Strengthening Competence-Based Education and Training Implementation for Humanities and Language Education through AI-Enabled Professional Development at a Public University in Uganda

DAVID KABUGO
Department of Humanities and Language Education
Makerere University
Corresponding author email: david.kabugo@mak.ac.ug

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Abstract

Recent studies in higher education indicate that the educational value of artificial intelligence (AI) depends not only on availability of digital tools, but also on lecturers' preparedness to apply them in pedagogically appropriate, ethically responsible, and contextually relevant ways. This study evaluated an AI-enabled Continuous Professional Development (CPD) intervention aimed at strengthening AI-Technological Pedagogical and Content Knowledge (AI-TPACK) and Competence-Based Education and Training (CBET) implementation in humanities and language education at a public university in Uganda. Using a mixed-methods pretest–posttest design, 40 lecturers participated in a one-week blended CPD programme delivered via the university learning management system and supported by accessible AI tools (e.g., ChatGPT, Copilot, Grammarly). Quantitative survey data were triangulated with rubric-scored instructional artifacts, post-intervention classroom observations, and follow-up interviews. Results showed significant improvements in AI-TPACK (ΔM = +0.48, $p < .001$) and CBET implementation capacity ($\Delta M = +0.44$, $p < .001$), alongside increased intentions to adopt AI-supported practices and reduced AI-integration anxiety. Instructional artifact quality improved (M = 1.73 to 2.23/4, $p < .001$), and classroom observations indicated strong CBET-aligned practices (M = 8.58/10). Qualitative findings attributed these gains to competence-first task design, expanded rubric-based formative feedback cycles, and reflective, "bounded" AI use prioritizing transparency, privacy, and human judgement. However, infrastructural limitations and unclear institutional guidance constrained sustainability. The study concludes that AI-enabled CPD can be an effective strategy for improving lecturers' pedagogical capacity and competence-based teaching practices in humanities and language education when it is grounded in authentic instructional tasks and responsible AI use. It is recommended that universities institutionalise sustained AI-focused professional development, strengthen digital infrastructure, and provide clear ethical and pedagogical guidelines to support long-term implementation. The study contributes context-sensitive evidence from African higher education that AI-enabled CPD can strengthen CBET-oriented assessment and feedback practices when supported by infrastructure, policy clarity, and ongoing professional learning.

Keywords: *Artificial intelligence; Competence-based education and training; Language education; Continuous professional development.*

Introduction

On a university campus where lecturers are expected to prepare students for real-world competence while also responding to the rapid rise of artificial intelligence (AI), the central question is no longer simply whether AI should be used in teaching, but how it can be used wisely, fairly, and in ways that protect the human work of learning. This study is grounded in contemporary scholarship on artificial intelligence in teacher professional development and competence-based education and training (CBET) reform in higher education. The central premise is that meaningful AI integration in university teaching depends less on access to digital tools than on sustained professional learning that strengthens lecturers' pedagogical judgement, curricular coherence, and ethical awareness (Copur-Gencturk et al., 2024; Du et al., 2024; Erhardt et al., 2025; Kasneci et al., 2023; Long et al., 2020). This premise is especially important in competence-based reform contexts, where the quality of teaching depends not simply on whether technology is used, but on whether it is used to support authentic learning, constructive alignment, and formative assessment. In other words, the educational significance of AI lies not in adoption alone, but in how lecturers interpret, adapt, and regulate its use in relation to curricular goals and student learning needs. It is on this basis that AI-enabled continuous professional development (CPD), CBET implementation, and AI-TPACK are treated as interrelated constructs. AI-enabled CPD provides the professional learning process through which lecturers can build the knowledge, confidence, and ethical awareness needed for responsible AI use; CBET implementation represents the pedagogical and curricular arena in which such learning is enacted through competence-oriented, student-centred teaching; and AI-TPACK offers the conceptual lens for understanding how lecturers integrate AI with pedagogy and disciplinary content in contextually appropriate ways.

In this study, AI-enabled CPD is conceptualised in two complementary ways. First, it functions as a professional learning goal: lecturers are supported to develop AI literacy, confidence, and competence for informed and responsible pedagogical use. Systematic reviews (e.g., Long & Magerko, 2020; Ng et al., 2023; Erhardt et al., 2025) consistently show that many educators feel underprepared for AI integration and that targeted CPD can improve knowledge, self-efficacy, attitudes, and readiness for classroom application. From this perspective, AI-enabled CPD responds to a structural gap between rapid technological change and educators' capacity to critically evaluate AI's affordances, limitations, and ethical implications. Second, AI-enabled CPD is understood as a pedagogical mechanism in which AI tools are embedded within the professional learning process itself. Empirical research (Darling-Hammond et al., 2017; Sims & Fletcher-Wood, 2021; Copur-Gencturk et al., 2024) demonstrates that AI-supported feedback, analytics, and generative tools can strengthen core features of effective professional development, including active engagement with authentic tasks, iterative reflection, and alignment between theory and practice. In this sense, AI supports learning about teaching rather than replacing professional expertise, positioning lecturers as reflective practitioners.

The second core construct is competence-based education and training and training implementation. CBET is understood not only as a design framework but as an enacted practice, shaped by how lecturers translate intended learning outcomes into teaching, assessment, and feedback. Drawing on literature on competence-based education and training (Cunningham & Capron, 2016; Kouwenhoven, 2009; Barman & Konwar, 2011; Johnstone & Soares, 2014; Biggs & Tang, 2011), CBET implementation is characterised by authentic learning tasks, constructive alignment, performance-based assessment, and formative feedback. These dimensions emphasise integrated demonstrations of knowledge and skills, coherence across curriculum elements, and feedback that supports learner agency and continuous improvement. In this study, CBET implementation is examined through rubric-based analyses of instructional artifacts and structured classroom observations. To connect AI-enabled CPD with CBET implementation, the study adopts AI-TPACK as an integrative framework. Extending the TPACK model (Mishra & Koehler, 2006), AI-TPACK incorporates AI-specific knowledge and ethical awareness, emphasising that effective AI integration lies at the intersection of content, pedagogy, technology, and critical engagement with issues such as academic integrity, data privacy, and bias (Kasneci et al., 2023; Mishra et al., 2024). In language education, this foregrounds lecturers' professional judgement in determining when and how AI adds pedagogical value without undermining disciplinary goals or learner autonomy. These relationships are situated within the Ugandan higher education reform context, where CBET implementation and digital transformation are policy priorities, yet constrained by uneven infrastructure, digital capacity, and ethical concerns. By framing AI-enabled CPD as a mechanism for strengthening CBET implementation rather than accelerating technology uptake, this study aligns with reform agendas while remaining attentive to contextual realities. AI integration is thus treated not as an end, but as a catalyst for pedagogical transformation grounded in reflective professional judgement.

Theoretical Framework

This study uses an integrative framework encompassing (1) AI-TPACK, (2) effective professional development theory, (3) the SAMR model, and (4) ethical and sociotechnical perspectives to explain how AI-enabled continuous professional development (CPD) can strengthen competence-based education and training (CBET) implementation in language education. TPACK extended as AI-TPACK to account for AI-specific professional knowledge, effective professional development theory explains how learning translates into sustained instructional change, the SAMR model is a lens for depth of pedagogical transformation, and ethical and sociotechnical perspectives to foreground risk, responsibility, and professional judgement.

Technological Pedagogical Content Knowledge (TPACK), extended here as AI-TPACK, conceptualises effective technology integration as emerging from the interaction of content, pedagogy, and technology rather than technical skill alone (Mishra & Koehler, 2006). AI introduces new demands that require explicit attention to AI affordances, limitations, and ethical implications (Kasneci et al., 2023; Mishra et al., 2023). AI-TPACK therefore captures lecturers' capacity to use AI as a pedagogical resource for planning, assessment, and feedback while exercising critical judgement about academic integrity, privacy, and bias. In language education, this includes evaluating how AI can scaffold language production and formative assessment without eroding learner agency or disciplinary goals. AI-enabled CPD is expected to strengthen AI-TPACK by deliberately integrating pedagogy, content, technology, and ethics, enabling more coherent CBET implementation.

Because professional knowledge does not automatically translate into changed practice, the framework also draws on theories of effective professional development. These emphasise coherence with instructional goals, active engagement with practice, feedback, and sufficient duration as conditions for meaningful instructional improvement (Darling-Hammond et al., 2017; Sims & Fletcher-Wood, 2021). Evidence from AI-related CPD similarly suggests that tool-focused workshops rarely produce transformation, whereas practice-based CPD aligned with curriculum reform is more likely to improve competence, confidence, and uptake (Tan et al., 2023). In this study, AI-enabled CPD is theorised to influence CBET implementation because it engages lecturers in authentic design and assessment work, supports iterative feedback cycles (including AI-assisted feedback), and aligns professional learning with institutional CBET priorities rather than technology adoption for its own sake.

To interpret the depth of change, the framework uses the SAMR model (Substitution, Augmentation, Modification, Redefinition) (Hamilton et al., 2016). While acknowledging critiques of its simplicity, SAMR is useful for distinguishing surface use from instructional redesign. Here, AI-enabled CPD is expected to support movement beyond substitution/augmentation towards modification/redefinition, for example, enabling scalable, rubric-aligned formative feedback cycles and task variation that are difficult to sustain manually, especially in large classes.

Finally, ethical and sociotechnical perspectives position AI integration as value-laden and institutionally mediated. AI systems carry risks related to integrity, privacy, surveillance, and bias, which are particularly salient where assessment credibility underpins CBET reform (UNESCO, 2023). Ethics is thus treated as integral to pedagogy: AI-TPACK entails boundary-setting, transparency, and human evaluative judgement. From a sociotechnical perspective, lecturers' use of AI is not determined by individual competence alone, but is mediated by institutional conditions such as infrastructure, policy clarity, leadership support, and ethical norms; accordingly, sustainable AI-enabled CBET implementation requires alignment between pedagogical goals, responsible AI practices, and the organisational conditions that enable their enactment.

Purpose

This study evaluated the effectiveness of an AI-enabled continuous professional development intervention in improving lecturers' AI-TPACK, competence-based education and training implementation capacity, and readiness for responsible AI integration in humanities and language education at a public university. The study also aimed to contribute evidence to higher education practice and policy in low-resource contexts.

Research Objectives

(i) Determine changes in lecturers' AI-TPACK following participation in AI-enabled CPD.

(ii) Examine shifts in CBET implementation capacity in instructional artifacts and classroom observations.

(iii) Analyse lecturers' perceptions, anxiety, and intention to adopt AI-supported practices.

(iv) Explore contextual and institutional factors influencing the sustainability of responsible AI integration.

Research Questions

(i) To what extent does AI-enabled CPD improve lecturers' AI-TPACK?

(ii) To what extent does AI-enabled CPD improve lecturers' CBET implementation capacity and the quality of CBET-aligned instructional practice?

(iii) How does AI-enabled CPD affect lecturers' perceptions of AI, AI-integration anxiety, and intention to adopt AI-supported practices?

(iv) What contextual and institutional factors enable or constrain the sustainability of responsible AI integration?

Research Hypotheses

(i) **H1:** Lecturers' AI-TPACK scores will be significantly higher after the intervention than before it.

(ii) **H2:** Lecturers' CBET implementation capacity and instructional artifact scores will be significantly higher after the intervention than before it.

(iii) **H3a:** Lecturers' perceptions of AI will improve significantly after the intervention.
H3b: Lecturers' AI-integration anxiety will decrease significantly after the intervention.
H3c: Lecturers' intention to adopt AI-supported practices will increase significantly after the intervention.

(iv) **Nil (Had no hypothesis for question iv**, because it is exploratory and would be better addressed through qualitative data).

Methodology

Research design

This study adopted an **embedded mixed-methods intervention design** organised within a **one-group pre-test–post-test framework**. The quantitative component constituted the core strand of the study and was used to assess measurable changes in lecturers' AI-TPACK, competence-based education and training (CBET) implementation capacity, AI-related anxiety, and intention to adopt AI-supported practices before and after participation in the AI-enabled continuous professional development (CPD) intervention. The qualitative component was embedded within this design to provide explanatory depth on how these changes were enacted in practice and which contextual conditions shaped their sustainability.

This design was selected because the primary aim of the study was evaluative: to determine whether the CPD intervention was associated with change in specified outcomes over time. That evaluative purpose is most directly served by a pre-test–post-test quantitative structure. However, the study also sought to understand dimensions of change that could not be adequately captured through survey scores alone, such as how lecturers redesigned instructional artifacts, how CBET principles appeared in classroom practice, and how participants interpreted the opportunities and constraints of responsible AI integration. For this reason, qualitative evidence from instructional artifacts, classroom observations, and follow-up interviews was embedded to complement, extend, and help interpret the quantitative results.

The integration of qualitative and quantitative techniques occurred at multiple points in the study. At the **design level**, qualitative methods were built into the intervention evaluation from the outset rather than added retrospectively. At the **methods level**, survey results were triangulated with rubric-scored instructional artifacts, classroom observations, and interview data. At the **interpretation level**, qualitative findings were used to explain the mechanisms underlying quantitative changes, such as the role of competence-first task design, rubric-based feedback cycles, reflective AI use, and institutional constraints. This form of integration made it possible to move beyond the question of effectiveness in a narrow statistical sense and towards a more analytically robust explanation of pedagogical change.

A mixed-methods approach was therefore appropriate because professional learning and CBET implementation are complex phenomena involving both observable outcome shifts and socially situated processes. Quantitative data provided evidence of direction and magnitude of change, while qualitative data captured the pedagogical, ethical, and institutional dynamics through which the intervention was experienced and enacted. Taken together, the embedded mixed-methods pre-test–post-test design offered a rigorous and contextually sensitive basis for evaluating the effectiveness of AI-enabled CPD in strengthening CBET implementation in humanities and language education at a public university.

The intervention consisted of a **one-week blended CPD programme**, designed and deployed on a university's **Model-Based Learning Management System.** The CPD combined synchronous workshops, asynchronous online activities, and practice-oriented tasks aligned to competence-based education and training implementation in humanities and language education courses. The programme was intentionally short but intensive, reflecting institutional realities while incorporating features identified as critical for effective professional development, such as coherence, active learning, and feedback. The CPD focused on **competence-based education and training (**CBET) **implementation in humanities and language education courses**, with explicit attention to authentic task design, constructive alignment, performance-based assessment, and formative feedback. AI tools were embedded as both learning content and pedagogical supports. Selected tools included **Bing Copilot, ChatGPT, Grammarly,** and **QuillBot**, chosen for their accessibility, relevance to language education, and potential to support planning, feedback, and reflective practice. Learning activities included AI-supported lesson and assessment design, peer review of instructional artifacts, guided reflection using AI-generated feedback, and discussions on ethical and responsible AI use in assessment and academic writing.

Study participants

The study involved **40 lecturers** drawn from the Department of Humanities and Language Education at a public university in Uganda. Participants taught a range of undergraduate language education courses and were purposively selected based on their involvement in CBET implementation and willingness to engage in AI-supported professional learning. The institutional context was characterised by ongoing CBET reforms and increasing pressure to integrate digital technologies in teaching, alongside infrastructural and capacity constraints typical of low-resource higher education settings. These contextual conditions informed both the design of the CPD intervention and the interpretation of findings.

Data sources and instruments

Data was collected from multiple sources to capture changes in lecturers' knowledge, practice, dispositions, and institutional experiences before and after the intervention. Quantitative data was obtained through pre- and post-intervention questionnaires administered to all participants. The survey instruments measured four constructs aligned with the study objectives, using Likert-type response scales (e.g., 1 = Strongly Disagree to 5 = Strongly Agree). All scales were adapted from existing instruments and conceptual frameworks in teacher professional development, educational technology, and AI-in-education research, with minor contextual modifications for higher education humanities and language teaching in Uganda.

Quantitative survey instruments

AI-TPACK

The AI-TPACK scale was used to measure lecturers' self-reported ability to bring artificial intelligence into teaching in ways that were pedagogically purposeful, relevant to their subject areas, and ethically responsible. In keeping with the study's wider concern that AI should strengthen competence-based education and training implementation rather than simply encourage tool use, the items asked lecturers to reflect not only on whether they could use AI, but also on whether they could make sound professional judgements about when its use genuinely supports learning. The scale was adapted from the TPACK framework of

Mishra and Koehler (2006), its later extension to generative AI contexts by Mishra et al. (2023), and related scholarship on AI literacy, ethical use, and responsible educational practice, including Kasneci et al. (2023), Long and Magerko (2020), and Ning et al. (2024). Participants rated the items on a **five-point Likert-type scale**, where **1 = Strongly Disagree, 2 = Disagree, 3 = Neutral/Not Sure, 4 = Agree, and 5 = Strongly Agree**. The indicative items were: *I can use AI tools to support the design of learning activities in my subject area; I can align AI-supported teaching strategies with course learning outcomes; I can use AI to support formative assessment and feedback in pedagogically appropriate ways; I can judge when AI use adds value to teaching and when it may undermine learning; and I can identify ethical issues such as bias, privacy, and academic integrity when using AI in teaching.* Taken together, these items captured the major dimensions of AI-TPACK: AI-supported content representation, pedagogical integration, assessment and feedback use, contextual judgement, and ethical awareness. This framing is important because it treats lecturers as thoughtful curriculum decision-makers rather than passive adopters of technology; it recognises that responsible AI integration depends on human judgement, local teaching realities, learner needs, and the ability to question AI outputs before bringing them into the classroom.

CBET implementation capacity

The **CBET Implementation Capacity** scale measured lecturers' perceived ability to translate competence-based education and training principles into practical teaching, assessment, and feedback decisions. In line with the article's emphasis on pedagogy-first AI-enabled CPD, this construct treated CBET implementation not as policy compliance, but as the lecturer's everyday capacity to design learning that helps students demonstrate applied competence. The scale was informed by competence-based education and training literature, constructive alignment, authentic assessment, and formative feedback, particularly Biggs and Tang (2011), and was rated on a **five-point Likert-type scale**, where **1 = Strongly Disagree, 2 = Disagree, 3 = Neutral/Not Sure, 4 = Agree, and 5 = Strongly Agree**. Indicative items included: *I can formulate learning outcomes in competence-based terms; I can design authentic learning tasks that require students to demonstrate applied competence; I can align teaching* *activities, learning outcomes, and assessment tasks; I can develop rubric-based assessments that make performance expectations explicit; and I can provide formative feedback that supports improvement in competence development.* These items captured competence-based outcome design, authentic task design, constructive alignment, performance-based assessment, and formative feedback capacity. Critically, the scale recognises that lecturers may understand CBET in theory but still struggle to enact it consistently in real classrooms; therefore, it focuses on practical curriculum judgement, the ability to make expectations visible to students, and the lecturer's role in guiding improvement rather than merely delivering content. This framing aligns with the article's finding that meaningful CBET implementation depends on authentic tasks, rubric-based assessment, formative feedback, and professional judgement rather than superficial adoption of reform language.

AI-related anxiety

The **AI-Related Anxiety** scale assessed lecturers' apprehension, uncertainty, and perceived professional risk when integrating AI into teaching and assessment. Rather than treating anxiety as resistance to innovation, the scale positioned it as a reasonable human response to a fast-changing educational environment where lecturers must protect academic integrity, student privacy, fairness, and their own professional credibility. The construct was informed by research on educators' trust, confidence, and concerns regarding AI-enabled educational technologies, particularly Nazaretsky et al. (2022), as well as broader AI integration studies addressing uncertainty, misuse, ethical risk, and professional unease. Items were rated on a **five-point Likert-type scale**, where **1 = Strongly Disagree, 2 = Disagree, 3 = Neutral/Not Sure, 4 = Agree, and 5 = Strongly Agree**; for this scale, **higher scores indicated greater AI-related anxiety**. Indicative items included: *I feel anxious about using AI tools in my teaching; I worry that AI may compromise academic integrity in student assessment; I am uncertain about how to use AI responsibly in my courses; I feel uncomfortable relying on AI-generated outputs when preparing teaching materials; and I am concerned that AI use in teaching may create ethical or professional risks.* These items captured emotional discomfort, uncertainty, perceived misuse risk, integrity concerns, and ethical apprehension.

Importantly, the scale does not pathologise lecturers' concerns; instead, it acknowledges that caution can be professionally responsible when AI use affects assessment credibility, learner autonomy, bias, and data privacy. In this sense, reduced anxiety after CPD should not be interpreted simply as greater comfort with technology, but as evidence that lecturers had begun to develop clearer boundaries, ethical routines, and confidence in using AI without surrendering human judgement.

Adoption intention

The **Adoption Intention** scale measured lecturers' willingness and intention to continue using AI-supported practices in future teaching. Conceptually, it drew from technology acceptance and adoption research, including teacher-focused studies linked to TPACK, AI readiness, and responsible innovation. The scale was rated on a **five-point Likert-type scale**, where **1 = Strongly Disagree, 2 = Disagree, 3 = Neutral/Not Sure, 4 = Agree, and 5 = Strongly Agree**; **higher scores indicated stronger intention to adopt AI-supported teaching practices**. Indicative items included: *I intend to use AI tools in my teaching in the future; I plan to incorporate AI into lesson preparation and instructional support; I am likely to use AI tools to enhance assessment and feedback practices; I would recommend appropriate AI-supported teaching practices to colleagues; and I expect to continue experimenting with AI in my courses after the CPD programme.* These items reflected future use intention, instructional uptake, assessment-related adoption, peer endorsement, and sustained experimentation. Critically, the scale frames adoption as thoughtful professional commitment rather than enthusiasm for technology for its own sake. A lecturer's intention to use AI is meaningful only when it remains tied to course outcomes, student learning needs, ethical safeguards, and the realities of institutional infrastructure. This is consistent with the article's argument that AI should serve as a scaffold for planning, feedback, and reflective practice, while lecturers retain responsibility for interpretation, adaptation, and final pedagogical decisions.

CPD participation

In addition to the four substantive scales, the dataset included a CPD participation variable capturing the extent of engagement in the intervention. This measure was operationalised using attendance records, participation in synchronous sessions, completion of asynchronous tasks, and submission of design activities through the learning management system. This variable served as a supporting indicator of participants' level of exposure to the intervention.

Qualitative data sources

Qualitative data was collected through three complementary sources to deepen interpretation of the quantitative findings and to capture enacted changes in practice. Pre- and post-intervention instructional artifacts, including lesson plans, assessment tasks, and rubrics, were collected and analysed using a structured CBET implementation rubric. The rubric assessed the extent to which artifacts demonstrated competence-based learning outcomes, constructive alignment, authentic task design, rubric-based assessment, and formative feedback opportunities. Post-intervention classroom observations were conducted using a structured observation schedule aligned to CBET principles. The observation tool focused on indicators such as clarity of learning outcomes, use of authentic and performance-based learning activities, alignment between instruction and assessment, formative feedback practices, and appropriate pedagogical use of AI where relevant. Follow-up interviews were conducted with a purposive subset of participants to explore their experiences of the CPD, perceived changes in teaching practice, confidence and anxiety related to AI use, ethical concerns, and institutional conditions influencing sustainability. The interview guide included prompts on the usefulness of AI tools, changes in lesson design and assessment, professional judgement in AI use, and infrastructural or policy constraints. All survey items were reviewed and contextually adapted to fit the realities of humanities and language education and public university teaching in Uganda. Wording was adjusted to reflect lecturers' roles, the competence-based education and training context, and the AI tools used during the intervention. The questionnaire was administered twice, once before the CPD and once immediately after it, to assess short-term changes associated with participation in the programme.

Data quality

To strengthen data quality, the study treated instrument validation as more than a procedural requirement; it was approached as a way of ensuring that the questionnaire genuinely spoke to lecturers' lived work of teaching, assessing, giving feedback, and making responsible decisions about AI in a Ugandan public university context. Because the survey scales were adapted from existing frameworks and then administered twice, before and immediately after the AI-enabled CPD intervention, both content validity and internal consistency reliability were examined separately and transparently. Content validity was established through expert review, using the Content Validity Index (CVI) to determine whether the items were relevant, clear, and contextually appropriate for measuring AI-TPACK, CBET implementation capacity, AI-related anxiety, and adoption intention. The content validity results were acceptable across the four scales: AI-TPACK, S-CVI/Ave = **0.94**; CBET Implementation Capacity, S-CVI/Ave = **0.92**; AI-Related Anxiety, S-CVI/Ave = **0.90**; and Adoption Intention, S-CVI/Ave = **0.93** . These values suggest that the expert reviewers judged the items to be strongly aligned with the intended constructs, while still recognising that the instruments had been adapted for a specific higher education and language education context. Internal consistency reliability was assessed using Cronbach's alpha at both pre-test and post-test stages, since the questionnaire was administered before and after the CPD programme. The reliability coefficients were as follows: AI-TPACK, α = **0.84** at pre-test and **0.88** at post-test; CBET Implementation Capacity, α = **0.82** at pre-test and **0.86** at post-test; AI-Related Anxiety, α = **0.79** at pre-test and **0.83** at post-test; and Adoption Intention, α = **0.81** at pre-test and **0.85** at post-test. The overall questionnaire reliability was also acceptable, with α = **0.89** at pre-test and **0.91** at post-test.

Table 1: *Validity and reliability of the survey scales*

Scale	Number of items	Content validity	Cronbach's alpha: pre-test	Cronbach's alpha: post-test	Interpretation
AI-TPACK	5	S-CVI/Ave = **0.94**	α = **0.84**	α = **0.88**	Strong content validity and good internal consistency
CBET Implementation Capacity	5	S-CVI/Ave = **0.92**	α = **0.82**	α = **0.86**	Strong content validity and good internal consistency
AI-Related Anxiety	5	S-CVI/Ave = **0.90**	α = **0.79**	α = **0.83**	Acceptable to good internal consistency
Adoption Intention	5	S-CVI/Ave = **0.93**	α = **0.81**	α = **0.85**	Strong content validity and good internal consistency
Overall questionnaire	20	S-CVI/Ave = **0.92**	α = **0.89**	α = **0.91**	Overall instrument showed strong reliability

For the qualitative strand, trustworthiness was strengthened using Lincoln and Guba's criteria: credibility was supported through triangulation of survey responses, instructional artifacts, classroom observations, and interviews; transferability was addressed through thick description of the institutional setting, including realities such as fluctuating internet reliability; dependability was supported through a structured CBET rubric and a clear audit trail; and confirmability was enhanced through reflexive interpretation and by grounding qualitative claims in the evidence collected. In this way, the study balanced psychometric checks with human judgement, recognising that strong data quality depends not only on acceptable numerical indices but also on whether the instruments, interpretations, and conclusions remain faithful to lecturers' professional realities and the ethical complexity of AI-supported teaching.

Data analysis procedures

Quantitative data was analysed using descriptive statistics (means and standard deviations) and inferential statistics, specifically **paired-samples *t* tests** to assess pre–post changes in AI-TPACK, CBET implementation capacity, AI-related anxiety, and adoption intention, with **effect sizes (Cohen's *d*)** computed to estimate the magnitude of observed differences. Effect sizes were calculated to assess the practical significance of observed changes. CPD participation data was used to examine patterns of engagement and their relationship to outcomes.

Qualitative data analysis followed a **thematic and rubric-based approach**. Instructional artifacts were independently rated using the CBET implementation rubric, with scores compared across pre- and post-intervention submissions to identify shifts in quality and alignment. Classroom observation data was summarised using descriptive statistics and analytic memos to capture enacted practices. Interview transcripts were coded inductively and deductively, with codes informed by the study's conceptual and theoretical frameworks (e.g., AI-TPACK, ethical considerations, institutional support). Qualitative findings were then integrated with quantitative results during interpretation to explain observed patterns and provide contextual depth.

The mixed methods design enabled **complementarity** between data strands. Quantitative results provided evidence of the magnitude and direction of change in lecturers' competencies and perceptions, while qualitative data explained how these changes manifested in instructional practice and why certain challenges persisted. For example, improvements in CBET implementation capacity scores were examined alongside artifact quality and observation data to confirm enacted change rather than self-reported improvement alone. Interview data further illuminated tensions between innovation and risk, particularly around assessment integrity and institutional readiness.

Ethical considerations

Data was anonymised and securely stored, with access restricted to the research team. Given the use of AI tools, the study explicitly addressed **responsible AI use**, including discussions with participants on data privacy, academic integrity, and appropriate boundaries for AI assistance in teaching and assessment. Participants were encouraged to critically evaluate AI outputs and to retain professional judgment in all pedagogical decisions.

Findings

This section presents the findings of the study in relation to the research objectives. It begins with a summary of the participant background profile, followed by quantitative results from the pre–post surveys for each outcome area. Qualitative findings from instructional artifacts, classroom observations, and interview records are then presented to explain how and why the observed changes occurred.

Participant background profile

The study involved **40 lecturers** from the Department of Humanities and Language Education at a public university. Participants represented English, Kiswahili, French, German, Arabic, and Luganda language education courses. As summarised in **Table 1**, participants varied in age, academic rank, teaching experience, teaching mode, and prior exposure to artificial intelligence (AI).

Table 2: *Participant background characteristics (n = 40)*

Variable	Summary
Gender	26 Male (65%); 14 Female (35%)
Mean age	43.2 years (SD = 9.6)
Academic rank	Lecturer (24); Senior Lecturer (9); Assistant Lecturer (5); Professor (2)
Mean teaching experience	18.9 years (range: 0–34.8)
Teaching mode	Face-to-face (26); Blended (11); Online (3)
Mean class size	39.7 students (range: 4–80)
Prior AI training	Yes (17); No (23)
Internet reliability	Reliable/Moderate (29); Unreliable (11)

Attendance records indicate that all participants attended at least four of the six core CPD sessions, with most completing the full set of synchronous and asynchronous activities.

Changes in lecturers' AI-TPACK

Before the intervention, the mean AI-TPACK score of **2.68** suggested that many lecturers were still at a **modest level of confidence and readiness** in using AI in ways that connected content, pedagogy, and ethical judgement. After the AI-enabled CPD programme, the mean score rose to **3.16**, indicating a shift to a **more solid and practical level of preparedness**. This improvement of **0.48 points** was statistically significant ($p < .001$), suggesting that the change was unlikely to have occurred by chance. Put simply, the programme appears to have helped lecturers move from tentative awareness of AI integration towards more confident and informed classroom use.

Table 2: *Pre–post changes in AI-TPACK (n = 40)*

Measure	Pre-test Mean	Post-test Mean	Mean Difference	*p*-value
AI-TPACK	2.68	3.16	+0.48	< 0.001

Changes in CBET implementation capacity and instructional artifacts

Before the intervention, the mean CBET implementation capacity score of **2.94** suggested that lecturers were already showing a **moderate level of readiness** to implement the competence-based education and training, but not yet with strong consistency or confidence. After the AI-enabled CPD programme, the mean rose to **3.38**, pointing to a **clearer and more assured ability** to design learning outcomes, align teaching and assessment, and use feedback in more competence-focused ways. The gain of **0.44 points** was statistically significant ($p < .001$), which suggests that this improvement was unlikely to be due to chance. In practical terms, the programme appears to have helped lecturers move from partial understanding of CBET implementation towards more confident and usable classroom practice.

Table 3: *Pre–post changes in CBET implementation capacity (n = 40)*

Measure	Pre-test Mean	Post-test Mean	Mean Difference	*p*-value
CBET Implementation Capacity	2.94	3.38	0.44	< .001

Analysis of instructional artifacts provided convergent evidence. Rubric-based scores for CBET-aligned artifacts increased from a **pre-intervention mean of 1.73** to a **post-intervention mean of 2.23** on a 0–4 scale. This increase was statistically significant ($p < .001$). The change is illustrated in **Figure 1.**

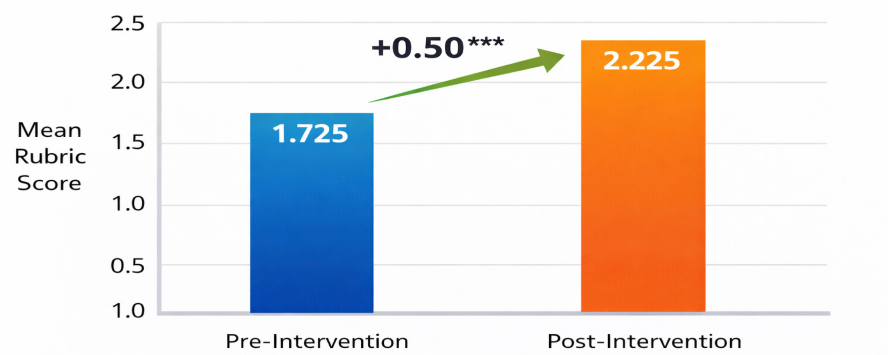

Figure 1: **Mean Rubric Scores for CBET-Aligned Instructional Artifacts (Pre-Post)**

Post-intervention artifacts demonstrated clearer constructive alignment between learning outcomes, teaching activities, and assessment tasks. Assessment designs increasingly emphasised authentic language use, such as oral presentations, applied writing tasks, and contextualised language analysis, rather than decontextualised exercises. Classroom observation evidence further demonstrated enacted CBET practices. Observation scores yielded a **post-intervention mean of 8.58 out of 10,** indicating high levels of competence-based teaching. Observers noted clearer communication of learning outcomes, increased use of performance-based activities, and more systematic formative feedback during lessons. These findings indicate that improvements extended beyond planning documents to classroom implementation.

Changes in perceptions, anxiety, and adoption intention

Before the intervention, lecturers' responses suggested a **cautious stance** towards AI. The mean score for adoption intention rose from **2.96** to **3.33**, showing that participants moved from **hesitant or moderate willingness** towards a **clearer readiness** to use AI-supported practices in their teaching. At the same time, the mean anxiety score fell from **3.01** to **2.71**, suggesting that initial unease about AI became **less pronounced** after the programme. These changes were statistically significant for both adoption intention (**+0.37,** $p < .001$) and AI-integration anxiety (**−0.30,** $p < .001$). In simple terms, the CPD seems to have helped lecturers feel **more open to AI and less worried about using it responsibly**.

Table 4: *Pre–post changes in adoption intention and AI-integration anxiety (n = 40)*

Measure	Pre-test Mean	Post-test Mean	Mean Difference	*p*-value
Adoption Intention	2.96	3.33	+0.37	< .001
AI-Integration Anxiety	3.01	2.71	−0.30	< .001

Qualitative findings

The qualitative findings illuminate how and why the observed gains in AI-TPACK, competence-based education and training (CBET) implementation, and readiness for responsible AI integration occurred. Drawing on instructional artifacts, classroom observations, and interviews, four interrelated patterns emerged: competence-first task and assessment design; enhanced formative feedback practices; strengthened reflective and ethical teaching; and the enabling (and constraining) role of institutional conditions.

Improved task and assessment design

Post-intervention artifacts showed a clear shift from content-driven lesson planning to competence-first design. Lecturers revealed that they began with the intended competence, then designed an authentic learning task, and only afterwards used AI to help generate possible variations, examples, or scaffolds that could be adapted for the local teaching context. One participant explained:

> Before the CPD, I would normally begin by asking myself what content I needed to finish in that week, and then I would look for exercises to match it. After the CPD, I changed that order completely. I now begin with the competence I want students to demonstrate, then I design a task that can show that competence in practice. Only after that do I use AI to suggest possible task variations, examples, or prompts. Even then, I do not use the output as it comes. I review it carefully and adapt it to our course context, our students' level, and the realities of teaching here before I take it into class. (CEES_DHLE_036, EX_01_1)

This competence-first workflow appeared to become routinised in weekly planning and was reflected in rubric gains for competence mapping and task authenticity. A second participant described the process as follows:

> What became normal for me after the training was a planning sequence that I can now follow almost every week. I first map the competence I want students to build, then I craft an authentic task that requires them to demonstrate that competence in a realistic way. After that, I may prompt AI to generate alternative versions of the task, possible instructions, or examples of student responses. But the final and most important step is refinement. I have to rework what the AI gives me so that it fits Ugandan examples, our course aims, and the resources students can realistically use. (CEES_DHLE_028, EX_02_3)

Departmental endorsement of shared CBET templates further supported consistency and transparency in task design. One participant noted:

> As a department, we agreed that if AI is being used in planning or in preparing aspects of an assignment, that support should not remain hidden. We started working with common CBET templates, and that made expectations clearer across courses. We also agreed to include an integrity statement on every assignment so that students understand the boundaries of acceptable AI use. That helped us make the process more transparent, both for staff and for students, and it reduced confusion about whether AI support was being used responsibly. (CEES_DHLE_033, EX_05_1)

Participants also linked authentic tasks and clearer rubrics to improved student engagement, while maintaining that AI should scaffold rather than replace student thinking:

> I noticed that when the task is authentic and the rubric is clear, students engage more seriously because they can see what they are expected to demonstrate. AI can help us create scaffolds, examples, or draft materials more quickly, but we have to be careful that it does not begin to do the thinking for the students. For me, the value is in using AI to support the learning design, not to replace the reasoning, interpretation, or language work that students themselves need to do. (CEES_DHLE_033, EX_05_3)

Enhanced formative feedback practices

A second pattern concerned formative assessment and feedback. Artifacts and observations indicated increased use of rubric-based drafting, feedback cycles, and revision opportunities, marking a departure from reliance on a single end-of-course examination. One lecturer explained:

> One of the biggest changes for me was moving away from depending almost entirely on one final exam. After the CPD, I began using draft submissions with a rubric so that students could receive feedback before the final grade. That created room for revision, which was not common in my earlier practice. It was easier to do this because we had shared rubrics and some moderation time as a department. The process became more manageable once expectations were clear and we were not all inventing assessment criteria individually. (CEES_DHLE_028, EX_02_2)

AI also appeared to support feedback at scale, especially by helping lecturers prepare rubric-aligned feedback language that they could then personalise. As one participant explained:

> What AI helped me with most was not making the judgement for me but helping me prepare feedback language more efficiently. I could ask it to generate feedback stems aligned to my rubric criteria, and then I would personalise those comments for the actual student draft in front of me. I still made the evaluative decisions myself, and I was careful about confidentiality and what material I entered the tool. But it helped me respond more consistently and more quickly, especially where class numbers made individual feedback difficult. (CEES_DHLE_025, EX_04_2)

However, infrastructural limitations shaped how far these feedback practices could be enacted in real time:

> In principle, we saw possibilities for using AI in more immediate classroom interaction, but in practice access was not always reliable enough for that. When connectivity is poor, or students do not all have stable access, the use of AI shifts. It becomes more realistic for planning, preparation, and feedback design before class rather than something you depend on during the lesson itself. So in our situation, it often becomes AI for planning rather than AI in-class, even when we can see the pedagogical value of doing more. (CEES_DHLE_009, EX_03_1)

Despite such constraints, observations suggested more consistent alignment between feedback and assessment criteria across courses.

Reflective, ethical, and context-sensitive teaching

A third pattern highlighted strengthened reflective practice and ethical awareness. Participants described reduced anxiety as they developed routines for disclosure, verification, and boundary-setting in their use of AI. One lecturer noted:

> I am much more open now about how I use AI in my teaching practice. I disclose my AI use openly, both to students and in my own preparation processes, because I no longer see transparency as a weakness. The CPD helped me understand that AI is most useful to me as a scaffold. I use it to generate starting points, alternative explanations, or planning support, but not as a final answer that I simply accept. Having those boundaries has made me more confident and much less anxious, because I feel clearer about what responsible use looks like. (CEES_DHLE_009, EX_03_2)

Lecturers also reported treating AI outputs as drafts to be critiqued rather than authoritative answers to be adopted uncritically:

> I now deliberately model for students that AI output is only a draft, not a final product to be trusted automatically. When I use it, I show that it must be checked, questioned, and revised. Sometimes the examples it gives are too generic, sometimes they miss the context, and sometimes the wording needs substantial adjustment. That has become part of my teaching approach: demonstrating that verification, interpretation, and revision are still human responsibilities, even when AI is used as a support. (CEES_DHLE_003, EX_07_1)

Integrity was increasingly embedded in task briefs and rubrics, and some participants described personal ethical checklists that helped them manage perceived risk:

> What reduced my anxiety most was having a clear routine for ethical decision-making. I now use a kind of personal checklist before I use AI in relation to any task or assessment. I ask whether the use is transparent, whether student privacy is protected, whether the task still requires genuine student thinking, and whether the final judgement remains mine as the lecturer. We also started embedding integrity expectations into task briefs and rubrics. Having these checks in place made AI feel less risky and more professionally manageable. (CEES_DHLE_032, EX_10_1)

Institutional conditions and sustainability

Across the themes, sustainability was linked less to individual enthusiasm and more to institutional conditions. Unreliable connectivity was repeatedly cited as a constraint on momentum and depth of implementation:

> The challenge is that enthusiasm alone cannot sustain the practice when the infrastructure is unstable. There were times when connectivity problems interrupted what we wanted to do, and that affects confidence over time. If the institution wants this change to continue, it must support more stable internet access and provide low-tech alternatives for cases where the technology is not dependable. Otherwise, people may retain the ideas from the CPD, but their actual classroom implementation will remain uneven. (CEES_DHLE_036, EX_01_2)

Clear institutional guidance on ethical AI use also appeared to increase confidence and consistency:

> What helped me most was not only learning how the tools work but knowing that there should be an institutional position on how they are to be used responsibly. When guidance is unclear, each lecturer is left to make individual decisions, and that creates inconsistency and uncertainty. Clear institutional direction on acceptable AI use, disclosure, privacy, and assessment boundaries gives staff confidence. It also makes students receive a more coherent message across courses instead of mixed expectations from different lecturers. (CEES_DHLE_036, EX_01_3)

Finally, departmental moderation structures and communities of practice were central to stabilising change:

> For me, the reason the change began to stick was that it did not remain at the level of individual experimentation. Once the department began using shared templates, moderation discussions, and common expectations around assessment and AI transparency, the new practices became more normal and easier to sustain. In that sense, the institutional structure made the change stick. It was not simply that individual lecturers became more motivated; it was that the department created routines that supported the new way of planning, assessing, and talking about AI use. (CEES_DHLE_033, EX_05_2)

Discussion of findings

This study examined the effectiveness of an AI-enabled continuous professional development (CPD) intervention in strengthening lecturers' AI-TPACK, competence-based education and training (CBET) implementation capacity, and readiness for responsible AI integration in language education at a public university. The convergent quantitative and qualitative findings demonstrate that well-designed AI-enabled CPD can support substantive pedagogical transformation rather than superficial technology adoption, while also highlighting the institutional conditions necessary for sustaining change in low-resource higher education contexts.

AI-TPACK development and pedagogical transformation

The significant gains in lecturers' AI-TPACK align with theoretical expectations that professional learning is most effective when technological knowledge is developed in close interaction with pedagogy and content, rather than as isolated skills training (Mishra et al., 2023). Qualitative evidence indicates that participants moved beyond operational familiarity with AI tools towards integrated professional judgement about when, why, and how AI could support competence-oriented humanities and language teaching. This finding reinforces AI-TPACK as a meaningful extension of the TPACK framework, foregrounding ethical awareness, contextual sensitivity, and critical evaluation of AI outputs alongside technical proficiency. Notably, lecturers' shift from content-first planning to competence-first task design suggests that AI functioned as a catalyst for pedagogical reorientation rather than a driver of change.

This extends prior studies that report improvements in AI literacy or confidence without corresponding changes in instructional coherence or curriculum implementation (Du et al., 2024; Yang et al., 2025).

CBET implementation as practice, not policy compliance

Improvements in CBET implementation capacity and instructional artifact quality address a persistent challenge in higher education reform: the gap between curriculum policy and classroom practice. In Uganda, CBET implementation has often been constrained by limited assessment literacy, entrenched examination practices, and insufficient professional learning opportunities. The findings suggest that AI-enabled CPD can help lecturers operationalise CBET principles, authentic tasks, rubric-based assessment, and formative feedback, into concrete instructional designs and enacted classroom practices. Crucially, classroom observations confirm that these changes extended beyond planning documents and self-reports. Lecturers demonstrated clearer articulation of learning outcomes, increased use of performance-based activities, and more systematic formative feedback during instruction. This addresses a limitation noted in the global literature, where evidence of AI-supported professional development often remains confined to teacher perceptions or design intentions (Erhardt et al., 2025).

Effective CPD features and sustained change

The findings strongly align with established theories of effective professional development, particularly coherence, active learning, feedback, and sufficient duration (Desimone, 2009; Sims & Fletcher-Wood, 2021). The CPD programme's emphasis on real course artifacts, collaborative rubric moderation, and iterative design–feedback cycles mirrors feature identified as critical for sustained instructional change (Darling-Hammond et al., 2017). Consistent with systematic reviews of AI in teacher professional development, this study shows that AI is most effective when conceptualised both as a learning objective and as a pedagogical tool. Lecturers developed AI literacy and ethical awareness while simultaneously using AI to support reflection, lesson design, and feedback. This dual conceptualisation is particularly salient in higher education contexts, where lecturers exercise substantial autonomy and rely on professional judgement rather than procedural compliance.

Anxiety reduction, adoption intention, and sustainability

Reductions in AI-integration anxiety and increases in adoption intention are central to sustainability rather than peripheral outcomes. Prior research shows that anxiety, uncertainty about academic integrity, and fear of misuse often inhibit AI adoption even when technical skills are present (Nazaretsky et al., 2022; Unal et al., 2025). In this study, reduced anxiety was closely linked to clearer ethical routines, transparency norms, and institutional signals of legitimacy. Lecturers' emphasis on disclosure practices, integrity statements, and bounded AI use reflects a sociotechnical understanding of AI integration, in which ethical judgement is integral to pedagogical decision-making. This finding addresses a gap in the literature, where ethical considerations are often discussed abstractly rather than empirically linked to confidence and sustained adoption (Bergdahl et al., 2024).

Institutional conditions

A key contribution of this study lies in illuminating the institutional conditions required to sustain gains. Infrastructure reliability, policy clarity, leadership support, and workload recognition shaped how AI-enabled practices were enacted. Even highly motivated lecturers adapted their AI use in response to connectivity constraints, shifting from in-class applications to planning-focused uses when resources were limited. This reinforces critiques that AI integration research often underestimates contextual constraints, particularly in low- and middle-income settings (Zawacki-Richter et al., 2019). Departmental structures, shared rubrics, moderation meetings, and emerging communities of practice, played a decisive role in stabilising change. This supports the argument that sustainable pedagogical innovation depends less on individual champions than on organisational routines that normalise new practices (Sims et al., 2021). Overall, the findings demonstrate that AI-enabled continuous professional development (CPD) can support meaningful CBET implementation when designed as a pedagogy-first intervention and embedded within supportive institutional ecosystems.

Conclusion

This study concludes that AI-enabled CPD can strengthen competence-based education and training (CBET) implementation in humanities and language education when it begins with pedagogy, not with the excitement of new tools. The evidence from lecturers' self-reports, instructional artifacts, classroom observations, and interviews shows a meaningful shift in practice: lecturers became more able to connect AI with subject content, teaching methods, assessment, feedback, and ethical judgement; they also moved closer to CBET-aligned teaching by designing clearer learning outcomes, more authentic tasks, better-aligned assessments, and more useful feedback opportunities. Just as importantly, the intervention helped lecturers approach AI with greater confidence and less anxiety, not because their concerns disappeared, but because they developed clearer ways of using AI responsibly, transparently, and with human judgement at the centre. The study therefore shows that AI can support curriculum reform when it helps lecturers think more carefully about learning, rather than when it simply makes teaching tasks faster. However, the findings also caution against placing the burden of change on individual lecturers alone. Sustained responsible AI use depends on reliable infrastructure, clear institutional guidance, supportive leadership, and departmental routines such as shared rubrics, moderation, peer learning, and open discussion of ethical boundaries. In this sense, the study's main contribution is that it presents AI-enabled CPD as a practical and context-sensitive route for improving CBET implementation in a low-resource higher education setting, while reminding institutions that meaningful change lasts only when lecturers are supported as reflective professionals, not treated as passive users of technology.

Recommendations

Universities should treat AI-enabled CPD as an ongoing form of staff development rather than a one-off training event. This study showed improvements in lecturers' AI-TPACK, confidence, and readiness to use AI, but these gains are more likely to last when they are supported through continued mentoring, peer learning, and clear institutional follow-up. Universities should also invest in the basic conditions that make responsible AI use possible, especially reliable internet access, fair access to digital tools, and practical alternatives for low-connectivity settings. In addition, institutions should provide clear guidance on ethical AI use, including expectations around transparency, privacy, and acceptable use in teaching and assessment. Departments should build on the teaching practices that improved most during the intervention. They should strengthen the use of authentic tasks, shared rubrics, feedback cycles, and moderation discussions, since these were closely linked to better CBET implementation in both instructional artifacts and classroom practice. Lecturers should also be supported to plan from competencies first and then use AI carefully as a tool for generating ideas, refining tasks, and supporting feedback, rather than replacing professional judgement. To protect academic standards, task briefs and rubrics should make expectations about AI use explicit.

Limitations and Recommendations for Future Research

This study had some limitations. It was conducted within a single institution and did not include a comparison or control group, which limits the generalizability of the findings and the extent to which causal claims can be made. More specifically, the study employed a **one-group pretest–posttest design**, in which participants' competencies and perceptions were assessed before and after the AI-enabled continuing professional development intervention. This design was appropriate for evaluating professional learning in a real-world institutional context where randomization was not feasible. The use of multiple data sources helped to mitigate some of these limitations by strengthening the credibility of the findings through triangulation. Despite these constraints, the study provides contextually grounded evidence of how AI-enabled CPD can support competence-based education and training implementation in higher education, particularly in low-resource settings. Future research should examine whether the reported improvements are sustained over time and whether similar outcomes can be achieved across other universities in Uganda and comparable contexts. Comparative, longitudinal, and quasi-experimental studies would also help clarify which forms of professional support, institutional infrastructure, and policy guidance are most effective in sustaining responsible AI use in competence-based teaching.

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