Personalized Learning Path Recommendation for System Integration and Architecture Through a Decision Tree–Based AI Engine

Lord Aeremist Pido Valdemoro[1], Edcel Bernabe Besa[2], Marc Daniel Rodriguez Lim[3], Ms. Anna Liza Ognita Villanueva[4], Dr. Jeusuel Nonnatus Noblezala De Luna[5]

[1,2,3]Student, College of Computer Studies, University of Perpetual Help System Manila
[4]Dean, College Of Computer Studies, College of Computer Studies, University of Perpetual Help System Manila
[5]Professor, College of Computer Studies, University of Perpetual Help System Manila

Abstract
Traditional Learning Management Systems (LMS) often utilize a "one-size-fits-all" curriculum, failing to accommodate the diverse proficiency levels of students in complex technical courses like System Integration and Architecture (SIA). This lack of adaptability leads to a mismatch between learner needs and instructional content, reducing engagement and learning efficiency. This study aimed to design, develop, and evaluate LearnScope, an AI-powered adaptive e-learning system. The primary goal was to utilize a Decision Tree algorithm to classify student proficiency and automate the delivery of personalized learning paths. The study employed a Descriptive-Developmental research design following the Agile methodology. The system architecture utilized a hybrid stack with Moodle as the frontend and a Python/Flask microservice for the AI logic. The dataset consisted of historical academic records from 23 students, augmented with 11 synthetic records (N=34) to ensure class balance. A Decision Tree classifier was trained to categorize students into Beginner, Intermediate, and Advanced tiers. System quality was evaluated using ISO/IEC 25010 standards. The student cohort exhibited diverse learning capacities, with 12% identifying as "at-risk" (Beginner). The Decision Tree model achieved a prediction accuracy of 90.91%, with 100% recall for the critical "Beginner" class, ensuring no at-risk students were overlooked. User acceptance testing yielded a high usability rating (Weighted Mean = 3.85), though security measures received a moderate rating (2.69). LearnScope successfully demonstrates that interpretable AI models can effectively automate personalized instruction in resource-constrained educational settings. The system proactively identifies struggling learners and provides targeted interventions, though future iterations require enhanced security protocols for production deployment.

INTRODUCTION

The paradigm of higher education has undergone a seismic shift in the last decade, transitioning from static, lecture-based pedagogies to dynamic, learner-centered environments facilitated by digital technologies. Central to this transformation is the integration of Artificial Intelligence (AI) and Machine Learning (ML) into Learning Management Systems (LMS), a development that promises to resolve the historical tension between educational scalability and individual personalization. However, despite the proliferation of digital tools, a critical inefficiency remains: the persistence of "one-size-fits-all" curricula. Traditional LMS platforms often function as passive repositories of content, delivering identical modules to students regardless of their disparate proficiency levels, learning paces, or cognitive styles. This lack of adaptability creates a significant "pedagogical mismatch," where struggling learners are overwhelmed by advanced concepts while high-performing students are disengaged by repetitive foundational material, ultimately compromising learning efficiency and motivation. The necessity for adaptive systems is particularly acute in technical disciplines such as Information Technology (IT) and Computer Science (CS). Courses like "System Integration and Architecture" (SIA) are inherently hierarchical and integrative; mastery of complex architectural patterns requires a solid grasp of foundational integration protocols. In such domains, a student's inability to bridge the gap between theoretical concepts and practical application can lead to rapid academic attrition. The existing literature highlights that while adaptive platforms exist, many suffer from algorithmic opacity or rely on rudimentary classification techniques that fail to accurately profile a student's "Zone of Proximal Development" (ZPD). This theoretical framework, proposed by Vygotsky, suggests that optimal learning occurs when instruction is scaffolded slightly beyond the learner’s current independent capability. Without robust, data-driven profiling, automated systems cannot effectively identify this zone, rendering the personalization superficial.1.2 The Context of Philippine Higher Education Within the specific context of Philippine higher education, particularly at institutions like Perpetual Help College of Manila (PHCM), the challenge is compounded by infrastructural and resource constraints. Recent studies on the digital educational landscape in the Philippines highlight a student body that is increasingly digitally native yet vulnerable to academic distress caused by systemic inefficiencies. The "digital divide" and varying levels of technological literacy among students necessitate systems that are not only intelligent but also highly usable and accessible. Current implementations of adaptive learning in this region have been sporadic. While various web applications have demonstrated the utility of digital tools for fostering self-awareness, they often lack real-time integration with professional academic standards and advanced AI decision-making capabilities. Furthermore, there is a marked scarcity of systems specifically tailored for complex IT subjects. Most local research has focused on predictive modeling for "at risk" identification rather than prescriptive intervention—identifying that a student will fail but not necessarily providing the automated remedial pathway to prevent it. This study addresses this critical gap by developing LearnScope, a system designed to move beyond passive prediction to active, automated intervention.

METHODS

This study adopted a Descriptive-Developmental Research Design, a methodological approach ideal for engineering-centric educational research. This dual-phase design allows for the systematic observation of existing phenomena (the "Descriptive" phase of analyzing student performance gaps) followed by the iterative creation of a technological intervention (the "Developmental" phase of building LearnScope). The software development lifecycle (SDLC) followed the Agile methodology, characterized by iterative "sprint" cycles of planning, development, testing, and review. This approach was selected to allow for continuous refinement of the AI model and user interface based on interim feedback from IT experts and pilot student users. The study utilized purposive sampling to select participants who could provide high-fidelity feedback relevant to the system's specific domain. The historical academic performance data was collected from 23 students enrolled in the "System Integration and Architecture" (SIA) course at Perpetual

Help College of Manila (PHCM) for the Academic Year 2024-2025. To ensure robust training of the Decision Tree classifier and to prevent class imbalance issues during the tertile analysis, this dataset was augmented with 11 synthetic records, resulting in a balanced total dataset of 34 instances. This approach allowed for the equal distribution of data points across proficiency tiers (Beginner, Intermediate, Advanced) for model validation. IT experts were provided with a survey for the technical evaluation based on ISO/IEC 25010. Their inclusion ensures that the system's architecture, security, and code quality were assessed by individuals with the requisite technical competency.

RESULTS AND DISCUSSION

The initial deployment of the system involved a diagnostic analysis of the student cohort using mid-semester academic data. This analysis, utilizing the balanced dataset (N=34), was critical to establishing the baseline necessity for adaptive intervention.

Table 1: Functional Suitability

Functionality	Weighted Mean	Interpretation
The AI-Based Recommendation Engine effectively processes Decision Tree outputs to suggest tailored resources.	3.13	Highly Functional
The Progress Tracking and Analytics module allows both students and instructors to accurately view learning trends.	3.00	Highly Functional
The Proficiency Classifier correctly classifies the student into three different proficiency levels.	2.94	Functional
The Teacher Dashboard/Analytics enables instructors to view group trends, common gaps, and completion rates effectively.	3.06	Highly Functional
Overall Weighted Mean	**3.06**	**Highly Functional**

Table 1 presents the evaluation results for the system's Functional Suitability, which achieved an Overall Weighted Mean of 3.06, interpreted as **Highly Functional**. The highest-rated feature was the AI-Based Recommendation Engine, showing strong performance in delivering personalized learning resources based on Decision Tree outputs. The Teacher Dashboard/Analytics was also rated Highly Functional, confirming that instructors can effectively monitor learning trends and completion rates.

Table 2: Performance Efficiency

Features	Weighted Means	Interpretation
The system responds quickly and efficiently to user interactions.	3.65	Highly Efficient

The AI model processes classification tasks without noticeable delay.	3.70	Highly Efficient
The system maintains good performance even during high usage or with large datasets.	3.13	Highly Efficient
The system is optimized for resource efficiency (e.g., computation, memory, and bandwidth).	3.38	Highly Efficient
Overall Weighed Mean	**3.36**	**Highly Efficient**

Table 2 presents the evaluation results for the system's Performance Efficiency, achieving an Overall Weighted Mean of 3.36, interpreted as Highly Efficient. The highest-rated aspect was the AI model's processing speed (3.70), indicating fast and delay-free classification performance. System responsiveness (3.65) also scored highly, confirming effective integration between the backend engine and frontend interface. These results demonstrate that the platform delivers immediate feedback and smooth navigation, supporting student engagement during tasks such as proficiency assessment and course placement.

Table 3: Usability

Features	**Weighted Mean**	**Interpretation**
The user interface is clear, intuitive, and easy to navigate.	3.75	Highly Usable
The system is easy to learn and operate, even for first-time users.	3.50	Highly Usable
The system effectively prevents user errors and provides helpful error messages.	3.50	Highly Usable
Overall, the system provides a positive and engaging user experience.	4.00	Very Usable
Overall Weighed Mean	**3.69**	**Highly Usable**

Table 3 presents the evaluation results for the system's Usability, achieving an Overall Weighted Mean of 3.69, interpreted as Highly Usable**.** This indicates that the system provides a generally functional and accessible environment, with a solid interaction design that enables users to complete tasks efficiently and satisfactorily despite minor friction points. The highest-rated indicator was overall user experience, which received a weighted mean of 4.00 and was interpreted as Very Usable**.** This suggests that the application's overall workflow is engaging and positive. The clarity and intuitiveness of the user interface also scored highly (3.75), reflecting effective visual hierarchy and logical placement of buttons, menus, and content. However, the learning curve and error handling were identified as areas for improvement. Both ease of learning for first time users and error prevention received weighted means of 3.50, still within the Highly Usable range. These results imply that while the system is manageable for new users, enhancements such as improved onboarding tutorials and more supportive error feedback could further strengthen usability, particularly for beginners.

Table 4: Reliability

Features	Weighted Means	Interpretation
The system performs its intended functions consistently without failures or crashes.	3.75	Highly Reliable
The system maintains stability even when processing complex or large inputs.	3.50	Highly Reliable
System features produce consistent results when given the same inputs.	3.50	Highly Reliable
The system rarely requires restarts or manual interventions.	4.00	Very Reliable
Overall Weighed Mean	**3.69**	**Highly Reliable**

Table 4 presents the evaluation of the system's Reliability, which garnered an Overall Weighted Mean of 3.69, interpreted as Highly Reliable. This composite score indicated that while the system is generally functional and dependable for daily use, it has passed initial development hurdles but still requires refinement regarding stability and consistency. The strongest finding in this category was the system's ability to operate without needing frequent restarts or manual interventions, which received a weighted mean of 4.00. This positive result implied that the core runtime environment is self-sustaining; once launched, the application is stable enough for standard sessions, and users rarely encounter critical interruptions that require administrator assistance or force-closing the app. However, the evaluation uncovered specific vulnerabilities when the system is subjected to complex tasks. The indicators for maintaining stability under large inputs and producing consistent results both received the lowest scores of 3.50, interpreted as Partially Reliable. Along with the score of 3.75 for performing functions without failure, these ratings suggested that the system handled standard traffic well but struggled with "edge cases" or heavy data loads, leading to potential glitches or unpredictable behavior. To elevate the system from "Partially Reliable" to a more robust standard, future development must prioritize stress testing the decision tree logic and optimizing database queries to ensure consistent performance regardless of data volume.

Table 5: Security

Features	Weighted Means	Interpretation
The system effectively protects user data and academic records from unauthorized access.	2.25	Moderate

User accounts and personal information are securely managed within the system.	2.25	Moderate
The system demonstrates adequate safeguards against data loss or misuse.	3.00	Highly Secured
Overall, I feel confident that the system ensures privacy and data protection.	3.25	Highly Secured
Overall Weighed Mean	**2.69**	**Moderate**

Table 5 presents the evaluation of the Security system's features, yielding an Overall Weighted Mean of 2.69, verbally interpreted as Moderate. This score suggested that while respondents believed that the system possesses the necessary framework to protect their information, the rating is notably lower than the metrics observed in previous sections. This discrepancy indicated a distinct divide in user sentiment: while users feel generally confident in the system's privacy promises, they harbor significant reservations regarding the technical implementation of access controls and account management. The positive aspect of this evaluation was reflected in the highest-rated indicator: overall user confidence in system privacy and data protection, which received a weighted mean of 3.25 and an interpretation of Highly Secured. This result highlighted a strong perception of the system's intent and general compliance posture. It suggested that users trust the institution or developers to respect their privacy rights and believe the overarching policies governing the system are sound. This perception of trust served as a vital baseline, establishing that the fundamental approach to data handling is viewed favorably. In sharp contrast, the technical execution received lower marks. Both the protection of data from unauthorized access and the management of user accounts received weighted means of 2.25, interpreted as Moderate. This significant dip highlighted specific vulnerabilities where users perceive a tangible risk of intrusion or find the security settings—such as password management or login history—to be opaque. Collectively, these results defined the security roadmap for the next iteration: while the backend data integrity is trusted, the frontend access controls and user management features require urgent upgrades to move from Moderate to Highly Secured.

Table 6: Maintainability

Features	Weighted Means	Interpretation
The system design allows for easy identification and correction of defects or bugs.	3.00	Highly Maintained
The system can be updated or enhanced with minimal risk of introducing new issues.	3.00	Highly Maintained
The system architecture supports future scalability and adaptation to new technologies.	3.33	Highly Maintained

Overall Weighed Mean	**3.67**	**Highly Maintained**

Table 6 details the evaluation of the system's Maintainability, resulting in an Overall Weighted Mean of 3.67. This score was verbally interpreted as Highly Maintained, indicating that the system's codebase and architectural design are sufficiently robust to support ongoing updates and troubleshooting. The high overall rating suggested that the development standards applied during the project's creation have successfully resulted in a product that is sustainable in the long term, rather than functioning as a temporary solution that would be difficult to manage after deployment.

Conclusions & Recommendations

This research establishes that the integration of a Decision Tree-based AI engine into the LearnScope system successfully addresses the pedagogical inefficiencies of "one-size-fits-all" instruction in System Integration and Architecture courses. The system demonstrated strong technical validity, with a classification accuracy of 90.9% and perfect recall for identifying at-risk students, ensuring that those most in need of intervention are reliably flagged. The high user acceptance (3.85) confirms that students perceive significant value in personalized, adaptive learning paths. However, the moderate security rating (2.69) underscores the critical need for robust data protection mechanisms in educational software. Ultimately, LearnScope serves as a proof-of-concept that interpretable, lightweight AI models can democratize adaptive learning, providing a scalable solution to the diverse learning needs of the modern classroom. To advance LearnScope from a successful prototype to a production-ready academic platform, the following recommendations are proposed starting by Prioritize Security Hardening, to provide immediate implementation of industry-standard security protocols, including Multi-Factor Authentication (MFA), end-to-end encryption, and rigorous Role-Based Access Control (RBAC), is necessary to elevate the security rating to "Highly Secure" (>3.5) and comply with data privacy laws. Enhance Explainability Interfaces explains while the algorithm is interpretable, the user interface should explicitly visualize why a recommendation was made (e.g., "Recommended because you scored low on API Integration"). This "Explainable AI" feature will further build trust and metacognitive awareness among students. Scale and Retrain helps to conduct a pilot deployment with a larger, multi-section cohort (N > 100) to validate the system's scalability. Use the expanded dataset to retrain the Decision Tree, potentially introducing ensemble methods (like Random Forest) if the data complexity grows, provided interpretability can be maintained. Integrate Engagement Analytics will expand the analytics dashboard to track not just performance, but engagement metrics (time on page, resource completion rates). Correlating these behavioral metrics with grade outcomes could reveal deeper insights into student learning patterns.

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