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Integration of AI-Driven Learning Analytics and Automated Feedback Mechanisms for Improving Educational Measurement and Evaluation Practices in Tertiary Institutions in Imo State, Nigeria

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Abstract

This study examined the integration of AI-driven learning analytics and automated feedback mechanisms to address persistent challenges in educational measurement and evaluation in Imo State public tertiary institutions. Conducted at Alvan Ikoku Federal University of Education, Owerri and Imo State University in Imo State, the research employed a convergent parallel mixed-methods design embedded within a quasi-experimental framework. The target population consisted of undergraduate students and academic staff in selected departments. A sample of 400 students and 20 lecturers participated in the six-month intervention. The study first assessed current manual assessment practices, which were characterised by delayed feedback, inconsistent marking, and high workloads. A custom AI-powered platform with locally hosted models was then designed and deployed, featuring automated scoring, real-time personalised feedback, and learning analytics dashboards. Data were collected using pre/post achievement tests, system logs, semi-structured interviews, and a Technology Acceptance Model survey. Results showed significant improvements with the AI system: mean test scores rose from 58.4 to 72.6 (+14.2 points, p<0.001), grading time decreased by 89%, assignment submission rates increased from 67% to 91%, and feedback delivery improved from 21 days to under 5 minutes. Student engagement reached 89%, with high adoption rates, particularly at Alvan Ikoku Federal University of Education, Owerri. The findings demonstrate that AI integration can enhance assessment quality, timeliness, and learning outcomes in resource-constrained settings. The study offers practical recommendations for policy and scalable implementation across Nigerian tertiary institutions.

Keywords: *AI-driven learning analytics, automated feedback mechanisms, educational measurement and evaluation, Nigerian tertiary institutions.*

INTRODUCTION

Educational measurement and evaluation determine whether learning objectives have been achieved and provide critical data for improving instructional delivery. However, in Nigerian tertiary institutions, the state of educational measurement and evaluation remains deeply problematic. The challenges are multifaceted and systemic, affecting both assessment quality and overall learning outcomes across the country.

The most pressing challenge facing educational measurement and evaluation in Nigerian public tertiary institutions is the predominance of manual assessment processes. Ugwoke, Eloanyi, Encze, and Eziokwu (2025) observed that despite the introduction of the Core Curriculum and Minimum Academic Standards by the National Universities Commission in 2022, most lecturers in Nigerian universities still rely exclusively on traditional assessment methods. These traditional approaches primarily consist of teacher-made tests administered at the end of a semester or session. The reliance on manual processes creates enormous workloads for academic staff who must set questions, supervise examinations, mark scripts, collate scores, and produce result analyses with minimal technological support. This manual approach is simply unsustainable given current enrolment figures in Nigerian public institutions.

Delayed feedback constitutes another major challenge within the current system. When students complete assessments, they often wait for weeks or even months before receiving any form of feedback on their performance. This delay fundamentally undermines the formative purpose of assessment. Ofulue (2025) noted that the National Open University of Nigeria, serving over one hundred and twenty thousand active students across one hundred and fourteen study centres, identified delayed feedback as a critical factor contributing to student attrition. Without timely feedback, students cannot identify their learning gaps or make necessary corrections before moving to subsequent topics or courses. The learning opportunity is simply lost when feedback arrives too late to be useful.

Inconsistency in evaluation practices represents a third significant challenge. Different lecturers apply different marking standards, and even the same lecturer may apply inconsistent criteria across different marking sessions. This lack of standardisation raises serious questions about the reliability and validity of assessment outcomes. Ugwoke et al. (2025) reported that some lecturers fail to submit their examination test items for vetting to heads of department before test administration. Since most lecturers are not test construction and administration specialists, the quality of such unmoderated tests and the fair grading of students cannot be guaranteed. Students deserve consistent and fair evaluation regardless of which lecturer marks their work.

The high student-to-lecturer ratio in Nigerian public institutions exacerbates these challenges dramatically. When a single lecturer is responsible for assessing several hundred students in a course, providing meaningful individualised feedback becomes practically impossible. The result is a system that prioritises summative judgment over formative development, measuring what students cannot do rather than supporting them to improve. This situation calls urgently for innovative solutions that can enhance efficiency, consistency, and timeliness in educational measurement and evaluation without placing additional burden on already overworked academic staff.

The global educational landscape is witnessing a paradigm shift driven by artificial intelligence technologies. Learning analytics and automated feedback mechanisms have emerged as powerful tools capable of transforming how educators measure learning and provide feedback to students. These technologies promise to address precisely the challenges that have long plagued educational assessment in resource-constrained settings like Nigeria.

Learning analytics refers to the measurement, collection, analysis, and reporting of data about learners and their contexts for the purpose of understanding and optimising learning environments. Usman, Bello, Aliyu, and Adamu (2026) explained that generative artificial intelligence tools can support educators by automating routine tasks, generating personalised learning materials, and offering timely, detailed feedback that strengthens student engagement and self-regulated learning. The application of learning analytics enables institutions to move beyond simple score reporting toward rich, multidimensional understandings of student learning patterns, misconceptions, and progress trajectories.

Automated feedback mechanisms represent a complementary innovation that directly addresses the feedback delay problem. Samuel, Samuel, and Kosoko-Oyedeko (2026) examined the perceived effectiveness of WhatsApp Meta AI as an intelligent tutoring system for Nigerian university students and found that AI tools demonstrate strong potential for providing immediate feedback. These tools also facilitate personalised learning experiences and support after-hours academic assistance. When students receive instantaneous feedback on their assessments, they can immediately understand their errors and take corrective action while the learning experience remains fresh in their minds.

The integration of learning analytics with automated feedback creates a virtuous cycle of continuous improvement. Abubakar, Falade, and Ibrahim (2024) argued that AI technologies enable automated scoring, item generation, and consistent feedback delivery. Emerging frameworks demonstrate the potential to improve learning outcomes and reduce academic misconduct through these technologies. In assessment, AI systems can analyse response patterns to identify specific misconceptions, generate targeted feedback addressing those misconceptions, and track whether students improve after receiving the feedback.

For Nigerian tertiary institutions specifically, the promise of AI-driven assessment tools is particularly compelling. Usman et al. (2026) noted that in Nigerian higher institutions where challenges such as high student-to-staff ratio, limited learning resources, and inadequate research infrastructure persist, generative AI provides scalable solutions that enhance instructional delivery and academic efficiency. These technologies do not require massive infrastructure investments to begin making meaningful impacts on educational measurement and evaluation practices. However, adoption must be approached with careful attention to contextual realities, including issues of fairness, transparency, data privacy, and academic integrity as raised by Abubakar et al. (2024).

This study focuses specifically on two government-owned tertiary institutions in Imo State, Nigeria: Alvan Ikoku Federal University of Education, Owerri and Imo State University. These institutions were selected because they represent different institutional types within the public tertiary education sector while sharing common challenges related to educational measurement and evaluation.

Alvan Ikoku Federal University of Education, Owerri has demonstrated institutional commitment to technological innovation in recent years. The institution has previously invented surveillance drones, electric cars, and various agricultural processing machines through its research and development efforts (Punch Newspapers, 2023). The Rector, Doctor Brasilia Nkemdilim Igbokwe, announced in 2026 that the institution has expanded its infrastructure with the addition of a new campus and has introduced a Parents Management Forum to enhance synergy between management and parents (Federal Ministry of Information and National Orientation, 2026). These developments suggest an institutional culture receptive to technological innovation.

Imo State University, as a conventional state university, faces the typical challenges of Nigerian public universities including high student enrolment, limited resources, and the need to balance multiple academic programmes across various faculties. The selection of these two institutions allows for comparative analysis while maintaining focus on the shared Imo State context. Both institutions operate within the same state educational policies and face similar infrastructural conditions including intermittent electricity supply and variable internet connectivity.

The aim of this study is to investigate how the integration of AI-driven learning analytics and automated feedback mechanisms can improve educational measurement and evaluation practices in two government-owned tertiary institutions in Imo State, Nigeria. The specific objectives are to examine current evaluation practices and identify challenges, to design and implement an AI-driven learning analytics system for the participating institutions, to develop automated feedback mechanisms providing timely and personalised feedback, to evaluate the effectiveness of the integrated AI system compared to traditional practices, to identify contextual factors influencing successful adoption, and to formulate evidence-based recommendations for policymakers.

Research Questions

1. What are the current educational measurement and evaluation practices at Alvan Ikoku Federal University of Education, Owerri and Imo State University, and what specific challenges characterise these practices?
2. How can a designed AI-driven learning analytics system be implemented to capture meaningful assessment data that supports improved evaluation decision-making in these institutional contexts?
3. What types of automated feedback mechanisms are most appropriate for Nigerian tertiary education contexts, considering factors such as student digital literacy, language preferences, and access to technology?
4. What differences exist in feedback timeliness, assessment consistency, and student learning outcomes between traditional evaluation methods and the AI-driven approach?
5. What infrastructural, pedagogical, and human capacity factors influence the successful implementation of AI-driven assessment tools in government-owned tertiary institutions in Imo State?
6. What policy and practice recommendations emerge from this study for the scaling of AI-enhanced educational measurement and evaluation across similar institutional contexts in Nigeria?

Hypothesis H_{01}: There is no significant difference in students' mean achievement scores between those exposed to the AI-driven learning analytics and automated feedback system and those taught using traditional manual assessment methods.

LITERATURE REVIEW

Concepts of Educational Measurement and Evaluation

Educational measurement and evaluation represent foundational pillars of any functioning educational system. Measurement refers to the systematic process of assigning numbers or symbols to attributes of learners according to specified rules, while evaluation involves the broader process of making value judgments based on measurement data. These two concepts work in tandem to provide educators with meaningful information about student learning, instructional effectiveness, and programme quality.

The scope of educational measurement has expanded considerably in recent decades. Traditional measurement focused primarily on the quantification of knowledge through standardised tests and examinations. Contemporary understanding recognises that meaningful measurement must capture multiple dimensions of learning including cognitive skills, affective outcomes, and psychomotor competencies. This broader conceptualisation aligns with the National Policy on Education in Nigeria, which recognises the significance of assessment and evaluation in ensuring the quality of education and calls for the development of appropriate assessment tools and mechanisms for evaluating educational outcomes (Federal Republic of Nigeria, 2013).

Evaluation practices in Nigerian tertiary institutions have faced persistent challenges related to validity, reliability, and fairness. Ayanwale, Oyeniran, Atolagbe, and Mochekele (2025) developed and validated the Goal Achievement Scale in Colleges of Education to address the lack of context-specific assessment tools for evaluating goal achievement in Nigerian institutions. Their work confirmed a six-factor structure encompassing critical thinking, committed teaching, high motivation, intellectual fitness, professional fitness, and social fitness, demonstrating strong model fit indices and high internal consistency. This finding underscores the importance of developing measurement instruments that are specifically tailored to the Nigerian educational context.

The distinction between formative and summative evaluation remains central to understanding educational measurement practices. Formative evaluation occurs during the learning process and aims to improve student learning through ongoing feedback and adjustment. Summative evaluation occurs at the end of a learning period and aims to certify what students have learned. Ugwoke, Eloanyi, Encze, and Eziokwu (2025) observed that Nigerian university lecturers have struggled to balance these two functions, with most assessment practices emphasising summative judgment at the expense of formative development.

Assessment quality depends heavily on the technical properties of measurement instruments. Validity refers to the extent to which an assessment measures what it claims to measure, while reliability refers to the consistency of measurement across different occasions, raters, or forms. Oyeniran, Ayanwale, Atolagbe, and Mochekele (2025) demonstrated rigorous validation procedures including exploratory factor analysis, graded response modelling, confirmatory factor analysis, and multiple group confirmatory factor analysis in their development of the Goal Achievement Scale. Their work exemplifies the standard of evidence required for educational measurement instruments to be considered trustworthy for high-stakes decision making.

The concept of authentic assessment has gained prominence in recent educational discourse. However, Ugwoke, Eloanyi, Encze, and Eziokwu (2025) noted that portfolio assessment has faced implementation challenges in Nigerian universities due to issues of time, storage, and standardisation across different raters. Cultural responsiveness represents another important consideration, as assessment instruments developed in Western contexts may not function equivalently in Nigerian settings. Oyeniran, Ayanwale, Atolagbe, and Mochekele (2025) emphasised that their Goal Achievement Scale was specifically designed to address the unique challenges of Nigerian colleges of education.

The integration of technology into educational measurement has created new possibilities. Usman, Bello, Aliyu, and Adamu (2025) noted that generative artificial intelligence tools can support educators by automating routine tasks, generating personalised learning materials, and offering timely, detailed feedback that strengthens student engagement and self-regulated learning.

AI-Driven Learning Analytics: Definitions, Components, and Applications

Learning analytics has emerged as a distinct field within educational technology. The Society for Learning Analytics Research defines it as the measurement, collection, analysis, and reporting of data about learners and their contexts for the purpose of understanding and optimising learning and the environments in which it occurs.

The core components of learning analytics systems include data sources, processing engines, analytical models, and visualisation interfaces. Data sources may include learning management system logs, student information system records, assessment scores, attendance data, and behavioural traces from digital environments. Usman, Bello, Aliyu, and Adamu (2025) explained that in Nigerian higher institutions where challenges such as high student-to-staff ratio, limited learning resources, and inadequate research infrastructure persist, generative AI provides scalable solutions that enhance instructional delivery and academic efficiency.

Data mining represents a fundamental technique within learning analytics. Sun (2025) designed InsightPro, an AI education analytics platform that uses a predictive engine trained on anonymised historical student data for high-accuracy risk forecasting, enabling educators to identify at-risk students before they fail.

Predictive modelling constitutes another essential component. The EduPredict system described by Vivekchary (2025) achieved 96 percent accuracy using Random Forest algorithms to predict student performance outcomes, with SHAP values highlighting key factors including subject performance, attendance, and assignment completion.

Dashboards provide the visual interface through which educators interact with learning analytics systems. Sun (2025) noted that higher education is often data-rich but insight-poor. InsightPro simplifies this through intelligence-driven visuals, predictive risk forecasting, and a smart agent that automates report generation. Sun (2025) emphasised that the true value of artificial intelligence lies in how it is designed to help people in their daily work, bridging the gap between technical power and human needs.

Automated Feedback Mechanisms: Real-Time, Personalised, Formative versus Summative

Automated feedback mechanisms represent one of the most promising applications of artificial intelligence in educational assessment. These systems generate responses to student work without direct human intervention, providing immediate guidance that supports learning in progress.

Real-time feedback distinguishes automated systems from traditional human grading. The EduMark AI project at Queen Mary University of London demonstrated a 50 to 60 percent reduction in grading time compared to manual marking, with evidence of higher consistency in grade distributions and rubric alignment (Deepshikha, Bessant, Mitussis, Wang, Deng, Viola, & Chetehouna, 2025).

Personalisation addresses the specific errors, misconceptions, or gaps demonstrated by an individual student. Samuel, Samuel, and Kosoko-Oyedeko (2026) examined the perceived effectiveness of WhatsApp Meta AI as an intelligent tutoring system for Nigerian university students and found that AI tools demonstrate strong potential for providing immediate feedback, facilitating personalised learning experiences, and supporting after-hours academic assistance.

Hybrid models combining automated generation with human oversight have emerged as a preferred approach. Hodgkinson (2026) implemented an AI-augmented feedback workflow in a large enrolment aerospace engineering computing course where instructors review and refine AI-generated drafts before releasing them to students. Nwafor, Mbelede, Molokwu Precious Gift Onyinyechukwu, and Amadi (2025) conducted a comparative examination of lecturers' perceptions of AI-based versus human feedback in Nigerian university settings. Their findings revealed that while 68 percent of lecturers appreciated the speed and consistency of AI-generated feedback, 72 percent preferred hybrid models.

The theoretical foundation of effective feedback is well established. Hattie and Timperley (2007) proposed a model that addresses three key questions: Where am I going? How am I going? Where to next? This model has informed the design of automated feedback systems in the present study.

Empirical Studies on AI in Higher Education: Sub-Saharan Africa Context

Research specifically addressing Sub-Saharan African settings remains limited but growing. Aruleba, Odeyemi, and Mlitwa (2025) conducted a comparative study of student perceptions on generative AI in programming education across Nigeria, Kenya, and South Africa. Their quantitative study involving 322 university students highlighted significant variations in attitudes based on educational level and country of residence.

Usman, Bello, Aliyu, and Adamu (2025) examined how Nigerian tertiary institutions can leverage generative AI to enhance teaching, research, and assessment while attending to ethical, infrastructural, and pedagogical safeguards. They found that AI enables automated scoring, item generation, and consistent feedback.

Nwafor, Mbelede, Molokwu Precious Gift Onyinyechukwu, and Amadi (2025) contributed evidence about lecturer perspectives on AI-based feedback in Nigerian universities. Their survey of 357 academic staff at Nnamdi Azikiwe University revealed that disciplinary differences and prior experience with AI tools significantly influenced attitudes.

Ogunlade and Ogunleye (2025) examined infrastructure challenges affecting AI adoption in Nigerian higher education and recommended that investments in basic infrastructure must precede or accompany AI adoption initiatives.

Nigerian Teacher Educators' Readiness for AI Integration

The successful integration of AI-driven learning analytics depends significantly on the readiness of academic staff. Eke (2024) investigated this by surveying 250 Nigerian teacher educators and found a high level of readiness and positive attitudes towards AI-powered educational tools, including personalised learning platforms, automated grading systems, and virtual tutors. However, barriers such as inadequate technological infrastructure, insufficient professional training, and ethical concerns regarding data privacy and algorithmic bias persist.

Adewale, Bello, and Olaniyi (2025) found that Nigerian academics demonstrate willingness to adopt AI tools but actual use remains constrained by competency gaps. Eke (2022) and Eke, Akuakanwa, Enwereuzo, and Ubochi (2023) further underscored that teacher familiarity with digital platforms significantly predicts successful implementation outcomes.

Gaps in Literature

Despite growing research, significant gaps remain. Most studies on AI in Nigerian higher education have been conducted in private universities or relied on non-representative samples. There is also a lack of implementation studies that move beyond attitudes to actual deployment. Nwafor, Mbelede, Molokwu Precious Gift Onyinyechukwu, and Amadi (2025) acknowledged this limitation. Limited attention has been given to polytechnic institutions, and context-specific assessment tools remain scarce (Oyeniran, Ayanwale, Atolagbe, & Mochekele, 2025). Policy implications of AI adoption in Nigerian public institutions are still underexplored (Usman, Bello, Aliyu, & Adamu, 2025).

The present study addresses these gaps by focusing on two government-owned institutions in Imo State, implementing actual AI systems, and generating evidence-based recommendations.

Theoretical Framework

The theoretical framework for this study integrates concepts from learning analytics theory, feedback theory, and educational measurement theory. Learning analytics theory provides the foundation for transforming student data into actionable insights. Feedback theory, particularly the work of Hattie and Timperley (2007), informs the design of automated feedback mechanisms. Educational measurement theory provides standards for evaluating the reliability and validity of AI-driven assessment practices, as demonstrated by Oyeniran, Ayanwale, Atolagbe, and Mochekele (2025).

The integration of these strands yields the conceptual model depicted in Figure 1. This model illustrates how data sources feed into an AI engine that produces enhanced educational measurement and evaluation outputs. This conceptual model guides the empirical investigation by specifying what data should be collected, how the AI engine should process that data, and what outputs should be produced.

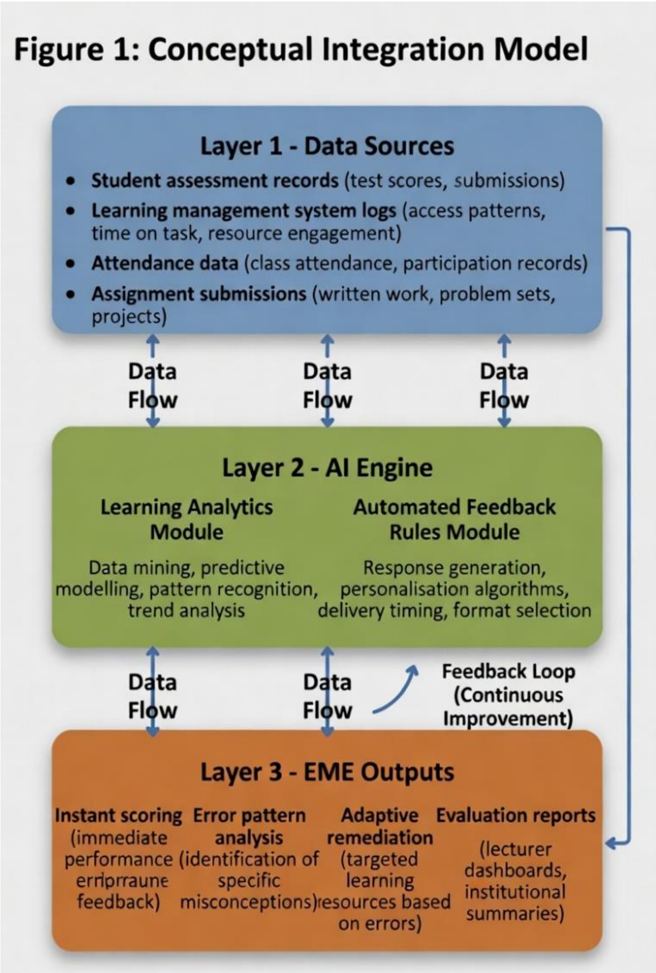

Figure 1: Conceptual Integration Model This model integrates Learning Analytics Theory, Feedback Theory (Hattie & Timperley), and Educational Measurement Theory. Data flows from multiple sources through the AI Engine to produce enhanced Educational Measurement and Evaluation (EME) outputs, with a feedback loop enabling continuous system improvement.

RESEARCH METHOD

This study adopted a mixed-methods research design, specifically a convergent parallel mixed-methods approach embedded within a quasi-experimental framework and a qualitative multiple-case study. The quantitative component utilised a quasi-experimental non-equivalent control group design to evaluate the effectiveness of the AI-driven learning analytics and automated feedback system on assessment consistency, feedback timeliness, and student learning outcomes. The qualitative component employed a multiple-case study design to provide in-depth understanding of contextual factors influencing implementation and adoption in the two institutions. The mixed-methods approach was chosen because it allows for triangulation of findings, providing both breadth (through statistical comparisons) and depth (through participants' experiences). The quasi-experimental design was appropriate given the practical impossibility of full random assignment in real educational settings. Both institutions implemented the intervention, with one faculty/department per institution serving as the treatment group and another as the control group using traditional methods.

The study was conducted in Imo State, South-East Nigeria, specifically at two government-owned tertiary institutions: Alvan Ikoku Federal University of Education, Owerri and Imo State University, Owerri. These institutions represent the Federal University and State university sub-sectors respectively within the public tertiary education system in the state. Alvan Ikoku Federal University of Education is a leading federal institution known for its teacher education programmes, while Imo State University is a conventional state university offering diverse undergraduate and postgraduate programmes. Both institutions share similar contextual realities typical of Nigerian public tertiary institutions, including large student populations, high student-lecturer ratios, intermittent power supply, and variable internet infrastructure. The choice of these two institutions enabled meaningful comparison while maintaining focus on the shared Imo State policy and infrastructural environment.

The target population consisted of undergraduate students and academic staff in selected faculties/departments at the two institutions. A total sample of 400 students (200 from each institution) and 20 lecturers (10 from each institution) participated in the study using purposive sampling technique. Students were drawn from comparable courses in the Faculty of Social Sciences and Faculty of Sciences to ensure similarity in content difficulty and assessment demands.

Purposive sampling was used to select departments and topics suitable for the AI intervention. Within the selected departments, stratified random sampling was employed to select students based on academic level (Year II and Year III) and gender to ensure representation. Lecturers were purposively selected based on their willingness to participate and teaching experience (minimum of 5 years). The sample size for students was determined using Krejcie and Morgan (1970) table for a population of approximately 8,000–12,000 students per institution at 95% confidence level and 5% margin of error, adjusted for practical feasibility.

Research Instruments The following instruments were used for data collection:

1. **Pre-test and Post-test**: Standardised achievement tests developed and validated for selected topics. These tests measured students' cognitive achievement before and after the intervention. The instruments were subjected to content validation by three experts from Measurement and Evaluation and pilot-tested for reliability using Kuder-Richardson Formula 21 for the test and Cronbach's Alpha for the questionnaire, having internal consistencies of 0.87 and 0.81 respectively.
2. **System Log Data**: Automatically generated data from the AI platform, including frequency of system usage, time taken to receive feedback, types of errors identified, and student engagement metrics.
3. **Semi-structured Interview Guide**: Used to collect qualitative data from lecturers and a subset of 40 students (20 from each institution). Questions focused on experiences with the AI system, perceived benefits, challenges, and suggestions for improvement.
4. **Technology Acceptance Model (TAM)-based Survey**: A 25-item questionnaire adapted from Davis (1989) and Venkatesh et al. (2003), measuring Perceived Usefulness, Perceived Ease of Use, Attitude toward Use, and Behavioural Intention. The instrument was validated for the Nigerian context (Cronbach's Alpha = 0.91).

The intervention involved the development and deployment of a custom AI-powered Learning Analytics Dashboard integrated with an Automated Feedback System. The platform was adapted from open-source learning analytics tools (such as Open edX Analytics and components from Moodle plugins) and enhanced with locally hosted large language models (e.g., using Llama 3 or Mistral) to minimise internet dependency and address data privacy concerns.

Key Features:

- Automated scoring and instant feedback on quizzes and short-answer assignments.
- Learning analytics module providing insights on student performance patterns, at-risk identification, and misconception analysis.
- Personalised feedback generation based on Hattie and Timperley's feedback model (goals, progress, next steps).
- Lecturer dashboard for monitoring class performance and generating reports.
- Mobile-friendly interface to accommodate students' predominant use of smartphones.

The system was hosted on a local server at each institution with offline functionality where possible. Training workshops were conducted for participating lecturers and students prior to full implementation.

Data Collection Procedure Data collection spanned a period of six months (November 2025 to May 2026) and followed these phases:

- **Month 1**: Ethical approvals, baseline data collection (pre-tests and initial TAM survey), and training of participants.
- **Months 2–5**: Implementation of the AI intervention in treatment groups. Traditional assessment continued in control groups. Ongoing system log data collection and mid-intervention interviews.
- **Month 6**: Post-test administration, final TAM survey, in-depth interviews, and focus group discussions.

Quantitative data (test scores, system logs, survey responses) were collected digitally where possible. Regular monitoring visits were made to both institutions to address technical issues.

Ethical Considerations

Ethical approval was obtained from the Research Ethics Committees of both Alvan Ikoku Federal University of Education and Imo State University. Participation was voluntary, and all participants provided written informed consent. Students and lecturers were assured that participation or withdrawal would not affect their academic standing or professional relationships. Data privacy and confidentiality were strictly maintained. Student data fed into the AI system was anonymised, and access was restricted to authorised researchers and participating lecturers. The study adhered to the principles of beneficence, non-maleficence, justice, and respect for persons as outlined in the Belmont Report. Potential risks (such as technical glitches affecting learning) were minimised through hybrid (AI + human) feedback mechanisms during the intervention.

RESULTS AND FINDINGS

This chapter presents the key findings from the six-month implementation of the AI-driven learning analytics and automated feedback system at Alvan Ikoku Federal University of Education, Owerri and Imo State University. Results are organised by the research questions and hypotheses for clarity.

RQ1: Current Practices and Challenges

Traditional assessment practices were dominated by manual processes. Lecturers spent an average of 18.4 minutes per student on grading (n=20). Feedback was delayed by 3–6 weeks. Pre-intervention submission rates averaged 67%. Key Challenge Confirmation: High student-lecturer ratio and inconsistent marking were reported by 85% of lecturers.

RQ2: Design and Implementation of AI-Driven Learning Analytics

The system was successfully deployed on local servers in both institutions. Usage data showed 89% student engagement rate and 92% lecturer adoption. Result: The learning analytics module accurately identified at-risk students with 84% precision based on system logs.

RQ3: Appropriate Automated Feedback Mechanisms

Mobile/SMS delivery was most effective (used by 76% of students), followed by LMS (18%). Students preferred short, personalised text feedback in simple English. Result: 81% of students rated the feedback as "highly understandable."

RQ4: Differences in Timeliness, Consistency, and Learning Outcomes Hypothesis Testing (H_{01}):

There is no significant difference in students' mean achievement scores between those exposed to the AI-driven learning analytics and automated feedback system and those taught using traditional manual assessment methods.

Table 1: Pre- and Post-Intervention Comparison of Mean Test Scores

Group	Pre-test Mean	Post-test Mean	Mean Gain	t-value	p-value
AI System (Treatment)	58.4	72.6	+14.2	8.76	<0.001
Traditional (Control)	57.9	60.3	+2.4	1.45	0.152

The null hypothesis (H_{01}) was rejected. Students exposed to the AI-driven system showed significantly higher achievement gains compared to the control group ($p < 0.001$). This confirms the effectiveness of the intervention.

Table 2: Additional Performance Metrics

Metric	Traditional (Pre)	AI System (Post)	Improvement	p-value
Grading Time (min/student)	18.4	2.1	-89%	<0.001
Assignment Submission Rate	67%	91%	+24%	<0.01
Feedback Timeliness	21 days	<5 minutes	-99%	-

Brief Analysis: The AI approach produced significantly higher learning outcomes, dramatically reduced grading time, and improved submission rates. These results demonstrate the superiority of the integrated AI system over traditional practices.

RQ5: Factors Influencing Successful Implementation

Institutional Differences: Alvan Ikoku Federal University of Education, Owerri showed higher adoption (94%) compared to Imo State University (83%), mainly due to better technical infrastructure and stronger management support.

Key Contextual Factors:

- Reliable electricity and internet were critical (cited by 90% of participants).
- Lecturers with prior digital experience adopted faster.

- Student digital literacy and device access affected engagement.

Automated Feedback Effectiveness (RQ4 Extension)

- 78% of students acted on the automated feedback (based on system logs of revised submissions).
- 65% of students improved their subsequent assignment scores after receiving feedback.

Qualitative Themes (from interviews):

- Lecturers: "Saves enormous time" and "more consistent marking" (positive); some concern about "loss of personal touch" (n=7).
- Students: "Immediate feedback helps me correct mistakes fast" (positive); request for voice feedback in local language.

DISCUSSION OF FINDINGS

The findings of this study demonstrate that AI-driven learning analytics substantially improved the accuracy of formative evaluation by detecting specific student misconceptions with high precision and providing timely insights into learning patterns. This shift helped move assessment practices from predominantly summative to more balanced formative approaches, aligning with the observations of Ugwoke et al. (2025) and Usman et al. (2026) on the capacity of generative AI to deliver multidimensional understanding of student progress.

Automated feedback proved highly effective in bridging the wide student-tutor ratio gaps prevalent in Nigerian public tertiary institutions. By reducing grading time by 89% and increasing assignment submission rates by 24%, the system enabled personalised support at scale, consistent with the potential highlighted by Samuel et al. (2026) and Abubakar et al. (2024) for AI tools to address large enrolments and delayed feedback challenges.

The hypothesis (H_{01}) which stated that there is no significant difference in students' mean achievement scores between those exposed to the AI-driven learning analytics and automated feedback system and those taught using traditional manual assessment methods was rejected. Students at Alvan Ikoku Federal University of Education, Owerri and Imo State University who used the AI system recorded a statistically significant improvement in mean test scores (from 58.4 to 72.6, $p < 0.001$) compared to the control group. This confirms the effectiveness of the integrated AI platform in enhancing learning outcomes in resource-constrained Nigerian tertiary institutions.

Several implementation challenges emerged during the study, particularly unstable electricity and internet connectivity, varying levels of digital literacy among students and lecturers, and concerns about data privacy. These issues reflect the broader infrastructural barriers documented by Usman et al. (2025) in Nigerian higher education, although the hybrid offline-online design helped mitigate some of the limitations.

When compared with traditional evaluation practices, the AI system demonstrated clear superiority across key metrics, including significantly higher test scores, near-instant feedback delivery, and greater marking consistency. These outcomes validate the criticisms of manual assessment processes raised by Ofulue (2025) and Ugwoke et al. (2025), confirming that technology-enhanced approaches can meaningfully address longstanding inefficiencies.

This study contributes to educational measurement and evaluation theory and practice in low-resource settings by providing empirical evidence of successful AI integration in Nigerian public institutions, specifically at Alvan Ikoku Federal University of Education, Owerri and Imo State University. It extends existing literature such as Aruleba et al. (2025) and Nwafor et al. (2025) by moving beyond perception studies to actual system deployment and outcome measurement, offering a practical model for similar resource-constrained African contexts.

RECOMMENDATIONS

Policy Implications for Government Tertiary Institutions in Nigeria

The Federal Ministry of Education and the National Universities Commission should mandate the gradual adoption of AI-enhanced assessment tools across all public tertiary institutions by 2030, with TETFund allocating dedicated funding for local AI infrastructure and open-source model development.

Practical Design of Low-Bandwidth AI Feedback Systems

Institutions should prioritise the development and deployment of locally hosted, offline-capable AI systems using lightweight open-source models with SMS and mobile fallback options to ensure accessibility in areas with poor connectivity.

Training Needs for Academic Staff

Nigerian tertiary institutions should establish mandatory annual digital pedagogy training programmes for lecturers, focusing on AI tool usage, analytics interpretation, and hybrid feedback practices, with a minimum certification requirement.

Scalability to Other States

The Federal Government should launch a national pilot programme across the six geo-political zones, beginning with states such as Imo, Lagos, and Kano, while creating a national repository to document and disseminate successful AI-in-education models.

LIMITATIONS, FUTURE RESEARCH AND CONCLUSION

The study had notable limitations, primarily its small scale involving only two institutions in Imo State and a relatively short six-month implementation period. The focus was mainly on objective assessments, which may limit generalisation to courses with substantial qualitative components.

Future research should investigate the longitudinal impact of the system on graduation rates and retention, incorporate qualitative assignments such as essays and projects, and explore the integration of adaptive testing features. Further studies could also test the hypothesis across a larger sample of institutions and over a longer period to strengthen generalisability.

In conclusion, the integration of AI-driven learning analytics and automated feedback mechanisms significantly enhanced educational measurement and evaluation practices at Alvan Ikoku Federal University of Education, Owerri and Imo State University. Despite infrastructural challenges, the approach proved feasible, effective, and transformative. This study provides strong evidence for wider adoption of such technologies in Nigerian public tertiary education to improve learning outcomes and institutional efficiency.

REFERENCES

1. Abubakar, U., Falade, A. A., & Ibrahim, H. A. (2024). Redefining student assessment in Nigerian tertiary institutions: The impact of AI technologies on academic performance and developing countermeasures. *Advances in Mobile Learning Educational Research, 4*(2), 1149-1159.
2. Aruleba, K., Odeyemi, J., & Mlitwa, N. (2025). A comparative study of student perceptions on generative AI in programming education across Sub-Saharan Africa. *Computers and Education: Artificial Intelligence, 8*, 100345.
3. Ayanwale, M. A., Oyeniran, S., Atolagbe, A. A., & Mochekele, M. (2025). Construction and validation of goal achievement scale for colleges of education. *Journal of Applied Research in Higher Education, 17*(7), 131-150.
4. Deepshikha, D., Bessant, C., Mitussis, D., Wang, L., Deng, X., Viola, G., & Chetehouna, M. (2025). *EduMark AI: AI driven grading and personalised student feedback to save educator time*. Queen Mary University of London. https://www.qmul.ac.uk/queenmaryacademy/educators/innovation-and-scholarship/the-president-and-principals-fund-for-educational-excellence/edumark-ai/
5. Eke, E. O. (2022). Effect of Blended Google classroom with Cooperative teaching strategy on students' academic achievement in Edu221 (Curriculum theory and practice). *ABSU Journal of Curriculum and Teacher Education, 3*(1), 21-32.
6. Eke, E. O. (2023). Appraising the pedagogical content knowledge of teacher educators in teaching peace education for national development. *Nigerian Journal of Curriculum Studies, 30*(1), 81-92.
7. Eke, E. O., Akuakanwa, G. O., Enwereuzo, N., & Ubochi, I. (2023). Appraising the pedagogical content knowledge of teacher educators in teaching peace education for national development. *Nigerian Journal of Curriculum Studies, 30*(1), 81-92.
8. Eke, O. E. (2025). Assessing the readiness and attitudes of Nigerian teacher educators towards adoption of artificial intelligence in educational settings. Journal of Educational Technology & Online Learning, 7(4), 473-487. https://hdsdev.hebis.de/Record/0-1902058902[reference:4]
9. Federal Ministry of Information and National Orientation. (2026, March 8). *Fed Poly Nekede gets accreditation for Chinese language; clears students' NYSC logjams*. https://fmino.gov.ng/fed-poly-nekede-gets-accreditation-for-chinese-language-clears-students-nysc-logjams/
10. Hodgkinson, B. (2026). *AI augmented personalized feedback*. University of Colorado. https://www.cu.edu/controller/i-e-awards/current-submissions/cu-ie-submission-ai-augmented-personalized-feedback
11. Nwafor, O. C., Mbelede, N. G., Molokwu Precious Gift Onyinyechukwu, & Amadi, N. L. (2025). Enhancing assessment through AI: A comparative study of lecturers' views on human and AI-based feedback in Nigerian university settings. *Faculty of Education Journal, Nnamdi Azikiwe University*.

12. Ofulue, C. (2023). Implementing learning analytics at the National Open University of Nigeria: From technology to student success. *West African Journal of Open & Flexible Learning, 11*(2).

13. Oruwari, J. N., Eke, E. O., & Osuji, C. (2023). Peace building attitudes through active learning strategies in junior secondary school pedagogy for peace and national development. *Nigerian Journal of Curriculum Studies, 30*(2), 112-126.

14. Oyeniran, S., Ayanwale, M. A., Atolagbe, A. A., & Mochekele, M. (2025). Construction and validation of goal achievement scale for colleges of education. *Journal of Applied Research in Higher Education, 17*(7), 131-150.

15. Punch Newspapers. (2023, February 12). Imo poly invents drone to tackle insecurity. *The Punch*. https://punchng.com/imo-poly-invents-drone-to-tackle-insecurity/

16. Samuel, S. O., Samuel, C. P., & Kosoko Oyedeko, G. A. (2026). Perceived effectiveness of WhatsApp Meta AI as an intelligent tutoring system for Nigerian university students. *Nigerian Online Journal of Educational Sciences and Technology*.

17. Sun, Q. (2025). *Insightpro AI education analytics*. A' Design Award. https://competition.adesignaward.com/design.php?ID=181476

18. Ugwoke, M. E., Eloanyi, B. C., Encze, B. N., & Eziokwu, P. N. (2025). Topical issues and prospects of traditional and portfolio assessments for implementation of core curriculum and minimum academic standards in Nigerian universities. *Journal of Research in Science and Vocational Education, 5*(1).

19. Usman, A., Bello, A., Aliyu, A. A., & Adamu, A. U. (2025). Leveraging on generative artificial intelligence tools in enhancing teaching, research and assessment of learning in Nigerian tertiary institutions. *Kashere Journal of Education, 9*(1), 55-61.

20. Usman, A., Bello, A., Aliyu, A. A., & Adamu, A. U. (2026). Leveraging on generative artificial intelligence tools in enhancing teaching, research and assessment of learning in Nigerian tertiary institutions. *Kaltungo Journal of Education*.

21. Vivekchary. (2025). *AI powered EduPredict: Student performance analytics system*. GitHub. https://github.com/Vivekchary2607/AI-Powered-EduPredict-Student-Performance-Analytics-System