KONTAGORA INTERNATIONAL JOURNAL OF EDUCATIONAL RESEARCH (KIJER)
AND
THE SOCIETY FOR EDUCATORS, UNITED KINGDOM

A Joint Publication of the Kontagora International Journal of Educational Research (KIJER) and The Society for Educators

Vol. [3] No. [3] ([2026]) | ISSN: [3027-0618] | DOI: [https://doi.org/10.5281/zenodo.23888348]

SPECIAL CONFERENCE PUBLICATION | SOCIETY FOR EDUCATORS

PREDICTORS OF TEACHERS' ADOPTION OF ARTIFICIAL INTELLIGENCE FOR EDUCATIONAL ASSESSMENT IN NIGERIAN SECONDARY SCHOOLS

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Received: [17 April 2026] | Accepted: [15 May 2026] | Published: [15 September 2026]

Abstract

This study investigated the association of AI self-efficacy and perceived usefulness with teachers' adoption of AI technologies in educational assessment in Nigerian secondary schools using a correlational survey design. The study targeted senior secondary school teachers in Ibadan Metropolis and Lagos State, and 214 teachers from purposively selected schools participated voluntarily. Data were collected using a self-designed Google Form questionnaire titled AI Self-efficacy & Perceived usefulness in Educators' adoption of Classroom Technology (ASPECT), with reliability a = .88. Four research questions guided the study. Findings revealed that AI self-efficacy had a significant positive association with teachers' adoption of AI in educational assessment (β = .45, p < .001). Similarly, perceived usefulness significantly predicted adoption in educational assessment (β = .20, p = .003), although with a relatively smaller effect size. In contrast, teachers' attitude toward technology adoption showed a very weak and non-significant relationship with adoption of AI for educational assessment (r = .06, p = .397). Furthermore, school support emerged as the strongest predictor of adoption of AI technologies for educational assessment (β = .73, p < .001). At the same time, access to technological resources was not a statistically significant predictor of adoption of AI in educational assessment (β = −.09, p = .073). The study concluded that teachers' confidence in using AI and the presence of strong institutional support systems are important factors associated with AI adoption in educational assessment. In contrast, general attitudes and mere access to technological resources are insufficient to ensure adoption. It was recommended that policymakers and educational stakeholders prioritise capacity-building initiatives, provide sustained institutional support, and develop clear implementation frameworks to enhance the effective integration of AI in educational assessment practices.

Keywords: AI in education, self-efficacy, perceived usefulness, technology adoption, educational assessment

1. Introduction

AI is a collection of computer science methods that enable systems to perform tasks that would typically require human intelligence, such as speech recognition, visual perception, decision-making, and language translation (Géron, 2023). The primary goal of AI technology is to build machines and systems that can replicate or simulate human intelligence, enabling them to analyse data, make well-informed decisions, and progressively refine their performance. Artificial intelligence (AI) is becoming increasingly relevant globally, integrated into various aspects of human life and society, including education (Long & Magerko, 2020). As interest in AI applications for education grows rapidly, so does interest in their use for classroom assessment.

The growing integration of artificial intelligence (AI) into education is transforming traditional teaching and assessment. AI assessments offer greater accuracy, adaptability, and scalability than conventional methods. AI technologies are used in various forms within educational assessments, primarily in three areas: formative assessments, summative assessments, and adaptive testing (Hansen, 2024). A range of digital and AI-enabled assessment tools is increasingly used to support classroom assessment. These include digital assessment platforms that facilitate online testing, formative assessment, and classroom responses, as well as emerging AI-enabled tools that analyse student responses, generate feedback, personalise assessment activities, and support teachers' assessment decisions. AI-enabled assessment systems can provide educators with valuable information about students' performance, learning outcomes, and instructional needs. For instance, AI-powered formative assessment tools can analyse student responses to assignments and provide individualised feedback, helping teachers identify students' strengths and weaknesses (Nazaretsky et al., 2022). Such AI tools can also provide teachers with insights into the effectiveness of their instruction and identify areas where they may need to adjust their teaching strategies in the classroom (Iorkyaan et al., 2023).

Teachers fulfil many roles in classroom assessment, and their role cannot be overstated. Teachers continue to play a critical role in ensuring the appropriate use of AI for measurement and evaluation. However, successful AI adoption does not depend solely on teachers. Institutional policies, technological infrastructure, school leadership, professional development opportunities, ethical considerations, and the availability of appropriate support and resources also shape it. While teachers remain central to implementing and mediating technological innovation within classroom contexts, their adoption decisions occur within this broader institutional and technological environment. It is therefore essential to explore the factors influencing teachers' intentions to use AI for educational assessment and the conditions that facilitate or constrain its adoption.

Factors influencing teachers' intentions to use AI include perceived usefulness and self-efficacy. These intentions, in turn, may shape attitudes towards AI use and ultimately contribute to its adoption. In educational assessment, the interplay between perceived usefulness and self-efficacy is particularly significant. Teachers may recognise the potential value of AI tools yet refrain from using them if they lack confidence in their ability to operate such technologies. Similarly, high self-efficacy alone may not lead to adoption if teachers do not perceive AI as beneficial to their specific assessment needs. In addition to these individual-level factors, institutional conditions such as school support and access to technological resources may also influence teachers' adoption of AI. This suggests that AI adoption in educational assessment is a multidimensional process involving both individual and institutional factors. This study therefore examines the extent to which AI self-efficacy, perceived usefulness, attitudes towards technology integration, school support, and access to technological resources are associated with teachers' adoption of artificial intelligence in educational assessment.

Research questions

The study examined the extent to which individual and institutional factors predict secondary school teachers' adoption of AI technologies in educational assessment. Specifically, the study considered AI self-efficacy, perceived usefulness of AI, attitudes towards technology integration, school support, and access to technology resources. Thus, the study answered the following questions:

1. To what extent does AI self-efficacy influence teachers' willingness to adopt AI technologies in educational assessment in Nigerian secondary schools?
2. How does perceived usefulness of AI affect teachers' adoption of AI technologies in educational assessment?
3. What is the relationship between teachers' attitudes toward technology integration and their willingness to adopt AI in educational assessment?
4. How do school support and access to resources influence teachers' adoption of AI in educational assessment?

2. Literature Review

Perceived Usefulness

Perceived usefulness is one of the independent constructs in the Technology Acceptance Model (TAM). It is defined as the extent to which a person believes that using a system will improve their job performance (Nadia et al., 2025). Perceived usefulness is typically measured using four indicators: improving job performance, increasing productivity, enhancing job effectiveness, and being useful (Puspitasari et al., 2023). As an individual's perceived usefulness of a given technology increases, their intention to adopt it may also rise. In education, teachers are more likely to consider adopting AI-enabled assessment technologies when they perceive them as useful for improving assessment-related tasks and professional practice. Perceived usefulness encompasses the recognised advantages of a technology for an individual and their work (Antika & Grobscbreg, 2022). If a technology offers meaningful benefits and can positively influence users' work, individuals are more likely to intend to use it (Nadia et al., 2025). Within the Technology Acceptance Model, perceived

usefulness is an important predictor of behavioural intention (Davis, 1989). In educational assessment, this suggests that teachers' perceptions of the practical value of AI technologies may influence their willingness to incorporate them into assessment practices. For example, when teachers perceive AI tools as capable of supporting assessment efficiency, feedback, or other assessment-related activities, they may be more inclined to consider their adoption. Technology adoption research has also documented relationships among perceived usefulness, attitude, and behavioural intention. Cheng (2019) showed that perceived usefulness is associated with users' attitudes towards technology, while Sarita and Martutiningrum (2025) identified perceived usefulness as an important factor influencing intention. Although some of these studies were conducted in broader digital-technology contexts, their findings provide a theoretical basis for understanding why perceived usefulness may influence teachers' acceptance of emerging technologies. In the present study, the construct is therefore examined specifically in relation to teachers' adoption of AI technologies for educational assessment.

Self-efficacy

Technology self-efficacy, rooted in Bandura's (1977) social cognitive theory, emerges as a pivotal determinant of how individuals approach and interact with technology. This psychological construct reflects an individual's belief in their competence to use technology effectively. It refers to the individual's self-perception as competent to carry out a specific behaviour regardless of difficulties. Various factors shape an individual's attitudes towards AI and their contribution to well-being. According to Park and Kwon (2023), personality traits, psychological elements such as inner motivation, voluntariness, and performance expectations, and technological factors such as perceived practicality, ease of use, technology complexity, and relative advantage were identified as predictors of individual attitudes towards AI technology. Kaya et al. (2024) and Sindermann et al. (2022) emphasised the intricate connection between AI attitudes and an individual's confidence (self-efficacy) in navigating and mastering these innovations. A person's belief that he or she can complete a particular task reflects their confidence in achieving specific goals.

According to Ayanwale (2023), self-efficacy is defined as an individual's belief that they can master AI concepts and applications. Individuals with high self-efficacy approach AI interactions with confidence, perceiving technology as an opportunity for growth rather than a source of anxiety. The impact of self-efficacy on attitudes toward AI is particularly evident in its influence on openness to learning (Balakrishnan et al., 2022). Those with strong self-efficacy are more inclined to acquire new AI-related skills, fostering a positive attitude rooted in a continuous learning mindset. This receptiveness not only facilitates the adoption of AI technology but also contributes to a sense of accomplishment and well-being as users master new skills (Latikka et al., 2021).

3. Methodology

The study adopted a non-experimental, cross-sectional correlational design. The target population comprised senior secondary school teachers in Lagos State and the Ibadan Metropolis. The study covered 52 selected senior secondary schools, comprising 27 in Lagos State and 25 in the Ibadan Metropolis. In terms of ownership, the selected schools comprised 34 private schools and 18 public schools. In Lagos State, 27 schools were purposively selected across the relevant educational districts. In the Ibadan Metropolis, 25 schools were purposively selected across the five urban Local Government Areas constituting the study area. The selection of schools was intended to provide coverage of the two study locations and to include schools with different ownership characteristics. The study focused on senior secondary school teachers because they are directly involved in classroom teaching and assessment and are therefore relevant to investigating AI adoption in educational assessment. After selecting the schools, individual teachers were invited to participate in the study via an online questionnaire. Links to the Google Form questionnaire were shared through teachers' WhatsApp groups within the selected schools. This approach facilitated access to teachers across the study locations and allowed respondents to complete the questionnaire at their convenience.

Participation was voluntary, and individual teachers decided whether to complete and submit the questionnaire. Thus, although the schools were purposively selected, the individual teacher respondents were self-selected rather than randomly selected. A total of 214 teachers completed and submitted usable questionnaires, forming the final sample. The respondents comprised 151 teachers from private schools (70.6%) and 63 teachers from public schools (29.4%). The study included teachers who were actively teaching at the senior secondary school level; teaching in one of the selected schools in Lagos State or the Ibadan Metropolis; involved in teaching the subject disciplines covered by the study; and who voluntarily consented to participate by completing and submitting the online questionnaire. Teachers who were not actively teaching at the senior secondary school level, did not meet the eligibility requirements, or submitted responses insufficient for the required analysis were excluded from the final dataset.

The AI Self-efficacy & Perceived usefulness in Educators' adoption of Classroom Technology (ASPECT) was used to collect data for this study. The instrument has two main sections, A and B. Section A collected demographic information about the respondents, including age, gender, highest educational qualification, their school type, years of teaching

experience, and the subject taught. Section B consisted of six sub-sections (i) to (vi), which measured adoption of AI in educational assessment. The (i) access and exposure to technology, (ii) AI self-efficacy, (iii) perceived usefulness in AI, (iv) attitude towards AI adoption, (v) AI adoption practices, and (vi) school support and access. These sub-sections, for uniformity, have five items each, which were placed on a 4-point Likert scale of Strongly Agree (4), Agree (3), Disagree (2), and Strongly Disagree (1). The instrument items were developed from concepts and an empirically informed literature review (Bond et al., 2021; Fullan et al., 2024; Karakose & Tülübaş, 2024; Bakhadirov et al., 2024).

To establish content and face validity, two experts in educational evaluation and educational technology independently reviewed the draft instrument. The experts assessed the draft instrument for the adequacy of the items in measuring the intended constructs, their alignment with the study objectives and research questions, and the appropriateness of the measurement approach, its relevance to AI, technology adoption, and the educational technology context, as well as the clarity and suitability of the items for secondary school teachers. Both experts also reviewed the item wording and identified ambiguous, repetitive, or potentially misleading statements. Their comments and recommendations informed revisions to the instrument before the pilot study. Following the expert review, the revised instrument was pilot-tested on a similar sample of secondary school teachers in Ondo State to ensure that it aligned with the study's context and objectives. The Cronbach's alpha technique was used to assess the instrument's reliability, yielding an index of 0.88.

The 40-item survey was distributed online to secondary school teachers in Lagos State and in Ibadan metropolis, Oyo State. The survey remained open for data collection for one month, during which daily reminders were sent across the selected secondary school teachers' platforms to encourage voluntary participation. After the one-month period, the survey was closed, and no further responses were accepted. This approach allowed for a diverse range of responses while ensuring that all teachers had equal opportunity to contribute to the survey. The data collected for this research were analysed using descriptive statistics (frequencies and percentages) and inferential statistics (Pearson product-moment correlation and multiple regression analyses) at a 5% significance level to obtain relevant answers to the formulated research questions

4. Results

The results of the data analysis are presented below. A total of 214 secondary school teachers in Lagos and Ibadan Metropolis participated in this study examining the association of AI self-efficacy and perceived usefulness with teachers' adoption of AI in educational assessment. The demographic analysis revealed several key characteristics of the sample population. The age distribution of participants showed considerable differences across different career stages. The largest proportion comprised teachers aged 31-35 years (n = 75, 35%). Teachers in the youngest age category (20-25 years) constituted 22.4% of the sample (n = 48), while those aged 26-30 years represented 16.8% (n = 36). Mid-career teachers aged 36-40 years comprised 12.1% of the sample (n = 26), and teachers above 40 years accounted for 13.6% (n = 29). The distribution indicates a predominantly younger-to-mid-career teaching population, with nearly three-quarters (74.3%) of participants aged 35 or younger. The sample demonstrated a fairly balanced gender distribution with a slight female majority. Female teachers comprised 55.1% of the sample (n = 118), while male teachers represented 44.9% (n = 96). This gender composition is consistent with the general demographics of the teaching profession in many educational contexts, where female teachers often constitute a slight majority.

The teachers possessed diverse educational backgrounds, with the majority holding bachelor's degrees. Teachers with bachelor's degrees (B.Sc/B.Ed/B.Eng/B.Tech) represented the largest group at 56.1% (n = 120), indicating that most participants had completed undergraduate education in their respective fields. Teachers with master's degrees (M.Sc/M.A/M.Ed) comprised 24.3% of the sample (n = 52), while those with diploma-level qualifications (OND/HND) represented 11.2% (n = 24). Teachers with National Certificate in Education (NCE) accounted for 5.1% (n = 11), and those with doctoral degrees (PhD) represented 3.3% (n = 7). The educational profile suggests a well-qualified teaching workforce, with 83.7% of participants holding at least a bachelor's degree.

The sample was predominantly drawn from private secondary schools, which constituted 70.6% of teachers (n = 151), while teachers from public schools comprised 29.4% (n = 63). Teaching experience was distributed across four distinct categories, showing a relatively even spread among early-career and veteran educators. Teachers with 6-10 years of experience represented the largest single group at 31.8% (n = 68), followed closely by those with above 15 years of experience at 33.6% (n = 72). Early-career teachers with 1-5 years of experience comprised 30.4% of the sample (n = 65). Notably, teachers with 11-15 years of experience represented the smallest group at only 4.2% (n = 9). This suggests a potential gap in mid-career teacher representation that may reflect broader patterns in teacher retention or career transitions. Teachers taught across three main subject areas, with arts-related subjects being most prevalent. Teachers of art-related subjects comprised 57.9% of the sample (n = 124), while Science-related subject teachers represented 30.8% (n = 66). Teachers of commercial-related subjects constituted the smallest group at 11.2% (n = 24). This distribution may

influence the interpretation of AI adoption patterns, as different subject areas may have varying degrees of compatibility with AI technologies in assessment practices.

Table 1: Teachers' Socio-Demographic Variables

Socio-Demographic Variables	n	Percent
Age Group of Teachers		
20–25 years	48	22.4
26–30 years	36	16.8
31–35 years	75	35
36–40 years	26	12.1
Above 40 years	29	13.6
Gender		
Male	96	44.9
Female	118	55.1
Highest Educational Qualification		
NCE	11	5.1
OND/HND	24	11.2
B.Sc/B.Ed/B.Eng/B.Tech	120	56.1
M.Sc/M.A./M.Ed	52	24.3
Ph.D.	7	3.3
School Type		
Public	63	29.4
Private	151	70.6
Years of Teaching Experience		
1–5 years	65	30.4
6–10 years	68	31.8
11–15 years	9	4.2
Above 15 years	72	33.6
Subject Taught in School		
Science-Related	66	30.8
Art-Related	124	57.9
Commercial-Related	24	11.2

Research Question 1: To what extent does AI self-efficacy influence teachers' willingness to adopt AI technologies in educational assessment in Nigerian secondary schools?

Table 2: Linear Regression Analysis Showing the Influence of AI self-efficacy and teachers' willingness to adopt AI in Educational Assessment in Nigerian secondary schools**.**

Variables	**B**	**SE**	**β**	t	p
Constant	0.273	2.281	-	.120	.905
AI Self-Efficacy	0.864	0.119	.446	7.26	< .001

$R^2 = .199$, *Adjusted* $R^2 = .195$, $F(1, 212) = 52.657$, $p < .001$

A simple linear regression was conducted to examine whether AI self-efficacy significantly predicts teachers' willingness to adopt AI technologies in educational assessment. The results indicated that the model was statistically significant, $F(1, 212) = 52.66$, $p < .001$, explaining approximately 20% of the variance in teachers' willingness to adopt AI ($R^2 = .20$, Adjusted $R^2 = .20$). AI self-efficacy was found to be a significant positive predictor of teachers' willingness to adopt AI technologies ($\beta = .45$, $p < .001$). This suggests that higher levels of AI self-efficacy are associated with increased willingness among teachers to adopt AI in educational assessment.

Research question 2: How does the perceived usefulness of AI affect teachers' adoption of AI technologies in educational assessment?

Table 3: Linear Regression Analysis Showing the Effect of Perceived Usefulness of AI on Teachers' Adoption of AI technologies in Educational Assessment in Nigerian Secondary Schools.

Variables	**B**	**SE**	**β**	t	p
Constant	8.280	2.781	-	2.977	.003
Perceived Usefulness of AI	0.415	0.138	.203	3.015	.003

$R^2 = .041$, *Adjusted* $R^2 = .037$, $F(1, 212) = 9.090$, $p = .003$

A simple linear regression analysis examined the effect of perceived usefulness of AI on teachers' adoption of AI technologies in educational assessment. The results showed that the model was statistically significant, $F(1, 212) = 9.09$, $p = .003$, indicating that perceived usefulness of AI significantly predicts teachers' adoption of AI technologies. However, the model explained a relatively small proportion of the variance in adoption ($R^2 = .04$, Adjusted $R^2 = .04$), which indicates a statistically significant but relatively small effect. Perceived usefulness of AI was a significant positive predictor of teachers' adoption ($\beta = .20$, $p = .003$). This implies that as teachers perceive AI technologies as more useful, their likelihood of adopting them increases.

Research Question Three: What is the relationship between teachers' attitudes toward technology integration and their willingness to adopt AI in educational assessment?

Table 4: Correlation Matrix Showing the Relationship Between Teachers' Attitude Towards Technology Integration and Adoption of AI Technologies in Educational Assessment in Nigerian Secondary Schools (N = 214)

Variables	**1**	**2**
1. Adoption of AI Technologies	1	.058
2. Attitude Towards AI Integration	.58	1

Note. r = *Pearson correlation coefficient.* p = *.397 (2-tailed)*

A Pearson product–moment correlation was conducted to examine the relationship between teachers' attitudes toward technology integration and adoption of AI technologies in educational assessment. The results revealed a very weak positive relationship between attitude toward AI integration and adoption of AI technologies, $r(212) = .06$, $p = .397$. This indicates that no statistically significant association was found in the sample. The findings indicate that teachers' attitudes toward AI adoption are not significantly related to their actual adoption of AI technologies in educational assessment. This suggests that positive attitudes alone are insufficient to drive adoption of AI technologies in educational assessment, reinforcing the importance of other factors such as AI self-efficacy and institutional support, which showed stronger effects in this study.

Research Question Four: How do school support and access to resources influence teachers' adoption of AI in educational assessment?

Table 5: Multiple Regression Analysis Showing the Influence of School Support and Access to Technological Resources on Secondary School Teachers' Adoption of AI in Educational Assessment in Nigerian Secondary Schools.

Variables	B	SE	β	t	p	T	VIF
Constant	8.280	2.781	-	2.977	0.003		
School Support Access	0.778	0.055	0.725	14.026	< .001	.902	1.109
Access to Technological Resources	-0.785	0.436	-.093	-1.801	0.073	.902	1.109

$R^2 = .49$, *Adjusted* $R^2 = .49$, $F(2, 211) = 102.12$, $p < .001$

A multiple regression analysis was conducted to examine the influence of school support and access to technological resources on teachers' adoption of AI technologies in educational assessment. The overall regression model was statistically significant, $F(2, 211) = 102.12$, $p < .001$, explaining approximately 49% of the variance in teachers' adoption of AI technologies ($R^2 = .49$, Adjusted $R^2 = .49$). This indicates that the model explained a substantial proportion of the variance in adoption. Although school support access and access to technology resources are conceptually related, the collinearity diagnostics showed high tolerance values (.902) and very low VIF values (1.109) for both predictors. The maximum condition index was also relatively low (7.848). Taken together, these findings suggest that the two predictors are related but are not sufficiently overlapping to constitute a problematic multicollinearity issue. Therefore, both constructs were retained as theoretically distinct predictors in the regression model.

School support was a strong, significant positive predictor of teachers' adoption of AI technologies ($\beta = .73$, $p < .001$). This suggests that increased institutional support, such as training, leadership encouragement, and policy backing, may increase teachers' likelihood of adopting AI in educational assessment. In contrast, access to technological resources was not a statistically significant predictor ($\beta = -.09$, $p = .073$), although it showed a weak negative relationship. This implies that merely providing technological resources may not be sufficient to drive AI adoption without adequate institutional support. Likewise, other factors such as study sample characteristics, measurement suppression, and contextual or confounding factors may have influenced this outcome.

5. Discussion

This study investigated the association of AI self-efficacy and perceived usefulness with Nigerian secondary school teachers' adoption of AI technologies in educational assessment. The findings provide significant insights into the factors that facilitate or hinder AI integration in educational contexts, with important implications for theory, practice, and policy. The demographic profile reveals a sample characterised by relatively young, well-educated teachers predominantly working in private schools with diverse teaching experience levels. The concentration of teachers in the 31-35 age range, the high proportion of bachelor's and master's degree holders, and the predominance of private school teachers may influence the generalisability of findings to the broader population of Nigerian secondary school teachers. The significant positive relationship between AI self-efficacy and adoption practices aligns with Bandura's (1977) self-efficacy theory and extends previous research on technology adoption in educational settings. The practical significance of this finding is substantial, as it indicates that teachers who believe they can effectively use AI technologies are more likely to integrate them into their assessment practices.

This relationship is particularly noteworthy given the complexity of AI applications compared to traditional educational technologies. The finding suggests that professional development programmes should prioritise building teachers' confidence alongside technical skills, as competence beliefs may be as important as actual competence in driving adoption behaviours. This result has important implications for AI implementation strategies. Teachers appear to make rational cost-benefit analyses when considering AI adoption, prioritising technologies that demonstrate clear practical advantages in their assessment work. The finding suggests that successful AI integration initiatives should lead with compelling demonstrations of AI's capacity to improve assessment efficiency, accuracy, or student learning outcomes rather than focusing solely on technological features.

6. Contribution to Literature

This study makes several important theoretical contributions to the technology adoption literature. First, the findings suggest that the Technology Acceptance Model (TAM) may benefit from contextual extensions when applied to AI technologies, as traditional constructs such as attitudes may operate differently in AI-related contexts. While this evidence does not warrant definitive conclusions about modifying TAM, it indicates that additional institutional and contextual factors may be relevant in explaining AI adoption among teachers. Second, the study highlights the important role of organisational support in technology adoption, suggesting that institutional factors may complement individual psychological variables in complex technology integration settings. Third, the findings provide preliminary evidence that AI adoption may follow patterns that differ from those associated with general technology integration, thereby opening avenues for future research to examine whether existing technology acceptance models adequately capture the unique characteristics of AI technologies.

Several limitations should be acknowledged when interpreting these findings. The sample's demographic characteristics, including the predominance of private school teachers (70.6%) and art-related teachers (57.9%), may limit the generalisability of the results to the broader population of Nigerian secondary school teachers. In addition, the cross-sectional design precludes causal inferences regarding the relationships among the study variables. Furthermore, the unexpected negative relationship between attitudes and AI adoption suggests possible measurement issues or context-specific dynamics that warrant further investigation.

Another limitation to acknowledge is the voluntary nature of online participation, which introduces the possibility of self-selection bias. Teachers with greater interest in artificial intelligence, greater exposure to digital technologies, higher confidence in using technology, or more favourable perceptions of AI may have been more likely to participate than those who were less familiar with or interested in AI. In addition, because the questionnaire link was distributed through teachers' WhatsApp groups, participation depended partly on teachers' access to and engagement with these communication channels. Consequently, the characteristics and responses of participating teachers may differ from those of eligible teachers who did not participate.

7. Practical Implications and Recommendations

The findings provide clear guidance for schools seeking to implement AI technologies in assessment practices. Institutions should prioritise developing comprehensive support systems that go beyond basic technology provision. This includes establishing dedicated AI support teams, creating communities of practice for teachers experimenting with AI, and providing ongoing technical assistance. The research suggests that schools should invest in AI-specific infrastructure and training rather than assuming that general technology competence will transfer to AI applications. The significance of AI self-efficacy and perceived usefulness suggests that professional development programmes should adopt hands-on, practical approaches that enable teachers to experience AI's benefits firsthand. Training should focus on building confidence through successful implementation experiences rather than theoretical knowledge alone. Programmes should clearly connect AI capabilities to improved assessment outcomes to increase perceived usefulness. The results suggest that AI technology providers should prioritise ease of use and clear demonstration of practical benefits when marketing to educational institutions. The importance of institutional support indicates that vendors should offer comprehensive implementation assistance, including training, technical support, and ongoing consultation services.

Importantly, AI adoption in educational assessment should be guided by principles of responsible and ethical AI use. Schools should ensure that AI-supported assessment processes maintain validity, so that AI-generated items, feedback, or scoring accurately reflect the intended learning outcomes and do not introduce systematic measurement errors. Fairness and equity should also be addressed by monitoring AI systems for potential biases that could disadvantage students based on their backgrounds, abilities, language, or other characteristics. Because assessment data may contain sensitive student information, institutions should establish appropriate privacy and data protection safeguards, including clear rules for data

collection, storage, access, and use. Transparency is equally important; teachers and other stakeholders should understand, at an appropriate level, how AI systems generate recommendations, scores, or assessment content, and what their limitations are. Finally, AI should complement, not replace, teacher professional judgement and oversight. Teachers should retain responsibility for reviewing AI-generated assessment materials, verifying automated scores or feedback where appropriate, identifying errors or biases, and making final instructional and assessment decisions. Consequently, institutions adopting AI for assessment should develop clear governance guidelines that integrate validity, fairness, privacy, transparency, and human oversight into the implementation process. This would support not only effective AI adoption but also responsible, trustworthy, and educationally appropriate use of AI technologies.

DECLARATIONS

Funding

The author received no specific funding for this work.

Conflict of Interest

The author declare no conflict of interest.

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Isieg, C. O., & Adeniran, F. V. (2026). Predictors of teachers' adoption of artificial intelligence for educational assessment in Nigerian secondary schools. *Kontagora International Journal of Educational Research, 7*(3), 1–10.

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Isieg, Christopher Orok and Adeniran, Fortunate Veronica. "Predictors of Teachers' Adoption of Artificial Intelligence for Educational Assessment in Nigerian Secondary Schools." *Kontagora International Journal of Educational Research* 7, no. 3 (2026): 1–10.