

Artificial Intelligence Readiness and Integration in Teaching Practices among Secondary School Teachers in Katsina State Nigeria

Original Research Article | Volume 1 | Issue 5 | 2026 | Article Number: 093

Accepted: 30 September 2026 | Published: 10 October 2026 | ISSN: 2979-8582 (Online)



Crossref : <https://doi.org/10.67693/BJCR-IJQSEEZ7>



Muhsin Mustapha Inuwa¹, Muhammad Sani Umar (PhD)²

¹Department of Information Technology and Security Studies, Bayero University Kano, Kano State Nigeria,

²Department of Educational Psychology and Counselling, Federal University Dutsin-Ma, Katsina State, Nigeria

Correspondence: Muhammad Sani Umar (PhD), kankiya26@gmail.com

Abstract

This study examines associations between technological self-efficacy, pedagogical readiness, ethical AI awareness, perceived relevance, institutional support, overall, AI readiness and self-reported AI integration among secondary school teachers in Katsina State, Nigeria. A supplied questionnaire dataset was analyzed using construct means, Cronbach's alpha, correlations and exploratory linear regression with HC3 robust standard errors. The Google Forms export contained 68 submissions recorded from 10 to 21 September 2026, all with affirmative participation consent and distinct timestamps. All 68 submissions were analyzed: 67 distinct structured-response patterns were examined separately as a sensitivity analysis. Mean readiness was 3.42 (SD = 1.36) and mean integration was 3.41 (SD = 1.39) on a five-point agreement scale. Institutional support had the lowest construct mean (3.00). 64.7% of records selected limited connectivity, while 65.7% of those answering the training-needs question selected basic AI literacy. Readiness and integration were strongly correlated ($r = .954$; 95% CI .926–.971). In the readiness model, pedagogical readiness and institutional support remained statistically distinguishable from zero after Holm adjustment across seven hypotheses; perceived relevance met the unadjusted threshold only. In the full integration model, readiness had a positive but imprecise coefficient ($B = 0.586$; 95% CI

-0.131-1.304; $p = .107$). High Inter construct correlations, response inconsistencies and undocumented sampling procedures restrict interpretation. The findings identify priorities for teacher development and infrastructure support, but do not establish causal effects or population estimates.

Keywords: Artificial Intelligence, Teacher Readiness, Pedagogical Readiness, Institutional Support, Secondary Education, Katsina State

INTRODUCTION

Artificial intelligence can assist teachers with lesson ideas, explanations, differentiated materials, formative questions and professional learning. However, its availability does not mean teachers can select suitable tools, evaluate their outputs, or use them responsibly. Classroom integration involves decisions about curricular relevance, learner needs, accuracy and the continuing role of teacher judgement. These decisions make readiness an educational issue as well as a technological one. Readiness is treated here as a teacher's perceived preparedness to use AI responsibly in professional practice. It is distinct from technological self-efficacy, which concerns confidence in handling tools, and from integration, which concerns reported teaching activities. Institutional support describes the environment in which these individual capacities are exercised. These distinctions matter because favorable attitudes and personal confidence may coexist with limited devices, connectivity, training or guidance.

Nigerian evidence provides a basis for investigating these relationships. Ayanwale et al. (2022) examined 368 teachers and found that perceived AI relevance predicted readiness to teach AI, while confidence predicted intention. Their focus on teaching AI as subject content differs from the present focus on using AI within everyday teaching. International work also connects readiness with educational use, while highlighting the need to distinguish technical, pedagogical and ethical competence. These findings motivate local investigation rather than justify transferring results from other settings to Katsina. The study addresses three related questions: how the seven constructs are distributed in the supplied records; how readiness and integration relate to the other constructs; and which practical barriers and professional-development needs are reported. It retains the original manuscript's theoretical model while distinguishing exploratory associations from causal explanations. The analysis uses the 68 timestamped submissions in the Google Forms response export. Its exploratory interpretation reflects the sample size, self-report measures and absence of a documented probability sampling procedure

LITERATURE REVIEW AND CONCEPTUAL FRAMEWORK

Technological and pedagogical preparedness

The Technological Pedagogical Content Knowledge framework situates effective technology use at the intersection of technological, pedagogical and subject knowledge (Mishra & Koehler, 2006). For this study, technological self-efficacy includes giving instructions to AI tools, checking outputs and selecting suitable applications. Pedagogical readiness concerns identifying worthwhile learning activities, adapting assessment and supporting students without surrendering professional judgement. The framework supplies a conceptual lens; the questionnaire does not measure every TPACK domain or validate the complete TPACK model. Yue et al. (2024) surveyed 1,664 K-12 teachers and identified gaps in AI-related content and technological knowledge. Their work supports examining AI-specific preparedness rather than

assuming that general teaching experience transfers to AI competence. It also concerns AI education in a different national and professional-development context, so direct comparisons of scale means would be inappropriate. AI literacy adds a critical-evaluation dimension to technical confidence. Long and Magerko (2020) frame it through competencies for understanding, interacting with and evaluating AI. Ng et al. (2021) distinguish conceptual understanding, practical application, evaluation and creation, and ethical considerations. Together, these accounts support treating readiness as multidimensional. In this study, however, agreement with capability statements remains a perception measure rather than a direct assessment of these competencies. Celik (2023) extends the TPACK discussion through Intelligent-TPACK, linking teachers' professional knowledge with the ethical integration of AI tools. This reinforces the rationale for examining technological, pedagogical and ethical dimensions together. It does not establish that the present scales capture the same constructs or that their highly correlated scores represent empirically distinct dimensions.

Ethical awareness and responsible practice

Ethical awareness includes recognizing confidentiality risks, biased or fabricated outputs, academic-integrity concerns and the need for human oversight. Ramazanoglu and Akın (2025; first published online in 2024) developed the 19-item Readiness for Artificial Intelligence Applications Scale with technology self-efficacy, interaction with students and ethical-awareness dimensions. Their validated instrument supports the relevance of these domains, but its psychometric evidence does not automatically transfer to the newly worded questionnaire used here. UNESCO's (2024) AI competency framework for teachers similarly joins technical capability with human agency, ethics, pedagogy and professional learning. In the present study, agreement with ethical statements is interpreted as self-reported awareness. It is not evidence that a respondent consistently follows safe practices or can resolve a complex classroom dilemma. Akgun and Greenhow (2022) locate ethical challenges within K–12 practice, including privacy, surveillance, bias and learner autonomy. Kasneci et al. (2023) likewise discuss educational opportunities from large language models alongside risks arising from inaccurate outputs and uncritical reliance on generated material. These arguments support practical safeguards such as evaluating outputs before classroom use and avoiding unnecessary disclosure of student information. Such safeguards are educational implications, not behaviors demonstrated by the present questionnaire.

Relevance institutional support and integration

Perceived relevance concerns whether teachers see AI as meaningful to their professional work. Institutional support covers access to devices and the internet, leadership encouragement, training, technical assistance and school guidance. These constructs may help explain why individual willingness does not always translate into reported classroom use. Integration is measured as endorsement of specific teaching practices, including preparing materials, supporting assessment, checking outputs and discussing responsible use. Nguyen and Nguyen (2025) studied 224 participants in Vietnam and reported a positive readiness–integration relationship. Their results table supported professional development and attitudes as predictors of readiness, while resources/accessibility and pedagogical knowledge had non-significant direct paths. This more precise reading of the results is used instead of the inconsistent wording in that article's abstract. The present analysis tests related associations with different measures and a substantially smaller sample. A systematic review by Celik et al. (2022) identifies potential support for teachers' planning, instructional implementation and assessment, while emphasizing teachers' roles in evaluating and developing AI applications. This helps explain why integration should be assessed through concrete activities. In higher education, Zawacki-Richter et al. (2019) identified weak connections between AI research and pedagogical perspectives. Although that review concerns a different educational sector, it reinforces the broader need to ground technology use in teaching purposes rather than assume that

availability produces educational value. Professional development may also shape how teachers interpret and trust AI systems. Nazaretsky et al. (2022) examined teachers' trust and a development programme designed to improve it, highlighting the value of both conceptual knowledge and concrete pedagogical tasks. This provides a rationale for studying training needs alongside institutional support. Trust was not separately measured in the present instrument, and no training effect can be inferred from its cross-sectional comparisons.

Research questions and hypotheses

Research questions 1–7 concern the levels of technological self-efficacy (TSE), pedagogical readiness (PR), ethical AI awareness (EAA), perceived relevance (PRA), institutional support (IS), overall, AI readiness (AIR) and AI integration in teaching practices (AITI), respectively. Research question 8 concerns their interrelationships; question 9 concerns their joint statistical associations with readiness and integration. The additional multiple-response items describe barriers and requested professional development. The conceptual model places TSE, PR, EAA, PRA and IS as correlates of AIR, and AIR as a correlate of AITI alongside those five constructs. H01–H05 specify zero partial associations of TSE, PR, EAA, PRA and IS, respectively, with AIR. H06 specifies a zero AIR coefficient in the integration model after adjustment for the five antecedents. H07 specifies that the five antecedent coefficients are jointly zero in an integration model without AIR. A simple AIR–AITI model is reported separately. The ordering is theoretical; no temporal sequence or mediation is established by these data.

METHODS

Study design and data source

The study uses a cross-sectional questionnaire administered through Google Forms to investigate AI readiness and integration among secondary school teachers in Katsina State. The response export contains 68 submissions recorded from 10 to 21 September 2026. Its 58 fields comprise a timestamp, participation consent, 10 background variables, 43 agreement items, two multiple-response questions and one optional open-ended support question. The 55 structured substantive fields were analysed quantitatively. The open-ended question received 26 non-empty responses and was not subjected to formal qualitative coding. School identifiers, local government areas, a verified sampling frame, recruitment records and the number invited were unavailable; the sampling mechanism and response rate therefore cannot be established. The study is not presented as a probability sample.

Data screening and analysis sample

All 68 response rows in the Google Forms export were retained, corresponding to spreadsheet rows 2–69. Each has a distinct timestamp and an affirmative answer to the participation-consent question. The 55 structured substantive fields match the first 68-record block in the earlier working file after normalizing the separators in multiple-response answers. The four repeated blocks in that earlier file are absent from this export and do not contribute observations. Two submissions have identical answers across those 55 fields but different timestamps. Both were retained because identical answers alone do not establish duplicate participation; a sensitivity analysis uses the 67 distinct structured-response patterns. Distinct timestamps identify submissions, but cannot independently establish participant identity. All 43 agreement items and all background variables were complete in the retained block. One record lacked a response to the professional-development question; its denominator is therefore 67, while barriers use 68. No values required imputation and all agreement responses mapped to the stated scale. Eleven records (16.2%) selected the same response across all 43 items: five selected strongly disagree, four agree and two strongly agree. Eleven reported never using AI for teaching, including five who nevertheless agreed or strongly

agreed with every integration statement. These patterns were flagged rather than automatically classified as invalid. Their overlap and removal are addressed in sensitivity analyses.

Responses were coded 1 = strongly disagree, 2 = disagree, 3 = neutral/undecided, 4 = agree and 5 = strongly agree. Within each construct, the score is the arithmetic mean of its items: TSE, PR and EAA each contain six items; PRA contains five; IS contains six; AIR contains five; and AITI contains nine. All items are positively keyed. AIR uses its own five items and is not calculated by averaging the five predictor scales, avoiding a mechanically constructed predictor–outcome relationship. Appendix A provides the exact item wording and item statistics. Means are described relative to the response anchors, without imposing unvalidated low, moderate or high categories. A construct score of at least 4 is reported as a descriptive agreement threshold, not as a validated competency cut-off. AITI is an agreement-based measure of self-reported practice, not an observed frequency or quality measure. The separate frequency question is therefore reported independently.

Cronbach's alpha (Cronbach, 1951) assesses internal consistency within each proposed scale. Expert review, pilot testing and independent validation were recommended in the source manuscript but were not documented as completed. Given the sample size and 43-item instrument, neither a seven-factor confirmatory model nor structural equation modelling was fitted. High alpha is not treated as evidence of discriminant validity. Following the caution about reliance on alpha discussed by Dunn et al. (2014), future validation should examine the factor structure and consider model-based reliability estimates such as omega; omega was not estimated here.

Analyses used Python with pandas, NumPy and SciPy. Counts, percentages, means and sample standard deviations describe the retained records. Figures were reconstructed from the spreadsheet responses: horizontal bars show respondent counts and percentages, stacked bars show pooled item-response distributions, and a size-scaled scatterplot shows overlapping readiness–integration scores. Pearson correlations summarise linear associations; Spearman correlations provide an ordinal sensitivity check. The readiness regression includes the five antecedent constructs. Integration regressions include AIR alone, the five antecedents alone, and all six predictors. Coefficients are ordinary least-squares estimates; standard errors use the HC3 heteroscedasticity adjustment (MacKinnon & White, 1985), and two-sided confidence intervals and tests use residual degrees of freedom. Standardised coefficients and variance inflation factors (VIFs) are reported. VIFs are interpreted alongside coefficient uncertainty and the measurement context, rather than through a single automatic cut-off (O'Brien, 2007). Joint tests use robust Wald F statistics.

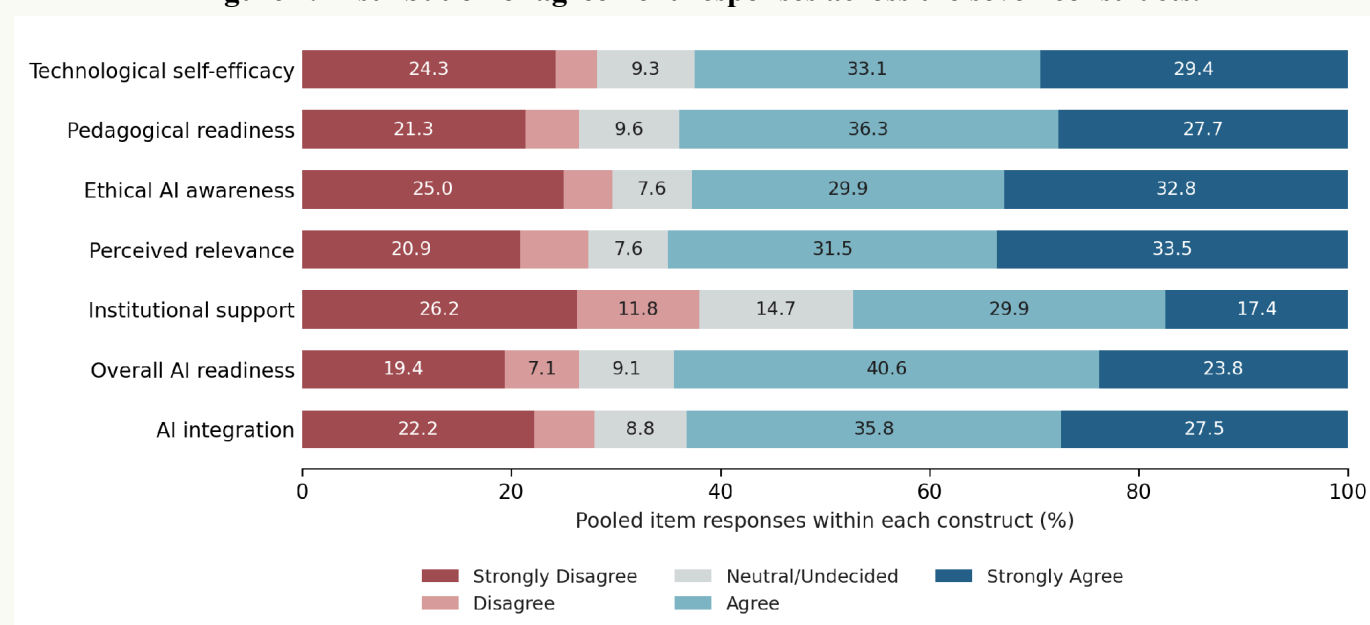
Seven original hypotheses were assessed using both unadjusted p values and Holm's (1979) correction, which controls familywise error across that set. Other analyses are exploratory. Welch comparisons examine school ownership and previous AI training for AIR and AITI. No additional demographic controls were fitted because the sample contains sparse categories and the main models already show substantial collinearity. Sensitivity analyses use 67 distinct structured-response patterns, exclude uniform-response records, exclude records reporting never using AI, and exclude uniform-response records plus the five most clearly inconsistent never-use records. All confidence intervals and p values assume independence of the 68 submissions; robust standard errors cannot establish that independence or correct unobserved school clustering. All 68 submissions recorded affirmative consent to participate. The export contains no names, email addresses or direct school identifiers. Recorded agreement does not establish whether institutional ethical approval or exemption and school administrative permissions were obtained; those details must be confirmed from the study records before submission. Author contributions, funding, conflicts of interest and data-sharing permissions also require confirmation. Individual response timestamps are not reproduced in the manuscript or figures.

RESULTS

All primary results below refer to the selected first 68 records; alternative sample sizes are explicitly labelled as sensitivity analyses. It contains 57 male records (83.8%) and 11 female records (16.2%). Most were aged 25–34 years (72.1%); 63.2% reported public-school employment and 57.4% urban school locations. Previous formal AI training was reported by 42.6%, while 76.5% identified smartphones as their main device. Only 26.5% reported using AI often or very often, despite relatively favorable agreement scores on the integration items. This difference reinforces the need to distinguish frequency from endorsement of practice statements.

At item level, school device access had a mean of 2.72, reliable internet 2.87 and clear AI guidance 2.90. Within integration, professional learning was most strongly endorsed ($M = 3.60$), while asking students to evaluate AI-generated information ($M = 3.19$) and using AI for assessment or feedback preparation ($M = 3.21$) were less strongly endorsed. These are descriptive contrasts; no item-ranking significance tests were performed.

Figure 2. Distribution of agreement responses across the seven constructs.



Source: Google Forms response export, $N = 68$. Each bar pools item responses within a construct: 408 responses for each six-item scale, 340 for each five-item scale and 612 for the nine-item integration scale. Segments show percentages of item responses, not percentages of teachers; labels are omitted for segments below 7%.

Figure 2 displays the full response distribution rather than reducing each domain to a mean. Institutional support shows a less favourable profile than individual preparedness domains. Because the bars pool multiple answers from each respondent, they are descriptive distributions and must not be treated as independent samples of 340–612 people.

Relationships between constructs

All pairwise Pearson correlations were positive, ranging from .692 to .954. Readiness and integration were strongly associated ($r = .954$, 95% CI .926–.971); the corresponding Spearman coefficient was .857. The rank-based association remained strong, although smaller than the Pearson coefficient. Population

generalisation remains unsupported by the available sampling information. Pedagogical readiness, perceived relevance and ethical awareness were also closely interrelated. The pattern is compatible with shared perceptions and response tendencies as well as substantive relationships.

Factors associated with readiness

The five-predictor readiness model accounted for 94.7% of the variance within the retained block (adjusted $R^2 = .942$; robust $F(5, 62) = 271.31$, $p < .001$). Pedagogical readiness ($B = 0.354$), perceived relevance ($B = 0.262$) and institutional support ($B = 0.215$) had positive coefficients with unadjusted p values below .05. Ethical awareness was imprecise ($p = .056$), and technological self-efficacy was not statistically distinguishable from zero ($p = .623$). After adjustment for seven hypothesis tests, pedagogical readiness and institutional support remained below .05; perceived relevance did not. The very high model fit should be interpreted alongside the measurement and data-quality limitations, rather than as evidence of exceptional predictive performance.

Table 4. Exploratory regression of overall AI readiness

Predictor	B	HC3 SE	Beta	95% CI for B	p
Intercept	0.087	0.106	—	-0.126 to 0.299	0.418
TSE	-0.042	0.085	-0.046	-0.212 to 0.128	0.623
PR	0.354	0.103	0.369	0.148 to 0.560	0.001
EAA	0.205	0.105	0.222	-0.006 to 0.416	0.056
PRA	0.262	0.107	0.281	0.048 to 0.477	0.017
IS	0.215	0.048	0.206	0.119 to 0.311	<.001

$N = 68$; five predictors; residual $df = 62$. Predictor VIFs range from 2.67 to 13.80. Values above 10 for PR, EAA and PRA indicate substantial coefficient instability. The confidence intervals and p values are unadjusted; see Table 6 for Holm adjustment.

Factors associated with integration

In the simple model, readiness was positively associated with integration ($B = 0.975$, HC3 95% CI 0.926–1.025, $p < .001$; $R^2 = .910$). The antecedent-only integration model explained 90.9% of within-block variance (adjusted $R^2 = .902$; robust $F(5, 62) = 221.61$, $p < .001$). Adding readiness increased R^2 by .018 to .927. In that full model, however, no individual coefficient met the unadjusted .05 threshold: readiness had $p = .107$ and pedagogical readiness $p = .067$. Joint explanatory power and individually imprecise coefficients can coexist when predictors overlap strongly.

Table 5. Exploratory integration model including readiness

Predictor	B	HC3 SE	Beta	95% CI for B	P
Intercept	0.044	0.090	—	-0.136 to 0.223	0.627
TSE	0.017	0.211	0.018	-0.404 to 0.439	0.935
PR	0.440	0.236	0.448	-0.031 to 0.911	0.067
EAA	-0.017	0.165	-0.018	-0.348 to 0.314	0.919
PRA	-0.054	0.169	-0.056	-0.391 to 0.284	0.752

Predictor	B	HC3 SE	Beta	95% CI for B	P
IS	0.009	0.089	0.008	-0.170 to 0.187	0.921
AIR	0.586	0.359	0.574	-0.131 to 1.304	0.107

$N = 68$; residual $df = 61$; $R^2 = .927$; adjusted $R^2 = .919$; robust $F(6, 61) = 314.11$, $p < .001$. VIFs range from 3.47 to 18.69; AIR has the largest VIF. The model does not establish mediation.

The largest Cook's distance was .178 for readiness and .683 for the full integration model. Four and nine records, respectively, exceeded the descriptive $4/N$ threshold. These records were not removed simply because they influenced estimates. Together with VIFs approaching 19, these diagnostics argue against strong rankings of independent predictor importance or definitive acceptance of the conceptual pathway.

Exploratory hypothesis assessment

Table 6. Decisions for the seven original null hypotheses

Null	Association tested	Raw p	Holm p	Holm decision
H01	TSE → AIR	0.623	0.623	Do not reject
H02	PR → AIR	0.001	0.005	Reject
H03	EAA → AIR	0.056	0.169	Do not reject
H04	PRA → AIR	0.017	0.070	Do not reject
H05	IS → AIR	<.001	<.001	Reject
H06	AIR → AITI adjusted	0.107	0.214	Do not reject
H07	Five antecedents jointly → AITI	<.001	<.001	Reject

Decisions are exploratory and conditional on the retained records representing independent participants. H06 is the adjusted coefficient in Table 5, not the separate simple readiness model. H07 is the robust joint test of the antecedent-only integration model. Non-rejection is not evidence of no relationship.

Barriers and professional development

Limited internet connectivity was the most frequently selected barrier (44/68, 64.7%), followed by data cost (37/68, 54.4%) and AI subscription cost (33/68, 48.5%). The leading requested training area was basic AI literacy (44/67, 65.7%), followed by academic integrity (33/67, 49.3%). These selections suggest practical areas for needs assessment; they do not estimate how much any intervention would improve readiness or teaching.

Table 7. Reported barriers to AI use

Selected option	n	%
Limited internet connectivity	44	64.7
Cost of internet data	37	54.4
Cost of AI subscriptions	33	48.5

Selected option	n	%
Limited access to digital devices	28	41.2
Unclear school policy on AI	27	39.7
Lack of training opportunities	26	38.2
Concern about inaccurate AI-generated information	21	30.9
Academic-integrity concerns	18	26.5
Lack of AI knowledge or skills	18	26.5
Privacy and data-protection concerns	17	25.0
Language or local-context limitations	16	23.5
Lack of time	15	22.1
Other	9	13.2
AI is not relevant to my current teaching	8	11.8

Table 8. Requested professional development

Selected option	n	%
Basic AI literacy	44	65.7
AI and academic integrity	33	49.3
Prompting and practical AI tool use	25	37.3
AI for lesson planning	24	35.8
Subject-specific AI applications	23	34.3
AI for assessment and feedback	23	34.3
School AI policy and governance	22	32.8
AI for inclusive/differentiated teaching	20	29.9
AI ethics, privacy and safety	17	25.4

Multiple selections were permitted. Denominator = 67 records; percentages need not total 100. One missing response was excluded.

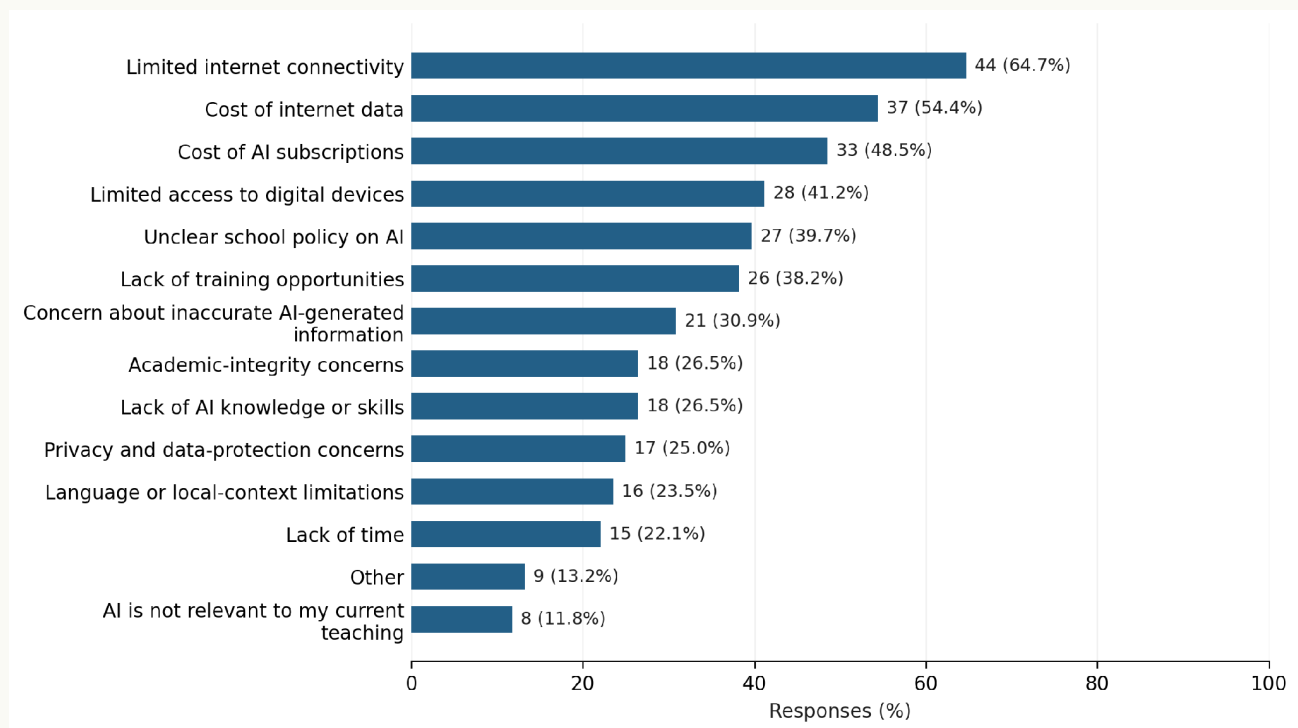


Figure 4. Reported barriers to using AI for teaching.

Figure 4 highlights access constraints: limited connectivity (44; 64.7%), internet data costs (37; 54.4%) and subscription costs (33; 48.5%) were the most frequently selected barriers. Training and school guidance also featured, indicating that professional development should be considered alongside practical access conditions.

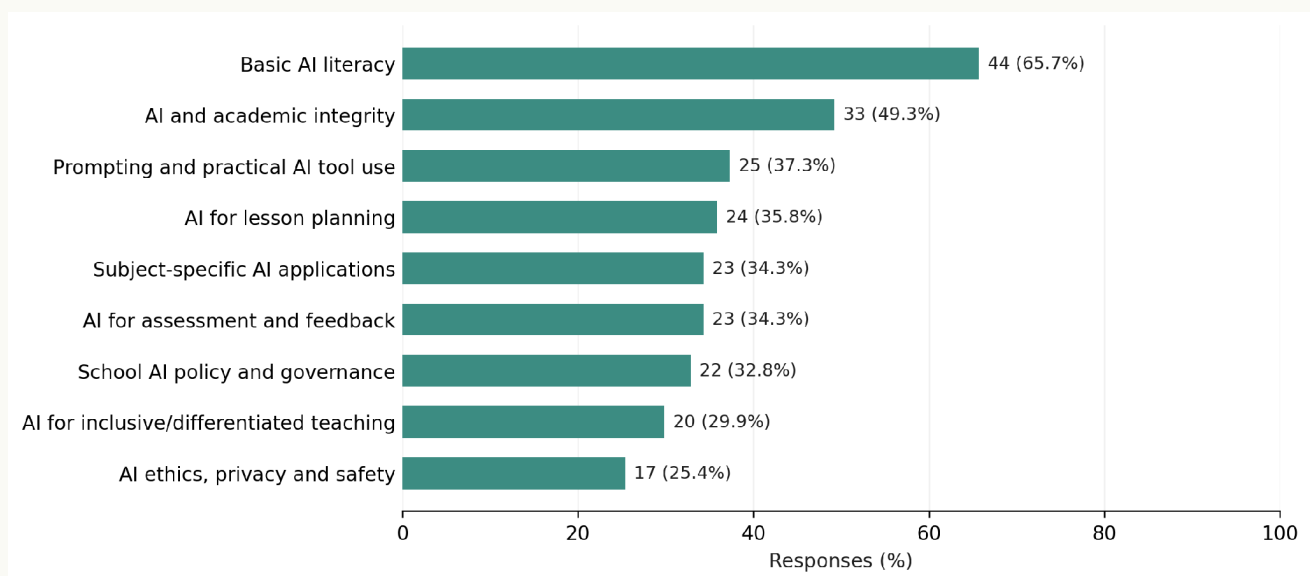


Figure 5. Requested AI-related professional development.

Figure 5 identifies basic AI literacy as the leading requested area (44/67; 65.7%), followed by academic integrity (33/67; 49.3%) and practical prompting/tool use (25/67; 37.3%). These preferences describe perceived needs; they do not measure competency deficits or demonstrate which training programme would be most effective.

Group comparisons and sensitivity analyses

Private-school records and records reporting prior training had higher readiness and integration means than their comparison groups. None of the four Welch comparisons met the unadjusted .05 threshold. The results therefore do not demonstrate an ownership difference or a training effect. Small and unbalanced groups, unknown selection processes and the absence of training-content information limit interpretation.

Table 9. Exploratory group comparisons

Comparison	Outcome	Mean 1	Mean 2	Difference and 95% CI	p
Private vs public	AIR	3.78	3.22	0.557 (-0.082 to 1.197)	0.086
Private vs public	AITI	3.80	3.17	0.631 (-0.019 to 1.281)	0.057
Trained vs untrained	AIR	3.70	3.22	0.476 (-0.176 to 1.128)	0.150
Trained vs untrained	AITI	3.76	3.14	0.623 (-0.046 to 1.292)	0.068

Welch tests; private n = 25, public n = 43; trained n = 29, untrained n = 39. Differences are group 1 minus group 2; all tests are exploratory and unadjusted.

Using only the 67 distinct structured-response patterns produced nearly identical estimates. Excluding 11 uniform-response records, all 11 never-use records, or the union of uniform responses and the five most inconsistent never-use records also left the main pattern broadly unchanged: PR, PRA and IS had positive unadjusted associations with readiness, while the adjusted AIR coefficient in the integration model remained imprecise. These checks show limited sensitivity to the selected exclusions; they do not verify that the data were collected from independent eligible teachers.

Table 10. Sensitivity analyses

Analysis set	n	AIR R ²	AITI R ²	AIR B in AITI	p
Distinct response patterns	67	0.944	0.923	0.586	0.107
Exclude uniform responses	57	0.925	0.898	0.586	0.108
Exclude all never-use records	57	0.947	0.930	0.592	0.138
Exclude uniform or conflicting records	53	0.923	0.895	0.584	0.117

AIR model uses five antecedents. AITI model uses those antecedents plus AIR. Uniform = the same answer to all 43 items. Conflicting = never-use response plus agreement with every integration item. Exclusion rules were analytical checks, not verified eligibility decisions.

DISCUSSION

Readiness and reported practice

The retained responses show favourable but uneven perceptions of AI preparedness and integration. Means between 3 and 4, substantial score dispersion and only half of records reaching the descriptive integration threshold caution against presenting the sample as uniformly ready. Furthermore, agreement with statements about practice exceeded reported frequent use. This distinction has practical importance: willingness, confidence, occasional experimentation and sustained classroom integration are related but different outcomes. The positive readiness–integration association is directionally consistent with Nguyen

and Nguyen (2025), but it's much stronger bivariate magnitude cannot be interpreted as stronger evidence. Measures, contexts and analytical methods differ, and the present dataset has exceptional overlap among scales. Once the overlapping antecedents enter the integration model, the readiness coefficient becomes imprecise. The data therefore support a descriptive association but do not establish a distinct readiness effect or a mediated pathway.

Pedagogy relevance and institutional conditions

Pedagogical readiness retained an association with overall readiness after multiplicity adjustment. This is conceptually compatible with TPACK's emphasis on integrating technology with teaching decisions (Mishra & Koehler, 2006). It does not show that pedagogical training caused readiness, nor that self-reported preparedness corresponds to demonstrated skill. A useful follow-up would combine the questionnaire with a lesson-design task or a classroom observation rubric, linking the AI-specific professional knowledge discussed by Celik (2023) to demonstrable practice. The unadjusted perceived-relevance coefficient is compatible with Ayanwale et al. (2022), although it did not survive Holm adjustment here. This suggests a relationship worth testing with verified data rather than a confirmed independent finding. Technological self-efficacy was strongly correlated with readiness but not distinguishable from zero conditionally. The result should not be interpreted as evidence that technical skills are unimportant; much of their measured variation overlaps with the other self-report constructs. Institutional support had the lowest mean and remained associated with readiness after Holm adjustment. Device access, connectivity and policy guidance were among its weaker items, while access and cost barriers were repeatedly selected. These observations justify assessing practical enabling conditions alongside training needs. They do not determine which investment would yield the greatest improvement or establish an institutional causal effect.

Responsible use and measurement quality

Ethical awareness was positively correlated with both outcomes but did not meet the adjusted hypothesis threshold. A non-significant conditional coefficient does not diminish the educational importance of confidentiality, bias checks or academic integrity. The ethical domain in Ramazanoglu and Akin (2025) and UNESCO's (2024) framework supports retaining these topics in training and future measurement. Scenario-based questions would help distinguish familiarity with ethical language from the ability to apply it. The measurement pattern warrants caution. Alpha near .98 may reflect consistent measurement, but the combination of high cross-construct correlations, uniform responses and contradictory frequency answers also raises the possibility of general response tendencies. The sample is too small and the response-quality concerns too substantial to establish the proposed seven-factor structure. A revised instrument should distinguish capability, attitudes, ethical knowledge and actual frequency, use explicit time frames for practice items and undergo cognitive interviews before further administration.

Implications for professional development

Three practical priorities emerge for further needs assessment. First, basic AI literacy can be taught through subject-relevant tasks such as improving a lesson explanation, checking generated information and deciding when a tool is inappropriate. Second, support should address the access conditions reported in the file: mobile-friendly resources, affordable connectivity and shared-device arrangements deserve consideration. Third, academic integrity and responsible handling of student information should accompany practical exercises rather than be confined to general awareness lectures. The combination of conceptual understanding and task-based learning is consistent with Ng et al. (2021) and Nazaretsky et al.

(2022). These proposals follow reported needs and educational principles; their effectiveness must be evaluated prospectively. A future evaluation should measure participation, demonstrated skills and classroom use at more than one time point. It should also document school context, training duration and prior experience, with enough independently verified participants to analyse those factors. The current group comparisons do not justify attributing higher mean scores to training or school ownership.

CONCLUSION

Among the 68 submitted responses, teachers' reported AI readiness and integration were strongly associated, while institutional support was less favorably rated than the other domains. Pedagogical readiness and institutional support remained associated with readiness after adjustment for seven hypothesis tests. The adjusted association between readiness and integration was imprecise, despite a strong bivariate relationship. Connectivity, data costs and demand for basic AI literacy identify useful topics for further needs assessment. The results support further investigation of pedagogical development and institutional conditions, while the sample and measurement limitations preclude generalization to all teachers in Katsina State. Future studies should combine documented recruitment with demonstrated teaching tasks, repeated observations and measures of student learning.

References

- Akgun, S., & Greenhow, C. (2022). Artificial intelligence in education: Addressing ethical challenges in K-12 settings. *AI and Ethics*, 2, 431–440. <https://doi.org/10.1007/s43681-021-00096-7>
- Ayanwale, M. A., Sanusi, I. T., Adelana, O. P., Aruleba, K. D., & Oyelere, S. S. (2022). Teachers' readiness and intention to teach artificial intelligence in schools. *Computers and Education: Artificial Intelligence*, 3, 100099. <https://doi.org/10.1016/j.caeai.2022.100099>
- Celik, I. (2023). Towards Intelligent-TPACK: An empirical study on teachers' professional knowledge to ethically integrate artificial intelligence (AI)-based tools into education. *Computers in Human Behavior*, 138, 107468. <https://doi.org/10.1016/j.chb.2022.107468>
- Celik, I., Dindar, M., Muukkonen, H., & Järvelä, S. (2022). The promises and challenges of artificial intelligence for teachers: A systematic review of research. *TechTrends*, 66, 616–630. <https://doi.org/10.1007/s11528-022-00715-y>
- Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika*, 16(3), 297–334. <https://doi.org/10.1007/BF02310555>
- Dunn, T. J., Baguley, T., & Brunsden, V. (2014). From alpha to omega: A practical solution to the pervasive problem of internal consistency estimation. *British Journal of Psychology*, 105(3), 399–412. <https://doi.org/10.1111/bjop.12046>
- Holm, S. (1979). A simple sequentially rejective multiple test procedure. *Scandinavian Journal of Statistics*, 6(2), 65–70. <https://www.jstor.org/stable/4615733>
- Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., ... Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, 103, 102274. <https://doi.org/10.1016/j.lindif.2023.102274>

- Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (pp. 1–16). Association for Computing Machinery. <https://doi.org/10.1145/3313831.3376727>
- MacKinnon, J. G., & White, H. (1985). Some heteroskedasticity-consistent covariance matrix estimators with improved finite sample properties. *Journal of Econometrics*, 29(3), 305–325. [https://doi.org/10.1016/0304-4076\(85\)90158-7](https://doi.org/10.1016/0304-4076(85)90158-7)
- Mishra, P., & Koehler, M. J. (2006). Technological pedagogical content knowledge: A framework for teacher knowledge. *Teachers College Record*, 108(6), 1017–1054. <https://doi.org/10.1111/j.1467-9620.2006.00684.x>
- Nazaretsky, T., Ariely, M., Cukurova, M., & Alexandron, G. (2022). Teachers’ trust in AI-powered educational technology and a professional development program to improve it. *British Journal of Educational Technology*, 53(4), 914–931. <https://doi.org/10.1111/bjet.13232>
- Ng, D. T. K., Leung, J. K. L., Chu, S. K. W., & Qiao, M. S. (2021). Conceptualizing AI literacy: An exploratory review. *Computers and Education: Artificial Intelligence*, 2, 100041. <https://doi.org/10.1016/j.caeai.2021.100041>
- Nguyen, T. H. C., & Nguyen, T. V. (2025). How teachers’ AI readiness affects AI integration: Insights from modeling analysis. *International Journal of Evaluation and Research in Education*, 14(2), 1496–1505. <https://doi.org/10.11591/ijere.v14i2.28242>
- O’Brien, R. M. (2007). A caution regarding rules of thumb for variance inflation factors. *Quality & Quantity*, 41(5), 673–690. <https://doi.org/10.1007/s11135-006-9018-6>
- Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879–903. <https://doi.org/10.1037/0021-9010.88.5.879>
- Ramazanoglu, M., & Akın, T. (2025). AI readiness scale for teachers: Development and validation. *Education and Information Technologies*, 30, 6869–6897. <https://doi.org/10.1007/s10639-024-13087-y>
- UNESCO. (2024). AI competency framework for teachers. <https://doi.org/10.54675/ZJTE2084>
- Yue, M., Jong, M. S.-Y., & Ng, D. T. K. (2024). Understanding K–12 teachers’ technological pedagogical content knowledge readiness and attitudes toward artificial intelligence education. *Education and Information Technologies*, 29, 19505–19536. <https://doi.org/10.1007/s10639-024-12621-2>
- Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? *International Journal of Educational Technology in Higher Education*, 16, Article 39. <https://doi.org/10.1186/s41239-019-0171-0>



© 2026 by the authors. Submitted for possible open access publication under the terms and conditions of the Creative Commons Attribution (CC BY 4.0) licence (<https://creativecommons.org/licenses/by/4.0/>)