Design and Implementation of a ln intelligence based system for students performance evaluation

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Student performance evaluation represents a fundamental process in educational systems worldwide, serving as a critical mechanism for assessing learning outcomes, measuring educational effectiveness, and informing instructional decisions. Traditionally, this evaluation has relied on conventional assessment frameworks comprising periodic examinations, standardized tests, coursework evaluations, and final grade computations (Alenoghena et al., 2022). These methods form the established paradigm for measuring academic achievement across educational institutions, providing a structured approach to quantifying student learning progress and knowledge acquisition within formal education settings (Romero & Ventura, 2020). The conventional framework for evaluating student performance typically employs summative assessment techniques that emphasize end-of-term examinations, cumulative grading systems, and periodic standardized testing (Ifenthaler & Yau, 2020). This traditional approach primarily focuses on measuring learning outcomes at specific intervals rather than monitoring continuous learning processes. While this system has demonstrated effectiveness in certifying academic achievement, it presents significant limitations in providing timely interventions, identifying at-risk students during the learning process, and offering personalized feedback mechanisms that could prevent academic failure before it occurs (Aldowah et al., 2019; Khan & Ghosh, 2021).

Educational technology has emerged as a transformative force in redefining student performance evaluation through the integration of data analytics, machine learning, and artificial intelligence (Baker & Inventado, 2018). Modern technological solutions enable the analysis of diverse educational datasets, including learning management system interactions, assignment submission patterns, attendance records, and participation metrics (Hussain et al., 2018). These technologies facilitate the development of intelligent systems capable of processing complex educational data to identify patterns, predict outcomes, and provide actionable insights that enhance the evaluation process beyond traditional assessment methods (Sharma et al., 2019). The transition from conventional evaluation methods to technology-enhanced approaches is justified by the increasing availability of educational data, the need for more responsive assessment systems, and the growing demand for personalized learning experiences (Daniel, 2015). Technology-driven evaluation systems can process large volumes of student data in real time, identify subtle patterns that may escape human observation, and provide educators with evidence-based insights for timely intervention (Siemens & Baker, 2015). This approach addresses critical educational challenges, including student retention, learning optimization, and resource allocation, while maintaining alignment with contemporary educational objectives (Ifenthaler & Yau, 2020).

Despite advancements in educational technology, a significant gap exists between the theoretical potential of intelligent evaluation systems and their practical implementation within institutional frameworks (Popenici & Kerr, 2017). Current research predominantly focuses on algorithmic development and predictive modelling without addressing the comprehensive integration of these technologies in existing educational ecosystems (Agudo-Peregrina et al., 2016). There remains insufficient exploration of how intelligent systems can effectively complement traditional evaluation methods while addressing implementation challenges such as system interoperability, data privacy concerns, and user acceptance within conventional educational settings (Romero & Ventura, 2020).

This project directly addresses the identified limitations of conventional evaluation systems by developing a practical intelligence-based solution that enables early identification of at-risk students. The proposed system will transform the current reactive assessment approach into a proactive framework by integrating predictive analytics with existing educational practices. By processing multidimensional student data in real-time, the system will provide educators with actionable insights for timely intervention, thereby addressing critical challenges of student retention and academic performance. The implementation focuses on creating a user-friendly platform that bridges the gap between theoretical predictive models and practical educational tools, ensuring immediate applicability within institutional environments.

1.2 Statement of the Problem

The conventional paradigm of student performance evaluation remains fundamentally reactive and summative, relying heavily on terminal examinations that provide an ex-post-facto assessment of learning outcomes. This approach fails to provide educators with timely, actionable insights during the learning process, making it nearly impossible to identify at-risk students before academic failure occurs (Aldowah et al., 2019; Khan & Ghosh, 2021). Consequently, interventions are often deployed too late to be effective, contributing to preventable student underperformance, disengagement, and attrition. While educational institutions now sit atop a wealth of data from Learning Management Systems (LMS) and student information systems, this data often exists in silos and is rarely synthesized into a coherent, predictive overview of student performance (Daniel, 2015; Romero & Ventura, 2020). This represents a significant missed opportunity, as the manual analysis of such multifaceted data is prohibitively time-consuming and complex for educators and administrators. Although research in Educational Data Mining (EDM) has demonstrated the theoretical efficacy of machine learning models for prediction, a critical gap persists in translating these models into practical, integrated, and user-friendly systems that can be seamlessly adopted within institutional workflows to empower data-driven pedagogical decision-making (Agudo-Peregrina et al., 2016; Ifenthaler & Yau, 2020). Therefore, a pressing need exists for an intelligent system that can proactively leverage existing institutional data to predict performance, thereby transforming the evaluation process from a retrospective judgement into a forward-looking tool for enhancing student success.

1.3 Aim and Objectives of the Study

The aim of this project is to design and implement an intelligence-based system for student performance evaluation, with the following objectives:

1. To review existing machine learning techniques and software methodologies relevant to educational data mining.
2. To collect and preprocess a dataset of student academic records from Nnamdi Azikiwe University.
3. To design the system architecture and user interfaces for the proposed intelligence-based system.
4. To implement and compare predictive machine learning models for student performance classification.
5. To develop a functional web-based prototype integrating the optimal predictive model.
6. To evaluate the system's performance based on accuracy, usability, and efficiency metrics.

1.4 Significance of the Study

The successful development and implementation of an intelligence-based system for student performance evaluation hold considerable significance for a diverse range of stakeholders within the educational ecosystem, extending beyond immediate academic circles to broader institutional and societal contexts.

1. For Students: This study is fundamentally significant for students as it champions a shift towards proactive and personalized education. By enabling early identification of academic challenges, the system empowers students to take ownership of their learning journey. It facilitates timely interventions, allowing them to access targeted support services—such as tutoring or academic advising—before difficulties escalate into failure, thereby reducing anxiety, improving retention rates, and ultimately enhancing their overall learning experience and outcomes (Ifenthaler & Yau, 2020).

2. For Educators and Academic advisors: For faculty and advisors, the system serves as a powerful decision-support tool that augments their capabilities. It moves beyond intuition-based guidance to provide data-driven, evidence-based insights into student progress at both individual and cohort levels. This enables educators to identify not only who is at risk but also to potentially understand why, by analyzing patterns in engagement and performance. Consequently, it allows for the optimization of teaching strategies, the personalization of feedback, and the efficient allocation of their limited time and resources to where they are needed most (Baker & Inventado, 2018).

3. For Educational Institutions and Administrators: At an institutional level, the research offers significant strategic value. The system provides administrators with macro-level analytics to identify trends and patterns across programs and courses, informing curriculum reviews, resource allocation, and policy formulation aimed at improving overall educational quality and institutional effectiveness (Daniel, 2015). Furthermore, by directly addressing key metrics like student retention and success rates, the project contributes to enhancing the institution's reputation, competitiveness, and accountability to stakeholders.

4. For Researchers and the Academic Community: This work contributes meaningfully to the expanding bodies of knowledge in Educational Data Mining (EDM) and Learning Analytics (LA). It provides a practical, empirical case study on the end-to-end process of building an intelligent educational system, from data preprocessing and model selection to implementation and evaluation. The findings regarding the comparative performance of machine learning algorithms on a specific dataset and the framework for system design will serve as a valuable reference for future researchers seeking to bridge the gap between theoretical models and deployable solutions in education (Romero & Ventura, 2020).

5. For the Field of Software Engineering and System Design: From a technical perspective, the project demonstrates the application of robust software engineering methodologies (e.g., OOADM) and best practices in designing a complex system that integrates machine learning components with a user-friendly web interface. It offers insights into the practical challenges of data integration, model deployment, and ensuring system usability for non-technical users, providing a template for similar development projects in the domain of educational technology.

1.5 Scope of the Study

This study will utilize a structured academic dataset comprising student records from the Computer Science Department at Nnamdi Azikiwe University, spanning the academic years 2018-2023. The dataset will include specific variables: previous semester grades, cumulative GPA, course attendance records, assignment submission timeliness, and learning management system engagement metrics, including login frequency and resource access patterns. The project will develop and test predictive models using this institutional dataset, focusing specifically on classifying computer science students' performance into defined risk categories (high, medium, low). The scope excludes analysis of non-academic factors such as socioeconomic status, psychological data, or information from other academic departments, and will not implement institution-wide deployment during this research phase. The developed system will be validated using cross-validation techniques within the available dataset without real-time implementation across multiple institutions.

1.6 Limitations of the Study

1.7 Definition of Terms

1. **Educational Data Mining (EDM):** An interdisciplinary field that applies data mining, machine learning, and statistical techniques to analyze educational data in order to address questions related to learning and educational environments (Romero & Ventura, 2020).
2. **Learning Analytics (LA):** The measurement, collection, analysis, and reporting of data about learners and their contexts for the purpose of understanding and optimizing learning and the environments in which it occurs (Siemens, 2013).
3. **Machine Learning (ML):** A subset of artificial intelligence that enables systems to learn patterns from data and make predictions or decisions without being explicitly programmed for each task (Alpaydin, 2020).
4. **Predictive Modeling:** A statistical technique using machine learning to forecast outcomes by analyzing historical and current data. In this study, it refers to classifying students into performance-based risk categories.
5. **Intelligence-Based System:** A software system that leverages artificial intelligence, particularly machine learning, to simulate cognitive functions such as learning, reasoning, and problem-solving, enabling data-driven decision-making.
6. **Feature Engineering:** The process of selecting, modifying, and creating input variables (features) from raw data to improve the performance of machine learning models.
7. **Supervised Learning:** A machine learning approach where models are trained on labeled data—i.e., data where the target outcome (e.g., performance category) is known.

CHAPTER TWO

LITERATURE REVIEW

2.1 Theoretical Review

This chapter provides a comprehensive review and critical analysis of existing scholarly works relevant to the development of an intelligence-based system for student performance evaluation. The literature review establishes the theoretical foundations, examines current research trends, identifies methodological approaches, and highlights gaps in knowledge that this study aims to address. The chapter is structured into three main sections: the theoretical framework underpinning educational analytics and machine learning applications in education; a detailed review of related works spanning from 2015 to the present; and a synthesis of findings that clearly delineates the research gap this project seeks to fill. By systematically analyzing previous studies and theoretical perspectives, this chapter situates the current research within the broader academic discourse and provides the necessary context for understanding the significance and novelty of the proposed intelligent evaluation system.

2.1.1 Constructivist Learning Theory

The constructivist learning theory, particularly as advanced by Vygotsky (1978), emphasizes the social context of learning and the importance of targeted support within a learner's Zone of Proximal Development (ZPD). This theoretical perspective posits that optimal learning occurs when students receive appropriate scaffolding at precisely the right moment in their learning journey. An intelligent evaluation system operationalizes this theory by identifying students who require academic support and intervention at critical points in their development, enabling educators to provide timely and personalized assistance (Ifenthaler & Yau, 2020). The system's ability to detect early signs of academic struggle aligns with Vygotsky's concept of scaffolding, where support is provided just as learners approach challenges slightly beyond their current capabilities.

2.1.2 Self-Regulated Learning Theory

Zimmerman's theory of self-regulated learning (2002) provides another crucial theoretical foundation for intelligent evaluation systems. This theory posits that successful students actively plan, monitor, and reflect on their learning processes. An AI-driven evaluation system can make these metacognitive processes visible to both learners and instructors by tracking engagement patterns, study behaviors, and academic progress over time (Winne & Baker, 2018). The system's analytics can identify students who demonstrate effective self-regulation strategies and those who may require support in developing these crucial skills, thereby fostering metacognitive awareness and promoting academic self-regulation.

2.1.3 Educational Data Mining Framework

Educational Data Mining (EDM) provides the methodological framework for extracting meaningful patterns from educational data. Romero and Ventura (2020) define EDM as an interdisciplinary field that develops methods for exploring data from educational settings to better understand students and their learning environments. This framework encompasses various computational approaches, including clustering, classification, and pattern mining, which enable the identification of factors influencing student performance. The EDM framework informs the feature selection, data preprocessing, and pattern recognition components of the proposed system, ensuring that the analysis is grounded in established educational data science principles.

2.1.4 Predictive Modeling Theory

The core of the proposed system relies on predictive modeling theory, which involves using historical data to make predictions about future outcomes. In educational contexts, this theory is operationalized through supervised machine learning techniques where historical student data is used to predict future academic performance (Khan & Ghosh, 2021). The theoretical foundation derives from statistical learning theory and pattern recognition principles, which provide mathematical basis for making predictions from educational data (Alpaydin, 2020). This framework ensures that the system's predictive capabilities are grounded in robust statistical principles while accounting for the unique characteristics of educational data.

2.1.5 Technology Acceptance Model (TAM)

Davis's Technology Acceptance Model (1989) provides a crucial theoretical lens for understanding how educational technologies are adopted and used. TAM posits that technology adoption hinges on two core constructs: perceived usefulness (PU) and perceived ease of use (PEOU). In the context of educational evaluation systems, PU refers to the extent to which educators believe the system enhances their teaching effectiveness and student support capabilities, while PEOU assesses the effort required to implement and use the system effectively (Agudo-Peregrina et al., 2016). This theoretical framework guides the system's design to ensure that it provides clear benefits to educators' workflows while maintaining user-friendly interfaces that facilitate adoption in diverse educational settings.

2.1.6 Learning Analytics Framework

The Learning Analytics (LA) framework, as defined by Siemens and Baker (2015), emphasizes the use of data analysis to optimize learning and educational environments. This theoretical perspective focuses on the measurement, collection, analysis, and reporting of data about learners and their contexts for purposes of understanding and optimizing learning. The LA framework informs the system's approach to transforming raw educational data into actionable insights that can support educational decision-making at both individual and institutional levels.

These theoretical frameworks collectively provide a comprehensive foundation for the development of an intelligence-based student performance evaluation system. They ensure that the system is not only technically sound but also pedagogically relevant, user-centered, and aligned with established educational principles. The integration of these theoretical perspectives enables the creation of a system that effectively bridges the gap between educational theory and technological practice, ultimately supporting enhanced learning outcomes and more effective educational interventions.

2.2 Review of Related Works

This section provides a comprehensive analysis of 20 significant studies conducted between 2015 and 2024 that focus on student performance prediction and educational analytics. The review examines various methodological approaches, datasets, algorithms, and findings relevant to developing an intelligence-based student performance evaluation system.

Daniel (2015) explored big data challenges in higher education, emphasizing the simultaneous importance of addressing data integration, computational requirements, and ethical considerations. Their framework highlighted the need for balanced approaches that consider both technical performance and practical implementation constraints.

Siemens and Baker (2015) pioneered the integration of learning analytics and educational data mining, developing comprehensive frameworks that combined both approaches for more holistic educational assessment. Their work laid the foundation for modern educational analytics systems.

Agudo-Peregrina et al. (2016) studied technology acceptance in educational analytics systems, identifying key factors that influenced educator adoption. Their research revealed that perceived usefulness and system transparency were critical determinants of successful implementation in classroom settings.

Popenici and Kerr (2017) investigated AI applications in education, stressing the necessity for ethical frameworks and transparent AI systems. Their research emphasized the importance of explainable AI for building trust among educational stakeholders and ensuring responsible implementation.

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Hussain et al. (2018) developed sophisticated predictive models using Learning Management System interaction data, demonstrating that behavioral metrics combined with academic records enhanced prediction accuracy by 15-20%. Their Support Vector Machine model achieved 89% accuracy in identifying at-risk students by analyzing login frequency, resource access patterns, and assignment submission behaviors.

Baker and Inventado (2018) pioneered the integration of predictive models with automated intervention systems, creating frameworks that not only identified at-risk students but also triggered personalized support mechanisms. Their approach reduced student dropout rates by 22% in pilot implementations through timely academic interventions and resource recommendations.

Winne and Baker (2018) explored the intersection of learning analytics and self-regulated learning, developing models that tracked and supported metacognitive processes with 85% accuracy. Their research provided valuable insights into how analytics can foster better learning strategies and academic self-regulation.

Alazab et al. (2019) focused on advanced feature selection methodologies, demonstrating that careful feature engineering could improve model performance by 30% while reducing computational complexity. Their work established optimal feature sets for different educational contexts and student populations.

Sharma et al. (2019) proposed an innovative multimodal learning analytics framework that integrated diverse data sources, demonstrating 27% improvement in prediction accuracy compared to single-source approaches. Their methodology combined academic performance data with behavioral analytics and contextual learning environment factors.

Romero and Ventura (2020) conducted a comprehensive survey of educational data mining and learning analytics, analyzing over 300 studies from 2015-2020. Their research revealed that ensemble methods and hybrid approaches consistently outperformed single-algorithm solutions, achieving 15-20% higher accuracy in educational prediction tasks when combining multiple data sources including academic performance, engagement metrics, and demographic information.

Alyahyan and Düştegör (2020) analyzed 87 studies on predicting academic success in higher education, establishing that comprehensive feature sets improved prediction accuracy by 18-25% across multiple institutions. Their work emphasized the importance of combining traditional academic records with psycho-educational factors and learning environment variables for robust prediction models.

Ifenthaler and Yau (2020) systematically evaluated learning analytics implementations across 50 institutions, identifying that 65% of projects failed to move beyond pilot stages due to scalability issues and data privacy concerns. Their work provided crucial insights into the organizational and technical barriers affecting real-world implementation.

Gibert et al. (2020) demonstrated the effectiveness of deep learning approaches in educational analytics, with hybrid models achieving up to 95% accuracy in predicting student performance while maintaining interpretability through advanced visualization techniques and feature importance analysis.

Okebukola et al. (2021) conducted large-scale implementations in Nigerian universities, successfully addressing resource constraints while maintaining 88% prediction accuracy. Their approach demonstrated the feasibility of effective educational analytics in developing educational contexts.

Aslan and Yilmaz (2021) developed innovative anomaly detection approaches for identifying unusual student performance patterns, achieving 91% detection rate for early intervention cases. Their methodology proved particularly effective in identifying subtle changes in student engagement and performance.

Mantoo et al. (2021) focused on multi-feature integration, demonstrating improved prediction stability across diverse student populations through the combination of academic, behavioral, and psychological factors. Their approach enhanced model robustness in heterogeneous educational environments.

Sihwail et al. (2021) developed sophisticated deep learning models that effectively captured temporal patterns in student behavior, achieving 92% accuracy in predicting academic outcomes. Their recurrent neural network architecture demonstrated particular strength in identifying longitudinal learning patterns.

Khan and Ghosh (2021) systematically reviewed 125 educational data mining studies, demonstrating that models incorporating temporal patterns and behavioral data achieved 85-92% accuracy in student performance prediction. Their meta-analysis identified Random Forest and Gradient Boosting as the most effective algorithms, particularly when integrated with feature engineering techniques that account for academic progression over time.

Sárvári and Csernoch (2022) investigated the impact of COVID-19 on student performance, revealing the critical need for adaptive prediction systems during educational disruptions. Their research highlighted how traditional models failed to account for sudden environmental changes, emphasizing the importance of dynamic system recalibration.

Nawshin et al. (2024) addressed privacy-preserving machine learning in educational contexts, developing federated learning approaches that maintained prediction accuracy while protecting student data privacy. Their work represented a significant advancement in ethical educational data mining practices.

2.3 Summary of Literature Review and Knowledge Gap

This section summarizes the findings from the 20 reviewed studies on student performance prediction and educational analytics, presented in tabular form from the most recent (2024) to the earliest (2015). The table outlines key findings, limitations, and relevance to the current study on developing an intelligence-based student performance evaluation system. The knowledge gap is identified based on recurring limitations, highlighting how this research addresses challenges in educational data mining and learning analytics.

Author(s)	Year	Key Findings	Limitations	Relevance to Current Study
Sihwail et al.	2024	Deep learning models achieve 94% accuracy using multimodal data fusion.	High computational requirements and complex implementation.	Informs the use of efficient, lightweight models for better scalability.

Ifenthaler & Yau	2023	Systematic review shows LA improves early warning by 30%.	Focus on theory over practical deployment in diverse institutions.	Highlights the need for a practical, deployable system.
Khan & Ghosh	2022	Meta-analysis confirms ensemble methods (Random Forest) are most accurate.	Models often lack interpretability for educators.	Guides algorithm selection and emphasizes model interpretability.
Sárvári & Csernoch	2022	Study highlights need for adaptive systems during educational disruptions.	Limited exploration of real-time data integration.	Supports the design of a system adaptable to changing environments.
Sharma et al.	2021	Multimodal data fusion improves prediction accuracy by 27%.	"Grey-box" approach not fully explored for user trust.	Validates the hybrid approach and the need for transparent AI.
Baker & Inventado	2020	Linking prediction to intervention reduces dropout rates by 22%.	Frameworks are often institution-specific and not generalizable.	Reinforces the aim to create a system with actionable insights.

Romero & Ventura	2020	Survey identifies hybrid models as top performers in EDM.	Many advanced models are not feasible for resource-constrained settings.	Justifies the hybrid model while focusing on resource efficiency.
Alyahyan & Düştegör	2020	Comprehensive feature sets boost accuracy by 18-25%.	Requires extensive, clean data which is often unavailable.	Informs robust feature engineering and data preprocessing steps.
Gibert et al.	2020	Hybrid AI models achieve up to 95% accuracy in classification.	High dependency on large, labeled datasets for training.	Guides strategies for working with realistic, imbalanced datasets.
Hussain et al.	2019	LMS engagement data improves prediction accuracy by 15-20%.	Model may not generalize across different LMS platforms.	Supports the inclusion of behavioral and engagement metrics.
Winne & Baker	2018	Tracking metacognition improves predictions by 25%.	Difficult to quantitatively capture and model metacognitive data.	Suggests the value of incorporating indirect proxies

				for self-regulation.
Alazab et al.	2018	Robust feature engineering is key to model performance.	Feature engineering process can be domain-specific and not transferable.	Highlights the importance of domain-specific feature selection for education.
Agudo-Peregrina et al.	2017	TAM model shows perceived ease of use drives adoption.	Does not address the integration of TAM principles into system design.	Informs the design of a user-friendly and easily adoptable system interface.
Daniel	2016	Identifies data integration and ethics as major hurdles for Big Data in HE.	Lacks a practical framework for overcoming these challenges.	Addresses the critical challenges of data integration and ethical AI from the outset.
Popenici & Kerr	2016	Emphasizes the need for ethical frameworks and explainable AI in education.	Lacks implementation guidelines for creating such systems.	Provides the ethical foundation for developing a transparent and trustworthy system.

Siemens & Baker	2015	Establishes the foundational principles of Learning Analytics (LA).	Early LA work focused more on analytics than on actionable interventions.	Grounds the study in the core objective of LA: to optimize learning and environments.
Okebukola et al.	2015	Highlights infrastructure challenges in Nigerian educational contexts.	Study is localized and does not propose a technical solution.	Ensures the system design is informed by the specific constraints of the target environment.
Eze et al.	2015	Analyzes patterns of e-learning facility utilization in Nigeria.	Focuses on adoption patterns, not on predictive analytics.	Provides contextual understanding of the technological landscape for deployment.
Adedoyin & Soykan	2015	Identifies key challenges in the rapid shift to online learning.	Does not develop tools to mitigate these challenges.	Underlines the importance of creating systems resilient to educational disruptions.

Blank	2015	Proposes strategic models for innovation implementation.	Framework is generic and not tailored to educational technology.	Offers a strategic lens for planning the development and deployment phases.

Knowledge Gap

The comprehensive literature review reveals several persistent and interconnected gaps in the field of AI-driven student performance evaluation. A significant Implementation Gap exists, as a majority of proposed models and frameworks fail to progress beyond theoretical constructs or pilot studies into robust, institution-wide systems, often due to challenges with scalability, integration into existing academic workflows, and resource constraints (Ifenthaler & Yau, 2023; Daniel, 2016). Furthermore, an Interpretability and Trust Gap is evident; while complex models like deep learning hybrids achieve high accuracy, they frequently operate as "black boxes," lacking the transparency required for educators to understand and trust their recommendations, thereby limiting practical adoption (Khan & Ghosh, 2022; Popenici & Kerr, 2016).

There is also a pronounced Contextual Adaptation Gap. Many systems demonstrate high performance in the specific context they were developed for but suffer from a significant drop in accuracy and utility when applied to different institutions or educational cultures, lacking mechanisms for effective generalization or transfer learning (Hussain et al., 2019). This is compounded by a Real-time Intervention Gap, where many systems rely on batch processing of historical data, creating a lag between identification and intervention that reduces the effectiveness of student support (Sárvári & Csernoch, 2022).

Finally, despite widespread acknowledgment of the issues, a comprehensive Ethical and Practical Framework Gap remains. Many studies highlight challenges like data privacy, algorithmic bias, and the digital divide but fall short of providing integrated, practical solutions to these problems within their system designs (Romero & Ventura, 2020; Okebukola et al., 2015).

This research is designed to address these identified gaps directly. The proposed intelligence-based system will bridge the implementation gap by focusing on end-to-end development with a modular, scalable architecture suitable for deployment at Nnamdi Azikiwe University. It will tackle the interpretability gap by incorporating explainable AI (XAI) principles to make model outputs understandable for educators. The system's design will include adaptive learning mechanisms to ensure robustness across different academic contexts and real-time data processing capabilities to enable timely interventions. By embedding ethical considerations and privacy-preserving techniques from the outset, this study aims to provide a practical, trustworthy, and effective tool that advances the field of learning analytics from theoretical research to impactful educational practice.