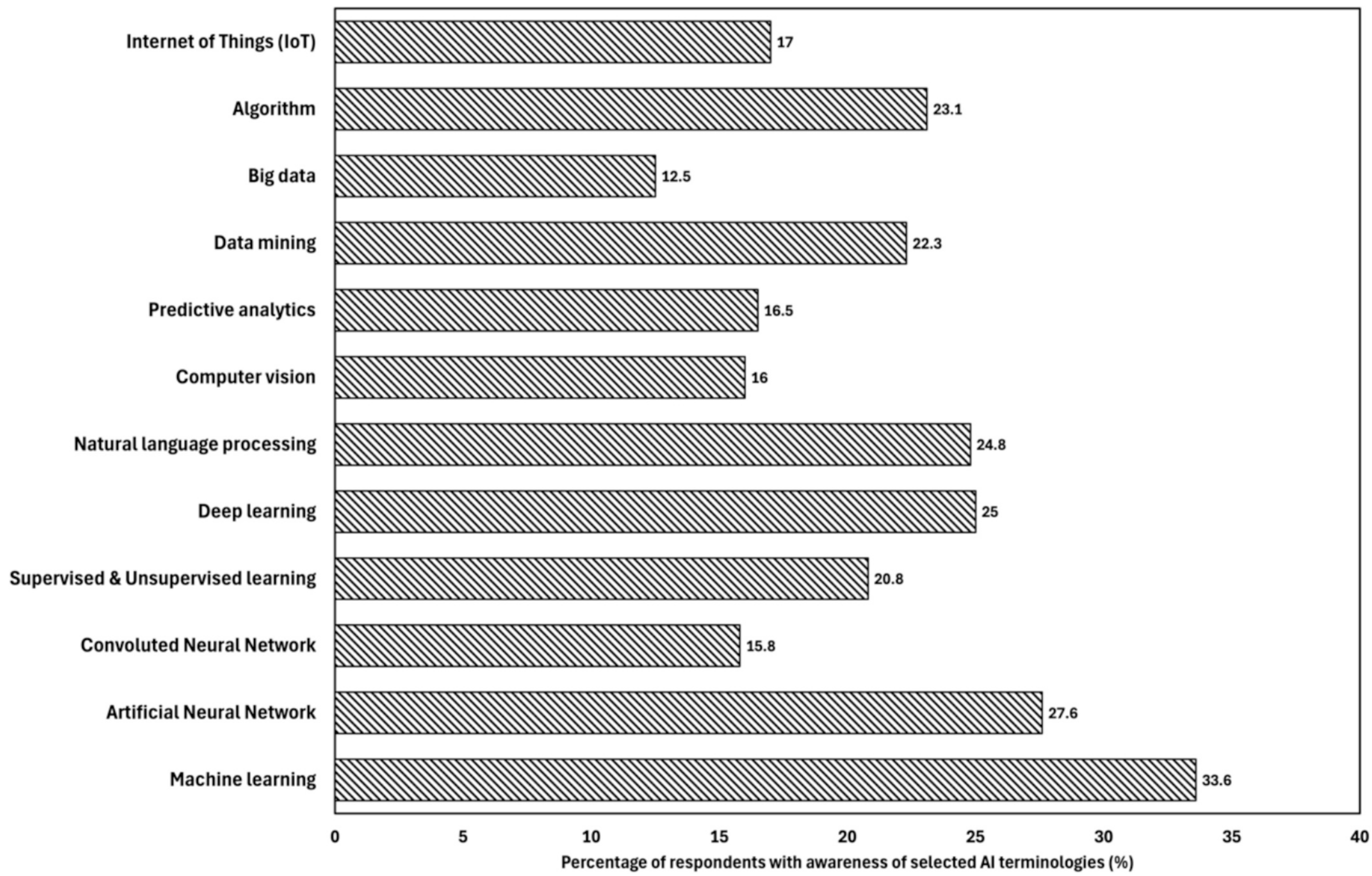

Fig. 3. Familiarity of students with common AI terminologies.

Table 4
Association between sociodemographic characteristics and average knowledge scores using one-way ANOVA.

Variable	Sum of squares	df	Mean square	F	p	w^2
Participants (students vs staff)	0.754	1.0	0.754	0.03	0.868	0.000
Residuals	16455.2	599.0	27.5			
Year of study	199.3	5	39.9	1.5	0.201	0.004
	14863.0	545	27.3			
Degree in view	372.4	4.0	93.1	8.8	0.0012*	0.018
Residuals	14689.9	5.8	2536.2			
Program of study	403.8	6.0	67.3	2.5	<0.022*	0.016
Residuals	14658.5	544.0	26.9			
Age of student	90.8	4.0	22.7	0.8	0.508	0.000
Residuals	14971.5	546.0	27.4			
Religion	554.4	1	554.4	20.6	0.152	0.004
Residuals	13256.4	431.4	30.7			

medical students and doctors demonstrated basic AI awareness (68.8 % and 74 % respectively) but limited understanding of specific medical applications [24]. Similarly, Syrian healthcare students showed 70 % basic AI knowledge but only 23.7 % awareness of medical applications [25].

The poor performance on fundamental AI concepts was particularly concerning, with only 12 % correctly defining machine learning, 7.5 % understanding supervised and unsupervised learning, and 10.2 % grasping Internet of Things concepts. These figures are considerably lower than those reported in systematic reviews of healthcare students globally, where knowledge levels, though still limited, showed greater variability across different populations [26]. The lack of understanding of fundamental concepts such as training data bias, model validation, and algorithmic transparency is particularly problematic, as these are essential for safe and effective AI implementation in healthcare [27,28]. Without this foundational knowledge, students may develop unrealistic expectations about AI capabilities and fail to recognize potential risks or limitations. This pattern suggests that Nigerian healthcare students may

Table 5
Willingness to adopt new AI technologies in healthcare.

Question	Yes	Undecided	No
I am willing to take a training course to learn about the application of AI in healthcare settings	507 (84.4 %)	64 (10.6 %)	30 (5.0 %)
I believe integrating AI in current healthcare processes will make workflow more efficient	546 (90.8 %)	45 (7.5 %)	10 (1.7 %)
I am confident AI integration will help improve health outcomes of patients and increase the productivity of health professionals	521 (86.7 %)	69 (11.5 %)	11 (1.8 %)
I am confident I will be able to adapt and learn how to use emerging AI technologies if introduced	527 (84.2 %)	69 (14.5 %)	6 (1.3 %)
I doubt we have the infrastructure to maintain such facilities if introduced	325 (54.2 %)	174 (29.0 %)	101 (16.8 %)
I feel AI should not be trusted, so its integration should be limited	198 (32.9 %)	216 (35.9 %)	187 (31.1 %)
I have concerns over privacy and ethical issues	291 (48.5 %)	167 (26.2 %)	152 (25.3 %)
I do not support AI integration as it is designed to take over human jobs and increase unemployment	128 (21.3 %)	122 (20.3 %)	351 (58.4 %)

be particularly disadvantaged in terms of exposure to AI education, reflecting broader challenges in technology integration within African educational systems [19,20].

The knowledge gaps identified in our study are particularly problematic given the rapid expansion of AI applications in healthcare globally. Recent developments have seen AI tools achieving performance levels that exceed those of medical students and residents on various medical assessments [29]. As medical education institutions in developed countries increasingly integrate AI literacy into their curricula [30], the risk of widening educational disparities between developed and developing countries becomes increasingly apparent.

4.2. Positive attitudes despite limited knowledge and the intention-behavior gap

Despite significant knowledge deficits, our participants demonstrated remarkably positive attitudes towards AI integration in healthcare. Over 90 % believed AI would improve workflow efficiency, 86.7 % were confident it would enhance patient outcomes, and 84.4 % expressed willingness to undergo AI training. These findings are consistent with international literature showing generally positive attitudes among healthcare students towards AI adoption [31]. Similar patterns have been observed in studies from China, where healthcare students demonstrated favourable attitudes despite limited knowledge [32].

However, substantial concerns exist regarding the translation of these positive attitudes into actual practice. Research in technology adoption has consistently demonstrated a significant "intention-behavior gap," where expressed willingness to adopt new technologies often fails to translate into actual implementation [33,34]. This gap is particularly pronounced in healthcare settings, where multiple barriers including institutional inertia, fear of liability, concerns about over-reliance on technology, and resistance from established professional practices can impede adoption [35,36]. Furthermore, when healthcare students enter clinical practice and encounter the realities of AI implementation, including technical failures, workflow disruptions, and patient resistance, their initial enthusiasm may significantly diminish.

Additionally, several psychological and professional concerns may only emerge during actual AI implementation, including fears about de-skilling, loss of clinical intuition, erosion of patient trust in human decision-making, and professional liability issues [37,38]. Early-year students may not fully appreciate these concerns due to their limited

Table 6
Knowledge vs willingness to adopt AI- Inferential.

Variable	Sum of squares	df	Mean square	F	p	w^2
willingness to take a training course to learn about the application of AI	324.5	2.0	162.2	6.0	0.003*	0.016
Residuals	16131.4	598.0	27.0			
believe integrating AI in current healthcare processes will make workflow more efficient	297.9	2.0	149.0	5.5	0.004*	0.015
Residuals	16158.0	598.0	27.0			
confident AI integration will help improve health outcomes of patients and increase overall productivity	341.7	2.0	170.8	6.3	0.002*	0.017
Residuals	16114.2	598.0	26.9			
Confidence in ability to adapt and learn how to use emerging AI technologies if introduced	458.0	2.0	229.0	8.6	<0.001*	0.025
Residuals	15998.0	598.0	26.8			
doubt we have the infrastructure to maintain such facilities if introduced	131.7	2.0	65.9	2.7	0.072	0.005
Residuals	16294.6	244.6	66.6			
feel AI should not be trusted, so its integration should be limited	179.1	2.0	89.6	3.3	0.038*	0.008
Residuals	16276.8	598.0	27.2			
concerns over privacy and ethical issues	501.6	2.0	250.8	9.4	<0.001*	0.027
Residuals	15924.7	597.0	26.7			
do not support AI integration as it is designed to take over human jobs and increase unemployment	717.2	2.0	358.6	13.6	<0.001*	0.040
Residuals	15738.7	598.0	26.3			

clinical experience and may therefore express unrealistically positive attitudes toward AI adoption.

This positive disposition represents a significant opportunity for educational intervention. Research has consistently shown that positive attitudes towards technology are strong predictors of successful adoption and implementation [39]. The enthusiasm demonstrated by Nigerian healthcare students suggests a receptive audience for AI education initiatives, which could facilitate rapid knowledge acquisition and skill development when appropriate educational resources become available.

Table 7
Exposure to AI Integration/Facilities in the hospital.

Variable	Yes	No
Electronic record keeping	261 (43.4 %)	340 (56.6 %)
Diagnostic differentials	80 (13.3 %)	521 (86.7 %)
Robot-assisted procedures	94 (15.6 %)	507 (84.4 %)
Disease detection from scans	176 (29.3 %)	425 (70.7 %)
Predictive analytics for patient outcomes	53 (8.8 %)	548 (91.2 %)
Personalized treatment plans	45 (7.5 %)	556 (92.5 %)
Drug interaction analysis	58 (9.7 %)	543 (90.3 %)
Virtual health assistants	102 (16.9 %)	499 (83.1 %)
Telemedicine platforms	86 (14.3 %)	515 (85.7 %)
Medical research assistance	120 (20.0 %)	481 (80.0 %)
AI in managing patient follow-up and adherence	44 (7.3 %)	557 (92.7 %)
Automated administrative tasks	88 (14.6 %)	513 (85.4 %)
AI in monitoring and managing chronic diseases	78 (13.0 %)	523 (87.0 %)

However, our findings also revealed important concerns that warrant attention. Over half of the respondents (54.2 %) doubted the adequacy of existing infrastructure to support AI implementation, while 48.5 % expressed concerns about privacy and ethical issues. These concerns reflect a nuanced understanding of AI challenges and align with broader discussions about AI implementation in resource-limited settings [40]. The fact that students with higher knowledge levels demonstrated greater scepticism about AI applications suggests that education should include balanced coverage of both benefits and limitations of AI technologies.

4.3. Limited practical exposure and curriculum implications

The study revealed minimal practical exposure to AI technologies among participants, with electronic record keeping (43.4 %) being the most commonly encountered application. More advanced AI applications showed much lower exposure rates, with only 8.8 % having experience with predictive analytics and 7.5 % with personalised treatment plans. This limited exposure reflects the broader challenge of AI adoption in sub-Saharan Africa, where healthcare systems face significant infrastructural constraints [41].

The limited practical exposure is particularly concerning as it may contribute to students' unrealistic expectations about AI capabilities and implementation challenges. Without hands-on experience with AI systems, students may not understand the importance of data quality, the potential for algorithmic bias, or the need for human oversight in AI-assisted decision-making [42,43]. This experiential gap may contribute to overconfidence in AI capabilities and insufficient appreciation of the complex socio-technical factors that influence successful AI implementation.

The low exposure rates in our study are consistent with reports that AI implementation in African healthcare has been largely confined to pilot projects and test cases [44]. While countries like South Africa have made progress with AI applications in human resource planning, and Nigeria has seen innovative startups like Ubenwa developing AI solutions for birth asphyxia diagnosis, widespread clinical integration remains limited [45]. This situation contrasts sharply with developed countries, where medical students increasingly have access to AI tools during their clinical training [46].

The limited practical exposure has important implications for curriculum development. Nigerian healthcare education institutions need to consider how to provide meaningful AI experiences even with limited resources. This might include partnerships with technology companies, simulation-based learning, case study analysis of AI implementations in other contexts, and collaborative projects with institutions that have more advanced AI capabilities [47,48].

The limited practical exposure has important implications for learning and skill development. Educational research has shown that hands-on experience with technology significantly enhances learning outcomes and confidence levels [21]. The absence of such opportunities may explain why many students in our study, despite positive attitudes, lacked practical skills in working with AI systems.

4.4. The knowledge-attitude-practice relationship

Our analysis revealed significant associations between knowledge levels and willingness to adopt AI technologies, providing support for the knowledge-attitude-practice (KAP) model in the context of AI adoption. Students with higher knowledge scores demonstrated greater willingness to undergo training and showed more nuanced understanding of AI applications. This relationship has been consistently observed in other healthcare contexts and supports the importance of foundational knowledge in driving technology adoption [22,23].

Interestingly, we also found that higher knowledge levels were associated with greater scepticism about certain aspects of AI implementation, particularly regarding trust and potential limitations. This finding highlights important professional concerns that may only become apparent with deeper understanding of AI technologies. Healthcare professionals with greater AI knowledge are more likely to recognize the potential for algorithmic bias, understand the limitations of training data, and appreciate the importance of maintaining clinical judgment and professional autonomy [49,50,51]. They may also be more aware of liability issues, the potential for over-reliance on AI systems, and the risk of de-skilling in clinical practice [52]. This finding suggests that education should aim not only to increase enthusiasm for AI but also to develop critical thinking skills that enable healthcare professionals to use AI tools appropriately and safely [27]. This balanced approach is particularly important in resource-limited settings where implementation challenges may be more pronounced.

Furthermore, concerns about de-skilling and loss of clinical intuition are particularly relevant for healthcare students who are still developing their clinical skills. The integration of AI into healthcare education and practice raises important questions about how to maintain and develop human clinical capabilities while leveraging the benefits of AI technology [53,54]. Students may worry that excessive reliance on AI could impede their development of clinical reasoning skills, pattern recognition abilities, and the intuitive aspects of patient care that are considered central to medical practice.

The strong correlation between knowledge and willingness to adopt AI (effect size = 0.025) highlights the potential impact of educational interventions. Students who received even basic AI education showed significantly higher confidence in their ability to adapt to AI technologies, suggesting that targeted curriculum modifications could yield substantial improvements in AI readiness.

4.5. The role of concrete AI applications in healthcare education

Our findings reveal that students' understanding of AI applications remains largely theoretical, with minimal exposure to practical implementations. This gap becomes particularly significant when considering that concrete AI applications, such as medical image delineation, could serve as effective educational tools for demonstrating AI capabilities. Image segmentation tasks provide tangible examples that healthcare students can easily comprehend and relate to their future clinical practice.

Medical image delineation represents an ideal educational application for several reasons. First, it addresses a well-defined clinical need, the accurate identification and measurement of anatomical structures from medical images. Second, the outcomes are measurable and directly comparable to expert annotations, providing clear performance metrics that students can understand. Third, these applications have demonstrated real clinical value, reducing the time required for routine delineation tasks from hours to minutes while maintaining or exceeding human-level accuracy [55,56].

The educational value of using concrete AI applications extends beyond knowledge acquisition to attitude formation. When students observe AI systems successfully performing complex tasks like cardiac contour extraction or liver segmentation, they develop more realistic expectations about AI capabilities and limitations. This practical exposure could address the knowledge-perception paradox we identified, where students overestimated their AI knowledge while demonstrating poor understanding of fundamental concepts.

Furthermore, AI-based delineation applications directly address workflow challenges that students will encounter in their professional practice. Automated segmentation tools can reduce radiologist workload by up to 70 % for routine tasks while improving consistency and reducing inter-observer variability [55]. Understanding these practical benefits helps students appreciate AI's role as a clinical support tool rather than a replacement technology, potentially addressing concerns about job displacement that were expressed by 21.3 % of respondents in our study.

4.6. Infrastructure and educational challenges

Our findings must be interpreted within the context of Nigeria's healthcare and educational infrastructure challenges. The concerns expressed by 54.2 % of students about inadequate infrastructure reflect realistic assessment of the current situation. Nigeria, like many African countries, faces significant challenges including limited internet penetration, unreliable electricity supply affecting health facilities, and inadequate digital health infrastructure [28,33].

These infrastructure limitations have direct implications for AI education and implementation. Medical schools in Nigeria typically lack the computing resources, high-speed internet connectivity, and technical support necessary for comprehensive AI education [34]. The absence of AI content in educational curricula, which was evident in our study, has been attributed to limited numbers of qualified teaching professionals and insufficient funding for AI technology resources across Africa [35].

The infrastructure challenges also affect the feasibility of implementing practical AI education components. Even basic AI literacy requires access to computing resources, stable internet connections, and software platforms that may not be reliably available in many Nigerian educational institutions [57]. This creates a significant barrier to providing the hands-on experience that is essential for developing realistic understanding of AI capabilities and limitations.

The challenges facing Nigerian healthcare education reflect broader patterns across sub-Saharan Africa. Recent analyses have shown that African medical schools struggle with outdated curricula, limited educational infrastructure, and chronic resource constraints that hinder their ability to keep pace with technological advances [36]. The Nigerian government's recent launch of the National Digital Literacy and Skills Framework represents a positive step towards addressing these challenges, but implementation will require sustained investment and commitment [58].

4.7. Curriculum comparability and generalizability

To assess the generalizability of our findings, it is important to consider how the curriculum at Obafemi Awolowo University compares to other Nigerian healthcare institutions. The Nigerian medical education system follows a standardized curriculum framework established by the Medical and Dental Council of Nigeria (MDCN), ensuring basic comparability across institutions [59]. However, significant variations exist in implementation quality, resource availability, and exposure to emerging technologies.

A federal university with established international partnerships and research collaborations, may provide students with better access to information about emerging technologies compared to state universities or private institutions with more limited resources. This suggests that our findings may represent a "best-case scenario" for AI readiness among Nigerian healthcare students, and that knowledge gaps and exposure limitations may be even more pronounced in other institutions with fewer resources.

The curriculum structure across Nigerian medical schools typically includes minimal coverage of health informatics or digital health technologies, with most programs focusing primarily on traditional biomedical sciences and clinical skills [60]. This standardized approach means that the knowledge gaps we identified are likely prevalent across the Nigerian healthcare education system, though the magnitude may vary based on institutional resources and faculty expertise.

Our findings have important implications for medical education reform in Nigeria and similar contexts. The positive attitudes demonstrated by students, combined with their recognition of knowledge gaps, create a compelling case for integrating AI education into healthcare curricula. International examples provide models for such integration, with institutions like Harvard Medical School, Stanford University, and others developing comprehensive AI curricula that span from basic concepts to advanced applications [37].

However, curriculum development for Nigerian institutions must account for local constraints and priorities. Rather than attempting to replicate resource-intensive programmes from developed countries, Nigerian medical schools might benefit from adapted approaches that emphasise conceptual understanding, critical evaluation skills, and ethical considerations [38]. Such programmes could focus on developing AI literacy rather than technical programming skills, preparing students to work effectively with AI tools developed by others.

The curriculum should also address the specific concerns raised by students in our study, particularly regarding infrastructure limitations, privacy issues, and ethical considerations. This approach would help develop healthcare professionals who can make informed decisions about AI adoption and implementation in resource-limited settings [42]. Integration of AI education with existing subjects, rather than creating entirely new courses, may be more feasible given the constraints faced by many Nigerian institutions.

Curriculum modules could include demonstrations of cardiac MR image analysis, showing how random walk algorithms can extract left ventricular contours with minimal user intervention [61,62]. Such practical examples help students understand both the capabilities and limitations of AI systems while building confidence in their ability to work with these technologies.

The integration of image delineation examples serves multiple educational objectives: it provides concrete evidence of AI's clinical utility, demonstrates the importance of proper training data and algorithm validation, and illustrates how AI can enhance rather than replace clinical expertise. These applications also highlight critical considerations such as algorithm robustness, handling of edge cases, and the need for ongoing human oversight, concepts that are essential for safe AI implementation in healthcare settings [58]. Additionally, educational programs should incorporate practical AI demonstration platforms that allow students to interact with image delineation algorithms firsthand. Virtual laboratories could provide access to cardiac and liver segmentation tools, enabling students to understand how AI systems process medical images and generate clinical outputs. Such platforms would address the practical exposure gap identified in our study while building technical competency alongside theoretical knowledge.

Educational institutions should consider forming partnerships with technology companies and international organizations to provide practical exposure to AI tools. Such collaborations can bridge the gap between theoretical knowledge and practical application, offering access to resources that individual institutions might not afford independently [45]. Moreover, partnerships with medical imaging departments could provide students with real-world exposure to AI-assisted diagnosis workflows. These collaborations would demonstrate how AI tools like automated liver delineation systems reduce radiologist workload while maintaining high accuracy standards, providing students with realistic expectations about AI integration in clinical practice [43].

4.8. Regional and global context

The challenges identified in our study reflect broader patterns of technology adoption in developing countries. Studies from Egypt, Jordan, and other developing countries have shown similar patterns of positive attitudes toward AI among medical students, despite limited knowledge and practical exposure to the technology [47,48]. This suggests that the issues we identified are not unique to Nigeria but represent systemic challenges that require coordinated regional and international responses.

The African Union and regional economic communities have recognised the importance of digital transformation for economic development and healthcare improvement. However, translating these policy commitments into practical educational and healthcare improvements remains a significant challenge. Our findings suggest that healthcare education could play a crucial role in building the human capital necessary for successful AI adoption across the continent.

International cooperation and support will likely be essential for addressing the challenges we identified. Partnerships between African institutions and universities in developed countries, funding for infrastructure development, and technical assistance programmes could help accelerate progress in AI education and adoption [49]. The success of such initiatives will depend on ensuring they are adapted to local contexts and priorities rather than simply transplanting approaches from different settings.

5. Limitations of the study

Several significant limitations of this study must be acknowledged, which affect the generalizability and interpretation of our findings:

I. **Study Design Limitations:** First, the cross-sectional design limits our ability to assess changes in knowledge, attitudes, or practices over time. Longitudinal studies would provide valuable insights into how students' AI readiness evolves throughout their educational programmes and early career phases. Additionally, the cross-sectional approach cannot establish causal relationships between knowledge levels and attitudes, and may not capture the dynamic nature of technology adoption in educational settings.

II. **Sampling and Representativeness Limitations:** Second, the study was conducted at a single institution, which significantly limits the generalisability of findings to other Nigerian universities or healthcare education programmes. Obafemi Awolowo University, while prestigious and representative of high-quality Nigerian healthcare education, may not reflect the experiences of students at institutions with fewer resources, different educational approaches, or varying levels of technology integration. This selection bias means our findings may overestimate AI readiness compared to the broader Nigerian healthcare student population. Furthermore, although we employed random sampling, the voluntary nature of participation may have introduced selection bias, as students with greater interest in technology or higher academic motivation may have been more likely to participate. Our response rate of 89.2 %, while high, does not eliminate the possibility that non-responders differed systematically from participants in ways that could affect our findings.

III. **Measurement and Instrument Limitations:** Third, the knowledge assessment instrument, while based on established frameworks, was developed specifically for this study and may not capture all dimensions of AI literacy relevant to healthcare practice, particularly practical skills, critical evaluation abilities, and understanding of ethical implications. The 21-question questionnaire with 56 response items, while comprehensive in scope, may have been insufficient to comprehensively assess the complex, multifaceted nature of AI readiness in healthcare settings.

IV. The reliance on self-reported measures introduces several potential biases, including social desirability bias, where students may have provided responses they perceived as more acceptable rather than their true beliefs. Additionally, students' limited exposure to AI technologies may have affected their ability to provide accurate assessments of their own knowledge and attitudes.

V. **Clinical Experience and Maturity Limitations:** Fourth, the study included predominantly early-year students (70.6 % in years 1–3) who lack significant clinical experience and may not fully understand the complexities of healthcare delivery or the practical implications of AI implementation. This limitation is particularly important because students' attitudes toward AI may change substantially once they gain clinical experience and encounter the realities of patient care, institutional constraints, and professional responsibilities. Early-year students may also lack the cognitive maturity and professional development necessary to fully appreciate the ethical, legal, and professional implications of AI in healthcare, leading to potentially unrealistic or oversimplified attitudes toward AI adoption.

VI. **Methodological and Analytical Limitations:** Fifth, the study did not include faculty perspectives, institutional assessments of readiness for AI education implementation, or broader stakeholder views. Understanding these perspectives would be valuable for developing comprehensive strategies for curriculum reform and institutional capacity building. The absence of faculty input means we cannot assess whether institutional capacity exists to support the AI education that students indicated they desire. Additionally, our analytical approach did not account for potential clustering effects within academic programs or years of study, which may have affected the accuracy of our statistical inferences. The use of tertile-based knowledge categorization, while based on expert consensus, may not reflect clinically meaningful distinctions in AI readiness.

VII. **Contextual and Temporal Limitations:** Sixth, the study was conducted during a specific time period (September-December 2024) and may reflect temporary influences such as recent media coverage of AI, specific university initiatives, or other time-bound factors that could affect students' responses. The rapidly evolving nature of AI technology means that findings may quickly become outdated as new developments emerge. The study also did not account for students' exposure to AI outside the healthcare context, such as through social media, consumer applications, or other academic programs, which may have influenced their perceptions and knowledge levels in ways not captured by our assessment.

VIII. **Scope and Depth Limitations:** Finally, the study focused primarily on quantitative measures and may have missed important qualitative insights about students' understanding of AI, their specific concerns, and their detailed perspectives on implementation challenges. The limited scope of open-ended questions may have constrained students' ability to express nuanced views about AI in healthcare. The study also did not examine practical competencies or assess students' ability to critically evaluate AI research, understand algorithmic bias, or navigate ethical dilemmas related to AI implementation, all of which are essential components of AI readiness in healthcare.

6. Recommendations

Based on our findings, we recommend several specific actions for healthcare education institutions, policymakers, and international partners:

For healthcare education Institutions

- Develop comprehensive, multi-year AI literacy curricula that progress from basic concepts in early years to advanced applications and critical evaluation skills in later years, accounting for students' developing clinical experience and professional maturity
- Integrate AI education into existing courses rather than creating entirely new programmes, to work within current resource constraints while ensuring sustained engagement across the curriculum
- Establish partnerships with technology companies, international institutions, and other Nigerian universities to provide practical exposure to AI tools and share resources for AI education
- Invest in faculty development programmes to build internal capacity for AI education, including training in both technical aspects and ethical considerations of AI in healthcare
- Create student research opportunities focused on AI applications in healthcare relevant to local contexts, encouraging critical thinking about implementation challenges and opportunities
- Implement regular assessment of AI literacy development throughout the curriculum to track progress and identify areas for improvement

For policymakers

- Increase targeted funding for digital infrastructure in healthcare education institutions, particularly internet connectivity, computing resources, and technical support capabilities
- Develop national guidelines for AI education in healthcare programmes that account for resource limitations while ensuring essential competencies are achieved
- Support public–private partnerships that can provide technology access and training opportunities while ensuring educational objectives rather than commercial interests drive these relationships
- Integrate AI literacy into continuing professional development requirements for healthcare workers, creating pathways for current practitioners to develop AI competencies
- Establish comprehensive ethical frameworks and regulatory guidelines for AI use in Nigerian healthcare settings, providing clear guidance for education and practice

For international partners

- Provide targeted, sustainable funding for AI education infrastructure development in African healthcare institutions, with emphasis on building local capacity rather than creating dependency
- Support faculty exchange programmes and collaborative research initiatives focused on AI in healthcare, enabling knowledge transfer and capability building
- Develop culturally appropriate AI education resources that address challenges specific to resource-limited settings and avoid direct transplantation of approaches from different contexts
- Facilitate access to AI tools and technologies for educational purposes in developing countries, while ensuring these initiatives support local educational goals

For future research

- Conduct longitudinal studies to track changes in AI knowledge, attitudes, and actual adoption behaviors throughout healthcare education and early career phases, paying particular attention to the intention-behavior gap
- Expand research to multiple institutions across Nigeria and other African countries to enhance generalizability and understand variations in AI readiness across different educational contexts
- Develop and validate culturally appropriate AI literacy assessment tools for healthcare education contexts, incorporating both technical knowledge and critical evaluation skills
- Investigate effective pedagogical approaches for AI education in resource-limited settings, including optimal sequencing of content, appropriate use of technology, and strategies for developing practical competencies
- Examine the impact of AI education interventions on student learning outcomes, professional development, and career choices, including long-term follow-up studies of graduates
- Conduct qualitative research to understand students' detailed perspectives on AI implementation challenges and to identify specific concerns that may not be captured through quantitative surveys
- Include faculty and institutional perspectives in future studies to develop comprehensive understanding of AI education readiness and implementation capacity

These recommendations, if implemented systematically, could help address the knowledge gaps identified in our study while building on the positive attitudes demonstrated by Nigerian healthcare students. Success will require sustained commitment from multiple stakeholders and recognition that AI readiness is not just an educational challenge but a broader developmental priority that requires comprehensive, coordinated responses.

7. Conclusion

This study provides a comprehensive assessment of artificial intelligence readiness among healthcare students at a major Nigerian university, revealing critical insights with significant implications for medical education across sub-Saharan Africa. Our key findings demonstrate a striking knowledge-perception paradox: while 60 % of students believed they possessed high AI knowledge, objective assessment revealed that 92 % actually had low knowledge levels, with only 12 % correctly defining machine learning and 7.5 % understanding supervised/unsupervised learning. Despite these knowledge deficits, students showed overwhelmingly positive attitudes toward AI adoption, with over 90 % believing AI would improve workflow efficiency and 84.4 % expressing willingness to undergo AI training.

Practical exposure to AI technologies was minimal, with electronic record keeping (43.4 %) being the most encountered application and advanced applications like predictive analytics having very limited exposure (8.8 %). Students expressed realistic concerns about infrastructure adequacy (54.2 %) and privacy/ethical issues (48.5 %), reflecting awareness of implementation challenges in resource-limited settings. This study confirmed significant associations between knowledge levels and willingness to adopt AI technologies, supporting the knowledge-attitude-practice model and highlighting the potential impact of targeted educational interventions. Higher knowledge scores correlated with greater confidence in AI adaptation while fostering more critical awareness of AI limitations.

These findings reveal both opportunity and urgency. The positive attitudes provide a receptive foundation for AI education, but the substantial knowledge gaps and limited exposure underscore the need for immediate action. Success requires coordinated efforts addressing curriculum development, infrastructure investment, and faculty training while accounting for local resource constraints.

The implications extend beyond individual institutions to encompass broader healthcare education policy and development strategies. The enthusiasm demonstrated by students, combined with their realistic assessment of implementation challenges, suggests that targeted educational interventions could yield significant improvements in AI readiness. However, such efforts must address not only curricular content but also the fundamental infrastructure and capacity constraints that currently limit practical exposure to AI technologies.

As artificial intelligence transforms healthcare globally, ensuring Nigerian healthcare professionals are prepared to participate in these advances represents both a critical opportunity and urgent imperative. The enthusiasm demonstrated by students provides a strong foundation, but realising this potential requires immediate, coordinated action to address systemic challenges while acknowledging the substantial gaps between expressed willingness and actual implementation capacity. With appropriate investment and strategic planning, Nigeria can position itself to harness AI's transformative potential for improved healthcare outcomes and enhanced professional capabilities across the continent.

CRediT authorship contribution statement

Aanuoluwapo Clement David-Olawade: Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Ojima Z. Wada:** Writing – review & editing, Writing – original draft, Validation, Software, Methodology. **Yinka Julianah Adeniji:** Writing – review & editing, Writing – original draft, Methodology. **Ibukunoluwa Victoria Aderupoko:** Writing – review & editing, Methodology, Investigation. **David B. Olawade:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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