Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

# AI-Aware but AI-Unprepared: The Curriculum Gap at a Health Sciences Higher Institution in Uganda

**Kavuma Sharif**

sharifbunhanifa@gmail.com

KAMPALA HOSPITAL LIMITED https://orcid.org/0009-0007-5784-3577

**Nakidde Mayimuna**

Mildmay Uganda

**Research Article**

**Keywords:** Artificial intelligence, Knowledge, Attitudes, Medical education

**Posted Date:** September 22nd, 2026

**DOI:** https://doi.org/10.21203/rs.3.rs-11092233/v1

**License:** This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

**Additional Declarations:** The authors declare no competing interests.

# AI-Aware but AI-Unprepared: The Curriculum Gap at a Health Sciences Higher Institution in Uganda


**ABSTRACT**

**Background:** Artificial intelligence is increasingly transforming healthcare education and practice, yet evidence on AI literacy among higher-institute health sciences students in Uganda remains limited.

**Methodology:** A descriptive cross-sectional study was conducted among 222 students. Knowledge was assessed using multiple-choice questions, and attitudes were assessed using Likert-scale items. The data were analyzed using descriptive and inferential statistics.

**Results:** Overall, 86.0% (n=191) demonstrated adequate AI knowledge, with a mean score of 3.44±0.85 out of 4. No significant associations were found between knowledge and sex, year of study, device ownership, or internet access ($p>0.05$). Positive attitudes were reported by 86.5% (n=192) of the participants, whereas 72.1% (n=160) felt confident in the use of AI tools. However, 55.4% (n=123) expressed concern that AI may reduce independent thinking.

**Conclusion:** The students possessed adequate AI knowledge and positive attitudes. However, concerns about independent thinking and a lack of structured AI education highlight the need for AI literacy training, institutional policies, and ethical guidance.



**Keywords:** Artificial intelligence, Knowledge, Attitudes, Medical education


## Introduction

Artificial intelligence (AI) has become an increasingly important part of healthcare systems in recent years, progressing from the initial expert systems created in the 1970s, which used Bayesian

statistics and decision theory to assist in the diagnosis of clinical cases, to the current applications of machine learning, which are helping with disease detection and treatment planning as well as increasing the efficiency of healthcare systems (Oladipo *et al.,* 2024). Today, the potential of AI tools in improving the quality, safety and effectiveness of health service delivery (Rajkomar *et al.,* 2019) is well known, including improving clinical decision-making, reducing errors in diagnosis (Topol, 2019), and supporting evidence-based practice.

In high-income countries such as the United Kingdom, Canada, and the United States, AI has been gradually incorporated into the practices of medicine and education in health professions. This integration seeks to provide the competencies needed for future health workers (Jiang *et al.,* 2017) to function effectively in technology-enhanced healthcare environments. Studies suggest that health science learners in these environments tend to have positive attitudes toward AI (Vasudevan *et al.,* 2025) and (Matheny *et al*., 2020), with AI-assisted tools being more reliable, efficient and supportive in understanding complex concepts in medicine than traditional learning methods are (Sami *et al.,* 2025). Such exposure enhances preparedness for AI-supported health service delivery.

Despite these advancements in the field globally, the use of AI in health profession education continues to vary widely among low- and middle-income countries. Structural challenges, including poor digital infrastructure, inadequate institutional policies and a lack of formal training in AI, have led to a substantial lack of knowledge and utilization among health sciences students. Evidence from multicountry studies shows that while many students are aware of the use of AI tools, their knowledge is often superficial, and most exposure is through informal rather than structured academic training, raising concerns about readiness for the responsible use of AI in healthcare settings (Issa *et al.,* 2024).

AI applications in healthcare span diagnosis, patient engagement, and real-time data analytics have the potential to enhance clinical research (Davenport & Kalakota, 2019; Kotecha *et al.,* 2022). Successful implementation requires foundational competencies in machine learning and data analytics, underscoring the need for standardized AI training in medical curricula (Sapci, 2020; Masters, 2019). The WHO has emphasized the ethical governance of AI technologies (WHO, 2021). Students hold predominantly positive attitudes toward AI, supporting its inclusion in medical training while rejecting concerns about physician replacement (Buabbas *et al.,* 2023; Santos *et al.,* 2018). However, evidence on the measurable educational outcomes of AI-powered interventions remain poor, with studies lacking methodological rigor (Feigerlova *et al.,* 2025). Large language models such as ChatGPT have demonstrated the potential to assist medical education by performing at or near passing thresholds on licensing examinations (Kung *et al.,* 2023). Challenges persist, including ethical dilemmas, a lack of validated curricula, and infrastructural constraints that hinder broader implementation (Ahsan, 2025). Healthcare workers show readiness to adopt medical AI and perceive organizational change positively, although targeted training remains necessary (Boyacı & Söyük, 2025). Medical education should therefore develop structured, ethically grounded AI curricula to equip future health professionals with responsible AI-enabled practices.

In Africa, the integration of AI into healthcare education is at an early stage. Studies in countries such as Nigeria and other developing countries have shown that although students in health sciences express positive attitudes toward AI, they lack technical knowledge, limited hands-on experience, and little formal instruction related to the applications of AI in health service delivery (Wobo *et al*., 2025). Additionally, challenges such as unreliable technological infrastructure, high costs and ethical concerns continue to limit the effective and equitable use of AI tools in training and practice (Wobo *et al.,* 2025).

In Uganda, empirical data on the literacy and use of AI among health sciences students are scarce. Available studies suggest that health profession educators demonstrate mixed perceptions and

levels of engagement with AI, with a need for institutional policies, curriculum guidance, and capacity-building initiatives to support the ethical and effective integration of AI in health training institutions (Mukunya *et al.,* 2025). However, little is known about the knowledge, attitudes and actual use of AI tools by students for health-related learning and preparation for health service delivery, especially in diploma-level training institutions such as the Mildmay Institute of Health Sciences.

This gap in knowledge has significant implications for student preparedness and future healthcare delivery. Without a clear understanding of how health sciences students perceive and use AI tools, institutions may produce graduates who lack adequate preparation for AI-enabled health systems. As the competencies in AI are becoming known to be essential for good clinical decision-making, patient safety, and efficient delivery of health services, the assessment of student knowledge, attitudes, and use of AI becomes a very important priority for education and public health research (Mousavi Baigi *et al.,* 2023)

## METHODOLOGY

### Study Design

A descriptive cross-sectional study was conducted. Cross-sectional designs were used to assess the distribution and relationships of key variables such as knowledge and attitudes within a defined population at a single point in time, as stated by (Creswell, 2020 and Creswell & Plano Clark, 2018). This design is appropriate for estimating the prevalence of knowledge levels and attitudes toward artificial intelligence among health science students without the need for longitudinal follow-up.

In a resource-limited setting such as the MildMay Institute of Health Sciences (MIHS), a cross-sectional approach provided a cost-effective and time-efficient method for collecting data from a

relatively large number of participants. Additionally, it allowed us to generate a snapshot of current knowledge and attitudes, which enabled us to provide informative information on curriculum development, institutional policy and future research directions.

**Study Setting**

The study was carried out at the MildMay Institute of Health Sciences in Lweza, Wakiso District, 12 km from Kampala. MIHS offers diploma and certificate nursing, midwifery, clinical medicine, nutrition and public health programs. The site is selected because it is a typical health training institution where there is limited evidence on AI literacy; therefore, the findings are of contextual relevance.

**Study population**

All the students enrolled in diploma or certificate courses at MIHS who participated in health-related programs during the data collection period were eligible to be part of our study population. Targeting all the years and programs maximized the heterogeneity and enabled analysis across several years and disciplines.

Given that they were enrolled MIHS students in health-related courses aged above 18 years and provided written informed consent, the participants had to have access to a smartphone, computer or internet-enabled device capable of completing the online questionnaire.

**The inclusion criterion was** students aged 18 and above who voluntarily consented to participate in the study (Ugandan, male and female).

**Exclusion criteria: -** Those who withdraw at the time of data collection or become sick.

**Sample Size Determination**

We used Krejcie and Morgan's table (1970) to determine the sample size for quantitative studies and considered the estimated population of students at the MildMay Institute of Health Science at approximately 500 students. According to the table (Appendix VII), a population of 500 requires a minimum sample size of 217 respondents. Therefore, a sample size of 217 was considered appropriate for this study.

**Sampling Procedure**

The student lists were stratified into cells on the basis of the program and year. Within each cell, the participants were chosen on the basis of computer-generated random numbers until the required number was reached. Stratification enabled us to reduce sampling bias and improve generalizability. If a selected student refused, the next randomly selected student in the same cell was invited to maintain and reach sample size.

**Data collection instrument and rationale.**

Data were collected by a self-administered structured questionnaire based on validated KAP tools used in AI education research. A written questionnaire was selected because it enabled the standardized measurement of multiple constructs and its practicality for large numbers of students made it ideal for my study.

The results were scored in terms of poor, moderate or good knowledge categorization as quantitative outcomes for analysis.

**Data collection procedures**

Data collection was conducted over four weeks. After ethical approval and institutional permission were obtained, the questionnaire link was distributed electronically to health students/participants at the diploma and certificate levels at MIHS. Participants first had to consent at the beginning of

the Google Form before proceeding to the questionnaire. Only those who provided consent electronically continued through to complete the form. Reminder messages were sent periodically to improve the response rate.

**Study Variables**

The dependent variables were level of knowledge (poor/moderate/good), attitude (positive/negative) and the extent of use of AI (none/low/high).

The independent variables were sociodemographic (age, sex, year, and program), technological access (ownership of devices, internet connections, and previous digital experience), and institutional (exposure to AI content in the curriculum, availability of guidance, and access to digital learning facilities). These variables are selected because they are variables that have been suggested in the literature to influence the awareness and adoption of AI.

**Quality Control Measures**

A number of strategies were applied to ensure data quality: Experts in the field of health education and AI reviewed the questionnaire for content validity, and no research assistants were used in the online data collection utilizing Google forms.

The principal investigator monitored the data collected and checked every day that the questionnaires in google forms were properly completed.

Two independent data checkers were used to double check the data during and after collection for any missing values or errors; discrepancies were resolved against the original questionnaires.

No forms had missing responses; no missing values were found in the data.

**Data Analysis**

Data analysis was performed with the help of the computer program "Statistical Package of Social Statistics 25" (SPSS 25). Descriptive statistics (frequencies, percentages, means, and standard deviations) were used to describe the demographic characteristics and outcome variables. Knowledge and attitude scores were classified. Chi-square tests were used to examine associations between independent variables and categorical outcomes (knowledge level and attitude category).

**Ethical Considerations**

The study followed the Declaration of Helsinki. Ethical approval was obtained from the MIHS Research and Ethics Committee and the Uganda National Council for Science and Technology. Participation was voluntary; informed consent was obtained after written and verbal information was provided. Anonymity was assured by using codes in place of names; no personal identifiers were collected. Data were securely stored after completion. There were no incentives, and nonparticipation did not affect academic standing. These measures were used to protect the rights and confidentiality of the participants. Electronic informed consent was obtained before the participants accessed the questionnaire. No names or personal identifiers were collected. The responses remained anonymous and were password protected in the researcher's secure Google account.

**Study Limitations**

The expected limitations include the following: Cross-sectional design: The design is unable to establish causality or temporal change; however, the design is pragmatic for resource-limited KA studies. self-reporting: Respondents were likely to be affected by social desirability or recall bias; anonymity and carefully worded items were used to combat this. Single-institution scope: The results may not be generalizable outside of MIHS; however, this provides critical baseline data for similar diploma-level programs in Uganda. Lack of objective usage data: AI knowledge and use

were based on self-reported frequency as opposed to verified logs; this is common in KA surveys, but future studies could include digital analytics. Online data collection may exclude students with limited internet access or poor connectivity.

**Dissemination Plan**

The results were disseminated through (1) a thesis that we submitted to the MIHS for the Diploma in Clinical Medicine program award and enables implementation of the study recommendations; (2) a study that was presented to MIHS administrators and curriculum committees to inform educational policy; (3) a manuscript submitted to a peer-reviewed journal; and (4) policy briefs distributed to stakeholders such as the Ministry of Health and other health training institutions in Uganda. These channels were used to ensure that evidence reached educators, policy makers and researchers.

# RESULTS

The findings of the study on knowledge and attitudes toward the use of artificial intelligence tools for learning among health sciences students at MildMay Institute of Health Sciences (MIHS), Uganda. All 222 students who were approached for participation completed the questionnaire, yielding a response rate of 100%. This was facilitated by the online self-administered nature of the Google Form questionnaire. Findings are presented using frequency distributions, percentages, and other statistics as appropriate.

4.1 Sociodemographic Characteristics of the Participants

A total of 222 health sciences students participated in the study. Table 1 presents the sociodemographic characteristics of the study participants, including sex, year of study, program of enrollment, device ownership, and internet access

**Table 1:** Sociodemographic Characteristics of the Participants (n=222)

| Variable | Frequency (n) | Percentage (%) |
|---|---|---|
| **Sex** | | |
| Male | 103 | 46.4 |
| Female | 119 | 53.6 |
| **Year of Study** | | |
| Year 1 | 54 | 24.3 |
| Year 2 | 67 | 30.2 |
| Year 3 and above | 98 | 44.1 |
| Other/Irregular | 3 | 1.4 |
| **Program of Enrollment** | | |
| Diploma in Clinical Medicine | 122 | 54.9 |
| Diploma in Nursing | 50 | 22.5 |
| Diploma in Midwifery | 27 | 12.2 |
| Certificate in Nursing | 8 | 3.6 |
| Certificate in Medical Laboratory | 7 | 3.2 |
| Diploma in Public health | 5 | 2.3 |
| Other | 3 | 1.3 |

| | | |
|---|---|---|
| **Owns Smartphone or Computer** | | |
| Yes | 214 | 96.4 |
| No | 8 | 3.6 |
| **Internet Access** | | |
| Yes, always | 119 | 53.6 |
| Yes, sometimes | 87 | 39.2 |
| No | 16 | 7.2 |
| **Total** | **222** | **100.0** |

were in Year 3 or above, while Year 1 and Year 2 students accounted for 24.3% (n=54) and 30.2% (n=67), respectively. Diploma in Clinical Medicine was the most represented program (54.9%, n=122), followed by Diploma in Nursing (22.5%, n=50) and Diploma in Midwifery (12.2%, n=27). Nearly all the participants owned a smartphone or computer (96.4%, n=214), and the vast majority had some form of internet access, either always (53.6%, n=119) or sometimes (39.2%, n=87). Only 7.2% (n=16) reported having no internet access.

### 4.2 Level of Knowledge of AI Use among Health Sciences Students

The first specific objective was to determine the level of knowledge of artificial intelligence (AI) usage among health sciences students at the MildMay Institute of Health Sciences. Knowledge was assessed using four multiple-choice questions (Q6–Q9) covering the definition of AI, identification of an AI learning tool, understanding of how AI helps students, and awareness of AI limitations. Each correct response was given a score of 1, yielding a total possible score of 4.

Students scoring 3 or above were classified as having adequate knowledge, while those scoring below 3 were classified as having inadequate knowledge.

**Table 2:** Percentage of Correct and Incorrect Responses per Knowledge Item (n=222)

| Knowledge Item | Correct (n) | Correct (%) | Incorrect (n) | Incorrect (%) |
|---|---|---|---|---|
| Q6: Definition of Artificial Intelligence | 181 | 81.5 | 41 | 18.5 |
| Q7: Example of an AI learning tool | 194 | 87.4 | 28 | 12.6 |
| Q8: How AI tools help students learn | 201 | 90.5 | 21 | 9.5 |
| Q9: Limitations of AI tools | 187 | 84.2 | 35 | 15.8 |
| **Overall mean score (out of 4): 3.44 (SD=0.85)** | | | | |

As shown in Table 2, the highest percentage of correct responses was recorded for Q8, which asked how AI tools help students learn (90.5%, n=201). The identification of ChatGPT as an AI learning tool was correct for 87.4% (n=194) of the students. Knowledge of AI limitations was correct for 84.2% (n=187) of the students, whereas the definition of AI was correctly identified for 81.5% (n=181) of the students.

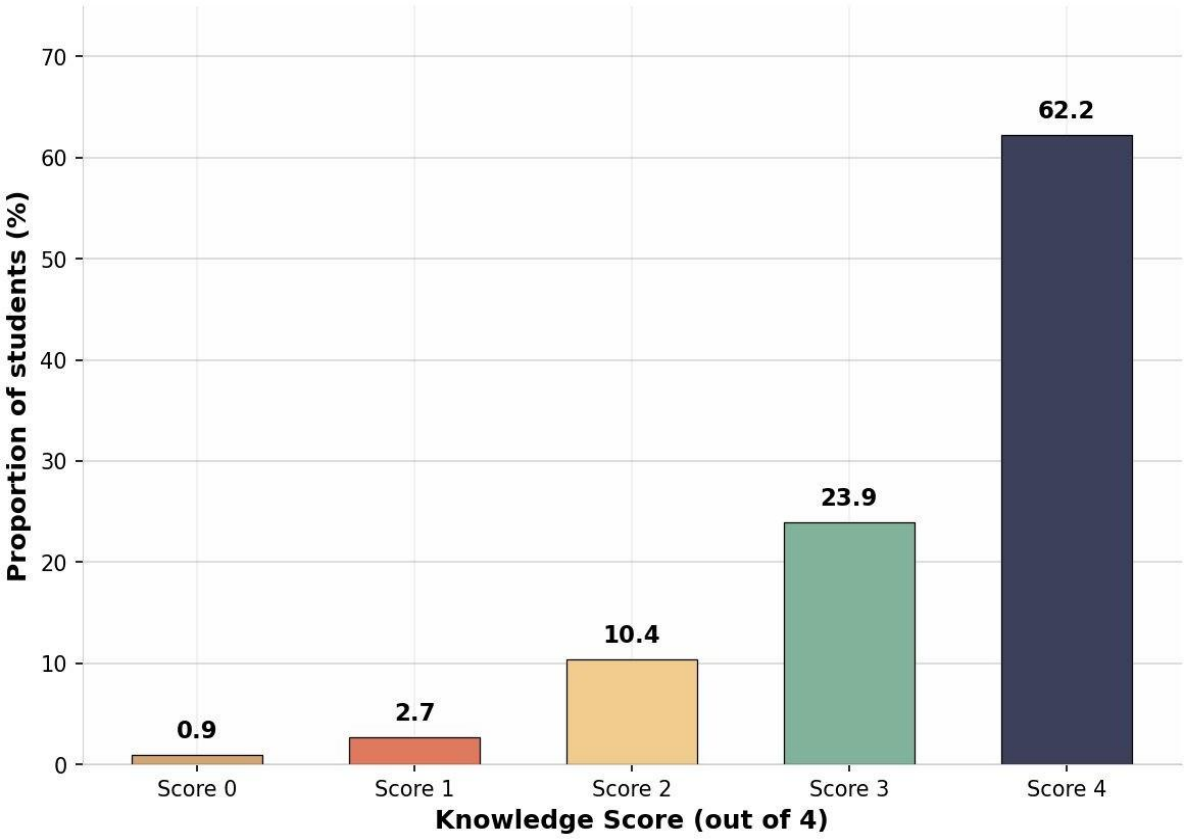



**Figure 1:** Distribution of knowledge scores among health sciences students at MIHS (n=222).

**Note.** Adequate knowledge was defined as a score of 3 or above out of 4.

As shown in Figure 1 above, the majority of the students (86.0%, n=191) demonstrated adequate knowledge of AI tools for learning, scoring 3 or 4 out of 4. The mean knowledge score was 3.44 (SD=0.85). Among those with adequate knowledge, 62.2% (n=138) achieved a perfect score of 4. Only 14.0% (n=31) of the students were classified as having inadequate knowledge (a score less than 3), with 10.4% (n=23) scoring 2, 2.7% (n=6) scoring 1, and 0.9% (n=2) scoring 0. These findings indicate that health sciences students at MIHS possess a predominantly adequate level of knowledge regarding AI tools for learning.

### 4.3 Attitudes toward Artificial Intelligence Use among Health Sciences Students

The second specific objective was to evaluate the attitudes of health sciences students toward artificial intelligence usage at the Mildmay Institute of Health Sciences. Attitudes were measured using four Likert-scale items on a five-point scale ranging from strongly disagree (1) to strongly agree (5). Q13 was a negatively worded item assessing concern about AI's impact on independent thinking; responses to this item are presented as follows to allow direct interpretation. Responses of 'Neutral' and 'Not Sure' were collapsed into a single midpoint category labeled 'Neutral/Not Sure' for reporting purposes. Reliability analysis was conducted using Cronbach's alpha, which yielded a coefficient of 0.32 across the four items. This below-threshold value indicates that the four items do not function as a unidimensional scale, suggesting that they capture distinct attitudinal dimensions rather than a single underlying construct. The results are therefore reported at the item level.

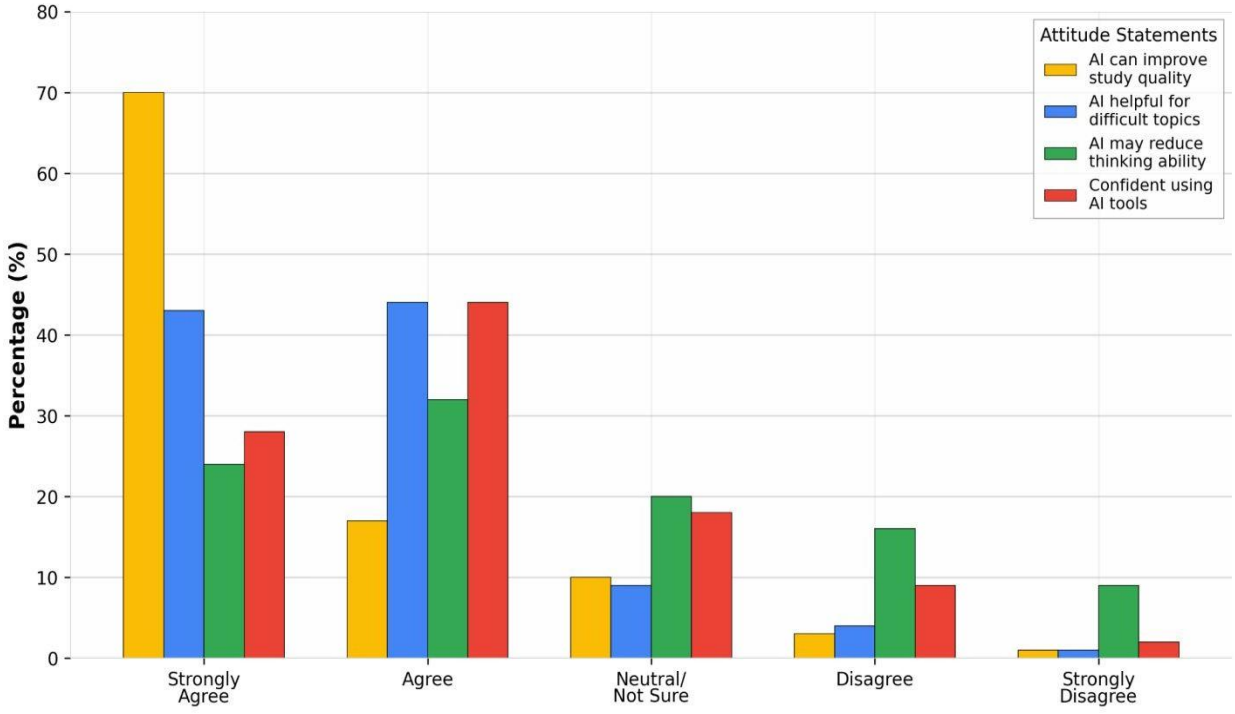



**Figure 2:** Distribution of student responses to attitude items

As presented in Figure 2, students generally expressed positive attitudes toward AI tools for learning. With respect to the perceived helpfulness of AI tools for understanding difficult topics, 86.5% (n=192) of the students agreed or strongly agreed, whereas only 5.0% (n=11) disagreed or strongly disagreed. With respect to confidence in using AI tools for learning, 72.1% (n=160) of the students expressed agreement, although 18.0% (n=40) were neutral or unsure, suggesting that some students remained hesitant in their practical engagement with AI tools. With respect to the most strongly endorsed item, which stated that AI tools can improve the quality of studies when used correctly, 86.5% (n=192) agreed or strongly agreed, including 70.3% (n=156) who strongly agreed.

The negatively worded item concerning worry that AI may reduce independent thinking yielded notably different results from the other three items. A total of 55.4% (n=123) of the students agreed or strongly agreed that they held this concern, while only 24.8% (n=55) disagreed or strongly disagreed. This divergent pattern, where the majority of students simultaneously endorse AI's helpfulness and express concern about its impact on independent thinking, reflects the multidimensional nature of student attitudes toward AI, which is consistent with the low Cronbach's alpha (0.32) recorded for the combined scale. Students appear to hold coexisting positive and cautious orientations toward AI.

### 4.4 Association between Demographic Characteristics and Knowledge Level

To explore whether knowledge level (adequate vs. inadequate) varied by selected demographic characteristics, chi-square tests of independence were conducted. Year 3 and Year 4 students were combined into a single category ('Year 3 and above') because Year 4 had only one respondent (n=1), which would have violated chi-square assumptions regarding minimum expected cell counts. For variables with expected cell counts less than 5 in a 2×2 table (device ownership and

internet access), Fisher's exact test was applied. The results of these analyses are presented in Table 3 below.

**Table 3:** Association between Demographic Characteristics and Knowledge Level (n=222)

| Variable | Adequate n (%) | Inadequate n (%) | Total n | Test Statistic | p value |
|---|---|---|---|---|---|
| **Sex** | | | | | |
| Male | 87 (84.5%) | 16 (15.5%) | 103 | $\chi^2$=0.188, df=1 | 0.664 (NS) |
| Female | 104 (87.4%) | 15 (12.6%) | 119 | | |
| **Year of Study** | | | | | |
| Year 1 | 42 (77.8%) | 12 (22.2%) | 54 | $\chi^2$=3.855, df=2 | 0.146 (NS) |
| Year 2 | 59 (88.1%) | 8 (11.9%) | 67 | | |
| Year 3 and above | 87 (88.8%) | 11 (11.2%) | 98 | | |
| **Device Ownership** | | | | | |
| Yes | 184 (86.0%) | 30 (14.0%) | 214 | Fisher p | 1.000 (NS) |
| No | 7 (87.5%) | 1 (12.5%) | 8 | | |
| **Internet Access** | | | | | |
| Yes (always or sometimes) | 179 (86.5%) | 27 (13.1%) | 206 | Fisher p | 0.250 (NS) |
| No | 12 (75.0%) | 4 (25.0%) | 16 | | |

**Note:** NS = not statistically significant. Fisher's exact test was used for device ownership and internet access because the expected cell counts were less than 5. Year 3 and above includes Year 3 (n=97) and Year 4 (n=1). Three irregular entries were excluded from the year-of-study analysis. All expected cell counts for sex and year chi-square tests met the minimum of 5 (min expected = 7.64 for year analysis). There was no statistically significant association between knowledge level and any of the demographic variables examined. Knowledge levels were similar across sex groups: 84.5% of male students (n=87) and 87.4% of female students (n=104) demonstrated adequate knowledge, with no significant difference (chi-square=0.188, df=1, p=0.664).

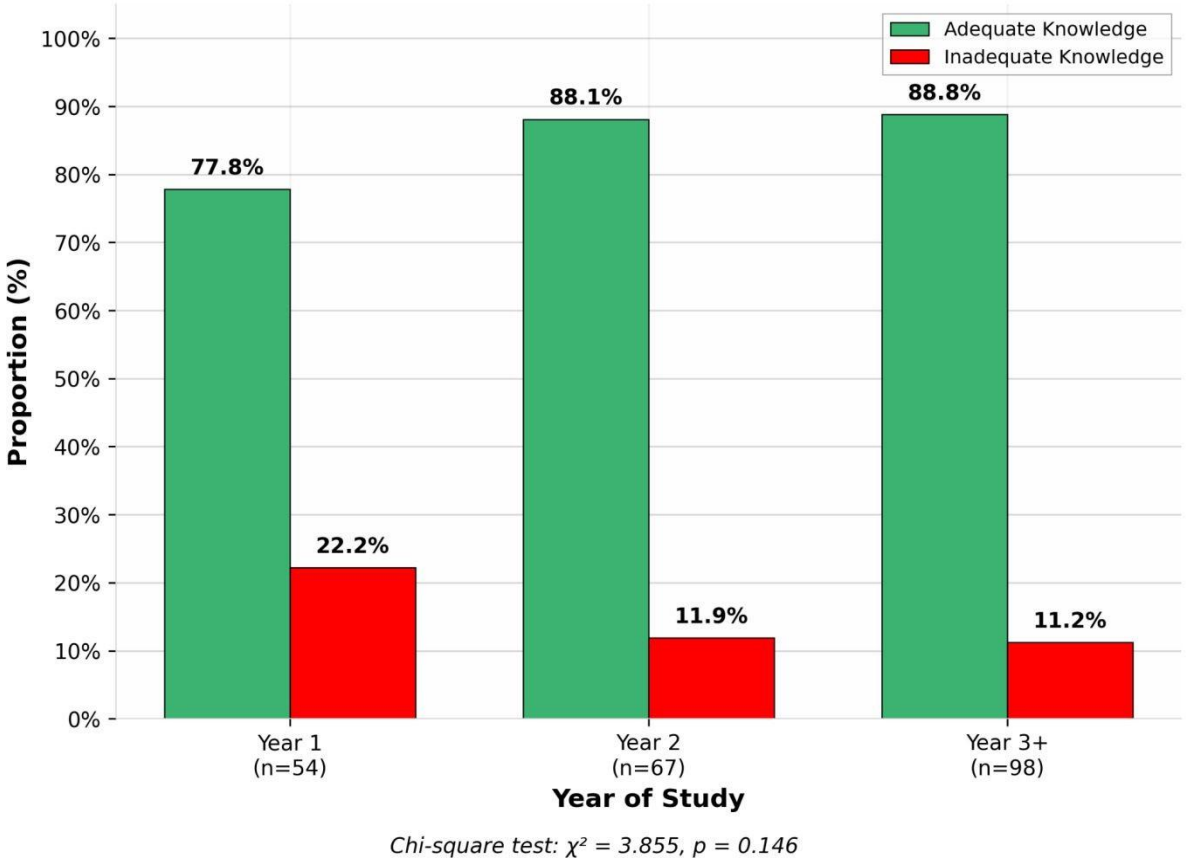



**Figure 3:** Knowledge level (adequate vs. inadequate) by year of study with chi-square test results.

Figure 3: Although there was a trend toward higher proportions of individuals with adequate knowledge in advanced years, 77.8% in Year 1, 88.1% in Year 2, and 88.8% in Year 3, and above this difference, the difference did not reach statistical significance (chi-square=3.855, df=2, p=0.146). Similarly, neither device ownership (Fisher's exact p=1.000) nor internet access (Fisher's exact p=0.250) was significantly associated with knowledge level. These findings suggest that knowledge of AI is distributed broadly across demographic subgroups within the student population at MIHS.

## DISCUSSION

The discussion below addresses each specific objective in a dedicated subsection. Findings are interpreted in relation to comparable studies from global, African and Ugandan contexts.

### 5.1 Level of Knowledge of AI Use among Health Sciences Students at MIHS

The findings of the present study revealed that the overwhelming majority of health sciences students at MIHS demonstrated adequate knowledge of AI tools for learning, with 86.0% (n=191) scoring 3 or above out of a possible score of 4 and a mean knowledge score of 3.44 (SD=0.85). Among those with adequate knowledge, 62.2% (n=138) achieved a perfect score of 4, indicating not only adequate knowledge but also a high level of familiarity with AI concepts as assessed by the instrument. Only 14.0% (n=31) were classified as having inadequate knowledge. Item-level analysis further reinforced this finding: the highest percentage of correct responses was recorded for the item on how AI tools help students learn (90.5%, n=201), followed by the identification of

ChatGPT as an AI tool (87.4%, n=194), knowledge of AI limitations (84.2%, n=187), and the definition of AI (81.5%, n=181).

These findings represent a notable departure from the global literature, which has consistently documented low knowledge of AI among health sciences students. A landmark multicountry cross-sectional survey conducted by Busch *et al*. (2024) involving 4,313 medical, dental, and veterinary students from 192 faculties across 48 countries reported critically poor median knowledge scores of only 2 out of 5, and 76.3% of the students lacked any AI-related courses in their curricula. Similarly, a systematic review and meta-analysis by Amiri *et al*. (2024), pooling data from 8,491 medical, dental, and nursing students across multiple countries, revealed a pooled knowledge proportion of only 44%, compared with the 86.0% adequate knowledge rate observed at MIHS. This difference is substantively meaningful and warrants careful consideration of the methodological and contextual factors that may account for it.

One important explanation for the comparatively higher knowledge scores at MIHS relates to the nature of the knowledge instrument employed. The multiple-choice questionnaire used in this study was used to assess basic AI literacy, including the definition of AI, identification of a common AI tool, and understanding of how AI supports learning and recognition of key limitations. By design, these items measured foundational awareness rather than deep technical literacy, such as algorithmic concepts, machine learning mechanisms, data governance, or clinical AI applications. It is well recognized in the literature that awareness-level knowledge, often acquired through informal self-directed use of AI tools, can be sufficient to score adequately on basic knowledge instruments, even in the absence of formal AI education (Mousavi Baigi *et al.,* 2023; Ajalo *et al.,* 2025). The present results therefore suggest that MIHS students have attained

a satisfactory baseline awareness of AI, not necessarily the deep functional literacy required for responsible AI-enabled clinical practice.

This interpretation is strongly supported by evidence from Uganda. In a cross-sectional study of medical students across public universities in Uganda, Ajalo *et al*. (2025) reported that 93% had heard about AI tools and that 75.7% had actively used them for academic tasks, including assignments, tutorial preparation, and examination studies. The widespread informal adoption of tools such as ChatGPT among Ugandan students is likely a major driver of the awareness-level knowledge captured in this study. The high degree of device ownership (96.4%, n=214) and internet access (92.8% with always or sometimes access) documented among MIHS participants further supports the plausibility of informal, self-directed AI tool exposure as a key source of knowledge at this institution. When nearly all students own a device and have internet access, informal engagement with AI tools is a realistic and likely pathway through which basic AI knowledge is acquired, even in the absence of structured curriculum content.

In terms of year of study, while a directional trend was observed, with adequate knowledge rates of 77.8% in Year 1 increasing to 88.1% in Year 2 and 88.8% in Year 3 and above, this difference did not reach statistical significance (chi-square=3.855, df=2, p=0.146). The absence of a statistically significant association between year of study and knowledge level is consistent with the view that knowledge acquisition in this context is driven primarily by informal exposure rather than formal cumulative learning through the curriculum. If AI were formally taught within the health sciences programs at MIHS, a more pronounced and statistically significant increase in knowledge scores across years of study would have been expected, as observed in settings with structured AI curricula (Abid *et al.,* 2024). The null finding here therefore indirectly confirms the informal, curriculum-independent nature of AI knowledge acquisition at MIHS.

The absence of significant demographic associations with knowledge, including sex (p=0.664), device ownership (Fisher's p=1.000), and internet access (Fisher's p=0.250), is also notable. The nonsignificant association with sex differs from that in the global literature, which has occasionally documented sex differences in AI knowledge and confidence levels, particularly in studies from high-income countries where males have been found to demonstrate higher AI familiarity (Busch *et al.,* 2024). One plausible explanation in the MIHS context is that the uniform near-universal ownership of devices and internet access across the student population minimizes the structural gender divide in technology access that, in some other settings, creates sex-based knowledge disparities. In a systematic review of AI knowledge, attitudes, practices, and barriers in nursing and health sciences education, Alqaissi and Qtait (2025) reported that access to digital technology was a stronger determinant of AI knowledge than sex was, which is consistent with the potential equalization effect at work in this study population. The equitable distribution of device ownership and internet access across the MIHS student population may thus have leveled the playing field for AI knowledge acquisition, producing broadly similar outcomes across demographic subgroups.

Despite the predominantly adequate knowledge scores, the finding that 14.0% of students remain inadequately informed about AI is educationally significant in a health profession training context. These students, while minority, may be at heightened risk of uncritical or unsafe AI use, misinterpreting AI-generated clinical content or being disadvantaged in AI-augmented health service delivery environments. Furthermore, the observed finding that even among those with adequate basic knowledge, a nontrivial proportion (10.4%, n=23) scored exactly 2 out of 4, placing them on the boundary of adequacy, suggests that the knowledge base of MIHS students remains fragile and disproportionately dependent on informal learning pathways. As Topol (2019) argued, the integration of AI into high-performance medicine demands not surface familiarity but deep

conceptual and critical literacy that enables health professionals to interrogate AI outputs, recognize error states, and communicate AI-mediated findings to patients and colleagues with accuracy and confidence. The present findings, while encouraging in terms of baseline awareness, thus point firmly toward the need for structured AI curriculum content that elevates student knowledge from awareness to competence.

From a methodological standpoint, the current study employed a cross-sectional design with a four-item binary-scored knowledge instrument. While this approach is pragmatic, widely used in KAP studies (Launiala, 2009), and appropriate for estimating the prevalence of knowledge levels within the population at a defined point in time (Creswell, 2020), it has acknowledged limitations in terms of knowledge depth and construct coverage. A more comprehensive multi-item knowledge instrument with items spanning algorithmic principles, clinical AI applications, data ethics and AI limitations would provide a richer and more nuanced picture of AI literacy among MIHS students in future research. The researcher's informed opinion is that the 86.0% adequate knowledge finding should be understood as a baseline of awareness rather than a declaration of AI literacy competence and that it should motivate targeted investment in deepening, formalizing AI education rather than complacency about the current state of student preparedness.

5.2 Attitudes toward AI Use among Health Sciences Students at MIHS

The second major area of inquiry concerned the attitudes of MIHS health science students toward the use of AI for learning. The findings reveal a predominantly positive attitudinal orientation, characterized by strong agreement with the perceived helpfulness and quality-enhancing potential of AI, alongside a simultaneously prominent concern about the impact of AI on students' capacity for independent thinking. This dual cooccurring pattern of enthusiasm and reservation constitutes

the defining attitudinal signature of the MIHS student population and represents the central finding of this objective.

With respect to the item assessing the perceived helpfulness of AI tools for understanding difficult health science topics, 86.5% (n=192) of the students agreed or strongly agreed, with only 5.0% (n=11) disagreeing or strongly disagreeing. The most strongly endorsed item across the entire attitude scale was the statement that AI tools can improve the quality of studies when used correctly, which resulted in 86.5% agreement (n=192), including 70.3% (n=156) who strongly agreed. This level of strongly positive endorsement is among the highest documented in comparable studies. In a cross-sectional study of 702 Pakistani medical students, Sami *et al*. (2025) reported that 80.3% held a favorable attitude toward AI, with 65.7% reporting that AI was more efficient than traditional methods for grasping medical concepts were. The MIHS figures of 86.5% are broadly consistent with, and in some cases exceed, these global benchmarks. Similarly, Tung and Dong (2023) reported that 87.36% of Malaysian medical students considered AI to be a key future feature of healthcare, and 71% believed that AI training would benefit their professional careers, which is closely aligned with the attitudinal orientation observed at MIHS.

These findings are also consistent with the global systematic review by El-Banna *et al*. (2025) of 42 studies from 2016 to 2024, which established that health sciences students worldwide hold predominantly positive perceptions of AI's educational potential, and with the systematic review by Alqaissi and Qtait (2025), which similarly reported that favorable attitudes toward AI integration in nursing and health sciences education are widespread across global settings. The high positivity of MIHS student attitudes despite the absence of formal AI curriculum content resonates with Mousavi Baigi *et al*. (2023), whose systematic review revealed that while 76% of healthcare students held positive outlooks on AI, positive attitudes did not necessarily follow from

formal education, often preceding it in institutions without structured AI training. This suggests that positive attitudes are organic and preinstitutional in origin at MIHS, fuelled by students' own informal engagement with AI tools and that they constitute a valuable motivational resource available to educators who wish to build structured AI learning experiences.

The finding regarding confidence in using AI tools for learning presents a more qualified picture. While 72.1% (n=160) of the students expressed agreement or strong agreement with confidence in AI use, 18.0% (n=40) remained neutral or unsure, and 9.9% (n=22) disagreed. This confidence gap, where the proportion of individuals who are confident in using AI (72.1%) is notably lower than the proportion who perceive AI as helpful or quality improving (both 86.5%), has important implications when interpreted through the lens of the technology acceptance model (TAM). Venkatesh *et al*. (2022) identified perceived usefulness and perceived ease of use as the two primary determinants of the behavioral intention to use a technology, with perceived ease of use feeding into perceived usefulness over time. The present findings suggest that while MIHS students strongly perceive AI as useful (high perceived usefulness), a meaningful subset has not yet internalized the ease of use associated with confident, self-directed AI tool engagement. This confidence deficit likely reflects the informal, unsupported nature of AI skill acquisition at MIHS, where students learn through trial and error rather than guided instruction. Tung and Dong (2023) similarly reported that among Malaysian medical students, only 44.5% felt confident that they would have sufficient AI knowledge by graduation, despite broadly positive attitudinal orientations, suggesting that the confidence gap is not unique to MIHS but reflects a global pattern in settings without formal AI education.

The most revealing attitudinal finding of the study emerged from the negatively worded item addressing concern that AI use may reduce students' capacity for independent thinking. A majority

(55.4%) of the students (n=123) agreed or strongly agreed with this concern, whereas only 24.8% (n=55) disagreed or strongly disagreed, and 19.8% (n=44) remained neutral. These findings are especially significant in a diploma-level health training context, where the development of foundational clinical reasoning, diagnostic thinking, and patient-centered decision-making is not merely an academic goal but a direct professional safety requirement. That more than half of all students are themselves concerned about the cognitive cost of AI reliance is a self-aware and educationally important finding that merits direct attention from educators and curriculum developers.

This concern is strongly corroborated by the international literature. In a qualitative study of 38 medical students in Sri Lanka, Seneviratne *et al*. (2025) reported that while students valued AI as a time-saving content synthesis tool, they expressed deep anxieties about the erosion of critical thinking, the inaccuracy of AI outputs, and the absence of faculty-guided ethical instruction. Longoni *et al*. (2019) documented patterns of resistance to medical AI rooted precisely in concerns about accountability and the perceived threat to professional cognitive agency. In a study of health profession students in Jordan, Al-Qerem *et al*. (2023) reported that skepticism regarding AI's ability to replace human educators coexisted with positive recognition of AI's educational value, a co-occurrence closely mirroring the pattern at MIHS. Vojdani *et al*. (2025) further reported that among Iranian medical students, 73.7% expressed concern that AI could discredit the medical profession and that professional anxiety frequently coexisted with positive views on AI usefulness, a pattern of psychological ambivalence consistent with the MIHS findings.

The low Cronbach's alpha of 0.32 obtained for the combined four-item attitude scale, which is below the conventional threshold of 0.7 for scale reliability, is an important finding in its own right. Rather than simply indicating psychometric inadequacy, this value reflects the

multidimensional nature of student attitudes toward AI, an interpretation that is empirically justifiable and theoretically grounded. Shishehgar *et al*. (2025), in a systematic review of health students' and academics' knowledge, perceptions, and experiences of AI, concluded that attitudes toward AI in health education are inherently multidimensional, varying across dimensions of utility, confidence, ethical concern, professional identity, and academic integrity, such that single-construct attitude scales frequently fail to capture attitudinal complexity in this domain. The finding that MIHS students simultaneously endorse AI's helpfulness and express concern about its cognitive impact does not contradict; it reflects the genuine tension between AI's functional utility and its potential to disrupt the cognitive development processes fundamental to health profession education. Reporting attitudes at the item level, as was done in this study, is therefore the methodologically appropriate approach for this population and is consistent with the recommendation by Shishehgar *et al*. (2025) that AI attitude measurement in health education research should address dimensional complexity rather than presupposing internal consistency.

From an African and Ugandan contextual lens, the attitudes documented at MIHS are broadly consistent with but extend the limited available evidence. Wobo *et al*. (2025) reported that medical students in Nigeria held positive views on the educational and diagnostic value of AI while simultaneously expressing concern about ethical issues, data privacy, and the appropriateness of AI tools in resource-limited settings. In Uganda, Mukunya *et al*. (2025) reported that health professional educators expressed a deeply ambivalent stance toward AI, acknowledging its pedagogical potential while articulating serious concerns about examination malpractice risks, the inability to afford paid AI versions, and the complete absence of institutional policy frameworks to guide AI use in health training. The student-level evidence from MIHS aligns with and extends this educator-level pattern: the absence of institutional policy and structured guidance does not

suppress positive attitudinal dispositions among students, but it leaves those dispositions unmoored from the ethical frameworks, critical literacies, and supervised practice experiences necessary to translate them into responsible and beneficial behavior.

The researcher is of the informed view that the dual attitudinal profile observed at MIHS, positive but cautious, represents both an opportunity and a responsibility for the institution. The majority of students are intrinsically motivated to use AI as a learning tool and possess device access and internet connectivity to do so. What they currently lack are structured guidance, ethical scaffolding, and supervised practice opportunities. Left to informal self-direction, the risk is that students develop uncritical AI dependence that undermines the clinical reasoning competencies that are central to safe health professional practices. Harnessed through evidence-informed curriculum integration, these same positive attitudes could become powerful drivers of AI-literate, ethically grounded, and critically capable health professionals. The urgency of this challenge is amplified by the finding that the majority of MIHS students are already using tools such as ChatGPT informally; the question is no longer whether to engage with AI in health training but how to do so responsibly, equitably, and with educational integrity.

**Limitations of the Study**

This study followed an established cross-sectional KAP methodology (Launiala, 2009; Creswell, 2014); however, several limitations must be acknowledged. First, the cross-sectional design offers only a single snapshot of knowledge and attitudes, limiting causal inference about the determinants of AI knowledge or attitude formation. Longitudinal studies are needed to assess the impact of curriculum interventions over time. Second, the basic binary-scored knowledge instrument is suitable for this baseline and aligns with the 75% adequacy threshold as stated by Daniel & Cross in 2013; it measures only basic awareness-level AI literacy. It does not capture a deeper conceptual

understanding, practical skills or applied AI literacy in clinical settings. Future studies should use more comprehensive validated instruments with proven reliability and validity in LMIC health education.

Third, the reliance on self-reported data may introduce social desirability bias, especially in terms of attitudinal items, as students could report more positive responses to align with perceived expectations. An anonymous online survey was used to reduce this risk, although it cannot be fully eliminated. Fourth, the findings are from a single institution (MIHS) and may not be generalizable to all diploma-level health training institutions in Uganda or Sub-Saharan Africa, as factors such as demographics, device access, internet provision, and culture differ across settings. Replication in other institutions is recommended.

Fifth, the Cronbach's alpha of the attitude scale is 0.32, indicating poor internal consistency and confirming that the four items do not form a unidimensional scale. While this may reflect the multidimensional nature of student attitudes toward AI, it limits the calculation of composite scores and constrains statistical analysis. Future research should use established, validated attitudinal instruments with demonstrated reliability, such as the MAIRS-MS (Tung & Dong, 2023) or other scales developed for health profession students.

### 5.4 Recommendations

#### 5.4.1 To MildMay Institute of Health Sciences Administration

First, a structured AI literacy module should be integrated into all diploma and certificate curricula. This should cover basic AI concepts, practical applications, ethical use, and supervised practice. Start with a pilot cohort, evaluate the results, and roll out broadly. Second, an institutional AI use policy covering acceptable uses, disclosure requirements, assessment standards, and safeguards

against misuse should be developed. Students, staff, and the research committee should be involved in policy development, which should be communicated through orientation programs. Third, regular case-based exercises that require students to make independent judgments before using AI tools are introduced. Provide staff with professional development on designing AI-complementary teaching that maintains critical reasoning.

5.4.2 Academic Staff and Curriculum Developers

First, they should engage in ongoing professional development on AI in health education. Faculty must stay ahead of student practice to guide ethical and effective AI use. MIHS leadership should facilitate access to relevant courses and learning communities. Second, reassign assessments to strengthen academic integrity. Shift focus to tasks requiring higher-order reasoning and real-world clinical application that cannot be easily completed by AI. Organize a workshop to update assessment practices and share best practices across departments.

5.4.3 To the Uganda Health Professions Assessment Board (UAHEB) and Ministry of Education

First, national minimum AI literacy standards for diploma-level health graduates should be established. Consultively with stakeholders to define clear competency benchmarks, following global best practices. Second, digital access inequities should be addressed by supporting subsidized institutional AI tool subscriptions, improving internet access, and integrating AI infrastructure into national planning. Launch a Digital Access for Health Training initiative focused on diploma institutions.

5.4.4 Future Researchers

Mixed-methods research is used to capture both quantitative and qualitative aspects of AI literacy, including student and faculty experience. Develop and validate comprehensive AI literacy assessment tools suited for low- and middle-income health education settings. Longitudinal and

multi-institutional studies should be conducted to measure the impact of interventions and assess the wider applicability of the findings.

**Conclusions**

The overarching aim of this study was to assess the level of artificial intelligence (AI) knowledge and attitudes among health sciences students at the MildMay Institute of Health Sciences (MIHS). The findings clearly indicate that MIHS students possess predominantly adequate basic AI knowledge, with 86.0% meeting the established adequacy threshold and a mean score of 3.44 out of 4. Additionally, 86.5% of the students reported demonstrating a generally positive orientation toward the use of AI in learning, with 86.5% agreeing that AI tools are helpful for understanding complex topics and improving study quality.

Despite these strengths, the study revealed that most knowledge is at the awareness level and is acquired informally rather than through structured curriculum content. Positive attitudes are characterized by a significant confidence gap in practical AI use and ongoing concerns about the impact of AI on independent thinking. These results highlight the absence of formal AI literacy education, clear institutional policies, and structured pedagogical support at MIHS. The practical and academic value of these conclusions is clear: Integrating comprehensive AI literacy into the health sciences curriculum, supported by robust institutional policies and faculty development, is urgently needed. Such steps ensure that students not only remain technologically and attitudinally prepared but are also equipped with the critical skills required for responsible and effective AI use in healthcare.

In summary, this study establishes a foundational evidence base for targeted curriculum reform and institutional policy at MIHS. By acting on these recommendations, MIHS has the opportunity

to lead AI literacy integration at the diploma level in Uganda, thereby shaping a future-ready, competent, and ethically grounded health workforce.

**Implications for Health Profession Practice**

This study reveals several important implications for health profession practices in Uganda, including clinical competency, patient safety, education reform, health system strengthening, and ethical AI governance, as stated below.

A majority (86.0%) of MIHS students have basic knowledge of AI, but they lack formal training. This gap between awareness and responsible practices exposes patients to safety risks, especially in primary and district-level facilities. Curriculum reform is needed to equip graduates with critical AI literacy, ensuring safe and effective AI integration in clinical practice. More than half (55.4%) of the students expressed concern that AI may reduce independent thinking. If AI is used to shortcut clinical reasoning during training, essential competencies may be weakened. Educators are urged to redesign teaching methods to preserve and strengthen critical thinking and independent judgment.

Professional identity is also affected. While students generally view AI positively, concerns about cognitive independence persist. Education must frame AI as a supportive tool that enhances rather than replaces core human skills such as empathy, ethics, and communication. At the system level, Uganda's digital health agenda depends on a workforce that is AI-literate and ethically grounded. Without adequate preparation at the diploma level, the benefits of digital health investments may not be realized. Embedding AI literacy and ethics in training is both an educational and strategic system priority.

In teaching, a flipped or inquiry-based model is recommended. Students' informal AI knowledge should be the foundation for structured, ethical, and practical skill development. This approach builds confidence and competence in AI use. Equity concerns are highlighted by the focus of most research and policy on university-level students, while diploma-level graduates make up the majority of Uganda's frontline health workforce. This study demonstrates the need for AI literacy investment at diploma institutions such as MIHS to ensure that all health professionals are prepared for AI-enabled care. Principles of transparency, fairness, and human agency must guide both AI development and the training of health professionals.

**REFERENCES**


1. Abid, A., Murugan, A., Banerjee, I., Purkayastha, S., Trivedi, H., & Gichoya, J. (2024). AI education for fourth-year medical students: Two-Year experience of a web-based, self-guided curriculum and mixed methods study. *JMIR Medical Education*, *10*, e46500. https://doi.org/10.2196/46500
2. Ahsan, Z. (2025). Integrating artificial intelligence into medical education: A narrative systematic review of current applications, challenges, and future directions. *BMC Medical Education*, *25*(1), 1187-. https://doi.org/10.1186/s12909-025-07744-0
3. Ajalo, E., Mukunya, D., Nantale, R., Kayemba, F., Pangholi, K., Babuya, J., Akuu, S. L., Namiiro, A. M., Nsubuga, Y. B., Mpagi, J. L., Musaba, M. W., Oguttu, F., Kuteesa, J., Mubuuke, A. G., Munabi, I. G., & Kiguli, S. (2025). Widespread use of ChatGPT and other Artificial Intelligence tools among medical students in Uganda: A cross-sectional study. *PLOS ONE*, *20*(1). https://doi.org/10.1371/journal.pone.0313776
4. Alqaissi, N., & Qtait, M. (2025). Knowledge, attitudes, practices, and barriers regarding the integration of artificial intelligence in nursing and health sciences education: A systematic review. *SAGE Open Nursing*, *11*, 23779608251374184. https://doi.org/10.1177/23779608251374185

5. Al-Qerem, W., Eberhardt, J., Jarab, A., Bawab, A. Q. A., Hammad, A., Alasmari, F., Alazab, B., Husein, D. A., Alazab, J., & Al-Beool, S. (2023). Exploring knowledge, attitudes, and practices toward artificial intelligence among health professions' students in Jordan. *BMC Medical Informatics and Decision Making*, *23*(1), 288-. https://doi.org/10.1186/s12911-023-02403-0
6. Amiri, H., Peiravi, S., Rezazadeh Shojaee, S. S., Rouhparvarzamin, M., Nateghi, M. N., Etemadi, M. H., ShojaeiBaghini, M., Musaie, F., Anvari, M. H., & Asadi Anar, M. (2024). Medical, dental, and nursing students' attitudes and knowledge toward artificial intelligence: A systematic review and meta-analysis. *BMC Medical Education*, *24*(1), 412. https://doi.org/10.1186/s12909-024-05406-1
7. Boyacı, H., & Söyük, S. (2025). Healthcare workers' readiness for artificial intelligence and organizational change: A quantitative study in a university hospital. *BMC Health Services Research*, *25*(1), 813-. https://doi.org/10.1186/s12913-025-12846-y
8. Buabbas, A. J., Miskin, B., Alnaqi, A. A., Ayed, A. K., Shehab, A. A., Syed-Abdul, S., & Uddin, M. (2023). Investigating students' perceptions toward artificial intelligence in medical education. *Healthcare*, *11*(9). https://doi.org/10.3390/healthcare11091298
9. Busch, F., Hoffmann, L., Truhn, D., Ortiz-Prado, E., Makowski, M. R., Bressem, K. K., Adams, L. C., & COMFORT Consortium. (2024). Global cross-sectional student survey on AI in medical, dental, and veterinary education and practice at 192 faculties. *BMC Medical Education*, *24*(1), 1066. https://doi.org/10.1186/s12909-024-06035-4
10. Creswell, J. W. (2014). Research Design Qualitative, Quantitative and Mixed Methods Approaches (4th ed.). Thousand Oaks, CA Sage. - References. (n.d.). Scientific Research Publishing. https://www.scirp.org/reference/ReferencesPapers?ReferenceID=1964849
11. Creswell, J. W., & Creswell, J. D. (2020). Research Design Qualitative, Quantitative, and Mixed Methods Approaches (5th ed.). SAGE. - References. (n.d.). Scientific Research Publishing. https://www.scirp.org/reference/referencespapers?referenceid=3491413

12. Creswell, J. W., & Plano Clark, V. L. (2018). Designing and Conducting Mixed Methods Research (3rd ed.). Thousand Oaks, CA SAGE. - References. (n.d.). Scientific Research Publishing. https://www.scirp.org/reference/referencespapers?referenceid=2697821
13. Daniel, W. W., & Cross, C. L. (2013). Biostatistics: A foundation for analysis in the health sciences (10th ed.). Wiley.
14. Davenport, T., & Kalakota, R. (2019). The potential for artificial intelligence in healthcare. *Future Healthcare Journal*, *6*(2), 94–98. https://doi.org/10.7861/futurehosp.6-2-94
15. El-Banna, M. M., Sajid, M. R., Rizvi, M. R., Sami, W., & McNelis, A. M. (2025). AI literacy and competency in nursing education: Preparing students and faculty members for an AI-enabled future-a systematic review and meta-analysis. *Frontiers in Medicine*, *12*, 1681784. https://doi.org/10.3389/fmed.2025.1681784
16. Feigerlova, E., Hani, H., & Hothersall-Davies, E. (2025). A systematic review of the impact of artificial intelligence on educational outcomes in health professions education. *BMC Medical Education*, *25*(1), 129. https://doi.org/10.1186/s12909-025-06719-5
17. Issa, W. B., Shorbagi, A., Al-Sharman, A., Rababa, M., Al-Majeed, K., Radwan, H., Ahmed, F. R., Al-Yateem, N., Mottershead, R., Abdelrahim, D. N., Hijazi, H., Khasawneh, W., Ali, I., Abbas, N., & Fakhry, R. (2024). Shaping the future: Perspectives on the Integration of Artificial Intelligence in health profession education: A multicountry survey. *BMC Medical Education*, *24*(1), 1166-. https://doi.org/10.1186/s12909-024-06076-9
18. Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., Wang, Y., Dong, Q., Shen, H., & Wang, Y. (2017). Artificial intelligence in healthcare: Past, present and future. *Stroke and Vascular Neurology*, *2*(4). https://doi.org/10.1136/svn-2017-000101
19. Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., Wang, Y., Dong, Q., Shen, H., & Wang, Y. (2017). Artificial intelligence in healthcare: Past, present and future. *Stroke and Vascular Neurology*, *2*(4). https://doi.org/10.1136/svn-2017-

20. Kotecha, D., Asselbergs, F. W., Achenbach, S., Anker, S. D., Atar, D., Baigent, C., Banerjee, A., Beger, B., Brobert, G., Casadei, B., Ceccarelli, C., Cowie, M. R., Crea, F., Cronin, M., Denaxas, S., Derix, A., Fitzsimons, D., Fredriksson, M., Gale, C. P., … Grobbee, D. E. (2022). CODE-EHR best-practice framework for the use of structured electronic health-care records in clinical research. *The Lancet Digital Health*, *4*(10), e757–e764. https://doi.org/10.1016/S2589-7500(22)00151-0
21. Krejcie, R. V., & Morgan, D. W. (1970). Determining sample size for research activities. Educational and Psychological Measurement, 30(3), 607–610.
22. Kung, T. H., Cheatham, M., Medenilla, A., Sillos, C., Leon, L. D., Elepaño, C., Madriaga, M., Aggabao, R., Diaz-Candido, G., Maningo, J., & Tseng, V. (2023). Performance of ChatGPT on USMLE: Potential for AI-assisted medical education using large language models. *PLOS Digital Health*, *2*(2). https://doi.org/10.1371/journal.pdig.0000198
23. Launiala, A. (2009). How much can a KAP survey tell us about people's knowledge, attitudes and practices? Some observations from medical anthropology research on malaria in pregnancy in Malawi. *Anthropology Matters*, *11*(1). https://doi.org/10.22582/am.v11i1.31
24. Li, Q., & Qin, Y. (2023). AI in medical education: Medical student perception, curriculum recommendations and design suggestions. *BMC Medical Education*, *23*(1), 852-. https://doi.org/10.1186/s12909-023-04700-8
25. Longoni, C., Bonezzi, A., & Morewedge, C. K. (2019). Resistance to medical artificial intelligence. *Journal of Consumer Research*, *46*(4), 629–650. https://doi.org/10.1093/jcr/ucz013
26. Ma, Q. (2005, January 1). *The technology acceptance model: a meta-analysis of empirical findings*. IGI Global Scientific Publishing. https://www.igi-global.com/gateway/chapter/4475
27. Masters, K. (2019). Artificial intelligence in medical education. *Medical Teacher*, *41*(9), 976–980. https://doi.org/10.1080/0142159x.2019.1595557
28. Matheny, M., Thadaney, S., & Beam, A. (2020). *Artificial intelligence in health care: The hope, the hype, the promise, the peril*. NAM.

https://nam.edu/publications/artificial-intelligence-in-health-care-the-hope-the-hype-the-promise-the-peril/

29. Mousavi Baigi, S. F., Sarbaz, M., Ghaddaripouri, K., Ghaddaripouri, M., Mousavi, A. S., & Kimiafar, K. (2023). Attitudes, knowledge, and skills toward artificial intelligence among healthcare students: A systematic review. *Health Science Reports*, *6*(3), e1138. https://doi.org/10.1002/hsr2.1138
30. Mukunya, D., Nantale, R., Paungholi, K., Epuitai, J., Kayemba, F., Jemba, B., Ajalo, E., Afodun, A., Musaba, M. W., Munabi, I. G., Kiguli, S., & Mubuuke, A. G. (2025). "I can no longer give take-home exams": Health professionals educators' experiences and perceptions regarding the use of artificial intelligence in health professions education in Uganda. *BMC Medical Education*, *25*(1), 1361-. https://doi.org/10.1186/s12909-025-07933-x
31. Okolo, C. T., Aruleba, K., & Obaido, G. (2023, January 1). Responsible AI in Africa—challenges and opportunities. Springer International Publishing. https://link.springer.com/chapter/10.1007/978-3-031-08215-3_3
32. Oladipo, E. K. (2024). Impact and challenges of artificial intelligence integration in the African health sector: a review. https://tmr.scione.com/cms/fulltext.php?id=144
33. Rajkomar, A., Dean, J., & Kohane, I. (2019). Machine learning in medicine. New England Journal of Medicine, *380*(14), 1347–1358. https://doi.org/10.1056/nejmra1814259
34. Sami, A., Tanveer, F., Sajwani, K., Kiran, N., Javed, M. A., Ozsahin, D. U., Muhammad, K., & Waheed, Y. (2025). Medical students' attitudes toward AI in education: Perception, effectiveness, and its credibility. *BMC* Medical Education, 25(1), 82. https://doi.org/10.1186/s12909-025-06704-y
35. Santos, D. P. dos, Giese, D., Brodehl, S., Chon, S. H., Staab, W., Kleinert, R., Maintz, D., & Baeßler, B. (2018). Medical students' attitude toward artificial intelligence: A multicenter survey. European Radiology, 29(4), 1640–1646. https://doi.org/10.1007/s00330-018-5601-1

36. Sapci, A. H. (2020). Artificial intelligence education and tools for medical and health informatics students: Systematic review. JMIR Medical Education, 6(1). https://doi.org/10.2196/19285
37. Seneviratne, T., Kodikara, K., Abeykoon, I., & Palpola, W. (2025). Perception of medical undergraduates on artificial intelligence in medical education: Qualitative exploration. JMIR Medical Education, 11, e73798. https://doi.org/10.2196/73798
38. Shaw, K., Henning, M. A., & Webster, C. S. (2025). Artificial intelligence in medical education: A scoping review of the evidence for efficacy and future directions. Medical Science Educator, 35(3), 1803–1816. https://doi.org/10.1007/s40670-025-02373-0
39. Shishehgar, S., Murray-Parahi, P., Alsharaydeh, E., Mills, S., & Liu, X. (2025). Artificial intelligence in health education and practice: A systematic review of health students' and academics' knowledge, perceptions and experiences. International Nursing Review, *72*(2), e70045. https://doi.org/10.1111/inr.70045
40. Srinivasu, P. N., Sandhya, N., Jhaveri, R. H., & Raut, R. (n.d.). From blackbox to explainable AI in healthcare: existing tools and case studies. Mobile Information Systems, *2022*(1). https://doi.org/10.1155/2022/8167821
41. Topol, E. J. (2019). High-performance medicine: The convergence of human and artificial intelligence. Nature Medicine, *25*(1), 44–56. https://doi.org/10.1038/s41591-018-0300-7
42. Tung, A. Y. Z., & Dong, L. W. (2023). Malaysian medical students' attitudes and readiness toward AI (artificial intelligence): A cross-sectional study. *Journal of Medical* Education and Curricular Development, 10, 23821205231201164. https://doi.org/10.1177/23821205231201164
43. Vasudevan, R., Alqahtani, T., Alqahtani, S., Devanandan, P., Kandasamy, G., Saad, R., Amer, A., Abduallah, R., Waleed, G., Hasan, R., & Ahmed, L. (2025). Integrating AI in healthcare education: Attitudes of pharmacy students at King Khalid University toward using ChatGPT in clinical decision-making. *Healthcare*, *13*(11). https://doi.org/10.3390/healthcare13111265

44. Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. MIS Quarterly, 36(1), 157–178.
45. Vojdani, S., Najibi, S. M., Niknam, B., Daneshfard, B., Salehi-Marzijarani, M., Azgomi, R. N. D., & Hashempur, M. H. (n.d.). Evaluation of knowledge, attitude, and practice of Iranian medical students toward complementary and alternative medicine: a cross-sectional survey. Health Science Reports, 8(3). https://doi.org/10.1002/hsr2.70539
46. WHO. (2021, June 28). Ethics and governance of artificial intelligence for health. *World Health* Organization. https://www.who.int/publications/i/item/9789240029200
47. Wobo, K. N., Nnamani, I. O., Alinnor, E. A., Gabriel-Job, N., & Paul, N. (2025). Medical students' perception of the use of artificial intelligence in medical education. International Journal of Research in Medical Sciences, *13*(1), 82–89. https://doi.org/10.18203/2320-6012.ijrms20244099