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Predictive Validation on Utilization of AI-Awareness Scale in Educational Assessment (AI-ASiEA) by lecturers: Using a Classical Modelling Approach

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Abstract

This study investigated the predictive validation on utilization of AI-Awareness Scale in Educational Assessment (AI-ASiEA) among lecturers in South-Eastern Nigeria using classical modelling. Three research questions and two null hypotheses guided the study's investigation of the internal consistency of the scale, differences in the perceived AI-supported learning and perceived learning outcomes, and the predictive relationship between AI awareness and these outcomes. A correlational research design was adopted, with a population of lecturers across five states and a sample of 300 selected through convenience sampling. Data were analyzed using Cronbach's alpha, mean, standard deviation, Pearson correlation, and multiple regression. Findings revealed that the AI-ASiEA demonstrated acceptable internal consistency and that lecturers showed moderate awareness of AI assessment tools such as Gradescope and Turnitin. The results further revealed a strong positive predictive relationship between AI awareness in educational assessment and perceived AI-supported learning, and a moderate significant relationship with perceived learning outcomes. This led to the rejection of both null hypotheses. The study concludes that AI awareness is a significant predictor of lecturers' perceptions of AI-driven learning effectiveness. Among all recommendations, the universities should implement structured professional development programs to deepen lecturers' AI literacy in assessment practices.

Keywords: Artificial Intelligence Awareness, AI-Supported Learning, Classical Test Theory, Educational Assessment, Predictive Validity

Introduction

Artificial Intelligence (AI) is increasingly transforming educational assessment practices globally, from automated grading systems and adaptive testing platforms to AI-driven analytics that predict student performance (Mahamuni, & Tonpe, 2024). Its integration into educational assessment has proliferated significantly in recent years. These developments present both opportunities and challenges for higher education institutions, particularly in global south context where there is disparity in technological adoption and digital literacy. Understanding lecturers' awareness of AI in assessment is therefore essential for ensuring effective implementation, ethical usage, and meaningful engagement (Perkins, Furze, Roe, & MacVaugh, 2024). In educational assessment, Akash in Onyeka and Dara (2024) stated that some of the tools needed to navigate the effective use of AI are not limited to the following; Gradescope, Turnitin, Proctorio, Aleks, Coursera, ExamSoft, Knewton, Questionmark, Thinker math, Tab hat, Codio etc.

Lecturers' AI awareness in educational assessment therefore refers to their exposure, knowledge, perceptions, and understanding of how artificial intelligence technologies are used in testing, feedback systems, and academic decision-making processes. Anyiam et al., (2024) revealed that students and lecturers AI awareness involve being familiar with the basic concepts of artificial intelligence, exposure, and formal training in the use of AI tools and technologies, for academic tasks such as conducting research projects and automated grading of students learning outcomes. Persons who possess higher awareness of AI-related assessment systems are more likely to engage efficiently with digital assessment tools (Granström, & Oppi, 2025), express reduced anxiety toward the use of the automated assessment (Biju, et al., 2024), and adapt more effectively to technology-sustained teaching and learning environments (Opre, et al., 2024). Conversely, limited awareness could lead to anxiety, mistrust, resistance, or misuse of AI-enhanced assessment tools.

Therefore, it becomes imperative to ensure that measurement instruments designed to assess AI awareness in education should demonstrate good and strong psychometric properties. Beyond reliability and construct validity of an assessment, predictive validity is specifically essential because it establishes whether a scale can significantly predict relevant academic or behavioural outcomes such as AI-supported learning, learning outcome, perceived learning outcome, AI-related readiness and anxiety. Predictive validation is essential in establishing the practical usefulness of a scale by demonstrating its ability to forecast related outcomes (Sliva, Reilly, Casstevens, & Chamberlain, 2015). Several researches have examined attitudes toward AI, digital literacy, and technology acceptance in education (Kabakus, Bahcekapili, & Ayaz, 2025, Park, & Woo, 2022), however, few of these studies have focused on AI for assessment awareness contextually. More so, few studies have examined predictive validation of AI-related scales using classical modelling approaches. Classical modelling under classical test theory remains widely used because it is easy to access, simple to interpret and apply in educational measurement. This is especially employed in contexts where large-scale item response modelling may not be feasible due to lack of expertise and technical supports.

Against these backdrops, the researchers conducted the predictive validation on utilization of the Artificial Intelligence awareness in educational assessment using classical modelling approach. The study targets to establish whether AI-awareness scale in educational assessment scores significantly predict relevant behavioural and academic outcomes. It is pertinent to note that this study contributes to literature in educational measurement and assessment by providing empirical evidence, which will serve as a diagnostic and research instrument. It offers to policymakers, educators, researchers and institutions powerful tool to gain insight that will inform the integration of AI responsibly into educational assessment systems, particularly in Nigeria's higher education contexts where technological transformation is rapidly evolving, though unevenly.

Research Questions

1. What is the internal consistency of the AI-awareness scale in educational assessment using classical modelling methods?

2. What is the difference in lecturers mean response scores on the lecturers perceived AI-supported learning (PAI-L), and perceived learning outcome (PLO)?

3. What is the relationship between lecturers scores on AI-awareness scale in educational assessment and their perceived AI-supported learning scores, as well as their perceived learning outcome scores?

Hypotheses

The following null hypotheses will guide the study:

1. Lecturers scores on AI-awareness scale in educational assessment do not significantly predict their perception of AI-supported learning scores

2. There is no significant relationship between lecturers scores on AI-awareness scale in educational assessment and their perceived learning outcome scores

Review of Literature

AI in Educational Assessment

Globally, the application of AI in educational assessment has increased over the years (Saputra et al., 2024), and its efficacy cannot be overemphasised. This technology supports automated essay scoring, intelligent tutoring systems, adaptive testing, plagiarism detection, and predictive learning analytics, which enhance efficiency, provide real-time feedback, and enable personalized learning pathways (Singh, 2025). Although, some issues have been raised regarding algorithmic bias, transparency, data privacy, and students' trust in AI-enhanced assessment systems. However, evidence from researches have emphasized that awareness of AI technologies influence acceptance and effective utilization. Empirically, studies on technology acceptance models consistently demonstrate that awareness significantly affect adoption behaviours (Abubakar, & Ahmad, 2013). So, in educational assessment contexts, awareness of AI processes can reduce anxiety, as well as foster confidence in automated assessment systems.

Concept of AI Awareness

AI awareness includes the cognitive, affective, and behavioural aspects which reflects individuals' level of exposure, understanding and practices related to its use. Cognitively, AI awareness involves personal knowledge about AI technologies and their applications, and affectively, AI awareness reflects personal attitudes, perceptions, and emotional responses toward AI use (Baltezarević, & Battista, 2025; Belli, & Leon, 2024). On the AI behavioural aspect, it relates to engagement with AI tools and willingness to interact with AI-enhanced systems (Wang, Yang, & Sengul, 2026). So, AI awareness reflects the general disposition of individual on AI cognitively, affectively and behaviourally. Psychometricians have structured measurement instruments assessing AI awareness among students and teachers which facilitate curriculum planning, digital skills development, and ethical AI implementation strategies. These instruments have focused broadly on digital technology and literacy (Lasbrey et al., 2024) or AI knowledge and use for teaching and learning (Anyiam et al., 2024), rather than specifically addressing AI in assessment contexts.

Predictive Validity in Scale Development

Predictive validity explains the extent to which a measure accurately forecasts future or related outcomes. In educational research, measurement and evaluation, predictive validation often involves the correlational or regression analyses that links a scale score to academic performance, behavioural scores, or psychological constructs (Nworgu, 2015). A high predictive validity index shows that a scale /instrument is practically relevant, thereby enhances confidence in practical uses (Arum, Khumaedi, & Susilaningsih, 2022). Studies revealed that individual awareness of technological tool predicts their improved learning outcome, greater acceptance of digital tools, and anxiety (Almaiah, et al., 2022, Lazar, Panisoara, & Panisoara, 2020). These studies underscore the need for the predictive validation of AI awareness instruments.

Classical Modelling Approach in Psychometrics

Classical test theory (CTT) is one of the frameworks in educational measurement (Frey, 2017). It is the foundational measurement framework, and emphasizes the observed scores, reliability estimation such as Cronbach's alpha, and correlational validation procedures. The approaches of this framework are widely accessible and does not require large sample sizes compared to modern item response theory framework. Under CTT, predictive validity involves the employment of regression modelling, correlation analysis, and analysis of variance techniques (Orban, 2026). These methods enable researchers to evaluate whether scale scores significantly predict criterion variables. Whereas item response theory provides advanced modelling capabilities (Chen, Li, Liu, & Ying, Z. 2025), CTT approaches remain relevant, particularly in early instrument validation stages or contexts with limited technical resources.

Studies have suggested that digital tool integration in education enhances digital assessment techniques which impacts students' engagement and learning outcomes (Anyiam et al., 2024). Again, studies have revealed positive relationships between AI awareness and technology acceptance, digital competence, and academic engagement, however, low awareness levels have been associated with AI-oriented assessments (Moguš, 2025). In furtherance, study on predictive validation of AI awareness scales within assessment contexts remains modest. This gap stresses the pertinence for systematic validation efforts to ensure reliable measurement of students' AI awareness and its implications for educational outcomes.

Methods

Design, Population and Sampling

This study employed a correlation research design to examine the predictive validation on utilisation of the AI-Awareness Scale in Educational Assessment (AI-ASiEA) using a classical modelling approach. The study targeted a population of lecturers in South Eastern Nigeria. Convenience sampling technique was used to select 60 participants across academic disciplines (Arts; 10, 16.67%; Sciences; 26, 43.33%; and Social Sciences; 24, 40%), Gender (Female; 38, 63.33%; Male; 22, 36.67%)and years teaching of experience (5-10yrs; 11, 18.33%; 11-15yrs; 16, 26.67%; 16-20yrs; 13, 21.67%; 21-above; 20, 33.33%) in one university in each of the five states. Therefore, the estimated sample size of 300 lecturers was drawn for the five states that constitute the South-East of Nigeria. This is adequate for classical psychometric analyses and regression modelling (Tabachnick, & Fidell, 2014). However, participants were selected based on their prior experience with AI technologies such as ChatGPT, and Perplexity in their teaching activities. The participant provided their demographic information which include years of experience and gender.

Instrumentation

The primary instrument for the study was the adapted AI awareness for assessment scale (**AI-ASiEA**) (Onyeka & Dara, 2024) which was used to generate the predictor scores. The scale included multiple Likert-type items assessing awareness of the use of the AI-based assessment practices. The criterion measures included students' perception of AI - supported learning, and perceived learning outcomes due to the use of AI. In Jeilani & Abubakar, (2025), students' perception of AI - supported learning adapted by Khan et al. (2019), and perceived learning outcomes (OECD, 2013) were extracted.

Content validity evidence was ensured through experts' review. In the preliminary phase, the adapted **AI-ASiEA** Likert scale items with response options of Very Much Aware (VMA), Aware (A), Not Aware (NA), Very Much Not Aware (VMNA), were pilot tested for reliability, which involved 30 respondents who are not part of the study. This procedure ensured the items were contextually relevant and interpreted consistently by participants. The internal consistency of the adapted **AI-ASiEA** was established using test re-test approach, and a reliability index of 0.76 was obtained on Pearson correlation. This ensured the reliability of the scale. The extracted criterion measures demonstrated a reliability index of $\alpha=0.72$ and $\alpha=0.75$ for perception of AI - supported learning, and perceived learning outcomes respectively when analysed.

Data were collected through structured questionnaire on SurveyMonkey tool, and was distributed electronically through WhatsApp groups. Data collection spanned a period of three weeks. Ethical issues were addressed by obtaining permission from Deans and Heads of Departments (HODs) to ensure ethical compliance. Participation was voluntary, and informed consent was obtained from all participants. Data confidentiality, anonymity, and secure storage was ensured. Participants retained the right to withdraw at any stage through out the study without any penalty.

Data Analysis

Data collected were analysed using, frequency distribution and percentage to explain the demography of the participants, while mean, and standard deviation, Pearson product moment correlation coefficients (PPMCC), and multiple regression were used to determine whether lecturers scores on AI awareness for assessment scale significantly predict AI - supported learning, and perceived learning outcomes **scores respectively.** Predictive validity was established when AI awareness for assessment scores significantly predicts the relevant criterion at acceptable statistical significance levels.

Result

Profile of the Respondents

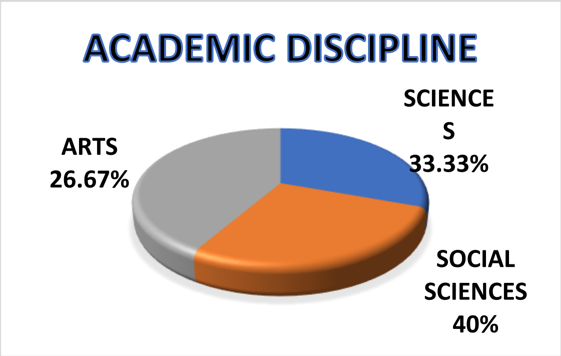

Fig.1

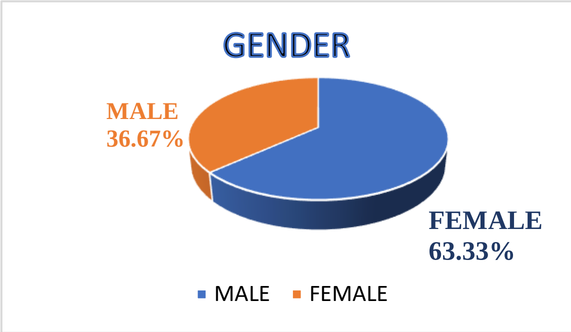

Fig.2

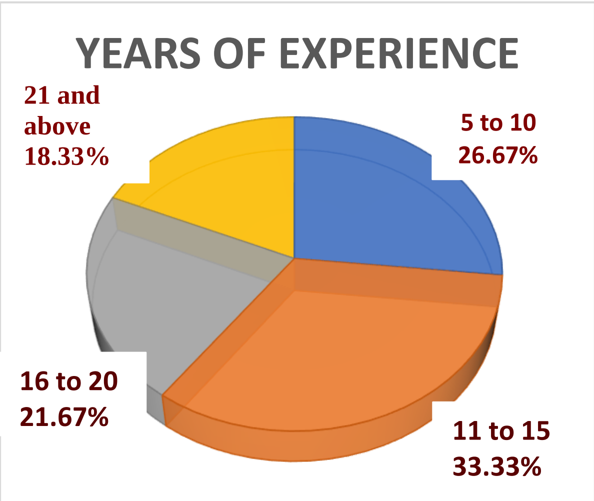

Fig. 3

The figures above revealed the demographic profile of the participants. Fig. 1, revealed a notable academic area of discipline which include Arts (N=80, **26.67%),** Sciences (N=100, **33.33%),** and Social Sciences (N=120, 40%). The data revealed that much of the participants include lecturers in social sciences, followed by sciences and arts. A slightly female-dominated sample, with 63.33% of participants being female (190 participants) and **36.67%** male (110 participants) in Fig. 2. In terms of years of teaching experience in Fig. 3, the majority of participants (100, **33.33%)** fall within the 11–15 years of teaching experience, followed by N=80, **26.67%** in the 5–10 years of teaching experience, N=65, **21.67%** in the 16-20 years of teaching experience, and N=55, **18.33%** in the 21 years and above. These results indicate that the participants are predominantly the younger lecturers who are engaged and acquainted with digital tools. Regarding the years of experience, younger lecturers are most represented, comprising 60% of the sample combined. This distribution highlights the level of lecturers' awareness of AI in educational assessment within the sample. This again reflects that more of social sciences lecturers, and female lecturers in higher institutions in south eastern Nigeria who are younger in the profession are aware embracing the novel AI technology especially in educational assessment.

What is the internal consistency of the AI-awareness scale in educational assessment using classical modelling methods?

Table 1: Estimated Item-Total Statistics for AI-Awareness Scale in Educational Assessment (AI-ASiEA) Using Cronbach's Alpha

S/N	Item Description	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted	X
1.	I am aware that Proctorio uses AI to monitor students by detecting eye movement, unusual sounds, and authenticating student identity during online assessment	.291	.755	2.90
2.	I am aware that ALEKS uses AI to assess students' knowledge levels by adapting questions based on students' learning outcome, and providing automated feedback to students	.215	.764	3.48
3.	I am aware that ExamSoft restricts internet access during online assessment, and provides targeted feedback to enhance learning outcome	.581	.718	3.32
4.	I am aware that Gradescope supports AI-assisted grading of exams and assignments, allows, rubric-based grading for consistency, and group similar student responses automatically	.357	.748	3.49
5.	I am aware that Turnitin uses AI algorithms to detect plagiarism in students' work, as well as AI-generated text in student assessment related submissions	.031	.783	3.55
6.	I am aware that Knewton Alta personalizes assessment content using AI to track students' learning progress in real time	.398	.743	3.48
7.	I am aware that Metacog tracks students' learning behaviours to support assessment, and to provides data to inform instructional decisions	.512	.728	3.36
8.	I am aware that Questionmark provides assessment solutions that incorporate AI for item banking, test delivery and result analysis	.544	.722	3.33
9.	I am aware that Top Hat supports interactive assessments during lectures by providing instant feedback on student responses	.548	.722	3.39
10.	I am aware that Thinkster Math uses AI to analyze students' problem-solving steps, and provides individualized feedback based on performance	.528	.726	3.44
11.	I am aware that Coursera uses AI to grade certain assignments automatically by providing data			

analytics on learner progress	.450	.737	3.43
N=300			**ΣX=3.38**
Overall Cronbach's (α) = .76			

Table 1 revealed the internal consistency of the AI-Awareness Scale in Educational Assessment (AI-ASiEA) which was evaluated using Cronbach's Alpha within the framework of classical test theory. The overall Cronbach's alpha coefficient of .76 indicates an acceptable level of reliability. This suggests that the AI-ASiEA has shown satisfactory internal consistency for research purposes. The coefficient implies that the items collectively measure the underlying construct of AI awareness in educational assessment with reasonable coherence. The corrected item–total correlations range from .031 to .581. This reflects the differences in how strongly each item aligns with the overall scale. Most of the items show moderate positive correlations above .30, indicating that they contribute meaningfully to the measurement of the construct. The Cronbach's alpha if item deleted values range from .718 to .783. Again, an average mean score of 3.38 (N = 300) revealed that lecturers in South-eastern Nigeria generally demonstrated a moderate level of awareness of AI in educational assessment. This shows that they are aware of the use of AI in educational assessment.

The difference in lecturers mean response scores on the lecturers perceived AI-supported learning (PAI-L), and perceived learning outcome (PLO)

Table 2a. Mean Response of Lecturers Perceived AI-Supported Learning (SPA)

S/N	Item Statements	X	SD
1.	AI technology improves students' overall learning experience	2.90	.50
2.	AI-supported learning tools are easy for students to use	3.48	.66
3.	AI technology enables the delivery of personalized learning to students	3.28	.59
4.	AI-supported learning contributes to improved student academic performance	3.49	.67
5.	AI tools provide students with timely feedback on their learning activities	3.54	.53
6.	AI-supported learning increases student engagement in academic tasks	3.46	.68
7.	AI-supported learning enhances students' motivation to learn	3.34	.78
8.	AI technology serves as an effective instructional support tool for lecturers	3.33	.82
	Average Mean Total	**3.35**	**.34**

N=300

Table 2a revealed that lecturers have a positive perception of AI-supported learning [SPA]. Their response has an overall average mean score of 3.35 from 300 respondents. The item with the highest mean pointed out that AI tools provide timely feedback to students [X = 3.54], followed closely by their contribution to improved academic performance [X = 3.49] and ease of use [X = 3.48]. Lecturers also agreed that AI enhances student engagement [X = 3.46], motivation [X = 3.34], personalized learning (X = 3.28), and serves as an effective instructional support tool [X = 3.33]. However, with slightly lower mean, the perception that AI improves students' overall learning experience [X = 2.90] still reflects a generally favorable view of AI integration in education.

Table 2b. Mean Response of Lecturers Perceived Learning outcome (LO)

S/N	Item Statements	X	SD
1.	AI-based learning tools have the capacity to improve students' academic performance	3.43	.71
2.	I feel that AI-supported learning helps students retain information better	3.41	.69
3.	I feel students' complete assignments and tasks more efficiently with AI assistance (ChatGPT)	3.30	.81
4.	AI tools have enhanced students critical thinking and problem-solving skills recently	3.42	.71
5.	Students overall learning experience is enriched		

with the use of AI technology	3.40	.34	
Average Mean Total		**3.39**	**.34**

N=300

Table 2b revealed that lecturers in the south-eastern Nigeria perceive AI-based learning tools as positively influencing students' learning outcomes, with an average mean score of 3.39 across 300 respondents. The item with the highest mean score [X = 3.43] reveals that lecturers agree that AI tools have the capacity to improve students' academic performance. Again, strong agreement is reflected in the perceptions that AI enhances critical thinking and problem-solving skills [X = 3.42], also helps students to retain information better [X = 3.41]. Lecturers also agree that AI improves the students learning experience [X= 3.40] and supports more efficient completion of assignments through tools such as ChatGPT [X = 3.30]. Finally, the consistently high mean scores above 3.0 indicates a moderate and positive perception of lecturers on the contribution of AI technologies to students' learning outcomes.

The relationship between lecturers scores on AI-awareness scale in educational assessment and their perceived AI-supported learning scores, as well as their perceived learning outcome scores

Table 3: Model summary of the relationship between lecturers scores on AI-awareness scale in educational assessment and their perceived AI-supported learning scores, as well as their perceived learning outcome scores

Model	**n**	**R**	**R^2**	**Adjusted R^2**
1	300	0.97	0.932	0.931
2	300	0.61	0.371	0.369

Table 3 revealed the model summary of the relationship between perception of lecturers on the AI-awareness scale in educational assessment and their perceived AI-supported learning, as well as their perceived AI- supported learning outcome. In Model 1, with a sample size of 300 lecturers across five universities in the five states in the eastern Nigeria, the correlation coefficient (R) was 0.97 revealed a very strong positive relationship between AI-awareness and perceived AI-supported learning. The coefficient of determination (R^2) for Model 1 was 0.932, suggesting that 93.2% of the variance in perceived AI-supported learning scores was explained by lecturers' AI-awareness for assessment scores. The adjusted R^2 value of 0.931 further confirms the robustness and stability of this model. In Model 2, also based on the sample size of 300 lecturers, the correlation coefficient (R) was 0.61, indicating a moderate positive relationship between AI-awareness and perceived learning outcome scores. The R^2 value of 0.371 implies that 37.1% of the variance in perceived learning outcome scores was accounted for by lecturers' AI-awareness for assessment scores. The adjusted R^2 of 0.369 indicates that Model 2 provides a reasonably good fit to the data.

Lecturers' scores on AI-awareness scale in educational assessment do not significantly predict their perception of AI-supported learning scores

Table 4: Regression ANOVA table showing that the lecturers scores on AI-awareness scale in educational assessment do not significantly predict their perception of AI-supported learning scores

Model	**Sum of Square**	***df***	**Mean Square**	**F**	**Sig.**
Regression	**1984.889**	**1**	**1984.889**	**4066.400.000**	
Residual	**145.441**	**298**	**.488**		
Total	**2130.330**	**299**			

α= 0.05

Table 4 shows a regression ANOVA which revealed that lecturers' scores on the AI-awareness scale significantly predicted their perception of AI-supported learning scores, $F(1, 298) = 4066.40$, $p < .05$. The regression sum of squares (1984.889) was substantially larger than the residual sum of squares (145.441). This indicates that a large proportion of the variance in perception scores was explained by

AI-awareness. With a mean square of 1984.889 for regression and 0.488 for residual, the model demonstrates a very strong predictive effect. Since the significance value is 0.000, which is less than the alpha level of 0.05. The null hypothesis stating that AI-awareness was rejected, revealing that lecturers AI-awareness in educational assessment significantly predict their perception of AI-supported learning of students.

There is no significant relationship between lecturers scores on AI-awareness scale in educational assessment and their perceived learning outcome scores

Table 5: Regression ANOVA table showing no significant relationship between lecturers scores on AI-awareness scale in educational assessment and their perceived learning outcome scores

Model	Sum of Square	*df*	Mean Square	F	Sig.
Regression	**1546.318**	**1**	**1546.318**	**175.92**	**0.000**
Residual	**2619.349**	**298**	**8.79**		
Total	**4165.667**	**299**			

α= 0.05

Table 5 reveals a regression ANOVA showing that lecturers' scores on the AI-awareness scale significantly predicted their perceived learning outcome scores. The regression sum of squares was 1546.318 with 1 degree of freedom, producing a mean square of 1546.318 and an F-value of 175.92. The result was statistically significant at $\alpha = 0.05$, and the p-value (0.000) less than 0.05. Therefore, the null hypothesis stating that there is no significant relationship between lecturers' AI-awareness scores in educational assessment and their perceived learning outcome scores is rejected. Therefore, lecturers' AI-awareness in educational assessment significantly predicted their perception on learning outcome of students.

Discussion

The findings of this study align with earlier research results that AI integration in educational assessment is gaining attention globally, and it is highly embraced by both educators and (Saputra et al., 2024; Singh, 2025). The acceptable internal consistency of the AI-Awareness Scale in Educational Assessment (AI-ASiEA) presented by this study aligns with the classical test theory assumptions proposed by Frey (2017), which emphasize that reliability estimation through internal consistency coefficients during early instrument validation is appropriate. The reliability of the study remained stable, and this supports Orban's (2026) assertion that CTT-based procedures remain practical and sufficient in applied educational research contexts. The lecturers' moderate level of AI-awareness suggests that they demonstrate appreciable knowledge and understanding of AI-oriented assessment tools. This supports findings by Anyiam et al. (2024) that digital assessment exposure can enhance AI-related competencies among lecturers. Furthermore, the strong relationship between AI awareness and perceived AI-supported learning aligns with the Technology Acceptance Model evidence reported by Abubakar and Ahmad (2013), which posits that awareness significantly influences technology adoption behaviours. It is also in alignment with Almaiah et al. (2022), who found that awareness of technological systems predicts positive perceptions and usage intentions. The significant predictive effect observed in the regression analysis supports Nworgu (2015) that predictive validity is established when scale scores significantly forecast related constructs. Furthermore, the moderate but significant relationship between AI-awareness in educational assessment and perceived learning outcomes aligns with Lazar, Panisoara, and Panisoara (2020), who reported that technological awareness contributes meaningfully to perceived academic success. However, while the high explanatory power in Model 1 suggests a strong perceptual linkage, it contrasts slightly with Moguš (2025), who reported generally low AI-oriented assessment awareness levels in some contexts. Finally, the findings validate the predictive relevance of AI awareness in educational assessment and confirm the necessity for systematic scale validation efforts, as emphasized by Arum, Khumaedi, and Susilaningsih (2022).

Conclusion

The study concludes that lecturers in South-eastern Nigeria, particularly those who are younger and in the social sciences, show clear awareness of artificial intelligence usage in educational assessment. Again, the AI-awareness scale used in the study is internally consistent and suitable for research purposes, in line with the reliability principles advanced by Lee Cronbach. The results further show that lecturers hold strong perceptions of AI-supported learning and believe that it can enhance students' academic performance, engagement, feedback processes, and overall learning outcomes. However, the strength of the relationship suggests the possibility of conceptual overlap between awareness and perception, which calls for cautious interpretation and further validation in future studies.

Recommendations

The following recommendations were made based on the findings;

1. Universities should implement structured professional development programs to deepen lecturers' AI literacy in assessment practices.
2. They should integrate AI pedagogy modules into institutional capacity-building frameworks.
3. Government should establish policy guidelines and monitoring systems to ensure effective and ethical integration of AI tools in teaching and assessment.

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