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# Adaptive Learning Management System with AI-Enhanced Personalized Curriculum

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**Abstract: This study aimed to develop and evaluate an Adaptive Learning Management System with AI-Enhanced Personalized Curriculum for Madridejos Community College (MCC) in Cebu, Philippines. Specifically, it sought to design a system capable of analyzing students' learning behavior, adapting instructional content and assessments, and providing personalized learning recommendations to address the limitations of traditional static learning management systems. A developmental research design was employed, utilizing the Agile Software Development Life Cycle (SDLC) in the design and implementation of the system. The system incorporates adaptive mechanisms driven by student performance data and rule-based and AI-supported personalization. Evaluation was conducted among MCC students, instructors, and Information Technology experts. System quality was assessed using McCall's Software Quality Model, while usability was measured through the USE (Usefulness, Satisfaction, Ease of Use, and Ease of Learning) questionnaire. Descriptive statistics, particularly mean scores, were used to analyze the collected data. Results revealed that the developed system achieved very high levels of acceptability and performance. Respondents rated the system as "Strongly Agree" in terms of usability, indicating that it is useful, easy to use, easy to learn, and satisfying. Similarly, the system obtained a "Very Good" rating in software quality, demonstrating strong reliability, efficiency, maintainability, and portability. These findings indicate that the system effectively supports personalized learning by adapting to students' needs and improving engagement and learning outcomes. The developed Adaptive Learning Management System is a viable and effective solution for enhancing personalized instruction in community-based higher education institutions, particularly in resource-limited settings.**

**Keywords: Adaptive Learning Management System, Artificial Intelligence in Education, Generative AI, Personalized Curriculum, Learning Analytics, Community College Education**

## I. INTRODUCTION

The rapid advancement of technology has significantly transformed educational practices, particularly through the integration of artificial intelligence (AI), learning analytics, and digital learning platforms (Wang et al., 2024). Learning Management Systems (LMS) have become essential tools for delivering instructional content, managing assessments, and supporting academic processes. However, many traditional LMS platforms remain static and uniform, offering the same content and assessments to all learners regardless of their individual needs. Studies have shown that such systems lack personalization and adaptive capabilities, limiting their effectiveness in addressing diverse learning behaviors and performance levels (Kabudi et al., 2021). This challenge is more evident in institutions with heterogeneous learners and limited access to advanced educational technologies.

Madridejos Community College (MCC), located in Cebu, Philippines, serves a diverse student population with varying academic preparedness, learning styles, and access to learning resources. Despite the growing need for digital learning support, the institution currently relies on conventional teaching approaches and has no dedicated Learning Management System (LMS) in place. As a result, students have limited access to supplementary learning materials and structured platforms that can support independent and continuous learning. Learning analytics studies emphasize that without data-driven systems, institutions may experience gaps in student engagement, inconsistent academic progress, and limited instructional support (Johar et al., 2023; Ramaswami, 2023).

Moreover, existing instructional practices present specific challenges in student preparation and knowledge acquisition. In some cases, assessments may include topics that were not fully discussed during class sessions, resulting in difficulty for students to adequately prepare. Additionally, the absence of supplementary learning tools restricts opportunities for students to reinforce their understanding or explore topics beyond classroom instruction. This limitation is particularly significant for learners preparing for major examinations, such as pre-board or qualifying exams, where broader knowledge and self-paced review are essential.

Although adaptive learning systems powered by AI have been shown to enhance personalization by analyzing learner data and recommending tailored learning pathways (Kabudi et al., 2021; Hariyanto & Maharani, 2025), such technologies have not yet been implemented in the context of MCC. Existing studies further highlight the effectiveness of AI-driven and machine learning-based approaches in predicting student performance and dynamically adjusting content difficulty (Gligorea et al., 2023), as well as the role of recommender systems in delivering personalized learning resources (Da Silva et al., 2021). However, there remains a gap in the application of these adaptive and intelligent systems in community-based institutions, particularly those with limited technological infrastructure.

To address these gaps, this study proposes the development of an Adaptive Learning Management System with AI-Enhanced Personalized Curriculum. The system is designed to provide data-driven and personalized learning experiences by analyzing student performance, adapting instructional content and assessments, and offering targeted recommendations. It also incorporates features such as adaptive assessments and real-time feedback, which have been shown to improve student engagement and learning outcomes (Ebenbeck et al., 2024; Istiyono et al., 2020; Xu et al., 2023; Ma et al., 2025; Salimi et al., 2024; Sinclair et al., 2019).

By introducing an adaptive and intelligent learning platform, this study aims to support both instructors and students at MCC in achieving a more responsive, inclusive, and effective educational environment. Thus, the proposed system seeks to bridge the gap between traditional instructional methods and modern AI-driven learning solutions, contributing to improved academic performance and enhanced learning opportunities in community-based higher education institutions.

### OBJECTIVES OF THE STUDY

General Objective

This study aims to develop Adaptive Learning Management System with AI-Enhanced Personalized Curriculum.

Specifically, it aimed to;

1. Develop a system which:

1.1 Collects and analyzes students' progress, learning patterns, and performance through the Student Data Analysis Module.

1.2 Adjust content, assessments, and recommendations based on student learning behavior because of the AI-powered Personalized Engine.

1.3 Implement a content recommendation system that aims to suggest learning materials tailored to each student.

2. To determine the quality of the developed system using McCall's software quality model.

3. To evaluate the usability of the developed system using the USE (Usefulness, Satisfaction, and Ease of Use) questionnaire (Lund, 2001).

**Conceptual Framework**

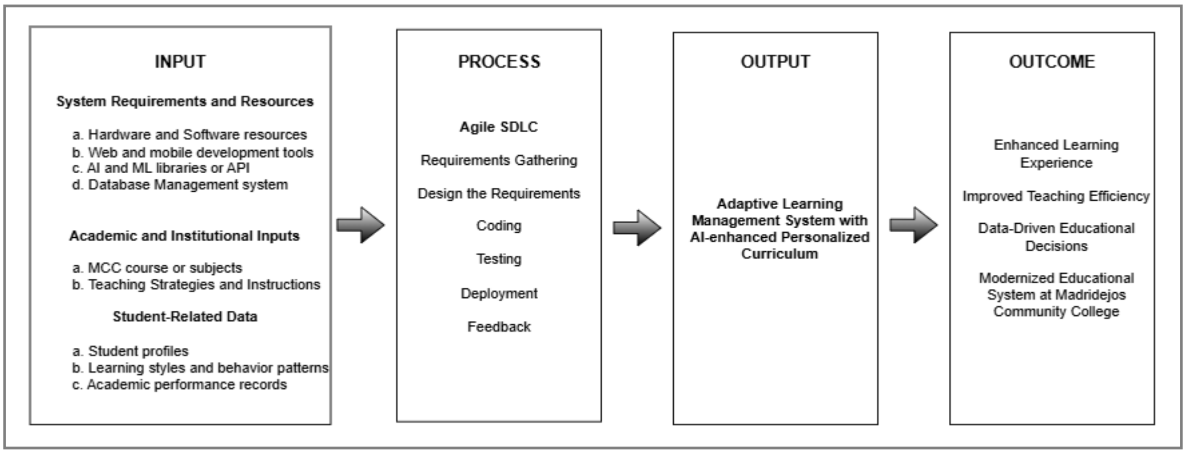


***Figure 1. Conceptual Framework of the Study***

Figure 1 presents the Input-Process-Output-Outcome (IPOO) conceptual framework that guides the development of the Adaptive Learning Management System with AI-Enhanced Personalized Curriculum for Madridejos Community College (MCC). This framework illustrates how various inputs are systematically transformed into an adaptive and intelligent learning system that produces meaningful educational outcomes.

The input component consists of three major elements: (1) system requirements and technological resources, including hardware, software, AI/ML libraries, APIs, and database management systems; (2) academic and institutional inputs such as MCC course content, subject structures, and teaching strategies; and (3) student-related data, including learner profiles, learning behaviors, and academic performance records. These inputs form the foundation of the system's learner model and domain model, which are essential for enabling adaptive learning.

The process component follows the Agile Software Development Life Cycle (SDLC), which includes requirements gathering, system design, coding, testing, deployment, and continuous feedback. Within this phase, the system integrates AI-driven and rule-based adaptation mechanisms, where student data is analyzed, learning patterns are identified, and personalization strategies are applied. This process operationalizes the system's adaptation model, enabling dynamic adjustment of content, assessments, and learning pathways.

The output of the framework is the developed Adaptive Learning Management System with AI-Enhanced Personalized Curriculum, which delivers personalized learning experiences through adaptive content, adaptive sequencing, adaptive assessment, and real-time feedback. The system also incorporates learning analytics dashboards that support data-driven monitoring of student progress.

Finally, the outcome reflects the intended impact of the system, including enhanced learning experiences, improved teaching efficiency, data-driven educational decision-making, and the modernization of instructional practices at MCC. These outcomes demonstrate how the integration of AI and adaptive learning technologies addresses existing gaps in traditional instruction and supports a more responsive and student-centered learning environment.

## II. MATERIALS AND METHODS

**Methodology**

This study employed a Developmental Research Design to design, develop, and evaluate the Adaptive Learning Management System with AI-Enhanced Personalized Curriculum for Madridejos Community College (MCC). Developmental research focuses on the systematic design, development, and evaluation of instructional products and interventions within authentic educational settings (Richey & Klein, 2007; Van den Akker, 1999). The research followed iterative cycles of planning, design, development, testing, deployment, and evaluation to ensure both technical functionality and instructional relevance. The system integrates an Artificial Intelligence (AI) component through the OpenAI ChatGPT API, which utilizes a GPT-based Large Language Model to perform Natural Language Processing (NLP) for the automated generation of structured lessons, adaptive assessments, and multi-level instructional materials based on instructor-provided keywords and student performance data.

Moreover, the technologies mentioned send structured prompts to the AI engine and store the generated outputs in the database for deployment across the Admin, Instructor, and Student portals. The AI-enhanced mechanism supports personalized learning by dynamically adjusting content difficulty (beginner, intermediate, and advanced) according to learner assessment results, thereby creating a continuous adaptive learning loop that aligns with principles of intelligent tutoring systems and AI-supported personalized instruction. To assess system usability during the evaluation phase, the study utilized the USE (Usefulness, Satisfaction, Ease of Use, and Ease of Learning) Questionnaire developed by Lund (2001), which provides a structured framework for measuring user perceptions of system effectiveness and usability.

**System Development Approach**

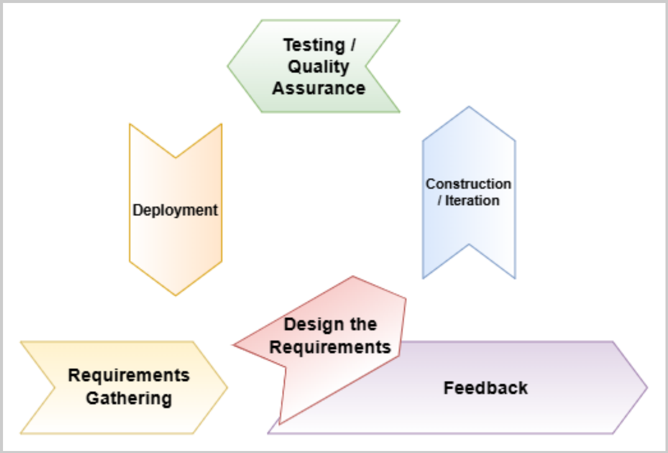


***Figure 2. Agile Software Development Life Cycle Model***

Figure 2 presents the Agile Software Development Life Cycle (SDLC) adopted in the development of the Adaptive Learning Management System. This approach emphasizes iterative development, continuous feedback, and flexibility, allowing the system to evolve based on user needs and evaluation results.

The development process began with requirements gathering, where data were collected from students, instructors, and institutional needs to identify the functional and non-functional requirements of the system. This stage ensured that the system addressed existing gaps, such as the absence of an LMS and the need for personalized learning support.

This was followed by the design of requirements, where the system architecture, database structure, user interface, and adaptive learning mechanisms were planned. At this stage, key components such as the learner model, domain model, and adaptation model were conceptualized to support system adaptivity.

The construction/iteration phase involved the actual development of the system through coding and incremental implementation of features. Modules such as student data analysis, adaptive assessments, and personalized recommendations were developed and refined through multiple iterations.

Subsequently, testing and quality assurance were conducted to evaluate system functionality, usability, and performance. Errors and inconsistencies were identified and resolved to ensure that the system met the required standards of reliability and efficiency.

After successful testing, the system proceeded to the deployment stage, where it was implemented and made accessible to users within the institution for actual use and evaluation.

The last phase involves the feedback phase, which allows users such as students, instructors, and IT experts. They need to provide insights and recommendations. These feedback inputs were used to further refine and improve the system in subsequent development cycles, ensuring continuous enhancement and alignment with user needs.

 

**System Architecture and Technologies**

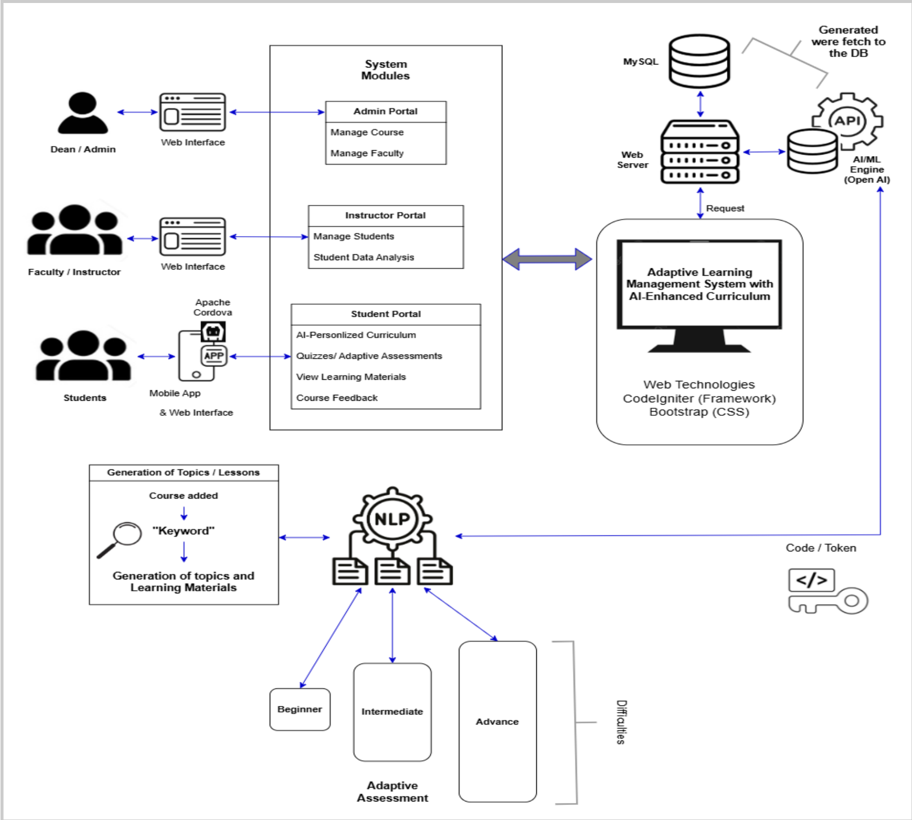


*Figure. 3. System Architecture of the Adaptive Learning Management System with AI-Enhanced Personalized Curriculum*

The system adopted a three-tier architecture consisting of a presentation layer, application layer, and data layer. It included three main portals: Admin, Instructor, and Student. The backend utilized a web server connected to a MySQL database, while an AI/ML engine processed learning data through APIs to generate personalized recommendations and adaptive assessments. The system was developed using web technologies, including the CodeIgniter framework and Bootstrap, with access provided through web and mobile interfaces.

The AI-enhanced methodology integrates a GPT-based Large Language Model through the OpenAI API to dynamically generate personalized learning content and adaptive assessments. The system analyzes student performance and adjusts curriculum difficulty accordingly. AI serves as a content generator, assessment designer, and personalization engine, making the learning experience data-driven, automated, and adaptive.

**The Adaptive Learning Management System with AI-Enhanced Personalized Curriculum**

The developed system adopts a hybrid adaptive learning management system (ALMS) model, integrating primarily rule-based adaptation with AI-enhanced data-driven support. This approach enables the system to personalize the learning experience based on the learner’s performance and interaction data.

In terms of adaptation strategies, the system incorporates adaptive content, adaptive sequencing, adaptive assessment, and real-time feedback. Adaptive content is achieved by presenting learning materials based on the learner’s performance level, while adaptive sequencing allows the system to adjust the order of topics depending on the learner’s mastery of prerequisite concepts. Furthermore, adaptive assessment is implemented by modifying the difficulty of questions in response to the learner’s previous answers. Real-time feedback is also provided to guide learners immediately after each assessment attempt, enhancing understanding and retention.

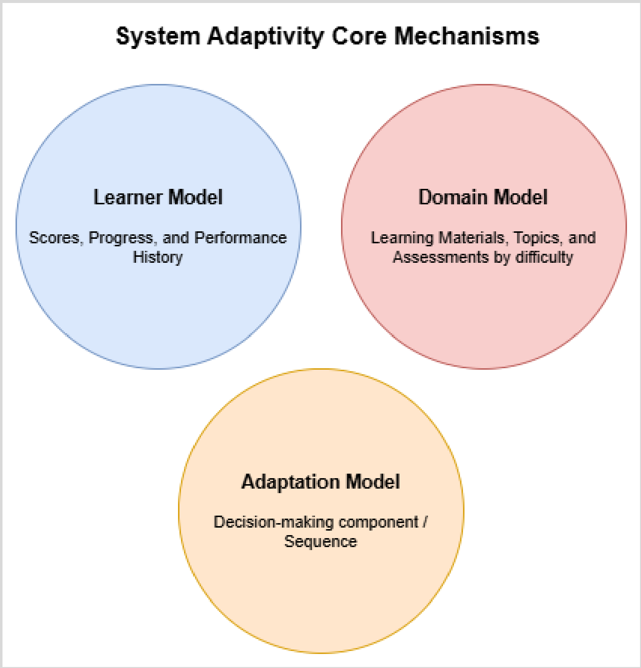


***Figure 4. System Adaptivity Core Mechanisms***

The system's adaptivity is driven by three core mechanisms: the learner model, domain model, and adaptation model. The learner model will maintain essential student information such as quiz scores, progress, and performance history. The domain model structures the learning materials, including topics and assessment items categorized by difficulty levels. Meanwhile, the adaptation model serves as the decision-making component, utilizing predefined rules to determine appropriate content, sequence, and assessment adjustments based on the learner's current performance.

In addition, the system features a learning analytics dashboard, which presents summarized data such as average scores, progress tracking, and performance trends. This supports both learners and instructors in monitoring learning outcomes and making informed decisions. Thus, the integration of these models and strategies enables the system to deliver a personalized, responsive, and data-driven learning environment.

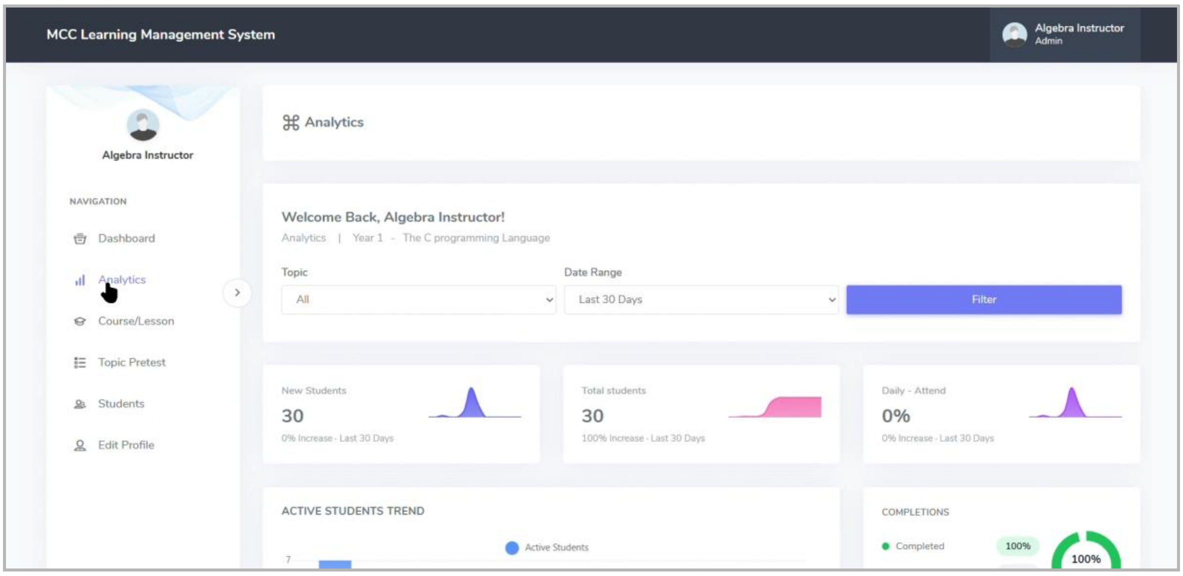


***Figure 5. Student Data Analysis Dashboard of the Adaptive Learning Management System***

Figure 5 presents the Student Data Analysis Dashboard of the system, which provides a comprehensive overview of learners' performance, engagement, and progress. The dashboard includes key metrics such as the number of students, attendance rate, completion rate, and average pretest score. It also features visual representations such as the Active Students Trend graph, which tracks student participation over time, and summary panels highlighting course completion and performance indicators.

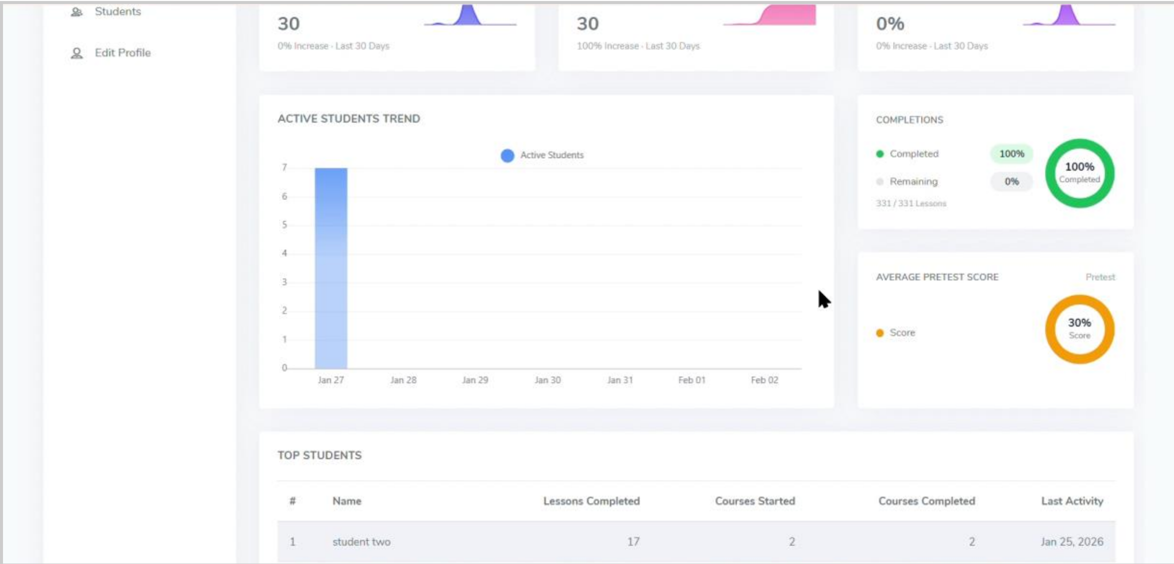


***Figure 5.1. Student Data Analysis Dashboard of the Adaptive Learning Management System***

Figure 5.1 demonstrates how the system collects and analyses student data to identify learning patterns. For instance, the Active Students Trend graph allows instructors to monitor fluctuations in student engagement across specific dates, while the Average Pretest Score (30%) indicates the overall competency level of learners prior to instruction. Additionally, the 100% completion rate suggests that students were able to complete assigned learning tasks within the given period. The system can detect patterns such as low initial performance but high completion rates, which may indicate that students require foundational support but are capable of progressing when guided appropriately. These insights are utilized by the system's adaptive engine to adjust content difficulty, recommend appropriate learning materials, and personalize instructional strategies.

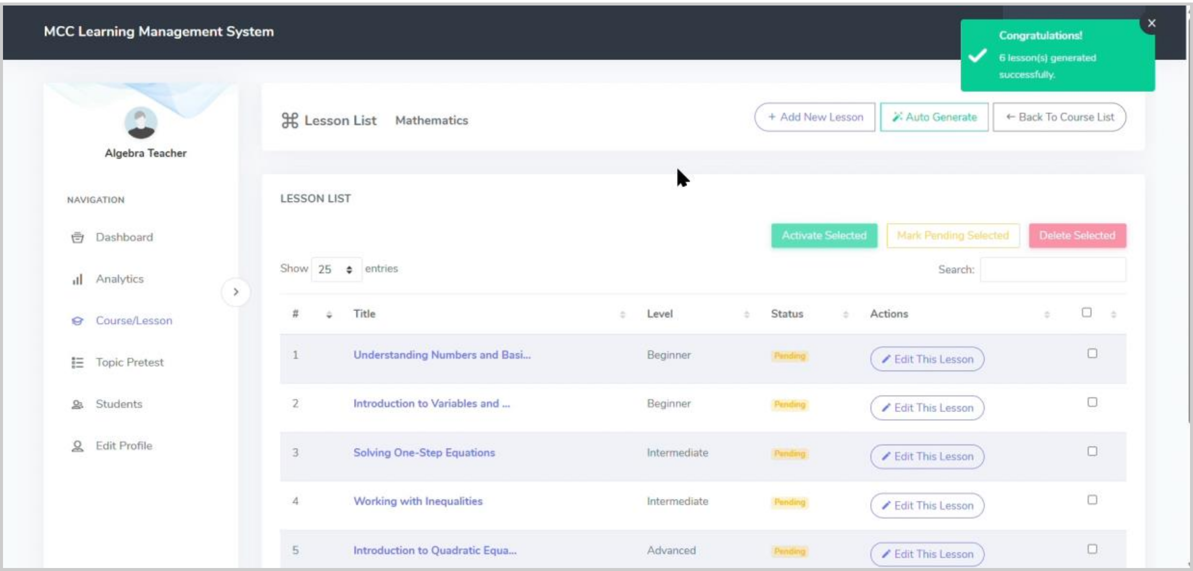


***Figure 6. Generative AI-Based Auto-Generation of Topics and Lessons***

Figure 6 illustrates the generative AI-based auto-generation feature of the Adaptive Learning Management System, which enables instructors to automatically create structured topics and lessons through an AI-powered module. Using the "Auto Generate" function within the Lesson List interface, the instructor inputs a course title or keyword (e.g., Algebra), which is then processed by the system through an integrated Generative AI model via the OpenAI ChatGPT API.

The generative AI analyzes the input and produces organized lesson titles, categorizes them into appropriate difficulty levels (Beginner, Intermediate, and Advanced), and generates corresponding instructional content. These outputs are automatically displayed in the lesson management table, including their assigned levels and status (e.g., Active), allowing instructors to review, edit, validate, or modify the generated materials prior to deployment.

The features shown above demonstrate the system's implementation of Generative AI for dynamic content creation, significantly reducing the need for manual lesson development while maintaining structured and pedagogically aligned materials. Furthermore, the integration of generative AI supports the system's adaptive learning framework by ensuring that content is not only automatically generated but also aligned with varying learner proficiency levels.

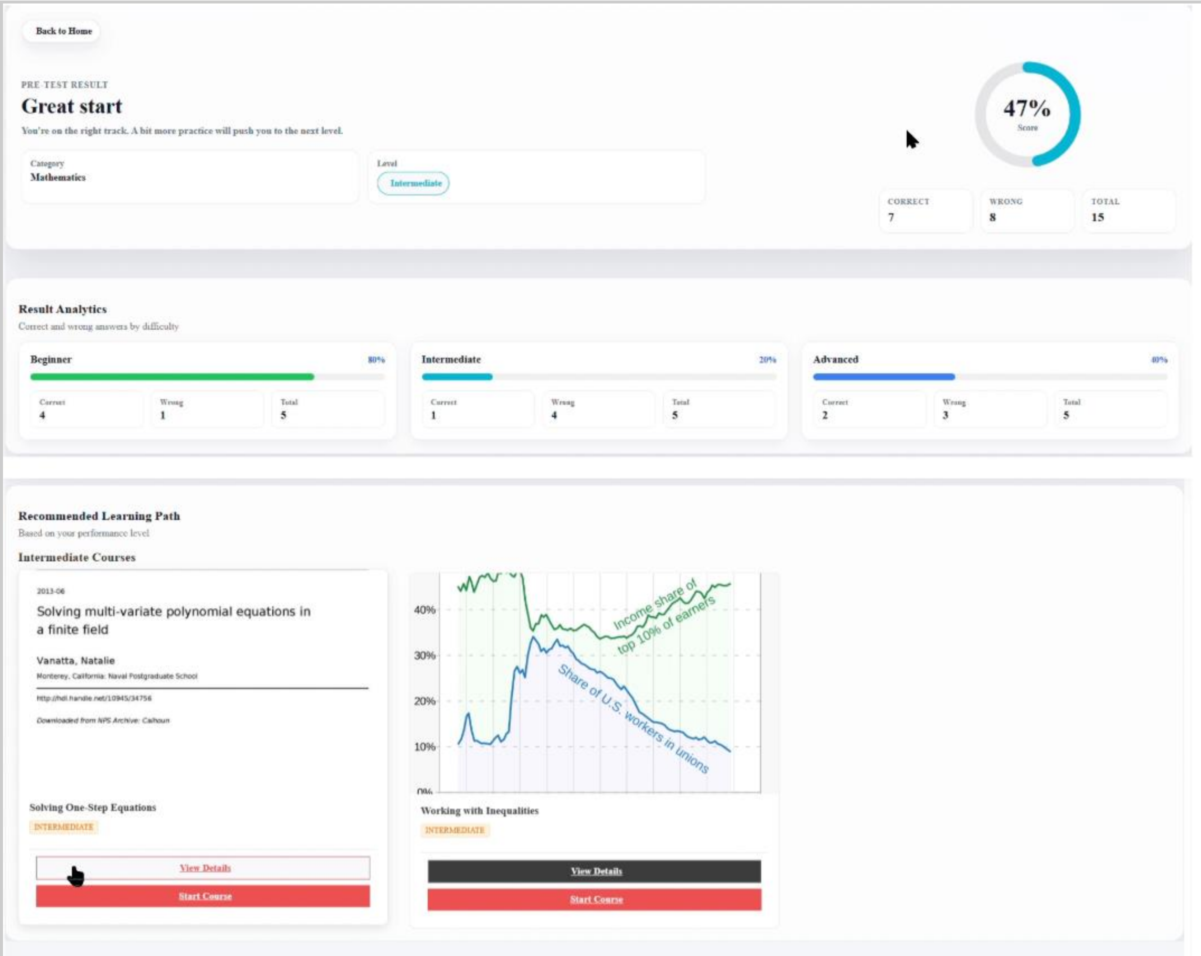


*Figure 7. AI-Powered Personalized Learning Result and Content Recommendation Interface*

The figure demonstrates how the system implements AI-powered personalization through dynamic content customization and rule-based decision-making. Based on the learner's score and performance distribution, the system identifies strengths and weaknesses across difficulty levels. For instance, the learner shows stronger performance in beginner-level questions but lower performance in intermediate and advanced levels, indicating a need for targeted reinforcement. Using this analysis, the system applies adaptive assessment and content recommendation strategies by assigning an appropriate difficulty level and suggesting relevant learning materials. This reflects a real-time behavioral analysis, where the learner's responses directly influence the next set of recommended activities.

The recommendation of intermediate-level courses demonstrates the system's capability for hyper-personalization, ensuring that learners receive neither overly difficult nor overly simplistic content. This supports gradual skill progression and improves learning efficiency. In addition, the figure highlights how the system integrates performance analytics, adaptive assessment, and personalized content delivery to create a responsive and learner-centered educational experience.

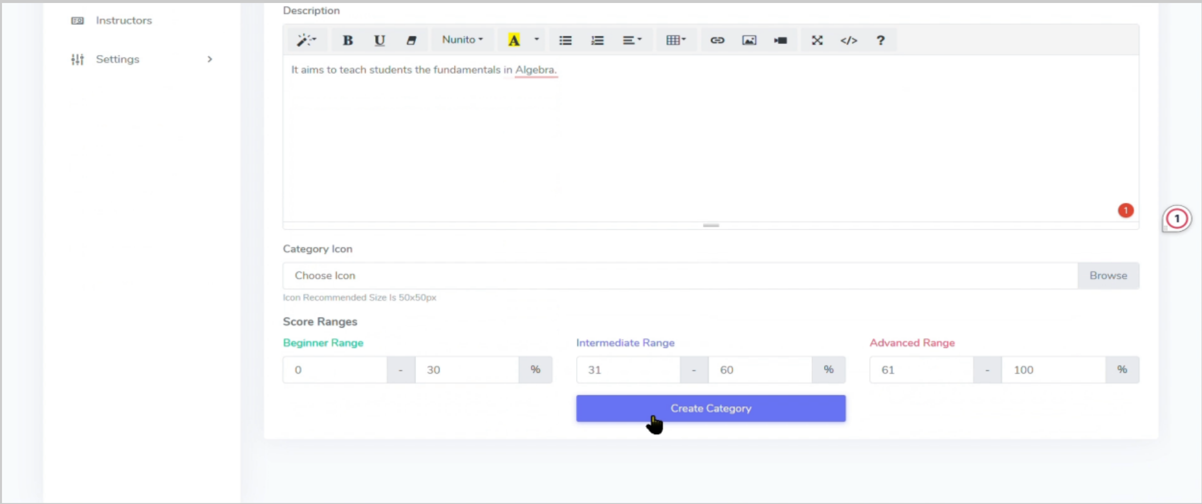


***Figure 8. Configuration of Score Ranges for Adaptive Content and Assessment***

Figure 8 presents the system interface used for defining score ranges that correspond to learner proficiency levels, specifically beginner (0–30%), intermediate (31–60%), and advanced (61–100%). These score thresholds serve as the basis for categorizing learners according to their performance in assessments. The score ranges are customizable.

This configuration plays a critical role in the system's adaptation model, where predefined rules are established to guide the personalization process. Based on the learner's score, the system automatically determines the appropriate difficulty level and assigns corresponding learning materials and assessments.

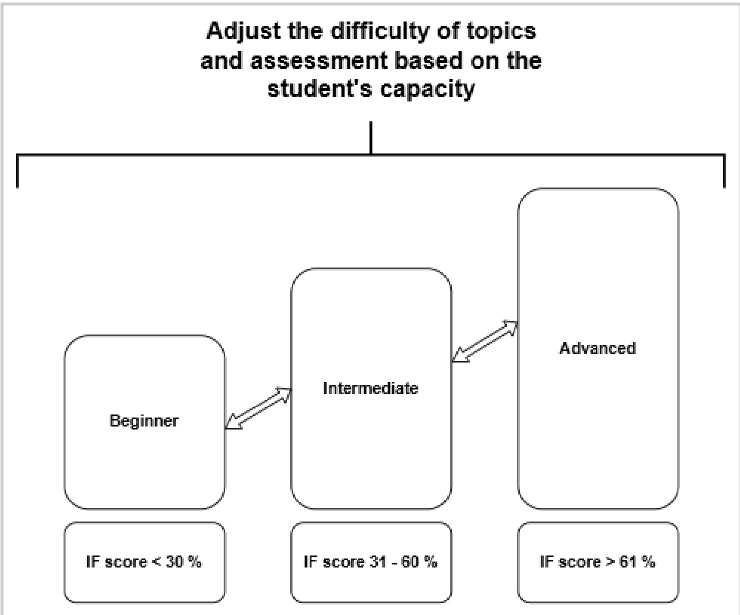


***Figure 9. Rule-Based Adaptive Mechanism for Difficulty Level Classification***

Figure 9 illustrates the system's rule-based adaptive mechanism used to adjust the difficulty of topics and assessments based on the learner's performance. The model categorizes learners into three proficiency levels: Beginner, Intermediate, and Advanced, each determined by specific score thresholds. Learners who obtain scores below 30% are classified as beginners, those with scores between 31% and 60% are categorized as intermediate, and those scoring above 61% are considered advanced.

This mechanism represents the core of the system's adaptation model, where predefined rules are used to determine appropriate instructional pathways. Based on the learner's classification, the system dynamically assigns suitable content, assessment difficulty, and learning activities. The diagram also demonstrates the system's implementation of adaptive sequencing and adaptive assessment, as learners may transition between levels depending on their performance. This ensures that learning progression is flexible and responsive to the learner's current capabilities.

**Locale and Respondents**

The study was conducted at Madridejos Community College (MCC) in Madridejos, Cebu, Philippines. Respondents included thirty MCC students, selected through purposive sampling; ten MCC instructors, chosen based on teaching involvement; and three IT experts with Master in Information Technology (MIT) qualifications, selected through convenience sampling. This combination ensured user, instructional, and technical perspectives in system evaluation.

**Data Collection and Analysis**

Data were analyzed using McCall's Software Quality Model and the USE (Usefulness, Satisfaction, Ease of Use, Ease of Learning) Questionnaire, both measured using a Likert scale. Mean scores and verbal interpretations were computed to assess software quality, usability, and user satisfaction. The system provides learning analytics such as usage frequency, assessment performance, and recommendation behavior. Those are being analyzed to evaluate the effectiveness of AI-driven personalization.

**Ethical Considerations**

Ethical standards were strictly observed. Informed consent was obtained from all participants, participation was voluntary, and confidentiality was maintained. No sensitive personal or academic data were used beyond system testing. Temporary accounts were deleted after evaluation, and data collection followed principles of data minimization and secure handling.

## III. RESULTS AND DISCUSSION

Students, instructors evaluated the Adaptive Learning Management System with AI-Enhanced Personalized Curriculum, and IT experts used objective questionnaires, McCall's Software Quality Model, and the USE Usability Questionnaire.

**Table 1. Likert Scale interpretation**

| Mean Range | Verbal Interpretation |
|---|---|
| 4.21 - 5.00 | Strongly Agree / Very Good |
| 3.41 - 4.20 | Agree / Good |
| 2.61 - 3.40 | Neutral / Average |
| 1.81 - 2.60 | Disagree / Fair |
| 1.00 - 1.80 | Strongly Disagree / Poor |

The study utilized a 5-point Likert scale to measure respondents' evaluation of the system in terms of usability and software quality. Each response was assigned a numerical value ranging from 1 to 5, where higher values indicate a more positive evaluation.

**Objective Evaluation of Adaptive System Features**

**Table 2. Objective Questionnaire Results**

| Criteria | Mean | Standard Deviation | Verbal Interpretation |
|---|---|---|---|
| Collects and analyzes students' progress, learning patterns, and performance | 4.78 | 0.48 | Strongly Agree |
| Adjust content, assessments, and recommendations based on learning behavior | 4.65 | 0.62 | Strongly Agree |
| Suggests tailored learning materials | 4.70 | 0.54 | Strongly Agree |
| **TOTAL** | **4.71** | **0.06** | **Strongly Agree** |

The results show that all components of the system were rated highly by the respondents, as reflected in the mean scores and standard deviation values. The Student Data Analysis Module obtained the highest mean (M = 4.78, SD = 0.48), indicating that respondents found it effective in collecting and analyzing student performance data. The system's ability to suggest tailored learning materials (M = 4.70, SD = 0.54) and adjust content, assessments, and recommendations based on learning behavior (M = 4.65, SD = 0.62) was also rated Strongly Agree, showing that users generally perceived these features as relevant and useful. The relatively low standard deviation values suggest that the responses were consistent among respondents.

These findings are aligned with previous studies on adaptive learning systems, which emphasize the importance of data-driven analysis and personalized content delivery in improving student learning experiences (Kabudi et al., 2021; Da Silva et al., 2021). Research also shows that systems capable of adapting content and providing targeted recommendations can enhance engagement and learning outcomes (Gligorea et al., 2023). This indicates that the developed system effectively implements adaptive learning strategies and is consistent with existing literature on AI-supported educational technologies.

**Software Quality Evaluation**

**Table 3. McCall's Software Quality Model Results**

| Criteria | Mean | Standard Deviation | Verbal Interpretation |
|---|---|---|---|
| Correctness | 4.44 | 0.50 | Very Good |
| Reliability | 4.44 | 0.50 | Very Good |
| Efficiency | 4.44 | 0.50 | Very Good |
| Integrity | 4.78 | 0.42 | Very Good |
| Usability | 4.33 | 0.47 | Very Good |
| Maintainability | 4.89 | 0.31 | Very Good |
| Flexibility | 4.67 | 0.47 | Very Good |
| Testability | 4.89 | 0.31 | Very Good |
| Portability | 4.89 | 0.31 | Very Good |
| Reusability | 4.67 | 0.47 | Very Good |
| Interoperability | 4.67 | 0.47 | Very Good |
| **TOTAL** | **4.65** | **0.07** | **Very Good** |

The evaluation based on McCall's Software Quality Model shows that the system achieved an overall mean of 4.65 (SD = 0.07), interpreted as Very Good. Among the quality attributes, Maintainability, Testability, and Portability obtained the highest ratings (M = 4.89, SD = 0.31), indicating that the system is stable, easy to maintain, and can be deployed across different environments with minimal issues. Integrity also received a high rating (M = 4.78, SD = 0.42), suggesting that the system effectively ensures data security and protection. Other attributes, including Flexibility, Reusability, Interoperability (M = 4.67, SD = 0.47), as well as Correctness, Reliability, and Efficiency (M = 4.44, SD = 0.50), and Usability (M = 4.33, SD = 0.47), were all rated Very Good, with relatively consistent responses among participants.

These findings are consistent with previous studies emphasizing that high software quality is essential for the successful implementation of educational systems. Research indicates that systems with strong maintainability, reliability, and efficiency are more sustainable and effective in long-term use (Gligorea et al., 2023; Wang et al., 2024). Additionally, studies on adaptive learning technologies highlight the importance of system integrity and flexibility in supporting personalized and data-driven instruction (Kabudi et al., 2021). This suggests that the developed system meets established quality standards and is suitable for deployment in an academic environment.

**Usability Evaluation**

**Table 4. USE Questionnaire Results**

| Criteria | Mean | Standard Deviation | Verbal Interpretation |
|---|---|---|---|
| Usefulness | 4.73 | 0.49 | Strongly Agree |
| Ease of Use | 4.55 | 0.58 | Strongly Agree |

| | | | |
|---|---|---|---|
| Ease of Learning | 4.55 | 0.59 | Strongly Agree |
| Satisfaction | 4.71 | 0.50 | Strongly Agree |
| **TOTAL** | **4.63** | **0.04** | **Strongly Agree** |

The usability evaluation using the USE questionnaire resulted in an overall mean of 4.63 (SD = 0.04), interpreted as Strongly Agree. Among the criteria, Usefulness obtained the highest rating (M = 4.73, SD = 0.49), followed by Satisfaction (M = 4.71, SD = 0.50), indicating that respondents found the system helpful and were generally satisfied with its performance. Ease of Use (M = 4.55, SD = 0.58) and Ease of Learning (M = 4.55, SD = 0.59) also received high ratings, showing that users were able to interact with the system with minimal difficulty. The relatively low standard deviation values suggest that the responses were consistent across participants.

These findings are consistent with previous studies, which emphasize that usability is a key factor in the successful adoption of learning systems. For instance, studies on adaptive and AI-supported learning platforms highlight that systems perceived as useful and easy to use tend to improve user engagement and learning outcomes (Wang et al., 2024; Kabudi et al., 2021). Similarly, research on usability evaluation indicates that high satisfaction and ease of learning contribute to positive user acceptance in educational technologies. This suggests that the developed system aligns with existing findings and is well-suited for implementation in an academic environment.

## IV. Conclusion and Recommendation

The findings of the study confirm that the developed Adaptive Learning Management System successfully achieved its intended objectives, particularly in analyzing student performance, adapting instructional content, and providing personalized learning recommendations. The system follows a hybrid adaptive learning model, primarily driven by a rule-based adaptation mechanism supported by generative AI for content creation. Through predefined rules, the system adjusts content difficulty, assessment levels, and learning pathways based on student performance, while generative AI is utilized to automatically generate structured lessons and instructional materials. The high evaluation results indicate that users found the system reliable, usable, and effective in supporting adaptive and personalized learning.

The study also demonstrates that combining rule-based decision-making with AI-supported features can enhance instructional delivery by making it more responsive to individual learner needs. This approach is particularly beneficial in institutions with diverse learners and limited access to supplementary learning tools, as it enables data-driven support and more flexible learning opportunities. Overall, the system contributes to a more inclusive and student-centered learning environment while assisting instructors in making informed academic decisions. In terms of recommendations, future studies may consider involving a larger and more diverse group of respondents to further validate the system across different academic contexts. The integration of more advanced techniques, such as machine learning and predictive analytics, may also be explored to enhance the system’s ability to forecast student performance and provide early interventions for at-risk learners.

The system may be scaled and implemented in larger educational institutions by expanding its infrastructure, integrating it with existing academic systems, and supporting a wider range of courses and users. This would allow the system to handle increased data volume while maintaining its adaptive capabilities. Lastly, future research may examine the long-term impact of the system on student performance, engagement, and retention through longitudinal studies.

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## APPENDIX

### Video Demonstration of the Developed System

Scan to access or through the link:
**https://bit.ly/MCCAdaptiveLMS**

 