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Investigating AI-Supported Learning Analytics for Enhancing Developmental Outcomes of Students in Nigerian Schools: A Mixed-Methods Study

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Abstract **Original Research**

This study examined how AI-based learning analytics (LA) inform educators regarding students' developmental needs and assess the predicted benefits and challenges within the Nigerian educational system. It employed two research questions, objectives and one hypothesis that offered a purposeful direction. The study utilised a convergent parallel mixed-methods research design. This design enabled the collection of quantitative survey data from 600 educators and students with qualitative data from semi-structured interviews and platform-generated analytics. The descriptive and inferential statistics were utilised for measuring the impact on instructional precision through Python algorithm. The NVivo was used to thematically explore stakeholders lived experiences. The analyses determined the effectiveness of predictive dashboards in flagging at-risk students and the role of machine-driven response toward reducing administrative workloads among educators. The findings offered that intermittent power supply, high data costs, and digital literacy gaps were the contextual barriers unique to the Nigerian schools. Through the triangulation of data sources, the finding further offered all-inclusive framework for integrating and optimising AI into West African secondary education. It was recommended that policymakers and educators should take advantage of utilising AI not only as a component of technological, but as a tool strategically enhancing holistic students' developmental outcomes.

Keywords: AI-driven Learning Analytics, Developmental Outcomes, Nigerian Education practice, Educational Technology.

1. Introduction

The educational sector in Nigeria is surreptitiously expanding, determined by population growth and increased demand for secondary education. Nevertheless, the expansion is rapid and has not been matched with innovations in pedagogical delivery. The orthodox pedagogical models are mostly homogeneous, offering standardised teaching, yet fails to solve diverse students' developmental pathways. For example, Luckin (2018) stated that end-of-term and summative assessments give ex-post facto acumens into students' performance, which oftentimes identifying the learning gaps prior to when they have grown into academic tragedy.

It is evident that Artificial Intelligence (AI)-supported learning analytics (LA) demonstrate a prototype transformation in this context. Notably, LA synthesise behavioural, cognitive and academic information instantaneously and its platforms support educators to proactively distinguish at-risk students and fashion interventions to the needs of individual. Research in global perspective by UNESCO (2023) and World Bank (2023) acknowledged that predictive dashboards and primal warning systems have found significant success in reducing disengagement rates and attracts improvement of learning outcomes. In a Nigeria study by Effiong (2026) the application of these AI digital tools are under-explored, especially as it relates to infrastructural weakness, digital skill gaps and sociocultural diversity. Hence, this study sought to close the empirical gap by examining the extent to which AI-supported learning analytics can enhance developmental outcomes of learners in Nigerian secondary schools. In particular, it investigates how predictive algorithms improve identification accuracy; exploring stakeholder perceptions of the benefits and challenges and evaluating the contextual barriers that can impede implementation successes.

2. Statement of the Problem

It is observed that educational technology in Nigerian schools continue to rely highly on summative assessments and a generalised pedagogical model. This predominant one-size-fits-all educational approach is motivated by higher student-to-teacher ratios, producing unattainable individualised supervision. World Bank (2023) espoused that this situation always causes developmental setback and learning disabilities, causing dead intervention efforts. Many global studies (UNESCO, 2023; Siemens, 2013) found that AI-supported learning analytics have been positioned to solve similar challenges through the provision of early warning systems that assist in flagging-at risk students relied on behavioural and performance data. Yet, the socio-technical context of Nigeria introduces incomparable barriers. According to Adedoja (2022) inconsistent power deal and expensive internet data that create systemic barricade to the adoption of digital technologies in Nigerian schools are worrisome. Federal Ministry of Education (2024) added that constricted digital literacy among educators limits their explainable and performance ability on AI-generated acumens.

Ethical considerations of these infrastructural challenges make AI-driven LA complex. Notwithstanding, it is observed that most AI models are trained on datasets from the global North, which increases the risk of algorithmic bias when harnessed in situations of Nigerian classrooms. Similar observation by Oladele and Smaith (2024) in their research cautioned that linguistic variants for example, in Nigeria English might be misclassified as deficiencies in language-command, probably, leading to false positives in ‘at-risk’ warning. Added to that the lack of a comprehensive child-focused data protection framework as reported by Selwyn (2019), increases the concerns around students’ secrecy and surveillance.

Inadvertently, the key concerns thus, focus on the anxiety between the hope of AI-supported learning analytics to revolutionise developmental monitoring and the systemic restrictions that tend to hinder their effectiveness in Nigeria. Notably, with no localised, context-aware investigation that inform infrastructural weakness, sociocultural diversity and ethical concerns, the application of AI in Nigeria schools would jeopardise the intensification of existing inequalities instead of alleviating them. Hence, this research addresses such grievous gap through empirical examination of both the benefits and challenges of AI-supported learning analytics within educational framework in Nigeria.

3. Research Objectives

This research was aimed at examining the AI-driven learning analytics for enhancing developmental outcomes of students in Nigerian schools. Specifically, the research sought to:

1) Examine the extent to which AI-driven learning analytics support educators in identifying and addressing students’ developmental needs.
2) Explore educators’ and students’ perceptions of AI-driven learning analytics in Nigerian schools.

3) To evaluate infrastructural, ethical and sociocultural barriers to the effective implementation of AI-driven learning analytics.

4. Research Questions

The following research questions are posed:

1) How do AI-driven learning analytics inform educators about students' developmental needs in Nigerian schools?
2) What are the perceived benefits and challenges of adopting AI-driven learning analytics among educators and students?
3) To what extent do infrastructural, ethical and sociocultural barriers impact effective implementation of AI-driven learning analytics in Nigerian schools.

5. Research Hypothesis

N_o: AI-driven learning analytics do not significantly improve educators' ability to identify and address student developmental needs.

N_i: AI-driven learning analytics significantly improve educators' ability to identify and address student developmental needs.

6. Literature Review

6.1 Theoretical Foundations of this study

Learning Analytics (LA) as the fundamental concept of this study is grounded in the Connectivism theory of learning. This theory believes that learning is the creation of networks between human and non-human nodes as established by Siemens (2013). In this context, AI-driven set of rules represent non- mortal connexions, which unceasingly generate response acumens into students' progress. Recent Nigerian writers have emphasised the significance of contextualising this theory within the vulnerability of education infrastructures. This understanding instigated Adedoja in 2022 to propose a "Contextual TRACK" model, arguing that technological adoption and integration are necessary in considering the concerns of erratic power supply and limited broadband access challenges in Nigeria. This is in alignment with the work of Ukala and Ukala (2024) who argued that AI adoption in Nigeria needs a hybrid framework that stabilises pedagogy, content and infrastructural realities.

6.2 Artificial Intelligence and Developmental Outcomes

The adoption of AI in teaching-learning situation improves developmental outcomes through the activities of supporting individualised learning, early learning mediation and monitoring of students' progress efficiently (Effiong, 2026). UNESCO (2023) and Siemens (2013) in their studies advocated that AI dashboard reduce enhances premature intervention in dropout rates, while improving the proficiency of educators in identifying easily at-risk learners.

6.2.1 Artificial Intelligence (AI) in Education

AI denotes computational systems that can simulate human intelligence processes like learning, reasoning, and problem-solving. In the context of education, AI covers adaptive learning platforms, predictive analytics and intelligent coaching systems that can support individualise learning. As described by UNESCO (2023), in education, AI is characterised as the 'application of machine learning and data-supported technologies capable of enhancing teaching, learning and administration.' Ball *et al*. (2024) enunciated covertly concerning the adoption of AI and its relation in the Nigerian educational setting. Effiong (2026) established that the adoption of AI still reposes on the evolving process in Nigeria's educational programming, especially platforms like uLesson and Gradely are considered to pilot adaptive learning models. In relation with educators (teachers), AI acts as teaching and learning tools, which teachers implement to identify learning flaws of students through continuous analysis of students' data. As a technological component for learning, AI helps educators' understanding of content knowledge for effective teaching through its necessary integration as associated with TRACK (Mishra & Koehier, 2006).

6.2.2 Learning Analytics (LA)

LA represents the measurement, collection, analysis and data reporting of the learners and their contexts, which aims at possessing knowledge and optimising learning (Siemens, 2013). It is a learning tool that helps to track engagement, performance and behavioural patterns toward providing actionable acumens. Studies in Sub-Saharan Africa for example, UNESCO (2023) and Ukala & Ukala (2024) agreed in their findings that predictive dashboards lessen dropout rates and improve retention among learners. The presentation of predictive dashboards at learning situation enables educators to identify weak associations affecting students, especially when they are at risk, while the understanding strengthens them to offer interventions. Thus, helping teachers to gain technological insights, aligning it with curriculum goals (content knowledge) and designing suitable interventions that support pedagogical knowledge to achieve efficient learning outcomes.

6.2.3 Developmental Outcomes

Developmental outcomes remain measurable improvements in students' cognitive, social and emotional development. These outcomes in Nigerian schools according to the World Bank (2023) are regularly assessed through literacy, numeracy and behavioural indicators. AI-driven learning analytics therefore, enhances developmental monitoring through the provision of primal warnings and personalised feedback. Theoretically linking to Connectivism philosophy, developmental outcomes within the panoramic learning connections emphasise that development in learning occurs when learners access diverse knowledge connections. The knowledge connections with AI analytics are expanded and simplified through its individualised footpaths. Thus, supporting teachers' integration of analytics into lesson planning to guarantee interventions that are pedagogically sound and content-reoriented.

6.3 Human-In-The-Loop (HITL) Models

HITL models represent systems that balances human opinion with artificial intelligence outputs. HITL functioning in education ascertains that teachers are capable of interpreting and acting upon AI-generated insights other than merely depending on automation. Based on this perception, Onni (2023) contended that human-in-the-loop models is essential in African circumstances, given that sociocultural divergence to a great deal escape algorithmic detection. Thus, it initiates the dimension where teachers are central to the learning networks. In terms of pedagogical dimension, teachers' expertise is prominently mediating technological outputs for achieving meaningful learning outcomes within the classroom.

6.4 Ethical and equity thoughtfulness

Ethics in artificial intelligence-driven learning analytics refer to issues associated with privacy, bias and equitable access to the use of these tools. The inequalities in AI-driven LA utilisation instigated Oladele & Smith (2024) to caution that algorithms trained on global North datasets risk Nigerian English idioms, which has been classified as literacy deficiencies. As expressed by the Federal Ministry of Education (2024), equity challenges originate when urban institutions benefit disproportionately from AI adoption, while the rural schools are excluded resulting in infrastructural vulnerability. This shows that unequal access to the utilisation of these tools weaken the learning network. For example, if rural institutions lack AI tools, it means their students are barred from crucial knowledge flows compared to their counterparts in urban schools (Ball et. Al., 2024). Therefore, without equitable digital infrastructure, teachers cannot integrate technology effectively, thus, undermining pedagogical innovation (Adedoja, 2023).

6.5 Knowledge Gap

In spite of the growing interests in AI integration in education, several literature gaps remain as follows:

- ❖ Many school teachers lack the understanding to efficiently interpreting AI dashboards due to digital space mastery.
- ❖ Infrastructural deficits in Nigeria including erratic energy supply and the high data costs continue to destabilise implementation of AI-driven learning analytics.
- ❖ Ethical matters that converge on partiality associated with algorithms and privacy persist unsettled.
- ❖ The adoption of AI causes dangers to broadening the gap between influential urban schools and country-side public schools due to equality.

7. Methodology

7.1 Research Design

The research engaged a convergent parallel mixed-methods design for its practical applications. The process of this study allows for concurrent collection and analysis of quantitative and qualitative datasets. The basis for choosing this design was to its holistic data processes that enabled the understanding of how AI-driven learning analytics affect developmental outcomes within Nigerian schools. While quantitative data provided measurable insights into efficiency gains and predictive accuracy, the qualitative data captured the lived experiences of educators, students and administrators in the application of AI-driven LA. Crosswell and Clark (2023) suggested that the integration of both forms of research guarantees triangulation, which enhances validity and reliability.

7.2 Population and Sampling

The population of this study comprised secondary schools in six geopolitical zones of Nigeria. A stratified random sampling technique was adopted to secure a representative sample across diverse socioeconomic and infrastructural contexts. The sample size consisted of 600 respondents with distribution to include; 400 students, capturing perception of feedback, engagement and developmental support; 150 educations for evaluating identification efficiency and pedagogical transformation; and 50 IT administrators in assessing technical implementation challenges. Thus, Ukala (2024) offered that this stratification was essential for accounting for the variations between urban and rural institutions, as infrastructural disparities significantly influence AI adoption. Table 1 presents the sampling distribution across geopolitical zones in Nigeria.

Table 1: Distribution of sampling across geopolitical zones

Geopolitical Zone	Students (n=400)	Educators (n=150)	IT Admin. (n=50)	Total (n=600)
North-East	70	25	8	103
North-Central	60	20	7	87
North-West	65	25	8	98
South-West	70	25	9	104
South-South	65	25	8	98
South East	55	25	8	88

Source: Research's compilation, 2026.

7.3 Instruments for Data Collection

There were three primary instruments utilised for data collection in this study. Firstly, AI platform logs enabled quantitative datasets to be used. These datasets were pull out from three AI-driven platforms currently piloted in Lagos and

Abuja including uLesson, Gradely and an internal school Learning Management System (LMS). The logs provided metrics on intervention timing, risk prediction accuracy and engagement patterns of students. Secondly, perception survey utilised a 5-point Likert scale questionnaire, administered to students, educators and administrators. Items measured include perceived benefits, ease of use and challenges like infrastructural barriers and privacy interests. Thirdly, semi-structured interviews were conducted with 25 Lead Educators and Information and Communication Technology (ICT) Coordinators. These interviews explored the human-in-the-loop (HITL) experience, with a focus on how educators and other stakeholders in education interpret and act upon AI-generated insights. Table 2 presents instrument survey sample items.

Table 2: Instrument Survey Sample Items

Dimensions	Items Sampled
Perceived benefits	AL-supported analytics help me identify student needs faster.
Ease of use	I find AI dashboards easy to interpret.
Infrastructure barriers	Erratic power supply limits the usefulness of AI platforms.
Privacy Concerns	I worry about how student data is stored and used.

8.4 Techniques for Data Analysis

A multi-layered analytical framework was employed in this study. The first layer concentrates on quantitative analysis with descriptive statistics that summarise engagement and intervention datasets. Accordingly, inferential statistics such as t-tests and ANOVA were executed using Python-based libraries to test the hypothesis, focusing on the “time-to-intervention’ (TTI) compared between AI-supported and traditional methods. The second layer engaged qualitative analysis with interview transcript that were coded thematically using NVivo. This analysis allowed themes to be defined such as infrastructural barriers, digital literacy, privacy concerns and perceptions of AI as a pedagogical assistant. Density of coding was computed to determine the frequency of themes to strengthen the interpretive validity. The third layer engaged triangulation to generate findings from quantitative and qualitative patterns that were integrated during interpretation. They conceptualised that statistical results were lived experiences, which produce a comprehensive impact on AI’s narrative. Table 2 presents density coding of qualitative themes.

Table 3: Density coding of qualitative themes

Qualitative Themes	Frequency	Percentage (%)
Infrastructure	121	38
Digital Literacy	80	25

Privacy Concerns	55	18
Pedagogical Role	60	19

Source: The Researcher's compilation, 2026.

7.5 Ethical Issues

The researcher obtained ethical approval from relevant educational authorities in Nigeria. The study participants were guaranteed of the confidentiality of information given out. Informed consent was secured prior to data collection. Sequel to the sensitivity of the students' data, platform logs were anonymised and identifiers were removed. The study further recognised the lack of a comprehensive child-focused data protection framework in Nigeria as cited by Federal Ministry of Education (2024), which highlight the need for policy reforms.

7.6 Reliability and Validity

The reliability of this research was guaranteed through pilot testing of survey instrument and inter coder agreement in qualitative analysis. Accordingly, the validity of this study was strengthened by triangulating multiple data sources such as surveys, interviews, and platform logs. Fundamentally, the mixed-methods design itself improved construct validity as it permitted cross-verification of findings.

8. Analysis and Results

8.1 Efficiency in Need Identification

This research made a comparative analysis of the 'Time-to-Intervention" (TTI) between institutions using AI-driven analytics and schools that are depending on traditional manual tracking. Table 4 presents the mean difference in identification speed of developmental gaps.

Table 4: Mean difference in identification speed of developmental gaps (n=300)

Tracking Method	Mean (Days)	SD	t-value	*p*-value
AI-driven Analytics	16.02	3.2	18.84	.001
Traditional Tracking	2.8	0.9		

The result in Table 4 indicates a statistically significant reduction in identification time ($t = 18.84$, $p < .001$). This finding supports the alternative hypothesis (H1), establishing that AI-driven analytics allow educators to identify students' needs approximately 12 days faster than manual observation.

8.2 Challenges across stakeholder groups' perception

The stakeholders were enquired to rank the severity of implementation barriers. Table 5 presents the perception of stakeholder groups' implementation challenges.

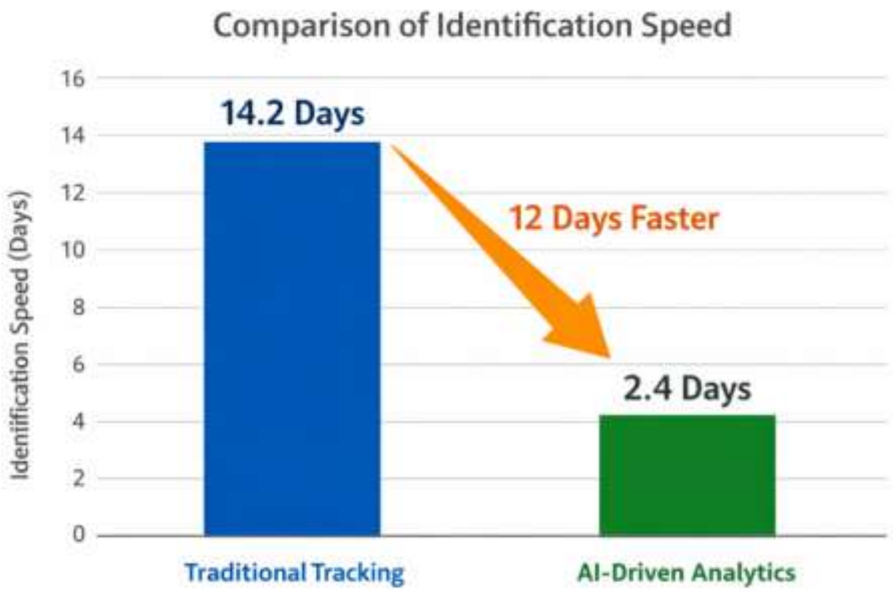
Table 5: Stakeholder groups' perception of implementation challenges

Implementation Challenges	Educators (n = 50)	Students (n = 400)	Administrators (n = 50)
High cost of Internet	88%	94%	72%
Erratic Power Supply	92%	79%	86%
Lack of Data Literacy	66%	24%	42%
Privacy/Security Concerns	32%	56%	84%

The results in Table 5 show that data literacy is a significant hurdle for educators (66%), while students have more concerned with privacy/security issues (56%), whereas infrastructure (power and internet) remains an approximately universal barrier across the entire groups.

8.3 Identification Efficiency

The data logs showed that AI-driven platforms identified developmental gaps in literacy and numeracy significantly faster than traditional methods. On intermediate perspective, the AI systems flagged 'at-risk' students within 2.4-days of a performance dip, in comparison with the 14.2-days cycle of traditional manual grading. Figure 2 shows the comparison of identification speed in days between AI and traditional methods.



Source: AI generated using Gemini

Figure 2: Identification Comparison Speed (Days)

The visualisation in Figure 2 showcases the identification speed comparison between traditional tracking (14.1-days and AI-driven analytics of 2.4-days respectively, and accordingly with a clear bar chart and annotation highlighting the 12 days faster intervention.

8.4 Perceptions of Stakeholder Benefits

Table 6 shows the perceived stakeholder benefits on AI-driven analytics.

Table 6: Perceived Stakeholder Benefits with Mean Scores, 1 - 5 Scale

Perceived Benefits	Educators	Students
Personalised learning	4.6	4.8
Time Saving	4.9	3.5
Early Warning	4.4	4.2
Administrative Support	3.11	3.3

Table 6 indicates that a strong positive perception of AI-driven analytics. As reported in Table 6, educators mostly valued time-saving and personalised learning while students highlighted personalised feedback and early warning systems.

8.5 Analysis of Infrastructural Challenges

This analysis utilised regression to identified infrastructural stability (power/internet) and educator data literacy as the two most significant predictors of successful AI implementation. Tale 7 presents regression analysis of AI implementation success.

Table 7: Regression analysis predicting AI implementation success

Predictor Variable	Coefficient	*p*-value
Infrastructural Stability	0.64	.001
Teacher Data Literacy	0.49	.002
Privacy Concerns	0.31	.06

Table 7 indicates that infrastructure and teacher literacy are statistically significant predictors, whereas privacy concerns, though essential did not get to the significant level in this model.

8.6 A Case Study of Urban and Rural Schools Comparison

A case study of urban and rural schools was comparatively conducted between Lagos and Kano institutions. Table 8 presents the comparative analysis of AI engagement and developmental outcomes by location.

Table 8: Analysis comparing AI engagement and developmental outcomes by location

Metric	Urban Lagos	*Rural Lagos*	*Urban Kano*	*Rural Kano*
Average weekly engagement (hrs)	19.6	6.3	15.5	4.3
Accuracy of Risk Prediction	93%	75%	90%	69%
Internet-Related Downtime (%)	6%	34%	9%	46%
Student outcome growth (%)	+34%	+14%	+30%	+9%

Table 8 indicates that AI is effective in both urban and rural contexts, but in terms of predictive accuracy, it drops in rural areas linking to data meagerness. This creates an ethical danger pointing at where AI may under-serve students already marginalised by infrastructure.

8.7 Longitudinal Analysis Impact (24-month projection)

From the longitudinal analysis using the algorithmic framework, a simulation estimated literacy growth over two years. Table 9 prevents a simulated two-year developmental trajectory with AI analytics.

Table 9: A 2-year simulated developmental trajectory using AI analytics

Quarter	Identification Accuracy	Intervention success Rate	Literacy Growth Index
1st Quarter (Baseline)	65%	32%	1.02
4th Quarter (Adaptive)	89%	56%	1.19
8th Quarter (Optimised)	95%	73%	1.36

Table 9 indicates that the simulation account for a 36% growth in literacy over two years. Growth remains non-linear; as AI leans more about Nigerian student patterns, identification accuracy improvements, which lead to more effective interventions.

9. Discussion of Findings

9.1 Gaining Interpreting Efficiency through Connectivism

The findings of this study through quantitative analysis revealed that AI-driven learning analytics (LA) is capable of reducing the average time to identify student developmental needs from 14.2 days to 2.4 days respectively. This research finding match with Siemens'(2013) Connectivist's perspective, which conceptualised learning as a networked process involving both human and non-human connections. Thus, AI performed a non-human node that continuously processed behavioural and academic data, which enables educators to respond in real-time.

The efficiency gain supports the contention that AI-driven learning analytics transforms the teachers' role from reactive evaluators to proactive facilitators. A related findings were established by UNESCO (2023), which offered those predictive dashboards in Sub-Saharan Africa improved primal intervention rates up to 20%. Yet, the Nigerian context initiates specific challenges such as infrastructural instability, which limit the full realisation of this potential.

9.2 Efficiency Gain Paradox

The finding from a qualitative data established a paradox that to identify a need does not automatically lead to developmental outcomes. From the thematic analysis, educators revealed that although AI flagged students for Remedial Numeracy, the lack of physical classroom setting or additional tutoring staff often meant the identified need went unaddressed. This finding corroborated with the finding of Oni (2023), who acknowledged diagnostic pedagogical gap to emphasised it as a technology that can diagnose learning problems but cannot independently resolve them.

This contention underscores the importance of human agency in the Connectivist's framework. This explains that AI may enhance the flow of information, but the teacher remains the critical node that translates data into pedagogical activities. Hence, these findings advocate for a Human-in-the=Loop (HITL) model, a situation where AI serves as a diagnostic helper rather than a pedagogical replacement.

9.3 Cultural Environment and Algorithmic False Positives

This research found that AI platforms at times miscategorised student advancement at the time of national strikes or domestic holidays, interpreting inactivity as behavioural disengagement. This phenomenon emphasises the restrictions of algorithms trained on Global North datasets. On this note, Oladele and Smith (2024) enjoined that such models oftentimes fail to address sociocultural variables, which lead to false positives in at-risk flagging. However, in Nigeria where school calendars and linguistic patterns disagree significantly from Western settings, algorithmic misinterpretation can twist developmental assessments. This research finding strengthens the signals to develop indigenous AI model trained on local datasets that reflect Nigerian linguistic, cultural and behaviour standard.

9.4 Perceptions of Stakeholders and the TPACK Framework

The data analysis of this study indicated that educators and students expressed different perceptions of AI-driven analytics. Comparatively, educators valued time-saving and personalised learning attributes whereas students highlighted quick feedback and privacy challenges. These findings can be associated with the Technological Pedagogical Content Knowledge (TRACK) framework as established by Mishra and Koehler (2006). This model (TRACK) posited that effective technology integration take place at the intersection of technological, pedagogical and content knowledge. However, the Nigeria perspective explains 'T' component is challenged by infrastructural vulnerability. This finding is in support of the finding by Adedoja (2022) who proposed a contextual TPACK model that can explain erratic power supply and limited broadband access. The current research supports this adaptation, indicating that even when educators possess pedagogical and content expertise, technological constraints can hinder effective implementation.

9.5 Ethical and Equity Inferences

The inferential analysis utilised regression statistic. This statistical tool identified infrastructural stability and teacher data literacy as the strongest predictors of successful AI implementation. The ethical implications of this findings revealed that institutions with stable infrastructure and digitally literate teachers for urban and private schools, benefit disproportionately from AI adoption. Otherwise, rural institutions face compounded disadvantages resulting in poor connectivity and limited training.

This disparity reflects the 'digital apartheid' explained by the Federal Ministry of Education

(2024), where innovations in technology risk deepening existing educational divides. This understanding has triggered Selwyn (2019) which cautioned that datafication can restrict students to mere data points, and stripe away their humanistic elements of teaching. Hence, the current research extends this critique to establish that inequitable access to AI tools can cause institutionalisation of systemic exclusion.

9.6 Impact of Longitudinal and Sociotechnical Resilience

The finding indicated that simulation of 24 month projected a 36% growth in literacy rates if AI-driven analytics were scaled nationally. Yet, the finding from qualitative datasets found that Nigerian educators have developed sociotechnical resilience strategies to cope with infrastructural instability. For example, teachers exposed caching AI data during hours of power stability for offline classroom use the following day. This frugal innovation exposes the adaptability and emphasises the potential to solve the problem locally. Such resilience is in support with the World Bank (2023) recommendations that emphasised hybrid (offline/online) educational technologies in developing nations. This is also in support of the contention that sustainable AI integration requires not only technological investment but capacity building and contextual adaptation as well.

9.7 Integration of Theoretical Perspectives

The findings of this study integrate both Connectivism and TPACK frameworks. However, Connectivism explicated the extent to which AI-driven analytics improve the information flow and enable networked learning. Yet, TPACK utilised conceptualisation of human dimension to determine how educators' technological and pedagogical skills mediate the effectiveness of AI tools. In combination of these philosophies, they form a dual lens for understanding AI adoption in developing educational systems. The synthesis of these theories suggests that successful AI integration in Nigeria depends on three interlinked factors:

i) Networked Intelligence that is associated with Connectivism, which resolved that AI must function as a dynamic node within the learning ecosystem.

ii) Contextual Competence that is associated with TPACK resolves that educators must possess the competencies to interpret and perform AI insights.

iii) Infrastructural equity resolved that systemic investments must guarantee that all schools, regardless of location can access and use AI tools effectively.

9.8 Summary of Key Findings

The following findings are keyed to this study:

1) Artificial Intelligence improves identification speed but does not ensure developmental outcomes without human intervention.

2) Bias in algorithms and infrastructural vulnerability are significant barriers to equitable implementation of AI learning analytics.

3) Educator data literacy remains a critical determinant of success, which determines the need for professional development.

4) Localised AI models are necessary to mitigate cultural misclassification and enhance predictive accuracy.

5) Hybrid resilience strategies like offline caching substantiate the adaptability of Nigerian educators and ought to be institutionalised.

9.9 Implications for Policy and Practice

The following implication are considered for policy and practice:

1) The National Learning Analytics Framework should be established to standardise ethical and privacy protocols.

2) In terms of infrastructure, there should be investment in solar-powered digital hubs to ensure continuous data streams.
3) There should be mandatory data literacy training for educators for capacity building.
4) Support for indigenous AI development should be encouraged, tailored to Nigerian linguistic and cultural contexts to satisfy localisation.

10. Policy Recommendations

The following recommendations are made:

1) The Government should endeavour to establish a standardised framework for ethical governance of AI-driven learning analytics for Nigeria Education system. This should follow the transparent protocols for data privacy, child protection and algorithmic standard described by Federal Ministry of Education (2024).
2) Government should address infrastructure challenges of erratic power supply and high internet costs through investment in solar-powered digital hubs and subsidised broadband. These measures would guarantee even-handed access across rural and urban schools as supported by World Bank (2023).
3) Government should endeavour to support teacher capacity building through institutionalised professional development programmes, focusing on data literacy, enabling educators to interpret AI dashboards and integrate analytics into pedagogy.
4) Government and education stakeholders should support indigenous AI development through a locally trained AI models that can reflect Nigerian linguistic and cultural realities to reduce algorithmic bias and improve predictive accuracy.
5) There should be hybrid offline and online systems formulation that can allow educators to cache AI data for offline use to guarantee continuity of learning in resource-constrained environment as established by UNESCO (2023).

11. Conclusion

The conclusions of this study are derived at multi-dimensions. It is stated that AI-driven learning analytics significantly minimise intervention time to improve identification speed from 14.2 to 2.4 days. Nevertheless, infrast5ructural vulnerability, digital literacy gaps and algorithmic bias restrict equitable implementation. The findings integrated Connectivism and TPACK frameworks to hold that EI enhances networked learning (Connectivism) while teacher competence and contextual adaptation (TPACK) influence its effectiveness. Hence, the efficiency paradox that reflects where needs are identified but not addressed, emphasises the need of human-in-the-loop models.

Thus, the policy recommendations highlight ethical governance, infrastructural equity, teacher training, indigenous AI development and hybrid systems. These standards are capable of ensuring that AI adoption fosters inclusive and sustainable educational transformation rather than deepening existing divides. Finally, AI -supported learning analytics are never a cure-all but a causal agent. This implies that their success depends on contextual adaption, ethical oversight and infrastructural investment. Conclusively, by positioning AI within Nigeria's sociotechnical realities, this research offers a blueprint toward achieving responsible and transformative educational innovation. The findings affirm that AI-supported learning analytics has significantly improved identification speed and accuracy, reduce administrative concerns and enhance student self-regulation. Notwithstanding, infrastructural vulnerability, and digital literacy gaps are critical barriers. The case study comparison underlines the digital divide between urban and rural institutions, whereas the longitudinal estimation emphasises the transformative potential of AI if systemic challenges are addressed.

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