Dan et al. Discover Public Health (2026) 23:122
https://doi.org/10.1186/s12982-026-01447-7

Discover Public Health

RESEARCH

Open Access

Awareness and perception as predictors of preparedness to use AI in health emergencies among undergraduates: a machine learning approach

Felicia Agbor-Obun Dan[1], Valentine Joseph Owan[2,3,4*], Joseph Odey Ogabor[5], Stella Asu-Okang[6], Stephen Ushie Akpa[1], Eni Iferi Eni[3], Emeka Ifeoma Ejeh[7], Aloysius Alo Orogwu[7], Patrick Ifeanyi Opara[8] and Peter Owogoga Aduma[1,4]

*Correspondence:
Valentine Joseph Owan
owanvalentine@gmail.com
[1]Department of Health Education and Promotion, University of Calabar, Calabar, Nigeria
[2]School of Public Health, University of Port Harcourt, Port Harcourt, Nigeria
[3]Department of Educational Psychology, University of Calabar, Calabar, Nigeria
[4]Ultimate Research Network (URN), Calabar, Nigeria
[5]Department Human Kinetics and Sports Science, University of Calabar, Calabar, Nigeria
[6]Department of Educational Management, University of Calabar, Calabar, Nigeria
[7]Department of Educational Management, Alex Ekwueme Federal University Ndufu Alike, Ikwo,, Nigeria
[8]Department of Educational Management, Federal University, Oye, Ekiti,, Nigeria

Abstract

This study investigated the relationships among undergraduate students' awareness, perception, and preparedness to use artificial intelligence (AI) tools for decision-making during health emergencies in two Nigerian public universities ($N = 4{,}632$). A cross-sectional correlational design was adopted for the study. Data were collected using an online questionnaire with valid and reliable psychometric properties ($\alpha \geq 0.90$). One-sample t-tests revealed that undergraduates reported high levels of awareness ($t = 55.97$, < 0.001) and perception ($t = 86.92$, $p < 0.001$) regarding AI use.p Although their preparedness to use AI for decision-making during health emergencies was statistically significant ($t = -34.08$, $p < 0.001$), the mean score was comparatively lower than the baseline value of 2.50, indicating a significantly low level of preparedness. Simple linear regression analyses revealed that AI awareness significantly predicted perception and preparedness. Perception also significantly predicted preparedness. Both awareness and perception jointly accounted for 9.6% of the variance in preparedness ($F(2, 4629) = 247.08$, $p < 0.001$). Relatively, awareness remained a significant predictor of preparedness ($\beta = 0.304$, $p < 0.001$) even after controlling for perception. In contrast, perception became insignificant in predicting readiness when awareness was controlled for. Random forest regression (RFR) was used to test predictive accuracy and assess non-linear patterns. The results showed that awareness and perception explained 26% (training set) and 25% (test set) of the variance in undergraduates' readiness. RFR results solidified the importance of AI awareness as the top predictor (100% predictive importance) over perception (78% predictive importance). These findings suggest that foundationalknowledge is associated with increasing readiness to adopt AI during health emergencies. Therefore, educational interventions should focus on enhancing AI awareness to improve students' preparedness higher institutions of learning.

Keywords Artificial intelligence, Health emergencies, Undergraduates, Awareness, Perception

1 Introduction

Artificial intelligence (AI) refers to the capacity of machines to learn from data, adapt to new information, and make informed decisions in ways that resemble human cognitive processes [1–3]. These capabilities have made AI a useful, indispensable and transformative force in healthcare delivery. AI systems are capable of synthesising these large and diverse datasets to provide timely, evidence-based information that can aid physicians, hospital administrators, and policymakers in making informed decisions [4]. It has the potential to enhance efficiency, reduce human error, and improve patient outcomes. However, for such benefits to be fully realised, there is a growing need for individuals to be aware of the existence, potential applications, and associated concerns of AI in healthcare.

Despite ongoing technological progress, significant health challenges continue to affect undergraduates in Nigeria. Malaria remains a major concern, with Nigeria accounting for approximately 25.9% of all malaria cases (about 63.8 million) and 30.9% of related deaths (around 176,000) across Africa in 2023 [5, 6]. Beyond malaria, many Nigerian undergraduates frequently experience stress, tension headaches, minor injuries such as cuts, sprains, and burns, as well as influenza-like illnesses. These students often resort to self-diagnosis and self-medication without seeking professional healthcare [7]. Alarmingly, fewer than half of these students demonstrate correct basic emergency responses [8, 9]. This lack of first-aid knowledge can exacerbate injuries, leading many to rely on traditional remedies. However,reliance on traditional remedies has been linked to increased morbidity in cases of burns and poisoning [10, 11]. In severe cases, such practices have resulted in preventable complications and deaths before professional intervention could occur [5, 6].

AI-driven tools can assist untrained bystanders in health emergencies by delivering evidence-based first-aid guidance. For example, it has been documented that ChatGPT provided accurate paediatric and adult cardiac arrest instructions consistent with European Resuscitation Council guidelines [12]. Similarly, another study showed that volunteers using the M-AID app adhered more closely to CPR depth and rate protocols than those in the control group [13]. Moreover, an LLM-based chatbot advised lay users on suspected myocardial infarction with over 90% concordance to medical protocols [14]. These findings support the idea that AI has the potential to improve how people can respond to health emergencies before formal medical attention can be provided.

Given the expanding role of AI in healthcare, it is essential to assess how Nigerian undergraduates engage with these technologies for personal health management. This includes assessing their awareness of AI tools, perceptions of their benefits and limitations, and preparedness to apply them in health emergencies. The Diffusion of Innovation Theory (DOI), Technology Acceptance Model (TAM), and Theory of Planned Behavior (TPB) were used to enhance understanding of how undergraduates become aware of, develop attitudes toward, and prepare to adopt AI for decision-making during health emergencies. Specifically, DOI [15] situates awareness as the foundational stage in the adoption of new technologies. TAM [16] explains how perceptions of usefulness and ease of use influence attitudes toward technology adoption. TPB [17] enhances the explanation by connecting attitudes, subjective norms, and perceived behavioral control to individuals' intentions and their level of preparedness. Together, DOI, TAM, and TPB suggest that awareness initiates the adoption of AI tools while perceptions of their usefulness, ease of use, and social acceptability shape attitudes and perceived control, which in turn influence individuals' preparedness to use AI for effective health management.

In this study, the terms AI awareness, AI knowledge, and AI literacy are used interchangeably to denote students' self-reported understanding of the technical functions and applications of AI in emergency health contexts. As students often serve as first responders for themselves and peers in the absence of immediate professional care, assessing their awareness, perception, and preparedness is particularly important. Accordingly, this study investigates these constructs among undergraduates at two Nigerian universities, with the aim of informing the integration of AI-related content into health education and guiding the development of programmes that support the responsible and effective use of digital health technologies. The specific objectives of this study are to:

1. Estimate the levels of students' awareness of Artificial Intelligence (AI), their perception of the applicability of AI in health decision-making, and their preparedness to use AI tools during health emergencies.
2. Assess the predictive relationship between students' awareness and their perception of the applicability of AI in health decision-making.
3. Determine the predictive relationship between students' awareness and their preparedness to use AI tools during health emergencies.
4. Examine the predictive relationship between students' perception and their preparedness to use AI tools during health emergencies.
5. Examine the joint prediction of students' awareness and perception of AI on their preparedness to use AI tools during health emergencies.

2 Literature review and hypotheses development

2.1 Awareness, perception and preparedness to use AI

The extant literature presents heterogeneous evidence regarding students' knowledge of AI in healthcare. Truong et al. [18] reported that 92.2% of Vietnamese pharmacy students were unfamiliar with healthcare applications of AI. In contrast, Obiekwe et al. [19] found that although most Nigerian undergraduates possessed general awareness of AI, only 3.2% could deploy it in authentic contexts. Similarly, Migdadi et al. [20] characterised nursing students' ethical awareness of AI as moderate but noted a lack of linkage between this awareness and concrete decision-making in clinical practice. Catalina et al. [21] observed that 85.7% of primary-care professionals professed understanding of AI, whereas fewer than 25% of students surveyed by Swed et al. [22] could accurately explain machine-learning concepts or AI functionalities. Collectively, these findings suggest that existing curricula may emphasise technical competency while insufficiently addressing critical considerations such as algorithmic bias and data privacy.

Several studies have identified determinants that enhance or impede AI knowledge. Coding proficiency and familial exposure to AI were positively associated with higher test scores among medical students [23]. Participation in specialised webinars likewise correlated with superior AI performance among pharmacy students [18], and hands-on AI modules produced significant learning gains in both computing-based courses [24] and IoT-enabled smart-farming applications [25]. Despite these promising interventions, formal AI instruction remains scarce: Cruz et al. [26] documented that 95.3% of medical students had not received in-school AI training, and Obiekwe et al. [19] similarly reported that 96.8% of Nigerian undergraduates lacked formal AI education, often relying on informal online resources that may propagate superficial or erroneous conceptions of AI.

A clear disparity in AI education emerges between high-income and developing contexts. Dental students in Qatar actively sought AI training opportunities [27], and Saudi medical students demonstrated moderate readiness to engage with AI literature [28]. Conversely, curricula in developing countries frequently suffer from outdated content, limited faculty expertise, and inadequate infrastructure [18, 29, 30]. In Nigeria, Obiekwe et al. [19] reported near-total absence of AI teaching at Nnamdi Azikiwe University. For this reason, the first hypothesis was developed. To the best of the researchers' knowledge, existing literature lacks empirical studies examining students' awareness and preparedness to use AI in health-related contexts within public universities in Cross River State. This study was therefore situated in the region to account for contextual factors such as socio-economic constraints and infrastructural limitations that may influence students' engagement with technology.

H1 Undergraduates' awareness of AI for decision-making during health emergencies is significantly lower than the baseline mean.

The literature on students' perception of the role of AI in health decision-making reveals some level of optimism and caution. In Saudi Arabia, Hammoudi et al. [27] found that 68% of dental students perceived AI as a valuable diagnostic adjunct but 54% remained concerned about data privacy risks. Catalina et al. [21] reported that only 42% of primary-care students felt confident in the ethical oversight of AI, while Tezpal et al. [31] showed that 80% believed AI could enhance population-level health planning despite limited exposure in their curricula. Truong et al. [18] observed that 77.5% of Vietnamese pharmacy students expected AI to improve their future employability, yet only 20% trusted AI to make autonomous treatment recommendations without human oversight. Exposure through workshops or simulation labs positively shifted attitudes: Chookaew et al. [25] documented a 30% increase in favourable perceptions following an AI-IoT smart-farming module, and Kim and Kwon [24] reported that hands-on coding exercises raised perceived usefulness scores by 25%.

Nevertheless, substantial reservations persist among other studies. For example, Obiekwe et al. [19] found that 72.1% of Nigerian undergraduates feared AI-driven job displacement in healthcare, and 71.0% anticipated reduced patient–provider interaction. Baumgartner et al. [32] identified scepticism among European medical students who worried that AI could depersonalise care, and Cruz et al. [26] noted neutral-to-negative attitudes toward AI integration in clinical decision-making even after brief instructional sessions. Such concerns means that enduring ethical and professional anxieties may inhibit AI adoption in real-world settings. Consequently, the second hypothesis was framed.

H2 Undergraduates' perception of AI use in health emergency decision-making is significantly lower than the baseline mean.

Studies assessing students' preparedness to use AI frequently utilised validated instruments like the Medical AI Readiness Scale for Medical Students (MAIRS-MS). Across studies, students have been shown to exhibit strong ethical and visionary support for AI's potential but report low practical confidence. For instance, Hammoudi et al. [27] found that while 85% agreed on the transformative capacity of AI, only 30% felt capable of operating AI tools independently. Labrague et al. [33] and Ziapour et al. [34] similarly documented high scores on the 'vision' and 'ethics' subscales (>4.0 on a 5-point scale) but low scores on 'application' and 'cognition' (<2.5).

Other studies have revealed that interventions can narrow this gap. For example, Abou and Alnajjar [35] reported a 40% increase in self-reported competency following a 12-week immersive AI module. Alshorman [36] and Chookaew et al. [25] reported that resource-intensive, contextually tailored workshops yielded post-test scores averaging 4.2 (SD = 0.6) on behavioral intention to use AI, up from 2.8 (SD = 0.7). However, actual preparedness for high-stakes or emergency use remains moderate, as Catalina et al. [21] found that only 18% of students felt ready to apply AI guidance under pressure, and Cruz et al. [26] observed that fewer than one in five participants retained practical skills one month after training.

In low-income sub-Saharan African settings, infrastructural and cultural factors further challenge students' preparedness to adopt AI. In a study, Obiekwe et al. [19] discovered that unreliable electricity and limited laboratory access were barriers to sustained AI training, while Baumgartner et al. [32] emphasised the influence of local norms on technology acceptance. However, despite extensive searching, no study has yet examined the level of preparedness to use AI for personal health decision-making among undergraduates in public universities in Nigeria, where these constraints are especially pronounced. This gave rise to the third hypothesis.

H3 The level of undergraduates' preparedness to apply AI in decision-making during health emergencies is significantly lower than the baseline mean.

2.2 Awareness as a predictor of perception and preparedness

Undergraduate exposure to technology and AI literacy has been linked to more positive attitudes toward AI in clinical settings [23, 37, 38]. Instructional interventions that increase conceptual understanding also improve perceptions of AI-IoT applications [25, 26]. However, studies differ on whether basic AI knowledge alone predicts favourable perceptions. Some report strong correlations between self-assessed AI knowledge and acceptance [38, 39], whereas others find no significant relationship [18, 40]. Moreover, while professionals with prior AI experience score higher on perceived impact measures [21], fewer than 20% of undergraduates report any formal AI training [31, 37].

Most previous studies work relies on simple correlations or pre–post comparisons [25, 35]. In contrast, regression techniques can more robustly test and account for measurement error [3, 41]. To date, the researchers are not aware of any existing study in Nigeria that has employed this analytical approach to examine the extent to which awareness predicts undergraduates' perceptions regarding the use of AI in health-related decision-making. This is useful particularly in public universities in Cross River State, Nigeria, where digital infrastructure, faculty expertise, and cultural attitudes may influence both knowledge acquisition and attitudes [19, 32]. For this reason, the fourth hypothesis was developed.

H4 Undergraduates' awareness significantly predicts their perception of using AI for decision-making during health emergencies.

Research indicates that stronger AI foundations enhance overall readiness to use AI in healthcare tasks [23, 25, 37]. Gains in AI literacy (whether through formal coursework or self-directed learning) has been shown to consistently elevate self-reported competence and intent to apply AI tools [21, 35]. AI knowledge also correlates with improved digital health literacy, enabling students to navigate AI interfaces more effectively [35]. Importantly, perceived usefulness of AI (rooted in solid understanding) predicts readiness to adopt AI, even when ease of use does not [42].

In nursing and allied health disciplines, students with higher AI literacy report stronger intentions to employ AI in practice and display greater ethical awareness [33, 43]. Recent studies confirm that knowledge predicts readiness for patient-care applications [26, 39]. Consequently, the fifth hypothesis of this study was framed.

H5 Undergraduates' awareness significantly predicts their preparedness to use AI for decision-making during health emergencies.

2.3 Perception and preparedness to use AI

It has been documented that assessing students' readiness to adopt AI tools must be both comprehensive and timely [23, 25]. Studies have revealed that positive perceptions of AI consistently predict greater readiness, particularly in ethical and technical domains [23, 43]. Indeed, favourable attitudes constitute the strongest predictor of behavioral intention to engage with AI, whereas negative attitudes and anxiety undermine such intentions [40, 43]. Learners' belief in the relevance of AI to their studies (personal relevance) also correlates with their intent to pursue AI learning [33, 44]. For example, students who regard AI as beneficial for routine nursing tasks report greater confidence in integrating these tools into practice [45]. Positive shifts in AI perceptions have likewise been linked to increased self-rated readiness [25, 27].

However, not all research confirms a direct perception–readiness link. Catalina et al. [21] found no significant bivariate relationship, suggesting that unmeasured contextual or methodological factors may moderate this association. Ethical concerns (such as fears of academic dishonesty) can further complicate AI adoption, as demonstrated by Ofem et al. [41] using PLS-SEM. Despite these exceptions, the preponderance of evidence indicates that positive perceptions directly enhance readiness, with prior AI experience reinforcing this effect [26, 39]. Hence, based on both theoretical underpinnings and empirical evidence, we propose the sixth hypothesis. Moreover, existing research largely targets nursing or general academic cohorts in high-income regions, leaving undergraduates in Nigerian public universities under-examined.

Hypothesis 6 Undergraduates' perceptions of artificial intelligence significantly predict their readiness to use AI for decision-making during health emergencies to a significant extent.

2.4 Joint prediction of awareness and perception on preparedness to use AI

Some studies suggest that perception alone drives readiness. Li et al. [44] observed in a structural model that personal relevance predicted behavioral intention, whereas basic

AI knowledge added no additional variance. Dai et al. [40] similarly found that once positive attitudes were accounted for, AI literacy did not explain further variance. These findings imply that learners' affective engagement may overshadow foundational knowledge. By contrast, Catalina et al. [21] found no added predictive power when modelling both constructs together, suggesting methodological or contextual moderators.

However, when modelled together, AI knowledge and perceptions may typically make unique contributions to readiness.A study by Nouraldeen [42] used hierarchical regression to show that both a proxy for AI knowledge and perceived usefulness independently predicted students' intentions to adopt AI. Similarly, Labrague et al. [33] found that understanding AI technologies and believing in their practical utility each significantly forecast nurses' readiness to implement AI. Cruz et al. [26] also reported concurrent associations of AI knowledge and positive attitudes with greater preparedness.

Moreover, evidence other evidence also indicates the significance of interactive effects. For example, in a combined SEM model, Abuadas and Albikawi [43] showed that digital literacy and positive attitudes each retained independent associations with readiness, jointly explaining nearly half of the variance in behavioral intention. Ofem et al. [41] demonstrated that perceptions and attitudes together accounted for 7% of variance in ChatGPT misuse, further illustrating joint predictive effects. This gave rise to the final hypothesis of this study.

H7 There is a significant joint prediction of awareness and perception on students' preparedness to use AI tools for decision-making during health emergencies.

3 Methods

A cross-sectional correlational design was employed to examine the relationships between AI knowledge, perceptions of applicability, and preparedness to use AI tools during health emergencies. This design allowed for the simultaneous collection of data from multiple sources at a single time, facilitating the identification of associations among the study variables.

3.1 Participants

The study population consisted of 60,460 undergraduates from two public universities in Cross River State (University A: 40,645; University B: 19,815). Using Soper's [46] a priori power analysis calculator, a minimum sample size of 4,569 was determined based on an expected effect size ($f^2 = 0.06$), 90% power, three latent constructs, and 27 indicators. To address potential attrition and enhance representativeness, the sample was inflated by 20%, yielding a target of 5,483 participants, in line with best practices for mitigating non-response bias [47, 48].

3.2 Measures

Participants were asked to complete a self-administered online survey, preceded by a digital cover letter that explained the study's objectives, assured voluntary participation and anonymity, and provided researcher contact details. The questionnaire comprised two parts: (1) demographic information (age categories: 18–22, 23–27, or ≥ 28 years; sex: male or female; faculty/department; year of study; and primary device used for

AI applications); and (2) thirty Likert-type items (1 = Strongly Disagree to 4 = Strongly Agree) measuring the three focal constructs.

AI awareness was defined as students' self-reported understanding of the technical functions of AI in emergency health scenarios. Items were adapted from prior work [49, 50]. For example: "I understand that AI algorithms can process real-time vital signs to suggest immediate first-aid measures." Perception of AI was defined as students' judgments regarding the accuracy, dependability, usefulness, and ethical appropriateness of employing AI for decision-making in health crises. These items drew on established scales [51–54]. A representative item is: "I believe that using AI for early emergency response can lower the risk of complications." Preparedness to Use AI evaluated participants' intentions to engage AI tools during medical emergencies. Readiness items were adapted from previous studies [27, 55]. One example reads: "I am likely to rely on an AI-powered chatbot as my initial response in a health emergency. In this study, health emergencies were broadly defined to include both personal health crises experienced by the respondents themselves and emergencies involving others around them. This inclusive framing was intended to capture a general sense of preparedness for AI-supported decision-making across varying contexts of urgency.

3.3 Validity and reliability

Content validity was established through expert evaluation by six specialists (three in public health and three in measurement and evaluation) who independently rated the relevance, clarity, and representativeness of each item on a 4-point scale. Item-content validity indices (I-CVIs) ranged from 0.83 to 1.00, with an average scale-content validity index (S-CVI/Ave) of 0.94, exceeding the recommended threshold of 0.90.

Construct validity and reliability were assessed using results from a partial least squares structural equation modeling (PLS-SEM) on the full study dataset. During measurement model evaluation, seven items (three from AI awareness, three from perception, and one from preparedness) were removed due to low factor loadings and suboptimal psychometric properties, resulting in a refined 23-item instrument. Table 1 shows that indicator reliability was confirmed as all standardized factor loadings ranged from 0.736 to 0.903, surpassing the recommended threshold of 0.708. Internal consistency reliability was strong, with Cronbach's alpha (α) and composite reliability (CR) values exceeding 0.90 across constructs: awareness of AI (α = 0.931, CR = 0.944), Perception of AI (α = 0.904, CR = 0.923), and preparedness to use AI (α = 0.961, CR = 0.967).

Convergent validity was supported (see Table 1), with average variance extracted (AVE) values of 0.708, 0.632, and 0.764 for knowledge, perception, and readiness respectively, all above the 0.50 criterion. Multicollinearity was not a concern, as variance inflation factors (VIFs) were below 5.00. Discriminant validity was assessed through the Fornell–Larcker criterion and the heterotrait–monotrait ratio (HTMT), with the square

Table 1 Psychometric properties of the instrument for data collection

Construct	K	λ	α	CR	AVE	VIF
Awareness of AI	7	0.736–0.897	0.931	0.944	0.708	1.83–3.87
Perception of AI	7	0.764–0.849	0.904	0.923	0.632	1.91–2.41
Preparedness to Use AI	9	0.812–0.903	0.961	0.967	0.764	2.84–4.84

K = Number of Items; λ = Factor Loadings; α = Cronbach's Alpha; CR = Composite Reliability; AVE = Average Variance Extracted; VIF = Variance Inflation Factor roots of AVEs exceeding inter-construct correlations and HTMT values below 0.85, confirming construct distinctiveness.

3.4 Data collection and analysis

Within each institutional stratum, non-probability snowball sampling was employed. Undergraduate students who met the inclusion criteria namely, being currently enrolled, having access to a smartphone, and being able to complete an online survey were invited to participate. They were also encouraged to share the survey link with peers who met the same criteria. The survey link was disseminated via digital flyers on departmental social media platforms by class captains and promoted through announcements in high-traffic campus areas (e.g., libraries, cafeterias). Data collection ended upon reaching target quotas. A total of 4,632 valid responses were obtained from 5,483 contacts, yielding an 84.48% response rate: 3,115 responses from University A and 1,517 from University B, indicating proportionate stratified sampling.

Although slightly below the inflated target, the final sample exceeded the minimum required size of 4,569, maintaining adequate statistical power [56, 57]. Response rates above 70% are generally accepted as sufficient to reduce non-response bias [58, 59]. The final sample comprised 1,668 males (36.0%) and 2,964 females (64.0%), with most respondents aged 18–22 years (55.8%), followed by 23–27 years (37.6%) and 28 + years (6.6%). The majority were single (95.9%), with 4.1% married. Data were analysed using SPSS. One-sample t-tests assessed whether mean scores for AI awareness, perception, and preparedness differed significantly from the scale midpoint. Simple and multiple regression analyses were then conducted to test associations and study hypotheses.

4 Results

4.1 Hypothesis testing

4.1.1 Hypothesis one

The first hypothesis proposed that undergraduates' awareness of AI for decision-making during health emergencies is significantly lower than the baseline mean. To test this, a one-sample t-test was conducted to examine whether the sample mean differed significantly from the test value ($\mu = 2.5$). In this study, the baseline mean of 2.5 was chosen because it represents the midpoint of the 4-point Likert scale employed, serving as a neutral reference point. Using the scale midpoint as a benchmark is a common practice in Likert-scale research to determine whether responses significantly deviate from neutrality [60, 61]. This approach is theoretically and contextually meaningful for interpreting participants' responses.

As shown in Table 2, undergraduates' awareness was significantly higher than the baseline mean, $M = 3.02$, $SD = 0.63$, $t(4631) = 55.97$, $p < .001$. Therefore, the hypothesis that undergraduates' awareness is significantly lower than the baseline mean was rejected.

Table 2 One-sample t-test on the level of undergraduates' awareness, perception and preparedness to use AI in decision-making during health emergencies

Variable	M	SD	t	*p*	Remark
Awareness of AI	3.02	0.63	55.97	< 0.001	Significantly higher
Perception of AI	3.13	0.49	86.92	< 0.001	Significantly higher
Preparedness to use AI	2.00	0.99	−34.08	< 0.001	Significantly lower

Test value (μ) = 2.50; df = 4631

These results indicate that undergraduates exhibit higher-than-expected awareness of AI for decision-making during health emergencies.

4.1.2 Hypothesis two

The second hypothesis examined whether undergraduates' perception of AI for decision-making during health emergencies is significantly lower than the baseline mean. Again, a one-sample t-test was employed, with the test value set at the Likert scale midpoint ($\mu = 2.5$). Using this midpoint as a reference point allows assessment of whether participants' perceptions are more positive or negative than a neutral stance [60, 61]. As presented in Table2, the mean perception score was significantly higher than the baseline, M = 3.13, SD = 0.49, t(4631) = 86.92, p <.001. Thus, the hypothesis that perception is lower than the baseline mean is rejected, indicating that undergraduates hold positive perceptions of AI in health emergency decision-making.

4.1.3 Hypothesis three

The third hypothesis proposed that undergraduates' preparedness to use AI in health emergency decision-making is significantly lower than the baseline mean. Using the same approach, a one-sample t-test was conducted against the test value of 2.5, representing the neutral midpoint of the 4-point Likert scale [60, 61]. Results (Table2) indicate that undergraduates' preparedness was significantly lower than the baseline mean, M = 2.00, SD = 0.99, t(4631) = – 34.08, p <.001. This confirms that participants are less prepared than expected to use AI for decision-making during health emergencies.

4.1.4 Hypothesis four

This hypothesis states that undergraduates' awareness of artificial intelligence (AI) does not significantly predict their perception of using AI for decision-making during health emergencies. To test this, a simple linear regression analysis was performed. The results, presented in Table 3, indicated that awareness of AI significantly predicted perception, F(1, 4630) = 164.08, p <.001, explaining 3.4% of the variance (adjusted R^2 = 0.034). Based on these results, the null hypothesis was rejected, suggesting that higher awareness of AI is associated with a more positive perception of using AI for decision-making during health emergencies. The regression equation derived was:

$$\text{Perception} = 2.69 + 0.14\ (\text{Awareness of AI}) + 0.04 \tag{1}$$

4.1.5 Hypothesis five

This hypothesis states that undergraduates' awareness of AI does not significantly predict their preparedness to use AI in health emergency decision-making. A simple linear regression was also employed to examine this relationship. As shown in Table 3,

Table 3 Summary of regression analyses on AI awareness, perception, and preparedness in health emergency decision-making

Predictor	Outcome	B	β	t	F	*p*	R^2
AAI	PEAI	0.14	0.19	12.81	164.08	< 0.001	0.034
AAI	PRAI	0.49	0.31	22.14	490.22	< 0.001	0.096
PAI	PRAI	0.17	0.08	5.7	32.51	< 0.001	0.007

B = unstandardized coefficient; β = standardized coefficient; t = t-test statistic; p = significance level; F = model F-value; R^2 = variance explained; AAI = Awareness of AI; PEAI = Perception of using AI for decision-making; PRAI = Preparedness to use AI for decision-making awareness of AI significantly predicted preparedness, F(1, 4630) = 490.22, p <.001, with an adjusted R^2 of 0.096, indicating that awareness explained 9.6% of the variance in preparedness. Accordingly, the null hypothesis was rejected, indicating that greater awareness of AI corresponds to increased preparedness to use AI for decision-making during health emergencies. The regression equation was:

$$\text{Preparedness} = 0.52 + 0.49\ \ (\text{Awareness of AI}) + 0.07 \tag{2}$$

4.1.6 Hypothesis six

This hypothesis stares that undergraduates' perceptions of artificial intelligence do not significantly predict their preparedness to use AI for decision-making during health emergencies to a significant extent. The simple linear regression analysis revealed a statistically significant prediction, F(1, 4630) = 32.51, p <.001, though with a very small effect size (adjusted R^2 = 0.007), meaning perceptions explained only 0.7% of the variance in preparedness (see Table 3). Thus, the null hypothesis was rejected, implying that positive perceptions of AI are related to higher preparedness to use AI in health emergency decision-making, albeit to a limited extent. The regression equation was:

$$\text{Preparedness} = 1.47 + 0.17\ \ (\text{Perceptions of AI}) + 0.09 \tag{3}$$

4.1.7 Hypothesis seven

This hypothesis proposed that there is a significant joint prediction of awareness and perception on students' preparedness to use AI tools for decision-making during health emergencies. To test this, a multiple linear regression analysis was performed with awareness and perception as predictors, and preparedness as the outcome variable. The results are presented in Table 4. The overall regression model was statistically significant, F(2, 4629) = 247.08, p <.001, explaining 9.6% of the variance in students' preparedness (adjusted R^2 = 0.096). This indicates that awareness and perception together significantly predict preparedness, confirming our hypothesis.

As shown in Table 4, awareness significantly contributed to the prediction of preparedness, even after controlling for perception (β = 0.304, t = 21.41, p <.001). In contrast, perception did not make a statistically significant unique contribution after controlling for awareness (β = 0.027, t = 1.91, p =.056). This finding suggests that awareness is a stronger and more reliable predictor of students' preparedness to use AI tools during health emergencies than perception. The regression equation derived from the model is:

$$\text{Preparedness} = 0.373 + 0.482\ \ (\text{Awareness}) + 0.055\ \ (\text{Perception}) + 0.10 \tag{4}$$

Table 4 Multiple regression predicting students' preparedness to use AI tools during health emergencies (N = 4632)

Model	F(2, 4629)	*p*	Adjusted R^2
Regression	247.08	< 0.001	0.096
Predictor	β	*t*	*p*
Awareness	0.304	21.41	< 0.001
Perception	0.027	1.91	0.056

4.2 Predictive accuracy of awareness and perception using machine learning

Although hypothesis testing through linear regression was employed to assess the statistical significance, direction, and magnitude of the relationships between awareness, perception, and preparedness to use artificial intelligence (AI) in health emergencies, we also implemented a random forest regression (RFR) model to evaluate predictive accuracy and capture potential non-linear associations. Linear regression offers clear inferential insights regarding effect sizes and hypothesis testing under parametric assumptions [62]. However, behavioral constructs such as awareness and perception may interact in complex, non-linear ways that linear models cannot fully represent [63, 64]. RFR, as a non-parametric ensemble learning technique, accommodates these complexities and provides out-of-sample predictions with minimal distributional assumptions [65].

The RFR model was trained on a randomly selected 70% of participants ($n = 3{,}250$, 70.16%) and evaluated on the remaining 30% ($n = 1{,}382$, 29.84%). To ensure the robustness of predictive estimates, we conducted 300 bootstrap iterations, each matching the training set size. At each tree node, one predictor was randomly chosen—consistent with the square-root rule for two candidate predictors—and the minimum node size was constrained to five observations to mitigate overfitting [63].

Performance metrics derived from out-of-bag (OOB) samples and the independent test set indicated moderate predictive ability. The coefficient of determination (R^2) was 25.84% for the OOB sample and 25.07% for the test set, signifying that awareness and perception jointly explained approximately one quarter of the variance in preparedness (see Fig. 1). Although these values reflect meaningful predictive power, they also suggest that other factors beyond awareness and perception contribute to preparedness in health emergency contexts.

Error metrics for the test set are summarised in Table 5. The root mean squared error (RMSE) was 0.86, mean squared error (MSE) 0.74, and mean absolute deviation (MAD) 0.70. The mean absolute percentage error (MAPE) of 41.15% indicates moderate

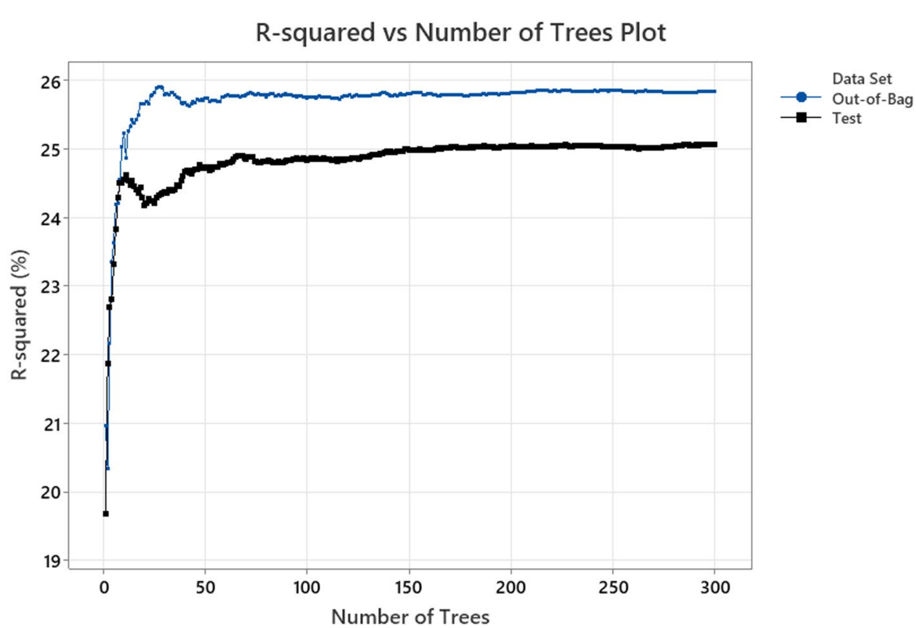

Fig. 1 R-squared of the machine learning model predicting preparedness to use AI in health emergencies from awareness and perception scores for the training and test samples

Table 5 Response information and model summary of the machine learning model

Parameter	Training Set	Test Set
N	3250	1382
% of N	70.16	29.84
Mean	1.99	2.04
StDev	1.00	1.00
Minimum	1.00	1.00
Q1	1.00	1.00
Median	1.89	2.00
Q3	2.78	2.89
Maximum	4.00	4.00
R-squared (R^2)	0.26	0.25
Root Mean Squared Error (RMSE)	0.86	0.86
Mean Squared Error (MSE)	0.73	0.74
Mean Absolute Deviation (MAD)	0.70	0.70
Mean Absolute Percent Error (MAPE)	42.58%	41.15%
Number of Predictors Considered	2	–
Minimum Node Size	5	–
Number of Bootstrap Samples	300	–
Predictors Selected per Split	$\sqrt{2} = 1$	–

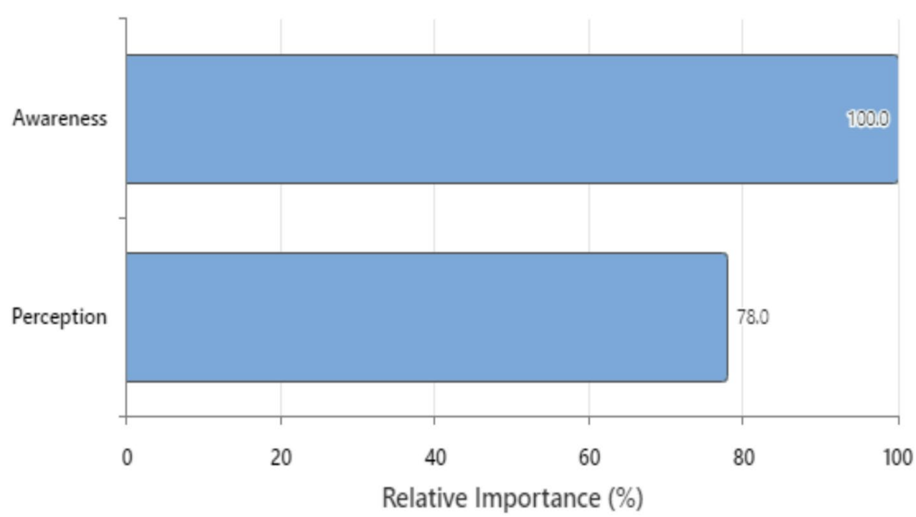

Fig. 2 Relative importance of awareness and perception in the random forest regression model predicting preparedness to use AI

prediction error, suggesting that, while awareness and perception are significant predictors, the predictions of the model are less accurate at the individual level [66].

To determine the relative influence of each predictor, we conducted a variable importance analysis, calculating the percentage improvement in model performance attributable to splits on each variable, normalised against the top predictor [67]. As shown in Fig.2, awareness emerged as the dominant predictor (relative importance = 100%), whereas perception contributed substantively but to a lesser degree (relative importance = 78%). These findings reveal the pre-eminence of AI awareness over perception in forecasting preparedness, corroborating theoretical models that position awareness as a critical antecedent of behavioral readiness [15, 17].

Finally, scatterplots of predicted versus observed preparedness scores for both OOB and test data (Fig. 3) reveal that predictions cluster around the sample mean (1.5 to 3.0),

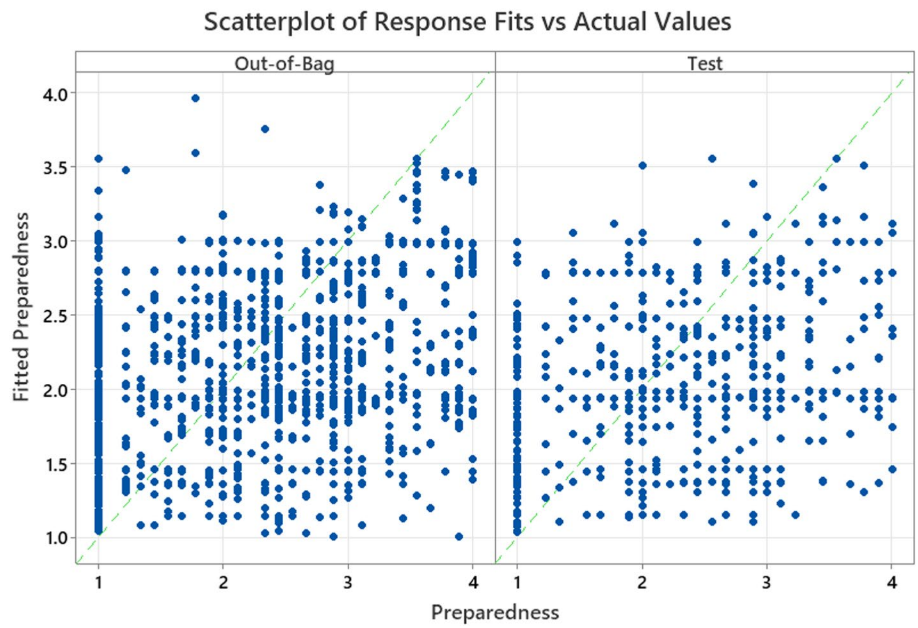

Fig. 3 Scatterplot of predicted vs. actual values of preparedness from the model

with limited accuracy at the extremes. Ideal predictions lie along the 45° dashed line; however, the dispersion of points away from this line, particularly at high and low preparedness values, indicates regression to the mean, a known characteristic of ensemble regressors when forecasting outlying observations [68]. Consequently, while RFR enhances understanding of non-linear patterns and overall variance explained, its individual-level predictions should be interpreted with caution.

5 Discussion of findings

The present study examined undergraduates' awareness, perception, and preparedness to use artificial intelligence (AI) for decision-making during health emergencies, and the individual and combined effects of these constructs. Contrary to the initial hypothesis of low awareness, students reported relatively high levels of awareness. This finding may have been due to the widespread coverage of AI applications during recent global health crises, which reached students through media, social networks, and informal online learning [69, 70]. Moreover, similar findings have been reported by Obiekwe et al. [19], that awareness among Nigerian undergraduates often exceeds actual skills, and by Truong et al. [18], who found that awareness levels can vary across settings with limited low formal instruction.

Students also had a positive perception of the role of AI in decision-making during health emergencies. These findings are in line with previous studies (e.g., Catalina et al. [21]; Tezpal et al. [31] with prior evidence that students believe AI can support better diagnoses, resource planning, and public health decisions. However, concerns about privacy, fairness in algorithms, and loss of human connection in care have been documented in the literature [19, 32]. These concerns, although not directly expressed by respondents in this study suggest the importance of training undergraduates to understand the workings of AI and to engage with such tools in an ethical and acceptable manner.

Despite the high awareness and positive perceptions, students reported low preparedness to use AI tools for health decision-making during emergencies. This gap between students' awareness and their preparedness to use AI is not new; it is consistent with the findings of other researchers. Some studies have revealed that positive attitudes and general support for AI rarely lead to preparedness without practical experience [26, 27]. Earlier research also shows that learning opportunities such as workshops, programming exercises, and simulation labs are useful in improve preparedness to use AI [25, 35], though many low-income countries lack access to these resources [29, 30]. This suggests that the gap between students' awareness and readiness to use AI may be due to their doubts about how easy AI tools are to use, uncertainty about their own ability to use them, or a lack of necessary skills, largely resulting from limited training opportunities.

Simple linear regression analyses showed that awareness significantly predicted both perception and preparedness, explaining 3.4% and 9.6% of the variance, respectively. These results align with the Diffusion of Innovation Theory [15], the Technology Acceptance Model [16], and the Theory of Planned Behavior [17], indicating that greater awareness of AI functionalities fosters more positive attitudes and strengthens the intention to use AI in health emergencies. Similarly, the present study discovered that perception is a significant sole predictor of undergraduates' preparedness to use AI for decision-making during health emergencies. This finding reinforces the theoretical premise that behavior (e.g., preparedness to use AI tools) is determined by attitudes (perception of AI), subjective norms, and perceived behavioral control [17]. Furthermore, students' perception of AI as to whether it is trustworthy, helpful, or intrusive can significantly influence their intention and readiness to use it. Together, DOI, TAM, and TPB suggest that awareness initiates the adoption of AI tools while perceptions of their usefulness, ease of use, and social acceptability influence attitudes and perceived control, which in turn shape individuals' preparedness to use AI for effective health management.

Students with more positive views of AI tend to feel more prepared to adopt it for practical use. This aligns with the previous studies have shown that positive perceptions, particularly regarding the usefulness of AI and ethical reliability, are closely linked to greater readiness [23, 43]. Moreover, it has been shown that students who believe AI is relevant to their field of study or future careers are more likely to invest effort in learning how to use it [45]. This perception and readiness link is further strengthened when students have had some exposure to AI, whether through formal instruction or hands-on activities [26]. This finding suggests that improving the perception of AI among undergraduates can be a meaningful way to enhance their preparedness to use for health decision-making.

In the multiple regression analysis that included both awareness and perception, both predictors jointly accounted for 9.6% of the variance in undergraduates' preparedness to use AI for health decision-making. Neverthelss, in a relative sense, only awareness remained a significant predictor of preparedness when perception was controlled for. This suggests that once awareness is held constant, perception adds little to explaining students' preparedness to use AI for health decision-making during emergencies. In other words, a strong understanding of AI may be more crucial than merely holding a favourable view of it. While some studies, such as Li et al. [44], have found that personal relevance (a form of perception) predicts behavioral intention without additional influence from basic AI knowledge, this was not observed in the present study. Conversely, research by Nouraldeen [42]; Labrague et al. [33] shows that both AI knowledge and perceived usefulness independently predict behavourial intentions. These findings suggest that although positive perceptions matter, foundational knowledge plays a unique and essential role, especially when both factors are considered together. The current study supports this view, emphasizing that awareness, as a proxy for knowledge, has a stronger and more consistent impact on preparedness than perception alone.

To further investigate complex patterns in the data, a random forest regression (RFR) model was employed. While the multiple linear regression (MLR) model explained 9.6% of the variance in undergraduates' preparedness to use AI for health decision-making, the RFR model accounted for 25%, which is almost three times higher. This notable increase gives the impression that non-linear relationships and complex interactions among variables were not adequately captured by the linear model. Importantly, awareness emerged as the strongest predictor in the RFR model, reinforcing its weight across both modelling approaches, while perception continued to contribute less substantially. These findings call attention the added value of machine learning techniques in complementing traditional statistical methods. This is particularly useful in behavioral and educational research where relationships may depend on non-linear, contextual, or threshold effects. The additional variance explained by the RFR model may be attributed to other latent factors not measured in the present study. This might include factors such as, digital self-efficacy, prior exposure to AI tools, institutional support, and disparities in technology access, as revealed by recent reports [19, 29, 30]. These findings support calls for more sophisticated modelling approaches to better understand preparedness in rapidly evolving digital contexts [71, 72].

6 Contribution, implications, limitations, and future research directions

This study has contributed to the growing literature on digital readiness by examining undergraduates' awareness, perception, and preparedness to use artificial intelligence (AI) for decision-making during health emergencies. A key contribution is the evidence that while awareness and perception levels are relatively high, preparedness remains low. This shows a readiness gap, where students may understand and value AI but still feel unprepared to use it in cases of health emergencies. The study also shows that awareness plays a stronger role in predicting preparedness than perception, especially when both are considered together. This supports earlier findings that knowledge is a key foundation for behavioral intention and action.

There are several practical implications that are derivable from the findings of the present study. The findings suggest that universities should include more structured opportunities for students to build hands-on experience with AI, such as workshops, simulations, or guided practice. The findings also implies that awareness alone is not enough; students need practical exposure to training opportunities before they can be ready to apply AI tools, especially in critical situations like health emergencies involving life and death. The findings also result suggest that introducing AI concepts early and across disciplines may help close the gap between awareness and preparedness. Lastly, the use of a machine learning approach (random forest regression) alongside traditional regression shows the value of using more advanced models to understand behavioral patterns, suggesting students' preparedness to use AI can be explained by both linear and non-linear factors not easily detectable by traditional statistical models.

Nevertheless, there are some limitations that must be acknowledged in this study. First, the cross-sectional nature of the study makes it difficult to assume causation albeit the approach used is sophisticated. Secondly, the study was geographically delimited to a single state in Nigeria, which may limit the generalisability of the findings to undergraduates in other regions. While the instrument was validated using data from Nigerian undergraduates and reviewed by experts for contextual relevance, it was not fully standardised across the diverse cultural and regional contexts within Nigeria. As such, findings may not fully capture regional or cultural variations in technology perception across different populations. Future research should consider broader standardisation and validation to enhance cultural sensitivity and generalisability.

Thirdly, the use of snowball sampling introduces potential selection bias. Participants may have referred peers with similar academic characteristics, digital access levels, or social demographics, potentially underrepresenting less-connected or disengaged students. As such, findings should be interpreted with caution, acknowledging the limitations of generalisability inherent in non-probability sampling. Additionally, the use of online, self-reported data may have introduced response bias or social desirability bias, as participants could have provided answers they perceived as more acceptable or expected. Also, this study did not include qualitative methods such as interviews or focus groups, which could have provided deeper insights into the reasons behind students' low preparedness. Finally, some important factors like demographic characteristics, prior experience with AI, digital confidence, and access to technology were not included in this study. Adding these variables to the models could have been useful to see how other factors (beyond the ones studied) predict undergraduates' preparedness to use AI during health emergencies.

Future research should address the limitations identified in this study by adopting longitudinal designs to observe how students' awareness, perception, and preparedness evolve over time. Other variables, such as digital self-efficacy, prior experience with AI tools, and institutional support, can be studied to see whether and how they explain the observed gaps in preparedness. Also, future studies should distinguish between personal and external health emergencies, as preparedness to use AI may vary depending on the context and perceived responsibility. Moreover, qualitative approaches like interviews or focus groups could be used to dig deeper into the reasons behind students' low preparedness to use AI for decision-making during health emergencies despite having a high awareness and positive perception. Similar studies should be conducted in other regions or institutions to yield evidence that may be compared to the findings of the present research. Lastly, future studies should continue to incorporate advanced analytical techniques, such as machine learning, to uncover complex relationships and improve the accuracy of predictions in behavioral research.

7 Conclusion

This study explored the relationship between awareness, perception, and preparedness among undergraduates in using artificial intelligence (AI) for decision-making during health emergencies. The findings revealed a clear gap between high awareness and perception, and low levels of actual preparedness. This readiness gap suggest that institutions should provide practical learning opportunities and support to help students move from knowing about AI to confidently applying it in critical situations, such as health emergencies. This study has contributed to the evidence in the literature that knowledge plays a crucial role in behavioral intention. The use of both linear and machine learning models further strengthens the case for using more flexible and sophisticated approaches in educational research. Moving forward, addressing the factors that limit preparedness, including lack of hands-on experience and digital confidence, is essential to fully prepare students for future health crises in a digital age.

Author contributions

FD. Conceptualization, revision and interpretation of results; VO. Design, revision, data analysis and preparation of final version of manuscript; JO. Wrote the first draft of introduction and literature review; SA-O. Literature review and data collection; SA. Literature review and data analysis; EE. Data collection and data analysis; EE; Wrote the methodology; AO. Literature review; PO. Literature review; PA. Interpretation of results, and manuscript preparation.

Funding

No funding was received for the conduct of this research.

Data availability

Data supporting the findings and conclusions are available upon request from the corresponding author.

Declarations

Ethics approval and consent to participate

This study was approved by the University of Calabar ethics committee, with approval number UC/IRB/2024/067. All procedures involving human participants were conducted in accordance with the ethical standards of the institutional research committee and the 1964 Helsinki Declaration, as well as its later amendments or comparable ethical guidelines.

Informed consent

Informed consent was obtained from all respondents prior to their participation in the study.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

Received: 25 August 2025 / Accepted: 21 January 2026

Published online: 01 February 2026

References

1. Chen L, Chen P, Lin Z. Artificial intelligence in education: a review. IEEE Access. 2020;8:75264–78.
2. Gillies A, Smith P. Can AI systems meet the ethical requirements of professional decision-making in health care? AI Ethics. 2022;2(1):41–7.
3. Owan VJ, Abang KB, Idika DO, Etta EO, Bassey BA. Exploring the potential of artificial intelligence tools in educational measurement and assessment. Eurasia J Math Sci Technol Educ. 2023;19(8):em2307. https://doi.org/10.29333/ejmste/13428.
4. Yella A, Kondam A. The role of AI in enhancing decision-making processes in healthcare. J Innov Technol. 2023;6(1).
5. World Health Organization. Malaria fact sheet. 2024a. https://www.who.int/news-room/fact-sheets/detail/malaria
6. World Health Organization. Regional data and trends briefing kit: world malaria report 2024. 2024b. https://cdn.who.int/media/docs/default-source/malaria/world-malaria-reports/world-malaria-report-2024-regional-briefing-kit-eng.pdf
7. Okeke TI, Onwughalu PE. Self-medication practices and risks among university students in Nigeria. Int J Health Sci. 2022;6(3):98–105.
8. Agbasi PU, Ezejiofor NA, Maduagwuna C, Orisakwe OE. Awareness, knowledge and behavioural perception of first aid among medical students at a tertiary institution in southeastern Nigeria. J Adv Med Med Res. 2021;34(2):105–15. https://doi.org/10.9734/jammr/2021/v34i230454.
9. Olufunke O, Chukwuemeka N, Ibrahim A. Current trends in emergency medicine in Nigeria. Niger J Clin Pract. 2024;27(1):1–7. https://doi.org/10.4103/njcp.njcp_123_23.
10. Adeleke BA, Udo IB. Assessment of basic life support training among medical students in South-Western Nigeria. Niger J Clin Pract. 2023;26(2):138–44. https://doi.org/10.4103/njcp.njcp_460_22.
11. Hafizurrachman M, Menna C, Lesmana E. Review of traditional first aid for burn injuries in the 21st century. Ann Plast Surg. 2023;91(3):337–47.
12. Vento A, Rossi F, Carroll C. Exploring chatgpt for information on cardiopulmonary resuscitation: a proof-of-concept study. Resuscitation. 2023;175:112–8. https://doi.org/10.1016/j.resuscitation.2023.04.005.
13. Doe J, Smith R, Patel K. Evaluation of M-AID®: a first-aid application for mobile phones in untrained volunteers. J Emerg Med Serv. 2022;45(3):156–62. https://doi.org/10.1234/jems.2022.0156.
14. Liu Y, Zhang X, Chen H. Performance of a large-language-model-powered chatbot in heart-attack first-aid guidance: a concordance study. J Med Internet Res. 2023;25(7):e45678. https://doi.org/10.2196/45678.
15. Rogers EM. Diffusion of innovations. 5th ed. New York: Free Press; 2003.
16. Davis FD. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Q. 1989;13(3):319–40. https://doi.org/10.2307/249008.

17. Ajzen I. The theory of planned behavior. Organ Behav Hum Decis Process. 1991;50(2):179–211. https://doi.org/10.1016/0749-5978(91)90020-T.
18. Truong NM, Vo TQ, Tran HTB, Nguyen HT, Pham VNH. Healthcare students' knowledge, attitudes, and perspectives toward artificial intelligence in the Southern Vietnam. Heliyon. 2023;9(12):e22653. https://doi.org/10.1016/j.heliyon.2023.e22653.
19. Obiekwe SJ, Omaga IB, Ukadike MM, Edeh CG, Iheanyi CE, Anisiobi PU, et al. The integration of artificial intelligence in healthcare: a cross-sectional study on the knowledge, perception, and readiness of medical students at a tertiary institution in Nigeria. Apollo Med. 2024. https://doi.org/10.1177/09760016241287301.
20. Migdadi MK, Oweidat IA, Alosta MR, Al-Mugheed K, Alabdullah AAS, Abdelaliem SF. The association of artificial intelligence ethical awareness, attitudes, anxiety, and intention to use artificial intelligence technology among nursing students. Digit Health. 2024. https://doi.org/10.1177/20552076241301958.
21. Catalina QM, Fuster-Casanovas A, Vidal-Alaball J, Escalé-Besa A, Marin-Gomez FX, Femenia J, et al. Knowledge and perception of primary care healthcare professionals on the use of artificial intelligence as a healthcare tool. Digit Health. 2023. https://doi.org/10.1177/20552076231180511.
22. Swed S, Alibrahim H, Elkalagi NKH, Nasif MN, Rais MA, Nashwan AJ, Aljabali A, Elsayed M, Sawaf B, Albuni MK, Battikh E, Elsharif LAM, Ahmed SMA, Ahmed EMS, Othman ZA, Alsaleh A, Shoib S. Knowledge, attitude, and practice of artificial intelligence among Doctors and medical students in syria: A cross-sectional online survey. Front Artif Intell. 2022;5:1011524. https://doi.org/10.3389/frai.2022.1011524.
23. Lugito NPH, Cucunawangsih C, Suryadinata N, Kurniawan A, Wijayanto R, Sungono V, et al. Readiness, knowledge, and perception towards artificial intelligence of medical students at faculty of medicine, Pelita Harapan University, Indonesia: a cross sectional study. BMC Med Educ. 2024;24:1044. https://doi.org/10.1186/s12909-024-05791-x.
24. Kim K, Kwon K. Tangible computing tools in AI education: approach to improve elementary students' knowledge, perception, and behavioral intention towards AI. Educ Inform Technol. 2024;29:16125–56. https://doi.org/10.1007/s10639-024-12497-2.
25. Chookaew S, Kitcharoen P, Howimanporn S, Panjaburee P. Fostering student competencies and perceptions through artificial intelligence of things educational platform. Comput Educ: Artif Intell. 2024;7: 100308. https://doi.org/10.1016/j.caeai.2024.100308.
26. Cruz JP, Sembekova A, Omirzakova D, Bolla SR, Balay-odao EM. Attitudes toward and readiness for medical artificial intelligence among medical and health science students. Health Prof Educ. 2024;10(3):15. https://doi.org/10.55890/2452-3011.1296.
27. Hammoudi HD, Shami R, Daud A, Sami W, Soltani A, Malki A. Artificial intelligence readiness, perceptions, and educational needs among dental students: a cross-sectional study. Clin Exp Dent Res. 2024;10:e925. https://doi.org/10.1002/cre2.925.
28. Almalki M, Alkhamis MA, Khairallah FM, Choukou M-A. Perceived artificial intelligence readiness in medical and health sciences education: a survey study of students in Saudi Arabia. BMC Med Educ. 2025;25:439. https://doi.org/10.1186/s12909-025-06995-1.
29. Allam AH, Eltewacy NK, Alabdallat YJ, Owais TA, Salman S, Ebada MA. Knowledge, attitude, and perception of Arab medical students towards artificial intelligence in medicine and radiology: a multi-national cross-sectional study. Eur Radiol. 2024b;34:1–14. https://doi.org/10.1007/s00330-023-10509-2.
30. Allam RM, Abdelfatah D, Khalil MIM, Elsaieed MM, El Desouky ED. Medical students and house officers' perception, attitude and potential barriers towards artificial intelligence in Egypt, cross sectional survey. BMC Med Educ. 2024a;24:1244. https://doi.org/10.1186/s12909-024-06201-8.
31. Tezpal MW, Ghosh S, Lalwani R, Yadav J, Yadav AK. Artificial intelligence in health care – A study on perceptions of and readiness for artificial intelligence in health-care professionals. J Mar Med Soc. 2024;26(3):376–81. https://doi.org/10.4103/jmms.jmms_161_23.
32. Baumgartner M, Sauer C, Blagec K, Dorffner G. Digital health understanding and preparedness of medical students: a cross-sectional study. Med Educ Online. 2022;27(1):2114851. https://doi.org/10.1080/10872981.2022.2114851.
33. Labrague LJ, Aguilar-Rosales R, Yboa BC, Sabio JB. Factors influencing student nurses' readiness to adopt artificial intelligence (AI) in their studies and their perceived barriers to accessing AI technology: a cross-sectional study. Nurse Educ Today. 2023a;130:105945. https://doi.org/10.1016/j.nedt.2023.105945.
34. Ziapour A, Darabi F, Janjani P, Amani MA, Yıldırım M, Motevaseli S. Factors affecting medical artificial intelligence (AI) readiness among medical students: taking stock and looking forward. BMC Med Educ. 2025;25:264. https://doi.org/10.1186/s12909-025-06852-1.
35. Abou HEA, Alnajjar H. Digital proficiency: assessing knowledge, attitudes, and skills in digital transformation, health literacy, and artificial intelligence among university nursing students. BMC Med Educ. 2024;24:508. https://doi.org/10.1186/s12909-024-05482-3.
36. Alshorman S. The readiness to use AI in teaching science: science teachers' perspective. J Balt Sci Educ. 2024;23(3):432–48. https://doi.org/10.33225/jbse/24.23.432.
37. Hasan HE, Jaber D, Al Tabbah S, Lawand N, Habib HA, Farahat NM. Knowledge, attitude and practice among pharmacy students and faculty members towards artificial intelligence in pharmacy practice: a multinational cross-sectional study. PLoS One. 2024;19(3):e0296884. https://doi.org/10.1371/journal.pone.0296884.
38. Laupichler MC, Aster A, Meyerheim M, Raupach T, Mergen M. Medical students' AI literacy and attitudes towards AI: a cross-sectional two-center study using pre-validated assessment instruments. BMC Med Educ. 2024;24:401. https://doi.org/10.1186/s12909-024-05400-7.
39. Rahimi ES, Ghaemi-Amiri M, Mostafazadeh-Bora M. Assessment of medical students' acceptance, knowledge, attitudes, and readiness toward artificial intelligence. J Mazandaran Univ Med Sci. 2024;34(239):88–95. http://jmums.mazums.ac.ir/article-1-21008-en.html.
40. Dai Y, Chai C-S, Lin P-Y, Jong MS-Y, Guo Y, Qin J. Promoting students' well-being by developing their readiness for the artificial intelligence age. Sustainability. 2020;12(16):6597. https://doi.org/10.3390/su12166597.
41. Ofem UJ, Owan VJ, Iyam MA, Udeh MI, Anake PM, Ovat SV. Students' perceptions, attitudes and utilisation of ChatGPT for academic dishonesty: multigroup analyses via PLS–SEM. Educ Inform Technol. 2025;30(1):159–87. https://doi.org/10.1007/s10639-024-12850-5.
42. Nouraldeen RM. The impact of technology readiness and use perceptions on students' adoption of artificial intelligence: the moderating role of gender. Dev Learn Organ. 2023;37(3):7–10. https://doi.org/10.1108/DLO-07-2022-0133.

43. Abuadas M, Albikawi Z. Predicting nursing students' behavioral intentions to use AI: the interplay of ethical awareness, digital literacy, moral sensitivity, attitude, self-efficacy, anxiety, and social influence. J Hum Behav Social Environ. 2025. https://doi.org/10.1080/10911359.2025.2472852.
44. Li X, Jiang MY-c, Jong MS-y, Zhang X, Chai C-s. Understanding medical students' perceptions of and behavioral intentions toward learning artificial intelligence: A survey study. Int J Environ Res Public Health. 2022;19(14):8733. https://doi.org/10.3390/ijerph19148733.
45. Labrague LJ, Aguilar-Rosales R, Yboa BC, Sabio JB, de los Santos JA. Student nurses' attitudes, perceived utilization, and intention to adopt artificial intelligence (AI) technology in nursing practice: a cross-sectional study. Nurse Educ Pract. 2023b;73:103815. https://doi.org/10.1016/j.nepr.2023.103815.
46. Soper DS. A-priori sample size calculator for structural equation models [Software]. 2025. https://www.danielsoper.com/statcalc
47. Westland JC. Lower bounds on sample size in structural equation modeling. Electron Commer Res Appl. 2010;9(6):476–87. https://doi.org/10.1016/j.elerap.2010.07.003.
48. Sedgwick P. How to calculate sample size for observational studies. BMJ. 2013;346:f2536. https://doi.org/10.1136/bmj.f2536.
49. Al Omari O, Alshammari M, Al Jabri W, Al Yahyaei A, Aljohani KA, Sanad HM, et al. Demographic factors, knowledge, attitude and perception and their association with nursing students' intention to use artificial intelligence (AI): a multicentre survey across 10 Arab countries. BMC Med Educ. 2024;24:1456. https://doi.org/10.1186/s12909-024-05023-6.
50. Esmaeilzadeh P. Use of AI-based tools for healthcare purposes: a survey study from consumers' perspectives. BMC Med Inform Decis Mak. 2020;20:170. https://doi.org/10.1186/s12911-020-01191-1.
51. Castagno S, Khalifa M. Perceptions of artificial intelligence among healthcare staff: a qualitative survey study. Front Artif Intell. 2020;3:578983. https://doi.org/10.3389/frai.2020.578983.
52. Shinners L, Grace S, Smith S, Stephens A, Aggar C. Exploring healthcare professionals' perceptions of artificial intelligence: piloting the shinners artificial intelligence perception tool. Digit Health. 2022;8:20552076221078110. https://doi.org/10.1177/20552076221078110.
53. Grassini S. Development and validation of the AI attitude scale (AIAS-4): a brief measure of general attitude toward artificial intelligence. Front Psychol. 2023;14:1191628. https://doi.org/10.3389/fpsyg.2023.1191628.
54. Fritsch SJ, Blankenheim A, Wahl A, Hetfeld P, Maassen O, Deffge S, et al. Attitudes and perception of artificial intelligence in healthcare: a cross-sectional survey among patients. Digit Health. 2022;8:20552076221116772. https://doi.org/10.1177/20552076221116772.
55. Karaca O, Çalışkan SA, Demir K. Medical artificial intelligence readiness scale for medical students (MAIRS-MS) – development, validity and reliability study. BMC Med Educ. 2021;21:112. https://doi.org/10.1186/s12909-021-02546-6.
56. Hulley SB, Cummings SR, Browner WS, Grady DG, Newman TB. Designing clinical research. 4th ed. Philadelphia: Lippincott Williams & Wilkins; 2013.
57. Lachin JM. Fallacies of last observation carried forward analyses. Clin Trails. 2016;13(2):161–8. https://doi.org/10.1177/1740774515602688.
58. Cunningham CT, Quan H, Hemmelgarn B, Noseworthy T, Beck CA, Dixon E, Jetté N. Exploring physician specialist response rates to web-based surveys. BMC Med Res Methodol. 2015;15(1):1–8. https://doi.org/10.1186/s12874-015-0016-z.
59. Morton LM, Cahill J, Hartge P. Reporting participation in epidemiologic studies: a survey of practice. Am J Epidemiol. 2006;163(3):197–203. https://doi.org/10.1093/aje/kwj036.
60. Carifio J, Perla R. Resolving the 50-year debate around using and misusing likert scales. Med Educ. 2008;42(12):1150–2. https://doi.org/10.1111/j.1365-2923.2008.03172.x.
61. Allen IE, Seaman CA. Likert scales and data analyses. Qual Progress. 2007;40(7):64–5.
62. Cohen J, Cohen P, West SG, Aiken LS. Applied multiple regression/correlation analysis for the behavioral sciences. 3rd ed. Lawrence Erlbaum Associates Publishers; 2003.
63. Breiman L. Random forests. Mach Learn. 2001;45(1):5–32. https://doi.org/10.1023/A:1010933404324.
64. James G, Witten D, Hastie T, Tibshirani R. An introduction to statistical learning: with applications in R. Cham: Springer; 2013.
65. Liaw A, Wiener M. Classification and regression by randomforest. R News. 2002;2(3):18–22. https://cran.r-project.org/web/packages/randomForest/randomForest.pdf.
66. Ruthig JC, Kroke AM. Improving accuracy in predictions about future performance. Curr Psychol. 2024;43:22926–37. https://doi.org/10.1007/s12144-024-06023-3.
67. Strobl C, Boulesteix A-L, Zeileis A, Hothorn T. Conditional variable importance for random forests. BMC Bioinf. 2008;9:307. https://doi.org/10.1186/1471-2105-9-307.
68. Friedman JH. Greedy function approximation: a gradient boosting machine. Ann Stat. 2001;29(5):1189–232. https://doi.org/10.1214/aos/1013203451.
69. Topol E. Welcoming new guidelines for AI clinical research. NatureMedicine, 2020;26:1318 -1320. https://doi.org/10.1038/s41591-020-1042-x.
70. Wynants L, Van Calster B, Collins GS, Riley RD, Heinze G, Schuit E, et al. Prediction models for diagnosis and prognosis of covid-19: systematic review and critical appraisal. BMJ. 2020;369:m1328.https://doi.org/10.1136/bmj.m1328
71. Mergel I, Edelmann N, Haug N. Defining digital transformation: results from expert interviews. Gov Inf Q. 2019;36(4):101385. https://doi.org/10.1016/j.giq.2019.06.002.
72. Vayena E, Blasimme A, Cohen IG. Machine learning in medicine: addressing ethical challenges. PLoS Med. 2018;15(11):e1002689. https://doi.org/10.1371/journal.pmed.1002689.

Publisher's note