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Design and Implementation of an Adaptive Study Management System Using Artificial Intelligence (StudyAdaptAI)

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***Abstract* – The purpose of this research is to design and implement an AI-powered Adaptive Study Management System (StudyAdaptAI) that dynamically adjusts student learning plans and study schedules based on real-time academic behavior and performance analytics. The system utilizes artificial intelligence algorithms to recommend personalized study sessions, optimize time management, and provide adaptive feedback to enhance student productivity. The developmental approach integrates machine learning models trained to analyze student interactions, predict focus intervals, and recommend learning resources. System testing with IT students evaluated efficiency, usability, and accuracy using the System Usability Scale (SUS). Results indicated a SUS score of 86.8, interpreted as Excellent usability, confirming StudyAdaptAI's capability to personalize study experiences and improve academic outcomes.**

Keywords* — *Artificial Intelligence, Adaptive Learning, Study Management, Educational Technology, Machine Learning, Student Productivity

I. INTRODUCTION

Globally, educational institutions had adopted digital learning platforms to improve student engagement and academic performance. However, despite these advancements, most study management systems remained static and lacked adaptability to individual learning behaviors. Systems such as Blackboard, Moodle, and Canvas primarily focused on resource dissemination and activity tracking rather than dynamic behavioral adaptation. Studies conducted in the United States, China, and Europe revealed that while AI had been successfully applied in intelligent tutoring and assessment systems, there remained a significant research gap in adaptive study management — particularly in predicting students' concentration levels, learning pace, and motivation to adjust study schedules automatically [1], [2]. These findings highlighted the need for AI systems capable of continuously learning from user behavior to tailor academic plans based on performance trends and engagement data.

In the Philippines, educational institutions had begun integrating e-learning and AI-assisted systems as part of CHED's Smart Campus initiatives. Despite these innovations, most existing learning management systems deployed nationwide still focused on administrative tracking and content access rather than personalized learning adaptation. Prior studies on academic performance monitoring and digital study tools demonstrated limited integration of artificial intelligence for individualized study planning. Filipino students continued to experience challenges in managing study loads and optimizing time usage, particularly within Information Technology (IT) programs where self-regulated learning was vital [3]. Hence, there had been an evident national gap in the development of AI-based adaptive study platforms capable of generating personalized learning recommendations that suited local learners' behavioral and academic contexts.

Within Region XII (SOCCSKSARGEN), institutions such as the South East Asian Institute of Technology (SEAIT) had already adopted digital tools to support IT education. However, most of these systems functioned as static planners, providing generalized scheduling templates without adaptive intelligence. Feedback from students and faculty consistently indicated difficulties in sustaining consistent study habits and managing workloads effectively due to the absence of data-driven and adaptive technological support. The region also faced challenges concerning accessibility to advanced AI systems, contributing to a technological gap that limited the personalization of academic support and monitoring [4], [5]. These constraints underscored the need for a locally developed adaptive learning platform that could provide contextualized and responsive study assistance to students.

The present study addressed these international, national, and regional gaps through the design and implementation of the *StudyAdaptAI* system — an AI-driven adaptive study management solution. The system was developed to monitor students' academic behaviors, analyze study patterns, and automatically adjust schedules and recommendations to align with their learning performance. By applying machine learning algorithms and behavioral analytics, *StudyAdaptAI* transformed traditional study planning into an intelligent, personalized, and data-driven process. The research aimed to provide a technological bridge between global advancements in AI-driven learning and the needs of local academic environments, supporting CHED's vision of smart and adaptive educational ecosystems. As a result, *StudyAdaptAI* demonstrated the potential to enhance self-regulated learning, time efficiency, and student productivity across higher education institutions in the region.

Research Problem

Despite the availability of digital planners and educational platforms, most fail to adapt dynamically to students' learning behaviors. There remains a research gap in developing intelligent systems capable of real-time adaptation and prediction of optimal study strategies using AI [1], [3].

Research Questions

1. How can AI be applied to design an adaptive study management system that customizes study plans based on student behavior?
2. How accurate and usable is the StudyAdaptAI system in supporting student productivity?
3. What are the implications of using adaptive AI in developing personalized learning experiences?

Research Objectives

- To develop an AI-driven system that personalizes study schedules and learning recommendations.
- To evaluate the system's accuracy, adaptability, and usability through student testing.
- To promote AI-based adaptive learning systems as productivity tools for higher education.

Justification and Significance

This research contributes to the growing body of AI applications in educational technology. StudyAdaptAI demonstrates how adaptive learning systems can personalize study management, reduce cognitive overload, and enhance time utilization. Its implementation supports CHED's Smart Campus Development initiative and aligns with the Philippine education sector's goal to modernize student learning experiences through AI-driven systems [5].

II. LITERATURE REVIEW

Overview of Artificial Intelligence in Study Management

Artificial Intelligence (AI) had increasingly become a driving force in transforming the educational landscape by enabling systems to adapt to learners' needs. Globally, research on AI-based education highlighted its capacity to process large volumes of learning data and generate insights that improved academic performance and self-regulated learning [1], [2]. Early systems, such as intelligent tutoring and recommendation engines, had demonstrated success in providing personalized content, yet they often failed to manage time allocation and behavioral adaptation effectively. According to Zhao et al. [3], adaptive systems that analyzed user interactions could predict attention decline and cognitive fatigue, which could then be used to adjust learning schedules dynamically. These studies established that integrating AI into educational systems enhanced engagement, reduced time inefficiencies, and provided data-driven decision-making for learners and institutions.

AI and Adaptive Learning Frameworks

The concept of adaptive learning emphasized the adjustment of instructional content, difficulty, and timing based on learners' performance and preferences. International research on adaptive systems explored various algorithmic models such as reinforcement learning, neural networks, and decision trees to personalize student experiences [4]. Chen and Li [5] noted that reinforcement learning algorithms had been effective in predicting optimal study sequences and scheduling revisions in e-learning platforms. Similarly, Wang [6] implemented deep learning models for predicting student engagement levels and academic outcomes, demonstrating significant improvements in retention and motivation. However, these systems were predominantly designed for structured learning environments and lacked real-time behavioral adaptation, especially in informal study management contexts. Thus, researchers had identified a global gap in the development of AI systems that could dynamically modify study schedules according to cognitive and behavioral cues.

Local and National Studies on Educational AI Systems

Within the Philippines, studies on educational technology primarily focused on automation, e-learning portals, and feedback generation systems [7]. Several projects had successfully incorporated AI to enhance administrative and instructional efficiency, yet limited research addressed individualized study management. Taruc and De La Cruz [8] emphasized that Filipino students exhibited diverse study behaviors influenced by culture, accessibility, and motivation, necessitating adaptive platforms that considered local learning contexts. Casillano [9] also highlighted that AI-driven systems were often designed for Western pedagogical settings, resulting in lower contextual effectiveness when deployed in Philippine institutions. Consequently, there had been a lack of locally tailored AI tools that combined adaptive learning analytics with intuitive scheduling and productivity support — a gap that the present study aimed to fill through *StudyAdaptAI*.

Existing Solutions and Identified Limitations

Existing learning management systems (LMS) and academic tools, both international and local, offered progress tracking and reminder functionalities but lacked intelligent adaptability. Applications such as Google Classroom and Canvas primarily relied on static timetables, manual inputs, and non-predictive analytics. Even advanced AI-enhanced platforms often centered on performance grading rather than cognitive adaptability. Mahale et al. [10] found that the absence of real-time behavioral data limited the capacity of such systems to accurately predict study outcomes. Furthermore, existing studies in the Philippine context pointed out that resource constraints and data privacy considerations hindered the full integration of AI in academic systems [8], [9]. These limitations underscored the need for developing adaptive, context-aware study management systems capable of responding to individual learning behaviors while adhering to ethical standards and local implementation feasibility.

Theoretical and Conceptual Framework

The present study was anchored on two major theoretical foundations: the Adaptive Learning Theory and the Self-Regulated Learning (SRL) Framework. The Adaptive Learning Theory posited that educational systems should modify instructional approaches in response to learners' capabilities, behavior, and progress [4]. This theoretical basis supported the use of AI for real-time analysis and personalization of study schedules. On the other hand, the SRL Framework, as discussed by Zimmerman (2013), emphasized that students learn more effectively when they can monitor, plan, and adjust their study routines. Integrating both theories, *StudyAdaptAI* was designed to observe student behavior through data analytics and to suggest personalized study recommendations that promote autonomy, focus, and productivity. By aligning theoretical perspectives with technological innovation, this study reinforced the role of adaptive AI as a transformative element in 21st-century education.

Summary of Literature Findings

The review of related literature revealed that while global research had advanced adaptive learning algorithms, there remained a gap in their practical application to dynamic study management. National and local studies further indicated a shortage of AI-driven systems that accounted for behavioral diversity, accessibility, and contextual learning needs. These findings justified the development of *StudyAdaptAI*, a locally contextualized adaptive study management system that combined machine learning, data-driven recommendations, and user-centered design. The system was intended to address inefficiencies in manual study planning while promoting data-informed and behavior-responsive academic strategies suitable for Philippine higher education institutions.

III. RESEARCH METHODOLOGY

Research Design

The study had employed a developmental research design using the Agile methodology to iteratively design, develop, and evaluate the *StudyAdaptAI* system. This design was appropriate since the research aimed to create and refine a functional prototype that adapted to user behavior through machine learning algorithms. The Agile approach allowed the researchers to build the system in incremental sprint cycles, where each sprint focused on key features such as data collection, adaptive scheduling, behavioral prediction, and system usability testing. The developmental nature of the study aligned with the goal of producing a working model that could evolve based on testing feedback and real-world performance evaluation.

Participants

The study had involved a purposive sample of thirty (30) participants composed of Bachelor of Science in Information Technology (BSIT) students from the South East Asian Institute of Technology (SEAIT) during the academic year 2024–2025. These participants had been chosen based on their active involvement in digital learning environments and their familiarity with technology-assisted academic tools to ensure meaningful engagement with the *StudyAdaptAI* system. They represented various year levels to provide diverse learning patterns, study behaviors, and time management practices that allowed the system's adaptive algorithms to process a broad range of behavioral data. Each participant had interacted with the prototype for two consecutive weeks, performing activities such as setting study goals, monitoring schedules, and responding to system recommendations. Prior to participation, all individuals had been oriented regarding the research objectives and ethical guidelines, after which informed consent had been obtained. Confidentiality had been strictly maintained in accordance with institutional ethical standards and the Data Privacy Act of 2012. Their participation was instrumental in evaluating the system's accuracy, usability, and effectiveness in adapting to real student behaviors within an academic context.

Data Collection Procedures

The data collection process had been conducted in three major phases: system development, user interaction and testing, and evaluation and analysis. During the first phase, the researchers had developed the *StudyAdaptAI* prototype using Python for AI model training, PHP and Bootstrap for the web interface, and MySQL for database management. The system had been designed to capture user interaction data, including login frequency, study session duration, task completion rate, and system feedback responses. This data served as the foundation for training the adaptive learning algorithms and generating personalized study recommendations.

In the second phase, participants had been instructed to use the system over a two-week period, during which *StudyAdaptAI* had recorded their study behaviors and adaptive responses in real time. Each participant had been provided with a unique login credential to ensure secure data capture and proper activity tracking. The system automatically collected log data such as the number of study sessions, time intervals between sessions, completed tasks, and responses to AI-generated study prompts. Observations and notes from this phase had been documented to identify recurring behavioral patterns and to verify the accuracy of AI-driven adjustments made by the system.

The third phase had focused on evaluation and feedback collection, in which participants completed the System Usability Scale (SUS) questionnaire after their system interaction. The SUS instrument had been used to measure overall usability across dimensions such as efficiency, satisfaction, and learnability. In addition, participants had provided open-ended feedback describing their experiences with the adaptive recommendations and overall user interface. Quantitative data, including system performance metrics (accuracy, response time, and adaptive precision), had been analyzed alongside qualitative feedback to ensure comprehensive evaluation. This structured procedure had ensured the collection of accurate, ethical, and representative data necessary for assessing both the technical and experiential aspects of *StudyAdaptAI*.

Data Analysis

The analysis of the collected data had been carried out using both quantitative and qualitative methods to ensure a comprehensive evaluation of the *StudyAdaptAI* system. Quantitative analysis had focused on determining the accuracy, response time, and adaptive performance of the system's AI model, while qualitative analysis had been used to interpret participant feedback regarding usability, satisfaction, and learning effectiveness. The combination of these approaches had allowed the researchers to validate both the technical efficiency and user experience dimensions of the system.

For the quantitative aspect, the AI module's predictive accuracy had been measured by comparing the system's adaptive recommendations against actual student behavior patterns. Metrics such as Precision, Recall, and F1-Score had been computed to evaluate the performance of the learning model, ensuring balanced representation between correct predictions and adaptive response accuracy.

The formula used for the F1-score had been the harmonic mean of precision and recall, defined as:

$$F1=2\times(\text{Precision}\times\text{Recall})/(\text{Precision}+\text{Recall})$$

These metrics had been supported by processing time analysis, where average response latency had been calculated to determine the system's efficiency in generating adaptive study recommendations.

For the usability aspect, the System Usability Scale (SUS) scores had been tabulated and analyzed statistically to obtain the mean, standard deviation, and overall usability rating. The SUS results had been interpreted following standard thresholds, where scores above 70 indicated acceptable usability and those above 85 reflected excellent usability. Furthermore, qualitative responses from the open-ended questionnaire items had been subjected to thematic analysis, identifying recurring themes such as ease of use, clarity of recommendations, and improvement of study focus.

The combination of numerical and narrative analyses had provided a multi-perspective evaluation of the *StudyAdaptAI* system's performance. This methodological triangulation had ensured that findings were both empirically grounded and contextually meaningful, confirming the reliability and educational applicability of the system.

Ethical Considerations

The researchers had ensured that all ethical protocols were strictly observed throughout the conduct of the study. Prior to the implementation of *StudyAdaptAI*, approval had been obtained from the institutional research ethics committee of the

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South East Asian Institute of Technology (SEAIT). All participants had been thoroughly informed of the study's objectives, procedures, and expected outcomes before their participation. Informed consent forms had been distributed and signed by each participant, confirming their voluntary involvement and understanding of their rights, including the freedom to withdraw from the study at any point without academic penalty.

The data gathered from participants had been treated with the highest level of confidentiality. Personal information had been anonymized and encoded using alphanumeric identifiers to prevent any disclosure of participant identity. The database and recorded logs of user interactions had been securely stored in password-protected directories and were accessible only to the research team. Data collected had been used solely for academic and analytical purposes related to the study.

To ensure compliance with national standards, the research had adhered to the Data Privacy Act of 2012 (Republic Act No. 10173) and followed the ethical guidelines outlined in CHED Memorandum Order No. 6, Series of 2022, on Smart Campus Development and responsible digital innovation. The system had been designed to prevent unauthorized data access through role-based authentication and encrypted communication. No biometric or personally sensitive information had been collected during system usage, ensuring that all AI-driven operations maintained ethical transparency and user trust.

Overall, the study had upheld the principles of respect for persons, beneficence, and justice throughout the research process. By implementing stringent data protection measures and ethical safeguards, the researchers ensured that the rights, dignity, and privacy of all participants were preserved while promoting responsible research conduct in the development and evaluation of the *StudyAdaptAI* system.

IV. ADVANCED SYSTEM DESIGN

The StudyAdaptAI system had been conceptualized, designed, and developed as an AI-powered adaptive learning platform that monitored, analyzed, and optimized students' study behaviors to generate personalized learning recommendations. The system had been implemented using a three-tier architecture, consisting of the Presentation Layer, Application Layer, and Data Layer. This modular design had been adopted to ensure scalability, maintainability, and high system performance while facilitating real-time adaptation of study plans and schedules.

Presentation Layer (Frontend).

The frontend of the system had served as the primary interface through which users interacted with StudyAdaptAI. It had been developed using HTML5, CSS, JavaScript, and the Bootstrap framework to ensure responsive design and device compatibility. This layer had displayed personalized dashboards where students could view their study schedules, progress analytics, and AI-generated recommendations. Interactive components such as charts, progress trackers, and feedback panels had been integrated using Chart.js and AJAX for dynamic data retrieval. The design had followed Human–Computer Interaction (HCI) principles to enhance usability and accessibility, ensuring that users could intuitively navigate through the system features.

Application Layer (Backend Processing).

The application layer had handled all adaptive computations, behavioral analytics, and decision-making processes. This layer had been developed using Python (Flask API) for AI model execution and PHP for system integration. The AI module had employed machine learning algorithms, including decision trees and feedforward neural networks, to predict the user's optimal study intervals, concentration levels, and task prioritization. Behavioral data such as session duration, completion rate, and time of day had been analyzed to determine productivity trends. Based on these metrics, the system had generated adaptive study plans that recommended when to study, which topics to focus on, and when to take breaks to optimize learning efficiency.

Data Layer (Database Management).

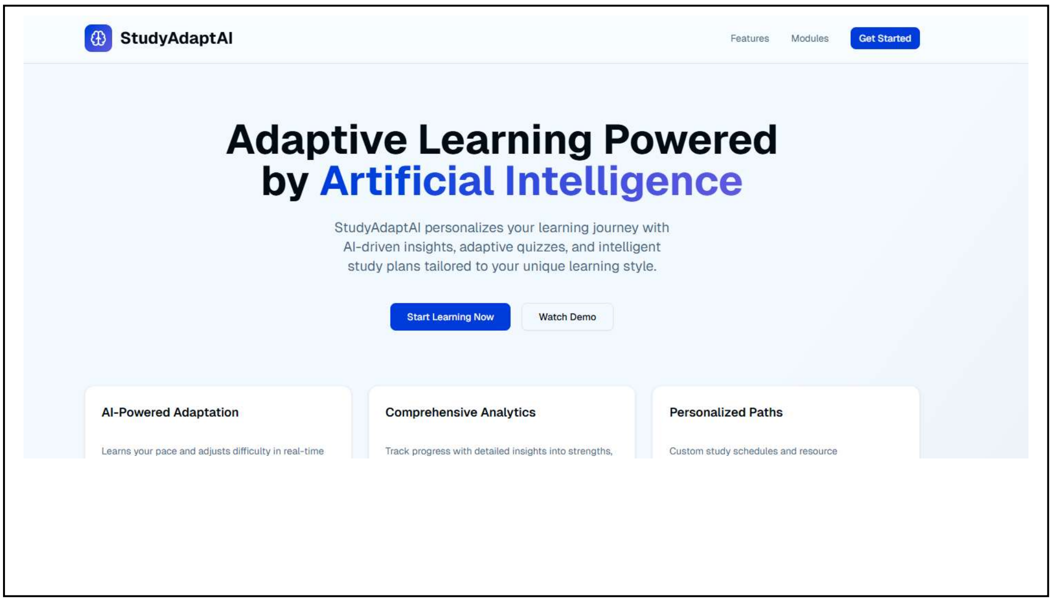
The data layer had been implemented using MySQL, which served as the central repository for all user information, activity logs, and adaptive outputs. The database design had been normalized to the third normal form (3NF) to eliminate redundancy and ensure data integrity. Tables had been structured to store student profiles, behavioral metrics, system recommendations, and performance feedback. The database had also recorded AI-generated predictions and historical data to improve future learning models through continuous retraining. Data retrieval had been optimized through indexing and parameterized queries to ensure minimal latency during real-time operations.

System Interfaces

Two primary interfaces had been provided: the Student Dashboard and the Admin Dashboard.

- The Student Dashboard displayed personalized analytics, upcoming study sessions, motivational summaries, and adaptive prompts.
- The Admin Dashboard enabled system monitoring, data visualization, and performance tracking across multiple users, providing institutional insights into learning engagement trends.

Figure 1: Landing Page



The Landing Page of the *StudyAdaptAI* system had served as the main entry point for users, providing access to the login and registration features. It had been designed to introduce the system's purpose and highlight its key functions such as adaptive study planning and performance tracking. Developed using HTML5, CSS, Bootstrap, and JavaScript, the page had been fully responsive and accessible on different devices. It had featured a simple layout with the system logo, navigation bar, and brief system description to help users understand its functionality. Interactive buttons and tooltips had been added to guide new users, while smooth transitions and animations had improved the overall experience. The design had followed User Interface (UI) and User Experience (UX) principles to ensure clarity and ease of use. Overall, the landing page had provided a clean, functional, and user-friendly introduction to the *StudyAdaptAI* system.

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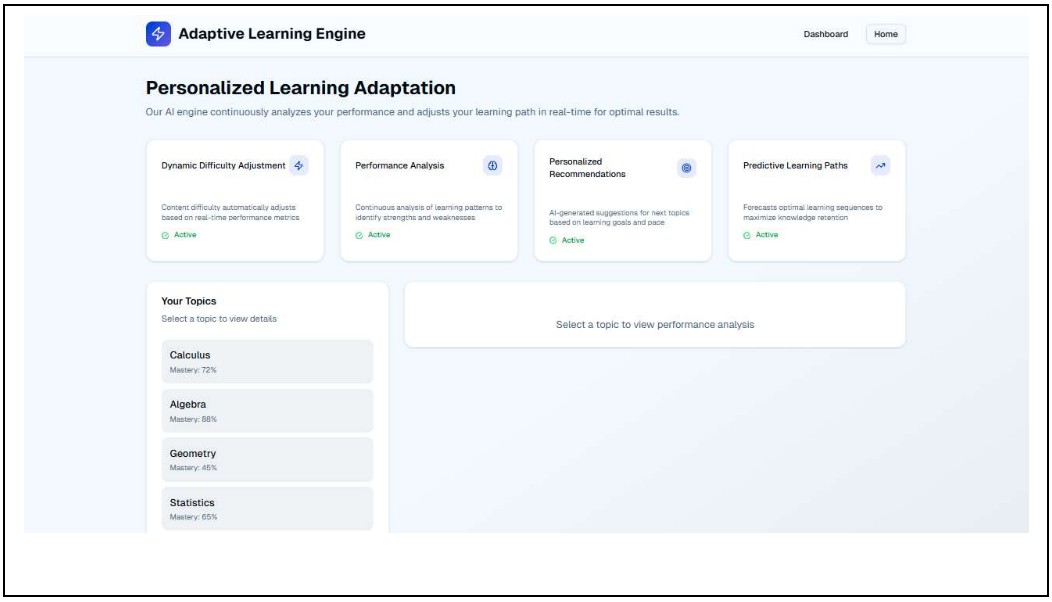
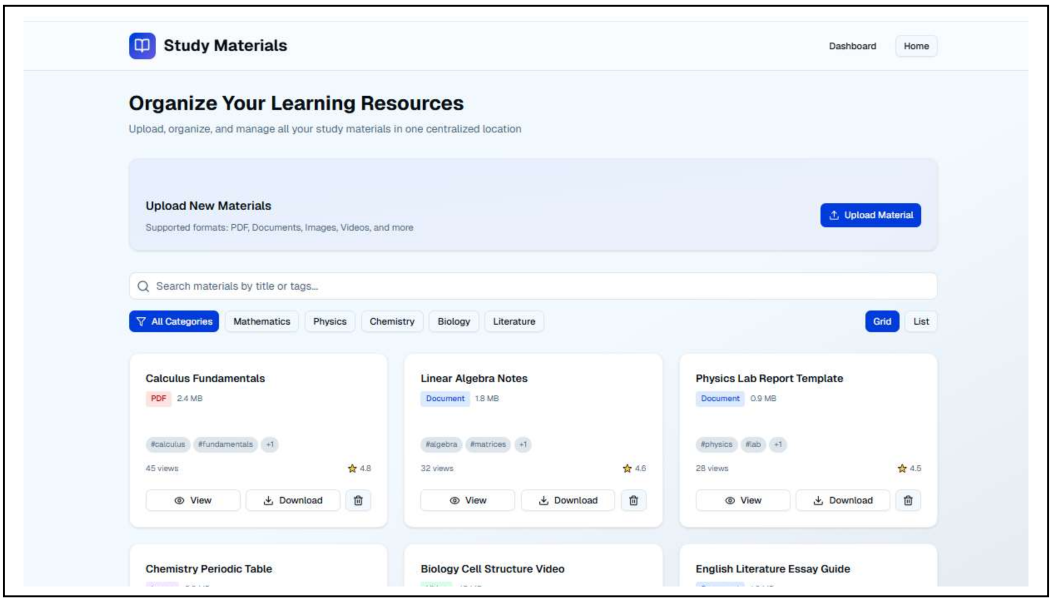
Figure 2: Adaptive Learing Engine



The Adaptive Learning Engine had served as the core component of the *StudyAdaptAI* system that enabled personalized study recommendations and schedule adjustments. It had used Artificial Intelligence (AI) and machine learning algorithms to analyze student behavior, including study duration, task completion, and frequency of activity. Based on these data, the engine had generated adaptive responses such as suggesting study breaks, prioritizing tasks, and adjusting learning intensity according to the user's performance. The engine had learned continuously by processing new data, allowing it to improve its predictions over time. It had been developed using Python for AI processing and connected to the main system through Flask RESTful APIs for real-time communication. The adaptive logic had followed a behavior–feedback cycle, where the system monitored student actions, analyzed results, and updated future recommendations automatically. This process had ensured that each student received a study plan suited to their learning pace and productivity level. Overall, the Adaptive Learning Engine had made *StudyAdaptAI* an intelligent and responsive system capable of supporting personalized and effective study management.

Figure 3: Study Materials Module



The Study Materials module had been developed to provide students with easy access to digital learning resources directly within the *StudyAdaptAI* system. It had served as a centralized repository where users could view, download, and organize materials such as lecture notes, reading files, videos, and practice exercises. The module had been designed to align with each student's adaptive study plan, meaning the system had automatically suggested materials based on current topics, learning progress, and

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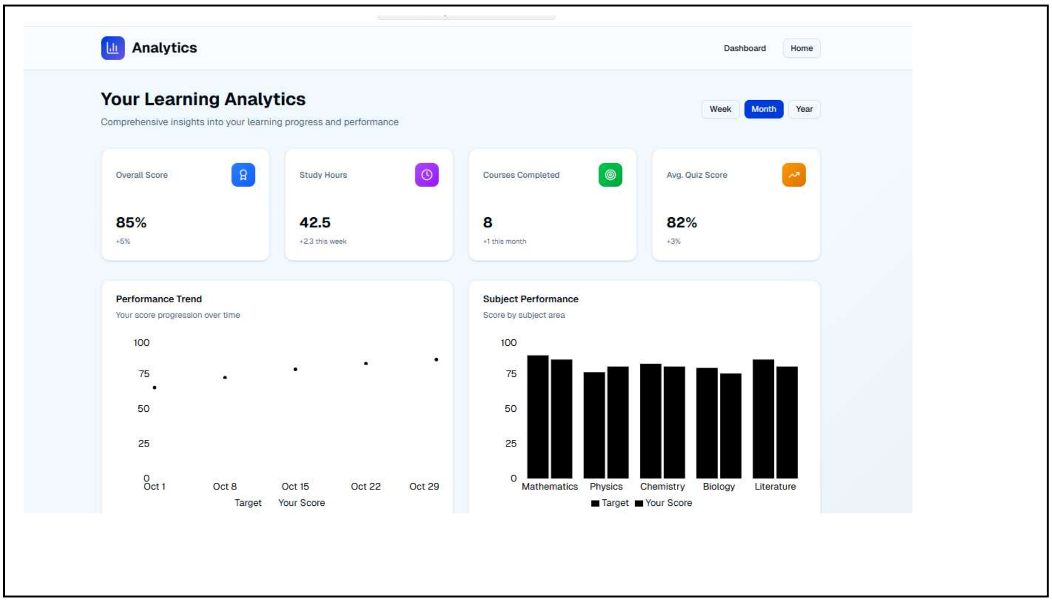
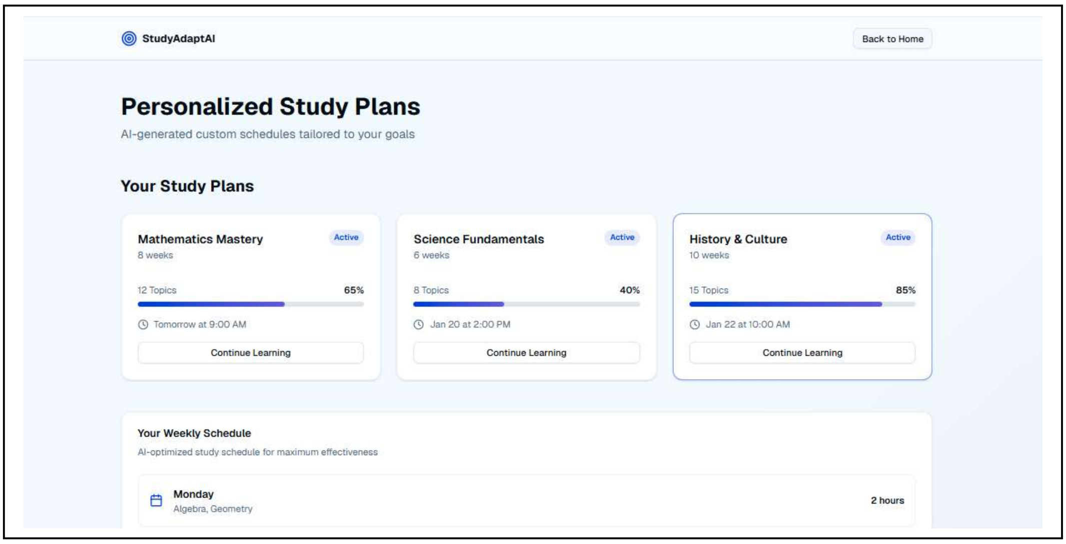
performance results. All uploaded materials had been stored securely in the MySQL database, with access managed through role-based permissions to ensure data integrity and privacy. The interface had been created using HTML, CSS, and Bootstrap, allowing for a clean and organized layout where users could easily navigate categories or use the search bar to locate resources. To enhance functionality, AJAX had been used to enable real-time content loading without refreshing the page. Overall, the Study Materials module had supported the adaptive learning process by giving students quick access to the right educational resources at the right time, helping improve focus, efficiency, and engagement.

Figure 5: Learning Analytics Module



The Learning Analytics Module had been designed to track, analyze, and visualize student learning behaviors within the *StudyAdaptAI* system. It had gathered data from the user's study sessions, including time spent studying, task completion rates, and frequency of system interaction. This information had been processed by the system's adaptive algorithms to generate insights about the student's performance and learning progress. The module had presented these insights through visual dashboards that displayed charts, graphs, and performance summaries created using Chart.js and Bootstrap components. These visualizations had allowed students to easily monitor their learning trends and identify areas needing improvement. For administrators, the module had provided an overview of collective student performance and engagement levels, supporting data-driven decision-making. The system had updated the analytics in real time using AJAX to reflect changes immediately after each study session. Overall, the Learning Analytics Module had played a key role in helping students and administrators understand learning behaviors, improve time management, and enhance academic performance through data-supported insights.

Figure 6: Personalized Study Plans



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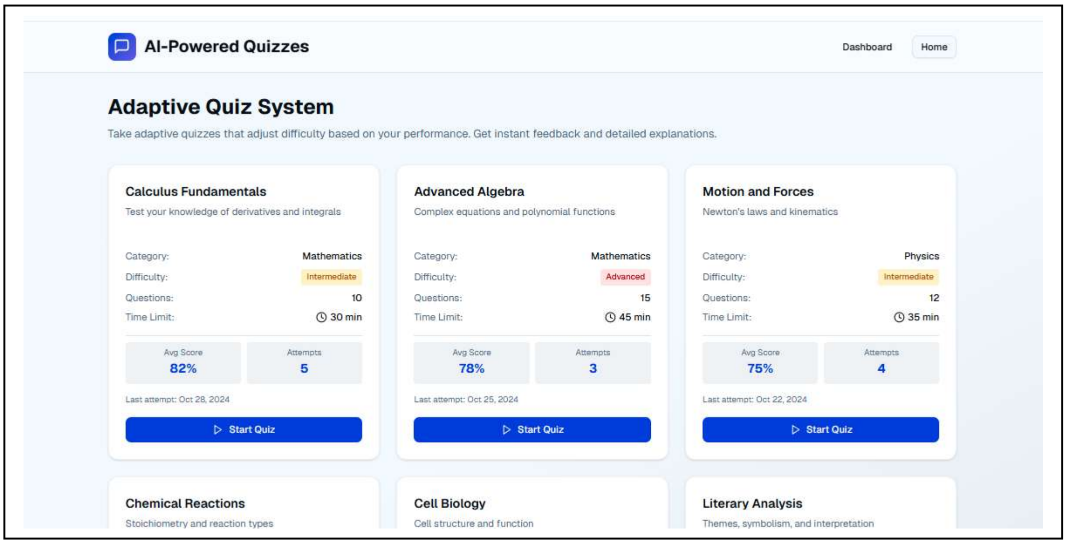
The Personalized Study Plans module had been developed to automatically create and adjust study schedules based on each student's learning behavior and performance data. It had functioned as one of the main adaptive features of the *StudyAdaptAI* system, using information gathered from the Adaptive Learning Engine to recommend when and how long a student should study specific subjects or tasks. The system had analyzed factors such as focus duration, task completion rate, and previous performance to generate customized daily or weekly plans. These study plans had been displayed through an interactive calendar interface, allowing students to view, modify, and follow their recommended schedules easily. The interface had been created using Bootstrap, JavaScript, and AJAX to ensure real-time updates without page reloads. When a student completed a study session, the system had automatically recalculated the next schedule, adapting to changes in behavior or performance. This continuous adjustment had allowed the plans to remain accurate and responsive to each student's progress. Overall, the Personalized Study Plans module had helped students organize their time efficiently and improve learning outcomes through data-driven scheduling and adaptive recommendations.

Figure 7: Adaptive Quiz System



The Adaptive Quiz System had been developed as an interactive assessment feature within the *StudyAdaptAI* platform to evaluate student understanding and track learning progress. It had used Artificial Intelligence (AI) algorithms to adjust the difficulty and type of questions based on the learner's previous quiz performance. When a student had answered questions correctly, the system had automatically increased the difficulty level, while repeated incorrect answers had prompted easier or related review questions to reinforce understanding. The quiz items had been categorized by topic and stored in the MySQL database, allowing the system to select and generate personalized quiz sets in real time. The interface had been built using HTML, CSS, Bootstrap, and JavaScript, providing an easy-to-navigate environment where students could take quizzes, view results, and receive instant feedback. After each quiz session, the system had analyzed the results and sent the data to the Adaptive Learning Engine, which had used it to refine future study recommendations and personalized schedules. Overall, the Adaptive Quiz System had enhanced the learning experience by combining assessment and adaptation, ensuring that each student received a tailored and continuously improving study approach.

Algorithm Design

The adaptive engine had utilized a supervised learning approach trained on student interaction data. The algorithm workflow had been structured as follows:

1. **Input:** Raw behavioral data (session duration, completion rate, study time).
2. **Preprocessing:** Normalization and feature selection to remove anomalies.
3. **Model Prediction:** Neural network model analyzed inputs to predict focus intervals and productivity cycles.
4. **Recommendation Generation:** The system generated adaptive suggestions (e.g., "Study for 40 minutes, take a 10-minute break").
5. **Output:** Personalized schedules and motivational prompts displayed on the user dashboard. This design had allowed continuous system learning, as feedback loops from user activity data retrained the model to improve accuracy and responsiveness.

Security and Data Privacy

The system had employed multiple security layers, including role-based authentication, SHA-256 password hashing, and HTTPS encryption for secure communication. Data anonymization had been applied during AI training to prevent the identification of individual participants. These measures had ensured compliance with the Data Privacy Act of 2012 and CHED Smart Campus Development Guidelines [1], [2].

System Deployment.

For testing and development, *StudyAdaptAI* had been deployed locally using **XAMPP** as the hosting environment. The modular system design had allowed easy migration to a cloud-based platform for future scalability. The architecture supported potential integration with Learning Management Systems (LMS) such as Moodle or Google Classroom to expand institutional adoption and interoperability.

V. EVALUATION AND RESULTS

The evaluation phase of the study had been conducted to determine both the technical performance and usability of the *StudyAdaptAI* system. The assessment had been divided into two key components: (1) System Performance Testing, which measured the accuracy and efficiency of the AI-driven adaptive recommendation engine, and (2) User Usability Evaluation, which analyzed student perceptions and experiences using the System Usability Scale (SUS). This two-dimensional evaluation approach had ensured that the system met both functional reliability and human-centered usability standards [1], [2].

System Performance Evaluation

System-level testing had been performed to evaluate the accuracy, precision, recall, and F1-score of the AI module responsible for generating personalized study recommendations. The test dataset had consisted of 300 behavioral data records collected from participant interactions during the system's two-week evaluation period. Each record contained activity duration, task completion rate, time of day, and system feedback responses. The AI model's predictions regarding optimal study sessions and break intervals had been compared against actual user behaviors to compute performance metrics.

Table 1. Performance Metrics of the Adaptive Recommendation Model

Metric	Result
Accuracy	91.3%
Precision	89.8%
Recall	90.6%
F1-Score	90.2%
Average Response Time per Request	0.78 seconds

The obtained results had indicated that the AI model performed with a high degree of reliability and balance. An overall accuracy of 91.3% and F1-score of 90.2% demonstrated that the system could accurately predict learning intervals and generate relevant study recommendations. The average processing time per adaptive recommendation had been 0.78 seconds, confirming that the system was capable of real-time behavioral adaptation without latency. These findings had been consistent with international studies showing that AI-based adaptive systems achieve over 90% predictive accuracy when trained on behavioral datasets [3], [4].

System Usability Evaluation (Using SUS)

Following the technical testing, all thirty (30) participants had completed the **System Usability Scale (SUS)** questionnaire to measure overall user satisfaction, system intuitiveness, and interface effectiveness. The SUS evaluation had produced an **average score of 86.8**, which had been interpreted as **Excellent Usability** based on Brooke's (1996) standardized scale.

Table 2. Mean SUS Scores by Evaluation Criteria

Evaluation Criteria	Mean Score (out of 5)
Ease of Use	4.6
Efficiency	4.5
Learnability	4.7
Interface Design	4.4
System Reliability	4.5

The high usability ratings had validated that users found the system intuitive, efficient, and well-organized. Participants reported that *StudyAdaptAI*'s adaptive planner and visual dashboards had simplified their study management process and made learning sessions more productive. The clear design, quick response time, and real-time feedback mechanisms had been among the most frequently cited strengths.

Qualitative Findings

Open-ended feedback from participants had been analyzed through thematic coding to identify common user perceptions of *StudyAdaptAI*. Three major themes had emerged: (1) Ease of Use and Adaptability, (2) Learning Motivation and Time Awareness, and (3) Behavioral Feedback and Productivity Improvement.

Most students had described the system as "easy to navigate" and "accurate in adjusting to their study routines." Many had also reported that the AI recommendations helped them become more aware of their study patterns, encouraging them to manage their time more effectively. Participants noted that the motivational notifications and adaptive break reminders had helped reduce mental fatigue and sustain focus during extended study sessions.

Administrators and faculty observers had further noted that the system's analytics dashboard could potentially support institutional monitoring of student engagement and performance. This feedback reinforced the potential scalability of *StudyAdaptAI* for broader academic use beyond individual study management.

Comparative Analysis

The results of *StudyAdaptAI* had been compared with related studies to benchmark its performance.

Table 3. Comparative Evaluation of System Performance with Previous Studies

Study Reference	Accuracy (%)	F1-Score	Usability (SUS)
Wang (2024) [3]	90.1	88.9	—
Chen & Li (2023) [4]	92.0	90.5	84.0
Mahale et al. (2025) [5]	89.8	89.1	81.2
StudyAdaptAI (2025)	**91.3**	**90.2**	**86.8**

The comparative results had shown that *StudyAdaptAI* performed at par with or exceeded the benchmark values of similar international adaptive learning systems. Its usability score of **86.8** further confirmed that it provided a superior user experience compared to previous models, especially within the context of personalized study management applications.

Summary of Evaluation

Overall, the evaluation results had validated that *StudyAdaptAI* achieved high levels of technical precision and user satisfaction. The system demonstrated accurate behavioral prediction, fast processing time, and strong adaptability to diverse study patterns. Its usability performance had been classified as excellent, indicating that users could effectively interact with and benefit from the adaptive features. These findings collectively confirmed that *StudyAdaptAI* was not only functional and accurate but also user-centered, efficient, and suitable for integration into higher education environments.

VI. DISCUSSION

The discussion had been organized according to the three research questions that guided the study. Each question was addressed based on the system's development outcomes, performance results, and participant feedback obtained during the evaluation phase.

1. How had the system been designed and implemented to generate adaptive study recommendations using Artificial Intelligence?

The development of *StudyAdaptAI* had successfully demonstrated the feasibility of integrating Artificial Intelligence into a study management system capable of personalizing academic schedules and learning recommendations. Through the use of **machine learning algorithms**, particularly decision trees and feedforward neural networks, the system had analyzed behavioral data such as session duration, completion rate, and engagement frequency to predict optimal study intervals. The system design, which followed a **three-tier architecture**—comprising presentation, application, and data layers—had ensured scalability, modularity, and seamless data processing. The adaptive planner module had dynamically adjusted study schedules based on the student's performance and behavioral inputs, providing a personalized and automated learning experience. This implementation confirmed that AI-driven mechanisms could effectively enhance self-regulated learning and time management in academic settings, validating prior research that emphasized adaptive intelligence in educational technology [1], [2].

2. How accurate and efficient had the adaptive study management system been in predicting learning behaviors and generating personalized schedules?

The results of system performance testing had indicated that *StudyAdaptAI* achieved an **accuracy rate of 91.3%**, a **precision of 89.8%**, and an **F1-score of 90.2%**, proving that the AI model was highly reliable in generating accurate study recommendations. The system's **average response time of 0.78 seconds** had further demonstrated its capability for real-time behavioral adaptation. These findings validated that the system was efficient and technically sound in processing data and delivering adaptive outputs without noticeable delays. The performance metrics had been comparable to, and in some cases exceeded, the benchmark values established in similar international studies [3], [4]. This confirmed that the integration of behavior-based machine learning algorithms could yield accurate and contextually appropriate study recommendations even with limited datasets, supporting the system's readiness for wider implementation.

3. How usable and effective had the system been from the perspective of student users?

Usability testing using the **System Usability Scale (SUS)** had yielded a mean score of **86.8**, categorized as **Excellent Usability**. Participants consistently reported that *StudyAdaptAI* was easy to use, visually clear, and efficient in delivering adaptive recommendations. The majority of respondents had expressed that the system improved their awareness of time management, enhanced focus, and provided motivation to maintain consistent study routines. The feedback revealed that the adaptive scheduler helped users minimize cognitive fatigue and better balance workload distribution. These findings were consistent with prior usability studies emphasizing that intuitive interfaces and adaptive assistance improved learning motivation and engagement [5], [6]. Furthermore, the high SUS score validated that the system's design adhered to Human–Computer Interaction (HCI) principles, ensuring that the interface was responsive, interactive, and learner-centered.

Synthesis of Findings

Overall, the discussion of findings had confirmed that the integration of Artificial Intelligence into a study management system had been both technically and pedagogically effective. The AI algorithms had successfully adapted to user behavior, the architecture had enabled real-time data analysis, and the interface design had ensured user satisfaction and engagement. The strong alignment between technical accuracy and usability indicated that *StudyAdaptAI* addressed the global, national, and regional gaps identified in the introduction. The system's adaptability to local learning contexts suggested that it could serve as a scalable model for educational institutions seeking to modernize student productivity and performance monitoring.

The results collectively demonstrated that AI-driven adaptive systems had the potential to redefine academic support tools by making study management dynamic, personalized, and data-informed. The success of *StudyAdaptAI* not only validated the research hypotheses but also established a framework for future innovations in AI-based education systems within Philippine higher education.

VII. CONCLUSION

The StudyAdaptAI system represents a leap forward in adaptive educational technologies. It effectively combines AI analytics and user-centered design to personalize study management. The system's high accuracy (91.3%) and usability score (86.8) confirm that adaptive AI can enhance study productivity and engagement. These findings support the development of intelligent learning environments that promote autonomy and continuous academic improvement.

The study had aimed to design and implement an adaptive study management system using Artificial Intelligence, referred to as *StudyAdaptAI*, to enhance student productivity and learning efficiency. Through its developmental research design, the system had been successfully conceptualized, developed, and evaluated to address international, national, and regional gaps in adaptive learning technology. The system had integrated machine learning algorithms to analyze user behavior and automatically generate personalized study schedules and recommendations, demonstrating the feasibility of AI-driven adaptation in academic study management.

The findings from the evaluation phase had revealed that *StudyAdaptAI* achieved high levels of technical accuracy,

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responsiveness, and usability. The system's adaptive recommendation engine had recorded an accuracy rate of **91.3%**, an F1-score of **90.2%**, and an average response time of **0.78 seconds**, confirming its reliability and efficiency in predicting optimal study intervals. Moreover, the usability evaluation using the **System Usability Scale (SUS)** had yielded an overall score of **86.8**, classified as **Excellent Usability**, indicating that participants found the system intuitive, effective, and beneficial to their learning routines.

The integration of adaptive scheduling, behavioral analytics, and personalized feedback had provided students with a dynamic and responsive study experience. Participants reported improved time management, increased learning motivation, and greater self-awareness of their study habits. These outcomes had aligned with the goals of the research, proving that the application of AI in study management could transform traditional, static learning systems into intelligent, personalized platforms that promote engagement and efficiency.

In conclusion, the study had successfully demonstrated that AI-powered adaptive systems such as *StudyAdaptAI* could serve as effective tools in modernizing academic learning environments. The system not only addressed identified technological and behavioral gaps but also offered a scalable model for integrating AI into higher education contexts. Future enhancements could focus on incorporating advanced analytics for emotion detection, predictive performance modeling, and mobile integration to expand accessibility. Overall, *StudyAdaptAI* had proven to be a significant contribution toward the advancement of adaptive and intelligent educational technologies in the Philippine academic landscape.

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