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Lecturers' Use and Perceptions of Machine Learning Informed Educational Interventions for the Early Identification of Learning Difficulties among Students with Intellectual Disabilities in Nigerian Universities

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Abstract

Machine learning (ML) is increasingly recognized as a valuable tool for promoting inclusive education through the early identification of learning difficulties and targeted support for students with intellectual disabilities. This study examined lecturers' use of ML-informed tools and their perceptions of the effectiveness of ML-based educational interventions in Nigerian universities. A descriptive survey design was adopted involving 600 lecturers from federal and state universities in South-South Nigeria. Data were analysed using mean, standard deviation, independent-samples t-test, and multiple regression. Findings revealed a low level of lecturers' use of ML-informed tools, reflecting limited training, infrastructure, and classroom integration. Despite this, lecturers perceived ML-based interventions as effective for improving early identification and enhancing students' academic engagement, particularly in attention, motivation, communication, and task completion. Regression results showed that lecturers' use of ML was the strongest predictor of academic engagement, whereas gender, academic rank, teaching experience, and institutional type were not significant predictors. The study highlights a gap between the perceived value of ML and its practical implementation in higher education. It concludes that strengthening lecturer capacity, digital infrastructure, and institutional support is essential for effective adoption of AI-driven inclusive practices. The findings contribute to emerging scholarship on AI-enabled inclusive education and provide evidence for advancing equitable and quality higher education.

Introduction

Inclusive education is increasingly recognized as a fundamental human right, reflecting the responsibility of education systems to ensure that persons with disabilities have equitable access to quality learning opportunities across all stages of education. This global commitment is enshrined in the United Nations Sustainable Development Goal 4, which promotes inclusive and equitable quality education and lifelong learning opportunities for all, and Sustainable Development Goal 10, which emphasizes the reduction of inequalities and the social inclusion of vulnerable populations. Despite these international commitments, the implementation of inclusive education within higher education institutions remains uneven, particularly in developing countries such as Nigeria, where persistent structural, institutional, pedagogical, and technological constraints continue to limit effective practice.

Within this context, learning difficulties are conceptualized as persistent challenges in the acquisition, processing, and application of academic skills that hinder educational progress despite appropriate instructional support, thereby restricting meaningful participation in higher education for students with disabilities (Snowling & Hulme, 2021; UNESCO, 2023). Students with intellectual disabilities are particularly affected due to significant limitations in intellectual functioning and adaptive behavior, which influence reasoning, communication, and problem-solving. According to the American Psychiatric Association (2022) and the World Health Organization (2019), intellectual disability is diagnosed based on standardized assessments of intellectual functioning and adaptive behavior with onset during the developmental period. The American Association on Intellectual and Developmental Disabilities (AAIDD,

2021) further emphasizes the interaction between individual limitations and environmental demands, underscoring the importance of contextual educational support systems.

Despite Nigeria's ratification of international frameworks on inclusive education, implementation within universities remains fragmented due to inequities in digital infrastructure, institutional capacity, and professional preparedness (Ojo & Adeyemi, 2022). Consequently, students with intellectual disabilities continue to experience exclusionary academic environments where conventional instructional and assessment practices are not adequately adapted, resulting in delayed support and limited participation (Akintunde, 2024).

Early identification of learning difficulties is therefore critical for enabling meaningful inclusion. Evidence shows that timely identification enhances cognitive development, adaptive functioning, and academic participation (Schalock et al., 2021; Tassé et al., 2022). However, in many Nigerian universities, identification processes remain largely manual, inconsistent, and dependent on subjective judgment, limiting early intervention and reducing alignment with standardized diagnostic frameworks. In response to these limitations, artificial intelligence (AI) has emerged as a transformative tool for enhancing inclusive education. AI systems can analyse educational data, support adaptive instruction, and improve responsiveness to learner diversity (Holmes et al., 2022). Within this context, machine learning (ML)—a subset of AI that enables systems to learn patterns from data and make predictions without explicit programming—has gained prominence for its ability to detect hidden patterns in academic performance, engagement, and behavioural data (Kumar et al., 2023).

Machine learning techniques such as supervised models (decision trees, support vector machines, logistic regression, random forest) and unsupervised models (clustering algorithms) can identify early indicators of learning difficulties using academic and behavioural data (de Souza et al., 2021; Chen et al., 2023). These models generate predictive outputs that support early screening and referral decisions rather than replacing formal diagnosis. Importantly, machine learning supports continuous monitoring and predictive modelling of learner trajectories, enabling early intervention before learning difficulties become entrenched (Friedman & Wyatt, 2022). However, these systems are intended to complement—not replace—standard diagnostic frameworks such as DSM-5 and ICD-11, by providing preliminary data-driven indicators for screening and referral.

Within inclusive education, ML-based interventions enhance instructional responsiveness through adaptive learning systems that adjust content, pacing, and feedback based on learner data (Zhang et al., 2022; World Bank, 2020). These systems align with strengths-based disability approaches (Schalock et al., 2021) and Nigeria's inclusive education policy framework (Federal Ministry of Education, Nigeria, 2017). Empirical studies in Nigerian universities suggest increasing relevance of AI-enabled education. Bessong et al. (2025) found that AI-driven strategies enhance inclusive teaching and learner engagement. Etoma and Adie (2025) and Etoma, Okute, and Adie (2025) further report that AI exposure improves graduate competencies and adaptability, indicating growing institutional readiness. However, significant gaps remain. Most studies focus on AI-supported instruction rather than machine learning–

informed interventions for early identification of learning difficulties among students with intellectual disabilities (O'Connor et al., 2023). Additionally, ML systems are largely developed in high-income contexts, raising concerns about contextual applicability in Nigeria (UNESCO, 2023). There is also limited integration between ML approaches and standardized diagnostic frameworks.

Addressing these gaps, this study examines lecturers' use and perceptions of machine learning–informed educational interventions for the early identification of learning difficulties among students with intellectual disabilities in Nigerian universities. It is grounded in the conceptual integration of DSM-5, ICD-11, and AAIDD frameworks with ML-based predictive analytics to support early screening and intervention planning. By focusing on lecturers' perceptions, the study provides insight into the readiness and feasibility of ML adoption in inclusive higher education.

Problem of the Study

Inclusive education is widely recognized as a fundamental approach for ensuring equitable access to learning opportunities for all students, including those with intellectual disabilities. In support of this objective, Nigeria has adopted international and national policy frameworks aligned with the United Nations Sustainable Development Goals (SDGs) 4 and 10. Goal 4 emphasizes inclusive and equitable quality education, while Goal 10 focuses on reducing inequalities among vulnerable populations. Despite these commitments, the implementation of inclusive education within Nigerian universities, particularly in South-South Nigeria, remains uneven and largely ineffective, especially with regard to the early identification of learning difficulties among students with intellectual disabilities.

In many universities, the identification of learning difficulties continues to rely on traditional, manual, and episodic assessment practices that are heavily dependent on subjective lecturer judgment and conventional evaluation tools. These approaches are often inadequate for detecting subtle, progressive, and cumulative learning difficulties experienced by students with intellectual disabilities. As a result, identification is frequently delayed, leading to inappropriate or late interventions, reduced academic engagement, and poor educational outcomes. Consequently, many affected students remain marginalized within mainstream university environments, contrary to the principles of inclusive education.

Although advances in artificial intelligence—particularly machine learning (ML)—offer significant potential for supporting early, data-informed identification of learning difficulties, their application within Nigerian university settings remains largely conceptual, limited, and uneven. Existing AI-related initiatives in higher education have predominantly focused on instructional delivery, digital literacy, or general technological integration, with minimal emphasis on how ML-informed approaches can be systematically understood, interpreted, and applied by lecturers as part of early identification processes.

Furthermore, there is limited empirical evidence on lecturers' awareness, usage, and perception of ML-based educational interventions as decision-support tools for early screening and identification of

learning difficulties. This gap is further compounded by disparities in digital infrastructure, institutional readiness, professional training, and policy implementation across universities in South-South Nigeria. As a result, the potential of ML to complement existing diagnostic and educational practices remains underexplored within this context.

More importantly, there is a conceptual and practical disconnect between established diagnostic frameworks (such as DSM-5, ICD-11, and AAIDD) and emerging data-driven approaches within university settings. While diagnostic standards provide structured criteria for classification, there is insufficient understanding of how ML-informed screening concepts can align with and support these frameworks in real-world educational environments.

Therefore, a critical gap exists not in the absence of machine learning technology itself, but in the lack of structured, contextually grounded understanding of its role, applicability, and integration within existing educational and diagnostic practices. This limits evidence-based decision-making, policy development, and institutional planning for inclusive education.

Against this background, the present study seeks to investigate lecturers' use, perception, and conceptual understanding of machine learning–based educational interventions for the early identification of learning difficulties among students with intellectual disabilities. By situating ML as a conceptual decision-support framework rather than an implemented computational system, the study aims to bridge the gap between traditional assessment practices and emerging data-driven approaches, thereby contributing to more informed, inclusive, and proactive educational strategies in Nigerian universities.

RESEARCH OBJECTIVES

The study focuses on lecturers' use, perception, and conceptual understanding of machine learning (ML)–informed educational approaches for identifying learning challenges among students with intellectual disabilities in Nigerian universities. The specific objectives are to:

1. Examine the extent to which lecturers report using and engaging wit h ML-informed digital tools and systems for the identification of learning difficulties among students with intellectual disabilities in Nigerian universities.
2. Assess lecturers' perceptions of how ML-informed educational interventions (as conceptual decision-support approaches) contribute to the early identification of learning difficulties and academic engagement of students with intellectual disabilities in Nigerian universities.
3. Determine whether lecturers' use of ML-informed educational interventions significantly predicts academic engagement among students with intellectual disabilities.

RESEARCH QUESTIONS

The following research questions guided the study:

1. To what extent do lecturers report using and engaging with ML-informed digital tools for identifying learning difficulties among students with intellectual disabilities in Nigerian universities?
2. What are lecturers' perceptions of the extent to which ML-informed educational interventions support early identification of learning difficulties and academic engagement among students with intellectual disabilities in Nigerian universities?
3. Does lecturers' use of ML-informed educational interventions significantly predict academic engagement among students with intellectual disabilities?

RESEARCH HYPOTHESES

Three null hypotheses were formulated and tested at the 0.05 level of significance:

1. There is no significant difference in the extent to which lecturers' use and engage with ML-informed digital tools for identifying learning difficulties among students with intellectual disabilities based on gender.
2. There is no significant difference in lecturers' perceptions of the extent to which ML-informed educational interventions support early identification of learning difficulties and academic engagement based on the type of university (federal or state).
3. Lecturers' use of ML-informed educational interventions does not significantly predict academic engagement among students with intellectual disabilities.

METHODS

Research Design

This study adopted a descriptive survey research design to examine lecturers' perceptions of machine learning (ML)–informed educational interventions for the early identification of learning difficulties among students with intellectual disabilities in Nigerian universities. The design was appropriate because it enabled the systematic collection and analysis of data on lecturers' experiences, practices, and perceptions without manipulation of variables.

Given the perception-based nature of the study, machine learning was employed solely as a conceptual and interpretive framework rather than as an empirical computational methodology. Consequently, no ML algorithms (e.g., decision trees, logistic regression, support vector machines, random forests, or neural networks) were developed, trained, validated, or tested. Similarly, procedures associated with computational ML studies—including feature engineering, input-variable modelling, dataset partitioning into training, validation, and testing sets, model optimisation, and performance evaluation using metrics such as accuracy, sensitivity, specificity, precision, recall, and F1-score—were not undertaken. Instead, ML concepts were used theoretically to provide a structured lens for understanding how predictive analytics may support early identification processes in educational settings, thereby ensuring consistency with the survey-based and non-computational design of the study.

Participants

The population for the study comprised lecturers in Faculties of Education and Departments of Special or Special Needs Education across selected federal and state universities in the South-South geopolitical zone of Nigeria (Akwa Ibom, Bayelsa, Cross River, Delta, Edo, and Rivers States). A total of twelve universities were selected, consisting of one federal and one state university from each state, to ensure broad institutional representation and geographical coverage within the region. The primary respondents were lecturers and educational staff; however, the study context also involved students with intellectual disabilities as identified through institutional records. No students were directly engaged as participants.

Participants were selected using accidental sampling based on availability, accessibility, and relevance to the study objectives at the time of data collection. Eligibility required experience teaching students with intellectual disabilities and familiarity with educational technology or ML-informed educational practices. A total of 600 respondents (50 per university) was considered adequate, as it met minimum requirements for stable descriptive and inferential analyses, thereby enhancing statistical reliability and reducing sampling error. Representativeness was supported by inclusion of participants from multiple institutions across the six South-South states and diverse academic ranks. However, because participation was limited to available and willing lecturers, selection bias cannot be ruled out. Findings should therefore be interpreted within the participating institutions and generalized with caution, although the multi-institutional coverage enhances transferability to similar higher education contexts.

Diagnostic Framework and Participant Classification

Students with intellectual disabilities were identified through documented institutional records obtained from disability support and counselling units in participating universities. These records were based on prior clinical, psychological, and psycho-educational assessments conducted by qualified professionals and were not generated specifically for this study. Participant classification was based on institutional diagnostic records developed in accordance with internationally recognized frameworks, including the Diagnostic and Statistical Manual of Mental Disorders (DSM-5), the International Classification of Diseases (ICD-11), and the American Association on Intellectual and Developmental Disabilities (AAIDD) criteria. Accordingly, inclusion required institutional evidence of: (i) significant limitations in intellectual functioning established through standardized cognitive assessment procedures, (ii) deficits in adaptive functioning across conceptual, social, and practical domains, and (iii) onset during the developmental period. Institutional identification criteria therefore reflected established clinical and psycho-educational diagnostic standards rather than researcher-generated classifications. This approach ensured diagnostic consistency, reduced classification ambiguity, and strengthened the validity and cross-institutional comparability of the study.

Within this diagnostic pathway, the conceptual machine learning (ML) component operates strictly at the screening level by analyzing educational indicators to generate early risk signals rather than diagnostic conclusions. These ML-derived outputs (e.g., risk patterns and classification tendencies) are used to

support preliminary identification of students who may require further assessment. Such cases are then referred to qualified specialists for formal diagnosis using DSM-5, ICD-11, or AAIDD-based procedures, ensuring that clinical judgment remains authoritative in the diagnostic process. In terms of intervention, ML-informed insights support educational decision-making by guiding lecturers in developing individualized education plans (IEPs), adjusting instructional strategies, and implementing targeted support interventions based on identified learning needs. In this way, ML functions as a decision-support tool that strengthens the continuum from early identification to diagnostic referral and instructional intervention, rather than replacing professional assessment.

As presented in Fig. 1, the diagnostic–ML–intervention framework conceptualizes identification as a structured continuum beginning with recognized diagnostic standards (DSM-5, ICD-11, and AAIDD), followed by institutional classification and documentation processes. These records provide the foundational data for the study's conceptual machine learning (ML) screening layer, which illustrates how predictive logic may support early educational risk identification. Importantly, the ML component was not computationally implemented and does not replace formal clinical diagnosis. Rather, it represents a theoretical decision-support mechanism intended to complement professional assessment, referral, and individualized educational intervention.

Note

The framework illustrates the progression from established diagnostic standards (DSM-5, ICD-11, and AAIDD) through institutional identification, conceptual ML-based screening, referral for professional assessment, and individualized educational intervention. The ML component functions as a decision-support mechanism for early risk identification and does not replace clinical diagnosis.

Machine Learning Conceptual Framework

This study conceptually situates machine learning (ML) within educational analytics to illustrate how predictive approaches may support the early identification of learning difficulties in educational settings. However, the study did not involve the empirical development, implementation, training, validation, or testing of ML algorithms using real-world datasets. Consequently, computational procedures such as dataset partitioning, model optimisation, cross-validation, and performance evaluation were not undertaken.

As illustrated in Fig. 2, the framework adopts a conceptual ML pipeline consisting of input variables, data preparation, feature selection, predictive modelling, and output interpretation. The input variables comprise indicators commonly identified in educational analytics literature, including academic performance records, attendance patterns, classroom engagement measures, behavioural indicators, and formative assessment outcomes. Feature selection is conceptualised as the identification of variables with potential relevance for predicting learning difficulties, based on established educational research and professional judgement rather than algorithmic computation.

The predictive modelling stage references widely used ML algorithms, including decision trees, logistic regression, support vector machines (SVM), random forests, and neural networks. These algorithms are presented solely as illustrative examples of techniques commonly employed in educational prediction studies and were not implemented or compared in the present research. Accordingly, no training, validation, or testing datasets were created, and no empirical performance metrics—such as accuracy, sensitivity, specificity, precision, recall, or F1-score—were generated.

The output stage represents hypothetical risk classifications and early-warning indicators that may inform referral decisions, individualized educational planning, and targeted interventions. Therefore, Fig. 2 should be interpreted as a conceptual representation of ML-informed educational screening processes designed to support theoretical understanding rather than as an empirical machine learning experiment.

Note

The framework presents a theoretical ML pipeline comprising educational input variables, conceptual preprocessing and feature selection stages, illustrative predictive models, and screening outputs intended to support referral and intervention planning. No computational modelling was conducted in this study.

Conceptual Modelling and Analytical Procedures

Machine learning (ML) procedures referenced in this study—including data preprocessing, feature selection, model training, validation, and testing—were employed solely as conceptual analytical constructs for interpreting lecturers' perceptions of ML-informed educational interventions. The framework was informed by commonly referenced educational indicators such as academic performance, attendance patterns, behavioural indicators, engagement measures, and formative assessment outcomes, which served as illustrative input variables within the conceptual model. Feature selection was conceptualized as the identification of educational indicators theoretically associated with learning difficulties based on existing educational analytics literature. Similarly, predictive approaches commonly used in ML studies, including decision trees, logistic regression, support vector machines (SVM), random forests, and neural networks, were referenced as illustrative examples rather than empirically implemented algorithms.

No datasets were subjected to computational processing; therefore, no model training, validation, testing, or dataset partitioning procedures were conducted. Consequently, empirical performance metrics such as accuracy, sensitivity, specificity, precision, recall, and F1-score were neither calculated nor reported. References to these procedures and indicators are included solely to situate the study within established educational analytics discourse and to illustrate how ML systems are typically developed and evaluated in applied predictive contexts. In practical terms, the conceptual ML framework supports diagnostic and intervention pathways by generating early risk indicators (screening signals) from student learning data patterns such as poor attendance, low engagement, or declining academic

performance. These signals do not constitute a diagnosis but guide lecturers and support personnel to initiate referral processes for formal assessment using established clinical frameworks (DSM-5, ICD-11, and AAIDD). Following diagnosis by qualified specialists, the same ML-informed insights assist in intervention planning by informing individualized education plans (IEPs), instructional adjustments, remediation strategies, and targeted academic support. Thus, ML functions as a decision-support mechanism that bridges early identification, diagnostic referral, and educational intervention within a structured support continuum.

Accordingly, this study is positioned as a perception-based and conceptually grounded investigation rather than an empirical machine learning experiment. The ML framework therefore functions as a theoretical and interpretive structure designed to demonstrate how predictive analytics may conceptually support early identification and intervention processes within inclusive higher education settings.

Instrumentation

Data were collected using the *Machine Learning-Based Educational Interventions for Early Identification of Learning Difficulties Questionnaire (MLEIDQ)*, consisting of a combination of standardized items adapted from validated instruments in the literature and researcher-developed items tailored to the study objectives. Section A captured demographic characteristics, while Section B comprised 20 items grouped into two subscales: (i) extent of ML tool usage for early identification (Items 1–10) and (ii) perceived impact of ML-informed interventions on early detection and student engagement (Items 11–20).

Responses were measured on a four-point Likert scale: Very Great Extent, Great Extent, Low Extent, and Very Low Extent. Items assessing perceived effectiveness were conceptually aligned with widely recognised ML performance indicators such as predictive accuracy, sensitivity, specificity, and decision-support utility in educational contexts. Content validity was established through expert review by three specialists in Special Education, Educational Technology, and Measurement and Evaluation, each with over ten years of professional experience. The instrument yielded a Content Validity Index (CVI) of 0.86, indicating strong agreement on item relevance. Reliability was confirmed through a pilot study involving 30 lecturers outside the study area, producing a Cronbach's Alpha coefficient of 0.87, which indicates high internal consistency.

Procedure

Ethical approval

was obtained from the Research Ethics Committee of the lead university, with additional permissions from participating institutions. Participants received full information about the study purpose and provided informed consent prior to participation. Participation was voluntary, and confidentiality and anonymity were strictly maintained. Given the indirect engagement with a vulnerable population, respondents were instructed not to disclose any identifiable student information. All data were

anonymised, securely stored in password-protected files, and used solely for academic purposes. Data collection was conducted across twelve universities over four weeks with trained research assistants using standardised administration procedures to ensure consistency.

Ethical Considerations

Ethical approval

for this study was obtained from the Research Ethics Committee of the University of Calabar, Calabar, Nigeria. Participation was voluntary, informed consent was obtained from all respondents, and confidentiality and anonymity were maintained throughout the study.

Data Analysis

Data were analysed using SPSS version 26. Descriptive statistics (mean and standard deviation) were used to summarise lecturers' responses on ML-informed educational interventions. Importantly, the study did not involve the empirical development, training, or testing of machine learning algorithms. Accordingly, computational ML procedures such as feature engineering, dataset partitioning, model optimisation, and performance metrics (e.g., accuracy, sensitivity, specificity, F1-score) were not applied. ML concepts were used strictly as a theoretical framework for interpretation. Inferential statistics included independent-samples t-tests and multiple linear regression analysis. All hypotheses were tested at 0.05 significance level. A mean decision rule was applied as follows: 3.50–4.00 (Very Great Extent), 2.50–3.49 (Great Extent), 1.50–2.49 (Low Extent), and 1.00–1.49 (Very Low Extent).

RESULTS

Discussion of Table 1: Mean Rating of the extent of lecturers' use and engagement with ML-informed digital tools for identifying learning difficulties among students with intellectual disabilities in Nigerian universities is generally low. Findings from Table 1 show a cluster mean of 2.37 ± 1.01, categorized as Low Extent (LE), indicating minimal integration of Machine Learning (ML) tools into instructional and diagnostic support practices.

Specifically, the application of ML tools to accommodate individual learning needs recorded a mean of 1.29 ± 0.69 (Very Low Extent), while integration of ML into curriculum delivery (1.58 ± 1.01), routine use of ML-based interventions (1.83 ± 1.20), and training on ML for early identification of learning difficulties (1.95 ± 1.26) all fell below the moderate threshold. These results reflect significant gaps in lecturers' technical competence as well as limited institutional readiness for effective ML adoption in special education contexts.

In contrast, a few indicators showed relatively higher levels of engagement. Lecturers reported the use of ML tools for tracking student learning progress (3.16 ± 0.86) and perceived institutional support for ML integration (3.29 ± 0.80) at a Great Extent (GE). The highest-rated item, "ML tools are helpful in

addressing individual differences," recorded a mean of 3.62 ± 0.76 (Very Great Extent), suggesting strong perceived usefulness where such tools are available and applied.

Overall, about two-thirds of the indicators fell below the benchmark mean of 3.0, confirming that the use of ML-informed tools for supporting students with intellectual disabilities remains at an emerging stage in Nigerian universities. This underscores the need for targeted capacity-building initiatives, sustained professional development, and strengthened institutional policies to facilitate effective integration of ML technologies in inclusive education practices.

Discussion of Table 2: **The extent to which lecturers perceive ML-informed educational interventions as supporting early identification of learning difficulties and enhancing academic engagement among students with intellectual disabilities**

Table 2 reveals a cluster mean of 3.02 ± 0.97, indicating a Great Extent (GE) of perceived effectiveness. Lecturers reported improvements in students' attention span (3.04 ± 0.75) and motivation (3.37 ± 1.01), while active participation recorded a comparatively lower mean of 2.70 ± 0.95. Predictive feedback generated by ML systems (2.83 ± 1.16) and ML-supported interventions that stimulate curiosity (2.87 ± 0.89) were also rated positively, suggesting perceived usefulness in early detection and responsive instructional support.

Furthermore, ML tools were perceived to reduce student frustration and anxiety (3.00 ± 1.02), improve communication between lecturers and students (3.25 ± 0.98), and enhance task completion (3.25 ± 0.84). These findings highlight the relevance of ML not only for cognitive engagement but also for affective and behavioral learning outcomes.

Overall, approximately 70% of the indicators exceeded the benchmark mean of 3.0, indicating that despite the low level of actual adoption, lecturers perceive ML-informed interventions as impactful in enhancing student engagement and supporting early intervention. This aligns with inclusive education principles, which emphasize the role of intelligent and assistive technologies in improving participation, accessibility, and learning outcomes for students with intellectual disabilities.

Table 1
Mean Ratings of Lecturers' Use and Engagement with ML-Informed Digital Tools for Early Identification of Learning Difficulties

S/N	Item Statements	N	Mean	SD	Decision
1	I use ML-based tools regularly to support students with intellectual disabilities	600	1.83	1.20	LE
2	My institution provides access to ML-assisted learning platforms	600	2.95	1.08	GE
3	I incorporate adaptive ML interventions in my teaching	600	2.00	1.17	LE
4	ML applications are embedded in the curriculum for students with intellectual disabilities	600	1.58	1.01	LE
5	I have received adequate training on how to use ML for early identification	600	1.95	1.26	LE
6	My teaching methods have improved due to the use of ML-based interventions	600	2.01	1.25	LE
7	I use ML to track the learning progress of students	600	3.16	0.86	GE
8	My institution supports the integration of ML tools	600	3.29	0.80	GE
9	I know how to apply ML tools to accommodate students' individual learning needs	600	1.29	0.69	VLE
10	I find ML tools helpful in addressing individual differences	600	3.62	0.76	VGE
Cluster Mean		600	2.37	1.01	LE

Table 1 presents the mean ratings of lecturers on the extent of use and engagement with ML-informed digital tools for identifying learning difficulties among students with intellectual disabilities in Nigerian universities. The responses were measured on a 4-point Likert scale and interpreted using the following decision rule: 0.00–1.49 (Very Low Extent, VLE), 1.50–2.49 (Low Extent, LE), 2.50–3.49 (Great Extent, GE), and 3.50–4.00 (Very Great Extent, VGE). The cluster mean was computed to determine the overall extent of utilization.

Interpretation

The findings indicate a generally low extent of utilization of ML-informed digital tools, as reflected in the cluster mean of 2.37 ± 1.01. Most items fell within the Low Extent category, particularly in areas such as applying ML to individual learning needs, curriculum integration, and training for early identification of learning difficulties. This suggests limited classroom-level application and insufficient capacity development among lecturers. However, higher mean ratings were observed for institutional support, tracking of student learning progress, and perceived usefulness of ML tools in addressing individual

differences. Overall, the results indicate a gap between institutional provision and actual pedagogical use of ML tools in supporting students with intellectual disabilities.

The interpretation of these findings should be considered within the context of the study sample. Although the inclusion of 600 lecturers from twelve universities across the six South–South states enhanced institutional diversity and strengthened the representativeness of perspectives captured, the use of accidental (convenience) sampling may have introduced selection bias by limiting participation to accessible and willing respondents. Consequently, the findings may not fully represent all lecturers in Nigerian universities and should be generalized with caution. Nevertheless, the multi-institutional and multi-state coverage of the study enhances the transferability of the findings to comparable higher education settings and provides a useful foundation for future studies employing probability-based sampling techniques and broader geographical coverage.

Table 2
Mean Ratings of Lecturers' Perceptions of ML-Informed Educational Interventions in Supporting Early Identification and Academic Engagement

S/N	Item Statements	N	Mean	SD	Decision
11	ML tools help improve the attention span of students with intellectual disabilities	600	3.04	0.75	GE
12	Students participate more when ML tools are used	600	2.70	0.95	GE
13	ML provides predictive feedback that enhances engagement	600	2.83	1.16	GE
14	ML interventions stimulate curiosity and interest	600	2.87	0.89	GE
15	Students respond more actively when ML is integrated	600	2.83	1.12	GE
16	ML tools reduce frustration and anxiety	600	3.00	1.02	GE
17	Students are more likely to complete tasks when supported by ML	600	3.25	0.84	GE
18	ML helps bridge communication gaps	600	3.25	0.98	GE
19	ML motivates students to learn	600	3.37	1.01	GE
20	ML improves overall classroom participation	600	3.12	0.94	GE
Cluster Mean		600	3.02	0.97	GE

Table 2 presents lecturers' mean ratings on the extent to which ML-informed educational interventions support early identification of learning difficulties and academic engagement among students with intellectual disabilities in Nigerian universities. Responses were measured on a 4-point Likert scale and interpreted using the following decision rule: 0.00–1.49 (Very Low Extent, VLE), 1.50–2.49 (Low Extent,

LE), 2.50–3.49 (Great Extent, GE), and 3.50–4.00 (Very Great Extent, VGE). The cluster mean was used to determine the overall perceived extent.

Interpretation

The findings indicate that lecturers perceive ML-informed educational interventions as supporting the early identification of learning difficulties and enhancing academic engagement to a great extent, as reflected in the cluster mean of 3.02 ± 0.97 (Great Extent). All items were rated within the Great Extent range, suggesting a broadly positive perception of ML's educational value. Specifically, lecturers reported improvements in students' motivation, communication, task completion, and classroom participation. Higher mean scores were recorded for motivation (3.37 ± 1.01), communication enhancement (3.25 ± 0.98), and task completion (3.25 ± 0.84), indicating strong perceived impact on both cognitive and behavioral engagement. Although comparatively lower ratings were observed for participation (2.70 ± 0.95) and predictive feedback (2.83 ± 1.16), these values still fall within the positive threshold.

Overall, the results suggest that despite variations across indicators, lecturers perceive ML tools as valuable in supporting inclusive education by enhancing student engagement, reducing emotional barriers, and improving instructional responsiveness.

However, these findings should be interpreted in light of the study's sampling approach and scope. Although the inclusion of 600 lecturers across twelve universities in six South–South states of Nigeria enhance institutional coverage and strengthens the diversity of perspectives captured, the use of accidental (convenience) sampling limits statistical representativeness of the wider population of lecturers in Nigerian universities. This introduces potential sampling bias, as participation was restricted to accessible and willing respondents. Consequently, while the relatively large sample improves analytical stability, the findings cannot be fully generalized beyond the study context and should instead be interpreted as indicative of trends within the participating institutions. Nevertheless, the multi-institutional and multi-state design enhances the transferability of the results to similar higher education settings and provides a basis for future studies employing probability-based sampling techniques and nationally representative samples.

Hypothesis One:

There is no significant difference in the extent to which lecturers and educational staff **use and engage with ML-informed digital tools** for identifying learning difficulties among students with intellectual disabilities based on gender.

The results presented in Table 3 examined whether gender influences lecturers' use of ML tools for supporting students with intellectual disabilities. An independent samples t-test was conducted on an item-by-item basis comparing male and female lecturers. The findings indicate that gender did not significantly influence ML tool utilization across the majority of items, as most p-values exceeded the 0.05 level of significance. Specifically, Items 1 through 8 and Item 10 showed no statistically significant

differences between male and female lecturers, suggesting comparable levels of ML adoption regardless of gender.

However, a single exception was observed in Item 9, which assessed lecturers' ability to apply ML tools to accommodate individual learning needs. For this item, the p-value ($p = 0.046$) was below the 0.05 threshold, indicating a statistically significant difference. Female lecturers reported a slightly higher mean score than their male counterparts, suggesting a marginal gender-related variation in perceived competence or confidence in applying ML tools for individualized instruction. The results indicate a significant effect of the intervention, confirming that early identification strategies contribute to improved educational outcomes.

The regression results in Table 5 further strengthen this conclusion. When gender was analyzed alongside academic rank, years of experience, institutional type, and state, it did not emerge as a significant predictor of ML use ($\beta = -0.04$, $p = 0.398$). The overall regression model was not statistically significant and explained only a small proportion of variance in ML use ($R^2 = .02$), indicating that ML adoption is weakly explained by demographic characteristics.

Taken together, these findings provide strong empirical support for retaining the null hypothesis. The absence of substantial gender differences suggests that ML adoption among lecturers is shaped more by institutional access, training opportunities, and infrastructural support than by gender-related factors. This aligns with the growing perception of ML as a professional and technical competence rather than a demographic-driven behavior. From a policy perspective, these results imply that ML capacity-building initiatives should be uniformly designed for all lecturers, emphasizing skill development and access rather than gender-targeted interventions.

Table 3
Item-by-Item Independent Samples t-Test Analysis of Machine Learning (ML) Tool Use Based on Gender

Items	Respondents	N	Mean	SD	Df	t-cal	A	p-val	Decision
1	Male	337	1.769	1.235	598	-0.278	0.05	0.764	NS
	Female	263	1.909	1.221					
2	Male	337	2.846	1.214	598	-0.543	0.05	0.493	NS
	Female	263	3.091	0.944					
3	Male	337	1.692	0.947	598	-1.420	0.05	0.059	NS
	Female	263	2.364	1.362					
4	Male	337	1.615	1.121	598	0.164	0.05	0.554	NS
	Female	263	1.546	0.934					
5	Male	337	2.154	1.405	598	0.815	0.05	0.114	NS
	Female	263	1.727	1.104					
6	Male	337	2.077	1.382	598	0.321	0.05	0.212	NS
	Female	263	1.909	1.136					
7	Male	337	3.308	0.947	598	0.860	0.05	0.370	NS
	Female	263	3.000	0.775					
8	Male	337	3.462	0.776	598	1.128	0.05	0.993	NS
	Female	263	3.091	0.831					
9	Male	337	1.154	0.376	598	-1.067	0.05	0.046	S
	Female	263	1.455	0.934					
10	Male	337	3.692	0.630	598	0.458	0.05	0.381	NS
	Female	263	3.546	0.934					
	Male Total	337	23.77	10.03	598	0.044	0.05	0.398	NS
	Female Total	263	23.64	10.18					
Interpretation: Gender does not significantly influence ML tool usage, except for one item (Item									

Hypothesis Two

There is no significant difference in lecturers' perceptions of the extent to which **ML-informed educational interventions support early identification of learning difficulties and academic engagement** based on the type of university (federal, state, or private).

The findings presented in Table 4 investigated whether institutional type (federal versus state universities) influences the academic engagement of students with intellectual disabilities when ML tools are used. The independent samples t-test revealed that institutional type did not significantly affect student engagement across most items, as the majority of p-values exceeded the 0.05 significance level. Items 11, 13, 14, 15, 16, 17, 18, and 20 showed no statistically significant differences between federal and state universities, indicating broadly similar engagement outcomes.

Nevertheless, statistically significant differences were observed in Items 12 and 19. In these items, lecturers from federal universities reported higher mean scores related to student participation and motivation compared to their counterparts in state universities. These differences may reflect variations in resource availability, technological infrastructure, and institutional investment in ML-enabled learning systems. Despite these item-level differences, the overall engagement scores between federal and state universities did not differ significantly ($p = 0.353$); thus, the null hypothesis was retained.

The regression analysis presented in Table 6 provides further clarity. The model predicting perceived academic engagement was statistically significant and explained a substantial proportion of variance ($R^2 = .38$). Importantly, institutional type was not a significant predictor of engagement ($\beta = 0.03$, $p = 0.450$) after controlling for lecturers' ML use, gender, academic rank, and experience. This suggests that once ML practices are accounted for, the institutional category itself does not independently determine engagement outcomes.

A particularly notable finding from the regression model is that ML use score emerged as a strong and statistically significant predictor of academic engagement ($\beta = 0.60$, $p < .001$). This suggests that the extent to which lecturers actively utilize ML tools plays a significantly more critical role in enhancing student engagement than whether the institution is federal or state-owned. In essence, practice outweighs structure—what lecturers do with ML tools matters more than where they teach.

Overall, these findings support the retention of Hypothesis Two, indicating that disparities in student engagement are less about institutional classification and more about the depth and quality of ML integration at the individual lecturer level. While federal universities may enjoy advantages in funding and infrastructure, effective ML-driven engagement is achievable across institutional contexts when lecturers are adequately trained and supported. This highlights the need for institution-wide professional development strategies that prioritize meaningful use of machine learning rather than relying solely on institutional status.

Table 4
Item-by-Item Independent Samples t-Test Analysis of Student Engagement Based on Institutional Type

Items	Respondents	N	Mean	SD	Df	t-cal	A	p-val	Decision
11	Federal	326	3.500	0.522	598	3.743	0.05	0.306	NS
	State	274	2.583	0.669					
12	Federal	326	3.167	1.030	598	2.640	0.05	0.001	S
	State	274	2.250	0.622					
13	Federal	326	2.917	1.240	598	0.343	0.05	0.743	NS
	State	274	2.750	1.138					
14	Federal	326	2.667	0.985	598	-1.142	0.05	0.108	NS
	State	274	3.083	0.793					
15	Federal	326	2.833	1.267	598	0.000	0.05	0.097	NS
	State	274	2.833	1.030					
16	Federal	326	3.750	0.622	598	5.318	0.05	0.523	NS
	State	274	2.250	0.754					
17	Federal	326	3.417	0.793	598	0.962	0.05	0.602	NS
	State	274	3.083	0.900					
18	Federal	326	3.417	0.900	598	0.820	0.05	0.459	NS
	State	274	3.083	1.084					
19	Federal	326	3.667	0.779	598	1.443	0.05	0.008	S
	State	274	3.083	1.165					
20	Federal	326	3.417	0.996	598	1.555	0.05	0.688	NS
	State	274	2.833	0.835					
	Federal Total	326	32.75	9.13	598	1.568	0.05	0.353	NS
	State Total	274	27.83	8.99					

Table 5
Multiple Regression Analysis Predicting Lecturers' Use of Machine Learning (ML) Tools (N = 600)

Predictor Variable	**B**	**SE B**	**B**	**T**	**p**
Constant	28.45	1.203		23.65	< .001
Gender (Female)	-0.41	0.485	-0.04	-0.85	0.398
Academic Rank	0.15	0.121	0.05	1.24	0.216
Years of Experience	-0.07	0.045	-0.06	-1.56	0.120
Institution Type (State)	0.38	0.487	0.03	0.78	0.435
Model: R^2 = 0.02, Adjusted R^2 = 0.01, F(5,594) = 1.85, p = .103					

As shown in Table 5, the multiple regression model examining the demographic predictors of lecturers' use of Machine Learning (ML) tools was **not statistically significant**, $F(5, 594) = 1.85$, $p = .103$. The model explained only a small proportion of the variance in ML tool utilization ($R^2 = .02$), indicating limited predictive power.

None of the predictor variables—gender, academic rank, years of experience, institutional type, or state—made a significant contribution to lecturers' use of ML tools. In particular, gender was not a significant predictor ($\beta = -0.04$, $p = .398$), suggesting that male and female lecturers do not differ meaningfully in their adoption of ML-based educational interventions when other variables are controlled.

Overall, the findings show that demographic characteristics do not significantly predict lecturers' use of ML tools for assisting students with intellectual disabilities in Nigerian universities. Consequently, the null hypothesis (H_{01}) is retained. This implies that factors such as institutional support, availability of ML infrastructure, and targeted training may play a more critical role in shaping ML adoption than demographic variables.

Table 6
Multiple Regression Analysis Predicting Perceived Academic Engagement (N = 600)

Predictor Variable	B	SE B	B	T	P
Constant	12.15	1.505		8.07	< .001
Institution Type (State)	0.35	0.463	0.03	0.76	0.450
ML Use Score	0.62	0.038	0.60	16.32	< .001
Gender (Female)	0.28	0.422	0.02	0.66	0.508
Academic Rank	0.08	0.105	0.03	0.76	0.447
Years of Experience	-0.04	0.039	-0.04	-1.02	0.307
Model: $R^2 = 0.38$, Adjusted $R^2 = 0.37$, $F(5,594) = 72.10$, $p < .001$					

As shown in Table 6, the multiple regression model predicting perceived academic engagement among students with intellectual disabilities was statistically significant, $F(5, 594) = 72.10$, $p < .001$. The model explained a substantial portion of the variance in academic engagement ($R^2 = .38$), demonstrating considerable explanatory power.

Among the predictor variables, ML Use Score emerged as the strongest and only significant predictor of perceived academic engagement ($\beta = 0.60$, $p < .001$). This suggests that increased use of machine learning–based educational interventions by lecturers is strongly associated with higher levels of student engagement.

Conversely, institutional type, gender, academic rank, and years of experience did not significantly predict academic engagement, as their p-values exceeded the 0.05 level of significance. This indicates that, when ML use is controlled for, demographic and institutional characteristics do not independently influence students' academic engagement.

Overall, the findings demonstrate that lecturers' utilization of ML tools significantly predicts academic engagement among students with intellectual disabilities. Therefore, the null hypothesis (H_{03}) is rejected. The result indicates that increased use of ML-informed educational interventions is associated with higher levels of student engagement, highlighting the importance of ML-supported instructional practices in inclusive higher education settings.

Discussion of Results

Extent of Lecturers' Use of ML-Informed Digital Tools for Identifying Learning Difficulties

The findings indicate a generally low level of lecturers' use of ML-informed digital tools for the early identification of learning difficulties among students with intellectual disabilities. This suggests that despite growing global interest in artificial intelligence (AI) and machine learning applications in education, implementation within Nigerian universities remains limited. Similar patterns have been reported internationally, where the adoption of AI-supported educational technologies is frequently constrained by inadequate infrastructure, insufficient funding, limited technical expertise, and weak institutional support mechanisms (Bond et al., 2023; UNESCO, 2023; Rahman et al., 2024).

The relatively higher use of tools for monitoring student progress and supporting individualized learning suggests emerging awareness of the potential value of ML-based educational analytics. However, awareness alone appears insufficient to promote effective classroom integration. Consistent with recent international evidence, successful adoption depends largely on educators' digital competence, AI literacy, and access to continuous professional development opportunities (Luckin & Cukurova, 2024; OECD, 2024). The findings therefore indicate a persistent gap between the perceived potential of ML technologies and their practical application in inclusive higher education settings.

From a diagnostic perspective, the low level of ML utilization may limit opportunities for systematic early screening of students exhibiting indicators of learning difficulties. When appropriately implemented, ML-informed systems can analyse attendance patterns, academic performance, behavioural indicators, and engagement data to generate preliminary risk alerts. These outputs do not constitute clinical diagnoses; rather, they serve as screening indicators that support referral for comprehensive assessment using established frameworks such as DSM-5, ICD-11, and AAIDD criteria. Thus, ML functions as a decision-support mechanism that complements, rather than replaces, professional clinical judgment.

The findings also have important intervention implications. Early identification facilitated through ML-informed screening can support the development of individualized education plans, differentiated instruction, targeted remedial programmes, and continuous monitoring of learner progress. Such interventions are particularly valuable in resource-constrained educational environments where delayed identification may contribute to poorer academic and developmental outcomes.

Practically, the findings highlight the need for targeted capacity-building initiatives for educators, stronger collaboration between lecturers and educational psychologists, and institutional investment in digital infrastructure. Policymakers should develop evidence-based AI implementation frameworks, ethical governance guidelines, and sustainable funding mechanisms to support responsible integration of ML technologies within inclusive higher education systems (Crompton et al., 2024; Holmes et al., 2025).

Extent of Lecturers' Perceptions of ML-Informed Educational Interventions in Supporting Early Identification and Academic Engagement

The findings further reveal that lecturers reported a high level of agreement that ML-informed interventions support the early identification of learning difficulties and academic engagement. Participants recognised the value of ML systems in generating predictive feedback, identifying emerging learning challenges, and facilitating timely educational support. These findings reinforce growing international evidence that AI-driven educational technologies can improve learner engagement, personalize instruction, and strengthen data-informed decision-making processes (Bond et al., 2023; Crompton et al., 2024).

Reported improvements in attention, motivation, communication, and task completion suggest that ML-informed interventions may positively influence both cognitive and behavioural dimensions of student engagement. Such outcomes support previous studies indicating that adaptive learning technologies can increase learner responsiveness and promote more inclusive educational experiences, particularly for students requiring individualized support (Qusef et al., 2024; Rahman et al., 2024).

Importantly, the findings clarify the role of ML within educational decision-making pathways. ML-generated outputs—including risk scores, behavioural indicators, and learning pattern analyses—should be interpreted as preliminary screening information rather than diagnostic outcomes. These indicators may assist lecturers and support personnel in identifying students who require referral for comprehensive multidisciplinary assessment. Formal diagnosis remains dependent on established professional procedures guided by DSM-5, ICD-11, and AAIDD frameworks. Consequently, ML strengthens the linkage between educational monitoring, diagnostic referral, and intervention planning while preserving the central role of clinical and educational specialists.

The significant predictive effect of lecturers' use of ML-informed tools on academic engagement further underscores the importance of educator competence in technology integration. The absence of significant effects for institutional and demographic variables suggests that successful implementation depends more on instructional practice and digital capability than on contextual characteristics alone. This finding aligns with recent international research identifying teacher preparedness and AI literacy as critical determinants of effective educational innovation (Luckin & Cukurova, 2024; OECD, 2024).

The practical implications are substantial. Educators require sustained training in educational data analytics, AI literacy, and inclusive technology-enhanced pedagogy. Clinicians and educational psychologists may benefit from ML-generated screening information as supplementary evidence during referral and assessment processes. Policymakers and institutional leaders should prioritize investment in digital infrastructure, ethical governance frameworks, and implementation policies that promote equitable, transparent, and evidence-based use of AI technologies in higher education (UNESCO, 2023; Holmes et al., 2025).

Finally, although the inclusion of 600 lecturers from twelve universities enhanced institutional diversity and strengthened the breadth of perspectives represented, the use of convenience sampling may have introduced selection bias and limited representativeness. Consequently, caution is required when generalizing the findings beyond the study context. Nevertheless, the multi-state and multi-institutional

coverage enhances the transferability of the findings to comparable higher education settings and provides a foundation for future studies employing probability sampling and empirical evaluations of ML-supported educational interventions.

Implications for Educational Policy

The findings underscore the need for comprehensive policy frameworks that support the responsible integration of ML technologies in inclusive higher education. Recent international evidence emphasizes that effective AI/ML adoption requires institutional readiness, ethical governance, data protection mechanisms, and sustained investment in digital infrastructure (Bond et al., 2023; UNESCO, 2023; Holmes et al., 2025). Therefore:

1. National and institutional policies should provide clear guidelines for the ethical, transparent, and inclusive use of ML in educational decision-making.
2. Policies should ensure equitable access to ML-enabled learning and screening systems for students with intellectual disabilities.
3. Governments and universities should invest in digital infrastructure, technical support, and sustainable implementation strategies.
4. ML-based screening systems should be integrated with established referral, diagnostic, and intervention pathways to strengthen coordinated student support services.

Implications for Teacher Training and Professional Development

The findings highlight the central role of lecturers in translating ML capabilities into meaningful educational outcomes. Consistent with recent international studies, educator competence and AI literacy remain critical determinants of successful technology integration (Luckin & Cukurova, 2024; OECD, 2024). Therefore:

1. Lecturer training programmes should incorporate AI literacy, educational data analytics, and ML-informed instructional decision-making.
2. Professional development should emphasize practical skills in interpreting predictive indicators, monitoring learner progress, and designing individualized education plans (IEPs).
3. Continuous capacity-building initiatives are required to improve lecturers' confidence and competence in using ML-supported educational technologies.
4. Exposure to international best practices should support contextual adaptation of AI/ML innovations within inclusive higher education environments.

Implications for Clinicians and Diagnostic Practice

The findings demonstrate the potential of ML-informed systems to complement existing diagnostic and intervention frameworks. Recent research indicates that AI-assisted screening can enhance early risk identification and referral efficiency when used alongside professional assessment procedures (Qusef et al., 2024; Rahman et al., 2024). Therefore:

1. ML-generated outputs may serve as preliminary screening indicators that support the identification of students requiring further assessment.
2. Such outputs should complement—not replace—formal diagnosis conducted using DSM-5, ICD-11, and AAIDD criteria.
3. Effective implementation requires multidisciplinary collaboration among lecturers, educational psychologists, counsellors, and clinicians.
4. ML-informed monitoring systems may provide valuable evidence for intervention planning, progress tracking, and individualized support.

Conclusion

This study demonstrates that although the adoption of ML-informed educational interventions in Nigerian universities remains relatively low, lecturers generally recognize their potential for enhancing early identification and academic engagement among students with intellectual disabilities. Consistent with emerging international evidence (Bond et al., 2023; Crompton et al., 2024; Holmes et al., 2025), the findings suggest that successful implementation depends on institutional readiness, educator competence, ethical governance, and sustained investment in digital infrastructure. Importantly, ML functions as a decision-support mechanism that strengthens early screening, facilitates timely referral for formal diagnosis, and informs individualized intervention planning rather than replacing professional judgment. Strengthening these systems can contribute significantly to inclusive education, improved learning outcomes, and the achievement of Sustainable Development Goals 4 (Quality Education) and 10 (Reduced Inequalities).

Recommendations

Based on the findings and recent international developments in AI-supported education (UNESCO, 2023; OECD, 2024; Holmes et al., 2025), the following recommendations are proposed:

1. Universities should strengthen digital infrastructure by providing reliable ML-enabled platforms, adaptive learning systems, and stable internet connectivity.
2. Continuous professional development programmes should be established to improve lecturers' AI literacy and capacity to utilize ML-generated insights for instructional decision-making.
3. Policymakers should develop ethical, legal, and operational frameworks that support responsible implementation of ML technologies in higher education.

4. Universities should promote interdisciplinary collaboration among educators, clinicians, data scientists, and policymakers to support evidence-based intervention systems.
5. Institutions should establish structured mechanisms linking ML-informed screening processes with referral, assessment, and intervention services.

Limitations and Future Research Directions

Although the study provides important insights into lecturers' perceptions and use of ML-informed educational interventions, several limitations should be acknowledged. First, reliance on self-reported responses may have introduced social desirability and response biases. Second, the use of convenience sampling may limit representativeness and generalizability beyond the participating institutions. Third, the study focused exclusively on lecturers' perspectives and did not include students, clinicians, support personnel, or institutional administrators.

Future research should therefore employ probability-based sampling techniques, broader national coverage, and multi-stakeholder perspectives to enhance external validity. Longitudinal studies are also needed to examine the sustained effects of ML-supported interventions over time. Furthermore, empirical investigations involving the development and evaluation of actual ML-based screening systems would provide stronger evidence regarding their effectiveness in supporting early identification, diagnostic referral, and intervention planning within inclusive higher education contexts.

Abbreviations

• **ML**
Machine Learning
• **SDG**
Sustainable Development Goal
• **SDG 4**
Sustainable Development Goal 4: Inclusive and equitable quality education and promotion of lifelong learning opportunities for all
• **SDG 10**
Sustainable Development Goal 10: Reduction of inequality within and among countries
• **UDL**
Universal Design for Learning
• **CAST**
Center for Applied Special Technology
• **ICT**
Information and Communication Technology

Declarations

Clinical Trial Number

Clinical trial number: Not applicable.

Ethics Approval and Consent to Participate

Ethical approval for this study was obtained from the Research Ethics Committee of the University of Calabar, Calabar, Nigeria, which served as the lead institution for the research, prior to data collection. Permissions were also obtained from the participating universities involved in the study. No formal ethical approval reference number was issued, as the institutional ethics committee did not routinely assign approval tracking numbers for survey-based studies of this nature at the time the research was conducted. Participation in the study was entirely voluntary. All respondents were fully informed about the purpose of the study, the procedures involved, the voluntary nature of participation, and their right to withdraw from the study at any stage without any adverse consequences. Written informed consent was obtained from all participants before data collection commenced. Confidentiality and anonymity were strictly maintained throughout the research process. No personally identifiable information was collected, and all data were analysed and reported in aggregate form. Although students with intellectual disabilities were not directly involved as study participants, institutional records accessed through relevant disability support units were utilized with official authorization. All records were anonymised prior to analysis and handled in accordance with established ethical principles, including beneficence, non-maleficence, confidentiality, and data protection.

Data Availability Statement

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Consent for Publication

Not applicable.

Competing Interests

The authors declare that they have no competing interests.

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References

1. Akintunde A. Digital inclusion and the learning outcomes of students with disabilities in Nigerian schools. Ibadan: Heritage; 2024.
2. Alkan BB, Kuzucuk S, Alkan N, Sinan A. Using machine learning to predict student outcomes for early intervention and formative assessment. Sci Rep. 2025;15:39797. 10.1038/s41598-025-23409-w.
3. American Association on Intellectual and Developmental Disabilities. Definition of intellectual disability. Washington (DC): AAIDD. 2021. Available from: https://www.aaidd.org
4. American Psychiatric Association. *Diagnostic and statistical manual of mental disorders: DSM-5-TR*. 5th ed., text rev. Washington (DC): American Psychiatric Association Publishing; 2022.
5. Bessong EB, Atah CA, Olom PA, Akeke MANG, Erim CM, Udie EA, et al. Leveraging artificial intelligence to enhance inclusive teaching for students with intellectual disabilities in Nigerian universities. J Intellect Disabil Diagn Treat. 2025;13:388–401. 10.6000/2292-2598.2025.13.04.4.
6. Bond M, Khosravi H, De Laat M, Bergdahl N, Negrea V, Siemens G. A meta-systematic review of artificial intelligence in higher education: A call for increased ethics, collaboration, and rigor. Int J Educ Technol High Educ. 2023;20(1):1–39. 10.1186/s41239-023-00370-8.
7. Chen L, Huang R, Wang S. Artificial intelligence-based assessment tools for learners with intellectual disabilities. J Intellect Disabil Res. 2023;67(4):321–34.
8. Creswell JW, Creswell JD. Research design: Qualitative, quantitative, and mixed methods approaches. 5th ed. Thousand Oaks (CA): Sage; 2018.
9. Crompton H, Burke D, Cobo C. Artificial intelligence in higher education: The state of the field and future directions for teaching and learning. Comput Educ Artif Intell. 2024;6:100234.
10. de Souza R, de Oliveira J, Moreira A. Machine learning approaches to early diagnosis of developmental and intellectual disabilities. Disabil Rehabil. 2021;43(18):2598–607.

11. Etikan I, Musa SA, Alkassim RS. Comparison of convenience sampling and purposive sampling. Am J Theor Appl Stat. 2016;5(1):1–4.
12. Etoma MG, Adie AU. Artificial intelligence marketing practices, digital influencers marketing practices and employers' expectation from marketing education graduates. AAU J Bus Educ. 2025;5(1):26–35.
13. Etoma MG, Okute AL, Adie AU. Influence of artificial intelligence on marketing competence of business education graduates as expressed by macro entrepreneurs. Niger J Bus Educ. 2025;12(2):174–84.
14. Federal Ministry of Education Nigeria. National policy on inclusive education. Abuja: FME; 2017.
15. Friedman C, Wyatt J. Predictive analytics in special education decision making. J Policy Pract Intellect Disabil. 2022;19(2):89–98.
16. Hair JF, Black WC, Babin BJ, Anderson RE. Multivariate data analysis. 8th ed. Boston (MA): Cengage; 2019.
17. Holmes W, Bialik M, Fadel C. Artificial intelligence in education: Promise and implications for teaching and learning. Boston: Center for Curriculum Redesign; 2022.
18. Holmes W, Miao F, Vijh M. Generative artificial intelligence and the future of education: Opportunities, challenges and policy considerations. Paris: UNESCO; 2025.
19. Kumar V, Singh S, Patel R. Educational data mining and machine learning: Implications for inclusive education. Comput Educ. 2023;192:104648. 10.1016/j.compedu.2023.104648.
20. Luckin R, Cukurova M. Artificial intelligence and teacher professional development: Building capacity for responsible educational innovation. Br J Educ Technol. 2024;55(2):425–41.
21. Mim MA, Khatun MR, Hossain MM, Rahman W. Exploring early learning challenges in children utilizing statistical and explainable machine learning. Algorithms. 2025;18(1):20. 10.3390/a18010020.
22. O'Connor C, McCormack J, O'Brien G. Technology-enabled assessment for students with intellectual disabilities. Br J Spec Educ. 2023;50(1):45–60.
23. OECD. Artificial intelligence and the future of skills and education. Paris: OECD Publishing; 2024.
24. Ojo TS, Adeyemi OA. AI in education: Bridging digital inequity in Sub-Saharan Africa. J Emerg Technol Learn. 2022;17(5):102–17.
25. Qusef A, Murad S, Alsalhi NR, Al Gharaibeh F. Leveraging artificial intelligence to identify students with learning challenges. Int J Learn Teach Educ Res. 2024;24(5):1–17.
26. Rahman MM, Islam MS, Hossain MA. Challenges and opportunities of artificial intelligence integration in higher education: A systematic review. Educ Inf Technol. 2024;29(4):4567–91.
27. Rahman NFA, Wang SL, Ng TF, Ghoneim AS. Artificial intelligence in education: A systematic review of machine learning for predicting student performance. J Adv Res Appl Sci Eng Technol. 2024;54(1):198–221.

28. Sanusi IT, Oyelere SS, Vartiainen H, Suhonen J. A systematic review of teaching and learning machine learning in K–12 education. Educ Inf Technol. 2023;28:5967–97. 10.1007/s10639-022-11416-7.
29. Schalock RL, Luckasson R, Tassé MJ. Intellectual disability: Definition, diagnosis, classification, and systems of supports. 12th ed. Washington (DC): AAIDD; 2021.
30. Snowling MJ, Hulme C. Do we really need a new definition of dyslexia? Ann Dyslexia. 2024;74(4):355–62. 10.1007/s11881-024-00305-y.
31. Tassé MJ, Luckasson R, Schalock RL. The relation between intellectual functioning and adaptive behavior. J Intellect Disabil Res. 2022;66(6):499–511.
32. UNESCO. Artificial intelligence and inclusive education: Policy implications. Paris: UNESCO Publishing; 2023.
33. UNESCO. Guidance for generative AI in education and research. Paris: UNESCO Publishing; 2023.
34. United Nations Educational, Scientific and Cultural Organization. Global Education Monitoring Report 2023: Inclusion and education – All means all. Paris: UNESCO; 2023.
35. World Bank. The role of technology in inclusive education. Washington (DC): World Bank. 2020. Available from: https://www.worldbank.org
36. World Health Organization. International classification of diseases for mortality and morbidity statistics (ICD-11). Geneva: WHO; 2019.
37. Zawacki-Richter O, Marín VI, Bond M, Gouverneur F. Systematic review of research on artificial intelligence applications in higher education. Int J Educ Technol High Educ. 2019;16(1):39. 10.1186/s41239-019-0171-0.
38. Zhang Y, Li H, Zhao L. Adaptive learning technologies for students with intellectual disabilities. Int J Incl Educ. 2022;26(12):1203–19.

Figures

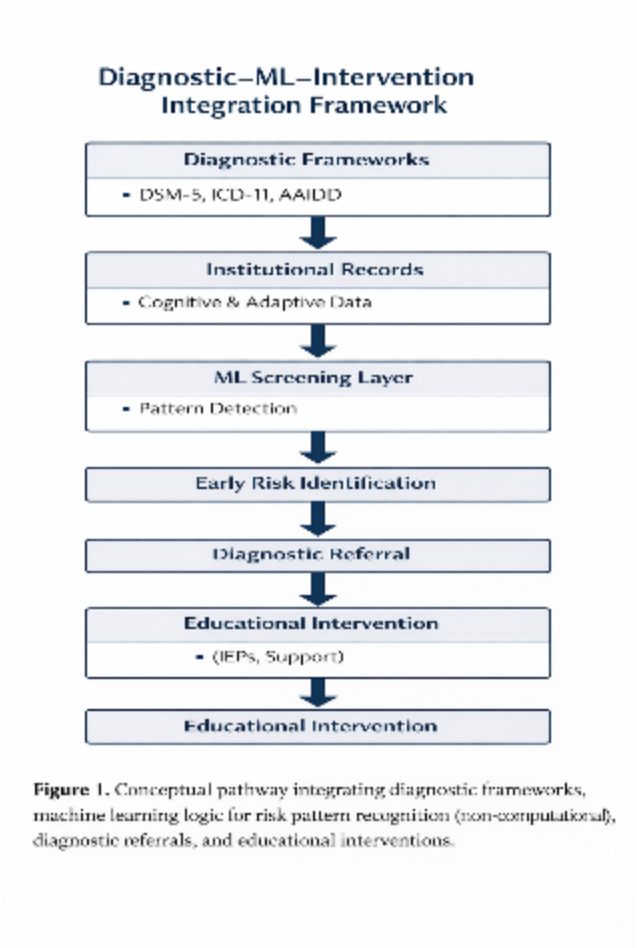


Figure 1. Conceptual pathway integrating diagnostic frameworks, machine learning logic for risk pattern recognition (non-computational), diagnostic referrals, and educational interventions.

Figure 1

Conceptual Diagnostic, Machine Learning Screening, and Educational Intervention Framework for Students with Intellectual Disabilities

Note. The framework illustrates the progression from established diagnostic standards (DSM-5, ICD-11, and AAIDD) through institutional identification, conceptual ML-based screening, referral for professional assessment, and individualized educational intervention. The ML component functions as a decision-support mechanism for early risk identification and does not replace clinical diagnosis.

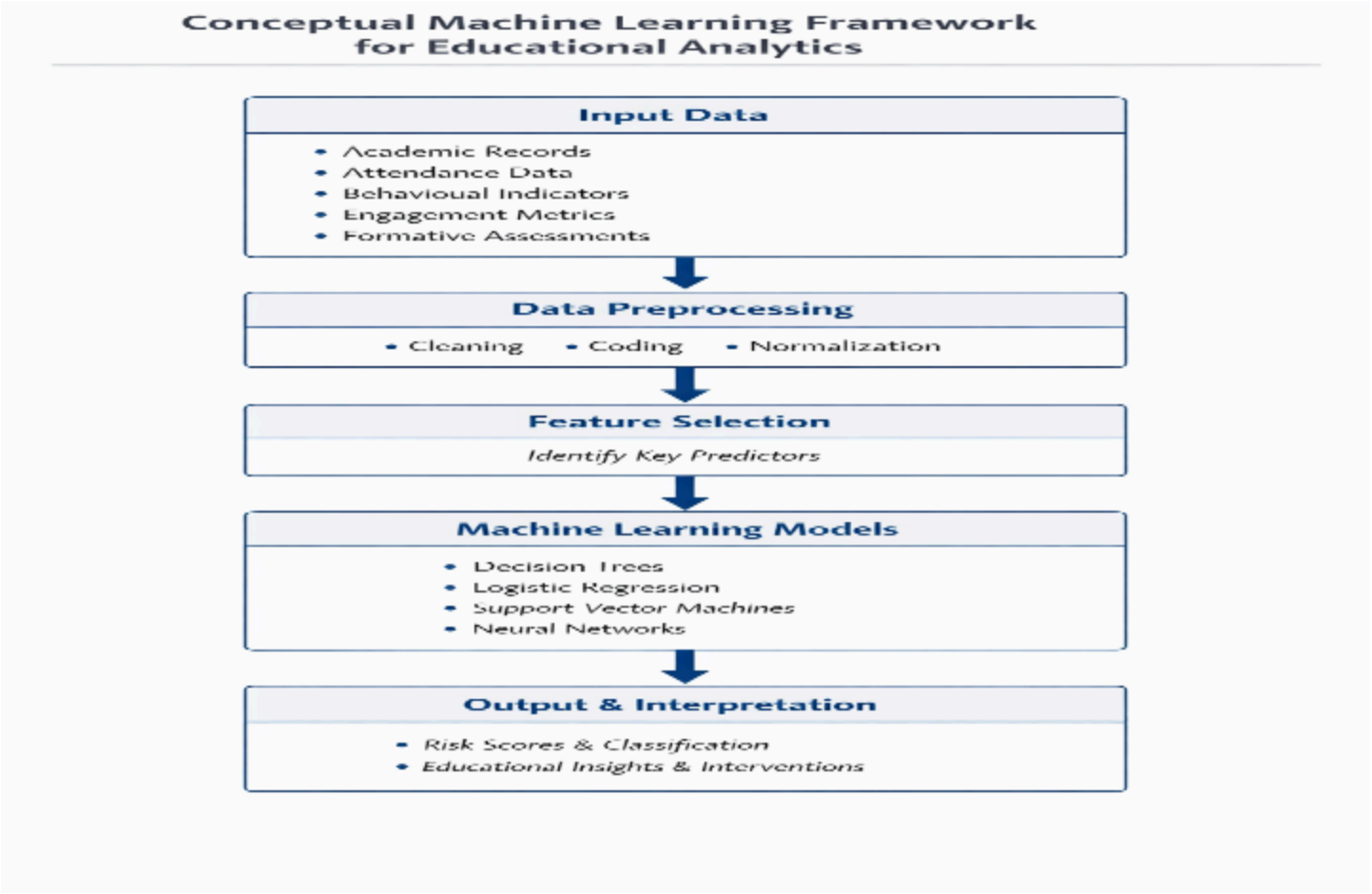


Figure 2

Conceptual ML-Based Screening Framework for Early Identification and Intervention in Students with Intellectual Disabilities”

Note. The framework presents a theoretical ML pipeline comprising educational input variables, conceptual preprocessing and feature selection stages, illustrative predictive models, and screening outputs intended to support referral and intervention planning. No computational modelling was conducted in this study.