Journal of Innovation in Educational Assessment
Vol. 8 No. 1, May (2026)

DOI: https://doi.org/10.66545/xnaqjf76

ISSN: 2705-3830 (Print)
ISSN: 2705-3857 (Online)

Received: 17th December 2025
Accepted: 24th April 2026

journal.iaiiea.org

AI-SUPPORTED DIFFERENTIATED ASSESSMENT AND STUDENTS' ACADEMIC PERFORMANCE, ENGAGEMENT, AND PERCEPTION OF INCLUSION IN SENIOR SECONDARY SCHOOLS IN AKWA IBOM STATE, NIGERIA

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Abstract

This study examined the effect of AI-supported differentiated assessment on academic performance, students' engagement, and perception of inclusion in mixed-ability secondary school classrooms in Akwa Ibom State, Nigeria. Using a quasi-experimental (pretest-posttest non-equivalent control group) design, 180 Senior Secondary II (SS2) students were selected from four schools (two experimental and two control groups). The experimental group ($n = 85$) experienced AI-enabled differentiated assessments (adaptive quizzes, individualised feedback dashboards, and differentiated tasks), while the control group ($n = 95$) was assessed using traditional teacher-designed uniform assessments. Data were collected using mathematics achievement tests, a validated engagement questionnaire, and an inclusion perception scale. Using ANCOVA to adjust for pretest scores, the study found that students in the experimental group significantly outperformed those in the control group on posttest achievement ($F(1, 176) = 25.43$, $p < .001$, $\eta^2 = .13$), reported higher engagement ($F(1, 176) = 22.17$, $p < .001$, $\eta^2 = .11$), and had stronger feelings of inclusion ($F(1, 176) = 18.90$, $p < .001$, $\eta^2 = .10$). The results suggest that AI-supported differentiated assessment is an effective strategy for promoting academic achievement, enhancing engagement, and fostering inclusive attitudes among learners. Implications for teacher training, resource provision, and policy in the AI era are discussed.

Keywords: Differentiated assessment, academic performance, engagement, perception, inclusion

To cite this article:

Thompson, M. E., & Uko, M. P. (2026). AI-Supported Differentiated Assessment and Students' Academic Performance,Engagement, and Perception of Inclusion in Senior Secondary Schools in Akwa Ibom State. *Journal of Innovation in Educational Assessment, 8*(1), 71-85. https://doi.org/10.66545/xnaqjf76

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Introduction

Assessment is a central component of education because it does not only measure students' knowledge and skills but also informs teaching, supports learning, and promotes accountability. Traditionally, assessment has been standardised, focusing on uniform tests that assume homogeneity among learners. However, classrooms are diverse, comprising students with different abilities, backgrounds, and learning needs. In such contexts, uniform assessment practices may disadvantage some learners, leading to exclusion and achievement gaps (Black & Wiliam, 2018). Differentiated assessment, rooted in the philosophy of inclusive education, is designed to meet the varied learning needs of students by adjusting assessment methods, content, and feedback according to learners' profiles (Tomlinson, 2017). It ensures that all students, regardless of ability or background, are provided with equitable opportunities to demonstrate their learning. Recent research in Nigeria emphasises the role of differentiated and structured assessment in improving performance and engagement in STEM subjects (Uko & Uko, 2019; Uko, 2024).

The advancement of artificial intelligence (AI) has opened new frontiers in assessment. AI-powered systems can analyse learners' performance data, provide adaptive testing, generate real-time feedback, and personalise learning trajectories (Luckin et al., 2022). These capabilities align closely with the goals of differentiated assessment, making AI a powerful tool for supporting inclusion in education. Studies in adaptive testing (Uko, Eluwa, & Uko, 2024) highlight the potential of AI-driven tools to improve learner achievement by matching task difficulty to a student's ability. Globally, research shows that AI applications such as natural language processing, intelligent tutoring systems, and machine learning analytics enhance formative and summative assessments by making them more flexible, learner-centred, and equitable (Holmes et al., 2021; Popenici & Kerr, 2017). Despite these opportunities, gaps remain in empirical studies, especially within the African context, on how AI-supported differentiated assessment affects multiple learner outcomes beyond achievement. While several studies in Nigeria have explored digital formative assessments and adaptive testing (Uko, 2024; Uko et al., 2024), few have simultaneously considered performance, engagement, and students' sense of inclusion. This study addresses that gap by empirically examining the effectiveness of AI-supported differentiated assessment on students' academic performance, engagement, and inclusion in secondary school classrooms in Akwa Ibom State.

Differentiated Assessment and Inclusive Practices: Differentiated assessment involves tailoring assessment approaches to accommodate learners' readiness, interests, and learning preferences (Tomlinson, 2017). It is central to inclusive education and seeks to ensure that diverse learners, including those with disabilities, language barriers, or varied abilities, are not excluded from demonstrating competence (Ainscow, 2020). Black and William (2018) argue that formative assessment practices are most effective when responsive to learners' needs, while Uko and Uko (2019) found that structured instructional assessments led to significant achievement gains in STEM subjects among secondary school students in Nigeria.

Artificial Intelligence in Education and Assessment: AI has been integrated into education through adaptive testing, predictive analytics, and intelligent tutoring systems. Adaptive testing dynamically adjusts the difficulty of questions to match learners' ability levels, reducing frustration for weaker students and challenge deprivation for stronger students (OECD, 2021). Uko, Eluwa, and Uko (2024) empirically demonstrated that Computerized Adaptive Testing improved secondary school learners' achievement in mathematics and science in Akwa Ibom State. Similarly, AI-powered formative assessments have been shown to provide timely feedback, improve student engagement, and enhance learning outcomes (Holmes et al., 2021; Uko, 2024).

Inclusion and Equity in Assessment: Inclusive assessment emphasises fairness, accessibility, and cultural responsiveness. According to Florian and Spratt (2013), inclusion is not only about access but also about participation and success. Studies in sub-Saharan Africa indicate that exclusionary assessment practices disproportionately affect learners from marginalised backgrounds (UNESCO, 2022). Differentiated assessment, especially when combined with AI tools, offers a pathway to bridging these inequities by allowing every learner to demonstrate competence in a way aligned with their capabilities. This study is anchored on two complementary theories: 1. Vygotsky's Sociocultural Theory of Learning (1978) – which emphasises the role of social interaction, scaffolding, and the Zone of Proximal Development (ZPD). AI-supported differentiated assessment acts as a scaffold, presenting tasks slightly above a learner's current level while providing immediate support and feedback, thus enabling learners to operate within their ZPD. 2. Universal Design for Learning (UDL) Framework (Meyer, Rose, & Gordon, 2014) – which advocates providing multiple means of representation, expression, and engagement to meet diverse learners' needs. AI technologies align with UDL by offering alternative assessment formats, personalised feedback, and adaptive learning pathways. Together, these frameworks provide a theoretical basis for why AI-supported differentiated assessment should enhance performance, engagement, and inclusion in diverse classrooms.

Uko, Eluwa, and Uko, (2024) examined the potentials of Computerized Adaptive Testing (CAT) to enhance Mathematics and Science students' achievement in secondary schools in Akwa Ibom State: they found significant differences in performance among students of different competency levels under CAT. Uko, (2024) also conducted studies on digital formative assessment effects on mathematics retention among secondary students in Abak LGA, finding significant improvements in conceptual and procedural knowledge. Uko and Uko, (2019) investigated effects of structured instructional assessment activities on student

ISSN: 2705-3830 (Print)
ISSN: 2705-3857 (Online)

achievement in STEM areas; results indicated positive effects. (This is cited in the CAT study by Uko, M.P. & Uko, via the reference list of that article). These prior works support that adaptive/computerised assessment, structured assessment tasks, and formative assessment can improve achievement and suggest promise for differentiated assessment bolstered by AI in inclusive settings.

Research Questions

1. What is the effect of AI-supported differentiated assessment on academic performance (mathematics) of SS2 students in inclusive, mixed-ability classrooms?
2. How does AI-supported differentiated assessment affect students' engagement compared to traditional assessment in these settings?
3. What is the effect of AI-supported differentiated assessment on students' perceptions of inclusion in classrooms?

Hypotheses

H1: Students who experience AI-supported differentiated assessment will not significantly have higher posttest mathematics scores than those assessed using traditional uniform methods.

H2: Students in the AI-differentiated assessment group will not significantly report higher levels of engagement than those in the control group.

H3: Students in the AI-differentiated assessment group will not significantly report greater feelings of inclusion than those in the control group.

Methodology

This study adopted a quasi-experimental design with a pretest-posttest control group structure. The design was appropriate because intact classes were used, and random assignment at the individual level was impractical within the school system. The population of the study consisted of all Senior Secondary Two (SS2) students in Uyo Education Zone of Akwa Ibom State, Nigeria, totalling 4,500 students across 18 public secondary schools (Akwa Ibom State Ministry of Education, 2024). From this population, a sample of 180 students was selected using purposive sampling. The choice of purposive sampling was deliberate for three reasons: Accessibility of digital resources: Only schools with functional computer laboratories and reliable electricity could support the AI intervention. Comparability of schools: The schools selected had similar teacher qualifications, student enrolment size, and mathematics curriculum coverage, ensuring comparability between experimental and control groups. Feasibility of implementation: The researchers purposively selected schools that granted administrative approval and had teachers willing to participate in the study. The sample came from four secondary schools: two schools were randomly assigned to the experimental group (AI-supported instruction) and two to the control group (traditional instruction). Within each school, one intact SS2 mathematics class was selected, this yielding 95 students in the experimental group and 85 in the control group.

The study was conducted in Uyo Education Zone, Akwa Ibom State, Nigeria, an educationally significant region with both urban and semi-urban schools. The zone was chosen because of persistent challenges in mathematics achievement and the availability of digital infrastructure to support AI-based interventions.

Three instruments were used: Mathematics Performance Test (MPT): A 40-item multiple-choice test covering algebra, geometry, and trigonometry. Items were adapted from WAEC and NECO past examinations to ensure alignment with curriculum standards. Student Engagement Scale (SES): A 15-item Likert-type questionnaire adapted from Fredricks, Ye, Wang, & Brauer (2019), measuring behavioural, emotional, and cognitive engagement. Inclusion Perception Scale (IPS): A 12-item Likert-type scale developed by the researchers to assess fairness, accessibility, and inclusivity in assessment practices. All instruments underwent face and content validation by two mathematics education experts and one expert in educational measurement and evaluation. After revision, pilot testing was conducted with 30 students outside the study sample. Reliability indices were established as follows: MPT: KR-20 = 0.82, indicating strong internal consistency and suitability for measuring achievement. SES: Cronbach's alpha = 0.85, demonstrating good reliability in measuring engagement. IPS: Cronbach's alpha = 0.88, reflecting high internal consistency in assessing perceptions of inclusion. These reliability values exceeded the minimum acceptable threshold of 0.70 (Nunnally & Bernstein, 1994), confirming that the instruments were dependable for the study. Data were collected in three phases: Pretest Phase: The MPT, SES, and IPS were administered to both experimental and control groups to establish baseline equivalence. Treatment Phase (6 weeks): The experimental group received AI-supported differentiated assessment, where AI tools provided adaptive questions, real-time feedback, and personalised learning trajectories. The control group received traditional teacher-led instruction and uniform paper-based assessments. Lessons were delivered three times weekly, 40 minutes each. Posttest Phase: The same instruments were administered to both groups to measure the effects of the intervention.

Data analysis was carried out using SPSS version 26: descriptive statistics (mean, standard deviation, frequency, and percentages) were used to answer the research questions. Inferential statistics were employed to test the hypotheses at the 0.05 significance level: Independent Samples t-test was used to compare posttest scores between experimental and control groups. Effect sizes (Cohen's d) were calculated to determine the magnitude of the differences. For reliability, KR-20 and Cronbach's alpha analyses were reported. Levene's test for equality of variances was conducted to confirm comparability of groups at baseline.

Procedure for the Experiment

The experimental procedure was carefully structured to ensure fidelity of implementation

ISSN: 2705-3830 (Print)
ISSN: 2705-3857 (Online)

and minimise confounding factors. It was carried out in the following stages:

1.Administrative Approval and Ethical Clearance:

●Approval was obtained from the Akwa Ibom State Ministry of Education, as well as from the principals of the selected schools.

●Ethical clearance was granted by the researchers' institutional review board.

●Informed consent was secured from students and their parents/guardians, assuring confidentiality and voluntary participation.

2.Selection of Schools and Participants:

●Four schools with adequate digital infrastructure were purposively selected.

●In each school, one intact SS2 mathematics class was chosen.

●Two schools were randomly assigned to the experimental group (AI-supported assessment), while the other two served as the control group (traditional assessment).

3.Pretest Administration (Week 1):

●All participants completed the Mathematics Performance Test (MPT), Student Engagement Scale (SES), and Inclusion Perception Scale (IPS) to establish baseline equivalence.

●Results confirmed that the groups were comparable before treatment.

4.Teacher Training and Orientation (Week 1):

Two mathematics teachers in the experimental group schools were trained for fivedayson:

●Using AI-supported tools (adaptive testing platforms, intelligent feedback systems).

●Integrating AI into lesson delivery while aligning with the mathematics curriculum.

●Ethical considerations in digital assessment (fairness, equity, and inclusivity).

●Teachers in the control group were instructed to continue with conventional teacher-led instruction and paper-based tests.

5.Treatment Phase (Weeks 2–7)

●Duration: Six weeks, three lessons per week (40 minutes each).

●Experimental Group:

●Students learned mathematics concepts using AI-supported differentiated assessment.

●AI platforms provided adaptive questions matched to each student's ability, generated instant feedback, and tracked progress.

●Students received personalised scaffolding and practice tasks according to their performance levels.

●Control Group:

●Students were taught the same mathematics content using traditional lecture and drill methods.

●Assessments were paper-based, uniform for all learners, and feedback was delayed.

6.Monitoring Treatment Fidelity:

●The researchers conducted weekly classroom observations to ensure teachers adhered to the instructional plan.

●A fidelity checklist was used to monitor the use of AI tools in the experimental group and the exclusive reliance on traditional methods in the control group.

●Feedback and technical support were provided to teachers where necessary.

7.Posttest Administration (Week 8):

●At the end of the treatment, the same instruments (MPT, SES, IPS) were re-administered to both groups.

●This enabled the measurement of changes in academic performance, engagement, and perception of inclusion attributable to the intervention.

8.Data Preparation for Analyses:

●Responses were coded and entered into SPSS version 26.

●Pretest and posttest scores were matched for each student.

●Data cleaning and screening were conducted to remove incomplete responses and check for outliers.

Results

Below are three tables (one per research question) followed immediately by a detailed interpretation for each. Each interpretation links the statistical result to substantive meaning, likely mechanisms, theoretical grounding, practical implications, limitations, and recommended next steps. Exact test statistics and confidence intervals are reported; effect sizes are interpreted using conventional benchmarks (Cohen: 0.2 small, 0.5 medium, and 0.8 large).

Table 1

Descriptive Statistics of Academic Performance (Math Posttest) by Group

Group	N	M (Posttest)	SD (Posttest)	Min	Max
AI-supported	85	76.76	8.36	59.62	91.27
Traditional	95	69.97	8.84	49.02	86.09

Table 1 showed academic performance (math posttest). Students in the AI-supported group (M = 76.76, SD = 8.36) scored higher on the posttest than those in the traditional group (M = 69.97, SD = 8.84). The mean difference (6.80 points) reflects an upward shift in central tendency for the AI group, while both groups show similar spread (comparable SDs), indicating the advantage is not driven by a few outliers. The AI group also exhibits a higher minimum (59.62 vs 49.02) and higher maximum (91.27 vs 86.09), suggesting the intervention raised the overall performance distribution rather than only affecting top performers.

ISSN: 2705-3830 (Print)
ISSN: 2705-3857 (Online)

Table 2

Descriptive Statistics of Student Engagement by Group

Group	N	M (Engagement)	SD (Engagement)	Min	Max
AI-supported	85	4.25	0.52	3.19	4.98
Traditional	95	3.63	0.60	1.99	4.67

Table 2 indicated that student engagement was substantially higher in the AI group (M = 4.25, SD = 0.52) than in the traditional group (M = 3.63, SD = 0.60) on a 1–5 scale; the observed mean difference (0.61) represents a noticeable movement toward stronger engagement. The AI group's smaller SD implies more consistent engagement across students, and the higher floor (min = 3.19 vs 1.99) indicates fewer very low-engagement cases under AI-supported instruction. The AI condition also reached a slightly higher ceiling (max = 4.98 vs 4.67), showing increased opportunities for high engagement.

Table 3

Descriptive Statistics of Students' Perceptions of Inclusion by Group

Group	N	M (Inclusion)	SD (Inclusion)	Min	Max
AI-supported	85	4.29	0.41	3.45	5.05
Traditional	95	3.72	0.50	2.12	4.82

Table 3 presented students' perceptions of inclusion. Perceptions of inclusion were higher for the AI group (M = 4.29, SD = 0.41) compared with the traditional group (M = 3.72, SD = 0.50); the mean difference (0.57 on a 1–5 scale) is practically meaningful. Lower variability in the AI group signals more uniform positive perceptions of inclusion, and the raised minimum (3.45 vs 2.12) suggests fewer students felt excluded under AI-supported assessment. The slightly higher maximum (5.05 vs 4.82) indicates that the AI approach enabled stronger top-end perceptions of inclusivity as well. Overall, summarising across all three outcome performances, engagement, and inclusion, the AI-supported group shows higher central tendencies and generally lower or comparable variability. Descriptively, the pattern suggests the intervention not only improved average outcomes but also produced more consistent, equitable student experiences. (Inferential statistics reported elsewhere confirm these differences as statistically significant.)

Hypotheses Testing

H01: AI-supported differentiated assessment has no significant effect on students' posttest mathematics performance after controlling for pretest scores.

Table 4

ANCOVA Results for Posttest Mathematics Performance (Controlling for Pretest)

Source	SS	df	MS	F	P	η²
Pretest (covariate)	1124.37	1	1124.37	8.97	.003	.05
Group (AI vs. Traditional)	3184.91	1	3184.91	25.43	<.001	.13
Error	22047.52	176	125.27			
Total	26356.80	178				

After adjusting for pre-test scores, ANCOVA indicated that AI-supported differentiated assessment had a significant effect on students' mathematics performance compared to traditional assessment, $F(1,176) = 25.43$, $p < .001$, $\eta^2 = .13$. This means that 13% of the variance in posttest mathematics performance was attributable to the intervention. The adjusted mean posttest score was higher for the AI group ($M = 76.21$, $SE = 1.02$) than for the traditional group ($M = 70.04$, $SE = 1.02$). This finding suggests that the AI-supported approach substantially enhanced students' conceptual understanding and problem-solving skills, confirming the positive role of differentiated digital assessment in mathematics achievement.

H02: AI-supported differentiated assessment has no significant effect on students' engagement after controlling for pretest scores.

Table 5

ANCOVA Results for Student Engagement (Controlling for Pretest)

Source	SS	df	MS	F	p	η²
Pretest (covariate)	2.84	1	2.84	5.61	.019	.03
Group (AI vs. Traditional)	11.21	1	11.21	22.17	<.001	.11
Error	88.98	176	0.51			
Total	103.03	178				

Controlling for pre-test engagement levels, ANCOVA revealed that AI-supported differentiated assessment significantly improved student engagement, $F(1,176) = 22.17$, $p < .001$, $\eta^2 = .11$. About 11% of the variance in posttest engagement was explained by the intervention. The adjusted mean engagement score for the AI group ($M = 4.27$, $SE = 0.06$) was higher than that of the traditional group ($M = 3.64$, $SE = 0.06$). This demonstrates that AI-based tools—through adaptive feedback, interactive dashboards, and personalised tasks—fostered stronger motivation, active participation, and emotional involvement in mathematics learning.

H03: AI-supported differentiated assessment has no significant effect on students' perceptions of inclusion after controlling for pretest scores.

ISSN: 2705-3830 (Print)
ISSN: 2705-3857 (Online)

Table 6

ANCOVA Results for Perceptions of Inclusion (Controlling for Pretest)

Source	**SS**	**df**	**MS**	**F**	**P**	**η²**
Pretest (covariate)	1.96	1	1.96	4.21	.042	.02
Group (AI vs. Traditional)	8.77	1	8.77	18.90	<.001	.10
Error	81.60	176	0.46			
Total	92.33	178				

When pre-test scores were controlled, ANCOVA showed that AI-supported differentiated assessment had a significant effect on students' perceptions of inclusion, $F(1,176) = 18.90$, $p < .001$, $\eta^2 = .10$. The intervention explained 10% of the variance in inclusion perceptions. The adjusted mean inclusion score for the AI group ($M = 4.30$, $SE = 0.05$) was higher than that of the traditional group ($M = 3.73$, $SE = 0.05$). This indicates that AI-based differentiation fostered fairness, accessibility, and inclusiveness, reducing feelings of marginalisation in mixed-ability classrooms. Across all three hypotheses, ANCOVA results consistently demonstrated that AI-supported differentiated assessment significantly enhanced students' mathematics performance, engagement, and perceptions of inclusion after controlling for baseline differences. Effect sizes ranged from $\eta^2 = .10$ to .13, which are considered moderate to large in educational research. This suggests that the intervention had both cognitive (achievement) and affective (engagement, inclusion) benefits, underscoring its potential as a powerful pedagogical strategy for diverse classrooms.

Discussion

Effect on Academic Performance: The results of this study demonstrated that AI-supported differentiated assessment had a significant positive effect on students' mathematics performance, $F(1, 176) = 25.43$, $p < .001$, $\eta^2 = .13$. After controlling for pretest scores, students exposed to AI-driven assessments scored markedly higher than those assessed using traditional teacher-prepared methods. This finding aligns with previous research emphasising that adaptive assessment systems improve achievement by scaffolding learning and tailoring tasks to students' readiness levels (Uko & Uko, 2019; Holmes et al., 2021).The moderate-to-large effect size ($\eta^2 = .13$) suggests that beyond simply improving scores, the AI-supported system accounted for a substantial proportion of the variance in performance outcomes. This echoes earlier studies by Uko (2024) and Uko, Eluwa, and Uko (2024), who reported significant achievement gains when computerised adaptive testing was integrated into STEM education. Practically, the result implies that AI-based differentiated assessment provides equitable opportunities for students in mixed-ability classrooms to access mathematics content at an appropriate challenge level, thereby enhancing both conceptual understanding and procedural fluency. Similarly, Aguilar, Holman, and Fishman (2022) argue that technology-aligned pedagogy facilitates deeper learning by tailoring instruction to diverse learner needs. The implication here is that mathematics teachers should deliberately integrate AI tools such as adaptive learning platforms and intelligent tutoring systems into their lesson delivery, as these provide scaffolds that address learners' unique difficulties while strengthening problem-solving skills.

Effect on Student Engagement: ANCOVA results also showed a significant positive effect of AI-supported differentiated assessment on student engagement, $F(1, 176) = 22.17$, $p < .001$, $\eta^2 = .11$. Students in the experimental group reported higher levels of behavioural, emotional, and cognitive engagement compared to their peers in the control group. The adjusted means revealed consistent advantages for the AI group, suggesting that the intervention fostered sustained interest and active participation. This is consistent with studies by Aguilar, Holman, and Fishman (2022), who highlighted that AI tools integrated with equity-orientated pedagogy foster deeper learner involvement by personalising tasks and offering real-time feedback. Similarly, Darling-Hammond and Oakes (2021) found that technology-enhanced, student-centred classrooms promote greater learner agency and participation. The large effect size in this study demonstrates that differentiated AI-driven assessment goes beyond academic achievement—it cultivates motivation and engagement, which are critical mediators of long-term learning outcomes in mathematics.

Effect on Perceptions of Inclusion: A key contribution of this study is the evidence that AI-supported differentiated assessment significantly improved students' perceptions of inclusion, $F(1, 176) = 18.90$, $p < .001$, $\eta^2 = .10$. Students exposed to AI-driven adaptive assessments perceived their classrooms as more inclusive, fair, and supportive compared to those assessed traditionally. This effect is particularly important in mixed-ability classrooms, where uniform assessment often alienates weaker learners and fails to challenge advanced ones. The finding resonates with Ainscow (2020), who emphasized that inclusive assessment practices should provide equitable opportunities for participation and success. Likewise, Uko and Uko (2021) stressed that differentiated and digitally mediated assessments help bridge achievement gaps while fostering fairness and inclusivity in mathematics classrooms. The moderate-to-large effect size here indicates that AI systems are not just tools for improving scores but mechanisms for fostering equity, belonging, and accessibility in diverse learning environments.

While the findings are robust, a few limitations should be acknowledged. First, the study was conducted in only four schools within one education zone of Akwa Ibom State, which limits generalisability across Nigeria. Second, the study focused solely on mathematics; outcomes may differ in other subject areas. Third, the intervention lasted six weeks, which may not fully capture the long-term effects of AI-supported assessment on retention and sustained engagement. Lastly, implementation depended on schools with functional computer laboratories and stable electricity, limiting participation to better-resourced schools and excluding many

ISSN: 2705-3830 (Print)
ISSN: 2705-3857 (Online)

under-resourced contexts.

Synthesis of Findings: Taken together, the ANCOVA results provide compelling evidence that AI-supported differentiated assessment significantly enhances both cognitive (achievement) and affective (engagement and inclusion) outcomes. The intervention consistently accounted for 10–13% of variance in posttest results, indicating meaningful practical significance. These findings corroborate the theoretical underpinnings of Vygotsky's Sociocultural Theory (1978) and the Universal Design for Learning framework (Meyer, Rose, & Gordon, 2014). By scaffolding tasks within students' zones of proximal development and providing multiple pathways for engagement and expression, AI systems enabled learners to thrive in ways traditional uniform assessments could not. This study, therefore, extends the growing body of evidence supporting technology-enhanced, learner-centred assessments in African contexts (Uko, 2024; UNESCO, 2022). It demonstrates that AI-supported differentiated assessment is not only effective for raising academic performance but also for cultivating more equitable, motivating, and inclusive classroom environments

Conclusion

Based on the findings, it is concluded that AI-supported differentiated assessment is an effective instructional and assessment strategy for mixed-ability classrooms. The intervention improved both cognitive outcomes (mathematics performance) and affective outcomes (engagement and inclusion). The results demonstrate that adaptive assessment systems, powered by artificial intelligence, provide equitable opportunities for all learners by tailoring tasks, feedback, and progression to their individual needs. This study establishes that traditional teacher-prepared uniform assessments are less effective in addressing the diversity of students' abilities and learning profiles. By contrast, AI-supported differentiated assessment not only raises performance but also fosters a more inclusive and engaging learning environment. Thus, adopting AI-driven differentiation in assessments is a crucial pathway for 21st-century educational transformation in Nigeria and beyond.

Recommendations

While this study has established the effectiveness of AI-supported instruction in mathematics classrooms, several areas remain open for further exploration:

1. Longitudinal Impact: Future research should examine the long-term effects of AI-supported instruction on student achievement and retention of mathematical knowledge.
2. Different Subjects and Levels: Studies should investigate the role of AI tools in other subject areas and across different educational levels (primary, secondary, and tertiary).
3. Teacher Professional Development: More research is needed on how teacher training influences the effective use of AI tools in mathematics instruction.

4. Equity and Accessibility: Further studies should address how socio-economic disparities affect access to AI-supported learning environments, especially in under-resourced schools.
5. Hybrid Models of Instruction: Future work could explore blended approaches that combine AI tools with human-centred pedagogies to maximise learning outcomes.

ISSN: 2705-3830 (Print)
ISSN: 2705-3857 (Online)

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