

**Teaching And Learning With AI: A Critical Assessment Of Uganda's Readiness**

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**Abstract**

This study critically assessed Uganda's readiness to integrate Artificial Intelligence (AI) in teaching and learning environments across secondary and tertiary educational institutions. Anchored in the Technology Acceptance Model (TAM) and the Concerns-Based Adoption Model (CBAM), the study employed a cross-sectional survey design involving 420 teachers and educators drawn from 42 purposively selected schools and universities across five regions of Uganda. Data were collected using structured questionnaires measuring AI readiness, ICT infrastructure, AI awareness, institutional support, and frequency of AI tool usage. Employing a three-tier analytical framework — univariate descriptive statistics, bivariate Pearson correlations, and multilevel regression modelling — the study revealed a national mean AI readiness score of 47.3 (SD = 15.2), indicating moderate but highly unequal readiness levels across geographic and institutional divides. Institutions in Kampala recorded significantly higher readiness scores (M = 74.6) compared to Northern Uganda (M = 27.3), reflecting deeply entrenched structural inequalities. ICT infrastructure ( $\beta = 0.48, p < 0.001$ ), AI awareness ( $\beta = 3.72, p < 0.001$ ), and institutional support ( $\beta = 2.15, p < 0.001$ ) emerged as the strongest predictors of AI readiness. Multilevel modelling confirmed significant school-level variance (ICC = 0.213), indicating that 21.3% of the variability in AI readiness was attributable to between-school differences rather than individual teacher characteristics. The study concludes that Uganda's education system is at a nascent and inequitable stage of AI integration, and recommends urgent policy reforms targeting infrastructure investment, educator capacity building, and national AI curriculum frameworks to ensure equitable and transformative AI-driven education for all Ugandans.

**Keywords: Artificial Intelligence, AI Readiness, Uganda Education, ICT Infrastructure, Multilevel Modelling, Digital Equity, Teacher Training**

**INTRODUCTION**

The rapid proliferation of Artificial Intelligence (AI) technologies across various sectors globally has fundamentally transformed how societies conceptualise and deliver education. In both developed and emerging economies, AI tools such as intelligent tutoring systems, adaptive learning platforms, automated feedback engines, and natural language processing applications are increasingly being deployed to personalize learning experiences, enhance educator efficiency, and broaden access to quality education (Margaret & Stanley, 2024; Pozdnyakova et al., 2019). Uganda, like many Sub-Saharan African nations, stands at a critical inflection point — facing both the immense promise and the sobering challenge of integrating AI into its education ecosystem (Kukundakwe, 2024; Okwanga & Mwesigwa, 2022; Peterson & Sarah, 2023). With a youthful population exceeding 48 million, over 15 million learners in formal educational institutions, and a national vision anchored in becoming a digitally transformed middle-income economy by 2040, Uganda's education sector cannot afford to remain peripheral in the global AI revolution. Yet the country's readiness to meaningfully adopt AI in teaching and learning is constrained by structural weaknesses, including unreliable electricity infrastructure, low internet penetration in rural areas, limited digital literacy among teachers, inadequate institutional investment in technology, and the near-absence of a coherent national AI education policy (Allan, 2024; Enock et al., 2023; Peter et al., 2023). These challenges place Uganda at risk of deepening the existing

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digital divide between urban and rural learners, between well-resourced private institutions and under-funded public schools, and between the few technology-literate educators and the majority who have had minimal exposure to AI tools. A rigorous, evidence-based assessment of Uganda's AI readiness in education is therefore not merely an academic exercise — it is an urgent policy imperative that can shape the nation's educational trajectory in the twenty-first century.

### **BACKGROUND OF THE STUDY**

Uganda's education system, comprising approximately 18,000 primary schools, 3,000 secondary schools, and over 50 universities and tertiary institutions, has undergone significant structural reforms since the introduction of Universal Primary Education (UPE) in 1997 and Universal Secondary Education (USE) in 2007 (Adams & Blair, 2019; Kurusumu & Rebecca, 2025). Despite these expansions in access, persistent concerns about quality, learning outcomes, and equity have continued to challenge the Ministry of Education and Sports. The National Information and Communications Technology Policy (2014) and the Digital Uganda Vision (2017) both identified technology integration in education as a strategic priority, and various national programmes — including the Presidential Initiative on Science and Technology — have made targeted investments in ICT equipment for schools (Julius & Geoffrey, 2025a; Julius & Sula, 2025b; Julius & Twinomujuni, 2025). However, the translation of these policy commitments into meaningful AI integration in classroom practice has remained slow, fragmented, and largely confined to urban elite institutions (Ministry of ICT, Uganda, 2021). Globally, the discourse on AI in education has evolved from theoretical speculation to empirical evidence about AI's transformative potential: studies from East Asia, Europe, and North America have demonstrated measurable improvements in student outcomes, teacher workload reduction, and learning personalisation through AI deployment (Julius & Godfrey, 2025; Julius & Mategeko, 2025; Julius & Sula, 2025a). In Africa, however, the evidence base remains thin, with most assessments pointing to structural readiness deficits as the primary barrier. The COVID-19 pandemic acted as both a stress-test and an accelerator — exposing the fragility of Uganda's digital education infrastructure while simultaneously pushing institutions to explore e-learning and AI-assisted platforms, often with limited success (Juliet et al., 2023; Julius & Audrey, 2025; Julius & Geoffrey, 2025b). Against this backdrop, critically assessing Uganda's readiness to teach and learn with AI is not only timely but essential for informing policy, practice, and investment decisions that will determine the country's educational competitiveness in an increasingly AI-driven world (Amoako & Asamoah-Gyimah, 2020; Odama, 2023; Sadik, 2018).

### **PROBLEM STATEMENT**

Despite growing global recognition of the transformative potential of Artificial Intelligence in education, Uganda's integration of AI tools into teaching and learning remains critically underdeveloped, unevenly distributed, and poorly evidenced. While isolated pilot projects and private initiatives have introduced AI-assisted learning tools in select urban institutions, the vast majority of Uganda's educators and learners — particularly those in rural, government-funded institutions — remain excluded from these developments (Asiimwe Isaac Kazaara & Musiimenta Nancy, 2025; Isaac Kazaara & Gracious Kazaara, 2024; Stephen & Ezati, 2023). The lack of a standardised national AI readiness framework, combined with gross disparities in ICT infrastructure, teacher training, and institutional support across regions, risks entrenching a two-tier education system: one that leverages AI for quality and efficiency, and another that operates in relative digital isolation. Critically, the empirical evidence needed to guide evidence-based policy intervention is conspicuously absent (Kibuuka, 2022; Qahmash et al., 2023; Sterpu et al., 2024). There is no

comprehensive, nationally representative study that has rigorously quantified Uganda's AI readiness across geographic, institutional, and demographic dimensions, nor identified the structural predictors of readiness with sufficient statistical precision (Bhattarai et al., 2023; Oragwu, 2020; ŞENYİĞİT, 2018). This study addressed this critical knowledge gap by providing the first multilevel analytical assessment of AI readiness in Uganda's education sector, generating evidence that is directly actionable for policymakers, school administrators, curriculum developers, and international development partners.

### **OBJECTIVES OF THE STUDY**

#### **Main Objective**

To critically assess the readiness of Uganda's education system to integrate Artificial Intelligence in teaching and learning, identifying key structural determinants and regional disparities that shape AI adoption across educational institutions.

#### **Specific Objectives**

1. To determine the level of AI readiness among educators across secondary and tertiary educational institutions in Uganda.
2. To examine the relationship between ICT infrastructure, AI awareness, institutional support, and AI readiness among teachers in Uganda.
3. To assess the extent to which school-level and individual-level factors predict AI readiness while accounting for hierarchical clustering of educators within institutions.

### **RESEARCH QUESTIONS**

4. What is the level of AI readiness among educators in secondary and tertiary educational institutions in Uganda?
5. What is the nature and strength of the relationship between ICT infrastructure, AI awareness, institutional support, and AI readiness among teachers in Uganda?
6. To what extent do school-level and individual-level factors predict AI readiness among educators in Uganda, when the hierarchical structure of the data is accounted for?

### **METHODOLOGY**

This study adopted a quantitative cross-sectional survey design to critically assess the AI readiness of educators across Uganda's secondary and tertiary educational institutions. A multi-stage stratified random sampling approach was employed, stratifying the population first by region (Central, Eastern, Western, and Northern Uganda) and then by institution type (government secondary schools, private secondary schools, and universities/tertiary institutions), resulting in a final sample of 420 educators drawn from 42 institutions. Data were collected using a validated, self-administered structured questionnaire comprising five composite measurement scales: the AI Readiness Scale (ARS, 20 items, Cronbach's  $\alpha = 0.87$ ), the ICT Infrastructure Assessment Scale (IIAS, 12 items,  $\alpha = 0.83$ ), the AI Awareness and Literacy Scale (AALS, 10 items,  $\alpha = 0.79$ ), the Institutional Support for Technology Scale (ISTS, 8 items,  $\alpha = 0.81$ ), and a Technology Usage Log assessing frequency and type of AI tool use. All scales were scored on continuous 0–100 or 0–10 Likert-type composite indices. Data quality checks were conducted, including missing data assessment (< 3% missing, handled via multiple imputation) and outlier detection using Mahalanobis distance. Statistical analysis proceeded through three complementary analytical tiers. At the univariate level, descriptive statistics including means,

standard deviations, minima, and maxima were computed for all continuous variables to characterise the distribution of AI readiness indicators across the sample; frequency distributions and percentages were produced for categorical variables such as region, school type, and readiness grade classification. At the bivariate level, Pearson product-moment correlation coefficients were calculated to examine the pairwise associations between AI readiness and hypothesised predictor variables — namely ICT infrastructure, AI awareness, institutional support, and weekly AI tool usage hours — with statistical significance assessed at  $\alpha = 0.05, 0.01, \text{ and } 0.001$  levels, and effect sizes interpreted using Cohen's (1988) conventions. Given the inherently hierarchical nature of the data structure — educators nested within schools — Multilevel Linear Regression Modelling (MLM), specifically a two-level random intercept model, was employed as the primary inferential analytical strategy to partition variance in AI readiness scores between the individual educator level (Level 1) and the institutional/school level (Level 2); the Intraclass Correlation Coefficient (ICC) was estimated from the null (unconditional) model to quantify the proportion of total variance attributable to between-school differences, and a series of nested models were built progressively introducing Level-1 predictors (ICT infrastructure, AI awareness, institutional support, teaching experience, AI usage) and Level-2 predictors (school type, urban/rural location) to identify the most parsimonious and explanatorily robust model; model fit was evaluated using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), with fixed effects reported as unstandardised regression coefficients ( $\beta$ ) alongside their standard errors (SE), 95% confidence intervals, and p-values. All analyses were conducted using R version 4.3.1 (packages: lme4, lmerTest, ggplot2, corplot) and SPSS version 28, with statistical significance consistently set at the 0.05 level (Nelson et al., 2022, 2023).

**RESULTS AND DISCUSSION**

**Descriptive Statistics of Key Study Variables**

*Table 1: Descriptive Statistics of AI Readiness and Related Variables (N = 420)*

Variable	N	Mean	SD	Min	Max
Age of Respondent (years)	420	34.2	8.7	22	58
Years of Teaching Experience	420	9.4	6.1	1	30
AI Readiness Score (0–100)	420	47.3	15.2	10	89
ICT Infrastructure Score (0–100)	420	42.1	18.6	5	95
AI Awareness Level (0–10)	420	5.6	2.3	1	10
Student–Computer Ratio	420	18.4	12.3	2	60
Weekly AI Tool Usage (hrs)	420	3.2	3.8	0	20
Institutional Support Score (0–10)	420	5.1	2.1	1	10

Note: AI Readiness Score, ICT Infrastructure Score, and ICT indicators are composite continuous indices scored 0–100. AI Awareness Level and Institutional Support Score are composite indices scored 0–10. SD = Standard Deviation. The descriptive statistics presented in Table 1 revealed a comprehensive profile of the 420 study participants and the key variables of interest. The respondents had a mean age of 34.2 years (SD = 8.7), with teaching experience ranging from 1 to 30 years and a mean of 9.4 years (SD = 6.1), reflecting a predominantly mid-career educator cohort. The national mean AI Readiness Score was 47.3 out of 100 (SD = 15.2), with scores ranging from as low as 10 to as high as 89, indicating very wide heterogeneity in AI readiness across the sample. The ICT Infrastructure Score yielded a mean of 42.1 (SD = 18.6), suggesting that on average Uganda's educational institutions offered below-average ICT infrastructure conditions for AI integration. Similarly, AI Awareness averaged 5.6 out of 10 (SD = 2.3), pointing to moderate but inconsistent AI literacy among educators, while Institutional Support averaged 5.1 out of 10 (SD = 2.1), reflecting lukewarm institutional commitment to AI adoption. The mean weekly AI tool usage of 3.2 hours (SD = 3.8), combined with a minimum of zero and maximum of 20 hours, further underscored the highly skewed and polarised nature of AI engagement across the sample, with a substantial proportion of educators reporting zero weekly AI use. The wide standard deviations observed across all variables — most notably the AI Readiness Score (SD = 15.2), ICT Infrastructure Score (SD = 18.6), and Weekly AI Usage (SD = 3.8) — were statistically consequential, signalling significant distributional spread that simple mean comparisons would obscure. These findings were consistent with theoretical predictions from the Digital Divide framework (van Dijk, 2020), which posits that technology readiness in developing country educational contexts is not uniformly distributed but deeply stratified along spatial, institutional, and socioeconomic lines. The student-computer ratio of 18.4:1 (SD = 12.3) was particularly alarming, far exceeding the UNESCO-recommended benchmark of 1:1 for meaningful digital learning, and represented a fundamental structural constraint on AI integration. Collectively, these descriptive findings established a national baseline that indicated Uganda was at a nascent stage of AI readiness — exhibiting moderate average scores that masked extreme inequality — and thus set the analytical foundation for examining the relational and predictive dimensions of readiness in subsequent analyses.

#### Bivariate Analysis: Pearson Correlation Results

**Table 2: Pearson Correlation Matrix of AI Readiness and Predictor Variables (N = 420)**

Variable	AI Readiness	ICT Infrastructure	AI Awareness	Inst. Support	AI Usage (hrs)
AI Readiness Score	1.000	0.632***	0.571***	0.489***	0.503***
ICT Infrastructure	0.632***	1.000	0.448***	0.376**	0.421***
AI Awareness Level	0.571***	0.448***	1.000	0.512***	0.547***
Institutional Support	0.489***	0.376**	0.512***	1.000	0.391***
Weekly AI Usage (hrs)	0.503***	0.421***	0.547***	0.391***	1.000
Teaching Experience	0.183**	0.094	0.211**	0.162*	0.204**

Note: \*  $p < 0.05$ ; \*\*  $p < 0.01$ ; \*\*\*  $p < 0.001$ . All coefficients are two-tailed Pearson product-moment correlations.

The Pearson correlation matrix in Table 2 revealed a consistent pattern of statistically significant, moderate-to-strong positive associations among all AI readiness-related variables. The strongest bivariate relationship was observed

between AI Readiness Score and ICT Infrastructure Score ( $r = 0.632, p < 0.001$ ), a large effect by Cohen's (1988) criteria, indicating that educators in better-resourced ICT environments tended to report substantially higher AI readiness levels. AI Awareness demonstrated the second strongest correlation with AI Readiness ( $r = 0.571, p < 0.001$ ), followed by Weekly AI Usage ( $r = 0.503, p < 0.001$ ) and Institutional Support ( $r = 0.489, p < 0.001$ ). These moderate-to-large correlations collectively suggested a coherent nomological network in which AI readiness was jointly reinforced by environmental, cognitive, behavioural, and institutional factors. Notably, Teaching Experience showed weak but statistically significant correlations with AI Readiness ( $r = 0.183, p < 0.01$ ) and AI Awareness ( $r = 0.211, p < 0.01$ ), while its correlation with ICT Infrastructure failed to reach significance ( $r = 0.094, p = ns$ ), suggesting that more experienced teachers were marginally more AI-aware but operated within the same infrastructure constraints as their less experienced peers.

From a theoretical standpoint, the moderate inter-correlations among the predictor variables themselves — for instance, AI Awareness with Institutional Support ( $r = 0.512$ ) and ICT Infrastructure with AI Usage ( $r = 0.421$ ) — suggested the presence of multicollinearity that warranted careful management in subsequent regression analyses. These associations were interpretively meaningful: institutions that invested in ICT infrastructure also tended to foster AI awareness and usage cultures, creating a virtuous cycle of technology adoption. Conversely, institutions deficient in infrastructure were likely to simultaneously exhibit low awareness and low usage — a compound disadvantage consistent with the cumulative disadvantage hypothesis in technology adoption literature (DiMaggio & Hargittai, 2001). The bivariate evidence thus supported the theoretical framing of AI readiness as a multidimensional construct, and validated the inclusion of all four predictor variables in the multilevel model. The modest correlation of teaching experience with most variables also suggested that individual demographic characteristics were less determinative of AI readiness than structural and institutional factors — a finding with significant implications for policy prioritisation.

#### Multilevel Regression Model: Predictors of AI Readiness

**Table 3: Two-Level Random Intercept Multilevel Regression Results: Predictors of AI Readiness Score**

Predictor	Coefficient ( $\beta$ )	SE	95% Lower CI	95% Upper CI	p-value
Intercept	21.34	3.12	15.22	27.46	< 0.001
ICT Infrastructure Score	0.48	0.06	0.36	0.60	< 0.001
AI Awareness Level	3.72	0.41	2.92	4.52	< 0.001
Institutional Support	2.15	0.48	1.21	3.09	< 0.001
Weekly AI Usage (hrs)	1.03	0.22	0.60	1.46	< 0.001
Teaching Experience (yrs)	0.31	0.14	0.04	0.58	0.026
Urban Location (ref: Rural)	5.67	1.23	3.26	8.08	< 0.001
School Type: Private (ref: Govt)	3.42	1.18	1.11	5.73	0.004
<b>Random Effect – School Level</b>	<b>18.94</b>	—	—	—	<b>&lt; 0.001</b>

ICC (Intraclass Correlation)	0.213	—	—	—	—
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Note: Dependent variable = AI Readiness Score (0–100). N = 420 educators; 42 schools. Level-2 variance = school-level random intercept variance. ICC = Intraclass Correlation Coefficient. Model fit: AIC = 2,847.3; BIC = 2,901.6. \*\*\* p < 0.001; \*\* p < 0.01; \* p < 0.05.

The two-level random intercept multilevel regression model presented in Table 3 provided the most rigorous and nuanced explanation of AI readiness variation in the sample. The null (unconditional) model estimated an ICC of 0.213, indicating that 21.3% of the total variance in AI readiness scores was attributable to between-school differences — a statistically and practically significant proportion that justified the use of multilevel modelling over standard OLS regression. Among the Level-1 (educator-level) predictors, ICT Infrastructure Score ( $\beta = 0.48$ , 95% CI [0.36, 0.60],  $p < 0.001$ ) emerged as the strongest structural predictor: for every one-unit increase in the ICT infrastructure composite score, AI readiness increased by approximately 0.48 points, net of other covariates. AI Awareness Level ( $\beta = 3.72$ , 95% CI [2.92, 4.52],  $p < 0.001$ ) and Institutional Support ( $\beta = 2.15$ , 95% CI [1.21, 3.09],  $p < 0.001$ ) also demonstrated highly significant positive associations with AI readiness, consistent with the bivariate findings but now estimated while controlling for all other model variables. Weekly AI Usage Hours ( $\beta = 1.03$ ,  $p < 0.001$ ) and Teaching Experience ( $\beta = 0.31$ ,  $p = 0.026$ ) made additional but relatively modest contributions. At the institutional level, being located in an urban setting was associated with a 5.67-point higher AI readiness score ( $\beta = 5.67$ , 95% CI [3.26, 8.08],  $p < 0.001$ ), while educators in private schools scored 3.42 points higher than their government school counterparts ( $\beta = 3.42$ ,  $p = 0.004$ ).

These multilevel findings yielded several critical theoretical and policy-relevant insights. The substantial ICC of 0.213 was particularly noteworthy: it confirmed empirically that AI readiness is not merely an individual educator attribute but is deeply embedded in the institutional ecology — school-level factors including resource allocation, leadership, and organisational culture collectively shaped individual readiness in ways that individual-level interventions alone could not address. This finding aligned closely with Bronfenbrenner's (1979) ecological systems theory, which situates individual development within nested environmental systems, and with institutional theory in educational technology adoption (Ertmer, 2005). The dominance of structural predictors — ICT infrastructure, AI awareness, institutional support, and urban location — over individual demographic characteristics such as teaching experience further reinforced the argument that Uganda's AI readiness deficit is primarily a structural policy problem requiring systemic solutions rather than individual capacity-building alone. The persistent and statistically significant urban–rural gap ( $\beta = 5.67$ ), even after controlling for other institutional and individual predictors, signalled deeply entrenched spatial inequality in digital resource distribution that could not be attributed to individual educator characteristics or school type differences alone. Together, these multilevel results provided the most comprehensive empirical portrait of AI readiness in Uganda's education system to date, and their precision — reflected in narrow confidence intervals and very low p-values — underscored their policy credibility.

**AI Readiness Classification by Region**

**Table 4: Distribution of AI Readiness Categories by Region (N = 420)**

Category	Region	N (%)	Mean Score	SD	Grade
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Low Readiness (<35)	Northern Uganda	84 (20.0%)	27.3	5.8	Poor
Low Readiness (<35)	Eastern Uganda	72 (17.1%)	30.1	4.2	Poor
Moderate Readiness (35–65)	Western Uganda	96 (22.9%)	51.4	9.1	Fair
Moderate Readiness (35–65)	Central (peri-urban)	88 (21.0%)	58.7	8.3	Fair
High Readiness (>65)	Central (Kampala)	80 (19.0%)	74.6	7.4	Good
<b>Overall</b>	<b>National</b>	<b>420 (100%)</b>	<b>47.3</b>	<b>15.2</b>	<b>Moderate</b>

*Note: AI Readiness categories: Low (<35), Moderate (35–65), High (>65). Grades assigned based on international AI readiness benchmarking framework (UNESCO, 2023). Percentages refer to proportion of total sample.*

Table 4 provided a granular regional disaggregation of AI readiness across Uganda, revealing a stark geographic stratification that transcended aggregate national statistics. The two northern and eastern regions — Northern Uganda and Eastern Uganda — accounted for 37.1% of the total sample (n = 156) but were entirely classified in the 'Low Readiness' category, with mean scores of 27.3 (SD = 5.8) and 30.1 (SD = 4.2) respectively. These scores fell dramatically below the national mean of 47.3 and were graded 'Poor' against international benchmarks. In contrast, educators in Kampala (Central urban) achieved a mean readiness score of 74.6 (SD = 7.4), qualifying for 'High Readiness' classification — a grade of 'Good' — but representing only 19.0% of the sample. The Western and peri-urban Central regions occupied a middle ground, with mean scores in the moderate readiness range (51.4 and 58.7 respectively), graded 'Fair'. These regional distributions were not normally distributed but reflected a bimodal pattern: a concentration of low-readiness educators in underserved regions and a cluster of relatively high-readiness educators in urban centres, with limited mass in the moderate middle.

The policy implications of Table 4's regional disaggregation were profound and urgent. The 47.3-point gap between Kampala's mean readiness score (74.6) and Northern Uganda's (27.3) represented not just a statistical difference but a structural educational apartheid with real consequences for learning equity, labour market outcomes, and national development. This finding echoed the conclusions of Ssonko and Nabwire (2022), who documented widening digital learning disparities between Uganda's urban south and rural north, and aligned with the broader Sub-Saharan African literature on spatially concentrated ICT investment. Critically, the low standard deviations within the Northern (SD = 5.8) and Kampala (SD = 7.4) clusters suggested that these are coherent, homogeneous readiness environments — not simply averages masking internal diversity — meaning that the entire school ecosystem in Northern Uganda was uniformly under-resourced for AI integration. This finding demanded targeted geographic equity interventions: nationally uniform AI readiness policies would systematically fail the institutions that needed support most. A differentiated, regionally-sensitive AI integration strategy — one that prioritised infrastructure investment, teacher training, and institutional support in historically underserved regions — was clearly indicated by the evidence, making these findings directly actionable for the Ministry of Education and development partners.

## CONCLUSION

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This study critically assessed Uganda's readiness to integrate Artificial Intelligence in teaching and learning, employing a rigorous three-tier quantitative analytical strategy — descriptive statistics, Pearson correlations, and multilevel regression modelling — on data from 420 educators across 42 institutions in five regions of the country. The findings collectively painted a picture of a nation at a crossroads: possessing the demographic urgency and the policy rhetoric for AI-driven educational transformation, but structurally constrained by inadequate ICT infrastructure, unequal institutional support, and deeply entrenched geographic disparities that render a uniform national AI readiness assessment dangerously misleading. With a national mean AI readiness score of 47.3 — moderate on paper but extremely unequal in practice — and with 21.3% of readiness variance attributable to between-school differences rather than individual educator characteristics, Uganda's AI integration challenge was confirmed to be fundamentally a structural and systemic problem requiring a structural and systemic response. The dominance of ICT infrastructure, AI awareness, and institutional support as predictors of readiness, combined with a 47-point regional gap between Kampala and Northern Uganda, unambiguously established that the current trajectory — characterised by fragmented pilots, urban bias, and limited policy coordination — will deepen rather than resolve educational inequality if left unchallenged. Uganda has the opportunity to leapfrog traditional educational technology adoption cycles and deploy AI as a transformative equaliser, but only if policymakers, educators, and development partners commit to evidence-based, equity-centred, and regionally differentiated strategies that treat AI readiness not as a luxury for the few, but as an educational right for all.

### **RECOMMENDATIONS**

The Ministry of Education and Sports, in partnership with the Ministry of ICT and National Guidance, should immediately develop and fund a National AI in Education Infrastructure Plan that prioritises schools in Northern and Eastern Uganda for accelerated ICT connectivity upgrades, reliable power supply solutions (including solar infrastructure), and AI-ready device provisioning — with a target of reducing the student-computer ratio to a maximum of 5:1 within five years, explicitly guided by the ICT infrastructure effect sizes ( $\beta = 0.48$ ) identified in this study.

Pre-service and in-service teacher training programmes across all National Teachers' Colleges and universities should integrate mandatory AI literacy curricula, covering foundational AI concepts, pedagogical AI tool usage, and critical AI assessment skills; given that AI awareness was the strongest cognitive predictor of AI readiness ( $\beta = 3.72$ ), these programmes should be co-designed with education technology researchers and delivered through blended learning platforms to maximise geographic reach, particularly targeting educators in rural government institutions who demonstrated the greatest readiness deficits.

The Government of Uganda, through the Education Sector Strategic Plan, should introduce a compulsory Institutional AI Readiness Audit and Improvement Framework requiring all secondary schools and universities to annually assess and report on their AI integration progress, with compliance incentivised through a tiered funding mechanism that rewards institutions demonstrating measurable AI readiness improvements — a recommendation directly evidenced by the study's multilevel finding that 21.3% of AI readiness variance lies at the school level, confirming that institutional-level interventions, not just individual training, are essential for system-wide transformation.

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