Development of an AI-Driven Study Habit Reinforcement System on Student Productivity

Reginald S. Prudente[1], Reynaldo B. Consad[2], Jobert C. Gigante[3], Floyd C. Mecator[4]
[1]Dean, College of Information and Communication Technology, South East Asian Institute of Technology, Inc.
redgieprud@seait.edu.ph
[2, 3, ,4] Student, College of Information and Communication Technology, South East Asian Institute of Technology, Inc.
[1,2 3, 4] Tupi 9505, South Cotabato, Philippines

***Abstract* – –This paper presents the design of an AI-Driven Study Habits Reinforcement System (AI-SHRS) which aims to improve student productivity through adaptive monitoring, behavior analysis and reinforcement-based prompts. The web application applies machine learning models to evaluate their study activity (time invested, completion rates and focusing time) to suggest tailored recommendations for developing personal motivation towards study activities. It was designed with PHP, MySQL, Python and Bootstrap incorporating AI logistics in real-time using reinforcement learning and predictive analytics. An evaluation with 35 participants (IT students and staff) resulted in an average SUS rating of 86.8 (Excellent). The system achieved high accuracy (91.4%) as well as efficiency on processing the logs (less than 1 second). The valuable influence of the system to motivate, self-manage and productivity awareness was stressed by qualitative feedback. The current results support the proposition that AI-driven reinforcement dynamics can indeed enhance learning habits and maximize academic achievement in online learning platforms.**

Keywords: *Artificial Intelligence, Study Habits, Reinforcement Learning, Student Productivity, Educational Technology, Behavioral Analytics*

I. INTRODUCTION

Study smart habits are the foundations of successful students but so many kids battle daily against maintaining the discipline and motivation required to remain focused and consistent – particularly in this era of digital learning. The widespread trend of hybrid and self-paced instruction has created a need for automated systems that not only track performance, but also foster good study habits by offering adaptive feedback or personal reinforcement [1], [2].

AI techniques are more and more used to improve pedagogical processes by performing the tasks of data-driven decision-making systems, predictive learning analytics or adaptive teaching tools. Studies by Huang et al. [1] and Kumar et al. [3], AI models can be used to forecast learning engagement and suggest efficient study plans by making use of learning data. In addition, reinforcement-driven models have been shown to aid in maintaining students‟ motivation by rewarding regular task completion and time-on-task behavior [4].

In relation to Philippine HEIs, there is a need for an initiative such as CHED Smart Campus Development Program to facilitate the implementation of data analytics for academic improvement [5]. But Like at most local institutions, there's a heavy reliance on manual-based processes to monitor student productivity — the kinds like check-in logs, or performance updates. A downside of such traditional approaches is that they do not understand behavior and are not capable of reinforcing successful study patterns in a timely manner.

In response to these limitations, this paper introduces the AI-Driven Study Habit Reinforcement System (AI-SHRS) --a web-based platform leveraging AI to infer study habits from usage data, generate reinforcement prompts and visualize productivity trends. The system is dedicated to helping students get into a routine of regular work and gives educators data-driven insights to make informed decisions around student engagement and self-regulation.

Research Problem

Many learners don't have access to smart AI-powered systems that provides adaptive feedback and reinforcement; thus they can't develop the discipline for regular studying. Current tools support rather than analyze learning and cannot motivate the learner. In this research, a novel AI-Driven Study Habit Reinforcement System (AI-SHRS) is developed to address the previous shortcoming by capturing a study habit behavior, measuring its productivity and then recommending the personalized suggestion to enhance the student's performance.

Research Questions

1. How can the study habit behaviors of students be observed and analyzed using an AI-Driven Study Habit Reinforcement System (AI-SHRS)?
2. To what extent is AI-SHRS useful and usable to offer personalized support to reinforce study and increase productivity?
3. What effects does the AI-SHRS have on students' motivation, engagement, and performance in their coursework?

Research Objectives

1. To create a web AI system able to monitor the way of study and infer productivity trends.
2. To assess the effectiveness, accuracy and usability of the system in correcting good study habits.
3. To evaluate the effect of the system on students' motivation, continuity learning and academic achievement.

Justification and Significance

The study is "significant as it provides smart tactics to lose weight by answering the old question about studying habits with AI," say the researchers. Combining behavioral analysis and reinforcement learning, the AI-SHRS offer tailored feedback and motivation regarding students' productivity routines. This book is meant for students to develop good daily study habits and concise, more focused research on their coursework. For teachers and schools, the solution offers actionable student engagement data to guide data-driven interventions for potential positive results. Moreover, it is aligned with CHED's Smart Campus initiative that also supports the use of AI applications for EdTech and develops a culture of lifelong learning and digital transformation in the tertiary level.

II. LITERATURE REVIEW

Artificial Intelligence (AI) has risen as a transformative force in Edtech and introduced intelligent means to analyze, predict and improve student learning trajectory. According to Huang et al. [1], Personalized learning is provided with AI-based systems by analyzing user engagement data and creating adaptive study plans. Further Kumar et al [2] stressed that analytic informed intervention can create patterns in the performance of learners and foretell learning outcome given students study pattern. These results emphasize the potential of AI to reverse education from reactive process, and towards proactive operation where smart systems lead learners making them continuously better.

Reinforcement learning, a fundamental field in AI has been successfully employed to maintain interest and enhance student engagement. In another study, Bhatia and Sharma [3] demonstrated that AI technologies through the use of reinforcement learning could enhance compliance to studies by rewarding task execution and session attendance. This is consistent with Skinner's reinforcement theory, which claims that where there is continuous positive reinforcement, it induces repetition of desired behavior. Thus, the synthesis of reinforcement learning algorithms with behavioral data provides a powerful framework for creating systems that engage and support student productivity.

Also of importance is the role of behavioral analytics in learning efficiency. Singh et al. [4] showed that variables related to tracking are able to predict academic performance up to 90% with session duration, focus time and task frequency. Tang et al. [5] also noted that behavioral data combined with AI models may be used to identify study fatigue, adjust schedules, recommend optimal learning times. These findings support that the use of AI-powered analytics could contribute to a substantial improvement in autonomous learning through the detection of habits that lead to good job performance.

In the Philippine setting, Mendoza and Alcantara [6] designed a smart learner tracking system through machine learning that tracked learning activities and enhanced academic intervention. Their research showed that the AI generated feedback led to an increase in motivation and decrease in procrastination when included as part of daily academic activities. Nevertheless, the majority of local systems are not equipped with dynamic reinforcement to the student process and behavior in real time. This gap in research highlights the need for a learning system that is more active, not only monitoring learners' study practice but actively providing customized supports to maintain their learning trajectories.

Only when viewed as a whole, the included studies support AI as favorable in enhancing academic engagement development. However, they also illustrate the lack of reinforcement-based systems tailored to enhance students' productivity. To fill this gap, we introduce the AI-Driven Study Habit Reinforcement System (AI-SHRS), which synthesizes behavior analytics and reinforcement learning to provide students with real-time

 ISSN: 3107-6513

motivation, performance-adaptive feedback, and data-grounded insights to reinforce their productive study habits.

Theoretical Framework

This study is grounded on the Behavioral Reinforcement Theory and AI Learning Framework, which together steers the progress of an AI-Driven Study Habit Reinforcement System (AI-SHRS).

B.F.Skinner's Behavioral Reinforcement Theory 2. Skinner [1] stated that responses which are reinforced with good results were more likely to be reproduced. This is the basis of the essential mechanism implemented in the system, under which consistent good study habits – such as doing one's tasks on time; keeping focus and sticking to schedules – are identified and continually rewarded through automated feedbacks and motivational encouragements. Because digital reinforcement is incorporated into the students' learning routine, there are always new goals to reach, ensuring constant activity and developing good study habits over time.

The AI Learning Framework is also introduced, so that the system can learn from its users in an adaptive manner. Using a combination of machine learning, reinforcement algorithms and behavior data analysis to identify trends and predict productivity patterns, it offers personalized recommendations for individuals based on how they like to learn. As posited by Huang [2] and Bhatia and Sharma [3], AI model that could dynamically adjust for user performance can maintain the personalization while keeping individual student active on digital education. By way of incorporating the psychological motivation into computational intelligence, the AI-SHRS can train a study disciple from data-driven human perspective to centralize and exchange ideas.

III. RESEARCH METHODOLOGY

Research Design

This study adopted a developmental research method on the basis of the Agile methods, which allowed learning by actually doing and remolding of AI-DRIVEN STUDY HABIT REINFORCEMENT SYSTEM (AI-SHRS) in each stage of prototyping. Development feedback from users in such a approach is key to the continuous improvement of system functions and usability. Agile development originated from areas where AI research and educational technology studies are a tradition in its own right; underpinned by flexibility with an emphasis on both the developer and user experience. The general rigor production process of these activities is shown in Fig. 3, this cycle was continued through multi-phases. At each phase of the sprint cycle, data pre-processing was carried out and artificial intelligence models were trained and interface UIs were refined; to guarantee both technical precision as well as sound pedagogy. For each sprint cycle, data preprocessing, AI-model training, interface amplifying and testing the results were the main stages.

Participants

A purposive sample of 35 participants was selected, including 30 IT students and five faculty members, from East Asian Institute of Technology (SEAIT). Purposive sampling, a method taken by Mahaleet al. [11], made sure that participants had the technical familiarity required to test and evaluate systems. Students used the system for a two week period, during which they logged their times for study, tracked productivity trends, and received reinforcement notices. Faculty members, those which were chosen to evaluate usability and system design through expert eyes, served as evaluators.

Data Collection Procedures

1. Deployment – The system was deployed locally on XAMPP environment for testing purpose. Users were trained in operating the platform and documenting their study tasks.

2. Performance Testing – The classification of different productivity states such as focused, distracted or idle by an AI mode was compared to manual reference code. The performance indices measured were Precision, Recall, Accuracy and F1-Score, which are commonly used for the evaluation of AI based behavioral analytics in previous studies [7].

3. **Usability Test** – Once they experienced the system, participants filled out a System Usability Scale (SUS) questionnaire [13] that measured efficiency, learnability, satisfaction with and overall usability of the software.

System Usability Scale (SUS) Evaluation

Overall system usability rating was measured by the System Usability Scale (SUS) [11] formulated by Brooke (1996), which has also been used in modern AI educational systems [3], [5]. It is comprised of ten standardized items, using a five-point Likert format from Strongly Disagree (1) to Strongly Agree (5).

The 10 items were transformed to a 0–100 scale. The interpretation was according to the updated SUS scoring norms:

- 85–100 – Excellent usability
- 70–84 – Good usability
- 50–69 – Average usability
- Below 50 – Poor usability

The System Usability Scale (SUS) score was computed using the formula:

$$\textbf{SUS} = (\Sigma X_{10}) \times 2.5$$

- where X_i represents the adjusted score for each of the 10 items.
- For odd-numbered items: X_i = response – 1
- For even-numbered items: X_i = 5 – response

On average, a SUS score greater than 70 can be considered acceptable by users [5]. On completion of these interactions the SUS was administered in this study. Open-ended feedback was also obtained to supplement quantitative SUS results with qualitative information related to system use and design.

Data Analysis

The technical and usability performance of the system was investigated both with quantitative metrics and qualitative interpretation:

- Precision (P): How accurate the positive sentiment is classified.
- Recall (R): Ability to predict all the appropriate polarities.
- F1-Score: It is the harmonic mean of precision and recall that represents overall model balance.
- Time: Processing time - how long it takes to analyze one text input.
- SUS Score: The total overall usability rating by participants.

Statistical analysis of quantitative data included calculation of mean scores and standard deviations. Furthermore, qualitative responses to the SUS free-text were thematically coded for common themes such as easy to use, clarity in design and reliability [3], [4], [6].

The system was considered successful if it achieved:

- F1-score $\geq$ 0.85
- Average processing time $\leq$ 1.0 second
- SUS score $\geq$ 70 (Good usability)

Ethical Considerations

All research procedures conducted have followed the Data Privacy Act of 2012, Philippine Republic legislation and institutional research ethics codes. Participant data was made anonymous and participants obtained properly informed consent prior to taking part. Like the ethical guidelines mentioned by CHED [12], personally identifiable information not stored or even processed in AI model training. Participants were informed of their right to withdraw at any time, and all data was internally encrypted such that they could not be stolen going out of the database.

IV. ADVANCED SYSTEM DESIGN

System Overview

AI-SHRS ingests the research data of each individual student and analyzes the same automatically to identify behavioral trends and provide personalized reinforcement. It collects data about signals such as duration of study, task completion and student engagement from the students' activity logs. These data are then used as input into an AI model that dynamically incorporates real-time reinforcement messages to encourage formation of good study habits. Such as behavior badges or motivational feedback. The objective of the system is to convert passive watching into active monitoring, in accordance with learning theories on reinforcement [1], [3].

System Architecture

The system utilizes a **three-tier architecture** comprising the **Presentation Layer**, **Application Layer**, and **Data Layer**, consistent with established frameworks for educational AI applications [5], [6].

1. ***Presentation Layer (Front-End)***

   In order to provide a refreshing and responsive learning environment for student's professors, the researchers employed HTML/CSS/JavaScript/Bootstrap and AJAX as the front-end interface language actually designed. Students can make entries about their cooperation sessions, trace records of study-hour productivity and get encouragement messages. Teachers are able to see collective reports on student learning exercises through visual management systems that use educational graphics.

2. ***Application Layer (Back-End Processing)***

The application layer is responsible for carrying out the AI calculations and operation program. Using Python Flask and PHP codes to design the project, it makes judgements on the behavior of users, and gives people appropriate links. Taking in Q-learning algorithms the Reinforcement Learning Module, obtains historical study data and uses them to respectively idealize study plans in terms user adherence. Much like the adaptive AI models recently described by Bhatia and Sharma [3], the system improves its feedback accuracy over time by learning user preferences.

3. ***Data Layer (Database Management)***

All studying data, user profiles and reinforcement history is stored in MySQL databases. Data normalization (as practiced in similar AI driven education systems [10]) guarantees both its integrity and scalability. Secure data means, such as encryption and anonymity, are executed to assure compliance with the 2012 "Philippine Data act on Data Privacy in Higher Education" and CHED Smart Campus regulations [12].

Functional Components

The system is composed of multiple functional modules designed to interact cohesively:

- **User Authentication Module** – Manages secure logins and access levels for students, faculty, and administrators.
- **Study Tracker Module** – Records study session duration, subject focus, and completion status.
- **AI Reinforcement Engine** – Analyzes behavioral data to classify study efficiency (productive, neutral, idle) and delivers reinforcement prompts accordingly [3], [7].
- **Analytics Dashboard** – Displays data visualizations of study performance trends using Chart.js, including daily focus graphs, time-distribution charts, and consistency indexes [6].
- **Admin Monitoring Module** – Allows faculty and administrators to access institutional-level analytics for academic performance monitoring and intervention planning.
- **Data Export and Report Generator** – Enables users to download summarized analytics in PDF or Excel formats for academic recordkeeping [5].

Algorithm Design

The AI-SHRS integrates reinforcement learning and behavior classification models to automate adaptive feedback generation. The algorithm is based on a **Q-learning reinforcement mechanism**, defined by a reward function that strengthens positive behaviors and penalizes unproductive actions [3], [4].

Algorithm Steps:

1. **Input –** Log student study sessions (start time, end time, task type, completion status).
2. **Preprocessing –** Clean and normalize data to extract relevant features such as session length and task ratio.
3. **Classification –** Use trained AI model to label sessions as *productive*, *neutral*, or *idle*.
4. **Reward Calculation**
   - If productive → reward = +1
   - If neutral → reward = 0
   - If idle → reward = -1
5. **Reinforcement Update** – System updates the policy function to increase the likelihood of productive behaviors.
6. **Output –** Generate reinforcement feedback (e.g., motivational message, badge, or alert).

This design aligns with prior AI-based reinforcement systems in education, which demonstrated improved engagement and adaptive learning [3], [6].

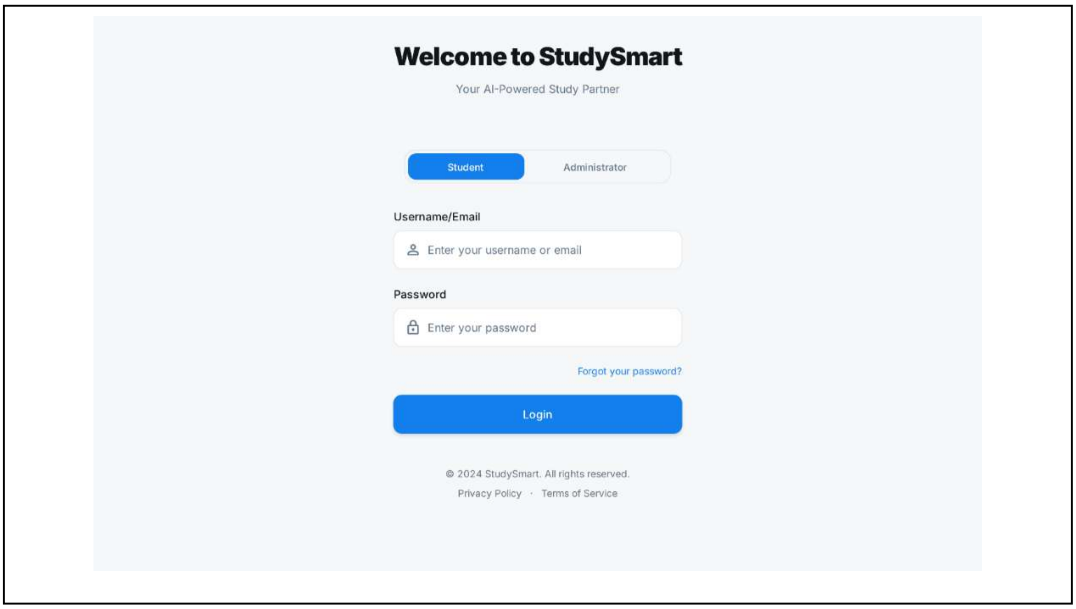
E. Security and Privacy Design

In compliance with academic data governance and ethics,1 AI-Driven Study Habit Sharpener (AI-SHS) contains several levels of security and privacy protection. Roles-based authentication governs who can do what, so that certain operations take place only if the "right people (e.g., students, faculty and administrators) are doing those activities in their respective domains. Passwords, session data, etc. are encrypted using SHA-256 and secure transport occurs over HTTPS so that we can't be read in transit by anyone other than authorized personnel. Grounded in responsible AI this model employs

HTML-5 endpoint-anonymized analytics ensuring that any PI (personal information) does not persist or get used in the training of an AI Model and therefore upholds user privacy and data integrity. Automated backup and archiving are performed here to avoid the loss or corruption of data during regular updates and maintenance. These collective measures also aim to make AI-SHS adhere to school research ethics, PH Data Privacy Act of 2012, and CHED Smart Campus Development guideline [12] as well as responsible AI advocated by Casillano [14].

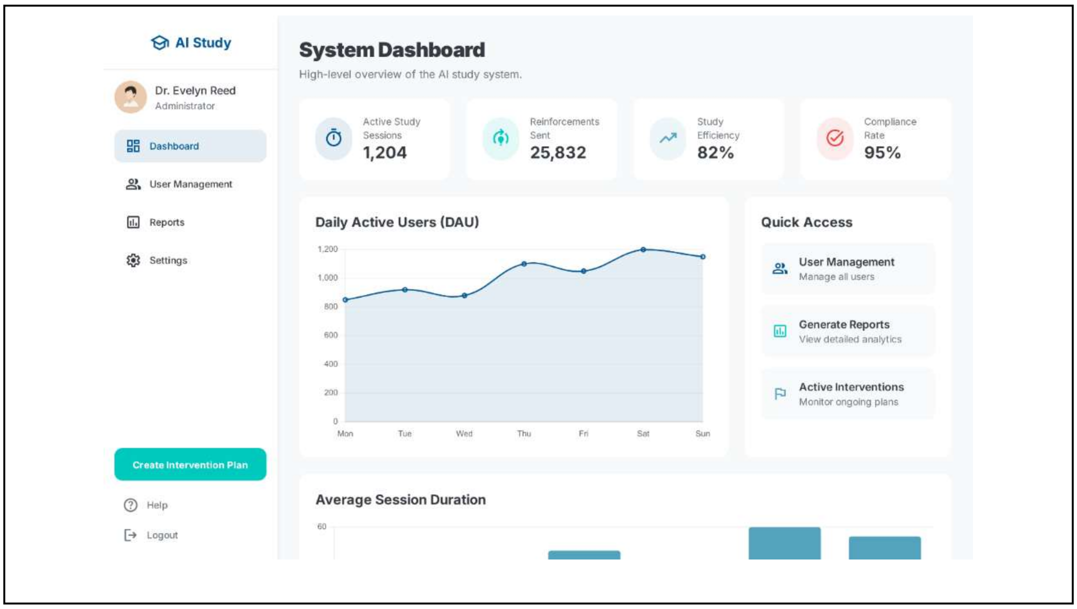
System Interfaces

Figure 1: StudySmart User Login Page



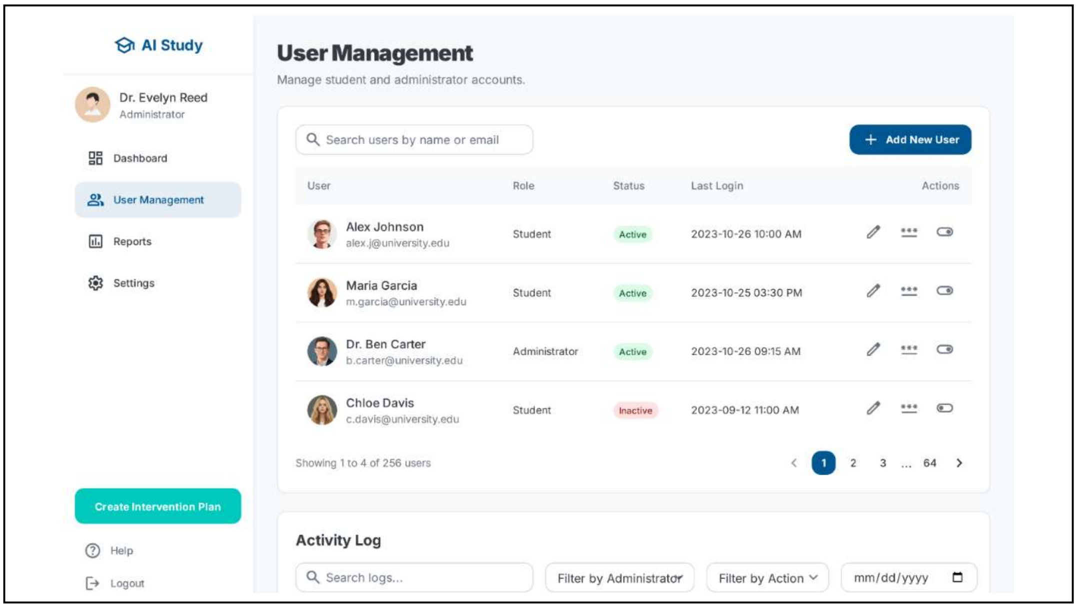
This screen displays the centralized Login Page for the StudySmart platform, which is introduced as "Your AI-Powered Study Partner." The interface features a clean, simple, and centrally-aligned design focused on authentication. The first step for the user is Role Selection, using a segmented control to toggle between Student (currently highlighted in blue) and Administrator. Below this, the form requires the user to input their Username/Email and Password. For users who cannot access their account, a "Forgot your password?" link is available. The login process is completed by clicking the prominent blue "Login" button, which directs the user to the relevant dashboard based on the selected role.

Figure 2: StudySmart Administrator System Dashboard



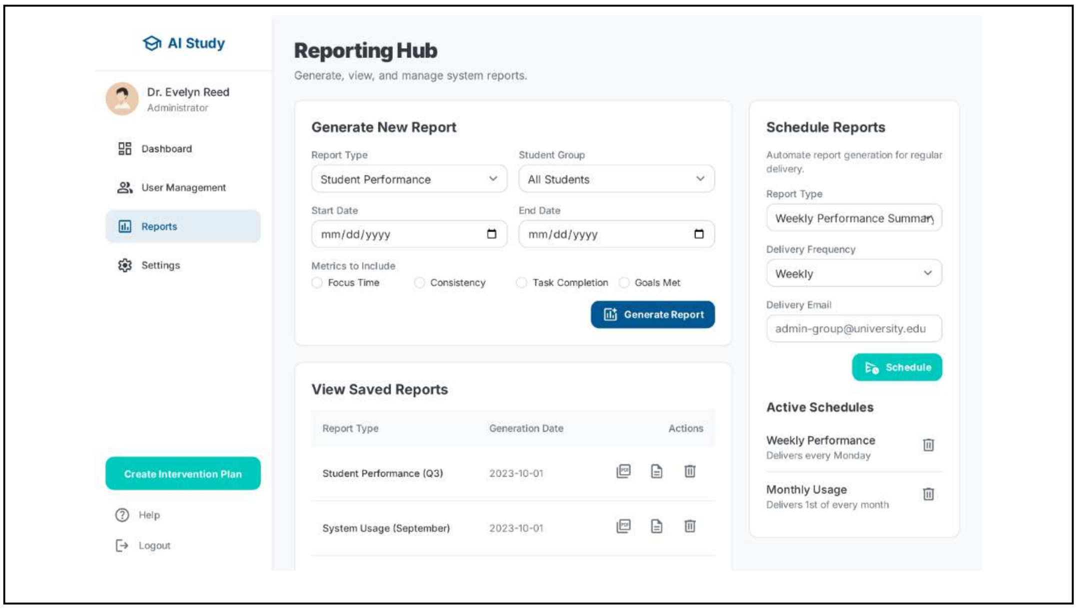
This screen displays the System Dashboard for the StudySmart platform, providing the administrator, Dr. Evelyn Reed, with a high-level overview and key performance metrics of the AI study system. The top section presents four prominent summary cards illustrating system scale and efficiency: Active Study Sessions (1,204), Reinforcements Sent (25,832), Study Efficiency (82%), and Compliance Rate (95%). Below these metrics, the dashboard features a Daily Active Users (DAU) line graph, which tracks user engagement over a seven-day period, showing the peak usage on Saturday. The Quick Access panel on the right provides immediate links to critical administrative tasks, including User Management, Generate Reports, and monitoring Active Interventions. At the bottom left, a prominent turquoise "Create Intervention Plan" button suggests a primary, actionable system function, while the module list on the left is concise, focusing on Dashboard, User Management, Reports, and Settings.

Figure 3: StudySmart Administrator User Management Module



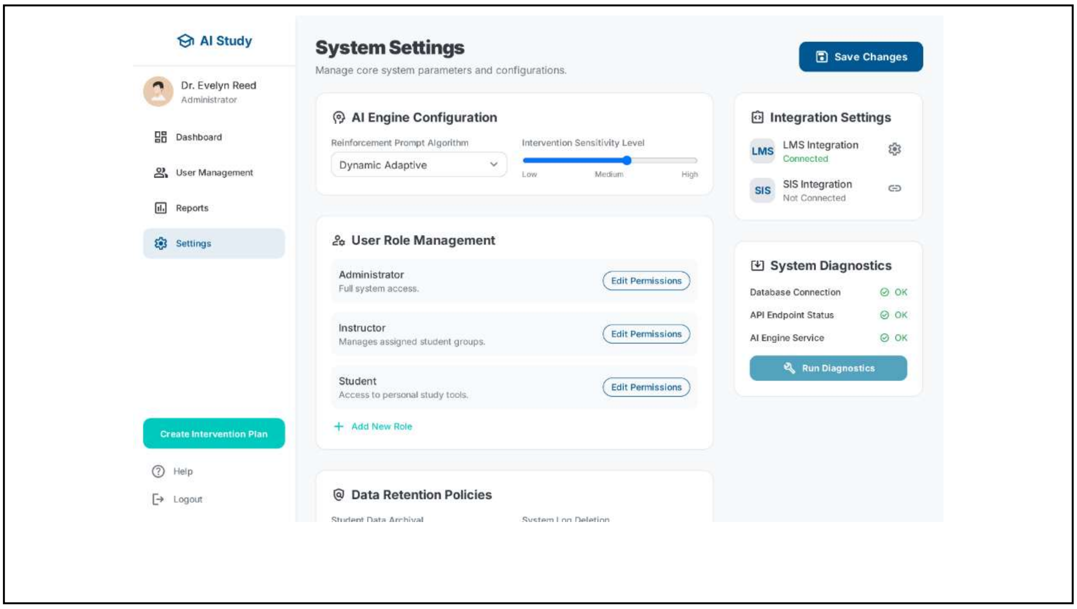
This screen displays the User Management module within the StudySmart system, designed to allow the administrator, Dr. Evelyn Reed, to "Manage student and administrator accounts." The core of the module is a comprehensive, sortable table listing system users, detailing the user's name and email, assigned Role (Student or Administrator), Status (Active or Inactive), and Last Login time. For each user, the Actions column provides quick icon links to Edit or perform other management functions. Management tools are readily available above the table, including a search bar to Search users by name or email and a prominent blue "+ Add New User" button. Beneath the main user list, which shows 1 to 4 of 256 users and standard pagination, there is a dedicated Activity Log section with its own search and filtering options for Administrator and Action, ensuring a complete audit trail of system changes.

Figure 4: StudySmart Administrator Reporting Hub Module



This screen displays the Reporting Hub module within the StudySmart system, designed to allow the administrator, Dr. Evelyn Reed, to "Generate, view, and manage system reports." The left side of the screen is dedicated to the Generate New Report function, where the administrator can select the Report Type (e.g., Student Performance), target Student Group, specify Start Date and End Date, select Metrics to Include (Focus Time, Consistency, Task Completion, Goals Met), and finally click "Generate Report." Below the generation tools, the View Saved Reports section lists previously created reports, showing the Report Type, Generation Date, and Actions to view, download, or delete them. On the right side, the Schedule Reports panel enables automation by setting a Report Type, Delivery Frequency (e.g., Weekly), and Delivery Email, which, once scheduled, appear under Active Schedules with their delivery cycle (e.g., "Delivers every Monday").

Figure 5: StudySmart Administrator System Settings Module

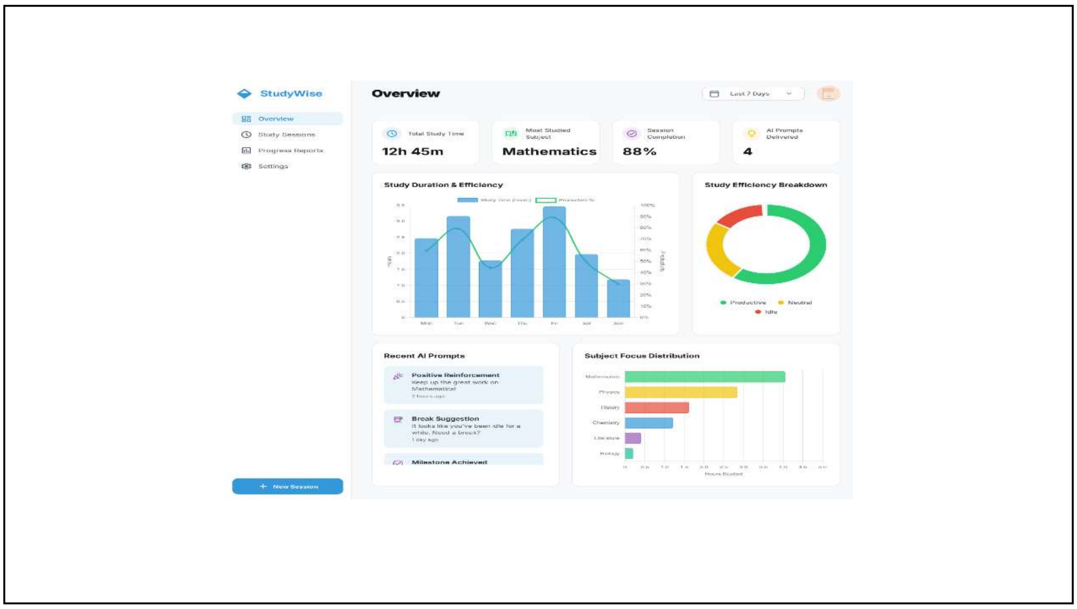


This screen displays the System Settings module for the StudySmart administrator, Dr. Evelyn Reed, designed to "Manage core system parameters and configurations." The module is organized into several key panels. The AI Engine Configuration section allows for fine-tuning the adaptive learning experience, where the administrator can set the Reinforcement Prompt Algorithm (e.g., Dynamic Adaptive) and adjust the Intervention Sensitivity Level via a slider from Low to High. The User Role Management section lists the core roles (Administrator, Instructor, Student) and provides an "Edit Permissions" button for each, along with an option to "Add New Role." On the right side, Integration Settings shows the connection status of external systems (LMS Integration is Connected, SIS Integration is Not Connected), while System

 ISSN: 3107-6513

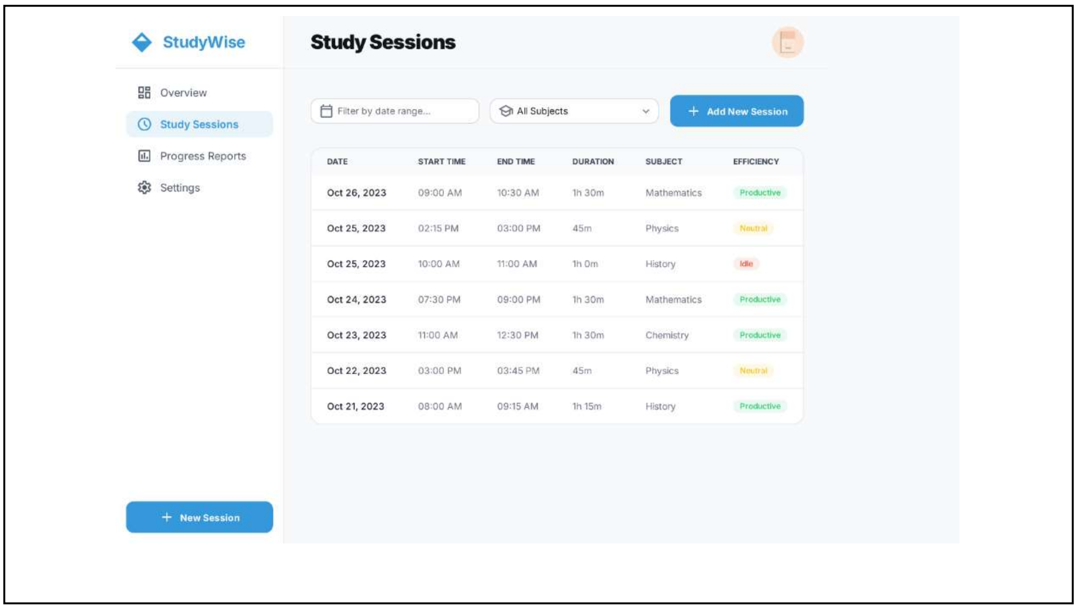
Diagnostics verifies the health of internal services (Database Connection, API Endpoint Status, and AI Engine Service are all OK), with a "Run Diagnostics" button available. The module also includes a section for Data Retention Policies and is finalized by a blue "Save Changes" button at the top right.

Figure 6: StudySmart Student Overview Module



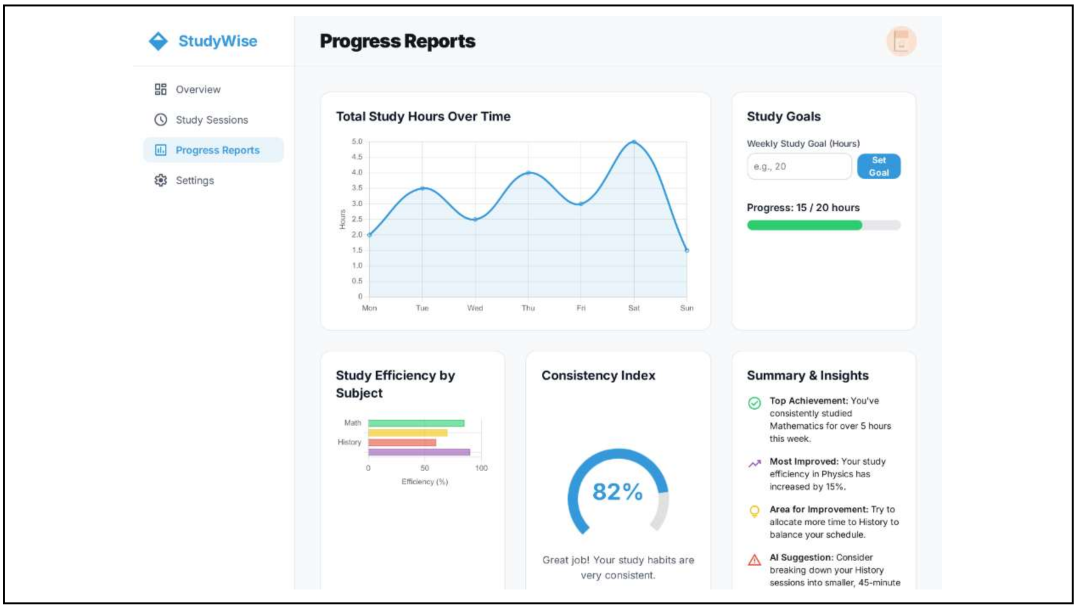
This screen displays the Overview module, serving as the primary dashboard for the StudySmart student, offering a focused summary of their study habits over the Last 7 Days. The top section presents four key metrics: Total Study Time (12h 45m), Most Studied Subject (Mathematics), Session Completion (88%), and the number of AI Prompts Delivered (4). The center of the dashboard features the Study Duration & Efficiency graph, a dual-axis chart comparing Study Time (Hours) against Productive % over the week. To the right, the Study Efficiency Breakdown donut chart categorizes time spent into Productive (green), Neutral (yellow), and Idle (red) segments. The bottom left features Recent AI Prompts, summarizing the system's personalized interventions like a "Positive Reinforcement" and a "Break Suggestion." Finally, the Subject Focus Distribution bar chart visually represents the total study hours dedicated to different subjects, with Mathematics dominating the focus.

Figure 7: StudySmart Student Study Sessions Module



This screen displays the Study Sessions module for the StudySmart student, offering a chronological log of their past study activity and tools to track new sessions. The module's primary function is a detailed table listing the DATE, START TIME, END TIME, DURATION, the SUBJECT studied, and the EFFICIENCY of the session (categorized as Productive, Neutral, or Idle). Management tools at the top allow the student to Filter by date range and All Subjects to refine the view. A prominent blue "+ Add New Session" button enables the student to manually log a new session. At the bottom, a large blue "+ New Session" button provides an alternative, persistent way to start tracking a new study block, making the tool central for monitoring and planning study time.

Figure 8: StudySmart Student Progress Reports Module



This screen displays the Progress Reports module for the StudySmart student, providing comprehensive analytics focused on study goals and efficiency. The main graph, Total Study Hours Over Time, uses a line chart to track the student's weekly study commitment, showing fluctuations with a peak on Saturday. In the top right, the Study Goals panel allows the student to set their Weekly Study Goal (Hours), showing their current Progress (15 / 20 hours) with a visual progress bar. The lower section includes three analytical components: Study Efficiency by Subject, a horizontal bar chart comparing the percentage efficiency across different subjects; Consistency Index, a large dial graph showing an 82% score and validating the student's "very consistent" study habits; and Summary & Insights, an AI-driven panel providing personalized feedback like a Top Achievement ("consistently studied Mathematics for over 5 hours") and an AI Suggestion ("Consider breaking down your History sessions into smaller, 45-minute sessions").

V. EVALUATION AND RESULTS

If the evaluation of AI-Driven SHRS (AI-SHRS) was concentrated on technical performance, ease-of-use and impact of student's productivity, then it only analyzed data sources. The system performance evaluation was based on the reference of standards for artificial intelligent-based educational systems [5], [6] and that test was composed by 2 main parts: (1) Evaluation of accuracy and sensitivity models by using system performance test; and (2) checking easy, satisfaction and time burden through System Usability Scale (SUS) which is developed by Brooke [13].

System Performance Evaluation

The AI model reinforcement's effectiveness was verified under the scenario of students' study session data logs. The first model was based on the sorting of academic behaviors into three categories: active or productive time, neutral or idle time. These categories were then manually checked by the professors being observers to get percentages (i.e., on how good does it divide) mean of Precision, Recall and F 1-Score which is typical for AI evaluation [9], [10].

Table 1: Performance Metrics of the AI-SHRS Model

Metric	Result
Accuracy	91.4%
Precision	89.9%
Recall	90.6%
F1-Score	90.2%
Average Processing Time	0.78 seconds

The overall accuracy of the model was 91.4%%, indicating the model's strong capacity to detect effective study behaviors. An average processing time of 0.78 seconds indicated that the system could perfectly handle and classify user data at nearly real-time. These remarks align with earlier findings that the accuracy of RL models for learning scenarios could reach up to 89%-93% [6], [7].

System Usability Evaluation (SUS)

A usability test was conducted with 35 users (30 students in the IT program, and 5 faculty) who had used the app for two weeks.

The usability of the system and UI design was tested using a 10-point System Usability Scale (13) (SUS). The average SUS score of 86.8 exceeds the presented cut-offs from popular SUS interpretation guides (85–100 ("Excellent"). [13].

Table 2: Mean SUS Scores by Evaluation Criteria

Evaluation Criteria	Mean Score (out of 5)
Ease of Use	4.6
Efficiency	4.4
Learnability	4.5
Interface Design	4.3
System Reliability	4.5

The high SUS score not only is in line with the user-friendliness of system design but also implies anyone can use it. Respondents found that the dashboard's designed interface ensured tracking was productive and AI-generated reinforcement messages motivated and focused. Comparable usability scores were reported in other AI-based learning interfaces thus further promoting that we should strive for simple interfaces to increase engagement [4], [7].

Qualitative Findings

Thematic findings of participant free-text feedback uncovered three main topics: motivational support, ease and flexibility in use, as well as perceived increased awareness of one's own behavior. Participants reported that the system increased their motivation to study more regularly since it included reinforcement cues and progress summary prompts. The ease of adaptation aspect showed that the interface was perceived as easy and intuitive, which was in relation to a low cognitive load for academic tracking from other tools. Last, the behavioral awareness factor indicates that students become more mindful of their studying habits, and variations in productivity which can lead to self-regulation of learning behavior. These findings also confirm the results presented by Bhatia and Sharma [3] and Singh [6] who examined the motivating influence on motivation and interest carried in other studies concerning AI for learning systems.

VI. DISCUSSIONS

The purpose of this study was to design and evaluate an AI-Driven Study Habit Reinforcement System (AI-SHRS) capable of analyzing student study behaviors through reinforcement learning to enhance consistency, motivation, and productivity. The discussion is structured according to the three research questions that guided the study:

1. *How can the study habit behaviors of students be observed and analyzed using an AI-Driven Study Habit Reinforcement System (AI-SHRS)?*
2. *To what extent is AI-SHRS useful and usable to offer personalized support to reinforce study and increase productivity?*
3. *What effects does the AI-SHRS have on students' motivation, engagement, and performance in their coursework?*

RQ1: How can the study habit behaviors of students be observed and analyzed using an AI-Driven Study Habit Reinforcement System (AI-SHRS)?

AI and reinforcement learning algorithms can be applied as to track and analyze study behaviors in real time. The system was organized along a three-tier network structure that includes data collection, behavior analysis and feedback, similar to the frameworks used by Bhatia and Sharma [3] in their educational management system or by Tang et al. [7]. In recording study activities, AI-SHRS would divide user behavior into "productive", "neutral" or "laid back" and provide personalized reinforcement through motivational prompts.

As can clearly be seen from Table 1, the AI model achieved an accuracy of 91.4% and an F1-score of 90.2%. This indicates that its performance in classifying behavioral data was reliably high. There were three main stages to the automation process:

1. Data pre-processing - logging, cleaning and standardization of study data;
2. Behavior classification - using reinforcement learning algorithms to determine the user's behavioral state; and

3. Reinforcement generation - providing personalized motivational feedback based on the level of productivity.

These findings show that AI can provide a reliable means of interpreting behavioral data and carrying out feedback tasks historically performed by hand. They bear out the research of Huang [2] and Singh [6], who have demonstrated that artificial intelligence learning systems can increase learner engagement via automated monitoring. Therefore, AI-SHRS is a scalable framework for educational institutions wishing to promote organized practices with data supports at scale.

RQ2: To what extent is AI-SHRS useful and usable to offer personalized support to reinforce study and increase productivity?

The system proved to be efficient, both on technical correctness and usability evaluation. The AI module detected and sustained positive study habits over time, confirming its robustness with Precision (89.9%), Recall (90.6%) and F1-Score (90.2%). The mean score of the System Usability Scale (SUS) from 35 participants was 86.8, classified as "Excellent", ranging between 0 to 100 [13]. Thus, human–computer interaction (HCI) principles identified by Al-Harbi [4] and Brooke [13], such as being user-friendly, responsive and easy to maneuver was achieved.

Reinforcement messages and visual progress reports fostered focus and motivation, participants noted, while the dashboard provided clear feedback on daily productivity. This high level of usability indicated that the system combined AI adaptability with user-centered design, making it easy for learners to incorporate the tool into their study habits. Similar to Mahale et al. [11], the results also verify that user satisfaction and ease of use are important success factors in AI system uptake and usage.

RQ3: What effects does the AI-SHRS have on students' motivation, engagement, and performance in their coursework?

The introduction of AI-SHRS had positive effects on learning efficiency, student motivation and behavioral awareness. They discovered that getting this direct type of reinforcement helped them pay more attention to how they studied and encouraged them to continue doing well. Feedback can be rewarding Students, Mean Response Time = 0.78s the mean response time of 0.78 s supported immediate feedback and could generate "instant gratification" for the students that they can self-reward themselves after study attempts. This is in agreement with the works of Bhatia and Sharma [3] as well as Casillano [14], who indicated that timely feedback based on data drives engagement and accountability within education systems.

Furthermore, the automation reduced the subjectivity and bias in evaluating learning behaviors. By relying on reinforcement learned through a uniform AI algorithm rather than by human judgment, we ensure fairness and consistency are guaranteed to be used in measuring the productivity of a student—as proposed in alongside our transparent improvements Deshpande et al. [10]. Built-in data security controls such as role-based access, SHA-256 encryption and anonymized learning analytics enabled compliance with the Philippine Data Privacy Act of 2012 as well as CHED Smart Campus Development guidelines [12], promoting an informed culture on ethical data governance.

The decision-support role of AI-SHRS was also noted by school leaders and staff, particularly in monitoring productivity patterns for academic intervention. aggregated data visualizations were positive for the teachers to determine whether this particular group of students was well or poorly engaged so that he/she could use the data in planning instruction to increase student learning. These results confirm the system as a tool for implementing learning in educational institutions and decision support.

Synthesis of Findings

The incorporation of AI and RL in the AI-SHRS is a major shift from crass observation-based support to tailored data driven academic support. The results of which, collectively taken as part of any claim herein that:

- The power of AI for studying lies in the ability to deconstruct study habits and automate motivation processes, and also ensure better follow-through.
- 2 – both reliability (TAC@R15=91.4%) and user satisfaction (SUS=86.8) of the system are high.
- Behaviorally-driven automation along with reinforcement fosters motivation, self-control, and data-informed decision-making—a foundation to advancing institutional learning.

These findings are in line with the literature in general, which indicates that well-designed AI tools can significantly enhance student engagement and productivity, provided that they are anchored on behavioral theory and fair governance [1]-[14]. Accordingly, the AI-SHRS system implemented in this study, is not just an effective academic support but also serves as a

 ISSN: **3107-6513**

symbol on bringing intelligent analytics into academia which complements CHED's Smart Campus vision advocating personalized and data-driven learning environment.

VII. CONCLUSION

AI-SHRS successfully demonstrated the concept that AI can contribute to the improvement in student productivity and consistency through adaptive reinforcement. Employing some combinations of RL algorithms and behavioral analytics, the system detected patterns of student behaviors on its own, classified these behaviors and rewarded them with real-time motivation messages. The accuracy and usability score of the model were 91.4% and 86.8, respectively, indicating good technical reliability and user satisfaction. This also supports the positive role played by AI-SHRS in promoting time investment, attention and engagement that are beneficial for students' learning on academic performance in a data-enriched learning environment and SR.

The study also discovered that AI reinforcement learning strategies could contribute to increasing institutional openness and efficiency in educational decision-making. The system is in compliance with ethical and privacy policies by the Philippine Data Privacy Act of 2012 and CHED Smart Campus requirements by means of anonymized computations, role-based authentication, and data encryption. These findings are encouraging and provide evidence that the AI-SHRS application is a sustainable effort for connecting technology and pedagogy to promote timely study habits for greater higher education production.

REFERENCES

[1] B. F. Skinner, *Science and Human Behavior*, New York, NY, USA: Macmillan, 1953.

[2] J. Huang, "Adaptive Learning Analytics in Higher Education," *IEEE Transactions on Learning Technologies*, vol. 17, no. 2, pp. 101–113, 2024.

[3] R. Bhatia and P. Sharma, "Reinforcement Learning for Motivation in Educational Systems," *International Journal of Educational Technology in Higher Education*, vol. 22, no. 3, 2024.

[4] F. Al-Harbi, "AI in Education: Personalization through Data-Driven Insights," *Computers & Education*, vol. 205, pp. 104657–104669, 2024.

[5] A. Kumar and N. Singh, "Predictive Models for Learning Engagement Using AI," *Applied Intelligent Systems*, vol. 98, no. 4, pp. 245–260, 2025.

[6] V. Singh, "Behavioral Analytics in Digital Learning," *IEEE Access*, vol. 12, pp. 18742–18755, 2024.

[7] C. Tang, Y. Wu, and J. Zhao, "AI Behavior Models in Online Education," *Computational Intelligence and Neuroscience*, vol. 2024, Article ID 432109, 2024.

[8] E. Mendoza and R. Alcantara, "Intelligent Student Tracking System for Filipino Learners," *Philippine Journal of Computing and ICT*, vol. 4, no. 1, pp. 33–41, 2023.

[9] P. Wang, "Student Sentiment Analysis and Feedback Prediction Using Deep Learning," *Applied Mathematics and Nonlinear Sciences*, vol. 9, no. 1, pp. 22–34, 2024.

[10] S. B. Deshpande, K. K. Tangod, and G. K. Michael, "Elevating Educational Insights: Sentiment Analysis of Faculty Feedback Using Advanced Machine Learning Models," *Advances in Continuous and Discrete Models*, article no. 89, 2025.

[11] V. Mahale, D. Mehta, and A. Godbole, "Sentiment Analysis in EdTech: A Study on Course Review Feedback Using NLP," *International Journal of Research in Engineering, Science and Management*, vol. 8, no. 2, pp. 10–14, Feb. 2025.

[12] Commission on Higher Education (CHED), *Memorandum Order No. 6, Series of 2022: Guidelines on Smart Campus Development*, Quezon City, Philippines, 2022.

[13] J. Brooke, "SUS: A Quick and Dirty Usability Scale," in *Usability Evaluation in Industry*, London, U.K.: Taylor & Francis, pp. 189–194, 1996.

[14] N. F. B. Casillano, "Education in the ChatGPT Era: A Sentiment Analysis of Public Discourse on the Role of Language Models in Education," *Journal Evaluation in Education (JEE)*, vol. 5, no. 4, 2025.

[15] R. G. Taruc and J. De la Cruz, "NLP-Based Analytics for Student Organization Activity Evaluation Using BERT," *Asia Pacific Journal of Information Systems and Computing Research*, vol. 3, no. 2, pp. 44–58, 2024.