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Design and Implementation of an AI-Driven Smart Learning Analytics System for Improving Teaching Quality, Student Performance, and Early Dropout Detection in Katsina State Institute of Technology and Management

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ABSTRACT

The increasing availability of educational data in higher institutions presents significant opportunities for improving academic monitoring, student performance prediction, and institutional decision-making. However, many tertiary institutions in developing countries continue to rely on traditional and reactive approaches to academic management, limiting their ability to identify struggling students early and provide timely interventions. This study presents the design and implementation of an AI-Driven Smart Learning Analytics System (AISLAS) developed for Katsina State Institute of Technology and Management (KSITM), Nigeria. The system integrates machine learning techniques, learning analytics, and educational data mining to monitor student academic activities, predict academic risk, and provide real-time insights for lecturers, Heads of Departments, and institutional administrators. The study adopted a Design and Development Research (DDR) methodology combined with a quantitative predictive analytics approach. Historical academic datasets comprising attendance records, continuous assessment scores, examination results, assignment completion rates, and student demographic information were collected, cleaned, and processed for model development. Three supervised machine learning algorithms, namely Logistic Regression, Decision Tree, and Random Forest, were trained and evaluated using standard classification metrics. Experimental results revealed that the Random Forest model achieved the highest predictive performance with an accuracy of 91.2%, precision of 90.6%, recall of 89.8%, and F1-

score of 90.2%. The developed system provides role-based dashboards, automated early warning alerts, intervention tracking mechanisms, and institutional performance analytics. User Acceptance Testing conducted among forty-two academic staff members demonstrated high usability, clarity, and adoption readiness, with an overall system quality rating of 4.6 out of 5. Findings indicate that AI-driven learning analytics can significantly improve academic monitoring, support proactive intervention strategies, enhance teaching quality, and strengthen evidence-based educational decision-making. The study concludes that the implementation of AISLAS offers a practical and scalable framework for improving academic outcomes in KSITM.

Keywords: Artificial Intelligence, Educational Data Mining, Student Performance Prediction, Early Warning System, Machine Learning,

INTRODUCTION

Artificial Intelligence (AI) has emerged as one of the most transformative technologies of the twenty-first century, revolutionizing diverse sectors including healthcare, agriculture, finance, transportation, and education. Within the educational sector, AI technologies have facilitated the development of intelligent tutoring systems, adaptive learning environments, automated assessment tools, and predictive analytics platforms. These innovations have enabled educational institutions to leverage large volumes of data for improved teaching, learning, and administrative decision-making. The rapid digitization of academic processes has resulted in the generation of substantial volumes of educational data from admissions, registration systems, attendance monitoring, learning management systems, continuous assessments, assignments, and examinations. While these datasets contain valuable information capable of supporting academic planning and student success initiatives, many institutions, particularly in developing countries, lack adequate mechanisms for transforming raw data into actionable insights. Learning Analytics (LA) has emerged as a powerful discipline that focuses on the measurement, collection, analysis, and reporting of educational data for the purpose of understanding and optimizing learning outcomes. By applying artificial intelligence and machine learning techniques to educational datasets, institutions can identify students at risk of academic failure, monitor performance trends, evaluate instructional effectiveness, and implement timely interventions. Globally, universities and colleges are increasingly adopting learning analytics systems to support evidence-based academic management. These systems enable educators and administrators to move beyond traditional reactive approaches and embrace proactive strategies that improve student retention, graduation rates, and overall academic performance. Despite these global advancements, the adoption of AI-driven learning analytics remains limited within many Nigerian tertiary institutions.

At Katsina State Institute of Technology and Management (KSITM), academic performance monitoring is predominantly conducted through manual processes and end-of-semester evaluations. Such approaches often delay the identification of struggling students until after poor academic outcomes have occurred. Consequently, opportunities for timely intervention and support are frequently missed, contributing to increased failure rates and reduced student success.

To address these challenges, this study designed and implemented an AI-Driven Smart Learning Analytics System (AISLAS) capable of continuously analyzing academic data, predicting student risk levels, generating early warning alerts, and providing interactive dashboards for academic stakeholders. The system seeks to transform academic monitoring at KSITM from a reactive process into a proactive, data-driven framework.

Problem Statement

Despite the increasing availability of student academic data within KSITM, several challenges continue to hinder effective academic monitoring and intervention. Academic performance tracking remains largely manual, time-consuming, and dependent on periodic assessments. Consequently, students experiencing academic difficulties are often identified only after poor examination results have been released.Furthermore, the institution lacks an automated early warning mechanism capable of identifying students at risk of academic failure before critical academic outcomes occur. Existing processes do not

adequately support evidence-based decision-making, and academic data is rarely utilized for predictive analysis or institutional planning. The absence of intelligent dashboards and analytics tools further limits the ability of lecturers, Heads of Departments, and administrators to monitor trends and implement timely interventions. These limitations contribute to persistent academic challenges, including elevated failure rates, delayed support mechanisms, ineffective intervention tracking, and underutilization of institutional data resources. Therefore, there is a need for an intelligent, scalable, and data-driven solution capable of transforming academic monitoring and supporting proactive educational management within KSITM.

Aim of the Study

The aim of this study is to design and implement an AI-Driven Smart Learning Analytics System (AISLAS) capable of improving academic monitoring, predicting student risk, enhancing teaching quality, and supporting evidence-based decision-making within Katsina State Institute of Technology and Management.

Objectives of the Study

The specific objectives of this study are to:

1. Develop a centralized role-based academic analytics platform for institutional stakeholders.
2. Collect, preprocess, and validate student academic data for predictive analytics.
3. Develop and evaluate machine learning models for predicting students at risk of academic failure.
4. Design and deploy interactive dashboards for lecturers, Heads of Departments, and administrators.
5. Implement an automated early warning system for timely identification of at-risk students.
6. Provide teaching quality analytics to support instructional improvement and reflective teaching practices.
7. Enhance student retention and academic success through data-driven intervention strategies.

Research Questions

The study seeks to answer the following research questions:

1. How can Artificial Intelligence improve real-time academic monitoring at KSITM?
2. Can machine learning models accurately predict students at risk of academic failure?
3. How effective are role-based analytics dashboards in supporting academic decision-making?
4. Does an AI-powered early warning system improve institutional intervention capabilities?
5. Can learning analytics improve teaching quality and student academic outcomes?

Research Hypotheses

The following hypotheses were formulated and tested:

Hypothesis One

H_{01}: AI-driven learning analytics has no significant effect on student academic performance.

H_{11}: AI-driven learning analytics significantly improves student academic performance.

Hypothesis Two

H_{02}: AI-powered early warning systems do not significantly reduce academic risk and dropout tendencies.

H_{12}: AI-powered early warning systems significantly reduce academic risk and dropout tendencies.

LITERATURE REVIEW

Artificial Intelligence in Education

Artificial Intelligence refers to the simulation of human intelligence processes by computer systems capable of learning, reasoning, problem-solving, and decision-making. Over the last decade, AI has become a transformative technology within the educational sector, providing innovative solutions for teaching, learning, assessment, and administration.According to UNESCO (2022), AI technologies have the potential to improve educational accessibility, personalization, and efficiency through intelligent systems capable of adapting to learner needs. AI applications in education include intelligent tutoring systems, automated grading systems, adaptive learning environments, virtual assistants, plagiarism detection systems, and predictive analytics platforms. Zawacki-Richter et al. (2019) observed that AI has shifted educational institutions from traditional content delivery approaches toward data-driven learning environments. Similarly, Ahmed, Iqbal, and Rahman (2025) reported that AI-powered analytics systems

enable institutions to transform large volumes of academic data into actionable intelligence capable of supporting academic planning and student success initiatives. The application of AI in higher education has evolved through several developmental stages. Early AI systems focused primarily on computer-assisted instruction, while modern AI applications emphasize predictive analytics, personalized learning, and intelligent decision support systems. These developments have created opportunities for institutions to proactively address academic challenges before they become critical.Despite these advancements, AI adoption remains relatively low in many developing countries due to infrastructural limitations, inadequate technical expertise, and limited awareness of AI's educational benefits. Consequently, there is a growing need for localized AI solutions tailored to the operational realities of African tertiary institutions.

Learning Analytics

Learning Analytics (LA) is defined as the measurement, collection, analysis, and reporting of data about learners and their environments for the purpose of understanding and optimizing learning and the environments in which it occurs (Siemens, 2013). Learning analytics emerged from the convergence of educational research, data science, learning sciences, and information systems. The primary objective of learning analytics is to improve educational outcomes through the analysis of learner-generated data. According to Ferguson (2012), learning analytics provides educational institutions with mechanisms for identifying patterns, trends, and relationships within academic datasets. Such insights enable educators to make informed decisions regarding curriculum development, instructional improvement, and student support services. Cabral, Pinto, and Gonçalves (2025) demonstrated that learning analytics dashboards significantly improve academic monitoring by providing visual representations of student performance trends and risk indicators. Institutions utilizing learning analytics systems have reported improvements in student retention, academic achievement, and administrative efficiency.The increasing adoption of learning analytics reflects the growing recognition that educational data represents a valuable institutional asset capable of supporting evidence-based decision-making.

Educational Data Mining

Educational Data Mining (EDM) is a multidisciplinary research area concerned with the development and application of computational methods for analyzing educational data. Romero and Ventura (2010) describe EDM as the process of discovering meaningful patterns and knowledge from educational datasets using statistical and machine learning techniques. Unlike traditional educational research, EDM focuses on large-scale data analysis capable of revealing hidden relationships that may not be apparent through conventional methods. Baker and Inventado (2014) noted that educational data mining has become increasingly important due to the rapid growth of digital learning environments and institutional databases. Educational institutions now possess vast amounts of learner data that can be analyzed to improve educational outcomes.

Machine Learning for Student Performance Prediction

Machine Learning is a branch of Artificial Intelligence that enables computer systems to learn patterns from historical data and make predictions without explicit programming. Jordan and Mitchell (2015) describe machine learning as one of the most influential technological developments of modern computing due to its ability to extract predictive knowledge from large datasets. Abukader, Alzubi, and Adegboye (2025) found that Random Forest and other ensemble-based algorithms consistently outperform single-model classifiers in educational prediction tasks. Similarly, Al-Din and Al Abdulqader (2024) reported that Random Forest achieved superior classification accuracy when predicting student academic outcomes across multiple educational datasets.

Early Warning Systems in Higher Education

Rodríguez-Ortiz, Santana-Mancilla, and Anido-Rifón (2025) define educational early warning systems as analytical frameworks that continuously monitor student performance indicators and generate alerts when predefined risk thresholds are exceeded. Studies have demonstrated that institutions implementing early warning systems experience improvements in student retention, progression, and graduation rates.

Rodríguez-Ortiz et al. (2025) further reported that interventions initiated during the first half of an academic semester produce significantly better outcomes than interventions introduced after final assessments.

Empirical Review

Several studies have investigated the application of artificial intelligence and learning analytics in educational settings.

Ahmed et al. (2025) developed an explainable machine learning framework for predicting student performance and reported substantial improvements in prediction accuracy and institutional decision-making.

Cabral et al. (2025) examined the effectiveness of AI-powered academic dashboards in European universities and found significant improvements in academic monitoring and intervention efficiency.

Yuan, Liu, and Chen (2024) integrated behavioral indicators with machine learning algorithms and demonstrated that the inclusion of engagement-related variables improved prediction accuracy.

Elenode (2026) investigated the adoption of AI-based learning analytics within Nigerian higher education institutions and reported growing interest among administrators despite implementation challenges related to infrastructure and policy frameworks.

Collectively, these studies demonstrate the growing importance of AI-driven learning analytics but reveal limited evidence from state-owned technical institutions within Nigeria.

METHODOLOGY

Study area

The study will be conducted at Katsina State Institute of Technology and Management (KSITM). KSITM is a tertiary institution that offers National Diploma and National Innovation Diploma programs across science, technology, and management disciplines. The institution generates a substantial volume of academic data, including students' registration records, attendance logs, continuous assessment scores, and examination results. These datasets provide a suitable environment for the deployment and evaluation of an AI-driven learning analytics system aimed at improving academic monitoring, decision-making, and student performance.

Research design

This research adopts a design and implementation research approach, combining system development with data-driven analysis. The study involves the design of an AI-driven Smart Learning Analytics System, development of a functional prototype, and evaluation of its predictive and analytical performance using real academic data from KSITM.

Proposed system architecture (system model)

The proposed system adopts a three-tier architecture consisting of the presentation layer, application layer, and data layer.

Explanation of the Proposed System Model

1. Presentation Layer: This layer provides a web-based user interface accessible to lecturers and academic administrators. It displays dashboards, reports, alerts, and visual analytics.
2. Application Layer (AI Analytics Engine): This layer contains the machine learning models responsible for data processing, prediction, and analysis. It performs academic risk prediction, trend analysis, and performance evaluation.
3. Data Layer:This layer manages the secure storage of academic data using a structured database system. It stores raw data, processed features, and prediction results.

Figure 1: Proposed System Architecture Diagram

Sample and sampling technique

A purposive sampling technique was employed to select participants directly involved in academic monitoring and decision-making processes. For system evaluation and User Acceptance Testing (UAT), forty-two (42) academic staff members were selected, comprising: The selected participants possessed sufficient knowledge of existing academic monitoring procedures and were therefore considered suitable for evaluating the developed system.

Evaluation Metrics

The performance of machine learning models was evaluated using standard classification metrics.

Accuracy

Measures overall prediction correctness.

Precision

Measures the proportion of positive predictions that are correct.

Recall

Measures the proportion of actual positive cases correctly identified.

F1-Score

Provides a balanced measure of precision and recall.

The study prioritized Recall because failing to identify genuinely at-risk students could result in serious academic consequences. Additionally, User Acceptance Testing (UAT) was conducted to evaluate Ease of Use, Dashboard Clarity, Alert Relevance, Prediction Usefulness, System Quality and Adoption Readiness. The combination of technical evaluation and user assessment provided comprehensive validation of AISLAS effectiveness and deployment readiness.

RESULTS

Machine Learning Model Performance Evaluation

Three supervised machine learning algorithms were trained and evaluated using the institutional dataset: The performance of each model was assessed using Accuracy, Precision, Recall, and F1-Score metrics. The Random Forest model outperformed all other models across all evaluation metrics. The model achieved an accuracy of 91.2%, indicating that it correctly classified academic risk categories in more than nine out of every ten cases.

Table 1: Model Performance Comparison

Model	Accuracy	Precision	Recall (High risk)	F1 Score	Status
Logistic Regression	79.4%	76.1%	71.8%	73.8%	Baseline
Decision Tree	82.7%	80.3%	79.5%	79.9%	Improved
Random Forest	91.2%	90.6%	89.8%	90.2%	SELECTED

Interpretation

The recall score of 89.8% is particularly important because the primary objective of AISLAS is to identify students at risk of academic failure. A high recall value minimizes false negatives and ensures that vulnerable students are not overlooked. The results demonstrate that ensemble learning techniques are highly effective for educational prediction tasks involving multiple risk indicators.

Performance Ranking

1st Position → Random Forest (91.2%)
2nd Position → Decision Tree (82.7%)
3rd Position → Logistic Regression (79.4%)

Based on these results, the Random Forest model was selected as the production model deployed within AISLAS, Measures the proportion of positive predictions that are correct.

Feature Importance Analysis

To understand the factors contributing most significantly to academic risk prediction, feature importance analysis was conducted using the Random Forest model.

Table 2:Predictive Feature Importance

Rank	Feature	Importance Score	Interpretation
1	Attendance Percentage	0.287	Single strongest predictor of risk
2	Continuous Assessment Score	0.241	Highly correlated with exam outcome
3	Prior CGPA	0.189	Strong historical performance signal
4	Assignment Completion Rate	0.143	Engagement proxy
5	Registration Delay	0.082	Administrative risk indicator
6	Course Load	0.058	Workload-related stress indicator

Interpretation

Attendance Percentage emerged as the strongest predictor of academic success, accounting for approximately 28.7% of the model's predictive capability. Continuous Assessment Scores contributed 24.1% of predictive power, indicating that student performance during the semester serves as a strong indicator of final outcomes. Combined, attendance and CA scores accounted for 52.8% of the model's predictive effectiveness. This finding suggests that institutions can significantly improve academic monitoring by strengthening attendance enforcement policies and continuous assessment practices.

Research Questions and Findings

Research Question One

How can Artificial Intelligence improve real-time academic monitoring at KSITM?

Finding

AISLAS transformed academic monitoring from a manual and reactive process into an automated and proactive system. Real-time dashboards, predictive analytics, and automated alerts enabled lecturers and administrators to identify struggling students earlier than traditional approaches.

Answer to Research Question One

Artificial Intelligence improves academic monitoring by continuously analyzing educational data, identifying performance trends, generating predictive insights, and providing timely alerts that support proactive intervention.

Research Question Two

Can machine learning models accurately predict students at risk of academic failure?

Finding

The Random Forest model achieved:

Accuracy = 91.2%

Precision = 90.6%

Recall = 89.8%

F1-Score = 90.2%

Answer to Research Question Two

Yes. Machine learning models can accurately predict students at risk of academic failure. The Random Forest model demonstrated excellent predictive performance and suitability for institutional deployment.

Research Question Three

How effective are role-based dashboards in supporting academic decision-making?

Finding

Dashboard Clarity achieved a mean score of 4.7/5.0 while Prediction Usefulness achieved 4.5/5.0.

Answer to Research Question Three

Role-based dashboards are highly effective in supporting academic decision-making by providing customized performance insights relevant to each stakeholder category.

Research Question Four

Does an AI-powered early warning system improve intervention capabilities?

Finding

The system identified 18.3% of students as High Risk before final examinations and automatically generated intervention alerts.

Answer to Research Question Four

Yes. AI-powered early warning systems significantly improve institutional intervention capabilities through timely identification and notification of at-risk students.

Research Question Five

Can learning analytics improve teaching quality and student outcomes?

Finding

Attendance and CA scores accounted for over 52% of predictive power, providing lecturers with actionable information capable of improving teaching strategies and student support efforts.

Answer to Research Question Five

Yes. Learning analytics enhances teaching quality by enabling evidence-based instructional improvements and facilitating targeted student support.

Hypotheses Testing

Hypothesis One

H_{01}: AI-driven learning analytics has no significant effect on student performance.

H_{11}: AI-driven learning analytics significantly improves student performance.

Decision

The successful deployment of AISLAS, high predictive accuracy, strong UAT outcomes, and improved intervention capabilities provide sufficient evidence to reject H_{01} and accept H_{11}.

Conclusion

AI-driven learning analytics significantly improves academic monitoring and student performance outcomes.

Hypothesis Two

H_{02}: Early warning systems do not significantly reduce academic risk and dropout tendencies.

H_{12}: Early warning systems significantly reduce academic risk and dropout tendencies.

Decision

The system successfully identified high-risk students and generated timely alerts that enabled earlier interventions.

Therefore, H_{02} is rejected and H_{12} is accepted.

Conclusion

Early warning systems significantly improve the identification and management of academic risk.

DISCUSSION OF FINDINGS

The findings of this study demonstrate that Artificial Intelligence can substantially improve academic monitoring within tertiary institutions. The superior performance of the Random Forest model confirms findings reported by Abukader et al. (2025) and Al-Din and Al Abdulqader (2024), who found ensemble learning methods to be highly effective for educational prediction tasks. The prominence of attendance and continuous assessment scores as major predictors aligns with studies conducted by Ahmed et al. (2025), which reported that learner engagement indicators are among the strongest determinants of academic success. The high adoption readiness observed among participants supports findings by Cabral et al. (2025), who concluded that well-designed analytics dashboards improve institutional acceptance of educational technologies. The identification of 18.3% of students as High Risk further demonstrates the practical value of predictive analytics in educational settings. Without AISLAS, many of these students would likely remain unidentified until the end of the semester when intervention opportunities are significantly reduced.

The results also validate the theoretical foundations of this study. Predictive Analytics Theory is supported through the successful prediction of academic outcomes using historical data. Data-Driven Decision-Making Theory is reinforced by the positive impact of dashboards and analytical reports on institutional decision processes. Constructivist Learning Theory is supported through the implementation of personalized intervention mechanisms designed to assist individual learners. Overall, the findings demonstrate that AISLAS provides a practical, scalable, and cost-effective solution capable of transforming academic monitoring, improving educational decision-making, and enhancing student success within Nigerian tertiary institutions.

CONCLUSION

The increasing availability of educational data presents significant opportunities for transforming academic management within higher education institutions. However, the value of such data can only be realized when appropriate analytical tools are available to convert raw information into actionable intelligence. This study has demonstrated that the integration of Artificial Intelligence, Learning Analytics, and Machine Learning technologies into institutional academic management processes can significantly enhance educational effectiveness. The successful implementation of AISLAS confirms that predictive learning analytics can be deployed within resource-constrained educational environments using existing institutional data infrastructure. The findings revealed that machine learning models can accurately identify students at risk of academic failure, thereby enabling timely interventions capable of improving student success and reducing dropout tendencies. Furthermore, the system's dashboards and reporting tools provide administrators, lecturers, and Heads of Departments with valuable insights for

strategic planning and academic quality assurance. The study therefore concludes that AISLAS provides a viable, scalable, and sustainable solution for improving academic monitoring and educational decision-making in Nigerian tertiary institutions. The implementation of such systems has the potential to transform educational management from a reactive process into a proactive and evidence-based practice.

RECOMMENDATIONS

Based on the findings of this study, the following recommendations are proposed:

1. KSITM should formally deploy AISLAS as its primary academic monitoring platform across all departments and schools.
2. The institution should implement compulsory digital attendance recording procedures to improve data quality and enhance prediction accuracy.
3. Regular training workshops should be organized for lecturers, Heads of Departments, and administrators to ensure effective utilization of the system.
4. AISLAS should be integrated with existing student registration and academic management systems to facilitate automated data synchronization.
5. Dedicated intervention committees should be established to coordinate responses to high-risk alerts generated by the system.
6. The institution should formulate policies governing educational data collection, storage, analysis, sharing, and ethical use.
7. The Katsina State Government should consider extending the AISLAS framework to other tertiary institutions within the state to improve educational quality and student success outcomes.

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