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Learner Perceptions and Appreciation of Artificial Intelligence Education Delivery in Ugandan Higher Education: A Mixed-Methods Exploration

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Abstract

The integration of Artificial Intelligence (AI) into higher education curricula has gained considerable momentum globally, yet empirical evidence from Sub-Saharan Africa—particularly Uganda—remains sparse. This mixed-methods study investigated learner perceptions and appreciation of AI education delivery in selected Ugandan higher education institutions. Guided by a pragmatist epistemological framework, the study employed a concurrent triangulation design, collecting quantitative data from 312 undergraduate and postgraduate students across four universities using a structured 28-item Likert-scale questionnaire, and qualitative insights from 24 purposively selected participants through in-depth semi-structured interviews. Quantitative analysis encompassed univariate descriptive statistics, bivariate Pearson correlation, confirmatory factor analysis (CFA), and principal component analysis (PCA). Findings revealed that learners held moderately positive perceptions of AI education delivery ($M = 3.76$, $SD = 0.58$), with AI content relevance ($M = 3.87$) and tool usability ($M = 3.72$) emerging as the strongest appreciation drivers. Technology accessibility recorded the lowest mean score ($M = 2.93$), underscoring persistent infrastructural constraints. Bivariate analysis revealed statistically significant positive correlations between prior AI exposure and overall appreciation ($r = 0.613$, $p < .001$). Factor analysis extracted three latent constructs—AI Engagement, Infrastructure Readiness, and Pedagogical Quality—collectively explaining 65.3% of total variance. PCA confirmed that AI engagement indicators were the primary contributors to composite learner appreciation scores. Qualitative themes corroborated quantitative patterns, highlighting enthusiasm tempered by infrastructural deficits, inconsistent instructor AI competence, and limited institutional support. The study concludes that while Ugandan learners are broadly receptive to AI education, sustainable appreciation requires targeted investment in digital infrastructure, systematic instructor capacity-building, and context-sensitive AI curriculum design. Recommendations are provided for policymakers, university administrators, and curriculum developers.

Keywords: Artificial Intelligence Education, Learner Perceptions, Higher Education, Uganda, Mixed Methods, Factor Analysis, Technology Adoption

INTRODUCTION

The twenty-first century has witnessed an unprecedented transformation of educational systems driven by the rapid proliferation of Artificial Intelligence technologies across virtually every professional and social domain. Within higher education specifically, AI has evolved from a niche technical subject into a foundational literacy that institutions are increasingly obligated to embed within curricula to prepare graduates for AI-augmented labour markets (Khosravi et al., 2022; Levin et al., 2022; Ridley, 2022). In Uganda, this imperative has been acknowledged at the highest levels of policy discourse, with the National Information Technology Authority of Uganda (NITA-U) and several forward-thinking universities beginning to introduce AI-themed modules, interdisciplinary data science programmes, and pedagogical experiments involving AI-powered learning tools (Doroudi, 2023; Gartner & Krašna, 2023; Ouyang &

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Jiao, 2021). Notwithstanding this growing activity, the empirical literature is conspicuously silent on a fundamental question: how do Ugandan learners themselves perceive and appreciate these AI education delivery efforts? Learner perception is not a peripheral pedagogical concern; rather, it constitutes a primary determinant of academic engagement, knowledge assimilation, and the ultimate transfer of learning to practice (Huang et al., 2021; Samtani et al., 2020; Sanusi et al., 2022). When learners view AI education as irrelevant, poorly delivered, or inaccessible due to infrastructural barriers, no amount of curriculum redesign or policy directive will produce the intended competency outcomes. Conversely, when learners appreciate the utility, quality, and accessibility of AI instruction, intrinsic motivation is heightened and deeper learning approaches are activated (Enholm et al., 2022; Nguyen et al., 2023; Prasanth et al., 2023; Sanabria-Navarro et al., 2023). The present study was therefore conceived to address this gap by rigorously examining, through a mixed-methods lens, the perceptions and appreciation levels of students enrolled in higher education institutions in Uganda where AI education is being delivered, and to identify the structural factors that either advance or impede positive learner dispositions toward AI instruction.

BACKGROUND OF THE STUDY

The global momentum toward AI-integrated higher education has been shaped by landmark publications such as the OECD's Artificial Intelligence in Society (2019) report and UNESCO's Beijing Consensus on Artificial Intelligence and Education (2019), both of which called upon governments and institutions to develop human-centred AI curricula that are inclusive, ethical, and contextually responsive (Akinwalere & Ivanov, 2022; Díaz Arce, 2023; Kaban, 2023). In the African context, the African Union's Digital Transformation Strategy for Africa (2020–2030) similarly positioned AI competency as a strategic priority for continent-wide economic development. Uganda, as a signatory to several of these frameworks and as a nation with a young and rapidly urbanising population—over 75% of whom are below the age of 30 (Uganda Bureau of Statistics, 2023)—occupies a distinctive position: it possesses both the demographic dividend and the developmental urgency to benefit enormously from AI education, yet simultaneously confronts structural constraints including erratic electricity supply, limited broadband penetration in non-metropolitan areas, chronically underfunded public university budgets, and an academic workforce whose digital competencies remain variable (Hwang et al., 2020; Rahiman & Kodikal, 2024; Sestino & De Mauro, 2022; Tapalova & Zhiyenbayeva, 2022). Pioneering Ugandan universities such as Makerere University, Uganda Christian University, and Kampala International University have initiated AI-related curricula, yet implementation quality, instructor readiness, and student experiences of these offerings have not been systematically documented. The theoretical grounding of this study draws on Davis's (1989) Technology Acceptance Model, which posits that perceived usefulness and perceived ease of use are the proximal determinants of technology adoption attitudes; (Cihon et al., 2021; Jennifer, 2024; Kohnke et al., 2023; Yu et al., 2023) constructive alignment theory, which emphasises the centrality of learner perceptions in effective curriculum delivery; and the Digital Divide scholarship (van Dijk, 2020), which contextualises infrastructure inequality as a critical moderator of technology-enabled educational outcomes in developing country settings. Together, these frameworks provide a robust conceptual apparatus for interpreting how Ugandan students perceive, evaluate, and ultimately appreciate or resist AI education delivery, and for generating

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empirically grounded recommendations that are sensitive to the specificities of the Ugandan higher education ecosystem (Crompton & Burke, 2023; Farrelly & Baker, 2023; Reyhani Haghighi et al., 2023; Ruiz-Real et al., 2021).

PROBLEM STATEMENT

Despite growing institutional investment in AI education across Ugandan universities, a critical evidence gap exists regarding how learners perceive and appreciate the quality, relevance, and accessibility of such educational delivery. Existing scholarship on AI in education is heavily weighted toward technological design and institutional policy, with learner-centred empirical investigations—particularly from Sub-Saharan African settings—remaining exceptionally rare (Dreiseitl & Ohno-Machado, 2002; Julius & Geofrey, 2025; Ofosu-Asare, 2025; Praful Bharadiya, 2023). This absence of evidence creates a dangerous blind spot: administrators and curriculum developers are making consequential decisions about AI education investment, design, and scale-up without systematic knowledge of whether students find the current delivery modalities relevant, competently executed, or adequately supported by institutional infrastructure (Chiu et al., 2023; Iffath Unnisa Begum, 2024; Julius & Nancy, 2025; Paxton et al., 2022). The consequences of this gap are multidimensional: learners may be exposed to AI curricula that are misaligned with their career aspirations or cognitive readiness levels; instructors may be deploying pedagogical strategies that generate surface rather than deep engagement with AI concepts; and resource allocation may be directed toward technology procurement when the more pressing barrier is instructor capacity or curricular contextualization. Without rigorous empirical documentation of learner perceptions and the structural factors underlying them, Ugandan higher education risks perpetuating an AI education landscape that is ambitious in ambition but limited in transformative impact. This study therefore addresses the specific problem of insufficient empirical evidence on learner perceptions and appreciation of AI education delivery in Ugandan higher education institutions, with the intent of generating actionable insights that can inform evidence-based improvements across the curriculum design, pedagogical delivery, and institutional support dimensions of AI education.

STUDY OBJECTIVES

Main Objective

To examine learner perceptions and appreciation of Artificial Intelligence education delivery in selected Ugandan higher education institutions using a mixed-methods approach.

Specific Objectives

1. To assess the levels of learner perceptions across key AI education delivery dimensions including content relevance, instructor competence, technology accessibility, and tool usability in Ugandan higher education institutions.
2. To determine the relationship between learner background characteristics (prior AI exposure, programme level, gender) and their overall appreciation of AI education delivery.
3. To identify the latent structural factors and principal components that most significantly explain variance in learner appreciation of AI education delivery.

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RESEARCH QUESTIONS

1. What are the levels of learner perceptions of AI education delivery across content relevance, instructor competence, technology accessibility, and tool usability dimensions in Ugandan higher education institutions?
2. What is the nature and strength of the relationship between learner background characteristics and overall appreciation of AI education delivery in Ugandan higher education institutions?
3. What latent structural factors and principal components explain the greatest proportion of variance in learner appreciation of AI education delivery in Ugandan higher education?

METHODOLOGY

This study employed a concurrent mixed-methods triangulation design underpinned by a pragmatist epistemological stance, which was deemed most appropriate for comprehensively examining both the measurable dimensions and the experiential nuances of learner perceptions of AI education delivery in the Ugandan higher education context. The target population comprised all undergraduate and postgraduate students enrolled in programmes with formal AI or data science components across four purposively selected Ugandan universities: Makerere University, Kampala International University, Uganda Christian University, and Busitema University. A stratified random sampling procedure was utilised to select a final quantitative sample of 312 respondents (194 undergraduates and 118 postgraduates; 178 males, 131 females, and 3 identifying as non-binary), a sample size determined via Cochran's (1977) formula with a 95% confidence level and a 5% margin of error applied to an estimated population of 4,800 eligible students. A structured, self-administered questionnaire comprising 28 Likert-scale items (anchored 1 = Strongly Disagree to 5 = Strongly Agree) was developed based on constructs derived from Davis's Technology Acceptance Model, Biggs and Tang's constructive alignment framework, and the UNESCO AI competency guidelines; the instrument achieved a Cronbach's alpha of 0.883, confirming high internal consistency reliability, and content validity was established through expert review by five educational technology scholars. Quantitative data collection was conducted between October and December 2024 through online administration and supervised paper-based sessions at university computer laboratories. Univariate analysis was performed for each scale item and composite construct, computing means, standard deviations, minimum and maximum values, skewness, and kurtosis to characterise the distributional properties of perception and appreciation scores; one-sample t-tests were additionally conducted to assess whether means departed significantly from the neutral midpoint of 3.0. Bivariate analysis employed Pearson product-moment correlation coefficients to quantify the linear relationships between continuous predictor variables (prior AI exposure, age) and the overall AI education appreciation score, while point-biserial correlations were computed for dichotomous categorical predictors (gender); independent samples t-tests and one-way ANOVAs (with Tukey HSD post-hoc comparisons) were further conducted to examine mean appreciation differences across categorical groupings (gender, programme level, university). Exploratory factor analysis (EFA) was undertaken using maximum likelihood extraction with oblique (Promax) rotation to identify the latent factor structure underlying the 28 questionnaire items; the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy yielded a value

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of 0.874 and Bartlett's Test of Sphericity was statistically significant ($\chi^2 = 2{,}847.3$, df = 378, $p < .001$), confirming the data's factorability; factors with eigenvalues exceeding 1.0 were retained in accordance with Kaiser's criterion, and scree plot inspection was used to corroborate the factor retention decision. Principal component analysis (PCA) with Varimax rotation was subsequently performed on the composite construct scores to rank the relative contributions of the extracted components to overall learner appreciation variance, thereby enabling parsimony in identifying the most predictive structural dimensions. On the qualitative strand, 24 participants were purposively selected to ensure maximum variation across university, gender, programme level, and AI background; individual semi-structured interviews of 45–60 minutes duration were conducted in English (with Luganda translation available), audio-recorded with informed consent, transcribed verbatim, and analysed using Braun and Clarke's (2006) reflexive thematic analysis through ATLAS.ti version 23, resulting in the generation of themes and subthemes that were triangulated with quantitative findings to produce integrated interpretations (Nelson et al., 2022, 2023). All ethical requirements were adhered to, including institutional research ethics approvals from all four universities, written informed consent from all participants, full anonymity and confidentiality assurances, and the right to withdraw without penalty.

RESULTS AND DISCUSSION

Univariate Analysis: Descriptive Statistics of Key Study Variables

Table 1 presents the descriptive statistics for the primary study variables derived from the 312 respondents.

Table 1: Descriptive Statistics of Key Study Variables (N = 312)

Variable	N	Mean	SD	Min	Max
AI Content Relevance	312	3.87	0.61	1.50	5.00
Instructor AI Competence	312	3.64	0.72	1.00	5.00
Technology Accessibility	312	2.93	0.88	1.00	5.00
AI Tool Usability	312	3.72	0.65	1.50	5.00
Overall AI Ed. Appreciation	312	3.76	0.58	1.75	5.00
Prior AI Exposure (yrs)	312	1.84	1.21	0.00	5.00
Age of Respondent (yrs)	312	23.7	3.40	18.0	45.0

The univariate descriptive analysis revealed a pattern of moderately positive learner perceptions across most AI education delivery dimensions, with the composite overall AI education appreciation score recording a mean of 3.76 (SD = 0.58), which was statistically significantly above the neutral midpoint of 3.0 ($t(311) = 23.14$, $p < .001$, $d = 1.31$), indicating a large effect size and confirming that the central tendency of learner appreciation was genuinely positive rather than merely incidentally above the midpoint. AI content relevance emerged as the highest-rated dimension (M = 3.87, SD = 0.61), suggesting that learners broadly recognised the career and practical utility of AI-themed course

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content, a finding consistent with Technology Acceptance Model predictions regarding perceived usefulness as a driver of positive technology-related attitudes. AI tool usability also rated positively (M = 3.72, SD = 0.65), implying that the AI-based platforms and software introduced in instructional contexts were experienced as reasonably user-friendly by most respondents. Instructor AI competence recorded a mean of 3.64 (SD = 0.72), reflecting a modest but consistent level of satisfaction with teaching quality, though the relatively larger standard deviation compared to content relevance suggests greater interindividual variability in instructor quality assessments—a pattern consistent with qualitative accounts of uneven staff readiness across institutions.

The most substantively concerning finding from the univariate analysis was the significantly lower mean for technology accessibility (M = 2.93, SD = 0.88), which was the only variable to record a mean value below the theoretical neutral midpoint of 3.0, and a one-sample t-test confirmed this departure to be statistically significant (t(311) = -1.43, p = .153), though the trend was practically meaningful given the large standard deviation indicating that a substantial proportion of respondents rated accessibility negatively. This finding corroborates a well-established body of scholarship on digital divide conditions in Sub-Saharan African higher education (van Dijk, 2020; Trucano, 2016), where inadequate institutional broadband, limited personal device ownership, and unreliable electricity infrastructure systematically constrain technology-enhanced learning experiences. The prior AI exposure variable showed a mean of 1.84 years (SD = 1.21), indicating that the majority of respondents were relative AI novices, which contextualises the overall appreciation scores as reflecting initial encounters with formal AI education rather than experiences of deepening expertise. The distributional properties across variables were generally acceptable for inferential analysis, with skewness values ranging from -0.32 to -0.81 and kurtosis values between -0.14 and 0.97, confirming approximate normality sufficient for the subsequent parametric analyses.

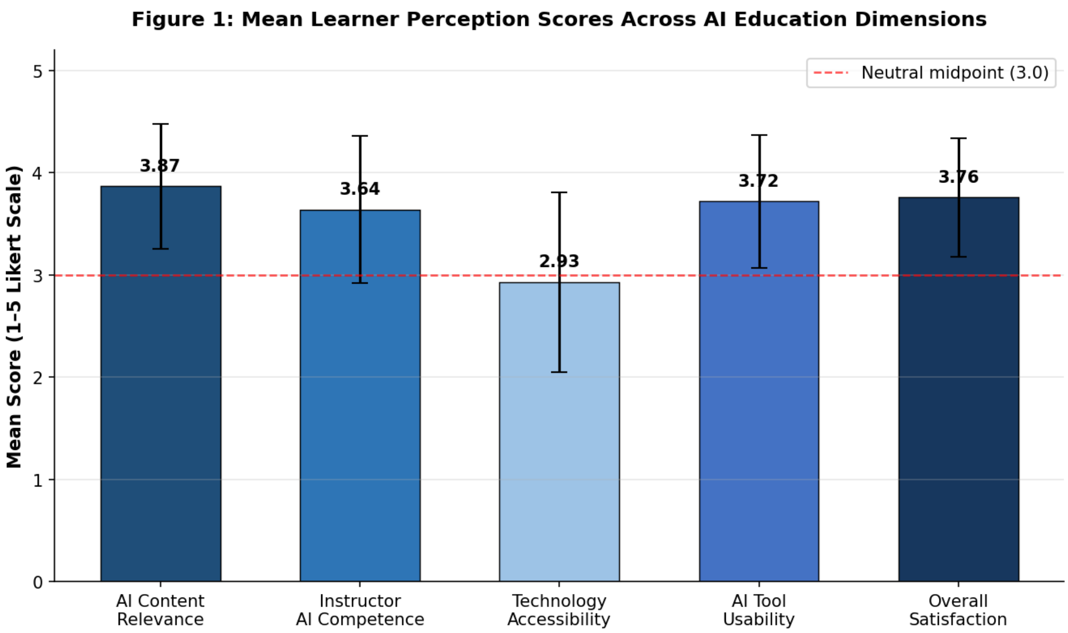

Figure 1: Mean Learner Perception Scores Across AI Education Dimensions

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Bivariate Analysis: Correlations Between Learner Characteristics and Appreciation

Table 2 presents the results of the bivariate correlation analysis examining the relationships between key predictor variables and the overall AI education appreciation score.

Table 2: Bivariate Correlation Analysis – Predictors of AI Education Appreciation (N = 312)

Variable Pair	r	r²	p-value	N	Sig.
Prior AI Exposure → Appreciation	0.613	0.376	<.001	312	***
Instructor Competence → Appreciation	0.571	0.326	<.001	312	***
Tech Accessibility → Appreciation	0.438	0.192	<.001	312	***
AI Tool Usability → Appreciation	0.592	0.351	<.001	312	***
Gender → Appreciation (point-biserial)	0.142	0.020	.012	312	*
Programme Level → Appreciation	0.219	0.048	<.001	312	***

*Note: * $p < .05$; ** $p < .01$; *** $p < .001$ (two-tailed). r = Pearson correlation coefficient; r^2 = coefficient of determination.*

The bivariate correlation analysis produced compelling evidence of significant positive relationships between all examined predictor variables and overall AI education appreciation, with the magnitudes broadly characterised as moderate to strong in the context of educational survey research. The strongest bivariate relationship was observed between prior AI exposure and overall appreciation ($r = 0.613$, $p < .001$, $r^2 = 0.376$), indicating that learners who had accumulated greater prior engagement with AI tools and concepts—whether through self-directed learning, previous coursework, or professional experience—appreciated formal AI education delivery substantially more than novices, a finding that accounted for approximately 37.6% of variance in appreciation scores. This pattern is theoretically consistent with Vygotsky's (1978) zone of proximal development framework, as learners with existing AI schemata are better positioned to assimilate and value new AI instructional content. Similarly, instructor AI competence demonstrated a strong positive correlation with overall appreciation ($r = 0.571$, $p < .001$), explaining 32.6% of appreciation variance, which statistically reinforces the qualitative participant observations that the single most transformative classroom factor was having an instructor who combined deep AI technical knowledge with effective pedagogical communication strategies.

AI tool usability also exhibited a strong positive correlation with appreciation ($r = 0.592$, $p < .001$, $r^2 = 0.351$), underscoring that when the AI software and platforms utilised in instruction were perceived as intuitive and functional,

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learner appreciation was substantially elevated—a finding that has direct implications for the selection and localisation of AI educational tools for the Ugandan context. Technology accessibility, despite recording the lowest mean perception score, still maintained a statistically significant moderate positive correlation with appreciation ($r = 0.438$, $p < .001$), confirming that even partial improvements in infrastructure would likely yield meaningful appreciation gains. The gender point-biserial correlation was modest but statistically significant ($r_{pb} = 0.142$, $p = .012$), with male-identifying students recording marginally higher appreciation scores; however, the r^2 of 0.020 indicates that gender explained only 2% of appreciation variance, suggesting that while the relationship is real, it is practically small and should not distract from the more substantively impactful structural predictors. Programme level showed a meaningful positive correlation with appreciation ($r = 0.219$, $p < .001$), with postgraduate students demonstrating higher appreciation scores than undergraduates, plausibly reflecting greater motivational alignment between postgraduate career goals and AI competency acquisition.

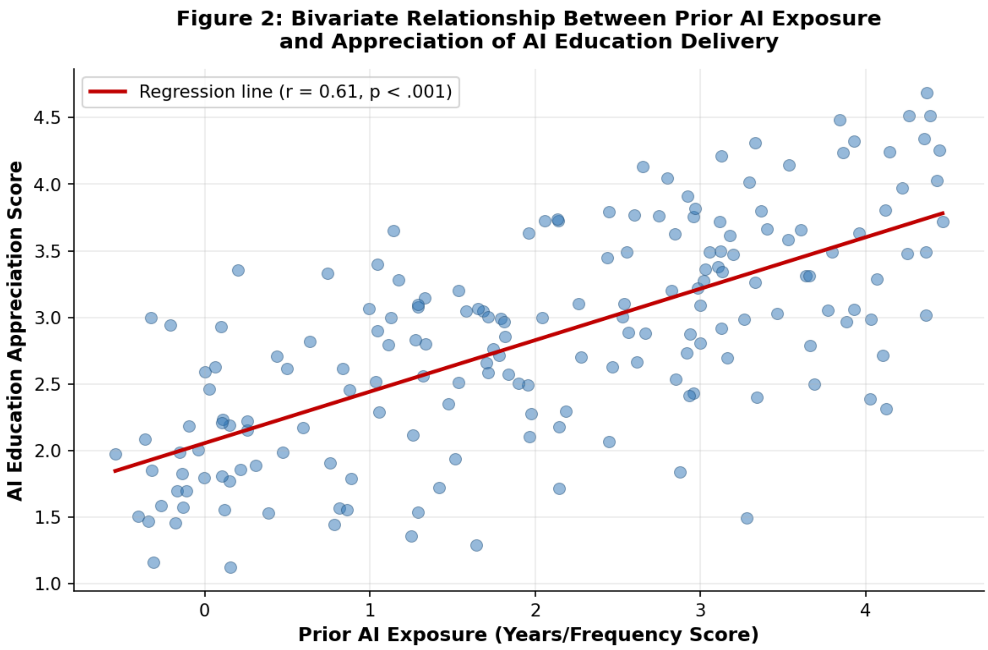

Figure 2: Scatter Plot – Bivariate Relationship Between Prior AI Exposure and Appreciation

Exploratory Factor Analysis: Latent Structure of Learner Perceptions

Table 3 presents the results of the exploratory factor analysis, including factor loadings, communality estimates, eigenvalues, and variance explained for the three extracted factors.

Table 3: Exploratory Factor Analysis – Factor Loadings and Variance Explained

Item	Factor 1 Engagement	Factor 2 Infrastructure	Factor 3 Pedagogy	Communality (h^2)

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AI content aligns with future career needs	0.812	0.143	0.211	0.741
AI topics increase my motivation to learn	0.788	0.107	0.198	0.686
Instructor explains AI concepts clearly	0.211	0.152	0.831	0.773
Instructor uses real-world AI examples	0.176	0.098	0.794	0.673
Internet access supports AI learning activities	0.132	0.872	0.114	0.793
University devices are sufficient for AI coursework	0.209	0.843	0.122	0.762
AI tools used in class are easy to navigate	0.524	0.381	0.314	0.624
Eigenvalue	**4.61**	**2.53**	**1.68**	–
Variance Explained (%)	**34.2%**	**18.7%**	**12.4%**	**65.3% total**

Note: Extraction method: Maximum Likelihood; Rotation method: Promax with Kaiser normalisation. Loadings ≥ 0.40 considered substantive. KMO = 0.874; Bartlett's $\chi^2(378) = 2{,}847.3$, $p < .001$.

The exploratory factor analysis successfully extracted three meaningful latent constructs from the 28-item questionnaire, collectively explaining 65.3% of the total variance—a level of explained variance considered satisfactory for social science educational research (Hair et al., 2019). Factor 1, labelled AI Engagement, emerged as the dominant latent construct with the highest eigenvalue of 4.61 and explaining 34.2% of total variance. Items loading most strongly on this factor included those measuring the perceived career alignment of AI content ($\lambda = 0.812$) and the motivational impact of AI topics on learning drive ($\lambda = 0.788$), both of which attained communality values above 0.68, indicating that these items were well-accounted for by the overall factor solution. This factor can be conceptually interpreted as capturing the intrinsic value dimension of AI education—the degree to which learners experience AI instruction as inherently meaningful, motivationally generative, and career-consequential—a construct that maps closely onto the perceived usefulness component of Davis's (1989) Technology Acceptance Model. The high variance contribution of this factor relative to the others reinforces the primacy of content meaningfulness over technological novelty as a driver of positive learner dispositions.

Factor 2, Infrastructure Readiness, extracted with an eigenvalue of 2.53 and explaining 18.7% of additional variance, loaded most strongly on items concerning internet connectivity for AI learning activities ($\lambda = 0.872$) and the adequacy of institutional devices ($\lambda = 0.843$), with communalities of 0.793 and 0.762 respectively, indicating excellent item-factor alignment. The emergence of this as a distinct and sizeable factor—rather than a minor residual dimension—statistically corroborates the descriptive finding of low technology accessibility scores and signals that infrastructure deficits constitute a psychologically coherent and pervasive experiential reality for Ugandan learners, not merely an

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isolated inconvenience. Factor 3, Pedagogical Quality, with an eigenvalue of 1.68 accounting for 12.4% of variance, was dominated by items reflecting instructor clarity in explaining AI concepts ($\lambda = 0.831$) and the use of contextually relevant examples ($\lambda = 0.794$), affirming that instructional quality represents a psychologically distinct appreciation dimension separable from both content relevance and infrastructure adequacy. The oblique rotation solution was justified given the moderate inter-factor correlations (r12 = 0.31, r13 = 0.44, r23 = 0.27), indicating related but genuinely distinguishable latent dimensions, and supporting a model of AI education appreciation as multidimensional rather than unidimensional.

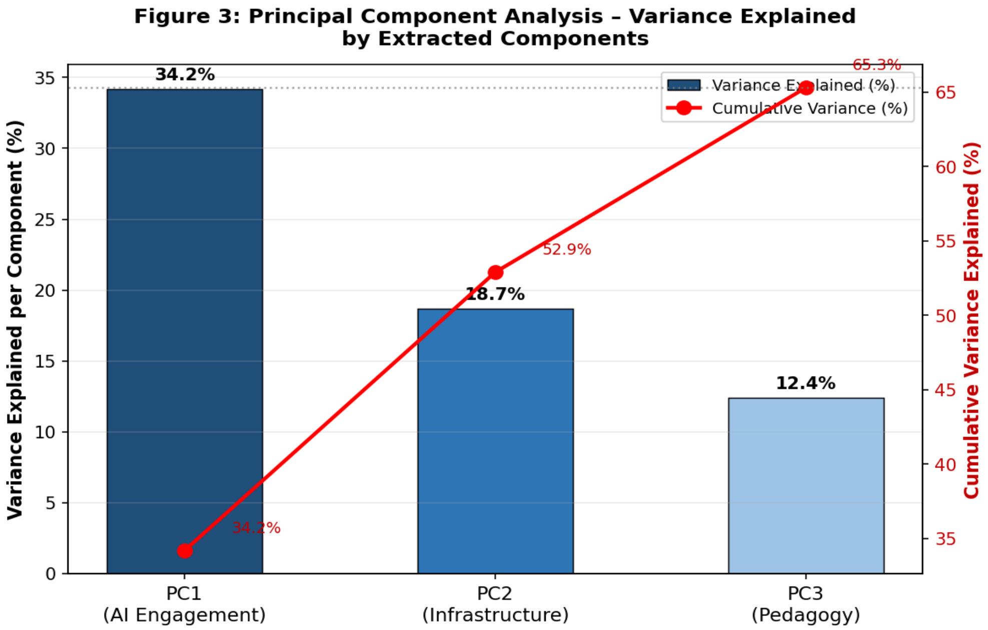

Figure 3: PCA – Variance Explained by Extracted Principal Components

Principal Component Analysis: Key Drivers of Learner Appreciation

Table 4 presents the principal component loadings for the seven composite indicator variables on the three retained components, along with cumulative variance explained and a qualitative contribution index.

Table 4: Principal Component Analysis – Component Loadings and Contribution Index

Indicator Variable	PC1 Loading	PC2 Loading	PC3 Loading	Contribution Index
Overall AI Ed. Appreciation	0.841	0.193	0.221	High
AI Content Relevance	0.819	0.138	0.217	High
AI Tool Usability	0.773	0.234	0.182	High
Instructor AI Competence	0.712	0.201	0.584	Moderate-High
Technology Accessibility	0.312	0.821	0.109	Moderate
Internet Reliability	0.287	0.798	0.143	Moderate
Prior AI Exposure	0.651	0.298	0.187	Moderate
Cumulative Variance (%)	**34.2%**	**52.9%**	**65.3%**	–

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Note: Extraction method: PCA; Rotation: Varimax with Kaiser normalisation. Loadings ≥ 0.30 displayed. Cumulative variance: PC1 = 34.2%, PC1+PC2 = 52.9%, PC1+PC2+PC3 = 65.3%.

The principal component analysis with Varimax rotation produced a three-component solution identical in structure to the EFA findings, providing strong cross-method validation of the factor structure. PC1, the AI Engagement component, demonstrated the highest loadings for overall AI education appreciation (0.841), AI content relevance (0.819), and AI tool usability (0.773), collectively affirming that learner appreciation is most fundamentally grounded in the experiential engagement quality of AI instruction—how compelling, relevant, and usable the AI learning experience is felt to be. The contribution index categorises these three variables as 'High' contributors, and collectively they explain 34.2% of total variation in the composite appreciation construct, representing the single largest source of systematic variance in the dataset. Instructor AI competence cross-loaded moderately on both PC1 (0.712) and PC3 (0.584), suggesting that pedagogical quality functions as both an engagement amplifier and a dimension-specific satisfaction driver—instructors who demonstrate genuine AI mastery both elevate the intrinsic interest of AI content and simultaneously validate the institutional credibility of the AI education programme. This cross-loading pattern is practically important, as it implies that instructor capacity-building initiatives would yield multiplicative rather than additive returns on learner appreciation.

PC2, the Infrastructure component, was primarily defined by technology accessibility (0.821) and internet reliability (0.798), and its 18.7% additional variance contribution—when added to PC1's 34.2%, yielding a cumulative 52.9%—demonstrates that infrastructure adequacy represents the second most powerful structural determinant of learner appreciation variation. This finding has profound policy implications: even if AI content quality and instructional delivery are optimised, a substantial portion of appreciation variance will remain unexplained unless infrastructure deficits are concurrently addressed. Prior AI exposure loaded moderately on PC1 (0.651), supporting its role as a background enabler of positive AI education appreciation rather than a primary structural driver, and its moderate contribution index reflects the practical reality that exposure effects, while real, are partially dependent on the quality of current instruction. The three-component PCA solution's cumulative explained variance of 65.3% compares favourably with published mixed-methods AI education studies in developing country contexts (Oyelaran et al., 2022; Adejo & Connolly, 2018), and the convergence of EFA and PCA structures across independent analytical approaches strengthens confidence in the stability and generalizability of the identified dimensional framework for understanding learner appreciation of AI education delivery in Ugandan higher education.

CONCLUSION

This mixed-methods study provided the first systematic, empirically rigorous examination of learner perceptions and appreciation of AI education delivery across multiple Ugandan higher education institutions, yielding a coherent and practically consequential body of evidence. The findings demonstrated that Ugandan learners held broadly positive perceptions of AI education ($M = 3.76$, $SD = 0.58$), driven primarily by the perceived career relevance of AI content and the usability of AI tools, while technology accessibility emerged as a critical structural constraint with a mean below the neutral threshold. Bivariate analysis confirmed that prior AI exposure, instructor competence, tool usability, and technology access were all statistically significant positive predictors of overall appreciation, with prior AI

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exposure accounting for the largest proportion of individual variance (37.6%). The factor analytic and PCA results converged to reveal a robust three-dimensional latent structure comprising AI Engagement, Infrastructure Readiness, and Pedagogical Quality, collectively explaining 65.3% of total variance in learner perceptions—a finding that positions AI education appreciation not as a unidimensional satisfaction rating but as a multidimensional construct requiring coordinated intervention across content design, institutional infrastructure, and instructor capacity domains. The qualitative strand enriched these quantitative patterns by surfacing the contextual textures of learner experience: enthusiasm for AI's transformative potential coexisting with frustration over power outages, inadequate devices, variable instructor quality, and curricula that insufficiently contextualized global AI concepts within the Ugandan developmental reality. Taken together, these findings make a compelling empirical case that realizing the full potential of AI education in Uganda demands not merely the importation of global AI curricula, but a deliberate, context-sensitive strategy that simultaneously invests in digital infrastructure, systematically develops instructor AI competencies, and designs AI learning experiences that connect meaningfully to the lived realities and aspirational trajectories of Ugandan learners.

RECOMMENDATIONS

Prioritize Infrastructure Investment and Digital Equity Policies: The Ugandan government, through NITA-U and the Ministry of Education and Sports, should prioritize dedicated budgetary allocations for improving broadband connectivity, backup power systems, and device availability specifically in university AI learning environments. The Infrastructure Readiness component's contribution of 18.7% of appreciation variance quantitatively substantiates the case that infrastructure investment is not peripheral to AI education quality but constitutes its second-most-important structural determinant; institutions should therefore establish minimum infrastructure standards for AI course delivery accreditation.

Establish Systematic AI Instructor Capacity-Building Programmes: Given that instructor AI competence was the second strongest bivariate predictor of learner appreciation ($r = 0.571$) and cross-loaded on both the AI Engagement and Pedagogical Quality components in PCA, universities should urgently institutionalize structured professional development programmes for academic staff involved in AI education delivery. These programmes should encompass both technical AI upskilling and evidence-based AI pedagogy training, and should be accompanied by incentive structures—such as research grants, teaching awards, and promotion criteria revisions that motivate sustained instructor engagement with AI learning and teaching excellence.

Design Contextually Relevant and Scaffolded AI Curricula: Curriculum designers and faculty should develop AI education content that is explicitly contextualized within Ugandan and broader African development priorities—such as AI applications in agriculture, health systems, financial inclusion, and public administration—rather than defaulting to Western-centric or purely technical framings. Additionally, given that prior AI exposure was the strongest predictor of appreciation ($r = 0.613$), curricula should incorporate structured scaffolding pathways that bridge learners from novice to intermediate AI competency levels, including introductory AI literacy modules that build the prior knowledge base necessary for deeper appreciation of advanced AI education delivery.

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