

Development and Preliminary Validation of a Questionnaire Assessing Artificial Intelligence Education Readiness and Integration among Medical Imaging Stakeholders in South-East Nigeria

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ABSTRACT

Background: Artificial intelligence (AI) is increasingly influencing healthcare delivery, clinical decision-making, and medical imaging practice, creating a need for appropriate AI-related competencies within undergraduate radiography education. In resource-constrained settings, curriculum capacity, infrastructure, faculty expertise, and digital access may influence how AI education can be integrated. Validated instruments that capture both stakeholders' perceptions and contextual barriers remain limited.

Objective: To develop and preliminarily evaluate a context-sensitive questionnaire assessing radiography students' perceptions of AI education readiness and integration in medical imaging in South-East Nigeria.

Methods: A cross-sectional pilot study was conducted among 39 undergraduate radiography students from three accredited universities in South-East Nigeria. The 56-item questionnaire was developed from a critical literature review, expert consultation, the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Medical Artificial Intelligence Readiness Scale for Medical Students (MAIRS-MS), and designed to evaluate stakeholders across radiography education, with this pilot psychometric evaluation purposely restricted to student cohort. Five subject-matter experts assessed item relevance and clarity using a four-point ordinal scale. Content validity was quantified using the Item Content Validity Index (I-CVI) and Scale Content Validity Index/Average (S-CVI/Ave). Preliminary construct validity was examined separately by construct using principal component analysis with Varimax rotation, while internal consistency was assessed using Cronbach's alpha.

Results: The overall S-CVI/Ave was 0.89. Fifty-two of 56 items had I-CVI values of at least 0.80; four items were rephrased after expert review. KMO values ranged from 0.626 to 0.849, and Bartlett's tests were statistically significant ($p < 0.001$). Most evaluated constructs produced a single component, whereas Implications and Concerns produced three components explaining 72.66% of cumulative variance. Cronbach's alpha ranged from 0.764 to 0.928.

Conclusion: The questionnaire demonstrated strong preliminary content validity, acceptable sampling adequacy for exploratory analysis, and good-to-excellent internal consistency. It provides a context-sensitive instrument for assessing student-reported AI education perceptions, readiness, competencies, and structural barriers. Its factor structure and broader measurement properties require confirmation in a larger independent sample before high-stakes use.

Keywords: Artificial Intelligence; Medical Imaging; Radiography Education; Questionnaire Development; Content Validity; Exploratory Factor Analysis; Psychometrics; Utaut; Nigeria.

INTRODUCTION AND LITERATURE REVIEW

Artificial intelligence (AI) has progressed from a specialised computational discipline to an important component of contemporary digital transformation. In healthcare, AI encompasses machine learning, deep

learning, natural-language processing, computer vision, and related computational approaches that can identify patterns within complex datasets and support clinical decision-making. Davenport and Kalakota (2019) described broad potential applications of AI across healthcare, while Bajwa et al. (2021) examined its expanding role in clinical practice and emphasised the need for reliable, safe, and appropriately governed implementation. Topol (2019) similarly described healthcare AI as a field in which computational capabilities and human clinical expertise are increasingly expected to operate together.

Medical imaging is particularly receptive to AI because image acquisition and interpretation generate large, structured datasets that are amenable to computational pattern recognition. Hardy and Harvey (2019) examined the implications of AI for diagnostic imaging and the radiography profession, including potential changes to image acquisition, workflow, interpretation, and professional roles. Malamateniou et al. (2021) likewise highlighted the importance of AI literacy, governance, professional responsibility, and safe adoption in clinical imaging and therapeutic radiography. Recent educational literature has further indicated the need for structured AI education tailored to medical imaging. Loi et al. (2025) identified a relative scarcity of established curricula specifically designed for medical imaging personnel, while broader curriculum literature has emphasised foundational data literacy, machine learning concepts, ethics, patient safety, governance, evaluation of AI systems, and clinical application.

The educational implications of AI extend beyond technical knowledge. Çalışkan et al. (2022) examined competencies required for AI-related medical education and identified the need for structured curricular domains that enable learners to understand how AI systems are developed, evaluated, and applied. McCoy et al. (2020) argued that medical students require clinically relevant AI literacy rather than an exclusively technical curriculum. Pupic et al. (2023) reported heterogeneity in approaches to AI education, supporting the need for contextually appropriate curricular frameworks. Mosch et al. (2022) similarly identified gaps in the depth and formalisation of AI teaching in undergraduate medical education.

A successful transition toward AI integrated education is dependent upon understanding stakeholder readiness, perceived usefulness, self-efficacy, and environmental challenges and facilitators. Theoretically, Venkatesh et al. (2003) formulated the Unified Theory of Acceptance and Use of Technology (UTAUT), framing technology adoption around performance expectancy, effort expectancy, social influence, and facilitating conditions. Building on this, Karaca et al. (2021) developed the Medical Artificial Readiness Scale for Medical Students (MAIRS-MS) to operationalize multidimensional AI readiness.

Recent studies have continued to document the educational and professional relevance of these issues. Buabbas et al. (2023) investigated students' perceptions of AI in medical education, while Jackson et al. (2024) examined medical students' perceptions and reported both enthusiasm and concerns regarding implementation. Lewis et al. (2024) investigated AI use among medical imaging and radiation science students for learning and assessment, illustrating the increasing presence of AI in students' educational environments. Van de Venter et al. (2023) evaluated an AI educational intervention for radiographers and demonstrated the feasibility of targeted AI education within professional training.

Despite these developments, instruments developed in high-resource settings may not fully capture the educational and infrastructural realities of developing educational environments such as South-East Nigeria. Access to reliable electricity and internet connectivity, computing resources, software, curriculum capacity, faculty expertise, funding, and digital literacy may profoundly influence AI education in ways that are not adequately represented by instruments focused primarily on individual readiness. Furthermore, because successful AI integration in medical imaging relies on a tripartite ecosystem involving undergraduate students, academic educators and clinical tutors, evaluating readiness and systemic barriers across these complementary cohorts is essential. A context-sensitive questionnaire therefore needs to consider both the learner and the environment in which AI education is expected to occur.

To address this methodological gap, a multi-stakeholder questionnaire was conceptualized. However, to preserve the limited population pool of academic educators and clinical tutors for the main study phase, this preliminary investigation focused intentionally on establishing the instrument's baseline psychometric

properties; content validity, construct validity, and internal consistency within the undergraduate radiography student cohort in South-East Nigeria.

Conceptual Framework for AI Education Integration

For this study, AI education integration is conceptualised as a student-perceived, multidimensional educational construct rather than a direct measure of institutional implementation. The framework links four broad elements: the educational content to which students are exposed; students' AI literacy and perceived competence; perceptions of the clinical, ethical, and professional implications of AI; and the environmental and technology-acceptance conditions that may facilitate or constrain adoption. UTAUT provides the technology-acceptance component through performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioral intention, and acts as the foundational building block for readiness while MAIRS-MS provides a complementary readiness perspective. Additional domains were included to represent the educational and infrastructural context of medical imaging in South-East Nigeria.

Framework domain	Operational focus in the questionnaire	Primary conceptual basis
AI perceptions and importance	Students' perceptions of AI in medical imaging and perceived importance of AI education	AI education literature
Personal AI competency and literacy	Students' perceived AI knowledge, competence, and technical literacy	MAIRS-MS and AI competency literature
Implications and concerns	Perceived clinical, ethical, professional, and implementation implications of AI	AI education, governance, and professional literature
Environmental and structural barriers	Perceived infrastructure, institutional, technological, and resource constraints	Contextual adaptation for South-East Nigeria
Technology-acceptance readiness	Performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioural intention	UTAUT

This framework also establishes the measurement boundary of the study. The questionnaire measures student-reported perceptions and readiness; it does not objectively test AI competence and does not independently establish the actual extent of institutional curricular implementation. This distinction is important when interpreting the psychometric findings.

Aim and Objectives

This study aimed to develop and preliminarily validate a context-sensitive quantitative questionnaire measuring undergraduate radiography students' perceptions of AI education readiness and integration in medical imaging in South-East Nigeria.

- To establish preliminary content validity through expert review.
- To examine preliminary construct validity using exploratory factor analysis.
- To determine the internal consistency reliability of the questionnaire domains using Cronbach's alpha.

METHODOLOGY

Study Design and Setting

A cross-sectional quantitative pilot study was conducted to examine the preliminary psychometric properties of a newly developed questionnaire. The study was designed as a pilot investigation rather than a definitive scale-validation study. The pilot involved undergraduate radiography students from three accredited

radiography programmes in South-East Nigeria: David Umahi Federal University of Health Sciences, Gregory University, Uturu, and Tansian University.

Target Population, Eligibility and Sampling

The respondent population comprised undergraduate radiography students in the third, fourth, or fifth year of study. These levels were selected because the students had completed introductory clinical rotations and were expected to have basic exposure to diagnostic imaging modalities. Participants were purposively recruited from the three programmes, which had been excluded from the planned primary study phase to minimise the risk of dataset contamination. Also, *to avoid exhausting or contaminating the limited population pool of educators and clinical tutors prior to the main study, pretesting and preliminary psychometric evaluation were deliberately conducted exclusively among radiography students.* Thirty-nine students completed the questionnaire (N = 39). The pilot sample was intended to support preliminary instrument refinement and feasibility assessment rather than definitive confirmation of the factor structure.

Questionnaire Development Process

Questionnaire development followed a staged process based on the evidence and procedures documented for the present pilot. First, a critical review of relevant literature was undertaken to identify domains and item concepts relevant to AI education, readiness, clinical application, professional implications, and contextual barriers. Second, the conceptual framework was developed by integrating UTAUT, MAIRS-MS, and literature on AI competencies in medical education and radiography. Third, an initial item pool was generated and organised into eight sections. Fourth, the draft instrument underwent independent expert review for relevance, clarity, construct representation, and contextual alignment and relevance across cohorts. Fifth, items with low initial content-validity ratings were rephrased in response to expert comments. Finally, the revised questionnaire was administered in the pilot sample and evaluated using preliminary construct and reliability analyses.

The documented development pathway therefore distinguishes content validation from statistical validation. Expert review was used, ensuring items were applicable to all target groups and I-CVI/S-CVI/Ave were used to evaluate content validity, whereas KMO statistics, Bartlett's test, principal component analysis, and Cronbach's alpha were used for preliminary statistical evaluation. The pilot did not constitute definitive validation; a larger independent sample is required for confirmation of the factor structure and other measurement properties.

Instrument Structure and Operationalisation

The resulting questionnaire contained 56 items organised into eight sections. Section A collected demographic characteristics and was unscored. Sections B–H assessed perceptions, educational importance, implications and concerns, barriers, personal competency, technology-acceptance readiness, and behavioural intention.

Section	Domain	Items
A	Demographic characteristics	Unscored
B	Perceptions of AI in medical imaging	6
C	Importance of AI education	5
D	Implications and concerns regarding AI integration	9
E	Perceived environmental and structural barriers	7
F	Personal AI competency and technical literacy	8
G	Educational readiness: performance expectancy, effort expectancy, social influence and facilitating conditions	16
H	Behavioural intention to use and adopt AI technologies	5

Items in Sections B–H were rated on a four-point Likert scale ranging from 1 (Strongly Disagree) to 4 (Strongly Agree). The four-point response format was selected to remove a neutral midpoint and encourage a

directional response. This was treated as a design decision rather than evidence of superior measurement properties.

Expert Review and Content Validity

Five subject-matter experts independently reviewed the questionnaire. The panel comprised two senior radiography lecturers, a senior imaging specialist, a health informatician, and an AI research specialist. Experts assessed relevance, clarity, construct representation, and contextual alignment using a four-point ordinal scale ranging from 1 (Not Relevant) to 4 (Highly Relevant).

The Item Content Validity Index (I-CVI) was calculated as the proportion of experts rating each item 3 or 4. The Scale Content Validity Index/Average (S-CVI/Ave) was calculated as the mean of the I-CVI values across the instrument. This approach was informed by established content-validity methodology (Lynn, 1986; Polit et al., 2007) and subsequent guidance emphasizing relevance, comprehensiveness, and comprehensibility (Terwee et al., 2018; Mokkink et al., 2025). Items with initial I-CVI values below 0.80 were rephrased based on expert feedback rather than automatically deleted.

Data Collection

The questionnaire was administered electronically using Google Forms. Participants were contacted through class communication groups with the assistance of class representatives, and the questionnaire was distributed through email and WhatsApp after consent. Responses were exported into IBM SPSS Statistics for Windows, Version 30, for analysis.

Statistical Analysis

Descriptive statistics were used to summarise participant characteristics. Preliminary construct validity was examined separately for each construct using principal component analysis with Varimax rotation. Sampling adequacy was assessed using the Kaiser–Meyer–Olkin (KMO) statistic, with values above 0.60 considered adequate for the pilot analysis. Bartlett’s test of sphericity was used to determine whether the correlation matrix contained sufficient inter-item relationships for component extraction. Internal consistency was assessed using Cronbach’s alpha, with coefficients of at least 0.70 considered acceptable for preliminary scale development. Because the pilot sample was small relative to the 56-item instrument, confirmatory factor analysis and definitive model-fit assessment were not undertaken.

Ethical Considerations

Ethical approval was granted by the Research Ethics Committee of Nnamdi Azikiwe University, Nnewi Campus (Approval No. FHST/REC/024/1343). Participation was voluntary, informed consent was obtained before access to the electronic questionnaire, and responses were collected anonymously.

RESULTS AND DISCUSSION

Participant Characteristics

Variable	Category	n	%
Gender	Female	22	56.41
	Male	17	43.59
Age	18–22 years	25	64.1
	23–34 years	13	33.33
	35–44 years	1	2.56
Institution	Tansian University	31	79.49
	Gregory University, Uturu	5	12.82
	David Umahi Federal University of Health	3	7.69

	Sciences		
Year of study	3rd year	20	51.28
	4th year	12	30.77
	5th year	7	17.95

A total of 39 students participated. Females constituted 56.41% (n = 22) and males 43.59% (n = 17). Most participants were aged 18–22 years (n = 25, 64.10%), followed by 23–34 years (n = 13, 33.33%), while one participant was aged 35–44 years (2.56%). Tansian University contributed 31 participants (79.49%), Gregory University, Uturu, contributed five (12.82%), and David Umahi Federal University of Health Sciences contributed three (7.69%). Third-year students constituted 51.28% (n = 20), fourth-year students 30.77% (n = 12), and fifth-year students 17.95% (n = 7).

Content Validity

Domain	Items	I-CVI	Decision
Perceptions of AI	B1–B6	1	Retained
Importance of AI education	C1, C3, C4	1	Retained
Importance of AI education	C2, C5	0.8	Retained
Implications and concerns	D3–D6, D8, D9	1	Retained
Implications and concerns	D1, D2	0.8	Retained
Implications and concerns	D7	0.6	Rephrased
Perceived barriers	E1–E4, E6, E7	1	Retained
Perceived barriers	E5	0.8	Retained
Personal AI competency	F1, F3–F5, F7	1	Retained
Personal AI competency	F2, F6, F8	0.8	Retained
UTAUT readiness	G10	1	Retained
UTAUT readiness	G1–G7, G12–G16	0.8	Retained
UTAUT readiness	G8	0.6	Rephrased
UTAUT readiness	G9	0.2	Rephrased
UTAUT readiness	G11	0.4	Rephrased
Behavioural intention	H1–H5	1	Retained
Overall instrument	56 items	0.89	Valid preliminary scale

The expert assessment produced an overall S-CVI/Ave of 0.89, indicating strong agreement regarding the relevance and contextual suitability of the instrument. Fifty-two of the 56 items had I-CVI values of at least 0.80. Four items—D7, G8, G9, and G11—had initial I-CVI values below 0.80 and were rephrased following expert feedback. D7 had an I-CVI of 0.60, G8 had 0.60, G9 had 0.20, and G11 had 0.40. The remaining items were retained without modification.

Preliminary Construct Validity

Construct	Items	KMO	Components	Variance explained (%)
Perceptions of AI	6	0.79	1	60.59
Importance of AI	5	0.626	1	59.94

education				
Implications and concerns	9	0.669	3	72.66
Perceived barriers	7	0.848	1	64.6
Personal AI competency	8	0.809	1	66.9
Performance expectancy	4	0.702	1	76.37
Effort expectancy	4	0.826	1	78.86
Social influence	4	0.815	1	72.93
Facilitating conditions	4	0.722	1	58.71
Behavioural intention	5	0.849	1	72.41

Construct-by-construct exploratory analysis demonstrated acceptable sampling adequacy for the pilot analysis. KMO statistics ranged from 0.626 to 0.849, exceeding the prespecified threshold of 0.60, and Bartlett's tests of sphericity were statistically significant for all evaluated domains ($p < 0.001$). Most domains yielded a single extracted component. The Implications and Concerns domain produced three components, indicating that this domain may contain distinguishable dimensions rather than a single homogeneous component structure. These findings are preliminary because the sample size was small relative to the number of questionnaire items.

Internal Consistency Reliability

Construct	Items	Cronbach's α	Interpretation
Perceptions of AI	6	0.858	Reliable
Importance of AI education	5	0.826	Reliable
Implications and concerns	9	0.782	Reliable
Perceived barriers	7	0.903	Reliable
Personal AI competency	8	0.928	Reliable
Performance expectancy	4	0.896	Reliable
Effort expectancy	4	0.902	Reliable
Social influence	4	0.876	Reliable
Facilitating conditions	4	0.764	Reliable
Behavioural intention	5	0.901	Reliable

Cronbach's alpha coefficients ranged from 0.764 for Facilitating Conditions to 0.928 for Personal AI Competency. The coefficients indicate acceptable-to-excellent internal consistency across the evaluated domains in this pilot sample. However, internal consistency should not be interpreted as evidence that students possessed high AI competence, nor should alpha alone be interpreted as proof of unidimensionality or construct validity.

DISCUSSION

The present pilot study examined the preliminary psychometric performance of a context-sensitive questionnaire designed to assess radiography students' perceptions of AI education readiness and integration. The principal findings were an overall S-CVI/Ave of 0.89, KMO statistics ranging from 0.626 to 0.849, statistically significant Bartlett's tests, predominantly single-component solutions, a three-component solution for Implications and Concerns, and Cronbach's alpha coefficients ranging from 0.764 to 0.928. Taken together, these results support continued development of the instrument but should be regarded as preliminary rather than definitive validation.

The content-validity findings indicate broad agreement among the five experts regarding item relevance and contextual suitability. The use of I-CVI and S-CVI/Ave provides a transparent quantitative approach to content review, consistent with established methodology (Lynn, 1986; Polit et al., 2007). The decision to rephrase

rather than automatically remove the four items with I-CVI values below 0.80 preserved the intended breadth of the questionnaire while responding to concerns identified by the expert panel. This approach is consistent with the broader view that content validity includes not only relevance but also comprehensibility and adequate representation of the intended construct (Terwee et al., 2018; Mokkink et al., 2025).

The conceptual structure of the questionnaire is supported by the combination of UTAUT and MAIRS-MS with additional domains specific to AI education in medical imaging. UTAUT provides constructs for understanding technology acceptance, including performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003), while MAIRS-MS demonstrates the multidimensional nature of AI readiness among medical students (Karaca et al., 2021). The present questionnaire extends these perspectives by incorporating AI perceptions, educational importance, implications and concerns, environmental barriers, personal competency, and behavioural intention. This broader structure is relevant where AI education may be influenced by both individual perceptions and institutional conditions.

The three-component solution observed for Implications and Concerns is also important for further instrument development. Rather than assuming that concerns about AI constitute one homogeneous dimension, the preliminary result suggests that this domain may contain distinguishable dimensions. Existing literature on student perceptions has similarly documented multifaceted views of AI in education (Buabbas et al., 2023; Jackson et al., 2024). The present result should nevertheless be treated as exploratory and should be reassessed in a larger independent sample before the domain is redefined or interpreted as comprising stable subscales.

The Perceived Barriers domain represents a contextual contribution of the instrument. AI-readiness measures may focus primarily on individual attitudes and knowledge, whereas the present questionnaire also considers environmental and structural conditions. In a resource-constrained educational setting, factors such as connectivity, computing resources, electricity, software access, faculty expertise, and curriculum capacity may influence the feasibility of AI education. This contextual orientation is consistent with the broader principle that health-professional education should be aligned with local workforce and system conditions (Couper et al., 2018).

The findings are also consistent with emerging evidence from medical imaging education. Hardy and Harvey (2019) and Malamateniou et al. (2021) highlighted changes in radiography practice and professional responsibilities associated with AI. Van de Venter et al. (2023) demonstrated the feasibility of targeted AI education for radiographers, while Lewis et al. (2024) documented the growing use of AI by medical imaging and radiation science students for learning and assessment. Loi et al. (2025) further identified a shortage of established AI curricula specifically designed for medical imaging personnel. These developments support the need for instruments that can identify educational needs within the specific professional and institutional context.

The educational content represented by the questionnaire should also remain clinically and ethically grounded. McCoy et al. (2020) emphasised the importance of understanding AI capabilities, limitations, evaluation, and clinical implications. Çalışkan et al. (2022) identified AI competencies relevant to medical education, while Pupic et al. (2023) reported heterogeneity in the evidence base for AI education. Ethical governance is also relevant to AI deployment in healthcare, including issues of transparency, accountability, equity, privacy, and human oversight (World Health Organization, 2021). For radiography education, these domains can complement technical knowledge by helping learners critically appraise AI outputs and understand professional responsibilities.

The sample size requires particular caution. Johanson and Brooks (2010) emphasised that pilot studies have a different purpose from full-scale psychometric validation. With 39 participants and 56 questionnaire items, the present study cannot establish a stable factor structure. The KMO and Bartlett results provide preliminary evidence of inter-item relationships, but they do not remove the need for replication. Future work should use a substantially larger independent sample to reassess item performance and factor structure, followed by confirmatory factor analysis and evaluation of additional measurement properties.

While this pilot study analysis established strong preliminary internal consistency and content validity among students, the instrument's multi-stakeholder design intends to capture broader structural perspectives. By reserving the educators and clinical tutors for the main study phase, the full-scale deployment will be equipped to compare learner readiness, faculty preparedness, and clinical tutor expectations. The questionnaire should therefore be interpreted as a preliminary research and curriculum-development instrument. It can be used in subsequent studies to examine areas of perceived readiness, educational need, and contextual constraint, but the present findings do not establish actual institutional implementation or objectively measured AI competence. This distinction is central to the interpretation of a student-perception instrument.

STRENGTHS AND LIMITATIONS

The principal strength of the study is the deliberate integration of individual readiness constructs with contextual barriers relevant to medical imaging education in a resource-constrained setting. The use of expert review, quantitative content-validity assessment, exploratory analysis, and internal-consistency testing provides a structured preliminary development pathway. The pilot also included students from three institutions rather than a single programme.

Several limitations should be acknowledged. The sample size of 39 is small relative to the number of questionnaire items and is insufficient for definitive factor-structure validation. Participants were purposively recruited from radiography programmes in South-East Nigeria, limiting generalisability to other Nigerian regions and other health-professional disciplines. The sample was unevenly distributed across institutions, with most participants drawn from Tansian University. The study relied on self-reported perceptions and did not objectively measure AI knowledge or practical competence, nor did it independently measure the actual extent of institutional curricular implementation. Test–retest reliability, criterion validity, convergent validity, discriminant validity, measurement invariance, and confirmatory factor structure were not assessed. *A key methodological boundary of this pilot evaluation was the restriction of the pre-test sample to radiography students. While this decision preserved the small, critical population of educators and clinical tutors for the main study phase, future psychometric evaluations must confirm factor stability and measurement invariance across all intended stakeholder groups*

Implications for Research and Educational Practice

In subsequent research, the questionnaire should be administered to a substantially larger and more diverse sample across multiple Nigerian geopolitical zones. Researchers should reassess item distributions, factor loadings, cross-loadings, communalities, and domain-level relationships. Confirmatory factor analysis should then be conducted in an independent sample to test the hypothesised measurement structure. Where feasible, objective AI-literacy assessments could be administered alongside the questionnaire to examine the relationship between self-perceived and measured competence.

For educational practice, the domains provide a structured basis for examining perceived gaps in AI knowledge, readiness, understanding of implications, and access to facilitating conditions. Curriculum planning can consider clinically relevant AI concepts, data literacy, interpretation of AI outputs, bias and fairness, privacy and data governance, patient safety, professional accountability, and critical appraisal of AI performance. At the current stage, the questionnaire should be used for research and programme-development purposes rather than high-stakes assessment.

CONCLUSION

This pilot study developed and preliminarily evaluated a 56-item questionnaire for assessing radiography students' perceptions of AI education readiness and integration in medical imaging in South-East Nigeria. The instrument demonstrated an overall S-CVI/Ave of 0.89, KMO values of 0.626–0.849, statistically significant Bartlett's tests ($p < 0.001$), and Cronbach's alpha coefficients of 0.764–0.928. The findings provide preliminary evidence that the questionnaire can capture multiple dimensions of AI education, including perceptions, educational importance, implications and concerns, structural barriers, personal competency, technology-acceptance constructs, and behavioural intention. However, these results do not constitute

definitive validation. A larger independent sample is required to confirm the factor structure and establish additional measurement properties before the instrument is used for high-stakes assessment, institutional comparison, or policy decisions.

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AUTHOR CONTRIBUTIONS

This study was conducted collaboratively. Bestman Izuchukwu Oriaku designed the study, performed the statistical analysis, wrote the protocol, and drafted the initial manuscript. Anthony Chukwuemeka Ugwu and Ngozi Eucharia Makata supervised the study. All authors reviewed and contributed to the development of the manuscript and approved the final version.

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