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Artificial Intelligence Literacy, Self-Perceived Competence, and Use Among Postgraduate Medical Trainees and Faculty in Tanzania: A Multi-Institutional Cross-Sectional Study

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Research Article

Keywords: artificial intelligence, medical education, postgraduate training, Tanzania, AI literacy, sub-Saharan Africa

Posted Date: November 1st, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10984431/v1

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Additional Declarations: No competing interests reported.

Abstract

Background

Artificial intelligence (AI) is being integrated into medical education globally, yet evidence from sub-Saharan Africa remains sparse. Postgraduate medical training institutions in this region face distinctive cultural, resource and infrastructure constraints that may shape how educators and trainees engage with AI. This study examined knowledge and self-reported use of AI among postgraduate medical residents and faculty in Dar es Salaam, Tanzania.

Methods

A cross-sectional study was conducted across three postgraduate medical training universities in Dar es Salaam the Aga Khan University (AKU), Muhimbili University of Health and Allied Sciences (MUHAS), and Hubert Kairuki Memorial University (HKMU). A census sampling approach was used, targeting all available residents and faculty. Data was collected via an online structured questionnaire assessing AI knowledge, exposure, and self-rated competence. Knowledge scores were derived from a ten-item questionnaire and compared across groups using Welch's t-test and multivariable linear regression to determine association with knowledge scores.

Results

A total of 155 participants participated in the study (116 residents, 39 faculty). Mean age group was 31–40 years. Formal AI training was rare (7.1%), yet 80.0% reported using AI in teaching or learning activities. Residents used AI substantially more than faculty (65.8% vs. 14.2%). Overall objective knowledge was moderate (mean score 59.0%, SD 18.2%), with no significant difference between residents and faculty ($p = 0.623$). Specialty was also associated with knowledge scores, with medical and radiology specialties outperforming non-clinical specialties Self-rated knowledge at Level 5 was the only independent predictor of higher objective scores in multivariable analysis ($\beta = 0.151$; 95% CI 0.022–0.302; $p = 0.049$).

Conclusions

AI use is widespread among postgraduate trainees in Dar es Salaam despite minimal formal training. Knowledge gaps are evident, particularly around foundational AI concepts. Self-perceived competence, rather than professional role or formal training, predicted objective knowledge. These findings underscore the need for structured, contextually adapted AI literacy curricula within postgraduate medical education in Tanzania and similar settings.

Introduction

Artificial intelligence (AI) is broadly understood as the capacity of machines to simulate human cognitive functions such as reasoning, learning, and perception[1]. It has become an increasingly prominent feature of both healthcare practice and medical education[2]. Applications range from image recognition in radiology and pathology to clinical decision support, natural language processing, and adaptive learning platforms[3, 4]. The emergence of widely accessible generative AI tools, particularly large language models such as ChatGPT, has further accelerated the integration of AI into everyday educational and clinical practice, fundamentally changing how learners access, process, and apply information[5, 6].

Reviews of the literature on AI in medical education suggest that exposure and attitudes vary considerably across training contexts[7, 8]. Studies from high-income settings, including the United Kingdom and Canada, have found generally positive attitudes toward AI among medical students and clinicians, with recognition that it may enhance diagnostic efficiency and support clinical learning [9, 10]. However, concerns persist around job displacement, the erosion of clinical reasoning, ethical accountability, and the accuracy of AI-generated clinical content[11]. Poor formal exposure to AI has been associated with heightened anxiety, and this has been shown to influence specialty career preferences [12].

Evidence on the use of AI in medical education from sub-Saharan Africa remains specifically is limited. Medical education in this setting is distinctively different from high income settings with high volume public hospitals being the training sites with very low faculty to trainee ratios Postgraduate medical education (PGME) occupies a distinctive position at the interface of clinical service delivery, academic development, and research training. Trainees at this level are simultaneously frontline providers and learners, and the competencies they develop including digital and AI literacy will shape healthcare delivery over the coming decades.

Emerging evidence from Africa suggests that AI tools are already being widely adopted by health professions students despite limited institutional support. A multicountry study involving medical and pharmacy students in Cameroon, Nigeria, and Uganda found high levels of generative AI use for academic activities, while 94.6% of participants reported receiving no formal AI training and most lacked institutional guidance, highlighting substantial gaps in AI education across African training institutions[13].

Similarly, a classroom-based AI educational intervention among medical imaging students in Ghana demonstrated significant improvements in AI knowledge following structured instruction, underscoring both the feasibility of AI education and the existing unmet training needs[14].

Tanzania has three universities in Dar es Salaam offering postgraduate medical training: AKU, MUHAS, and HKMU. These institutions serve a combined population of over 400 residents and faculty members across a range of clinical specialties. To date, no published study has characterised the knowledge, self-

perceived competence, or patterns of AI use in post graduate medical education in Tanzania. Generating evidence on knowledge, current utilisation and competencies in using AI will support the design of targeted educational interventions or institutional AI policies for PGME in Tanzania or for similar settings across the continent.

This study aimed to: (i) determine the level of AI knowledge among postgraduate medical residents and faculty in Dar es Salaam; (ii) assess self-reported AI use and formal training exposure; (iii) identify factors independently associated with knowledge scores; and (iv) compare knowledge levels between residents and faculty. The findings are intended to inform curriculum development, faculty development priorities, and institutional policy for AI integration in PGME in resource-limited settings.

Methods

This was a cross-sectional study design in which we used census sampling to capture knowledge, self-reported use, and formal training on AI across all eligible participants at the three postgraduate medical training universities in Dar es Salaam, AKU, MUHAS, and HKMU.

AKU is a private institution offering five PGME programmes, with 40 faculty members and 38 residents. MUHAS is the country's largest medical university, with 16 postgraduate programmes and approximately 160 faculty and 300 residents. HKMU is a private institution with four PGME programmes, 34 faculty and 84 residents.

The study population comprised all postgraduate medical residents and faculty members at the three universities. Participants were eligible regardless of specialty, year of training, or academic rank. All who provided informed consent were included with no further exclusion criteria.

An online structured questionnaire was developed de novo by the research team (supplementary appendix 1) and distributed via institutional channels with the support of programme directors. The questionnaire comprised three sections, (i) sociodemographic and professional background, including specialty, training year, and years of teaching experience; (ii) AI exposure, capturing formal training received, mode of training, self-reported AI use in teaching or learning, and awareness of AI tools in medical education; and (iii) AI knowledge, assessed via ten items covering the following domains, the definition of AI, diagnostic applications, educational applications, research use, virtual patient simulation, personalised learning, and the distinction between AI-based tools and conventional search engines.

No existing validated instrument was identified that assessed AI knowledge within a postgraduate medical education context in sub-Saharan Africa. The initial item pool was reviewed iteratively by all co-investigators for relevance, clarity, and appropriateness to the study population, and items were refined until consensus was reached. Face validity was established through this process. Knowledge was scored as the proportion of the ten knowledge items answered correctly, expressed as a percentage.

Self-rated AI knowledge was assessed on a five-point Likert-type scale (1 = no knowledge; 5 = expert knowledge). Data were collected between April and August 2025.

Data Analysis

Categorical variables were summarised as frequencies and proportions. Continuous knowledge scores were expressed as means with standard deviations and medians with interquartile ranges. An independent samples Welch's t-test was used to compare mean knowledge scores between residents and faculty, given unequal group sizes and the lack of assumption of equal variances.

Multivariable linear regression was performed to identify independent predictors of knowledge, with role (resident vs. faculty), formal AI training (yes vs. no), self-rated knowledge level (1–5), and specialty (medical, surgical, radiology, non-clinical (Pharmacology, Physiology, Biochemistry)) included as predictors. Subgroup analyses were conducted separately for residents and faculty. Statistical analyses were performed using SPSS version 29. A two-tailed p-value of < 0.05 was considered statistically significant.

Ethical Considerations

Ethical approval

was obtained from the Aga Khan University Ethics Review Committee **AKU/2024/27/fb/012/150**. Permissions were also sought from MUHAS (Ref No. CA.301/374/01/) and HKMU (Ref No. KU/ARG/14.2.19/139) for data collection. Study information was provided at the beginning of the online questionnaire, and informed consent was implied by participants' decision to complete and submit the questionnaire. No personally identifying information was collected, and all data were analysed in a de-identified form. Participation was voluntary.

Results

A total of 155 participants completed the questionnaire, 116 residents (74.8%) and 39 faculty members (25.2%). The overall gender distribution was nearly equal (52.3% male, 47.7% female). The largest university contributor was AKU (41.3%), followed by MUHAS (36.8%) and HKMU (21.9%). Most participants were aged 31–40 years (49.0%), Medical specialities constituted the majority of participants (58.1%), followed by surgical specialities (33.5%). Among residents, the largest cohorts were in years 1 and 2 of training. Faculty experience was distributed across all ranges, with the most experienced group (> 6 years) comprising 29.5% of faculty (Table 1).

Table 1
Sociodemographic Characteristics of Participants (N = 155)

Variable	n	%
Gender		
Female	74	47.7%
Male	81	52.3%
University		
Aga Khan University	64	41.3%
Hubert Kairuki University	34	21.9%
Muhimbili University	57	36.8%
Role		
Resident	116	74.8%
Faculty	39	25.2%
Age Group (years)		
20–30	55	35.5%
31–40	76	49.0%
41–50	16	10.3%
> 50	8	5.2%
Specialty		
Medical specialties*	90	58.1%
Surgical specialties**	52	33.5%
Radiology	7	4.5%
Non-clinical specialties	6	3.9%
Year of residency (residents only, n = 116)		
Year 1	41	35.3%
Year 2	44	37.9%
Year 3	21	18.1%
Year 4	10	8.6%

**Medical specialties: Paediatrics, Internal Medicine, Oncology, Family Medicine, Haematology, Microbiology & Immunology, Psychiatry, Emergency Medicine. Surgical specialties*

Variable	n	%
Faculty teaching experience (faculty only, n = 39)		
< 1 year	1	2.6%
1–3 years	6	15.4%
4–6 years	15	38.5%
> 6 years	17	43.6%
**Medical specialties: Paediatrics, Internal Medicine, Oncology, Family Medicine, Haematology, Microbiology & Immunology, Psychiatry, Emergency Medicine. Surgical specialties*		

*** Surgical specialities, ENT, Anaesthesiology, Obstetrics & Gynaecology, Orthopaedics.*

***Non clinical specialities: Pharmacology, Physiology, Biochemistry

Despite widespread AI use, structured training was rare, reported by only 11 participants (7.1%). Online courses were the predominant mode (81.8% of those trained). Despite this, the majority of participants (80.0%) reported currently using AI in their teaching or learning activities. Residents accounted for most of this use (65.8% of total respondents), compared with 14.2% among faculty. Awareness of AI-specific tools in medical education was limited overall, with only 31.0% of respondents aware of such tools (Table 2).

Table 2
Exposure to Artificial Intelligence and Self-Reported Use among Participants

Variable	Total, n (%)	Residents, n (%)	Faculty, n (%)
Received formal AI training			
Yes	11 (7.1%)	6 (3.9%)	5 (3.2%)
No	144 (92.9%)	110 (71.0%)	34 (21.9%)
Type of AI training* (n = 11)			
Online course	9 (81.8%)	5 (45.5%)	4 (36.4%)
Workshop	1(9.1%)	1 (9.1%)	1 (9.1%)
Professional study	1 (9.1%)	1 (9.1%)	0 (0%)
Uses AI in teaching/learning			
Yes	124 (80.0%)	102 (65.8%)	22 (14.2%)
No	31 (20.0%)	14 (9.0%)	17 (11.0%)
Aware of AI tools in medical education			
Yes	48 (31.0%)	35 (22.6%)	13 (8.4%)
No	107 (69.0%)	81 (52.3%)	26 (16.8%)

Across the ten knowledge items, participants demonstrated the strongest understanding of AI's benefits in medical education (98.1% correct), its role in medical diagnosis (93.5%), use in medical research (96.8%), and application in teaching and learning processes (95.5%). Knowledge of virtual patient simulations (91.0%) and the difference between AI chatbots and conventional search engines was also relatively high (80.0%). In contrast, knowledge of the formal definition of AI (54.8%) and awareness of specific AI applications in education (65.8%) were comparatively lower. Residents generally performed better than faculty on items concerning AI applications in education and the distinction between AI chatbots and search engines (Table 3).

Table 3
Proportion of Participants with Correct Responses to Knowledge Items

Knowledge item	Total correct, n (%)	Residents, n†	Faculty, n†
Correct definition of AI	85 (54.8%)	65	20
AI applications in medical education	102 (65.8%)	83	19
Benefits of AI in medical education	154 (98.1%)	116	38
Role of AI in medical education	139 (89.6%)	105	34
AI in medical diagnosis	145 (93.5%)	108	37
AI-driven virtual patient simulations	141 (91.0%)	104	37
Difference between AI chatbots and search engines	124 (80.0%)	97	27
AI use in medical research	150 (96.8%)	112	38
AI use in teaching/learning	148 (95.5%)	111	37
AI in personalised learning	117 (75.5%)	91	26

† Raw counts within residents (n = 116) and faculty (n = 39).

The overall mean knowledge score for all participants was 59.0% (SD 18.2%). Scores were similar between residents (mean 58.6%, SD 18.1%) and faculty (mean 60.3%, SD 18.6%). Among institutions, mean scores were highest at MUHAS (65.2%, SD 16.2%) and lowest at HKMU (58.7%, SD 21.2%), with AKU in an intermediate position (60.9%, SD 18.4%). An independent samples Welch's t-test found no statistically significant difference between residents and faculty (t (63.7) = 0.494, p = 0.623; mean difference = 0.017, SE = 0.034) (Table 4).

Table 4
Overall Objective Knowledge Scores by Group and Institution

Group	Mean % (SD)	Median % (IQR)	p-value
All participants	59.0% (18.2)	60.9% (45.7–73.9)	
Residents	58.6% (18.1)	60.9% (46.7–70.7)	0.623‡
Faculty	60.3% (18.6)	65.2% (45.7–73.9)	
Institution			
AKU	60.9% (18.4)	60.9% (42.4–73.9)	
MUHAS	65.2% (16.2)	65.2% (47.8–69.6)	
HKMU	58.7% (21.2)	58.7% (43.5–72.8)	

‡ Welch's t-test comparing residents vs. faculty.

In multivariable linear regression, self-rated AI knowledge at Level 5 (highest confidence) was the only predictor that reached statistical significance (β = 0.151; 95% CI 0.022–0.302; p = 0.049), suggesting that high self-perceived competence was associated with meaningfully higher objective knowledge scores. Professional role (resident vs. faculty) and formal AI training were not significantly associated with knowledge after adjustment. Speciality showed an association, with medical and radiology specialities performing better than non-clinical specialities (medical: β = 0.204, p = 0.009; radiology: β = 0.268, p = 0.009); surgical specialities bordered on significance (β = 0.153, p = 0.050) (Table 5).

Table 5
Multivariable Linear Regression: Factors Associated with Objective Knowledge Scores (N = 155)

Predictor	β Estimate	95% CI	p-value
Role (ref: Faculty)			
Resident	−0.039	−0.108 to 0.029	0.264
Received AI training (ref: No)			
Yes	0.038	−0.155 to 0.078	0.516
Self-rated knowledge (ref: Level 1)			
Level 2	0.027	−0.074 to 0.128	0.610
Level 3	0.036	−0.062 to 0.133	0.468
Level 4	0.079	−0.041 to 0.199	0.195
Level 5	0.151	−0.022 to 0.302	0.049
Specialty (ref: Non-clinical)			
Medical	0.204	0.053 to 0.355	0.009
Radiology	0.268	0.069 to 0.467	0.009
Surgical	0.153	0.109 to 0.307	0.050

Subgroup Analyses

Among the 39 faculty members, no demographic, training-related, or specialty variable reached statistical significance in the subgroup linear regression model. Self-rated knowledge at Levels 3 and 4 showed positive β estimates (0.165 and 0.211 respectively), but neither was statistically significant, most likely reflecting the limited sample size of this subgroup.

Residents

Among the 116 residents, no predictor reached conventional statistical significance in the subgroup model. Non-clinical specialty was negatively associated with knowledge scores (β = −0.249; 95% CI − 0.440 to − 0.059; p = 0.011), suggesting that residents in non-clinical programmes had relatively lower scores compared with those in medical specialties. No significant associations were found for age, year of training, or prior AI training.

Mean objective knowledge scores increased with self-rated knowledge level, though the relationship was not uniform across the scale (Fig. 1). Scores were similar across Levels 1, 2, and 3, with overlapping confidence intervals indicating no meaningful difference between these groups. A modest increase was observed at Level 4, and the most notable step occurred at Level 5, where mean scores were highest (~ 0.65) with a narrower confidence interval, consistent with the regression finding that only Level 5 self-rating was a statistically significant predictor of objective knowledge.

Discussion

This study contributes baseline evidence on AI knowledge, training exposure, and self-reported use among postgraduate medical residents and faculty in Tanzania. Findings reveal that the majority of participants are already using AI tools despite having almost no formal training and residents use AI substantially more than faculty.

The high prevalence of self-reported AI use (80.0%) is consistent with patterns observed in higher-income settings following the popularisation of large language model tools[7, 8]. In a cross-sectional study of German medical students, it was found that only 5.3% had received formal AI education within their curriculum despite significant proportions actively using AI-based tools in their studies [15].

A multinational survey of Arab medical students across nine countries similarly found that 92.4% had received no formal AI training, yet use of AI tools was common[16]. The pattern observed in our study therefore reflects a global phenomenon, but its consequences may be more significant in a setting where institutional guidance frameworks, ethical policies for AI use, and quality assurance mechanisms are still absent. Although it is important to note that this study did not assess the nature, depth, or quality of participant engagement with AI. Participants who answered "yes" may range from those integrating AI systematically into clinical reasoning to those who have used a chatbot once to paraphrase an assignment. This distinction is important because AI use without conceptual understanding creates educational risks, most notably automation bias which is the tendency to accept AI-generated outputs uncritically without independent verification [17].

Findings that residents reported substantially higher AI use than faculty (65.8% vs. 14.2%) is notable. This likely reflects both generational familiarity with digital tools and the specific pressures residents face; high clinical loads, examination preparation, assignment writing, and literature searching are tasks for which AI tools offer immediate accessibility and efficiency gains.

While younger trainees may be more comfortable with consumer digital tools, it is equally plausible that faculty underreport use due to professional conservatism, concerns about being seen to endorse AI in the context of academic integrity debates, or genuine uncertainty about what institutional policy permits. A survey of faculty and students conducted by Schaye and colleagues at a US medical school found that many faculty expressed uncertainty about their institution's AI policy and their own role in guiding AI use, and that this uncertainty itself suppressed reported engagement [18]. Furthermore, social desirability bias likely operates differently across the two groups: residents may overreport use given its perceived modernity, while faculty may underreport for the same reason. Neither direction of bias can be excluded.

The notable observation in this comparison, however, is that despite substantially higher use, residents had virtually identical objective knowledge scores to faculty (58.6% vs. 60.3%, $p = 0.623$). This finding directly challenges any assumption that informal AI engagement constitutes meaningful AI literacy. A systematic review by Mousavi and colleagues examining attitudes, knowledge, and skills toward AI among healthcare students found that while students generally held positive orientations toward AI, their knowledge and skills remained limited irrespective of tool usage, primarily due to the absence of structured curricula [19]. The present study extends that observation to a postgraduate setting and adds the important comparator of faculty showing that the knowledge gap is not a trainee-specific problem but a systemic one that spans roles.

The modest overall knowledge score (59.0%) and the weakness in foundational AI literacy most evident in the low proportion correctly defining AI (54.8%) and identifying specific educational applications (65.8%) is a finding of practical importance. Participants demonstrated stronger applied awareness, recognising AI's role in diagnosis, research, and teaching, but without a conceptual framework to underpin this, their capacity to evaluate AI outputs critically or use tools safely may be limited. This pattern, where applied awareness surpasses foundational understanding, has been described in other digital health literacy assessments and may reflect learning through informal use rather than structured education [11].

The finding that only the highest self-rated knowledge level (Level 5) was an independent predictor of objective knowledge scores ($\beta = 0.151$, $p = 0.049$) suggests that individuals with the very highest confidence in their AI knowledge may possess genuinely higher knowledge, while at intermediate confidence levels (Levels 2–4), scores were not meaningfully different from those at Level 1. This pattern is consistent with evidence from Allam and colleagues, who found that students with high or moderate AI knowledge and formal training had higher odds of accurate self-assessment than those without, suggesting that calibration improves with actual competence rather than preceding it [20]. Although it is important to acknowledge that Level 5 self-raters may simply be those with greater prior exposure to AI, stronger intrinsic interest in the field, or more frequent informal use are factors that were not measured in this study. The implication for educational design is that AI curricula should include structured opportunities for self-assessment with immediate feedback, helping learners accurately gauge where their understanding stands rather than relying on uncalibrated self-appraisal.

The specialty-level differences with medical and radiology specialties outperforming non-clinical ones may reflect differential AI exposure in clinical practice. AI applications in diagnostic imaging and internal medicine have been developed and publicised more extensively than in public health [2]. Residents in radiology, in particular, are trained in settings where AI image analysis tools are increasingly deployed, creating authentic learning opportunities that other specialties may lack.

A study of surgical residents and postgraduates in China by Dai et al found that while 76.7% reported prior experience with clinical AI applications, self-reported preparedness to critically appraise AI and use it responsibly was modest, with over 75% expressing limited confidence in evaluating model reliability or identifying algorithmic bias [21]. The practical risk in the absence of structured education is that learners develop confidence in AI tools that exceeds their ability to use those tools safely, a concern amplified in resource-limited clinical environments where AI errors may be harder to detect and correct, and This concern is amplified in low- and middle-income countries, where many AI models are developed using data from high-income settings. As a result, AI outputs may not always be applicable to local populations, reinforcing the need for critical appraisal and human oversight [22].

Taken together, these findings are broadly consistent with international literature while contextualising it within a resource-limited, sub-Saharan African PGME environment. Existing reviews note that AI literacy curricula in medical education are predominantly developed in North American and European contexts [4, 5], and their content and assumptions may not apply to settings like Tanzania, where connectivity infrastructure, access to AI platforms, and institutional AI governance are at different stages of maturity. Frameworks such as AI-PACE [23] provide useful structural guidance, but their adaptation for African PGME settings including contextually appropriate case examples, and feasible delivery modalities remains to be done.

This study is, to our knowledge, the first to assess AI knowledge and use among postgraduate medical trainees and faculty in Tanzania, addressing a recognised gap in the literature from sub-Saharan Africa. The census sampling approach across three institutions with different ownership models and programme profiles enhances the representativeness of the findings.

Limitations should also be acknowledged, the knowledge instrument was developed by the study team and has not been externally validated; the ten-item format, while sufficient for an exploratory baseline assessment, may not capture the full breadth of AI literacy. Self-reported AI use is subject to social desirability bias, particularly if participants perceived a socially desirable answer. Finally, the sample, while representing the complete population of PGME trainees and faculty in Dar es Salaam, remains modest particularly for the faculty subgroup limiting the statistical power of subgroup analyses.

These findings have direct implications for curriculum design, faculty development, and institutional policy. The disjunction between widespread informal AI use and limited formal training creates a situation in which trainees are using AI tools without a structured framework for evaluating their reliability, understanding their limitations, or applying them safely in clinical or research contexts. Institutions offering PGME in Tanzania should consider integrating foundational AI literacy into existing

training programmes, covering conceptual understanding of how AI systems function, critical appraisal of AI-generated outputs, ethical and legal dimensions of AI use in healthcare, and discipline-specific applications.

At an institutional policy level, the finding that 80% of trainees are already using AI without formal guidance underscores the urgency of developing clear institutional policies on AI use in academic work, clinical decision support, and research. the current findings provide an empirical basis to extend and contextualise such policies across all three institutions studied.

Future research should focus on validating a contextually adapted AI knowledge and competency assessment tool for use in African PGME settings.

Declarations

Ethics approval and consent to participate

This study adhered to the ethical principles outlined in the Declaration of Helsinki. Ethical approval was received from all Universities with approval number AKU/2024/27/fb/012/150. Written informed consent was obtained from all participants. Participants were also made aware that all the information obtained during and after the study was confidential.

Consent to publish:

Not applicable

Competing interests

The authors declare no competing interests.

Registration Details

This study is not a Clinical trial. Registration details are not applicable.

Funding

This study was supported by the Aga Khan University Scholarship of Teaching and Learning (SoTL) Grant 2024. The funder had no role in study design, data collection, analysis, interpretation, or the decision to submit for publication.

Author Contribution

NW: Study conception, collection of data, drafting and revision of manuscriptEN: Drafting manuscript, data collection and data analysis DG: Drafting manuscript, data collection and data analysis HB: Data collection and revision of the manuscriptAZ: Data collection and revision of the manuscriptHS: Data collection and revision of the manuscriptMN: Study conception, supervision of data collection and analysis, and revision of the manuscript and proofreading.

Acknowledgement

The authors thank all postgraduate medical residents and faculty members at the Aga Khan University, Muhimbili University of Health and Allied Sciences, and Hubert Kairuki Memorial University who gave their time to participate in this study. We also acknowledge the programme directors at the three institutions for their facilitation.

Data Availability

Data can be available on reasonable request

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Figures

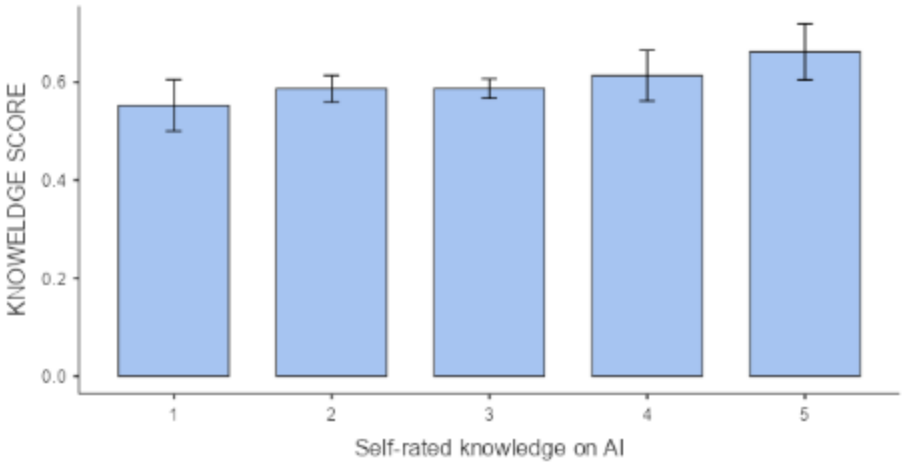


Figure 1

Relationship between self-rated and objective knowledge scores.

Supplementary Files

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- Supplementaryfile1QuestionaireScoresheet.docx