AI-Powered Academic Program Effectiveness Evaluation System with an Integrated Recommendation Engine for Bsit and Bscs Programs

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ABSTRACT

The growing complexity of higher education needs the institutions to embrace sophisticated, data-driven strategies that enable them to constantly assess and advance the academic programs. The proposed paper is the creation of an Academic Program Effectiveness Evaluation System based on AI and aimed at collecting, integrating, and analyzing multidimensional data on the Bachelor of Science in Information Technology (BSIT) and Bachelor of Science in Computer Science (BSCS) programs. The system employs the machine learning algorithms, namely: Random Forest, Linear Regression, and K-Means Clustering, as well as the Natural Language Processing to perform predictive analytics and classify performance trends, and obtain insights based on qualitative stakeholder feedback. The platform produces recommendations through a cohesive system of program evaluation to improve curriculum design, enhance student support, and improve the overall outcomes of the program. The suggested system will facilitate the evidence-based decision making of the administrators, faculty, and stakeholders, which will aid in the continuous quality improvement of the academic institution.

Keywords: Natural Language Processing (NLP), Artificial Intelligence, Random Forest, Linear Regression, K-means Clustering, Program Evaluation.

INTRODUCTION

Over the past years, the relevance and quality of higher education programs have been put under a lot of scrutiny especially in rapidly changing fields like Computer Science (CS) and Information Technology (IT). The fast technological change and the need of the world market to have industry-based, data-based skills have led to an increase in the pressure on higher education institutions to provide flexible and adaptive curricula. Such pressure increases the need to conduct constant and objective student performance evaluation to understand whether curricular objectives and learning outcomes are successfully achieved. The College of Computer Studies at Laguna State Polytechnic University – Sta. Cruz Campus (LSPU–Sta. Cruz) offers undergraduate programs in Computer Science and Information Technology that aim to equip students with technical competencies in programming, software engineering, data structures, algorithms, systems analysis and design,and emerging technologies. However, the current mechanisms used to evaluate the effectiveness of these programs primarily rely on traditional approaches such as student feedback, faculty assessments, and graduate tracer studies. These conventional methods, while useful, often lack objectivity, scalability, and the ability to deliver real-time, data-informed insights essential for timely curricular enhancement. The importance of aligning assessment with learning outcomes is emphasized by Biggs (1996) in his study, "Enhancing Teaching Through Constructive Alignment," which advocates for the alignment of instructional activities and assessments with clearly defined objectives. According to Biggs, such alignment leads to deeper learning and more accurate representation of student capabilities, while misalignment results in superficial learning and poor curriculum efficacy. Supporting this, a study by De Castro Figueiredo et al. (2004) found that students in a revised, outcomes-based curriculum significantly outperformed those in traditional curricula in objective assessments, highlighting the value of systematic evaluation in curriculum development. To address the drawbacks associated with the conventional evaluation techniques, the proposed research will develop an AI- Powered Academic Program Effectiveness Evaluation System with an Integrated Recommendation Engine that will rely on the machine learning algorithms to study the past data on the students, such as grades, rubric-based assessment, and the history of academic gaps. The system will learn to recognize patterns and trends that will determine the common subjects or learning areas that will either result in good or bad performance. Such insights will form the foundation of strategic changes in the curriculum design and delivery. This research paper will provide an intelligent and scalable student record transformation into actionable knowledge that will assist in improving the quality of the curriculum in the College of Computer Studies at LSPU-Sta. Cruz. The ultimate objective is to enable academic excellence and institutional quality assurance through development of a cycle of continuous optimization of the curriculum, based on real and reliable data. By doing so, the study takes a step towards localizing OBE principles as well as providing administrators and faculty with the analytical tools to make evidence-based decisions regarding their curriculums.

Research Objectives

The study developed an AI-powered evaluation system to analyze student data and identify curriculum gaps for the Specifically, this study sought to find out the following:

1. To structure and preprocess historical student performance data (e.g., grades, deficiency rates, class profile) for use in machine learning models that evaluate the effectiveness of the CS and IT curriculum.

2. To apply machine learning algorithms such as Random Forest, K-means Clustering, and Linear Regression for detecting underperforming subjects and predicting curriculum-related academic risks.

3. To assess the selected supervised and unsupervised machine learning algorithms using classification metrics, including:

3.1 Accuracy

3.2 Precision

3.3 Recall

3.4 F1-score

4. To apply machine learning models in identifying patterns and trends in student performance data that may indicate the need for curriculum updates or revisions.

5. To evaluate the effectiveness of the proposed intelligent assessment system in providing actionable insights for academic administrators to support continuous, data- driven curriculum improvement.

RELATED LITERATURES

This chapter presents a review of related literature and studies on the AI-Powered Academic Program Effectiveness Evaluation System with an Integrated Recommendation Engine for BSIT and BSCS Programs. This part of the study will enable readers to understand the primary goal, concept, and design of the proposed project, as well as its function, application, and the importance of developing the system. Several recent studies have explored the application of machine learning techniques for student outcome assessment and curriculum optimization, providing valuable insights and also highlighting existing research gaps relevant, despite these technical advancements, a recurring limitation across the literature is the translational gap between data-driven predictions and practical curriculum redesign. Chen et al. (2025), Xuan Lam et al. (2024), and Su et al. (2022) all note that while ML models accurately predict academic outcomes, their insights are rarely systematically applied to optimize actual curricula. Additionally, Qu et al. (2023) and Arashpour et al. (2023) emphasize that the "black box" nature of complex algorithms and their frequent isolation to specific exams hinder interpretability. This lack of transparency limits educators' trust and prevents the direct application of these insights into actionable instructional changes. While Integrated Library Management Systems (ILMS) have significantly improved operational efficiency and information retrieval, many institutions still face barriers to full implementation. A study by Hussain and Ameen (2023) on university libraries in Pakistan found that despite the clear time-saving benefits of automation, many facilities remain only partially automated (primarily in cataloging) due to infrastructural limitations, power outages, and resource constraints. Furthermore, as libraries transition to cloud computing, they face new cybersecurity vulnerabilities. Traditional ILMS often fail to provide fully secure, tamper-resistant environments, leaving highly valuable institutional data exposed to DoS attacks, hacking, and unauthorized manipulation (S., Malik et al., 2022). To address day-to-day administrative bottlenecks—such as human resource shortages, inaccurate book availability data, and asset safety— libraries are increasingly adopting automated identification technologies. Putra and Labasariyani (2022) developed a management system that effectively combines Near Field Communication (NFC) and QR Code technology. By embedding member data into NFC cards and assigning QR codes to individual books, libraries can seamlessly automate borrowing and returning transactions, ensuring highly accurate, real-time tracking of library resources. To counter the severe vulnerabilities of modern cloud-based systems, recent literature strongly advocates for the integration of blockchain technology. S., Malik et al. (2022) proposed a blockchain-based ILMS utilizing Hyperledger Fabric to create a distributed, secure, and fraud-free environment. In this model, every library transaction is validated by a pool of nodes and locked into cryptographically encrypted hash-blocks, ensuring complete transparency and tamper resistance. However, technical capability must be matched with institutional readiness. Dada and Mohammed (2025) emphasize that revolutionizing library practices requires active engagement from library professionals. They recommend that library councils launch websites, webinars, and policy whitepapers to foster awareness and safely guide the adoption of blockchain and other emerging technologies for enhanced service delivery.

METHODOLOGY

Research Design

A combination of developmental research design and experimental research methods was used so that the techniques utilized in this research could be in line with the goals of the study. The developmental approach was aimed at the systematic design and development as well as evaluation of an AI-driven academic program effectiveness assessment system, including a holistic data model and a built-in recommendation engine.

This was done by the systematic gathering and assembly of multi- dimensional program data such as graduate performance, curriculum relevance, student satisfaction, competencies and class profiles. The research employed the experimental aspect in the development and testing of machine learning models and natural language processing algorithms to guarantee predictive accuracy, sentiment analysis reliability and overall system performance.

According to Seels and Richey (1994), developmental research creates and tests instructional and technological products systematically to make sure that the products are effective and applicable. Such a two-fold approach corresponds to the mixed methods approach that research designs may be parallel or sequential, relying on the schedule and combination of quantitative and qualitative elements (Johnson et al., 2017).

In addition, the use of experimental design in the research shows the standpoint that experimental designs are needed to implement the relationship between the cause and the effect by manipulating variables and observing the results (Cherry, 2023), whereas descriptive strategies were also used to describe the current state of programs through surveys and institutional records (Cherry, 2022).

Population of the Study

The table below shows the survey respondents. The table also includes the total population and sample size of respondents; the data in the table was required during the evaluation phase of the developed system.

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Table 1. BSIT/BSCS Course

Student ID	Unique student identifier	0122-1234
Academic Year	Year level of the subject being evaluated	3rd Year
Subject	Course/subject evaluated	CMSC 309 Software Engineering
Instructor Knowledge	Rating (1–5)	1
Communication	Rating (1–5)	4
Relevance to Real-World	Rating (1–5)	4
Learning Materials	Rating (1–5)	5
Hands-on/Lab	Rating (1–5)	5
Assessments	Rating (1–5)	4
Knowledge Gained	Rating (1–5)	5
Positive Feedback	What the student liked	*"Creating UI"*
Suggestions	Improvement areas	*"Teach us more about creating UI/UX"*
Overall Experience	Rating (1–5)	4

Table 2. BSIT/BSCS Graduate Tracer

Column	Description	Content
Program	Degree program	BSIT
Gender	Gender of graduate	Male
Employment Status	Employed / Unemployed / Self-employed	Employed
Job Role	Current occupation	Software Developer
Industry	Field of work	IT Services
Time to Employment	Months taken to get first job	3

System Architecture

This diagram represents the five layers that work together to assess curriculum effectiveness using machine learning. At the base, the data layer stores academic records such as grades, rubrics, and syllabi.

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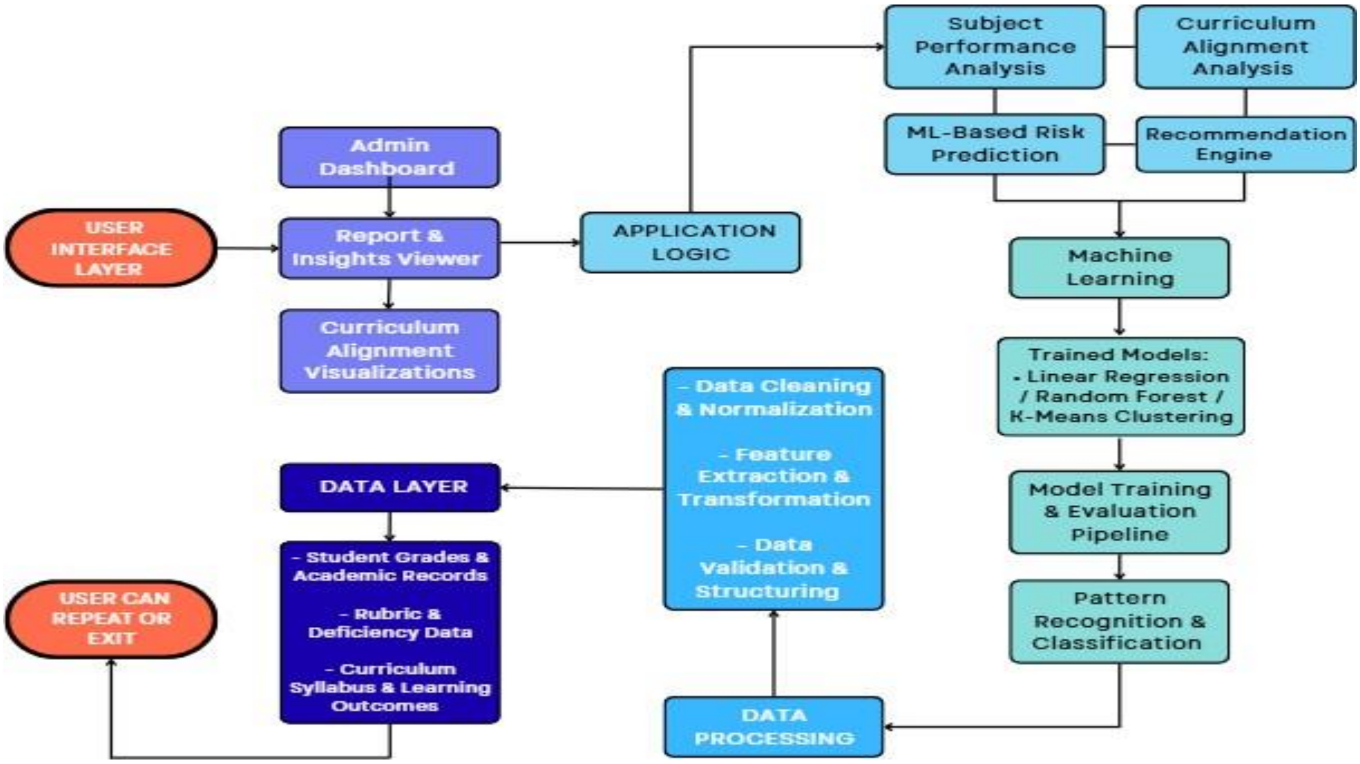

Figure 1. AI-Powered Academic Program Effectiveness Evaluation System

The data processing layer prepares this data through cleaning, normalization, and feature extraction. The machine learning layer uses models like Linear Regression and Random Forest to analyze student performance, detect patterns, and identify curriculum gaps. These insights are handled by the application logic layer, which interprets the results and provides recommendations. Finally, the user interface layer presents the findings through dashboards and reports, enabling academic administrators to make informed, data-driven decisions for curriculum improvement. By seamlessly bridging the gap between raw academic data and actionable strategies, the system ensures that the curriculum remains strictly aligned with established Program Educational Objectives (PEOs) and Outcomes- Based Education (OBE) standards.

Software Development Model

This study aims to solve the problem of evaluating the performance and effectiveness of the Computer Science and Information Technology curriculum at LSPU – Sta. Cruz by developing an intelligent assessment system powered by machine learning.

Figure 2. Agile Development

The Agile approach is implemented in the current study to facilitate the flexibility, ongoing improvement, and active cooperation in the development process. Since the system is expected to collect and process academic data, train machine learning (ML) models, design an intuitive interface and consider feedback of academics and administrators, it is practically divided into manageable sprints. In every sprint, the team is focused on specific deliverables, including preprocessing of student records, building and testing predictive ML models, and incorporating performance data into the system dashboard. This iterative development process enables the systematic testing, refinement and enhancement on the basis of performance measures and user feedback. Using Agile, the project will ensure that the resulting intelligent assessment tool to be used in the assessment and optimization of Computer Science and Information Technology curricula is precise, flexible, and human-centered.

RESULTS AND DISCUSSION

This chapter discusses and presents the research findings based on the objectives established by the researchers for the investigation. This chapter also includes the analysis and interpretation of data gathered during software testing and evaluation of the developed system.

Research Objective 1: aimed to gather and prepare historical student performance data (grades, deficiency rates, and class profiles) to evaluate the CS and IT curriculum. Institutional records were collected and preprocessed. This involved cleaning (handling missing and inconsistent values), transforming (normalizing and encoding categorical variables), and merging multiple datasets into a single, standardized model. The preprocessing yielded structured, machine-readable data ready for training models like Linear Regression, Random Forest, and K-Means Clustering. This successfully fulfilled the objective, laying the groundwork for the system's predictive analytics and recommendations.

Research Objective 2: was successfully achieved by deploying machine learning algorithms to detect underperforming subjects and predict curriculum-related academic risks. Linear Regression established baseline trends between curriculum components and student outcomes to identify potential risk factors. Random Forest analyzed complex, non-linear patterns to pinpoint the specific subject and curriculum features driving poor academic performance. Finally, K-Means Clustering grouped students and subjects into distinct performance profiles—such as high-performing, average, and at-risk. Collectively, these models provided a comprehensive framework for evaluating and identifying academic risks within the program.

Research Objective 3: To assess the selected supervised and unsupervised machine learning algorithms using classification metrics, including: (3.1) Accuracy, (3.2) Precision, (3.3) Recall, (3.4) F1- score. In order to assess the efficiency of the chosen machine learning algorithm deployed in the AI-based academic evaluation system, conventional classification metrics were used. These measures are accuracy, precision, recall and F1-score which are usually employed to evaluate the performance of classification models. The following performance metrics were obtained based on the results of the experimental studies on the trained model.

Metrics	Results
Accuracy	0.98 (98%)
Precision	0.96 (96%)
Recall	0.91 (91%)
F1-Score	0.92 (92%)

Table 3. Evaluation Metrics

Research Objective 3 was successfully achieved by validating the machine learning model's performance using standard classification metrics. The model demonstrated exceptional reliability, achieving a 98% accuracy rate which proves the chosen features and training methods effectively forecast academic outcomes for the BSCS and BSIT programs. A 96% precision rate minimizes false positives, preventing unnecessary academic interventions, while a 91% recall ensures the system successfully identifies the majority of at-risk students who genuinely need support. Finally, a 92% F1-score highlights a stable, well-balanced system capable of handling potentially imbalanced academic datasets. Ultimately, these strong metrics confirm that the model is a highly dependable tool for data-driven academic assessment, risk detection, and curriculum evaluation.

Research Objective 4: was successfully achieved by employing machine learning models to identify patterns in student performance that signal a need for curriculum revisions. By analyzing historical data, the system utilized Random Forest to calculate feature importance scores, highlighting the key variables that most heavily impact student outcomes. K-Means Clustering was used to group students with similar performance traits, while Linear Regression tracked gradual shifts in academic performance over time. Collectively, these models effectively pinpointed academic risks and ongoing areas of underperformance, providing clear, data- driven evidence to justify and guide future curriculum updates.

Research Objective 5: was successfully achieved by validating the intelligent assessment system's ability to deliver actionable insights for continuous curriculum improvement. The system effectively translated complex data—including predictive analytics, clustering results, and sentiment analysis—into an interactive, easy-to-use dashboard. Through system evaluation and expert validation, academic administrators and faculty confirmed that the generated insights were clear, highly reliable, and directly useful for decision-making. Ultimately, the evaluation proved that the system successfully converts sophisticated data into practical recommendations, empowering administrators to make evidence-based enhancements to the curriculum.

RESULTS AND DISCUSSION

Summary

The purpose of the research is to create an intelligent academic assessment system that will allow for evidence-based assessment and continuous quality improvement of the BSIT and BSCS degree programs. This intelligent assessment system will combine measures of students' academic performance, their deficiencies, feedback received, and alumni tracers for comprehensive analysis of student achievement and course/program relevance. In order to achieve the research objectives, supervised and unsupervised machine learning techniques have been utilized. For detecting performance clusters within the courses, the k-means clustering technique was used. Random Forest Classification was employed for the prediction of student performances. Linear Regression was utilized for analyzing temporal trends in academic performance. Performance of the supervised models was analyzed based on their accuracy, precision, recall, and F1 score.

CONCLUSIONS

In conclusion, the researchers reached the following determinations based on the study's outcomes:

1. The AI-driven evaluation system demonstrates competence in academic assessment and decision- making processes. The system successfully analyzed institutional academic data, thereby generating substantial insights into student performance, course effectiveness, and academic deficiencies. This suggests that artificial intelligence has the potential to improve academic evaluation within higher education institutions.

2. The machine learning model, once trained, exhibited commendable classification capabilities. The Random Forest classifier attained an accuracy rate of 82 percent, demonstrating equilibrium in its precision, recall, and F1-score metrics. These findings suggest that the model is capable of accurately forecasting student academic outcomes and pinpointing those students who would benefit from academic support. Unsupervised learning yielded pertinent insights atthe course level. K-Means clustering successfully categorized courses according to performance metrics, thereby enabling the identification of both high-achieving and underperforming subjects. Such categorizations could prove beneficial to academic administrators in determining the focus of curriculum evaluations and instructional enhancements.

RECOMMENDATION

Based on the study's findings, the researchers suggest the following recommendations for future development and improvement:

6. Future versions of the system should include quantitative analyses of course evaluation survey data to assess instructor effectiveness and course relevance.

7. Future research could explore the use of deep learning or hybrid models to improve predictive accuracy.

8. The dataset could be expanded to include more academic institutions, which would increase the external validity of the results

9. Long-term studies should be conducted to determine the lasting effects of the AI-based academic evaluation system on student achievement and curriculum content.

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