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Teaching Artificial Intelligence in Ugandan Higher Education: Timing, Pedagogy, and the Competence Dilemma

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Abstract

This study examined three linked questions in the teaching of artificial intelligence (AI) in Ugandan higher education: when in a student's programme AI should be introduced, how it should be taught, and how institutions should respond to the competence dilemma that arises when the people expected to teach AI have not themselves been trained in it. The argument combined a conceptual analysis, drawing on constructive alignment, AI literacy and teacher knowledge frameworks, with a quantitative illustration. The study results indicated that the integration index averaged 50.9, and that self-rated competence (beta = 0.54, $p < 0.001$), STEM discipline, the use of AI tools in one's own teaching, prior AI training and reliable computing resources were associated with greater integration, while years of teaching and academic-integrity concern were associated with less. Prior training (odds ratio = 4.34, $p = 0.016$) was the only significant predictor of support for early introduction. The diagnostic tests were satisfactory. The study concluded that competence was the binding constraint, and it recommended staged introduction, competence-building for lecturers before curriculum mandates, and assessment redesign.

Keywords: artificial intelligence; higher education; curriculum timing; pedagogy; lecturer competence; AI literacy; Uganda

1.0 Background

Artificial intelligence has moved quickly from specialised research into everyday tools used by students, lecturers and employers(Kazaara et al., 2024). The release of widely accessible generative systems made it possible for students to draft essays, write code, summarise readings and solve problems with little technical knowledge, and it prompted universities across the world to rethink what they taught and how they assessed learning(Nicholas & Nancy, 2024). Holmes et al. (2019) set out the promises and implications of artificial intelligence for teaching and learning, Zawacki-Richter et al. (2019) reviewed research on AI applications in higher education and observed that educators were rarely involved in the design and study of those applications, and Kasneci et al. (2023) discussed both the opportunities and the challenges of large language models for education. Concerns about academic integrity accompanied this enthusiasm (Cotton et al., 2024), and international bodies issued guidance on the ethics and the educational use of AI (UNESCO, 2021, 2023).

The question of what it meant to teach AI was itself contested. One meaning was the technical teaching of AI as a subject, including machine learning, data science and programming, which belonged mainly in computing, engineering and mathematics programmes(Winny et al., 2023). A second meaning was AI literacy, the set of competencies that enabled people to evaluate AI technologies critically, communicate and collaborate with AI and use it as a tool, which Long and Magerko

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(2020) argued should be a part of general education for all. A third meaning was teaching with AI, in which AI tools were used within ordinary courses to support learning, feedback and assessment(Moses & Ntirandekura, 2022). These meanings had different implications for the timing of introduction, the pedagogy employed and the competence required of teachers, and they were often conflated in policy discussion.
The Ugandan higher education system comprised public and private universities and other tertiary institutions regulated under the Universities and Other Tertiary Institutions Act (2001, as amended in 2006), which established the National Council for Higher Education to set minimum standards and to accredit programmes and institutions. National policy emphasised the use of ICT for development in the National Information and Communications Technology Policy (Ministry of Information and Communications Technology, 2014), the pursuit of the Fourth Industrial Revolution in Uganda's national strategy of 2020, and the role of human capital in Uganda Vision 2040 (National Planning Authority, 2013). The Data Protection and Privacy Act (2019) governed the processing of personal data, which was relevant to the use of AI systems that collected and processed student data. Universities operated under constraints of large class sizes, uneven computing resources and limited funds for staff development, and these constraints shaped what could be done in practice.

Three issues were central to the debate and formed the structure of this article. The first was timing: whether AI should be introduced early, in the first year of a programme, so that students could build on it throughout, or later, once students had acquired the disciplinary foundations to use it critically(Akankwasa et al., 2022). The second was pedagogy: whether AI should be taught through lectures about concepts, through hands-on projects, or through integration into disciplinary assignments, and how assessment should be designed when AI could produce plausible work(Nancy & Prudence, 2024). The third was the competence dilemma: the observation that institutions were being urged to teach AI at a time when many lecturers themselves had no formal training in it, so that a mandate for teaching could run ahead of the capacity to teach well(Ntirandekura et al., 2022). Mishra and Koehler (2006) described the knowledge that teachers needed to integrate technology as an interaction of technological, pedagogical and content knowledge, and Shulman (1986) had earlier argued that teaching depended on an understanding of content as well as of how to teach it, which together implied that competence could not be assumed(Julius & Kazaara, 2026).
Against this background, this study examined the timing, pedagogy and competence dilemma in teaching AI in Ugandan higher education. It combined a conceptual analysis with an study quantitative study of which lecturer and institutional characteristics, including self-rated AI competence, prior AI training, access to reliable computing resources, discipline, years of teaching, rank, the use of AI tools in one's own teaching and concern about academic integrity, were associated with the extent to which AI was integrated into teaching and with support for introducing AI from the first year(Florence & Julius, 2023).

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2.0 Problem Statement

Universities in Uganda faced pressure from employers, students and national strategies to prepare graduates for an AI-influenced economy, yet there was no settled view on when and how AI should be introduced, and there was a risk that institutions would mandate AI content before lecturers were able to teach it competently (Zawacki-Richter et al., 2019). The literature offered frameworks for teacher knowledge (Mishra & Koehler, 2006) and for AI literacy (Long & Magerko, 2020), but there was little evidence from Uganda on the relationship between lecturers' competence, training and resources and the actual integration of AI into teaching, or on the factors that shaped lecturers' views on timing(Christopher et al., 2022). Without such evidence, curriculum reform risked being driven by enthusiasm or fear and not by an understanding of capacity(Nancy & Prudence, 2024). The problem addressed was therefore the lack of a clear conceptual treatment of timing, pedagogy and competence in the teaching of AI in Ugandan universities and of empirical evidence on their relationship.

3.0 Main Objective

To determine factors shaping the teaching of artificial intelligence in Ugandan universities.

4.0 Literature Review

The literature on AI in education divided broadly into work on AI as a tool for learning and work on AI as a subject of learning(Julius & Kaazara, 2025). Luckin et al. (2016) argued for the potential of AI to personalise learning and support teachers, and Holmes et al. (2019) analysed the promises and risks, including the need for human judgment in teaching. Zawacki-Richter et al. (2019) reviewed a large body of research and concluded that it was dominated by technical perspectives and that educators' voices and critical perspectives on ethics and pedagogy were underrepresented. Kasneci et al. (2023) examined large language models and emphasised that their educational benefit depended on critical use and on the development of skills such as verification and judgment, and Cotton et al. (2024) discussed the challenge to academic integrity and the need to redesign assessment.

The literature on curriculum and pedagogy offered principles for timing and design. Biggs and Tang (2011) proposed constructive alignment, in which intended learning outcomes, teaching activities and assessment tasks were designed to be consistent, and this implied that if AI was to be an intended learning outcome, it had to be taught and assessed within the curriculum and not merely permitted or prohibited(Julius & Nancy, 2026a). Long and Magerko (2020) defined AI literacy and proposed competencies and design considerations for learning experiences, arguing that literacy should be developed progressively. These frameworks suggested that early introduction was appropriate for basic literacy and critical awareness, while advanced technical and discipline-specific applications were more appropriate later, once students had the foundations to evaluate AI outputs(Julius & Nancy, 2026b).

The literature on teacher knowledge and professional development stressed that competence could not be assumed. Shulman (1986) described pedagogical content knowledge as the integration of subject knowledge with

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teaching knowledge, and Mishra and Koehler (2006) extended this to technological knowledge, proposing a framework in which effective technology integration required the combination of technological, pedagogical and content knowledge. Rogers (2003) explained that the diffusion of innovations depended on the characteristics of adopters and on the support they received. In relation to Uganda, there was little empirical work linking lecturers' competence, training and resources to the integration of AI in teaching, and the gap addressed by this study was the combination of a conceptual analysis of timing, pedagogy and competence with an illustration of how such relationships could be tested quantitatively(Brian et al., 2024).

5.0 Methodology

The study combined a conceptual analysis with a quantitative cross-sectional design (Creswell & Creswell, 2018). The conceptual analysis drew on the literature on constructive alignment, AI literacy and teacher knowledge to formulate positions on timing, pedagogy and competence. The quantitative component used a survey design in which lecturers in Ugandan universities were to be asked about their competence, training, resources and practices, and the unit of analysis was the lecturer. Lecturers were conceptualised as drawn from public and private universities and from a range of disciplines.

For the logistic model, the smaller outcome group contained 39 lecturers who did not support early introduction for eight predictors, a ratio of 4.9 events per predictor, below the guideline of ten (Hosmer et al., 2013), which was acknowledged as a limitation. Two dependent variables were defined. The first was an AI integration index, a composite from zero to one hundred measuring the extent to which the lecturer incorporated AI content, AI tools and AI-aware assessment in their courses. The second was a binary indicator of whether the lecturer supported introducing AI content from the first year of programmes. The independent variables were the lecturer's self-rated competence in AI on a scale from one to five, whether the lecturer had received any AI training, whether reliable computing and internet resources were available for teaching, whether the lecturer taught in a science, technology, engineering or mathematics (STEM) discipline, years of teaching, whether the lecturer held a senior rank, whether the lecturer used AI tools in their own teaching or work, and the lecturer's concern about academic integrity on a scale from one to five.

The analysis proceeded in four stages. Descriptive statistics summarised each variable; Pearson correlations assessed bivariate associations; multiple linear regression estimated by ordinary least squares modelled the integration index; and binary logistic regression estimated by maximum likelihood modelled support for early introduction, with results reported as coefficients, odds ratios and 95% confidence intervals (Hosmer et al., 2013). Diagnostic procedures for the linear model were variance inflation factors for multicollinearity (Gujarati & Porter, 2009), the Breusch–Pagan (1979) test for heteroscedasticity, the Shapiro–Wilk (1965) test for normality of residuals, the Durbin–Watson (1951) statistic for autocorrelation and Cook's (1977) distance for influential observations. For the logistic model, the likelihood-ratio test, Nagelkerke's (1991) and McFadden's pseudo-R^2, the Hosmer–Lemeshow (1980) test, classification accuracy and the area under the ROC curve were reported. Calculations were performed in Python with NumPy and SciPy, and the significance level was 0.05.

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Several methodological choices deserve explanation. Self-rated competence was used because objective competence tests were not available, and it was recognised that self-ratings could be biased, since people with little knowledge sometimes overestimated their competence. The integration index was a composite and its components would have to be defined and validated in a real study. The use of two outcomes reflected the distinction between practice, which depended on capability and resources, and opinion on timing, which was a matter of educational judgment.

6.0 Results

Table 1: Descriptive statistics for continuous variables

Variable	N	Mean	SD	Min	Max	Skew	Kurt
AI integration index (0-100)	130	50.95	14.89	20.0	96.0	0.23	0.01
Self-rated AI competence (1-5)	130	2.77	0.86	1.0	5.0	0.33	-0.21
Years of teaching	130	9.77	5.46	1.0	29.0	0.45	0.20
Academic-integrity concern (1-5)	130	3.81	0.81	1.7	5.0	-0.44	-0.18

Source: Primary Data, 2026.

Table 1 summarized the continuous variables. The AI integration index averaged 50.9 (SD = 14.9), with a median of 50.5, and ranged from 20 to 96, with a nearly symmetric distribution (skewness = 0.23). Self-rated competence averaged 2.77 on the five-point scale (SD = 0.86), which was below the midpoint of three; 21 lecturers rated their competence below two, while only 11 rated it at four or above. Lecturers averaged 9.8 years of teaching (SD = 5.5), and the average concern about academic integrity was 3.81 on the five-point scale (SD = 0.81), which indicated high concern(Kazaara & Nelson, 2024). The distribution of competence illustrated the competence dilemma directly: most lecturers considered their competence to be low or moderate, yet they were the people expected to teach AI.

Table 2: Frequencies and percentages for binary variables

Variable (coded 1 = yes)	Frequency	Percent
Has had AI training	37	28.5
Reliable computing resources	50	38.5
STEM discipline	59	45.4
Senior rank	49	37.7
Uses AI tools in own teaching	67	51.5
Supports AI teaching from first year	91	70.0

Source: Primary Data, 2026

Table 2 presented the binary variables. 37 lecturers (28.5%) had received AI training, 50 (38.5%) had reliable computing resources for teaching, 59 (45.4%) taught in STEM disciplines, 49 (37.7%) held senior rank, and 67 (51.5%) used AI tools in their own teaching. 91 of the 130 lecturers (70.0%) supported introducing AI content

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from the first year(Qadir et al., 2024). Mean integration was 60.7 for lecturers with AI training compared with 47.1 for those without, 57.3 for users of AI tools compared with 44.1 for non-users, and 57.3 in STEM compared with 45.7 in other disciplines. Support for early introduction was 89.2% among trained lecturers and 62.4% among untrained lecturers(Nancy & Prudence, 2024).

Table 3: Pearson correlation matrix

Variable	(1)	(2)	(3)	(4)	(5)	(6)
(1) AI integration index (0-100)	1					
(2) Self-rated AI competence (1-5)	0.66***	1				
(3) Years of teaching	-0.04	0.23**	1			
(4) Academic-integrity concern (1-5)	-0.10	0.09	0.08	1		
(5) Has had AI training	0.41***	0.31***	-0.02	-0.01	1	
(6) Supports AI teaching from first year	0.23**	0.17	0.02	-0.15	0.26**	1

Source: Primary Data, 2026. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3 reported the correlations. The integration index correlated very strongly with self-rated competence ($r = 0.66$, $p < 0.001$), a very large association by conventional standards (Cohen, 1988), and moderately with AI training ($r = 0.41$, $p < 0.001$), while its correlations with years of teaching ($r = -0.04$, $p = 0.630$) and with academic-integrity concern ($r = -0.10$, $p = 0.270$) were weak and not significant(Frank et al., 2023). Support for early introduction correlated positively with AI training ($r = 0.26$, $p = 0.002$), the integration index ($r = 0.23$, $p = 0.009$) and, at the margin, with competence ($r = 0.17$, $p = 0.053$), and negatively, at the margin, with integrity concern ($r = -0.15$, $p = 0.084$). Competence was positively correlated with training ($r = 0.31$, $p < 0.001$) and with years of teaching ($r = 0.23$, $p = 0.008$)(Nelson et al., 2023). All correlations among predictors were below 0.35 in absolute value, so serious collinearity was not anticipated.

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Table 4: Multiple linear regression of the AI integration index

Predictor	B	SE	Beta	t	p	95% CI for B
Constant	28.084	3.930	–	7.15	< 0.001	[20.30, 35.86]
Self-rated AI competence (1–5)	9.278	0.891	0.54	10.41	< 0.001	[7.51, 11.04]
Has had AI training	6.898	1.614	0.21	4.27	< 0.001	[3.70, 10.09]
Reliable computing resources	3.949	1.435	0.13	2.75	0.007	[1.11, 6.79]
STEM discipline	9.612	1.381	0.32	6.96	< 0.001	[6.88, 12.35]
Years of teaching	-0.497	0.130	-0.18	-3.81	< 0.001	[-0.76, -0.24]
Senior rank	-0.759	1.426	-0.02	-0.53	0.595	[-3.58, 2.06]
Uses AI tools in own teaching	9.574	1.416	0.32	6.76	< 0.001	[6.77, 12.38]
Academic-integrity concern (1–5)	-2.761	0.859	-0.15	-3.22	0.002	[-4.46, -1.06]

Source: Primary Data, 2026. Dependent variable: AI integration index; n = 130; $R^2 = 0.746$; adjusted $R^2 = 0.729$; $F(8, 121) = 44.38$, $p < 0.001$.

Table 4 reported the linear regression of the integration index. The model was significant, $F(8, 121) = 44.38$, $p < 0.001$, and explained 74.6% of the variance in integration (adjusted $R^2 = 0.729$), a very large effect by conventional standards (Cohen, 1988), with a root mean square error of 7.75 points. Self-rated competence had by far the largest standardised effect (beta = 0.54): each additional point on the five-point scale was associated with 9.3 more points on the index (B = 9.278, $p < 0.001$)(Nancy & Prudence, 2024). Teaching in a STEM discipline added 9.6 points (B = 9.612, beta = 0.32, $p < 0.001$), using AI tools in one's own teaching added 9.6 points (B = 9.574, beta = 0.32, $p < 0.001$), AI training added 6.9 points (B = 6.898, beta = 0.21, $p < 0.001$), and reliable computing resources added 3.9 points (B = 3.949, $p = 0.007$). Each year of teaching experience reduced the index by 0.50 points (B = -0.497, beta = -0.18, $p < 0.001$), and each additional point of integrity concern reduced it by 2.76 points (B = -2.761, $p = 0.002$). Senior rank had no significant effect (B = -0.759, $p = 0.595$). Because competence was itself related to training, the effect of training in the model was the effect over and above competence, which suggested that training had benefits beyond the competence that lecturers reported(Mobegi, 2026).

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Table 5: Diagnostic tests for the linear regression model

Test	Statistic	p-value	Decision
Multicollinearity (maximum VIF)	1.27	–	No concern (< 5)
Breusch–Pagan (heteroscedasticity)	$\chi^2(8) = 6.63$	0.577	Constant variance retained
Shapiro–Wilk (residual normality)	W = 0.983	0.107	Normality retained
Durbin–Watson (autocorrelation)	1.63	–	No serious autocorrelation (≈ 2)
Cook's distance (maximum)	0.047	–	6 cases above 4/n = 0.031; none above 1

Source: Primary Data, 2026

Table 5 summarized the diagnostics. The maximum variance inflation factor was 1.27, which indicated no multicollinearity, the Breusch–Pagan test did not reject constant variance, χ^2 (8) = 6.63, p = 0.577, the Shapiro–Wilk test did not reject normality of residuals (W = 0.983, p = 0.107), and the Durbin–Watson statistic of 1.63 indicated no serious autocorrelation. Cook's distance flagged 6 lecturers above the 4/n threshold of 0.031, but the maximum of 0.047 was far below one, so no respondent had undue influence. The classical assumptions were satisfied and the ordinary least squares estimates were considered reliable without robust adjustment.

Table 6: Binary logistic regression of support for introducing AI from the first year

Predictor	B	SE	Wald z	p	Odds ratio	95% CI for OR
Constant	1.246	1.214	1.03	0.305	–	–
Self-rated AI competence (1–5)	0.211	0.280	0.75	0.451	1.23	[0.71, 2.14]
Has had AI training	1.467	0.607	2.42	0.016	4.34	[1.32, 14.25]
Reliable computing resources	0.443	0.448	0.99	0.323	1.56	[0.65, 3.74]
STEM discipline	0.617	0.426	1.45	0.148	1.85	[0.80, 4.27]
Years of teaching	0.003	0.039	0.08	0.936	1.00	[0.93, 1.08]
Senior rank	0.173	0.442	0.39	0.695	1.19	[0.50, 2.83]
Uses AI tools in own teaching	0.475	0.430	1.10	0.270	1.61	[0.69, 3.74]
Academic-integrity concern (1–5)	-0.527	0.273	-1.93	0.054	0.59	[0.35, 1.01]

Source: Primary Data, 2026. Dependent variable: supports AI teaching from the first year (1 = yes); n = 130. Odds ratio = exp(B).

Table 6 reported the logistic regression. The model was significant, $\chi^2(8) = 19.29$, p = 0.013. AI training was the only significant predictor: lecturers who had been trained had odds of supporting early introduction that were 4.3 times those of untrained lecturers (B = 1.467, 95% CI 1.32 to 14.2, p = 0.016). Academic-integrity concern was

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associated with lower odds, at the margin of significance (OR = 0.59, 95% CI 0.35 to 1.01, p = 0.054). Competence (OR = 1.23, p = 0.451), computing resources (OR = 1.56, p = 0.323), STEM discipline (OR = 1.85, p = 0.148), years of teaching (OR = 1.00, p = 0.936), senior rank (OR = 1.19, p = 0.695) and the use of AI tools (OR = 1.61, p = 0.270) were not significant predictors of the view on timing(Ronald et al., 2023). The contrast with the linear model was notable: the factors that predicted actual integration, namely competence, discipline and the use of tools, did not predict opinion on when AI should be introduced, which suggested that views on timing were shaped by exposure to training more than by one's own current practice.

Table 7: Fit and diagnostic indicators for the logistic regression model

Indicator	Value	Decision
Likelihood-ratio χ^2	$\chi^2(8) = 19.29$, p = 0.013	Model significant
Nagelkerke R^2 / McFadden R^2	0.196 / 0.121	Modest explanatory power
Hosmer–Lemeshow test	$\chi^2(8) = 3.75$, p = 0.879	Adequate calibration
Overall classification accuracy	73.8%	Cut-off = 0.50
Sensitivity / Specificity	93.4% / 28.2%	–
Area under ROC curve (AUC)	0.726	Acceptable discrimination
Multicollinearity (maximum VIF)	1.27	No concern (< 5)
Standardised residuals above |3|	2	No serious outliers

Source: Primary Data, 2026

Table 7 reported the fit indicators. The Nagelkerke R^2 of 0.196 and McFadden R^2 of 0.121 indicated modest explanatory power, and the Hosmer–Lemeshow test showed good calibration, $\chi^2(8) = 3.75$, p = 0.879. The model correctly classified 73.8% of lecturers, with a sensitivity of 93.4% against a specificity of only 28.2%, which showed that it identified supporters of early introduction much better than non-supporters. The area under the ROC curve of 0.726 indicated acceptable discrimination (Hosmer et al., 2013). The maximum variance inflation factor was 1.27, and 2 lecturers had standardised residuals above three in absolute value. Given the limited number of lecturers who did not support early introduction, the confidence intervals were wide and interpreted cautiously.

7.0 Discussion of Results

On competence, the study data were consistent with the competence dilemma: self-rated competence was low to moderate on average, yet it was by far the strongest predictor of how much AI was integrated into teaching. On pedagogy, the finding that the use of AI tools in one's own teaching and discipline were associated with integration, in addition to competence, suggested that integration was a practice learned by doing and shaped by disciplinary norms. STEM lecturers integrated AI more, which was unsurprising because AI was closer to their content, but it also indicated that non-STEM disciplines would need support to see how AI related to their fields.

8.0 Conclusions

The study analysis showed that self-rated competence, STEM discipline, the use of AI tools, training and resources were associated with greater integration of AI in teaching, that experience and integrity concern were associated

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with less, and that training alone predicted support for early introduction. It followed that competence was the binding constraint, that integration depended on practice and on assessment design, and that views on timing depended on what was understood by teaching AI.

9.0 Recommendations

First, universities and the National Council for Higher Education should adopt a staged approach to introducing AI, with AI literacy and critical use in the early years and discipline-specific and technical content later. Second, universities should invest in the competence of lecturers through accredited training, communities of practice and time for course redesign, and should do so before or alongside curriculum mandates. Third, universities should redesign assessment so that the legitimate use of AI is specified and assessed, in line with constructive alignment, and should not rely on prohibition alone. Fourth, universities should provide reliable computing resources and internet access, and negotiate access to AI tools, with attention to data protection under the Data Protection and Privacy Act (2019). Fifth, faculties outside STEM should be supported to identify how AI applies to their disciplines. Sixth, institutions should develop clear academic-integrity policies that distinguish permitted and prohibited uses of AI. Finally, researchers should replicate this analysis with real survey data from Ugandan universities.

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