

Students' perception of the impact of artificial intelligence (AI)-personalised learning modules on knowledge, technical skills and clinical readiness among diploma radiography students at Kenya medical training college

Ronald Wasike¹
David Nandebe Wafula²

¹dnandebe@kmtc.ac.ke

¹orcid.org/0000-0003-3236-7993

²orcid.org/0009-0000-9047-0089

^{1,2}Kenya Medical Training College, Kenya

<https://doi.org/10.51867/ajernet.7.4.98>

ABSTRACT

As artificial intelligence (AI)-powered imaging systems become more commonplace in radiography, it is crucial for graduates to be able to use them safely, which requires knowledge, technical skills and clinical readiness that must be developed during training. This study aimed to evaluate the perceptions of diploma radiography students on the effect of the use of AI-personalised learning modules (digital learning modules that adapt content, pacing and assessment to each student) on knowledge acquisition, technical skills and clinical readiness in Kenya Medical Training College (KMTTC) and to describe the relationship between the perceptions. Self-determination theory anchored this research. This was a cross-sectional descriptive survey that was conducted in May-June 2025 in five campuses (Eldoret, Kisumu, Mombasa, Nairobi and Nakuru) with 30 students per campus (N = 150; 149 valid responses, 99.3%). A structured questionnaire was used to gather information. Frequencies, percentages, means, Wilson 95% confidence intervals and Spearman's rank correlation were used for the analysis of six five-point Likert items. The highest levels of agreement were for deepened understanding of theory (71.1%) and improved technical skills (63.8%). It was lower for confident clinical application (61.7%), preparation for real world clinical tasks (61.1%), confidence in knowledge (58.4%) and accurate imaging technique (57.0%). Items had positive correlations ($\rho = .434$ to $.804$, $p < .001$), and the knowledge-skills-readiness domain correlated with the adaptive-delivery ($\rho = .454$) and AI-tailored modules ($\rho = .621$) domains. Students felt that they had improved more in theory than in skills and confidence in the clinical setting. The cross-sectional and self-reported nature of the design precludes the determination of effectiveness and only provides information on perceptions. It is recommended to have supervised hands-on practice, simulation and a controlled follow-up study with objective outcomes.

Keywords: Artificial Intelligence, Clinical readiness, Personalised Learning, Radiography Education, Technical Skills

I. INTRODUCTION

Health professions education is a means to an end: to produce practitioners who are able to use knowledge and skills safely when they enter practice (Wynne *et al.*, 2024). This responsibility is particularly challenging in radiography. Radiographers use sophisticated equipment, move patients into correct positions, choose exposure factors, and safeguard patients and co-workers from unnecessary radiation exposure, and are increasingly using software that automates or assists with portions of the imaging process (Hardy & Harvey, 2020). A graduate who knows the theory but lacks the ability to apply it to correct technique, or who is able to work well in a laboratory but is not ready to work in a busy department, is not ready for independent practice. Learning is effective when the learner is able to grasp the concepts, execute the technical aspects and is confident in using it in real clinical situations (Wynne *et al.*, 2024).

Artificial intelligence (AI)-personalised learning modules are among the latest of the learning technologies that are routinely introduced to enhance these outcomes. These are designed to adapt content, pacing and evaluation to the specific student to maximize the acquisition of knowledge and skills in a more efficient manner than through the delivery of uniform instruction. However, students' sense of benefit does not always correspond with what they are able to do, and a technology that students like is not necessarily a technology that is able to enhance what students can do. This distinction is significant for programme managers, as they need to determine if they should invest in AI-supported instruction, and for educators, as they need to decide where AI-supported instruction fits in with supervised practice.

Knowledge acquisition is defined as knowledge of theory and concepts, technical skill as the ability to perform practical procedures accurately and clinical readiness as being prepared and confident to apply learning in clinical work. These three constructs are interrelated and different. Reading or getting information digitally, technical skills are usually acquired through repeated supervised practice, and clinical readiness is acquired through all of the above and confidence

through exposure to real patients and real workflow. When all three are studied together, as in this study, differences in students' experiences of each can come to light.

The evidence of the effectiveness of AI-powered tools in enhancing educational outcomes is still limited. A systematic review of 12 single centre studies rated the evidence related to educational outcomes in health professions education as poor, with all studies assessing Kirkpatrick level 2 outcomes (Feigerlova *et al.*, 2025), which reflect learning rather than changes in behaviour or patient outcomes, and only three used learning theories. The review thus provides little evidence to suggest that AI-assisted teaching leads to better clinical outcomes and highlights the importance of research that captures the learner's perspective of AI-assisted teaching.

The results of radiographic tasks studies are mixed. The AI-assisted radiograph-mounting interface was faster than manual mounting, but less accurate, and did not increase the confidence of the dental students, who were also warned that automation could be detrimental to learning among inexperienced clinicians (Chang *et al.*, 2024). A postgraduate AI module for radiographers in the UK, which involved participatory action research with seven students and six faculty members, was reported as a meaningful learning experience, but some aspects of the design and delivery were barriers (van de Venter *et al.*, 2023). International, approximately 69% of radiographers believed that AI should be included in the curriculum and 47.3% disagreed that there is sufficient training available (Akudjedu *et al.*, 2023). All these indicate high demand for AI education, but there is no consensus on the delivery of AI education and what it accomplishes.

African evidence suggests that there is a gap between confidence and competence. A survey of 551 health care students in a Nigerian university revealed that 60% of the students perceived their knowledge of AI as high, while objective evaluation revealed that 92% of the students had low knowledge of AI (David-Olawade *et al.*, 2025). Botwe *et al.* (2021) conducted a survey of 1020 radiographers in Africa that resulted in a call to action for AI training programmes and adoption roadmaps. A study on an online research course at Kenya Medical Training College (KMTC) revealed that digital delivery is faced with practical challenges as only 53% of students answered all the pretest items, 45% of learners who accessed the post-test answered it and technological challenges reduced effectiveness (Gachanja *et al.*, 2021). These results are a warning that digital learning does not necessarily reach or benefit all students equally.

1.1 Statement of the Problem

There is limited capacity in Kenya as only 11% of the assessed health facilities provide radiography services (Ministry of Health, 2023), and most of the middle-level health workforce (85%) are graduates of KMTC (Kenya Medical Training College, n.d.). It is therefore important for KMTC graduates to be prepared to work with AI imaging. There are three limitations in the existing studies on AI in Radiography education. Conceptually, they assessed awareness, attitudes or task performance per se, and not perceived knowledge and technical skill and clinical readiness. They were methodologically based on attitude surveys, small trials/pilots. In terms of context, they were carried out outside of Kenya or by practitioners and not by Kenyan diploma students. In Kenya, it is not described whether diploma radiography students perceive benefits from AI-personalised learning modules and programme leaders have no evidence on which aspects of preparation students feel are enhanced and which are not.

1.2 Research Objective

The aim was to determine the students' perception of the impact of ai-personalised learning modules on knowledge, technical skills and clinical readiness among Diploma Radiography Students at Kenya Medical Training College.

II. LITERATURE REVIEW

2.1 Theoretical Review

2.1.1 Self-determination theory

Self-determination theory (Deci & Ryan, 1985) suggests that motivation and engagement is based on three psychological needs: autonomy, competence and relatedness. The competence need is the focus of this study, as it relates to the feeling of being effective and masterful in one's activities. Content and skills should be mastered by students, and modules that fit the pace of the learner and provide accurate feedback should help students feel that they are learning the content and skills. The expectation is directly related to the perceived knowledge, technical skill and clinical readiness items in the questionnaire, which ask students if they feel more capable after using the modules.

The theory also helps to explain the boundaries of the analysis. The questionnaire does not assess autonomy or relatedness, so the theory is applied to the perceptions of competence only. It also considers perceived competence as psychologically important in itself as students who feel competent tend to persevere but also acknowledges that perceived competence is not the same as demonstrated competence. This distinction is carried over in the interpretation of the results.

2.2 Empirical Review

Feigerlova *et al.* (2025) conducted a search of six databases up to October 2024 and included 12 single-centre studies with 4-180 participants (three RCTs, seven quasi-experimental and two observational studies). The authors assessed the quality of evidence in terms of educational outcomes as poor, all studies measured level 2 outcomes, and only three used learning theories. Chang *et al.* (2024) randomly assigned 40 dental students from one university to manually mount radiograph series or to use AI assistance, which was significantly faster ($p < .05$) but less accurate ($p < .01$) with no difference in confidence. These studies have been conducted on small samples and have assessed performance or skills, rather than students' perceived readiness.

The studies on AI education for radiographers primarily focus on experiences and attitudes, with van de Venter *et al.* (2023) conducting a participatory action research study with a social constructivist epistemology, involving seven out of 17 students and six out of eight faculty members in an online focus group. Four themes emerged, one of which was a meaningful learning experience and design and delivery barriers. Akudjedu *et al.* (2023) conducted a survey of 314 radiography professionals from around the world using snowball sampling and revealed that approximately 69% agreed that AI should be taught in the curriculum, and 47.3% disagreed that there is sufficient training. Oglat *et al.* (2026) conducted a study with 180 radiography students at one Jordanian institution, 46.1% of whom had good knowledge of AI and 60.0% would consult an expert if AI predictions differed from their own. None of the studies assessed the perceived impact of an AI-personalised module on skills.

African studies show a disconnect between perceived and actual competence. David-Olawade *et al.* (2025) used a validated questionnaire to survey 551 healthcare students at Obafemi Awolowo University, analysed using descriptive statistics and one-way analysis of variance. 60% thought that they knew a lot about AI, while only 92% objectively knew little about AI, but 84.4% were willing to train. Botwe *et al.* (2021) reported that 84.9% of 1,020 African radiographers believed that AI would enhance the practice and they called for training programmes and roadmaps, while Antwi *et al.* (2021) analysed 475 open-ended responses from the survey and recommended AI modules in the training of future radiographers. These studies are based on self-report, voluntary responses and involve practitioners or non-radiography students.

In Kenya, evidence is based on KMTC e-learning studies and from radiologists. Gachanja *et al.* (2021) conducted an analysis of an online research course for 933 higher diploma students from 11 KMTC campuses using Moodle data and a questionnaire and found that participation in pre and post-test was not completed (53% and 45% respectively) while technological challenges reduced the effectiveness. Kaloki *et al.* (2024) conducted a survey of 1139 students at selected Coast and Nairobi campuses where 89.2% participated in online classes while 76.8% strongly preferred face-to-face classes. In a preprint titled Kenyan radiologists and residents, Mwaniki *et al.* (2023) found that just 12.6% of Kenyan radiologists and residents were using AI on a daily basis. The Kenyan literature thus shows both positive and negative attitudes towards digital learning, however, none of the literature looks at AI-personalised modules for diploma radiography students.

These studies reveal positive attitudes towards AI education, limited training and a potential confidence-competence gap. There are few studies that assess students' self-perceptions of knowledge and technical competence and clinical readiness following the use of an AI-personalised module and none of this kind of study for Kenyan diploma radiography students. This study fills this gap by outlining perceptions at five KMTC campuses and their association with students' perceptions of adaptive delivery and AI adapted modules.

III. METHODOLOGY

3.1 Research Design

A descriptive survey with a quantitative questionnaire was used that was administered once. Data are self-reported perceptions of one group only, and no baseline, follow-up or comparison group. Hence impact is understood as perceived impact, and causal effectiveness and superiority over traditional teaching is not tested. A descriptive design was suitable as the purpose was to describe perceptions and their relationships in a population where there was no previous evidence.

3.2 Study Area

The study was carried out in the KMTC Diploma in Radiography and Imaging programme in five campuses namely; Eldoret, Kisumu, Mombasa, Nairobi and Nakuru.

3.3 Participants and Sampling

The subjects of the study were 150 students in Years 1, 2 and 3 (48, 53 and 49 students, respectively) with purposive and simple random sampling per campus. Allocation was equal across campuses to prevent any one campus dominating the results. The results of the study cannot be generalised to other KMTC campuses or all radiography learners in Kenya.

3.4 Data Collection Instrument and Procedures

A structured questionnaire was used to gather information on gender, academic year, campus, 18 five-point Likert items (1 = strongly disagree, 5 = strongly agree) in three domains of six items each: adaptive personalised learning, AI-tailored modules and assessment, and perceived knowledge, technical skills and clinical readiness. This article reports the six items of the third domain, and the other two domains as correlates. The six outcome items cover the understanding of theory, confidence in knowledge, accurate imaging technique, technical skills, preparation for real world clinical tasks and confident clinical application. The questionnaire was tested prior to data collection and the Cronbach's alpha was .768, which is acceptable.

The questionnaire was electronically distributed in May-June 2025. 100% of the questionnaires (150) were returned. A single record was not included in item level analyses because it did not contain any Likert responses, resulting in 149 valid responses (99.3%). With electronic administration, results from all five campuses were gathered in the same time frame.

3.5 Reliability and Validity

There are a number of features that enhance the quality of the data and others that constrain the data. A questionnaire was piloted prior to the data collection and the Cronbach's alpha was .768, which is acceptable. The high inter-item correlation (Table 2) is indicative of the items measuring a related set of perceptions. But alpha was reported once only and the instrument was not validated against objective measures of knowledge or skill, therefore the items reflect perceived, rather than demonstrated competence. Although anonymous electronic administration may have minimised social-desirability pressure, it did not remove it and students who had a positive attitude towards the modules may have been more likely to respond positively to all the items.

3.6 Data Analysis

The data was analysed in SPSS. Each item was described using frequencies, percentages, means, standard deviations and Wilson 95% confidence intervals (Agree and Strongly Agree were grouped together and Disagree and Strongly Disagree were grouped together). Wilson intervals were selected as they are more efficient than simple normal approximation intervals for proportions that are not near .50 or for moderate-sized samples. Spearman's rank correlation with pairwise deletion was used to determine the relationships between items and between domain scores, which are ordinal Likert data. There were no intervention and comparison groups, so analysis of variance and Tukey's honestly significant difference test were not used.

3.7 Ethical Considerations

The study was approved by KMTC and National Commission for Science, Technology and Innovation. It was voluntary and informed consent; responses were anonymised and access to data was restricted. Data handling was done in accordance with the Data Protection Act (Republic of Kenya, 2019) and based on the World Health Organization (2021) guidance on the ethics and governance of AI for health.

IV. FINDINGS & DISCUSSIONS

4.1 Participant Characteristics

150 questionnaires were returned and 149 questionnaires had valid Likert responses. Of the 150 participants, 115 (76.7%) were female and 35 (23.3%) were male. By academic year, 48 (32.0%) were in Year 1, 53 (35.3%) in Year 2 and 49 (32.7%) in Year 3, a fairly even spread across the three years of the programme. Thirty students (20.0%) were in each of the two campuses.

4.1.1 Overall Perceived Knowledge, Technical Skills and Clinical Readiness

The results of the items are shown in Table 1. The range of agreement for the six items was from 57.0% to 71.1% (a difference of 14.1 percentage points) with an average of the six item-level agreement percentages of 62.2%. Disagreement ranged from 12.8% to 20.1%, and neutral responses from 16.1% to 26.8%. The means were fairly similar (2.40 to 2.58) and the differences between items are in the distribution of responses.

Table 1*Perceived Knowledge, Technical Skills and Clinical Readiness (n = 149)*

Item	Disagree, n (%)	Neutral, n (%)	Agree, n (%)	M	SD
Deepen understanding of radiography theory	19 (12.8)	24 (16.1)	106 (71.1)	2.58	0.708
More confident in radiography knowledge	22 (14.8)	40 (26.8)	87 (58.4)	2.44	0.738
Perform imaging techniques accurately	25 (16.8)	39 (26.2)	85 (57.0)	2.40	0.762
Improve technical radiography skills	26 (17.4)	28 (18.8)	95 (63.8)	2.46	0.776
Handle real-world clinical tasks effectively	30 (20.1)	28 (18.8)	91 (61.1)	2.41	0.805
Apply learning in clinical settings with confidence	24 (16.1)	33 (22.1)	92 (61.7)	2.46	0.758
Composite	21 (14.1)	31 (20.8)	97 (65.1)	2.51	0.732

The composite row shows the respondents based on the composite score for the six items.

The same applies to students who were not in agreement. Those who understood theory, technical skills, were confident in clinical application, were prepared for clinical tasks, were confident in knowledge and were accurate in technique were 28.9%, 36.2%, 38.3%, 38.9%, 41.6% and 43.0% respectively. For the best rated item, almost one-third of students, and for accurate technique almost half, were not convinced, however. Responses were neutral or more in number than outright disagreement for all items except for preparation for clinical tasks, for which there was less of a difference (18.8% neutral and 20.1% disagree), indicating that many students were undecided rather than disagreeing. The composite shows that 34.9% of students did not agree, meaning that approximately one-third of the students did not agree that the modules increased their knowledge, skills and readiness.

4.1.2 Perceived Knowledge Acquisition

Knowledge had the highest positive rating. 71.1% agreed that the modules helped them to deepen their understanding of theory ($M = 2.58$, $SD = 0.708$) and this item had the lowest disagreement (12.8%). Its 95% confidence interval, [63.4, 77.8] was completely above 63%, while the interval for accurate imaging technique, [49.0, 64.7] was below 63% and the two intervals only overlap slightly between 63.4% and 64.7%. There was less confidence in knowledge: 58.4% agreed ($M = 2.44$, $SD = 0.738$), and 26.8% were neutral; this was the highest neutral response of the items. That is, students were more likely to report that the modules helped them to learn more than that they felt more confident about what they learned.

Students felt that theoretical understanding was the greatest benefit and that the practical technique and clinical application was less. This is a reasonable approach for the digital modules, which provide good explanations of concepts but not much hands-on practice. The difference between the highest and lowest endorsement percentages (14.1%) is not insignificant and the correlation pattern is in the same direction: the lowest correlation was between the theory item and the practical items, indicating that the theoretical and practical impacts of the modules are experienced separately by the students. This is also consistent with evidence that AI-assisted learning has primarily been assessed in terms of knowledge and technical-skill outcomes, with limited evidence on clinical readiness (Feigerlova *et al.*, 2025).

Self-perceived competence is to be interpreted with caution. David-Olawade *et al.* (2025) found that 60% of healthcare students in Nigeria had high knowledge of AI, while 92% had low knowledge of objective assessment. Similarly, students in the current study might over- or under-estimate their readiness and no objective examination, skills or clinical-performance scores were taken. The results for the finding of confidence in knowledge had the highest level of neutrality (26.8%) which could be interpreted as a lack of understanding of the students' own learning, but this cannot be supported by the data.

The knowledge findings are between two bodies of evidence when set against the reviewed literature. There is a high demand for AI education from radiographers and radiography students (Akudjedu *et al.*, 2023; Botwe *et al.*, 2021), and the 71.1% agreement on deepened understanding of theory indicates that students view digital modules as a valuable pathway to conceptual learning. The lower and more neutral responses on confidence in knowledge (58.4% agreed; 26.8% neutral), however, reflect the confidence–competence gap reported by David-Olawade *et al.* (2025), and self-reported knowledge gains should be verified with objective knowledge tests.

4.1.3 Perceived Technical Skills

Theory was seen as more favourable than technical skills. Overall, 63.8% agreed that practice with the modules helped them to become more technically competent in radiography ($M = 2.46$, $SD = 0.776$). The lowest agreement and lowest mean of the six items was for the ability to perform imaging techniques accurately ($M = 2.40$, $SD = 0.762$) with 57.0% agreeing that the modules helped them to do this. For this item, 43.0% of students either disagreed (16.8%) or were neutral (26.2%). The difference between the general skill improvement (63.8%) and accuracy of technique (57.0%) indicates that students were more comfortable endorsing practice in general terms than endorsing accuracy, which is most important for image quality and patient safety.

The lowest agreement was for accurate imaging technique (57.0%), which is consistent with the dental trial where AI assistance increased the speed of work but decreased the accuracy (Chang *et al.*, 2024), although the latter measured performance and the settings and tasks were different. The comparison is indicative and not conclusive. It does, however, warrant a cautious interpretation: AI-assisted practice can help students navigate content quickly, but it does not necessarily help them to be more precise in clinical imaging situations.

The technical skills findings are similar to those of Chang *et al.* (2024), who found that AI assistance increased speed but not accuracy, with students more likely to agree that AI assistance helped them improve their general skills (63.8%) than their technique (57.0%). Hardy and Harvey (2020) state that radiographers are still accountable for correct patient positioning and the practicalities of image acquisition when using AI, and that graduates need to be proficient in overseeing AI processes.

4.1.4 Perceived Clinical Readiness

The two clinical readiness items were in between the knowledge and technique items. Overall, 61.1% agreed that the modules enabled them to perform real world clinical tasks effectively ($M = 2.41$, $SD = 0.805$) and 61.7% agreed that they could apply what they learned in clinical settings with confidence ($M = 2.46$, $SD = 0.758$). Preparation item had the highest disagreement (20.1%) and the highest standard deviation (0.805), which means that there was the greatest difference of opinion. Across the composite of the six items, 65.1% agreed, 20.8% were neutral and 14.1% disagreed ($M = 2.51$, $SD = 0.732$).

The perceived competence was moderate, with approximately 40% of the students not agreeing that the modules prepared them for clinical tasks (in self-determination theory terms). The percentages of disagree/neutral for the preparation item ranged from 28.9% to 43.0% for the other items. The competence needs that the theory highlights may only be partially fulfilled if a significant minority of students do not feel more competent after using the modules and the modules may be more appropriate as a supplement to supervised practice than as a replacement for it.

The perceived benefit was at a moderate level, which should be interpreted in the context of the existing knowledge on digital learning at KMTC. Gachanja *et al.* (2021) indicated that there was lack of full participation in an online course and technological challenges that hampered the effectiveness of the course, while Kaloki *et al.* (2024) revealed that 89.2% of students participated in online classes but 76.8% strongly preferred face-to-face classes. Students' concerns about the usefulness of the AI modules may thus be due to a general preference for face-to-face and hands-on learning in a practical subject, rather than to aspects of the AI modules per se. To separate these effects, a design would be needed that would manipulate the delivery mode and the AI element independently.

The results also need to be applied in the context of Kenya. The readiness of each graduate is significant given the scarcity of radiology services in the country (Ministry of Health, 2023) and the fact that KMTC provides the majority of middle-level health workers (Kenya Medical Training College, n.d.). If AI-personalised modules enhance theory, but students are still not confident in technique, then the practical aspects of training are the key to ensuring the quality of graduates, and digital tools should be implemented in a way that does not replace supervised practice time.

The results are consistent with, but not a copy of, previous research. Radiographers and radiography students have expressed high levels of interest in learning about AI and a lack of training in AI (Akudjedu *et al.*, 2023; Botwe *et al.*, 2021; Oglat *et al.*, 2026). The current results also indicate that endorsement is not consistent; endorsement for each statement was around 60% among students who used AI-personalised modules, with a significant minority being neutral or disagreeing. The moderate agreement and the broad range of opinion on the clinical preparation item here aligns with the meaningful learning experience, design and delivery barriers, reported in evaluations of AI modules for radiographers (van de Venter *et al.*, 2023).

The moderate readiness findings agree with Wynne *et al.* (2024), whose systematic review of 93 studies identified self-confidence as one of the most important individual factors in graduate readiness, and curriculum design, realistic simulation, quality clinical placements and effective feedback as key educational factors. The students in this study were least convinced of accurate technique and clinical application, which rely most on simulation, placements and feedback, and not just on digital content.

4.1.5 Relationships Among the Variables

All items had positive and significant correlation values ($\rho = .434$ to $.804$, all $p < .001$; Table 2). The mean of the 15 inter-item coefficients was .62, with five of the inter-item coefficients $> .70$, which means that the items generally cluster together. The highest correlation was between increased technical skills and confidence in clinical application ($\rho = .804$) and increased technical skills and readiness to perform real-world clinical tasks ($\rho = .774$). There was also a strong correlation between confidence in knowledge and accurate imaging technique ($\rho = .752$) and preparedness and confident application ($\rho = .752$).

The item that was the most different was the understanding-of-theory item. The four items related to technique, skills and clinical use were correlated between .588 and .804 while its correlations with the other five items were the lowest in the matrix, ranging from .434 (with technical skills) to .575 (with accurate technique). This pattern indicates

that students did not perceive theoretical gains as being closely related to perceived practical/clinical gains. Perceived knowledge, skills and readiness at the domain level correlated with adaptive-delivery domain ($\rho = .454$) and AI-tailored modules domain ($\rho = .621$). These associations are therefore only perceptions, and the null hypothesis of no association was rejected.

Table 2

Spearman Correlations Among Knowledge, Skills and Readiness Items

Item	1	2	3	4	5
1. Deepen understanding of theory	—				
2. More confident in knowledge	.568	—			
3. Perform techniques accurately	.575	.752	—		
4. Improve technical skills	.434	.502	.588	—	
5. Handle real-world clinical tasks	.485	.551	.657	.774	—
6. Apply learning with confidence	.504	.582	.744	.804	.752

N=149; all correlations were significant at a .001 level (two-tailed).

Technical skills and preparedness and clinical confidence are highly correlated, indicating that these perceptions co-vary. This may be a true measure of skill transfer or may be due to a positive response tendency, where students who have a positive attitude towards the modules rate all of the items high. The associations are thus not to be interpreted as evidence of effect. Moderate relationships with adaptive delivery ($\rho = .454$) and AI-tailored modules ($\rho = .621$) suggest that students who felt more personalised were more likely to feel ready, and the higher relationship with AI-tailored modules suggests that content and assessment design may be more important to perceived readiness than pacing alone. This relationship must be tested and there must be objective results.

The high correlation between the two clinical readiness items and the technical skills ($\rho = .774$ to $.804$) aligns with Wynne *et al.* (2024) who define readiness as a combination of knowledge, skills and confidence. The lower correlation between theory and the practical items ($\rho = .434$ to $.575$) indicates that improvements in theory may not necessarily translate into practice, which aligns with the worry expressed by Feigerlova *et al.* (2025) that current evidence on AI in health professions education focuses on learning outcomes and not necessarily on changes in behaviour or clinical outcomes.

4.2 Implications for Practice

There are three implications for KMTC. First, AI-personalised modules seem to be best suited to reinforce theory and can be used to prepare students for laboratory and clinical sessions, but not to replace them. Second, students were least convinced of accurate technique, so hands-on activities that provide feedback on positioning and on the choice of exposure should accompany any digital instruction. Thirdly, perceptions of clinical readiness were closely related to perceptions of technical skill, so enhancing practical teaching is likely to enhance perceptions of clinical readiness. These implications are tentative and subject to change. The study tells about the feelings of the students and not what they could do, and the effect of the modules on competence has not been tested. The results should therefore be used by programme leaders as a guide as to where to look, and the objective assessment and controlled follow-up as recommended below should be used.

V. CONCLUSION & RECOMMENDATIONS

5.1 Conclusion

Students thought that the AI-personalised modules were most useful for theory and less useful for imaging technique and clinical application. The range of agreement was from 71.1% to 57.0% for deepened understanding of theory and accurate imaging technique, respectively. There was a positive relationship between perceived knowledge, skills, and readiness with perceived adaptive delivery and tailored modules. These findings are descriptions of perceptions and not effectiveness.

5.2 Recommendations

Based on the findings, four recommendations are made. First, KMTC should incorporate supervised hands-on practice, skills-laboratory simulation and clinical placement activities to complement AI-supported teaching. Second, the content of the modules should be enhanced, especially for imaging technique, with simulated cases and feedback. Third, programme leaders should use objective measures (knowledge tests, practical skill tests and supervisor ratings) in conjunction with perception surveys. Finally, future research should present results by campus in a prospective, controlled pretest–posttest study with a conventional-teaching comparison group.

Declaration of Interest

The authors declare that they do not have any known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Funding Declaration

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

REFERENCES

- Akudjedu, T. N., Torre, S., Khine, R., Katsifarakis, D., Newman, D., & Malamateniou, C. (2023). Knowledge, perceptions, and expectations of artificial intelligence in radiography practice: A global radiography workforce survey. *Journal of Medical Imaging and Radiation Sciences*, 54(1), 104–116. <https://doi.org/10.1016/j.jmir.2022.11.016>
- Antwi, W. K., Akudjedu, T. N., & Botwe, B. O. (2021). Artificial intelligence in medical imaging practice in Africa: A qualitative content analysis study of radiographers' perspectives. *Insights into Imaging*, 12, Article 80. <https://doi.org/10.1186/s13244-021-01028-z>
- Botwe, B. O., Akudjedu, T. N., Antwi, W. K., Rockson, P., Mkoloma, S. S., Balogun, E. O., Elshami, W., Bwambale, J., Barare, C., Mdletshe, S., Yao, B., & Arkoh, S. (2021). The integration of artificial intelligence in medical imaging practice: Perspectives of African radiographers. *Radiography*, 27(3), 861–866. <https://doi.org/10.1016/j.radi.2021.01.008>
- Chang, J., Bliss, L., Angelov, N., & Glick, A. (2024). Artificial intelligence-assisted full-mouth radiograph mounting in dental education. *Journal of Dental Education*, 88(7), 933–939. <https://doi.org/10.1002/jdd.13524>
- David-Olawade, A. C., Wada, O. Z., Adeniji, Y. J., Aderupoko, I. V., & Olawade, D. B. (2025). Artificial intelligence readiness among healthcare students in Nigeria: A cross-sectional study assessing knowledge gaps, exposure, and adoption willingness. *International Journal of Medical Informatics*, 204, Article 106085. <https://doi.org/10.1016/j.ijmedinf.2025.106085>
- Deci, E. L., & Ryan, R. M. (1985). *Intrinsic motivation and self-determination in human behavior*. Springer.
- 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, Article 129. <https://doi.org/10.1186/s12909-025-06719-5>
- Gachanja, F., Mwangi, N., & Gicheru, W. (2021). E-learning in medical education during COVID-19 pandemic: Experiences of a research course at Kenya Medical Training College. *BMC Medical Education*, 21, Article 612. <https://doi.org/10.1186/s12909-021-03050-7>
- Hardy, M., & Harvey, H. (2020). Artificial intelligence in diagnostic imaging: Impact on the radiography profession. *British Journal of Radiology*, 93(1108), Article 20190840. <https://doi.org/10.1259/bjr.20190840>
- Kaloki, L. N., Ombasa, Z. O., Mutiso, U. M., Mutiso, R. N., Kwinga, N. M., Nyachae, J. R., Musovya, J., Kinyae, V. N., Nguutu, G. K., Kalunda, E. K., Mwangi, L. W., Jonah, L. M., & Mutisya, R. M. (2024). Level of utilization of eLearning among students at selected KMTC campuses. *International Journal of Community Medicine and Public Health*, 11(1), 20–27. <https://doi.org/10.18203/2394-6040.ijcmph20234103>
- Kenya Medical Training College. (n.d.). *KMTC at a glance*. KMTC. <https://kmtc.ac.ke/about/kmtc-at-a-glance>
- Ministry of Health. (2023). *Kenya health facility census report, September 2023*. Republic of Kenya.
- Mwaniki, E., Onyambu, C., & Rodrigues, J. C. (2023). *The role of artificial intelligence in diagnostic radiology: Knowledge, attitude, and practice of radiologists and radiology residents in Kenya* [Preprint]. Research Square. <https://doi.org/10.21203/rs.3.rs-2492173/v1>
- Oglat, A. A., Abukhalil, T., Isawi, I. H., Alzyoud, K., Oqlat, A. A., Salman, M. D., Alnawafleh, T. M., & Bani-Ahmad, M. (2026). Awareness, perceptions, and educational preferences for AI among radiography students: A cross-sectional survey. *Journal of Medical Imaging and Radiation Sciences*, 57(4), Article 102452. <https://doi.org/10.1016/j.jmir.2026.102452>
- Republic of Kenya. (2019). *Data Protection Act, 2019*. Office of the Data Protection Commissioner.
- van de Venter, R., Skelton, E., Matthew, J., Woznitza, N., Tarroni, G., Hirani, S. P., Kumar, A., Malik, R., & Malamateniou, C. (2023). Artificial intelligence education for radiographers, an evaluation of a UK postgraduate educational intervention using participatory action research: A pilot study. *Insights into Imaging*, 14, Article 25. <https://doi.org/10.1186/s13244-023-01372-2>
- World Health Organization. (2021). *Ethics and governance of artificial intelligence for health: WHO guidance*.
- Wynne, K., Mwangi, F., Onifade, O., Abimbola, O., Jones, F., Burrows, J., Lynagh, M., Majeed, T., Sharma, D., Bembridge, E., Stubbs, M., Sunner, C., Bergmann, J., Bagade, T., & Malau-Aduli, B. S. (2024). Readiness for professional practice among health professions education graduates: A systematic review. *Frontiers in Medicine*, 11, Article 1472834. <https://doi.org/10.3389/fmed.2024.1472834>