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Knowledge, attitudes and practices regarding artificial intelligence among pharmacy students in Guinea and Malawi: a cross-national, multicentre cross-sectional study

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Abstract

Background

Generative artificial intelligence (AI) has entered pharmacy education faster than curricula have adapted, yet evidence on how pharmacy students in sub-Saharan Africa understand and use it is almost absent. We assessed knowledge, attitudes and practices (KAP) regarding AI among pharmacy students in a Francophone (Guinea) and an Anglophone (Malawi) country, and identified their determinants.

Methods

A multicentre online cross-sectional survey (29 March–12 June 2026) included pharmacy students from three universities in Conakry, Guinea, and from Kamuzu University of Health Sciences, Malawi. A bilingual self-administered questionnaire measured knowledge (9 items), attitudes (8 Likert items) and practices (7 items, score 0–11). Prespecified cut-offs defined adequate knowledge (≥ 70%), favourable attitude (≥ 75%) and adequate practice (≥ 8/11). Multivariable logistic regression models, structured along the KAP pathway, estimated adjusted odds ratios (aOR) with 95% confidence intervals (CI).

Results

Of 322 participants (Guinea 115, Malawi 207; median age 23 years), 99.7% had heard of AI and 96.2% had used AI tools, but only 27.9% had received formal AI training. Adequate knowledge was found in 32.0% (95% CI 27.1–37.3), favourable attitudes in 30.2% (25.4–35.4) and adequate practices in 64.3% (58.9–69.3). Half of the students (49.8%) believed that AI always provides correct results, and only 18.9% always verified AI-generated information. The two countries showed mirror-image profiles: Malawian students knew AI applications better and were more favourable to AI (aOR 3.77; 1.79–7.97), whereas Guinean students more often recognised AI's limitations and verified its outputs. Adequate practice was independently associated with adequate knowledge (aOR 2.28; 1.26–4.13) and favourable attitude (aOR 2.57; 1.40–4.73), and inversely with age > 23 years (aOR 0.39; 0.21–0.74) and studying in Malawi (aOR 0.39; 0.19–0.81). Advanced years of study predicted adequate knowledge (≥ 5th year: aOR 4.62; 1.27–16.87), while self-reported formal AI training was not associated with better knowledge.

Conclusions

Pharmacy students in both countries use AI almost universally but lack the critical knowledge needed to use it safely, with a high risk of automation bias. Curricula should move beyond tool familiarity towards structured, competency-based AI literacy centred on output verification, limitations, ethics and pharmacist accountability, adapted to each national context.

Background

Artificial intelligence (AI) is reshaping health care by supporting diagnosis, clinical decision-making and health-system efficiency [1]. In pharmacy, AI is already used to accelerate drug discovery [2], detect drug–drug interactions, optimise prescribing and dispensing, and strengthen pharmacovigilance [3]. Future pharmacists will therefore practise in an environment where algorithmic recommendations are routine, and where their professional value will depend on their capacity to evaluate those recommendations rather than simply to retrieve information.

Since late 2022, generative AI tools built on large language models, such as ChatGPT, have been adopted by health-professions students at unprecedented speed, often well before any institutional guidance existed [4, 5]. These tools produce fluent but sometimes fabricated or outdated content ("hallucinations") [6]. In clinical settings, users who over-trust automated advice tend to accept erroneous outputs without verification, a phenomenon known as automation bias [7, 8]. Because the pharmacist is the last safeguard between a prescription and the patient, uncritical use of AI by pharmacy students is not only an educational issue but a future patient-safety issue.

International surveys consistently describe a gap between high exposure to AI and limited formal preparation. A global survey of 4,596 medical, dental and veterinary students from 192 faculties found that 76.3% reported a lack of AI courses, while attitudes were broadly positive [9]. Among pharmacy students in six Middle Eastern and North African countries, 92.6% were aware of AI but only 39.5% had adequate knowledge and 18.6% had received formal training [10]. In Jordan and Palestine, 81.3% of medicine and pharmacy students had heard of AI programs but only 42.1% had used them [11].

Evidence from sub-Saharan Africa remains sparse. In Zambia, 96.6% of pharmacy students were familiar with AI, yet 71.3% had poor knowledge [12]. In Nigeria, 88% of pharmacy students were familiar with chat-based AI tools and 82.8% used ChatGPT for assignments and study [13]. At the same time, AI is widely seen as a lever to compensate for workforce shortages in resource-limited health systems [14, 15], and the World Health Organization has called for health workers to be trained in the safe, ethical and accountable use of AI, including large multimodal models [16–18]. Medical-education scholars have long argued that AI literacy must become a core competency rather than an optional skill [19, 20].

Three gaps limit current evidence. First, no study has examined AI readiness among pharmacy students in Guinea or Malawi, and Francophone West Africa is almost absent from this literature. Second, most KAP surveys report each domain descriptively without testing whether knowledge and attitudes actually translate into practice, as the KAP framework assumes [21]. Third, few studies assess critical-use behaviours, such as verification of AI outputs, that matter most for safety. Guinea (Francophone, West Africa) and Malawi (Anglophone, Southern Africa) share constrained digital infrastructure and the absence of AI in formal pharmacy curricula, but differ in language, academic tradition and access to digital tools, which makes their comparison informative.

This study therefore aimed (i) to assess the knowledge, attitudes and practices of pharmacy students regarding AI in Guinea and Malawi; (ii) to compare these domains between the two countries; and (iii) to identify factors independently associated with each domain, testing the knowledge → attitude → practice pathway.

Methods

Study design and reporting

We conducted a multicentre, cross-national, analytical cross-sectional survey. The study is reported according to the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) statement [22] and the Checklist for Reporting Results of Internet E-Surveys (CHERRIES) [23].

Setting

In Guinea, the study took place in Conakry, which hosts the country's main pharmacy training programmes: Université Gamal Abdel Nasser de Conakry (UGANC, public), Université Kofi Annan de Guinée (UKAG, private) and Université La Source (ULS, private). Teaching is in French. In Malawi, the study took place at Kamuzu University of Health Sciences (KUHeS), the national public institution training pharmacists, where teaching is in English. In neither country was AI part of the formal pharmacy curriculum at the time of the study.

Participants and recruitment

Eligible participants were students officially enrolled in a pharmacy programme during the 2025–2026 academic year, from the first year onwards, who gave electronic informed consent. Students on academic leave were excluded. All eligible students were invited to participate through official class groups and student representatives at each institution. Data were collected from 29 March to 12 June 2026 (Guinea: 29 March–28 April; Malawi: 29 March–12 June). Participation was voluntary and anonymous; no incentive was offered. Because recruitment was based on all reachable students rather than a random sample, the sample is a non-probability census-type sample.

Sample size

No a priori sample size was imposed because all reachable eligible students were invited. A posteriori, 322 participants estimate a proportion of about 32% (adequate knowledge) with a precision of ± 5.1% at 95% confidence. The regression models had 6.8 to 7.7 outcome events per estimated parameter, below the traditional threshold of 10 [26] but above the level at which adjusted estimates remain acceptable [27]; wide confidence intervals for sparse categories (notably year of study) are interpreted cautiously.

Instrument

The self-administered questionnaire was developed from previously published KAP surveys of AI among pharmacy and health-professions students [10–13] and reviewed by experts in pharmacy education, public health and digital health for content validity. It was prepared in English, translated into French by forward–backward translation, and displayed bilingually. It was pretested on students who were not included in the analysis, and minor wording changes were made. The questionnaire was administered online through KoboToolbox.

The questionnaire had five sections: (A) sociodemographic and academic characteristics; (B) digital access and exposure to AI, including formal AI training (course, workshop or seminar); (C) knowledge, nine true/false/don't-know statements on AI applications in diagnosis, drug-interaction detection and drug discovery, on its limitations (accuracy, bias, need for human supervision, ethical issues, replacement of pharmacists) and on health-care efficiency; (D) attitudes, eight five-point Likert statements; and (E) practices and perceptions.

Scoring and outcome definitions

Knowledge. Each correct answer scored 1 and each incorrect, "don't know" or unanswered item scored 0 (range 0–9). The two statements that are false in fact ("AI always provides correct results" and "AI could completely replace pharmacists") were reverse-keyed. Knowledge was categorised with Bloom's cut-offs as good (≥ 80%), moderate (60–79.9%) or poor (< 60%) [24]. For regression, adequate knowledge was defined a priori as ≥ 70% (≥ 7/9 correct). Two sub-scores were derived for exploratory analysis: *application knowledge* (diagnosis, drug interactions, drug discovery, efficiency; 0–4) and *critical knowledge* (accuracy, bias, human supervision, ethics, replacement; 0–5).

Attitudes. Likert items were scored 1–5, with the two negatively worded items (AI may reduce the importance of health professionals; AI may reduce human interaction with patients) reverse-scored. The total (8–40) was rescaled to 0–100% as (score − 8)/32 × 100. Attitudes were classified as favourable (≥ 75%) or not favourable (< 75%); a three-level description (negative < 50%, neutral/mixed 50–74.9%, positive ≥ 75%) is also shown.

Practices. Seven items formed a score from 0 to 11: use of AI for studies (0/1), frequency of use for learning (rarely 1, sometimes 2, often 3), use for assignments (0/1), for research (0/1) and for understanding clinical or pharmaceutical concepts (0/1), verification of AI-generated information (never 0, rarely 1, sometimes 2, always 3) and intention to use AI in future practice (0/1). Adequate practice was defined a priori as a score ≥ 8/11 (≥ 72.7%). Trust in AI outputs, perceived usefulness, support for curricular integration and self-confidence were analysed descriptively and not scored.

Independent variables

Covariates were selected a priori from the conceptual framework and the literature, not by stepwise selection: age (≤ 23 vs > 23 years, the sample median), sex, marital status (single vs married/other), country, year of study (1st to ≥ 5th), self-rated academic performance (low/average vs good/excellent), self-rated digital skills (low/moderate vs high), formal AI training (yes/no) and regular internet access (yes/no).

Statistical analysis

Categorical variables are presented as frequencies and percentages of valid responses, and continuous variables as medians with interquartile ranges (IQR) because of non-normal distributions. Proportions of the three main outcomes are given with Wilson 95% CIs. Countries were compared with Pearson's χ^2 test, or Fisher's exact test when expected counts were < 5, and with the Mann–Whitney U test for scores. Internal consistency was estimated with Kuder–Richardson 20 (KR-20) for knowledge and Cronbach's α for attitudes and practices [25]. Associations between KAP scores were assessed with Spearman's correlation coefficient (ρ). The overlap between adequate knowledge, favourable attitude and adequate practice was described with Venn diagrams (VennDiagram package), overall and by country, and the proportion of students meeting all three criteria was compared between countries with the χ^2 test.

Three multivariable binary logistic regression models were fitted, following the KAP framework: model 1 for adequate knowledge with the covariates above; model 2 for favourable attitude, adding adequate knowledge; and model 3 for adequate practice, adding adequate knowledge and favourable attitude. Crude (cOR) and adjusted odds ratios (aOR) with 95% CIs are reported. Multicollinearity was checked with variance inflation factors (all < 3.3). Calibration was assessed with the Hosmer–Lemeshow test and discrimination with the area under the ROC curve (AUC) [28]. Missing data were below 6% for every variable, so complete-case analysis was used (n = 313, 309 and 309 for models 1–3). As a sensitivity analysis, the three continuous percentage scores were modelled with linear regression with heteroskedasticity-robust (HC3) standard errors and the same covariates. Two-sided $p < 0.05$ was considered significant. Confidence intervals of odds ratios were computed with the Wald method. All analyses were performed with R version 4.5.3 (R Foundation for Statistical Computing, Vienna, Austria), using the readxl, sandwich, lmtest and VennDiagram packages; the analysis script is available from the corresponding author.

Ethical considerations

Data were collected exclusively online. The first screen of the questionnaire presented the purpose of the study, the voluntary and anonymous nature of participation, the absence of any consequence for refusal and the right to withdraw at any time before submission. Only participants who selected "Yes, I agree to participate" could access the questions, and those who declined were taken directly to the end of the form; electronic informed consent was therefore obtained from every participant. No names, student numbers or other personal identifiers were collected, and the data were stored on a password-protected account accessible only to the investigators. The study was minimal-risk and conducted in accordance with the Declaration of Helsinki.

Results

Participants

A total of 322 students consented and completed the questionnaire: 115 (35.7%) in Guinea and 207 (64.3%) in Malawi (Table 1). The median age was 23 years (IQR 21–26) and 51.9% were men. Exposure to AI was almost universal: 99.7% had heard of AI and 96.2% had used AI tools, and 48.7% used them often. Yet only 27.9% had received any formal AI training. Compared with Guinean students, Malawian students more often had regular internet access (98.5% vs 83.8%), used a laptop or tablet as their main device (52.0% vs 8.0%) and reported formal AI training (34.0% vs 16.8%; all $p \leq 0.002$). The distribution of years of study also differed: 31.3% of Guinean participants were in their fifth year or above, against 1.9% in Malawi.

Table 1
Sociodemographic, academic and digital characteristics of participants, overall and by country (N = 322)

Characteristic	Total, n (%)	Guinea, n (%)	Malawi, n (%)	p
Age, years, median (IQR)	23 (21–26)	23 (20–26)	23 (21–26)	0.301
Sex				0.039
Male	167 (51.9)	69 (60.0)	98 (47.3)	
Female	155 (48.1)	46 (40.0)	109 (52.7)	
Marital status				< 0.001
Single	285 (88.8)	91 (79.8)	194 (93.7)	
Married	28 (8.7)	17 (14.9)	11 (5.3)	
Other	8 (2.5)	6 (5.3)	2 (1.0)	
University				—
UGANC	24 (7.5)	24 (20.9)	—	
UKAG	18 (5.6)	18 (15.7)	—	
ULS	73 (22.7)	73 (63.5)	—	
KUHeS	207 (64.3)	—	207 (100.0)	
Year of study				< 0.001
1st	33 (10.2)	8 (7.0)	25 (12.1)	
2nd	97 (30.1)	43 (37.4)	54 (26.1)	
3rd	100 (31.1)	14 (12.2)	86 (41.5)	
4th	52 (16.1)	14 (12.2)	38 (18.4)	
≥ 5th	40 (12.4)	36 (31.3)	4 (1.9)	
Self-rated academic performance				0.021
Low	2 (0.6)	2 (1.8)	0 (0.0)	
Average	76 (23.7)	30 (26.3)	46 (22.2)	
Good	200 (62.3)	74 (64.9)	126 (60.9)	
Excellent	43 (13.4)	8 (7.0)	35 (16.9)	
Regular internet access (yes)	296 (93.4)	93 (83.8)	203 (98.5)	< 0.001
Main device for internet				< 0.001

Characteristic	Total, n (%)	Guinea, n (%)	Malawi, n (%)	p
Smartphone	193 (60.5)	94 (83.2)	99 (48.1)	
Laptop	71 (22.3)	6 (5.3)	65 (31.6)	
Tablet	45 (14.1)	3 (2.7)	42 (20.4)	
Other	10 (3.1)	10 (8.8)	0 (0.0)	
Self-rated digital skills				0.012
Low	19 (6.0)	12 (10.7)	7 (3.4)	
Moderate	257 (80.8)	90 (80.4)	167 (81.1)	
High	42 (13.2)	10 (8.9)	32 (15.5)	
Ever heard of AI (yes)	317 (99.7)	112 (100.0)	205 (99.5)	1.000‡
Formal AI training received (yes)	89 (27.9)	19 (16.8)	70 (34.0)	0.002
Ever used AI tools (yes)	308 (96.2)	108 (94.7)	200 (97.1)	0.359‡
Frequency of AI use				0.035§
Never	2 (0.6)	1 (0.9)	1 (0.5)	
Rarely	19 (6.2)	12 (11.1)	7 (3.5)	
Sometimes	137 (44.5)	50 (46.3)	87 (43.5)	
Often	150 (48.7)	45 (41.7)	105 (52.5)	

Values are n (%) of valid responses unless stated. ‡ Mann–Whitney U test; ‡ Fisher's exact test; § χ^2 test with some expected counts < 5, interpret with caution; other p values from Pearson's χ^2 test. UGANC, Université Gamal Abdel Nasser de Conakry; UKAG, Université Kofi Annan de Guinée; ULS, Université La Source; KUHeS, Kamuzu University of Health Sciences.

Knowledge

The median knowledge score was 66.7% (IQR 55.6–77.8), with no difference between countries (p = 0.949) (Table 2). Only 13.0% had good knowledge by Bloom's criteria and 32.0% (95% CI 27.1–37.3) reached the adequate-knowledge threshold. The weakest items concerned AI's limitations: 49.8% believed that AI always provides correct results and 41.4% that AI could completely replace pharmacists.

Behind identical total scores, the two countries had opposite knowledge profiles. Malawian students scored higher on application knowledge (mean 2.89 vs 2.31 out of 4; p < 0.001), recognising more often that AI is used in drug discovery (71.8% vs 38.9%) and improves efficiency (79.1% vs 52.6%). Guinean students scored higher on critical knowledge (3.27 vs 2.80 out of 5; p < 0.001): 65.5% correctly rejected

the statement that AI is always correct (vs 26.7% in Malawi) and 81.6% rejected the idea that AI could replace pharmacists (vs 34.1%).

Table 2
Knowledge of artificial intelligence, overall and by country (N = 322)

Statement (correct answer)	**Total, correct n (%)**	**Guinea, n (%)**	**Malawi, n (%)**	**p**
Application knowledge				
AI can assist in medical or pharmaceutical diagnosis (True)	247 (77.2)	86 (75.4)	161 (78.2)	0.678
AI can detect drug interactions (True)	202 (63.3)	76 (67.3)	126 (61.2)	0.338
AI is used in drug discovery (True)	192 (60.2)	44 (38.9)	148 (71.8)	< 0.001
AI improves health-care efficiency (True)	223 (69.7)	60 (52.6)	163 (79.1)	< 0.001
Critical knowledge				
AI requires human supervision (True)	242 (75.6)	86 (75.4)	156 (75.7)	1.000
AI can raise ethical issues, e.g. privacy (True)	221 (69.1)	67 (58.8)	154 (74.8)	0.005
AI can have biases (True)	201 (63.0)	56 (49.6)	145 (70.4)	< 0.001
AI could completely replace pharmacists (False)	163 (51.1)	93 (81.6)	70 (34.1)	< 0.001
AI always provides correct results (False)	129 (40.4)	74 (65.5)	55 (26.7)	< 0.001
Scores				
Knowledge score, %, median (IQR)	66.7 (55.6–77.8)	66.7 (44.4–77.8)	66.7 (55.6–77.8)	0.949
Application sub-score (0–4), mean ± SD	2.68 ± 1.13	2.31 ± 1.31	2.89 ± 0.96	< 0.001
Critical sub-score (0–5), mean ± SD	2.97 ± 1.23	3.27 ± 1.37	2.80 ± 1.11	< 0.001
Knowledge level (Bloom)				0.002
Good (≥ 80%)	42 (13.0)	25 (21.7)	17 (8.2)	
Moderate (60–79.9%)	136 (42.2)	41 (35.7)	95 (45.9)	
Poor (< 60%)	144 (44.7)	49 (42.6)	95 (45.9)	
Adequate knowledge (≥ 70%)	103 (32.0)	38 (33.0)	65 (31.4)	0.859

Item percentages use valid responses; in the scores, unanswered items were counted as incorrect. Mann–Whitney U test; other p values from Pearson's χ^2 test.

Attitudes

Attitudes were receptive but rarely strongly positive (Table 3). Most students were interested in learning more about AI (84.7%), supported its integration into pharmacy education (80.6%) and wanted it regulated in health care (77.9%). Concerns were also common: 47.2% thought AI may reduce human interaction with patients and 43.8% that it may reduce the importance of health professionals. Overall, 30.2% (95% CI 25.4–35.4) had a favourable attitude. Malawian students had higher attitude scores than Guinean students (median 68.8% vs 59.4%; $p < 0.001$) and were twice as likely to hold a favourable attitude (37.1% vs 17.3%).

Table 3
Attitudes towards artificial intelligence, overall and by country

Statement	Total, agree n (%)	Guinea, n (%)	Malawi, n (%)	p
AI can improve the quality of health care	179 (56.1)	55 (48.7)	124 (60.2)	0.009
AI should be integrated into pharmacy education	258 (80.6)	78 (68.4)	180 (87.4)	< 0.001
I am interested in learning more about AI	271 (84.7)	95 (83.3)	176 (85.4)	< 0.001
AI will be useful in my future career	254 (79.4)	88 (77.2)	166 (80.6)	0.004
AI may reduce the importance of health professionals (−)	140 (43.8)	47 (41.2)	93 (45.1)	0.790
AI may reduce human interaction with patients (−)	151 (47.2)	60 (52.6)	91 (44.2)	0.063
AI should be regulated in health care	247 (77.9)	64 (57.1)	183 (89.3)	< 0.001
I feel comfortable using AI tools	230 (72.3)	69 (61.6)	161 (78.2)	< 0.001
Attitude score, %, median (IQR)	65.6 (59.4–75.0)	59.4 (53.1–68.8)	68.8 (62.5–81.3)	< 0.001
Attitude level (n = 315)				< 0.001
Favourable (≥ 75%)	95 (30.2)	19 (17.3)	76 (37.1)	
Neutral/mixed (50–74.9%)	195 (61.9)	75 (68.2)	120 (58.5)	
Negative (< 50%)	25 (7.9)	16 (14.5)	9 (4.4)	

"Agree" combines agree and strongly agree. (−) negatively worded item, reverse-scored in the attitude score. Mann–Whitney U test on the score; Mann–Whitney U test on the five-point item score; attitude level compared with Pearson's χ^2 test.

Practices and perceptions

AI was used for studies by 95.9% of students, mainly for assignments (87.6%), research (82.3%) and understanding clinical or pharmaceutical concepts (77.8%) (Table 4). Verification was the weakest practice: only 18.9% always checked AI-generated information, while 48.3% did so rarely or never. Adequate practice was found in 64.3% (95% CI 58.9–69.3), more often in Guinea than in Malawi (73.9% vs 58.9%; p = 0.010). Malawian students used AI more for assignments and trusted its outputs more (20.9% vs 7.3% highly trusting), but verified less (59.2% vs 27.9% rarely or never). Guinean students used AI more for research (93.6% vs 76.2%) and to understand concepts (85.3% vs 73.8%). Nearly all students intended to use AI in future practice (92.7%) and wanted it formally taught (89.0%).

Table 4
Practices and perceptions related to artificial intelligence, overall and by country

Practice / perception	Total, n (%)	Guinea, n (%)	Malawi, n (%)	p
Used AI tools for studies (yes)	305 (95.9)	104 (92.9)	201 (97.6)	0.071
Frequency of AI use for learning				< 0.001
Rarely	22 (7.2)	14 (13.6)	8 (4.0)	
Sometimes	202 (66.4)	52 (50.5)	150 (74.6)	
Often	80 (26.3)	37 (35.9)	43 (21.4)	
Uses AI for assignments (yes)	276 (87.6)	89 (80.9)	187 (91.2)	0.014
Uses AI for research (yes)	260 (82.3)	103 (93.6)	157 (76.2)	< 0.001
Uses AI to understand clinical/pharmaceutical concepts (yes)	245 (77.8)	93 (85.3)	152 (73.8)	0.028
Verifies AI-generated information				< 0.001
Never	26 (8.2)	5 (4.5)	21 (10.2)	
Rarely	127 (40.1)	26 (23.4)	101 (49.0)	
Sometimes	104 (32.8)	48 (43.2)	56 (27.2)	
Always	60 (18.9)	32 (28.8)	28 (13.6)	
Trust in AI-generated information				0.016
Not at all	15 (4.7)	7 (6.4)	8 (3.9)	
Slightly	76 (24.1)	30 (27.3)	46 (22.3)	
Moderately	174 (55.1)	65 (59.1)	109 (52.9)	
Highly	51 (16.1)	8 (7.3)	43 (20.9)	
Plans to use AI in future practice (yes)	293 (92.7)	91 (82.7)	202 (98.1)	< 0.001
Perceived usefulness of AI in pharmacy practice				< 0.001
Not useful	4 (1.3)	4 (3.6)	0 (0.0)	

Practice / perception	Total, n (%)	Guinea, n (%)	Malawi, n (%)	p
Slightly useful	55 (17.5)	32 (29.1)	23 (11.2)	
Moderately useful	205 (65.1)	51 (46.4)	154 (75.1)	
Very useful	51 (16.2)	23 (20.9)	28 (13.7)	
AI should be formally taught in the curriculum (yes)	282 (89.0)	90 (81.1)	192 (93.2)	0.002
Confidence in using AI tools				< 0.001
Not confident	9 (2.8)	6 (5.4)	3 (1.5)	
Slightly confident	69 (21.8)	34 (30.6)	35 (17.0)	
Moderately confident	188 (59.3)	63 (56.8)	125 (60.7)	
Very confident	51 (16.1)	8 (7.2)	43 (20.9)	
Practice score (0–11), median (IQR)	8 (7–9)	9 (7–10)	8 (7–9)	0.002
Adequate practice (≥ 8/11)	207 (64.3)	85 (73.9)	122 (58.9)	0.010

Values are n (%) of valid responses. Mann–Whitney U test; Fisher's exact test; χ^2 test with some expected counts < 5, interpret with caution; other p values from Pearson's χ^2 test.

Reliability and relationships between domains

Internal consistency was acceptable for attitudes (Cronbach's α = 0.67; 0.74 for the six positively worded items), modest for practices (α = 0.55) and low for knowledge (KR-20 = 0.39), as expected for a short index covering heterogeneous content. The three domains were positively correlated: knowledge with attitude (ρ = 0.26), knowledge with practice (ρ = 0.31) and attitude with practice (ρ = 0.19; all $p < 0.001$). Critical knowledge was the sub-score most closely linked to practice (ρ = 0.27; $p < 0.001$), whereas application knowledge was linked to attitude (ρ = 0.27; $p < 0.001$).

Overlap between knowledge, attitudes and practices

Among the 315 students with complete data, only 34 (10.8%) combined adequate knowledge, a favourable attitude and adequate practice, whereas 77 (24.4%) met none of the three criteria (Fig. 1). The most frequent profile was adequate practice alone, without adequate knowledge or a favourable attitude (85; 27.0%). The complete KAP profile was three times more frequent in Malawi than in Guinea (29/205, 14.1% vs 5/110, 4.5%; p = 0.015). In Guinea, adequate practice most often occurred without the other two components (45; 40.9%), and no student had a favourable attitude alone; in Malawi, favourable attitudes were more evenly shared across profiles.

(A) All students; (B) Guinea; (C) Malawi. Adequate knowledge: score ≥ 70%; favourable attitude: score ≥ 75%; adequate practice: score ≥ 8/11. Each region shows the number of students and the percentage of the panel total. Seven students with incomplete attitude data were excluded.

Factors associated with knowledge, attitudes and practices

In model 1, year of study was the only factor associated with adequate knowledge, with a gradient towards senior years: fourth-year (aOR 3.53; 95% CI 1.11–11.20) and fifth-year-or-above students (aOR 4.62; 1.27–16.87) had higher odds than first-year students (Table 5). Neither formal AI training, digital skills nor country was associated with knowledge.

In model 2, studying in Malawi (aOR 3.77; 1.79–7.97) and adequate knowledge (aOR 2.15; 1.25–3.70) were associated with a favourable attitude. Students who reported formal AI training were less likely to hold a favourable attitude (aOR 0.45; 0.24–0.85); descriptively, they also had lower critical-knowledge scores (mean 2.64 vs 3.11) and more often verified AI outputs rarely or never (60.7% vs 43.2%).

In model 3, adequate practice was independently associated with adequate knowledge (aOR 2.28; 1.26–4.13) and favourable attitude (aOR 2.57; 1.40–4.73), supporting the knowledge–attitude–practice pathway. Students older than 23 years (aOR 0.39; 0.21–0.74) and those studying in Malawi (aOR 0.39; 0.19–0.81) had lower odds of adequate practice. The Malawi effect on practice strengthened once knowledge and attitude were added to the model (aOR 0.51; 0.26–0.99 without them), which suggests that more favourable attitudes in Malawi partly masked less careful use. All models were well calibrated (Hosmer–Lemeshow $p \geq 0.16$); discrimination was modest for knowledge (AUC 0.62) and acceptable for attitude (0.70) and practice (0.73). Crude odds ratios are given in Additional file 1.

Table 5
Factors associated with adequate knowledge, favourable attitude and adequate practice regarding AI: multivariable logistic regression

Variable	Model 1: adequate knowledge, aOR (95% CI)	p	Model 2: favourable attitude, aOR (95% CI)	p	Model 3: adequate practice, aOR (95% CI)	p
Age (ref. ≤ 23 years)						
> 23 years	0.94 (0.52–1.71)	0.841	1.07 (0.57–2.03)	0.833	**0.39 (0.21–0.74)**	**0.004**
Sex (ref. male)						
Female	0.73 (0.44–1.20)	0.219	0.93 (0.55–1.57)	0.789	0.93 (0.55–1.57)	0.781
Marital status (ref. single)						
Married/other	0.90 (0.40–2.03)	0.792	0.71 (0.27–1.82)	0.471	1.55 (0.62–3.91)	0.350
Country (ref. Guinea)						
Malawi	1.42 (0.76–2.66)	0.276	**3.77 (1.79–7.97)**	**< 0.001**	**0.39 (0.19–0.81)**	**0.011**
Year of study (ref. 1st)						
2nd	2.63 (0.94–7.36)	0.065	0.93 (0.35–2.46)	0.882	1.57 (0.62–3.99)	0.340
3rd	1.51 (0.52–4.37)	0.448	0.84 (0.32–2.25)	0.736	1.25 (0.48–3.22)	0.648
4th	**3.53 (1.11–11.20)**	**0.032**	1.43 (0.46–4.40)	0.533	2.32 (0.75–7.16)	0.142
≥ 5th	**4.62 (1.27–16.87)**	**0.021**	1.68 (0.44–6.43)	0.447	1.64 (0.45–6.02)	0.454
Academic performance (ref. low/average)						
Good/excellent	1.31 (0.72–2.38)	0.373	1.27 (0.67–2.42)	0.463	0.76 (0.41–1.43)	0.400
Digital skills (ref. low/moderate)						

Variable	Model 1: adequate knowledge, aOR (95% CI)	p	Model 2: favourable attitude, aOR (95% CI)	p	Model 3: adequate practice, aOR (95% CI)	p
High	1.06 (0.51–2.20)	0.865	1.13 (0.53–2.39)	0.752	0.93 (0.44–1.96)	0.846
Formal AI training (ref. no)						
Yes	0.79 (0.44–1.40)	0.419	**0.45 (0.24–0.85)**	**0.014**	0.96 (0.53–1.72)	0.883
Regular internet access (ref. no)						
Yes	1.01 (0.36–2.84)	0.980	0.87 (0.27–2.82)	0.815	1.93 (0.66–5.64)	0.229
KAP pathway						
Adequate knowledge (ref. inadequate)	—		**2.15 (1.25–3.70)**	**0.006**	**2.28 (1.26–4.13)**	**0.007**
Favourable attitude (ref. not favourable)	—		—		**2.57 (1.40–4.73)**	**0.002**
Model performance						
Observations / events	313 / 100		309 / 95		309 / 200	
Hosmer–Lemeshow p	0.605		0.164		0.968	
AUC	0.62		0.70		0.73	

aOR, adjusted odds ratio; AUC, area under the receiver operating characteristic curve; CI, confidence interval; ref., reference category. Each model includes all variables listed in its column. Bold: p < 0.05.

Sensitivity analysis

Linear models of the continuous scores gave consistent results (Additional file 2). Knowledge rose with year of study (≥ 5th vs 1st year: +21.1 percentage points; 95% CI 9.5–32.7). Attitude was higher in Malawi (+ 9.7 points; 5.7–13.7) and with higher knowledge (+ 0.19 points per percentage point of knowledge; 0.12–0.27), and lower with formal AI training (− 3.3 points; −6.5 to − 0.2). Practice increased with knowledge (+ 0.19; 0.08–0.30) and attitude (+ 0.22; 0.10–0.35) and was lower in Malawi (− 5.7 points; −10.8 to − 0.6). The age effect on practice was in the same direction but weaker (− 4.2 points; −9.0 to 0.5; p = 0.077).

Discussion

This first cross-national study of AI readiness among pharmacy students in Guinea and Malawi reveals a marked use–competence gap. Almost every student uses AI, but only one in three has adequate knowledge, half believe that AI always produces correct results and fewer than one in five systematically verify its outputs. Knowledge and attitudes were independently associated with adequate practice, which supports the KAP pathway. The two countries, while identical on the total knowledge score, showed mirror-image profiles: enthusiastic but less critical users in Malawi, and more sceptical but more careful users in Guinea.

Comparison with previous studies

The level of exposure we observed (96.2% of users) exceeds that reported among medicine and pharmacy students in Jordan and Palestine in 2023 (42.1%) [11] and is close to recent African figures from Zambia and Nigeria [12, 13]. This difference most likely reflects the rapid diffusion of generative AI after 2023 rather than regional differences [4, 29]. In contrast, the proportion with adequate knowledge (32.0%) is similar to that reported in the Middle East and North Africa (39.5%) [10], and the low share of formally trained students (27.9%) is consistent with the 76.3% of health-professions students worldwide who report lacking AI courses [9]. Exposure has therefore grown much faster than understanding: AI has entered students' daily study habits without passing through the curriculum.

Critical knowledge and the risk of automation bias

The most concerning finding is the weakness of critical knowledge. That 49.8% of future pharmacists believe AI always provides correct results, and that 48.3% rarely or never verify AI-generated information, runs counter to what is known about large language models, which can produce plausible but fabricated drug information and references [5, 6]. Over-reliance on automated advice is a well-documented source of error in clinical decision support [7, 8]. In pharmacy, where an unchecked dose, interaction or contraindication reaches the patient directly, this combination of high trust and low verification is a latent patient-safety risk. Critical knowledge, rather than knowledge of applications, was the dimension most strongly correlated with good practice, which identifies it as the main lever for education. The overlap analysis reinforces this picture: only one student in ten combined all three components, and more than a quarter used AI adequately without either adequate knowledge or a favourable attitude, which suggests that habits of use are forming ahead of understanding.

Two national profiles

The contrast between countries is the study's most original contribution. Malawian students had better digital access, more frequent use and more formal training; they knew AI applications better and were nearly four times more likely to hold favourable attitudes. However, they trusted AI more, verified it less and were less likely to recognise its limitations, so that their practices were less adequate once knowledge and attitudes were accounted for. Guinean students, with fewer resources and mostly

smartphone access, were more sceptical but more careful. Several non-exclusive explanations can be proposed. Greater ease of access may normalise AI as a reliable tool, whereas intermittent access may encourage selective, purposeful use. Language may also matter: generative tools perform best in English, and students who use them in French may meet more visible errors, which could foster vigilance. Finally, 81.6% of Guinean students, against 34.1% of Malawian students, rejected the idea that AI could replace pharmacists; how students view their professional future may colour their stance towards AI, as observed among medical students [30, 31]. These hypotheses require qualitative exploration, but they show that a single regional "AI readiness" score would hide opposite educational needs.

The formal-training paradox

Formal AI training was not associated with better knowledge, and was associated with less favourable attitudes, lower critical knowledge and less frequent verification. This is unlikely to mean that training is harmful. It more probably reflects the nature of the training students reported: short, heterogeneous and often tool-oriented workshops, outside the curriculum and without assessment. Such sessions may increase confidence without building the conceptual understanding needed to judge one's own competence [32]. The result is a warning for curriculum designers: exposure and tool demonstrations are not AI literacy [33]. What matters is the content of training, particularly the limits of AI, verification methods and professional accountability.

Other determinants

Knowledge increased steadily with year of study, which suggests that it is built indirectly, through pharmacology, pharmacotherapy and clinical exposure, rather than through dedicated teaching. Older students had lower odds of adequate practice in the logistic model, although this effect was weaker in the linear sensitivity analysis and should be confirmed. Sex, academic performance, self-rated digital skills and internet access were not associated with any domain once other factors were controlled for, indicating that AI readiness is shaped more by educational and national context than by individual characteristics.

Implications for pharmacy education and policy

Four actions follow from these results. First, AI literacy should become a compulsory, assessed competency from the early years of the pharmacy curriculum, as advocated in medical education [19, 20, 34]. Second, teaching should prioritise critical use: how AI works, why it errs, how to verify drug information against primary sources, and who is accountable for decisions. Systematic verification should be practised in drug-information and pharmacotherapy courses rather than taught as an abstract principle. Third, faculties should adopt explicit policies on the academic use of generative AI, in line with WHO guidance on ethics and governance [16–18]. Fourth, strategies should be adapted to context: in Malawi, the emphasis should be on limitations, bias and verification; in Guinea, on exposure to evidence-based pharmaceutical applications, improved digital access and teaching resources in French.

Strengths and limitations

This study has several strengths. It is the first to document AI readiness among pharmacy students in Guinea and Malawi, and one of the few to compare Francophone and Anglophone African settings with a single bilingual instrument. It assessed verification behaviour, a safety-relevant practice rarely measured, and it tested the KAP pathway with prespecified models and a sensitivity analysis.

Several limitations should be considered. First, recruitment was online and non-probabilistic, and the response rate could not be computed; students interested in AI may have been more likely to respond, which would overestimate use and attitudes. Second, Malawi was represented by a single institution, and Guinean participants were unevenly distributed across universities (63.5% from ULS), which limits generalisability and did not allow a reliable cluster-level analysis. Third, all data were self-reported and subject to social desirability bias, particularly for verification. Fourth, the knowledge index had low internal consistency, which is expected for nine heterogeneous items but limits its use as a unidimensional scale; the cut-offs, although prespecified, remain conventional. Fifth, "formal AI training" was not defined by duration or content. Sixth, the number of events per parameter was moderate, so estimates for sparse categories are imprecise. Finally, the cross-sectional design does not establish causality, and the KAP model itself simplifies the relationship between knowledge and behaviour [21]. Future studies should use probability sampling across more institutions, objective measures of AI-assisted performance, and qualitative methods to explain the national differences observed, and should evaluate the effect of structured AI-literacy curricula.

Conclusions

Pharmacy students in Guinea and Malawi have already adopted AI, but most lack the critical knowledge required to use it safely: half believe AI is always right and few verify its outputs. Knowledge and attitudes drive adequate practice, yet the two countries need different emphases: limitations and verification in Malawi, applications and access in Guinea. Ad hoc, tool-oriented training does not close this gap. Pharmacy schools should integrate a structured, assessed AI-literacy competency centred on critical appraisal, verification, ethics and pharmacist accountability, so that future pharmacists remain the safeguard between algorithms and patients.

Abbreviations

AI
artificial intelligence
aOR
adjusted odds ratio
AUC
area under the receiver operating characteristic curve
CHERRIES

Checklist for Reporting Results of Internet E-Surveys
CI
confidence interval
cOR
crude odds ratio
IQR
interquartile range
KAP
knowledge, attitudes and practices
KR-20
Kuder–Richardson formula 20
KUHeS
Kamuzu University of Health Sciences
SD
standard deviation
STROBE
Strengthening the Reporting of Observational Studies in Epidemiology
UGANC
Université Gamal Abdel Nasser de Conakry
UKAG
Université Kofi Annan de Guinée
ULS
Université La Source
WHO
World Health Organization.

Declarations

Ethics approval and consent to participate.

The survey was conducted online in accordance with the Declaration of Helsinki. Electronic informed consent was obtained from all participants on the first screen of the questionnaire before any question was displayed; participation was voluntary and anonymous, and no personal identifiers were collected.

Consent for publication.

Not applicable.

Competing interests.

The authors declare that they have no competing interests.

Use of generative artificial intelligence.

A generative AI tool (Claude, Anthropic) was used for the formatting and language editing of the manuscript and of the cover letter. The authors reviewed and verified all content, data, analyses and references, and take full responsibility for the integrity and accuracy of the work.

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Author Contribution

AO and IKK conceived and designed the study. AO performed the statistical analysis, interpreted the data and drafted the manuscript. IKK supervised the study and data collection in Guinea. KAK coordinated data collection in Malawi. TAB, MNA, RN, DS, DBB, MSA, SC, HNB and EI contributed to the development and translation of the questionnaire and to data collection in Guinea. All authors critically revised the manuscript, read and approved the final version.

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Availability of data and materials.

The anonymised dataset and analysis code are available from the corresponding author on reasonable request.

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35. Additional. file 1 — Table S1. Crude odds ratios (cOR, 95% CI).

Figures

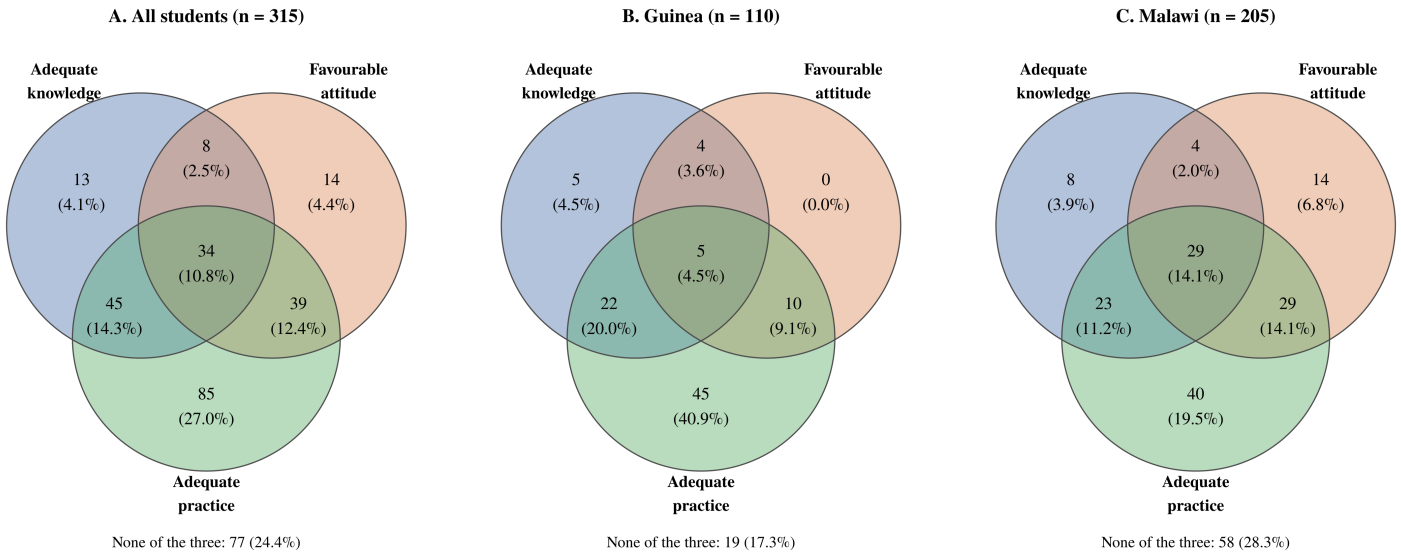


Figure 1

Overlap between adequate knowledge, favourable attitude and adequate practice regarding AI

(A) All students; (B) Guinea; (C) Malawi. Adequate knowledge: score ≥ 70%; favourable attitude: score ≥ 75%; adequate practice: score ≥ 8/11. Each region shows the number of students and the percentage of the panel total. Seven students with incomplete attitude data were excluded.

Supplementary Files

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