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# Artificial intelligence integration and learner achievement in competence-based education in higher education institutions in Uganda

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## Abstract

The rapid emergence of Artificial Intelligence (AI), is reshaping higher education through real-time tutoring, personalised learning, and advanced knowledge synthesis. In Uganda, the adoption of Competence-Based Education (CBE) emphasises learner-centered pedagogy, critical thinking, and practical skill development. While AI presents opportunities to strengthen CBE, its unstructured use may undermine independent inquiry, critical thinking, and authentic competency development. The study investigated how institutional readiness, stakeholder perceptions, and AI use patterns relate to learner achievement within a competence-based curriculum in an AI-powered environment. It further identified strategies for integrating AI to support competency attainment, academic performance, assessment outcomes, and learning outcomes while preserving the principles of CBE in Ugandan higher education institutions. A cross-sectional quantitative design was employed, involving academic staff ( $n=52$ ) and students ( $n=513$ ) from public and private universities in Uganda. Participants were recruited through convenience sampling using online platforms. Data were collected using structured questionnaires measuring institutional readiness, stakeholder perceptions, AI usage patterns, learner achievement, and pedagogical strategies for AI integration. Both descriptive and inferential statistics were analysed using the JASP statistical tool and Python-based data analysis tools. The findings revealed moderate institutional readiness for AI adoption, with technology recording the highest readiness ( $M=3.2$ ), followed by pedagogy ( $M=2.9$ ), while policy and governance readiness remained low ( $M=2.4$ ). Stakeholders perceived AI as supporting competency achievement ( $M=4.1$ , 85%) and self-directed learning ( $M=4.0$ , 80%), although concerns were raised regarding independent problem-solving ( $M=3.6$ , 65%) and assessment authenticity ( $M=3.8$ , 70%). Students reported frequent use of AI tools, particularly ChatGPT (81.1%), Gemini (56.8%), and Copilot (38.8%), primarily for concept clarification (89.2%), research (81.1%), and idea generation (70.3%). Correlation analysis revealed a moderate positive relationship between AI use frequency and academic performance ( $r=0.544$ ), while chi-square analysis confirmed a significant association between AI use and academic performance ( $\chi^2 = 241.898$ ,  $p < 0.001$ ). The study concludes that effective AI



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integration in CBE requires AI literacy training, lecturer capacity building, institutional policy frameworks, and competency-oriented assessment approaches to enhance learner achievement while preserving the integrity of competency development.

**Keywords** Artificial intelligence, Competence-based education, Higher education, AI integration, Learner achievement

## 1 Introduction

The rapid evolution of Generative Artificial Intelligence (GenAI), especially large language models (LLMs), has introduced a new era in educational innovation [37, 38]. Tools such as ChatGPT, Gemini, Claude, and other transformer-based systems now demonstrate capabilities previously exclusive to human cognition, including real-time tutoring, complex text generation, multimodal reasoning, and knowledge synthesis [15, 25]. Globally, the integration of such tools into teaching and learning ecosystems is accelerating, prompting educators to redefine the nature of digital literacy, instructional design, and student competencies in the 21st century [39, 49]. Recent literature emphasizes that GenAI can support feedback generation, personalise instructional pathways, support inquiry learning, model real-world problem-solving, and democratise access to expert-level support such as academic writing, coding, and research guidance [24, 51].

Concurrent with this technological shift, education systems across sub-Saharan Africa, including Uganda, are undergoing structural curriculum reforms aimed at preparing learners for contemporary living and socioeconomic demands [2, 5]. Uganda's adoption of Competence-Based Education (CBE) represents a strategic effort to transition from content-heavy, teacher-centered pedagogy to learner-centered approaches that emphasize creativity, critical thinking, problem-solving, communication, collaboration, innovation, and digital literacy [35]. The CBE model aims to equip learners with complex capabilities and transferable competencies, aligning education with national and global workforce needs [16]. This shift requires learning approaches that provide opportunities for hands-on engagement, inquiry, problem-solving, and the demonstration of performance in real-world contexts, enabling learners to develop mastery and autonomy in what they do.

Within this context, emerging discussions in international curriculum reform literature suggest that AI-driven tools have strong potential to support the implementation of competence-based learning. For example, AI can facilitate inquiry-based tasks, formative assessment, personalized learning, and problem-based learning, which are important approaches for developing and assessing the competencies emphasized in Competence-Based Curriculum (CBC) [3].

It is also possible that AI can dilute authentic learning [7, 47] when it is used uncritically or adopted blindly, for instance, through plagiarism and overreliance on automated reasoning [27]. Furthermore, AI can hinder critical reflection, creativity, guided inquiry, active participation and engagement of rich learning tasks [47] which contribute to natural mastery and may therefore undermine the intentions of competence-based curricula [4, 8]. Uganda's education sector also faces infrastructural constraints, digital literacy gaps, and limited training in AI pedagogy, which could widen inequalities if integration is not thoughtfully managed [18, 44]. These challenges raise critical questions about how AI can be adopted in ways that support rather than undermine the intended outcomes of CBC reforms.

## 2 Problem statement

A competence-based curriculum is designed to develop learners' ability to know, learn, and learn how to learn, as well as to apply knowledge, work collaboratively, and function effectively in real-life contexts [29]. The curriculum emphasizes a shift from content-driven assessment to the evaluation of clearly defined learning outcomes [31] and promotes inquiry-based teaching and learning strategies grounded in real-world phenomena through classroom, outdoor, and laboratory activities [21]. Through this approach, CBC aims to nurture learners' critical thinking, creativity, problem-solving skills, sound judgement, and positive attitudes and behaviors [34].

Despite these intentions, the rapid integration of Artificial Intelligence (AI) technologies in higher education has introduced new challenges to the effective implementation of CBC. AI-powered tools and simulation platforms often simplify academic tasks, potentially limiting learners' engagement, reflection, and independent inquiry [30]. As a result, competencies such as critical thinking, creativity and problem-solving, which CBC seeks to promote, may be undermined when learners rely excessively on AI-generated outputs [7, 47]. This raises concerns that AI may function as a shortcut to learning rather than a facilitator of deep competence development. This study explores how the benefits of both the CBC and AI can be maximized in higher education institutions without one compromising the other. Specifically, the study investigates how learners can derive maximum benefit from the CBC within an AI-enabled learning environment.

## 3 Purpose of the study

The purpose of this was to investigate how AI influences learner achievement within a CBE framework in Ugandan higher education institutions. Specifically, the study aimed at:

- i. To assess the prevalence of enabling institutional conditions (technological, pedagogical, and policy-related) supporting responsible AI adoption in higher education institutions.
- ii. To examine academic staff and student perceptions regarding the utility, challenges, and ethical implications of AI within a CBE framework.
- iii. To investigate learners' patterns of AI use and determine their relationship with competency attainment, academic performance, assessment outcomes, and learning outcomes.
- iv. To identify predictors of learner achievement in AI-supported learning environments.
- v. To propose pedagogical guidelines for integrating AI into teaching and learning while preserving the integrity of competency development and assessment.

## 4 Conceptual and theoretical framework

The study is anchored in four interrelated conceptual domains: the adoption of AI in education, responsible use of AI, the Competence-Based Education model, and the contextual considerations within Ugandan higher education institutions.

### 4.1 Adoption of AI in education

The adoption of AI in education is conceptualised as a dynamic process through which educational institutions, instructors, and learners incorporate AI-enabled tools to

enhance pedagogical effectiveness, optimise learning outcomes and support competency development [6]. Contemporary studies indicate that AI adoption is influenced by factors such as institutional readiness, digital infrastructure, educator competence, perceived usefulness of AI, and socio-cultural attitudes towards technology [14, 45, 48].

In competence-based education, AI adoption is particularly significant because it mediates the alignment between technological tools and competency attainment [36, 50]. GenAI can offer adaptive support, personalised feedback, scenario simulations, and automated assessment of higher-order skills, potentially accelerating learner progression if integrated thoughtfully [42]. Equally, unregulated adoption may disrupt authentic skill acquisition, encourage superficial learning, and compromise assessment integrity [22, 43].

Thus, AI adoption is conceptualised not merely as access to technology, but as a deliberate process of integrating AI into pedagogical design to enhance CBE outcomes without undermining core competencies.

#### 4.2 Responsible use of AI

Responsible AI use in education refers to practices and policies that ensure AI tools are employed ethically, transparently, and in alignment with pedagogical objectives [9]. Key dimensions include the accuracy of AI outputs, bias mitigation, data privacy, academic integrity, and maintenance of human oversight in decision-making [1, 40].

Within CBE, responsible AI use is essential because the educational value of competencies depends on authentic learner engagement, reflective practice, and critical thinking [6]. AI that is used irresponsibly, such as for completing assessments without student effort can sabotage learning outcomes and undermine the fidelity of competence demonstration [20].

This study conceptualises responsible AI use as a set of institutional, instructional, and learner-driven safeguards that mediate the relationship between AI adoption and the achievement of CBE competencies, ensuring that AI functions as an enabler rather than a disruptor.

#### 4.3 The competence-based curriculum (CBC) model

Higher education institutions in Uganda are attempting to detach themselves from the ‘ivory tower syndrome’ in which intellectuals are disconnected from realities within their communities. One way of doing this is by adopting the CBC model of education. CBC which is an action based [19] pedagogy, enables the “integration of learning experiences in education institutions with practical realities and requirements” [34]. This sharpens the capabilities of learners and also helps to reduce the gap between theory and practice.

Competence-based curriculum model should be anchored in a wide range of contexts that speak to learners’ backgrounds and environments for instance: the historical, philosophical, psychological, and sociological. This further allows learners to relate classroom practices to the realities they live, hence foregrounding what they learn. Philosophically, CBC is underpinned by constructivism, pragmatism and realism hence learners are expected to construct their own meaning and understanding of the different engagements. This means that CBC allows the use of numerous learning aids that range from local lived experiences, library materials, classroom/laboratory experiences and others.

They are expected to engage their cognitive, affective, and psychomotor skills. As Mwita and Onyango ([34]:486) assert:

*“Makes learners have a positive attitude, enjoy and appreciate their subjects, develop functional knowledge and manipulative skills, visualize or experience something, facilitate different learning styles, stimulate learners’ interest and curiosity, reduce verbalism or repetition and posse opportunities for individual study”.*

In other words, competence-based learning supports and empowers learners to learn at their own pace while promoting meaningful and authentic learning experiences. Central to this approach is the development and demonstration of competencies rather than the acquisition of theoretical knowledge alone. Although competence requirements may vary across disciplines, CBE generally emphasises learners’ ability to solve problems, communicate effectively, collaborate with others, and apply creativity in addressing real-world challenges [33]. These competencies are demonstrated through the application of knowledge, skills, and attitudes in authentic learning contexts rather than through memorisation or examination performance alone.

Within the context of this study, these competency constructs provide the basis for understanding learner achievement in AI-supported learning environments. They are reflected in learners’ ability to solve problems, communicate effectively, collaborate with others, and apply creativity in authentic learning situations. These competencies underpin the study variables on competency attainment, academic performance, assessment outcomes, and learning outcomes, providing a basis for integrating how AI supports or constrains competency development within competency-based education.

#### 4.4 The controversy between CBC and AI adoption

There are growing concerns regarding the adoption of AI in higher education especially those that have adopted the competence-based model of education. It is argued that blind adoption of AI may undermine the intended outcomes of a CBC curriculum [37]. For instance:

1. CBC is action - based and promotes practical learning experiences in all fields of study. This may conflict with AI which provides simulated experiences in some of the subject areas. For instance, whereas CBC wishes that learners’ psychomotor skills are sharpened by real-life experiences, AI offers simulated experiences therefore, may not fully support the philosophical (pragmatism, realism and constructivism) premises of the curriculum.
2. The CBC addresses the learner’s holistic background and context e.g., historical, philosophical, psychological and sociological. The AI may not afford to provide this wide range of context at a go hence limiting learner’s reflection on lived realities and construction of meaning.
3. CBC also takes cognizance of the importance of nurturing generic skills such as critical thinking, collaboration, teamwork and team building and behavioral competences like acting in ways that keep the environment clean, promoting efforts towards disease control after studying some topics etc. These and other attitudinal and observable changes, cannot be offered; neither can they be assessed through the outputs provided by AI platforms alone.

#### 4.5 The theoretical basis of the study

This study is anchored in the Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al., [46] and the Task-Technology Fit (TTF) theory, developed by Goodhue and Thompson [11]. The UTAUT theory was proposed to explain factors influencing the acceptance and use of information technologies and integrates elements from eight earlier technology adoption models, including Technology Acceptance Model (TAM), Theory of Planned Behaviour (TPB), and Diffusion of Innovation Theory (DIT). UTAUT posits that an individual's intention to use a technology and subsequent usage behaviour are influenced by four key constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions [46].

Performance expectancy refers to the belief that technology improves performance, while effort expectancy relates to the perceived ease of use [46]. In this study, these constructs are reflected in students' and lecturers' perceptions that AI enhances learning, supports competency attainment, improves academic performance, and facilitates self-directed learning. Social influence refers to the impact of lecturers, peers, institutional leadership, and broader technological trends on AI adoption, whereas facilitating conditions relate to the availability of technological infrastructure, pedagogical support, governance structures, and AI-related policies.

UTAUT is particularly relevant to this study because it explains how institutional readiness, stakeholder perceptions, and AI use patterns influence learner achievement within a CBE environment. The theory provides a lens for understanding why students and academic staff adopt AI technologies and how institutional factors shape their use. The study extends UTAUT by linking AI adoption and responsible AI use to performance, assessment outcomes, including competency attainment, academic performance, and learning outcomes. Thus, it provides a foundation for explaining how AI can be integrated into CBE while preserving the integrity of competency development and assessment.

The TTF theory states that information technology is only likely to have a positive impact on individual performance if the capabilities of the technology match the tasks that users must perform [13, 28]. The theory supports this study because CBC requires tasks that mould and sharpen the cognitive, the affective and the psychomotor skills of the learner. AI technology on one hand provides instant responses to tasks that may require learners to use their cognition; hence by passing, crippling and sabotaging the development of those cognitive abilities such as processing skills, attention skill and analytical skills. On the other hand, AI technology may be 'too little' [13]:85 to perform tasks that lead to the development of the affective and the psychomotor skills. In such a case, it is considered a misfit neither enabling or sabotaging competence development.

The two theories complement each other in supporting the study. While TTF concentrates on whether AI technology has the appropriate mechanisms for supporting competence development across three domains of learning (the cognitive, the affective and the psychomotor), the UTAUT focuses on factors within learning environments that determine AI adoption.

#### 4.6 Conceptual framework

Figure 1 illustrates the conceptual framework guiding this study. The framework proposes that institutional readiness (technological, pedagogical, and policy readiness)

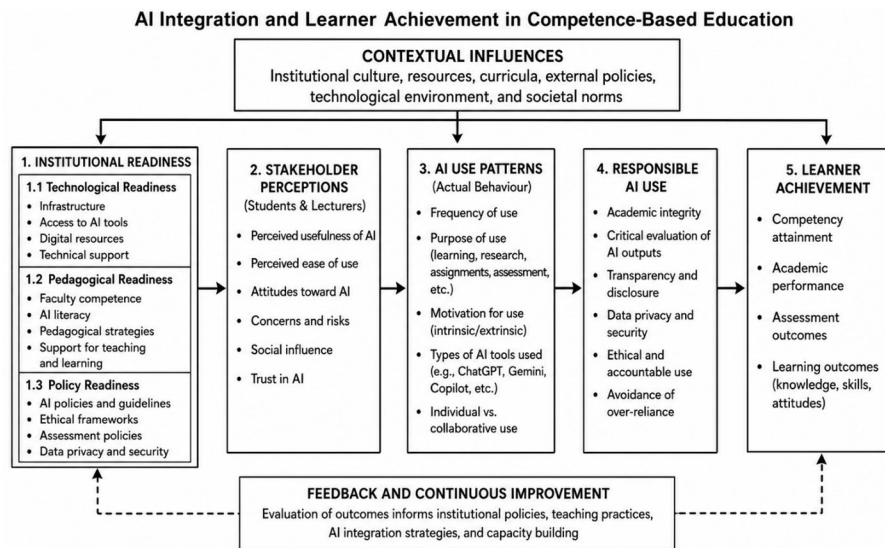


**Fig. 1** AI integration and learner achievement in competence-based education

influences stakeholder perceptions of AI, which in turn shape AI use patterns. Responsible AI use mediates the relationship between AI use and learner achievement outcomes, including competency attainment, academic performance, assessment outcomes, and learning outcomes. The framework further recognises that feedback from learner achievement can inform future institutional policies, teaching practices, and AI integration strategies.

## 5 Materials and methods

### 5.1 Study design and setting

The study adopted a cross-sectional research design to investigate the influence of AI on learner achievement within a CBE framework in Ugandan higher education institutions. Learner achievement was conceptualised in terms of competency attainment, academic performance, assessments outcomes, and learning outcomes. The design enabled the collection of data from academic staff and student at a single point in time, facilitating the assessment of institutional readiness, stakeholder perceptions, AI-use practices, and their relationship with learner achievement indicators.

The study was conducted across five universities in Uganda: Kabale University, Mbarara University of Science and Technology, Bishop Stuart University, Uganda Martyrs University, and Busitema University. These institutions were purposively selected to provide variations in institution type, technological infrastructure, and pedagogical practices.

### 5.2 Study population and sample

The study comprised academic staff and students enrolled in the selected universities. Academic staff included lecturers and teaching assistants involved in curriculum delivery and assessment, while students represented active participants in competence-based learning environments.

A convenience sampling approach was employed due to the accessibility of respondents through digital platforms. Although this approach may introduce self-selection

and technology-access biases, it was considered appropriate for exploratory investigations of emerging educational technologies. A total of 565 respondents completed the survey, comprising 52 academic staff and 513 students drawn from diverse academic disciplines and institutions.

### 5.3 Instrument development, validation and data collection

Data were collected using a structured online questionnaire developed from literature on AI adoption, educational technology, and competence-based education. The questionnaire consisted of five sections:

1. Demographic characteristics;
2. Institutional readiness for AI adoption;
3. Stakeholder perceptions of AI utility and challenges;
4. Learner AI-use patterns;
5. Learner achievement indicators, including competency attainment, academic performance, assessment outcomes, and learning outcomes.

The measures of competency attainment, academic performance, assessment outcomes, and learning outcomes were primarily based on participants' self-reported responses rather than verified official academic records. The questionnaire consisted primarily of Likert-scale, closed- and open-ended items. Prior to deployment, the questionnaire underwent expert review to assess content validity and alignment with the study objectives. A pilot test was conducted to improve the clarity and wording of questionnaire items. Questionnaire reliability was assessed using Cronbach's alpha to determine the internal consistency of the multi-item Likert-scale constructs. The questionnaire demonstrated acceptable internal consistency, with Cronbach's alpha coefficients ranging from  $\alpha = 0.78$  to  $\alpha = 0.91$  across the assessed constructs. Participation was voluntary and anonymous, and no personally identifiable information was collected.

### 5.4 Data quality control

To enhance the validity and reliability of the data, the researchers sought the opinions of subject-matter experts in addition to piloting the instruments. This was done to ensure that the instruments would collect the required data. They also used a multi-channel recruitment strategy by posting the instruments across varied, highly distinct university online communities' platforms in five selected universities. In each university, the researchers had at least one focal person to encourage staff and students to fill the online questionnaires.

### 5.5 Data analysis

Data were analysed using JASP statistical software. Descriptive statistics, including frequencies, percentages, mean, mode, and standard deviations were used to summarise respondent characteristics and study variables.

To address relationship, between variables and strengthen the analytical contribution of the study, inferential statistical analyses were conducted. These included:

- Independent samples t-test to examine differences in learner achievement across academic disciplines.

- Chi-square test to determine associations between institutional characteristics and AI-use patterns.
- One-way analysis of variance (ANOVA) to assess differences in academic performance across institutions.
- Pearson correlation analysis to examine relationships between AI use frequency, competency attainment, academic performance, and learning outcomes.
- Multiple regression analysis to identify predictors of learner achievement in AI-supported learning environments.

Statistical significance was assessed at  $\alpha=0.05$ . Results were presented using tables, charts, scatter plots, heat maps, and regression visualisation.

## 6 Results

### 6.1 Participants' characteristics

#### 6.1.1 Demographic characteristics of academic staff

The demographic characteristics of academic staff ( $n=52$ ) are presented in Table 1. The gender distribution was relatively balanced, with males accounting for 57.7% and females 42.3% providing perspectives from both groups regarding AI adoption and CBE in higher education. Most respondents were between 30 and 39 years (42.3%) and 40–49 years (32.7%), indicating that the study largely captured the views of academics in their active professional and instructional years. This age profile is particularly relevant because these educators are often directly involved in curriculum implementation and technology-enhanced teaching practices.

In terms of academic rank, Assistant Lecturer (50.0%) and Lecturer (30.75%) constituted the majority of respondents, suggesting that the perspectives were predominantly drawn from academics who are actively engaged in day-to-day teaching, assessment, and student supervision. The inclusion of Senior Lecturers and Professors, although smaller

**Table 1** Demographic characteristics of academic staff respondents ( $n=52$ )

| Variable            | Category                                     | Frequency (n) | Percentage (%) |
|---------------------|----------------------------------------------|---------------|----------------|
| Gender              | Male                                         | 30            | 57.7           |
|                     | Female                                       | 22            | 42.3           |
| Age group           | 20–29 years                                  | 8             | 15.4           |
|                     | 30–39 years                                  | 22            | 42.3           |
|                     | 40–49 years                                  | 17            | 32.7           |
|                     | 50 years and above                           | 5             | 9.6            |
|                     | Teaching Assistant                           | 4             | 7.7            |
| Academic rank       | Assistant Lecturer                           | 26            | 50.0           |
|                     | Lecturer                                     | 16            | 30.7           |
|                     | Senior Lecturer                              | 3             | 5.8            |
|                     | Associate Professor/Professor                | 3             | 5.8            |
| Teaching experience | Less than 5 years                            | 22            | 42.3           |
|                     | 5–10 years                                   | 10            | 19.2           |
|                     | Above 10 years                               | 20            | 38.5           |
| Institution         | Kabale University                            | 18            | 34.6           |
|                     | Mbarara University of Science and Technology | 7             | 13.5           |
|                     | Bishop Stuart University                     | 6             | 11.5           |
|                     | Uganda Martyrs University                    | 14            | 26.9           |
|                     | Busitema University                          | 7             | 13.5           |

in proportion, provided additional insights from more experienced educators involved in curriculum design and academic leadership.

The distribution of teaching experience revealed a combination of early-career and experienced educators, with 42.3% having less than five years of teaching experience and 38.5% having more than ten years. This mix enabled the study to compare diverse perspectives regarding AI adoption, competency-based assessment, and learner achievement.

Institutional representation was distributed across the five participating universities, with Kabale University (34.6%) and Uganda Martyrs University (26.9%) contributing the largest proportions. The participation of both public and private institutions enhanced the diversity of viewpoints regarding institutional readiness, AI integration, and competence-based learning practices.

### 6.1.2 Demographic characteristics of student respondents

The demographic characteristics of student respondents ( $n=513$ ) are presented in Table 2. The sample comprised students from different age groups, year of study, academic disciplines, and institutions, providing diverse perspectives on the use of AI within competence-based learning environments.

The gender distribution was relatively balanced, with males accounting for 56.3% of respondents and female accounting for 43.7%. This distribution ensured that the study captured views from both male and female students regarding AI adoption, learning experiences, and competency development.

With respect to age, the majority of respondents (60.0%) were aged between 20 and 24 years, while 19.9% were below 20 years and 20.1% were aged 25 years and above. This indicates that the sample was predominantly composed of traditional university-age students, although mature learners were also represented. Given that younger learners are generally more exposed to digital technologies and online learning platforms, this age profile is particularly relevant when examining AI usage patterns and their influence on learning outcomes.

**Table 2** Demographic characteristics of student respondents ( $n=513$ )

| Variable       | Category                                     | Frequency ( $n$ ) | Percentage (%) |
|----------------|----------------------------------------------|-------------------|----------------|
| Gender         | Male                                         | 289               | 56.3           |
|                | Female                                       | 224               | 43.7           |
| Age group      | Below 20 years                               | 102               | 19.9           |
|                | 20–24 years                                  | 208               | 60.0           |
|                | 25 years and above                           | 103               | 20.1           |
| Year of study  | Year 1                                       | 72                | 14.0           |
|                | Year 2                                       | 118               | 23.0           |
|                | Year 3                                       | 130               | 25.3           |
|                | Year 4                                       | 102               | 19.9           |
|                | Year 5                                       | 41                | 8.0            |
|                | Postgraduate                                 | 50                | 9.8            |
| Field of study | STEM Discipline                              | 308               | 60.0           |
|                | Humanities                                   | 205               | 40.0           |
| Institution    | Kabale University                            | 120               | 23.4           |
|                | Mbarara University of Science and Technology | 100               | 19.5           |
|                | Bishop Stuart University                     | 83                | 16.2           |
|                | Uganda Martyrs University                    | 140               | 27.3           |
|                | Busitema University                          | 70                | 13.6           |

The distribution across years of study revealed that Year 3 students constituted the largest proportion of respondents (25.3%), followed by Year 2 (23.0%), Year 4 students (19.99), and Year 1 students (14.0%). Smaller proportions were observed among post-graduate students (9.8%) and Year 5 students (8.0%). The concentration of respondents in the intermediate years of study is advantageous because these students are more likely to have accumulated substantial experience with university learning systems, assessment practices, and emerging educational technologies, including AI tools.

Regarding academic discipline, STEM students constituted 60.0% of the sample, while humanities students accounted for 40.0%. The relatively higher representation of STEM students may reflect greater exposure to digital technologies and AI-related applications within their academic programmes. However, the inclusion of both STEM and humanities students provided an opportunity to explore AI adoption across diverse disciplinary contexts.

Institutional representation was distributed across the five participating universities. Uganda Martyrs University contributed the largest proportion of respondents (27.3), followed by Kabale University (23.4%), Mbarara University of Science and Technology (19.5%), Bishop Stuart University (16.2%), and Busitema University (13.6%). The participation of students from multiple institutions provided a broader perspective on institutional readiness, AI adoption practices, and learning experiences within different higher education settings.

## 6.2 Institutional readiness for responsible AI adoption

Institutional readiness for responsible AI adoption was assessed across three key dimensions: technological, pedagogical, and policy and governance readiness. The results are presented in Table 3.

The findings indicate that participating institutions demonstrate a moderate level of readiness for AI adoption, although substantial differences exist across the three dimensions. Overall, technological readiness emerged as the strongest dimension, while policy and governance readiness represented the most significant institutional gap.

The technological dimension recorded the highest mean score ( $M = 3.2$ ,  $SD = 0.9$ ), with 60% of the respondents reporting a moderate level of readiness and 20% indicating a high level of readiness. These findings suggest that many institutions have established foundational digital infrastructure, including internet connectivity, learning management systems, digital learning platforms, and access to AI-enabled tools. Such infrastructure provides an important foundation for AI-supported teaching and learning, particularly within CBE, where learners require continuous access to learning resources, feedback mechanisms, and personalised learning opportunities. However, the relatively low proportion of institutions reporting high technological readiness suggests that AI integration remains at an early development stage and has not yet been fully institutionalised.

Pedagogical readiness recorded a moderate mean score ( $M = 2.9$ ,  $SD = 1.0$ ), with half of the respondents (50%) indicating moderate readiness and 30% reporting low readiness.

**Table 3** Institutional conditions for AI adoption

| Dimension           | Low (%) | Moderate (%) | High (%) | Mean | Mode     | SD  |
|---------------------|---------|--------------|----------|------|----------|-----|
| Technology          | 20      | 60           | 20       | 3.2  | Moderate | 0.9 |
| Pedagogical         | 30      | 50           | 20       | 2.9  | Moderate | 1.0 |
| Policy & governance | 70      | 20           | 10       | 2.4  | Low      | 0.8 |

This finding suggests that while some AI-supported teaching practices are emerging, their implementation remains inconsistent across institutions. The results imply that educators are beginning to incorporate AI into instructional activities; however, structured pedagogical approaches that deliberately align AI tools with competency development, formative assessment, and learner-centered instruction are not yet fully established. Within a CBE framework, this limitation may reduce the potential of AI to support higher-order competencies such as critical thinking, problem-solving, communication, and creativity.

Policy and governance readiness recorded the lowest mean score ( $M = 2.4$ ,  $SD = 0.8$ ), with 70% of respondents indicating low levels of institutional support. This finding highlights a substantial absence of an institutional framework governance AI use in teaching, learning, and assessment. The lack of clear policies raises concerns regarding academic integrity, ethical use of AI, data privacy, ownership of AI-generated content, and the validity of competency assessment. In competence-based learning environments, where assessment outcomes are intended to reflect actual learner capabilities, weak governance structures may undermine confidence in assessment processes and learner achievement outcomes.

Taken together, these findings suggest that institutions are better prepared technologically than pedagogically or administratively for AI integration. While the existing technological infrastructure provides a foundation for AI adoption, sustainable and responsible implementation requires complementary investments in educator capacity development, curriculum redesign, assessment reform, and institutional governance frameworks. Strengthening these dimensions is likely to enhance the effectiveness of AI-supported learning and improve competency attainment, academic performance, assessment quality, and overall learning outcomes.

### 6.3 Stakeholder perceptions of AI utility, challenges, and ethical implications

Stakeholder perceptions regarding the utility, challenges, and ethical implications of AI were assessed using a five-point Likert scale ranging from Strongly Disagree (SD) to Strongly Agree (SA). The findings presented in Table 4 indicate that respondents generally held favourable views regarding the educational value of AI, while simultaneously expressing concerns about its implications for authentic competency development and assessment integrity.

The results reveal strong support for the educational benefits of AI within CBE. A substantial majority of respondents (85%) agreed or strongly agreed that AI supports the achievement of learning competencies ( $M = 4.1$ ,  $SD = 0.7$ ). Similarly, 80% agreed that AI enhances self-directed and personalised learning ( $M = 4.0$ ,  $SD = 0.8$ ). These findings suggest that stakeholders perceived AI as an important enabler of learner-centered education by facilitating access to information, providing immediate feedback, supporting

**Table 4** Stakeholder perceptions of AI utility, challenges, and ethical implications

| Variable                                                | SD (%) | D (%) | N (%) | A (%) | SA (%) | Mean | Mode  | SD  |
|---------------------------------------------------------|--------|-------|-------|-------|--------|------|-------|-----|
| AI supports achievement of learning competencies        | 2      | 3     | 10    | 55    | 30     | 4.1  | Agree | 0.7 |
| AI enhances self-directed and personalised learning     | 3      | 5     | 12    | 50    | 30     | 4.0  | Agree | 0.8 |
| AI undermines independent problem-solving skills        | 8      | 12    | 15    | 45    | 20     | 3.6  | Agree | 1.0 |
| AI poses risks to authentic competency-based assessment | 5      | 5     | 20    | 45    | 25     | 3.8  | Agree | 0.9 |

independent learning, and enabling personalized learning pathways, allowing adaptive learning and intelligent tutoring, assisted critical thinking, and supporting simulation-based competency development. Such capabilities are particularly valuable within CBE environments where learners are expected to progress through competency attainment at their own pace while demonstrating mastery of specific skills and knowledge. The challenge that remains however, is whether the facilitators and the learners can ably manipulate these AI applications for maximum benefits related to competency development.

The positive perceptions of AI are further supported by findings presented in Sect. 5.4, where students report using AI primarily to understand difficult concepts, support studying, generate ideas, and improve academic performance. Collectively, these findings suggest that AI is increasingly viewed as a learning support tool capable of enhancing competency development, academic achievement, and overall learning outcomes.

Despite these perceived benefits, respondents also expressed concerns regarding the potential unintended consequences of AI use. Approximately 65% of respondents agreed that AI may undermine independent problem-solving skills ( $M = 3.6$ ,  $SD = 1.0$ ), while 70% believed that AI poses risks to authentic competency-based assessment ( $M = 3.8$ ,  $SD = 0.9$ ). These findings indicate that stakeholders recognize a potential tension between the efficiency gains provided by AI and the need to ensure that learners genuinely develop and demonstrate competencies independently. The relatively higher standard deviations associated with these variables suggest some variation in opinions, implying that perceptions may differ according to individual experiences, disciplines, and levels of AI engagement.

These findings should not be interpreted as evidence that AI inherently weakens critical thinking or learner competence. The educational effects of AI depend largely on how the technology is integrated into teaching and learning activities. Learning environments that encourage passive acceptance of AI-generated responses may limit opportunities for deeper cognitive engagement.

The ethical and pedagogical concerns identified by respondents are further illustrated by the challenges reported in Fig. 2. Academic dishonesty and plagiarism were the most frequently cited concerns (94.4%), followed by over-reliance on AI by learners (88.3%) and difficulties in verifying the originality of student work (66.7%). Challenges related to assessing practical skills (38.9%) and reduced validity of assessments (30.6%) were also

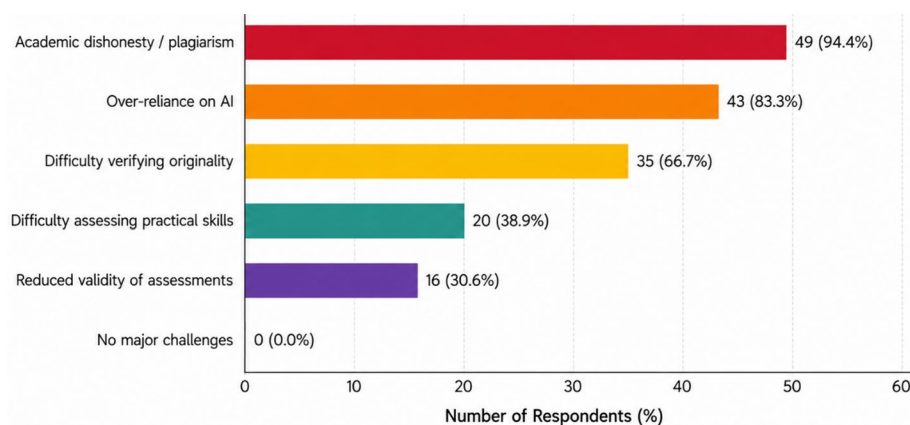


**Fig. 2** Challenges faced by educators when assessing competencies in the presence of AI

reported. These findings indicate that educators face increasing difficulties in ensuring that assessment outcomes accurately reflect learner competencies and authentic performance.

The concerns expressed by respondents are closely linked to the institutional readiness findings presented in Sect. 5.2. While technological readiness was relatively moderate, policy and governance readiness remained low. The absence of clear institutional guidelines may contribute to uncertainty regarding acceptable AI use, assessment practice, academic integrity, and responsible AI adoption. Strengthening governance frameworks may therefore play a critical role in addressing many of the challenges identified by respondents.

The findings demonstrate that stakeholders view AI as both an educational opportunity and a source of emerging challenges within competence-based education. AI is perceived as supporting personalized learning, learner autonomy, competency attainment, and academic performance. At the same time, concerns regarding assessment authenticity, academic integrity, and learner dependence highlight the need for institutional policies, AI literacy programmes, lecturer capacity development, and assessment approaches that preserve the integrity of competency-based learning and evaluation.

#### 6.4 Learners' patterns of AI use and learning outcomes

This section examines learners' patterns of AI use and explores their implications for competency attainment, academic performance, assessment outcomes, and learning outcomes. The analysis focuses on the AI tools commonly used by students, frequency of engagement, primary purposes of use, motivation for adoption, and perceived effects on independent learning. Figures 3, 4, 5 and 6 present the major patterns of AI use among students.

Figure 3 shows that ChatGPT is by far the most widely used AI tool among students, with more than four out of every five respondents (81.1%) reporting its use. Google Gemini (56.8%) and Microsoft Copilot (38.8%) followed at a considerable distance, while specialised tools such as Elicit, Semantic Scholar, Connected Papers, and RapidMiner attracted very limited use. What stands out from these findings is not merely the popularity of ChatGPT, but the extent to which students rely on general-purpose AI tools for

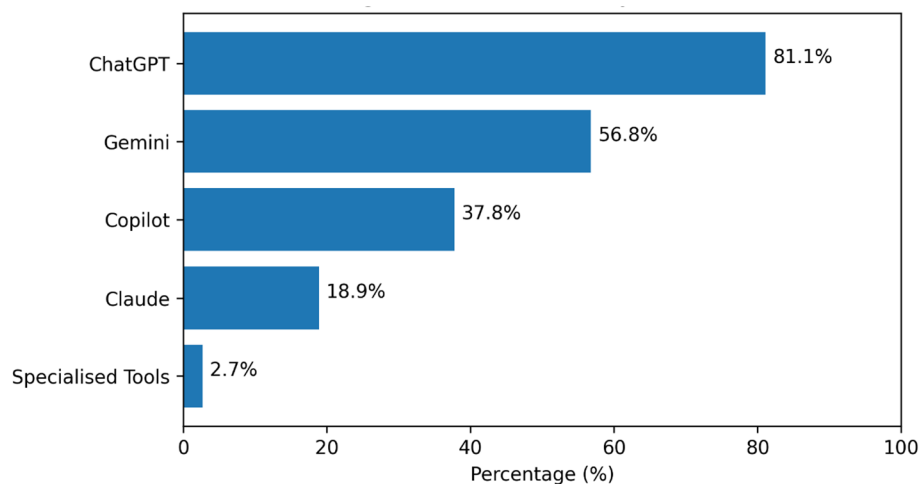


**Fig. 3** Distribution of AI tools used by students for learning and academic activities

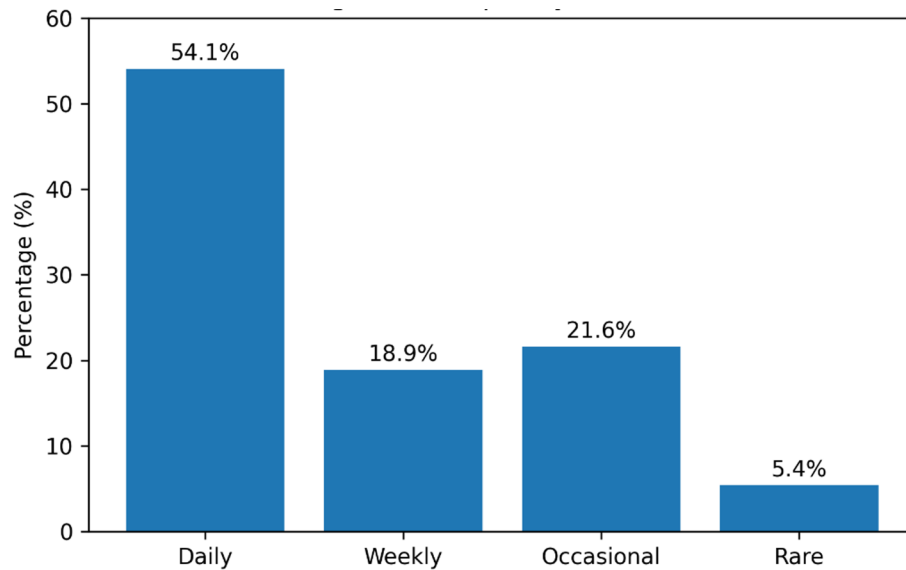


**Fig. 4** Frequency of students' engagement with AI tools for learning

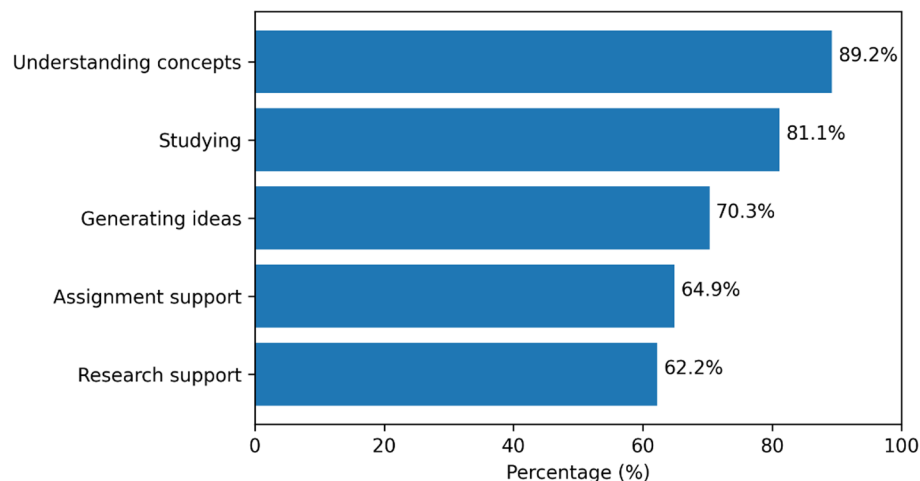


**Fig. 5** Academic purposes for which students use AI tools

academic support. This pattern suggests that students value accessibility, convenience, and versatility when selecting AI tools. The low uptake of specialised research-oriented tools may indicate limited awareness of their existence or limited capacity among students to leverage AI beyond routine learning tasks. From a competence-based education perspective, this finding raises an important question regarding whether students are fully exploiting the range of AI technologies available to support deeper inquiry, research, and professional skill development.

The findings presented in Fig. 4 reveal that AI use is no longer an occasional activity among students. More than half of the respondents (54.1%) reported using AI tools on a daily basis, while a further 18.9% used them weekly. Only a small proportion indicated rare use. Such frequent engagement suggests that AI has become embedded within students' everyday learning practices. The significance of this finding lies in the fact that learning support is no longer limited to interactions with lecturers, peers, or institutional resources. Students now have immediate access to AI-generated explanations,

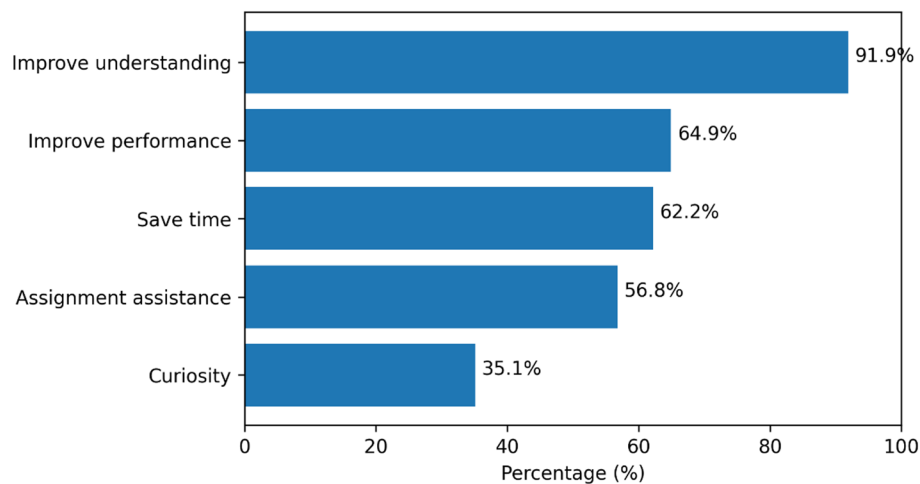


**Fig. 6** Motivation influencing students' adoption of AI tools for learning

feedback, and guidance whenever learning challenges arise. While this level of access can strengthen self-directed learning and support competency development, it also creates the possibility that learners may become dependent on AI-generated solutions rather than developing confidence in their own reasoning and problem-solving.

The purposes for which students use AI provide further insight into the role AI is playing in learning. As shown in Fig. 5, the most common use was understanding difficult concepts (89.2%), followed by studying and revision (81.1%). Substantial proportions of students also reported using AI for idea generation, assignment support, and research-related activities. These findings suggest that students are primarily engaging with AI as a learning support tool rather than simply as a mechanism for completing coursework. The prominence of concept clarification is particularly encouraging because it reflects the use of AI to address learning gaps and enhance understanding. Within a competence-based framework, such use has the potential to strengthen mastery of competencies by allowing learners to access explanations and learning support at the point of need.

At the same time, the substantial proportion of students using AI for assignments deserves careful consideration. Assignment tasks are often designed to evaluate independent learning, critical thinking, and the application of knowledge. Excessive reliance on AI during such tasks may therefore make it difficult to determine whether demonstrated performance genuinely reflects learner competence or the capabilities of the technology being used.

The motivations for AI adoption shown in Fig. 6 provide perhaps a clearer indication of why students are embracing these technologies. An overwhelming majority of respondents (91.9%) reported using AI to improve their understanding of course content. Improving academic performance and saving time were also frequently cited motivations. These findings suggest that students are not adopting AI primarily because it is fashionable or technologically appealing. Rather, they perceive AI as a practical resource that helps them achieve educational goals. The strong emphasis on understanding course content aligns closely with the objectives of competence-based education, where the emphasis is placed on mastery of knowledge and skills rather than the single completion of academic tasks.

The prominence of performance-related motivations also highlights the increasingly strategic role AI plays in contemporary learning environments. Students appear to recognise AI as a tool that can enhance efficiency and improve academic outcomes. Whether such improvements translate into genuine competency attainment, however, depends on the extent to which AI use encourages active engagement with learning rather than passive consumption of generated responses.

Taken together, the findings reveal that AI has become deeply integrated into students' learning experience. Students use AI frequently, rely heavily on small number of general-purpose tools, primarily engage with the technology to support understanding, studying, and academic improvement. These patterns suggest considerable potential for AI to support learner autonomy, competency attainment, and improved learning outcomes. At the same time, the findings point to emerging concerns regarding dependences on AI and the authenticity of assessment outcomes. The evidence therefore suggests that the educational impact of AI is shaped less by the technology itself and more by how learners and instructors choose to use it.

### 6.5 Relationship between AI use and learner achievement

Inferential statistical analysis was performed to ascertain whether learner achievement and AI usage trends were related. The association between the frequency of AI use, competency achievement, academic performance, and responsible AI use were investigated using Pearson correlation analysis. In addition, a one-way Analysis of Variance (ANOVA) and chi-square test of independence were computed to determine whether differences and associations existed among key study variables.

The correlation analysis presented in Table 5 revealed a moderate positive relationship between AI use frequency and academic performance ( $r=0.544$ ). This finding suggests that students who engaged more frequently with AI tools were more likely to report improvement in their academic performance. Although AI use frequently demonstrated only a weak positive relationship with competency attainment ( $r=0.045$ ), competency attainment itself was positively associated with academic performance ( $r=0.234$ ). This indicates that students who reported greater understanding and mastery of course content also tended to report better academic outcomes.

The analysis further revealed a positive relationship between responsible AI use and academic performance ( $r=0.313$ ), suggesting that students who used AI ethically and appropriately were more likely to achieve positive academic outcomes. The findings also indicate that AI use contribute more directly to academic performance than competency attainment. While frequent AI use was associated with improved academic performance, its relationship with competency attainment was weak, implying that competency development depends not merely on access to AI tools but on how learners engage with AI-supported learning activities and apply the knowledge gained.

**Table 5** Correlation analysis of AI use and learner achievement variables

| Variable              | 1     | 2       | 3     | 4     |
|-----------------------|-------|---------|-------|-------|
| AI use frequency      | 1.000 |         |       |       |
| Competency attainment | 0.045 | 1.000   |       |       |
| Academic performance  | 0.544 | 0.234   | 1.000 |       |
| Responsible AI use    | 0.132 | − 0.120 | 0.313 | 1.000 |

**Table 6** Multiple linear regression predicting academic performance

| Predictor             | B     | SE    | $\beta$ | t      | p       |
|-----------------------|-------|-------|---------|--------|---------|
| Constant              | 1.024 | 0.160 | –       | 6.399  | < 0.001 |
| AI use frequency      | 0.437 | 0.031 | 0.486   | 14.210 | < 0.001 |
| Competency attainment | 0.282 | 0.046 | 0.217   | 6.143  | < 0.001 |
| Responsible AI use    | 0.193 | 0.026 | 0.256   | 7.444  | < 0.001 |

**Table 7** One-way ANOVA of academic performance by level of study

| Source | F-value | p-value |
|--------|---------|---------|
| Level  | 6.194   | 0.002   |

### 6.5.1 Regression analysis of factors associated with academic performance

To further examine the independent contribution of AI use to learner achievement, a multiple linear regression analysis was conducted with academic performance as the dependent variable and AI use frequency, competency attainment, and responsible AI use as predictor variables. The overall regression model was statistically significant,  $F(3, 509) = 129.5$ ,  $p < 0.001$ , explaining 43.3% of the variance in academic performance ( $R^2 = 0.433$ ; adjusted  $R^2 = 0.429$ ).

As presented in Table 6, AI use frequency was a significant positive predictor of academic performance ( $B = 0.437$ ,  $SE = 0.031$ ,  $\beta = 0.486$ ,  $t = 14.210$ ,  $p < 0.001$ ). This implies that, holding competency attainment and responsible AI use constant, higher frequency of AI use was associated with higher reported academic performance. Competency attainment was also a significant positive predictor ( $B = 0.282$ ,  $SE = 0.046$ ,  $\beta = 0.217$ ,  $t = 6.143$ ,  $p < 0.001$ ), indicating that students who reported stronger alignment between their academic achievement and intended learning outcomes tended to report better academic performance. Similarly, responsible AI use significantly and positively predicted academic performance ( $B = 0.193$ ,  $SE = 0.026$ ,  $\beta = 0.256$ ,  $t = 7.444$ ,  $p < 0.001$ ).

Among the three predictors, AI use frequency had the largest standardised coefficient ( $\beta = 0.486$ ), suggesting that it made the strongest unique contribution to academic performance in the model, followed by responsible AI use ( $\beta = 0.256$ ) and competency attainment ( $\beta = 0.217$ ). These findings extend the bivariate correlation results by showing that the positive association between AI use and academic performance remains significant even after accounting for competency attainment and responsible AI use.

### 6.5.2 Differences in academic performance by level of study

A one-way ANOVA was conducted to examine whether academic performance differed across levels of study. The results presented in Table 7 revealed a statistically significant difference in academic performance among students at different levels of study ( $F = 6.194$ ,  $p = 0.002$ ). These results indicate that the relationship between AI use and academic performance varies according to students' academic progression. One possible explanation is that students at advanced levels of study have greater experience in identifying appropriate learning resources, evaluating information critically, and integrating AI tools into their academic work. More experienced learners may therefore be better positioned to leverage AI technologies in ways that enhance learning and academic achievement. The findings also suggest that institutional interventions aimed at promoting effective AI use need to consider differences in learners' academic maturity and educational needs.

**Table 8** Chi-square test of association between AI use frequency and academic performance

| Statistic               | Value   |
|-------------------------|---------|
| Chi-Square ( $\chi^2$ ) | 241.898 |
| Degrees of Freedom (df) | 9       |
| <i>p</i> -value         | < 0.001 |

**Table 9** Recommended Strategies for AI integration in CBE framework

| Strategy                   | Agree (%) | Mean | Mode  | SD  |
|----------------------------|-----------|------|-------|-----|
| AI literacy training       | 80        | 4.2  | Agree | 0.6 |
| Development of AI policies | 75        | 4.1  | Agree | 0.7 |
| Process-based assessment   | 70        | 4.0  | Agree | 0.8 |
| Lecturer capacity building | 78        | 4.2  | Agree | 0.6 |

A chi-square test of independence was computed to examine the association between AI use frequency and academic performance. The analysis presented in Table 8 revealed a statistically significant association between the two variables ( $\chi^2 = 241.898$ ,  $df = 9$ ,  $p < 0.001$ ). Students who reported frequent use of AI tools were substantially more likely to report higher levels of academic improvement than those who used AI less frequently.

The findings indicate that regular engagement with AI tools is associated with improved academic achievement. However, the educational benefits derived from AI depend largely on how learners interact with the technology and the extent to which they remain actively engaged in the learning process.

The inferential analyses collectively demonstrate that AI is significantly associated with learner achievement, particularly academic performance. While the direct relationship between AI use frequency and competency attainment was relatively weak, the moderate positive relationship between AI use and academic performance, together with the highly significant chi-square results, suggest that AI is increasingly contributing to students' academic success. These findings provide empirical support for the view that AI can serve as a valuable learning support tool within competence-based education when used responsibly and in ways that promote active engagement with learning tasks.

### 6.6 Pedagogical guidelines for AI integration

The findings indicate strong support for structured, guided, and competency-oriented integration of AI into teaching and learning processes. Respondents emphasised the need for interventions that strengthen AI literacy, build lecturer capacity, establish institutional governance frameworks, and reform assessment practices to ensure that AI supports rather than undermines competency development. The proposed strategies are summarised in Table 9.

The high level of agreement was recorded for AI literacy training (80%,  $M = 4.2$ ), highlighting the importance of equipping learners with the knowledge and skills required to use AI effectively and responsibly. Respondents viewed AI literacy as essential for enabling students to critically evaluate AI-generated outputs, formulate effective prompts, and apply AI tools in ways that support independent learning and competency acquisition. This finding suggests that educational benefits of AI are likely to depend not only on access to the technology but also on learners' ability to engage with it critically and purposefully.

Lecturer capacity building also received strong support (78%,  $M = 4.2$ ), reflecting the central role of instructors in guiding AI-supported learning. Respondents recognised that effective AI integration requires lecturers to redesign learning activities, provide appropriate guidance, and align AI use with competency-based outcomes. Strengthening lecturers' capacity to utilise AI for formative feedback, learning analytics, and assessment design may therefore enhance the quality and effectiveness of AI-supported teaching practices.

The development of institutional AI policies was supported by 75% of respondents ( $M = 4.1$ ), reflecting the need for clear institutional governance frameworks to regulate AI use in educational settings. This finding suggests that institutional policies are necessary to promote responsible AI use, safeguarding academic integrity, clarifying acceptable practices, and address emerging concerns related to ethics, data privacy, and assessment authenticity. Such frameworks are particularly important within CBE, where assessment outcomes are expected to reflect genuine learner competence and performance.

Support for process-based assessment approaches (70%,  $M = 4.0$ ) further reflects concerns regarding the authenticity of learning and assessment in AI-enabled environments. Respondents emphasised the need for assessment methods that evaluate learners' reasoning, application of knowledge, and demonstration of competencies rather than focusing solely on final outputs. Approaches such as project-based assessment, portfolios, practical demonstrations, and oral presentations were viewed as more appropriate for verifying competency attainment in contexts where AI tools are readily available.

The findings collectively suggest that effective AI integration within CBE requires a comprehensive approach that combines learners' preparation, lecturers' readiness, institutional governance, and assessment reforms. These strategies are mutually reinforcing and provide a foundation for maximising the educational benefits of AI while maintaining the integrity, authenticity, and quality of competency development and learning outcomes.

## 7 Discussion

The study provides insights into the state of AI integration within competence-based education across selected Ugandan universities, highlighting both opportunities and challenges. The demographic analysis shows a diverse sample of academic staff and students, dominated by early-to mid-career academics and undergraduate students, respectively. This aligns with prior studies [23, 41] that emphasised the importance of engaging both instructors and learners at various career stages to understand AI adoption dynamics and their implications for teaching, learning, and competency development.

Institutional readiness for responsible AI adoption was found to be moderate, with technological infrastructure being more developed than pedagogical practices or policy frameworks. The relatively high readiness in technology mirrors global trends, where universities invest in digital platforms and AI tools but lag behind in structured pedagogical integration [10, 17, 26]. The low level of policy and governance readiness is particularly concerning, as prior research highlights that clear institutional guidelines are critical to ensuring ethical AI use and maintaining academic integrity [27]. Without robust policies, the risk of AI misuse and compromised competency assessments increases, highlighting a significant policy gap in safeguarding competency-based

assessment in the CBE context. The strong support for institutional AI policies reported by respondents further strengthens the urgency of addressing this governance gap.

These findings are consistent with the UTAUT, which emphasizes the role of facilitating conditions in influencing technology adoption and use [46]. The moderate technological readiness and positive stakeholder perceptions observed in this study suggest that institutions are gradually creating conditions that support AI adoption, although weaknesses in policy and governance may constrain its effective integration within competence-based education.

Stakeholder perceptions reveal a dual perspective: AI is recognised as enhancing personalised, self-directed learning and supporting competency achievement, yet concerns persist regarding over-reliance, reduced problem-solving skills, and threats to assessment authenticity. These findings are consistent with literature on AI in higher education, which notes that while AI fosters engagement and individualised learning, it may also undermine critical thinking if not appropriately scaffolded [32]. The challenges reported – academic dishonesty, plagiarism, and reduced assessment validity – support this tension between AI as a facilitator and a disruptor of learning outcomes. However, these risks can be mitigated through deliberate pedagogical design. For example, facilitators can adopt CBE-aligned strategies that emphasise authentic, problem-solving-based learning, and performance-based assessment that require students to demonstrate application of competencies. By embedding AI within structured learning activities that promote critical thinking, reflection, and contextual application, universities can minimise overreliance while embracing AI to improve higher-order intellectual skills and competency mastery. This finding suggests that the educational value of AI is determined less by the technology itself and more by the pedagogical approaches that guide its use.

A notable observation is the difference between stakeholder perceptions and the measured relationship between AI use and competency attainment. While respondents strongly perceived AI as supporting competency achievement, the relationship between AI use frequency and competency attainment was weak. This suggests that positive perceptions of AI do not necessarily translate into measurable competency development. One possible explanation is that students may use AI primarily for information retrieval, clarification, and task completion rather than engaging in activities that require application, reflection, and demonstration of competencies, especially those that relate to the affective domain of learning such as values and attitudes. This speaks to the Task-technology Fits Theory which accordingly guides that AI technology can only lead to competency development if it fits the task. This study suggests that although AI can aid the development of some cognitive skills, it may be a misfit for the development of some psychomotor and affective skills. It is imperative to note, however, that the AI tools can fit some of the cognitive and psychomotor skills, but due to limited ICT-related pedagogical skills, limited technical support, and negative peer influence, the tools may be underutilized and later labelled inadequate for aiding competency development.

Further examination of the findings reveals that, at times, AI is used as a trend, not necessarily as a tool that aids competence development. This is revealed by the  $p$  value of less than 0.001 in the Chi-Square Test of Association Between AI Use Frequency and Academic Performance. In such a case, the intent for AI adoption does not support competency development but merely responds to trends. This finding is supported by the UTAUT theory, which emphasizes the role of environmental factors that influence

individuals' adoption of technology. In this context, these factors encourage learners to adopt AI during the learning process.

Student patterns of AI tool usage indicate frequent and purposeful engagement, mainly general-purpose tools such as Google Gemini, ChatGPT, and Copilot. The majority used these tools to understand concepts, generate ideas, and refining research work, indicating their potential to enhance autonomy and cognitive competence. However, the high frequency of AI use, coupled with performance-driven inspiration, raises concerns about possible dependency and reduced engagement in independent reasoning. Importantly, this concern is not unique to AI. As with traditional learning resources such as textbooks, libraries, and instructional videos, the impact on cognitive development depends on the depth of learner engagement rather than the tool itself. Learners who actively question, reflect on, and apply information from any source tend to develop higher-order thinking, whereas passive consumption – whether from books or AI, may lead to superficial understanding. Therefore, the major issue is not AI use per se, but the manner in which it is integrated into the learning process. This aligns with studies suggesting that while AI can support self-directed learning, unstructured or indiscriminating reliance may result in to surface-level engagement with content [25, 39]. From a Competency-Based Education and Training (CBET) perspective, this highlights the need to design learning activities that require learners to demonstrate applied competencies, justifying their reasoning, and critically engaging with AI-generated content, hence transforming AI from a potential crutch into a cognitive partner that supports deeper learning.

The inferential analyses provide further insight into the important distinction between academic performance and competency attainment. The moderate positive correlation between AI use frequency and academic performance ( $r=0.544$ ), together with the significant chi-square association between AI use frequency and academic performance ( $\chi^2 = 241.898$ ,  $p<0.001$ ), suggests that regular engagement with AI tools is associated with improved academic performance. In contrast, the relationship between AI use frequency and competency attainment was very weak. This difference is particularly important within a CBE framework, where academic performance does not necessarily equate to the acquisition and demonstration of competencies. While AI may help learners understand concepts, complete academic tasks, and improve performance in conventional academic activities, competency attainment requires learners to demonstrate the practical application of knowledge, problem-solving, critical thinking, and other context-specific abilities. The findings therefore suggest that AI use alone may be more readily reflected in academic performance than in deeper competency development. This reinforces the need for AI-supported learning activities and assessments to deliberately require learners to apply, demonstrate, justify, and reflect on their competencies rather than simply use AI to obtain information or complete academic tasks.

The study also identifies key pedagogical strategies for effective AI integration, emphasizing AI literacy, lecturer capacity building, institutional policies, and process-based assessment. These findings mirror global recommendations advocating for structured AI training for learners and faculty, policy guidance, and assessment reforms to safeguard the authenticity and effectiveness of CBE [12]. Overall, these results emphasise the need for coordinated, multi-level approaches that adopt AI's benefits while mitigating risks to competency development and academic integrity.

These findings provide empirical evidence that informs the conceptual controversy between CBE and AI adoption presented in Sect. 3.4. While respondents acknowledged the contribution of AI to personalised learning, competency achievement, and academic performance, concerns regarding independent problem-solving and assessment authenticity indicate that AI cannot fully substitute for the experiential and performance-based learning that underpins CBE. The findings further demonstrate that effective AI integration requires institutional readiness, AI literacy, lecturer capacity building, and governance frameworks that enable learners to apply AI within authentic learning contexts. In addition, concerns regarding overreliance on AI supports the view that competencies such as critical thinking, collaboration, creativity, and problem-solving are unlikely to develop through AI use alone but require deliberate pedagogical strategies that promote active learner engagement. These findings therefore suggest that the relationship between AI and Competency-Based Education is complementary rather than contradictory, provided AI is integrated in ways that preserve the authenticity of competency development and assessment.

## 8 Conclusion

The study concludes that AI has significant potential to enhance competence-based education by supporting self-directed, personalised learning and facilitating the acquisition of competencies. Effective integration, however, remains contingent on addressing gaps in pedagogical practices, policy frameworks, and assessment design. Frequent use of AI by learners highlights both opportunities for learning autonomy and risks of over-reliance. To maximise the benefits of AI in CBE, institutions must adopt a holistic strategy encompassing AI literacy training, faculty capacity development (such as the design of AI-resilient learning activities, performance-based and authentic assessment design, assessment integrity and academic honesty strategies, and digital and AI literacy for education), policy and governance, and competency-focused assessment reforms.

## 9 Limitations of the study

The study employed convenience sampling through online platforms, which may have introduced self-selection bias and technology-access bias. As a result, participation was largely limited to specific communities, particularly individuals with access to digital technologies and the internet.

In addition, the study did not provide any incentives to respondents, meaning that participation was voluntary and largely dependent on individuals' intrinsic motivation and personal interest in the study. Thus, the sample may have been skewed toward participants who were more motivated or engaged with the subject matter.

Another limitation is that measures of competency attainment, academic performance, assessment outcomes, and learning outcomes were primarily based on participants' self-reported responses rather than verified official academic records. This may have introduced self-reporting or response bias and should therefore be considered when interpreting the findings.

## 10 Future work

Future research could explore the longitudinal impacts of AI use on the development of higher-order competencies, including critical thinking, problem-solving, and creativity. Comparative studies across disciplines could provide insights into field-specific adoption patterns and challenges. Additionally, experimental studies evaluating the effectiveness of structured AI literacy programs and process-based assessment would help to refine best practices for integrating AI responsibly within CBE. Investigating the ethical and policy implications of AI adoption in assessment and learning analytics also remains a priority to ensure sustainable, equitable, and responsible AI use in higher education in Uganda.

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### Author contributions

V.M. contributed to the conception and design of the work, data collection tools, data collection, analysis and interpretation, and drafting and revision of the manuscript. F.K.N. contributed to the conception and design of the work, data collection tools, data collection, draft and revision of the manuscript, C.K, G.B.M, B.K, and D.O contributed to the data collection, interpretation and manuscript revision. S.K pre-tested the data collection tools to ensure that were aligned with research objectives, performed data analysis, and manuscript revision. All authors proof read the manuscript.

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### Data availability

The dataset used in this study are available from the corresponding author and can accessible with consent from the study participants.

## Declarations

### Ethics approval and consent to participate

The study protocol was approved by the Mbarara University of Science and Technology Research Ethics Committee (MUST-REC) in accordance with the ethical guidelines and regulations of the Uganda National Council of Science and Technology (UNCST). All participants were provided with detailed information regarding the study objectives, procedures, potential risks, and benefits before enrollment. Written informed consent was obtained from all participants prior to data collection. Participation was entirely voluntary, and participants were informed of their right to withdraw from the study at any stage without penalty. The confidentiality and anonymity of participants were rigorously maintained throughout the study by de-identifying data and restricting access to study information to authorized research personnel only.

### Consent for publication

All participants provided informed consent to participate in the study. No personally identifiable information was collected, and all data are presented in aggregate form. Participants were informed that the findings would be published in academic journals, conference proceedings, and other scholarly outlets.

### Competing interests

The authors declare no competing interests.

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