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# Design and evaluation of an artificial intelligence-powered LMS-based learning analytics dashboard

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**ABSTRACT**

In the era of digital transformation and flexible learning modalities, educators face challenges in monitoring student performance and engagement in online environments. This study presents the development of an intelligent learning analytics dashboard designed to enhance educators' capacity to monitor and support student performance and engagement in an online environment. This study integrates supervised and unsupervised machine learning models trained using 25 learning management system course log data, comparing multiple models for predicting student performance, and applying the k-means algorithm for clustering engagement levels. It also incorporates a large language model to provide personalized academic intervention strategies. Developed using the Shiny framework and grounded in the cross-industry standard process for data mining, with the technology acceptance model as an evaluation framework, the dashboard underwent iterative design and testing. Results showed that random forest is the most accurate predictive model, achieving an accuracy of 92.79%. K-means effectively identified engagement clusters, with an average silhouette width of 0.59. Technology acceptance testing among 34 educators indicated high levels of perceived usefulness and ease of use. The intelligent dashboard showcases the application of artificial intelligence and learning analytics in education, enabling timely, data-driven interventions that align with institutional goals and national education initiatives.

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## 1. INTRODUCTION

Information technology (IT) has paved the way for dashboards to become significant tools in the educational landscape, especially with the continued use of learning management systems (LMS) and the rise of artificial intelligence (AI) [1]. An AI-powered LMS-based learning analytics dashboard can provide educators with real-time insights from LMS data, support their teaching strategies, and provide timely interventions to struggling students [2], [3]. This tool is vital in online and blended learning modalities, where the LMS generates vast amounts of student data [4]. The need for this type of dashboard arises from the current characteristics of LMSs, which lack the necessary features to predict student performance, monitor engagement levels, and provide effective intervention strategies [5], [6]. Furthermore, educational institutions often lack intelligent dashboards and the skills to analyze LMS data, which limits their capacity to take timely actions [7], [8].

Educators worldwide struggle to predict student performance and monitor engagement levels in online and blended learning environments due to the reduced interactions in virtual environments [9], [10]. In the Philippines, educators experienced challenges in predicting student performance and monitoring engagement in online and blended learning environments due to their limited technical skills in analyzing LMS data [11]. Currently, there is a lack of deployed solutions to address such concerns [12]–[14]. Existing LMS platforms lack comprehensive analytics capabilities, limiting educators' ability to provide effective interventions that meet students' needs, prompting the need for more advanced and user-friendly solutions through an intelligent learning analytics dashboard [15].

Previous studies lack learning analytics dashboards for predicting student performance and clustering engagement in LMS. Moodle, one of the most popular open-source LMS platforms worldwide [16] and widely used in the Philippines [17], has been a subject of multiple AI and educational data mining (EDM)-related studies. The studies [18], [19] have developed supervised tree-based machine learning models to predict student performance using Moodle LMS. The studies [20]–[22] developed unsupervised machine learning models using Moodle LMS to cluster student engagement levels. However, the models developed from these studies were not deployed into production, limiting their educational utilization. While studies [23], [24] developed dashboards with Moodle LMS as the data source, these applications are limited to being descriptive, without AI integration. Recent work has also emphasized the importance of teacher-facing learning analytics dashboards that visualize participation and discourse patterns to support instructional decision making [25]. However, these dashboards primarily provide descriptive analytics and do not integrate predictive machine learning and generative AI for personalized interventions.

While dashboards with AI model integrations were developed [6], [26], [27], these applications were limited to either supervised, unsupervised, or large language models (LLMs) alone. Therefore, as an opportunity, this study aimed to develop and evaluate an AI-powered dashboard that leverages AI through Moodle LMS data to predict student performance and engagement, utilizing machine learning. The study also aimed to integrate a LLM for personalized intervention support strategies. After student performance predictions and engagement clusters are generated, an LLM component of the dashboard provides personalized intervention strategies that can be either individualized for each student or applied to the entire course, providing pedagogical intervention recommendations for enhanced usefulness. Developed using a data mining framework and evaluated through a technology acceptance framework, the AI-powered LMS-based learning analytics dashboard provides educators with a platform to identify high-performing, low-performing, engaging, and non-engaging students, offering early intervention before it is too late.

The design of the dashboard was informed by educational psychology frameworks, such as self-regulated learning (SRL), which emphasizes the importance of timely feedback and monitoring to support students' metacognitive processes [28]. The clustering of engagement aligns with the behavioral dimension of engagement theory [29]. At the same time, predictive analytics supports early-warning mechanisms consistent with SRL and cognitive load models. By integrating supervised learning, unsupervised clustering, and LLM-generated pedagogical interventions, this study extends prior learning analytics frameworks by connecting machine-generated insights directly to motivational and regulatory constructs in educational psychology.

With the AI-powered dashboard, educators using Moodle LMS can instantly upload their course logs to the dashboard and obtain student performance predictions and engagement clusters based on learning analytics. Educators can query an LLM through a chat feature and receive personalized, suggested intervention strategies tailored to their specific needs. The dashboard application not only helps educators offer timely interventions for students who need assistance but also empowers them with data-driven insights, contributing to the sustainable development goal (SDG) of quality education. The AI-powered dashboard also contributes to the Philippine education and research roadmaps. Beyond monitoring, the dashboard also provides affordances for AI-supported instructional redesign, including classroom flipping and student-centered learning made possible through generative AI capabilities [30], [31].

## 2. METHOD

This study used the design science research methodology (DSRM). This methodology was deemed ideal for the study because it focuses on creating an innovative and helpful tool, a characteristic of DSRM [32]. DSRM is commonly used in educational technology and research involving information systems, where a problem is addressed using IT solutions [33]. Multiple trained machine learning models, along with an LLM, were integrated into a dashboard application. The application was deployed and evaluated by a group of educators. The following sub-sections summarize the methods used in this study without detailing the steps of DSRM.

### 2.1. Data collection and preparation

The study collected a dataset comprising 25 Moodle logs and grades, which included data points from various science, technology, engineering, and mathematics (STEM) and non-STEM courses at the University of Southeastern Philippines, a state university in the Davao region. Due to the chronological nature of the logs, where each entry corresponds to a particular student's action, the data were data-wrangled and feature-engineered, generating rows of students' number of actions. Missing values were checked, and no imputation was required. The grade threshold of 86 and above for "high" and 85 and below for "low" followed institutional grading standards and prior EDM literature, which used binary labels for performance prediction.

The data-wrangled and feature-engineered Moodle logs were combined with the feature-engineered grade data accordingly, creating a dataset appropriate for analysis. This created a dataset suitable for the next step. The dataset comprises eight columns with 3,602 rows, and its characteristics are presented in Table 1. The features include submission actions, forum actions, quiz actions, create actions, read actions, update actions, delete actions, and days logged in. The label is the performance. The data collection and preparation aspect of the study used the tidyverse package from the R programming ecosystem.

Table 1. Characteristics of the dataset used after preprocessing

| Features | Data type | Class |
|---|---|---|
| Submission actions | numeric | feature |
| Forum actions | numeric | feature |
| Quiz actions | numeric | feature |
| Create actions | numeric | feature |
| Read actions | numeric | feature |
| Update actions | numeric | feature |
| Delete actions | numeric | feature |
| Days logged in | numeric | feature |
| Performance | character | label |

### 2.2. Machine learning

Using the tidymodels package from the R programming ecosystem, the study performed supervised machine learning to develop models for predicting student performance and unsupervised machine learning to develop models for clustering student engagement levels during different stages of the course. The supervised machine learning process compared three tree-based machine learning algorithms: random forest, extreme gradient boosting (XGBoost), and decision tree. The unsupervised machine learning process employed the k-means clustering algorithm.

From the dataset, a subset was generated for creating models that will be used around the midterm period of the course. The complete dataset was intended for the models that will be used during the near-final period of the course. The machine learning process of the study aimed to develop two models to predict student performance for the midterm and final periods, as well as two models to cluster student engagement levels for the same periods.

#### 2.2.1. Supervised machine learning

The features of the dataset were designed as predictors of students' performance (as indicated by the performance label). The complete and subset datasets were split into training and testing with an 80-20% split. The training set was resampled using 10-fold cross-validation, and the testing set was reserved for evaluating the best models at a later stage. The modeling process compared multiple random forest, XGBoost, and decision tree models using an 18-grid hyperparameter search and 10 resamples from the cross-validation, with different combinations of the algorithm's hyperparameters. Tree-based algorithms were selected because of their established performance and interpretability in EDM studies involving LMS data. The 18-grid hyperparameter space represents the optimal balance between depth of tuning and computational feasibility, consistent with prior analytics-focused modeling studies. The tune race analysis of variance (ANOVA) from the tune package, an extension of the tidymodels package, was utilized to save computational resources by dropping non-performing models early on and continuing the comparison, leaving only the best-performing models.

The models that performed best for the near-final and midterm predictions were selected as the top-performing models. The metric used in the comparison was the receiver operating characteristics-area under the curve (ROC-AUC), as well as accuracy, sensitivity, and specificity metrics. The ROC-AUC was chosen as the primary metric due to its robustness to class imbalance. Accuracy, sensitivity, and specificity were added to provide a more holistic evaluation. The best models from the complete and subset datasets were later deployed to the dashboard application to predict student performance and cluster student

engagement levels. The best models were evaluated using the testing set split for each dataset. The accuracy metric was used to assess the models' performance on the testing set.

#### 2.2.2. Unsupervised machine learning

The k-means algorithm was applied to both the complete and subset datasets, excluding the performance column. K-means was selected due to its efficiency with large numerical datasets and its wide use in Moodle engagement studies. Using the within-cluster sum of squares (WSS) via the elbow method plot, the study determined the optimal value of k as two, which served as the basis for the number of clusters. The k-means algorithm was applied to both datasets, yielding two unsupervised models for clustering student engagement levels during the near-final and midterm periods of the course. The clustering performance for both models was evaluated using the average silhouette width (ASW). The clusters were named accordingly based on the characteristics of the combined features of the dataset.

### 2.3. Model deployment and dashboard development with LLM-integration

The supervised and unsupervised machine learning models were deployed as RDS files, a file type native to R, embedded into the dashboard application. Using the Shiny framework package from the R ecosystem, the AI-powered LMS-based learning analytics dashboard was designed and developed with consideration for web development best practices and dashboard design. The dashboard was deployed as a progressive web application on a live server, enabling users to download and run the application as a desktop application.

An LLM was integrated via an application programming interface (API) using OpenAI's GPT-4.1 model. The LLM was system-tuned to provide intervention strategies based on pedagogical principles. The LLM was integrated using the ellmer package from the R ecosystem. The LLM prompting schema was grounded in instructional design principles, specifying structured parameters for generating actionable recommendations while avoiding hallucinated pedagogical claims.

The AI-powered dashboard was designed for educators to upload Moodle logs from their courses and generate predictions and engagement clusters for their students. The learning analytics feature provides valuable insights into student performance and engagement. Educators are informed of intervention strategies based on predictions and clusters. The educators can also ask an LLM via the chat feature. The decision to integrate prediction, clustering, and LLM-generated interventions within a single dashboard is theoretically supported by the literature on early warning systems, data-driven decision-making, and feedback loops in learning analytics. Prior studies often treat these components separately; thus, integrating them addresses a gap in moving from analysis to pedagogically meaningful action. The overall implementation design, including the components of the AI-powered dashboard, was based on the framework in Figure 1.

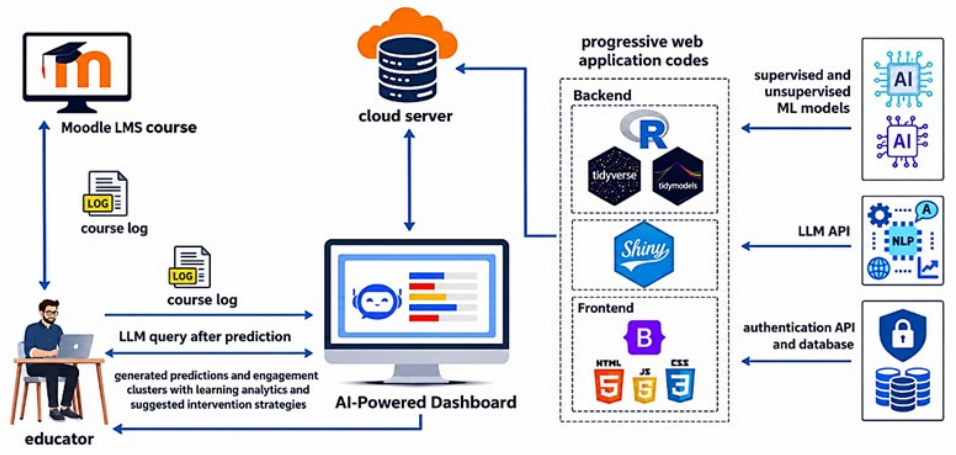



Figure 1. Implementation design framework of the AI-powered dashboard

### 2.4. Technology acceptance evaluation

A questionnaire was formulated based on the technology acceptance model (TAM) framework [34], utilizing only the perceived usefulness (PU) and perceived ease of use (PEOU) constructs [35]. Five subject matter experts validated the questionnaire, and its reliability was tested with a Cronbach's alpha of 0.95 for

PU and 0.96 for PEOU. The questionnaire was distributed to 34 University of Southeastern Philippines faculty members who tested the dashboard and were selected via a purposive sampling method, with inclusion criteria that included being already using AI tools or being willing to use AI tools in their teaching strategies. Participation was voluntary, and no compensation was provided. Demographically, the group included instructors aged 26–58, with teaching experience ranging from 2 to over 20 years. This diversity ensured representation across different teaching domains and varying levels of familiarity with LMS-based analytics tools.

This evaluation component of the study aimed to measure the potential level of acceptance of the AI-powered dashboard technology, using descriptive statistics to calculate the mean and standard deviation. Although TAM served as the core evaluation framework, the use of AI-driven analytics and LLM-generated recommendations represents a context where traditional TAM constructs intersect with factors such as algorithmic transparency and trust in automated decision support. Thus, this study contributes to expanding the theoretical understanding of the applicability of TAM to modern AI-enabled educational tools.

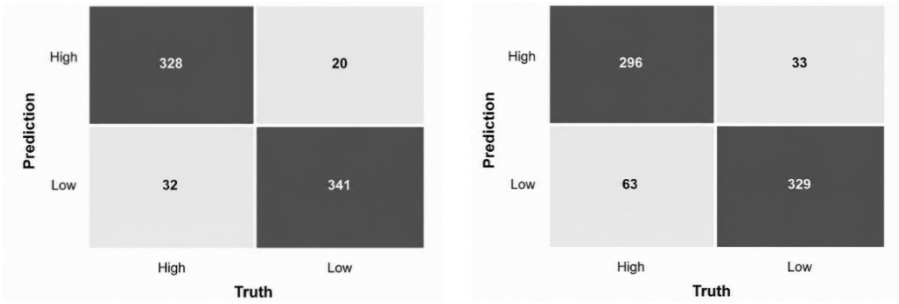
## 3. RESULTS AND DISCUSSION

### 3.1. Results

The supervised machine learning process of the study revealed that the random forest model is the best-performing model for near-final and midterm predictions of student performance, as shown in Table 2. In the training process, the random forest performed best in both modeling phases, across all four metrics. The random forest models were evaluated on the testing set, as shown in Figure 2, as part of the evaluation process. The near-final random forest model achieved an accuracy of 92.79%, correctly predicting 328 out of the 360 high-performing students and 341 out of the 361 low-performing students, as shown in Figure 2(a). The midterm random forest model achieved an accuracy of 86.69%, correctly predicting 296 out of 359 high-performing students and 329 out of 362 low-performing students, as shown in Figure 2(b).

Table 2. Modeling comparison of different tree-based models for near-final and midterm modeling

| Model | Near-final | | | | Midterm | | | |
|---|---|---|---|---|---|---|---|---|
| | AUC | Accuracy | Sensitivity | Specificity | AUC | Accuracy | Sensitivity | Specificity |
| Random forest | 0.95 | 88.41 | 84.99 | 91.82 | 0.93 | 86.78 | 81.66 | 91.85 |
| XGBoost | 0.92 | 85.7 | 83.25 | 88.14 | 0.88 | 81.99 | 77.48 | 86.45 |
| Decision tree | 0.84 | 79 | 74.56 | 83.43 | 0.81 | 77.79 | 71.49 | 84.04 |



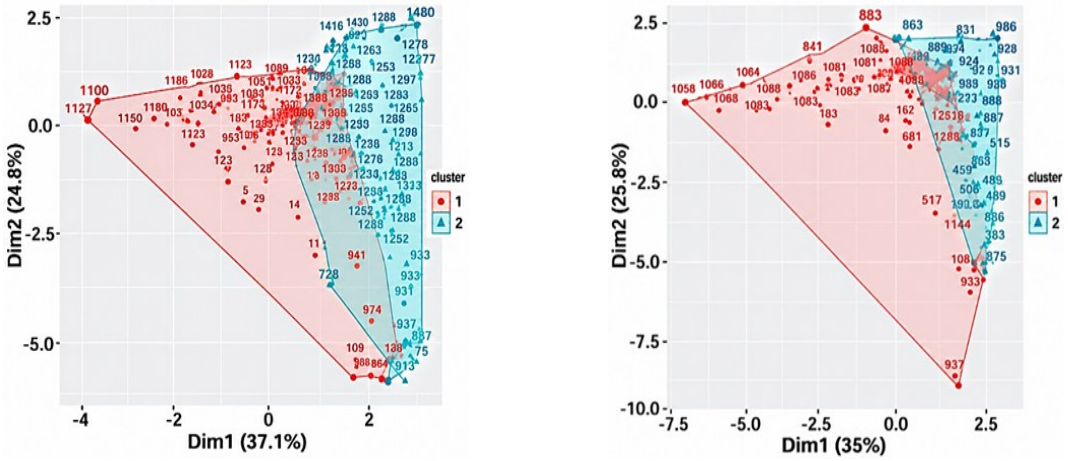

(a) (b)

Figure 2. Confusion matrix of (a) near-final and (b) midterm model evaluation on the testing set

The unsupervised machine learning process of the study identified two clusters, as grouped by the k-means algorithm. In the near-final clustering, 599 students were assigned to cluster 1, while 1,136 were assigned to cluster 2. In the midterm clustering, 378 students were assigned to cluster 1, while 1,306 were assigned to cluster 2. The clustering performances were evaluated as shown in Figure 3. The near-final clustering had an ASW of 0.55, as shown in Figure 3(a), while the midterm clustering had an ASW of 0.59, as shown in Figure 3(b).

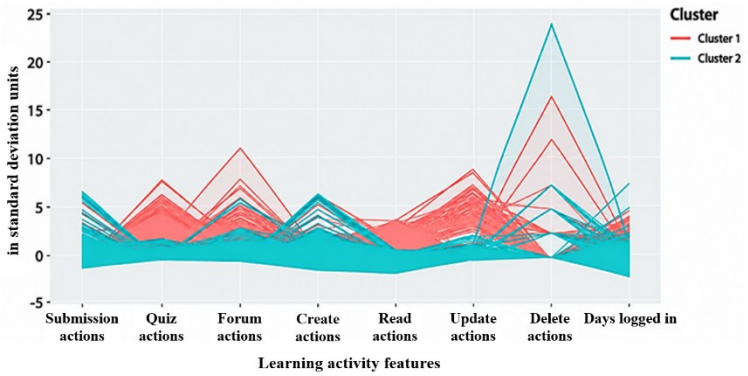
Exploring each cluster's features, the study named the clusters according to their characteristic features, as shown in the clustering analysis plots in Figure 4. Figure 4(a) shows the near-final stage, while Figure 4(b) shows the midterm stage. This naming is consistent with both the near-final and midterm cluster naming analyses. Cluster 1 heavily utilizes features such as quiz actions, forum actions, and update actions in both the final and midterm datasets. This cluster is more uniform and consistent across the features, with less

variance in delete actions. Hence, students in cluster 1 are named “Consistent learners”. Consistent learners demonstrate steady activity across different features. Cluster 2 is low primarily across features, with a few extreme outliers and very high delete actions, indicating sporadic participation. Therefore, students in cluster 2 are named “Sporadic learners”. Sporadic learners tend to exhibit low engagement, with occasional spikes in specific areas.




(a) (b)

Figure 3. Cluster plots of the (a) near-final and (b) midterm clustering




(a)




(b)

Figure 4. Clustering analysis plots of the (a) near-final and (b) midterm features

The AI-powered dashboard was developed by integrating two supervised and two unsupervised machine learning models, as well as the LLM, through the Shiny web development framework as a

progressive web application. The dashboard is deployed on Posit Connect Cloud, a cloud service provider. The dashboard is accessible via browser and as a progressive web application. Once logged in, educators can use the dashboard by navigating to the Modeling section and consequently predicting student performance and clustering engagement. Figure 5 shows a screenshot of the dashboard's user interface after successful modeling.

Two value boxes at the top display the predicted number of high-performing and low-performing students. Two additional value boxes display the clustered numbers of consistent and sporadic learners. The primary tab, PredClust, shows the students' predicted performance and engagement clusters, filtered by a drop-down menu of student names, along with a summary of the modeling results. In this tab, users can query the LLM via the "Generate insight" button to generate personalized student insight. The modeling data can be saved and downloaded via the "Save data" and "Download" buttons on the left panel.

Additional tabs are provided for learning analytics, offering data-driven decision support, including overview, ranking, correlation, comparison, distribution, frequent actions, time series, and class data. These tabs enhanced the dashboard's features with value-added insights. The insights tab is where the LLM generates insights, including recommended interventions for the course, all at the click of a button, as shown in Figure 6. The generative AI tab is where the educator can communicate with the LLM through chat.

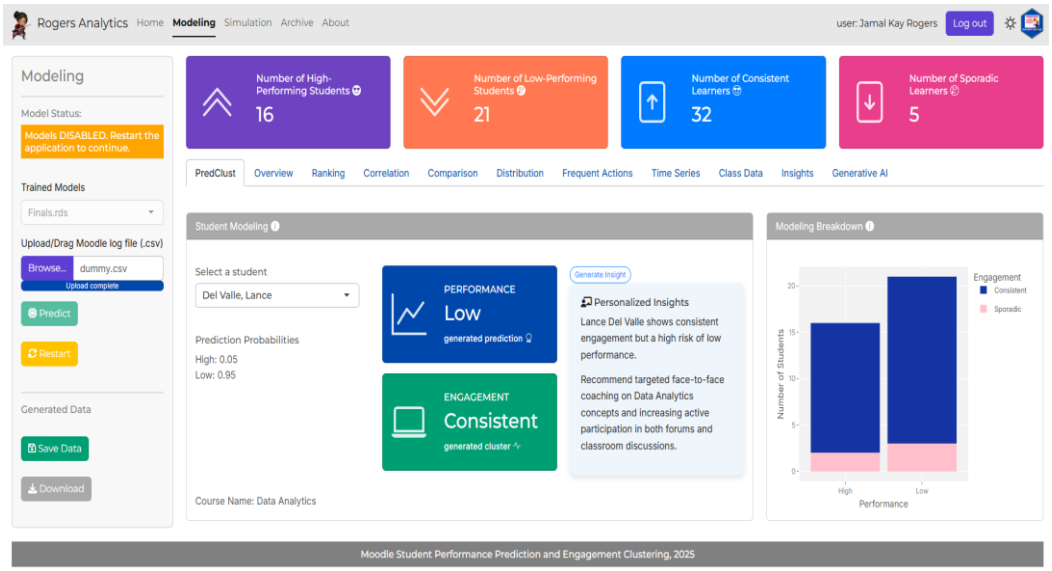



Figure 5. Screenshot of the dashboard's modeling interface showing generated predictions and clusters

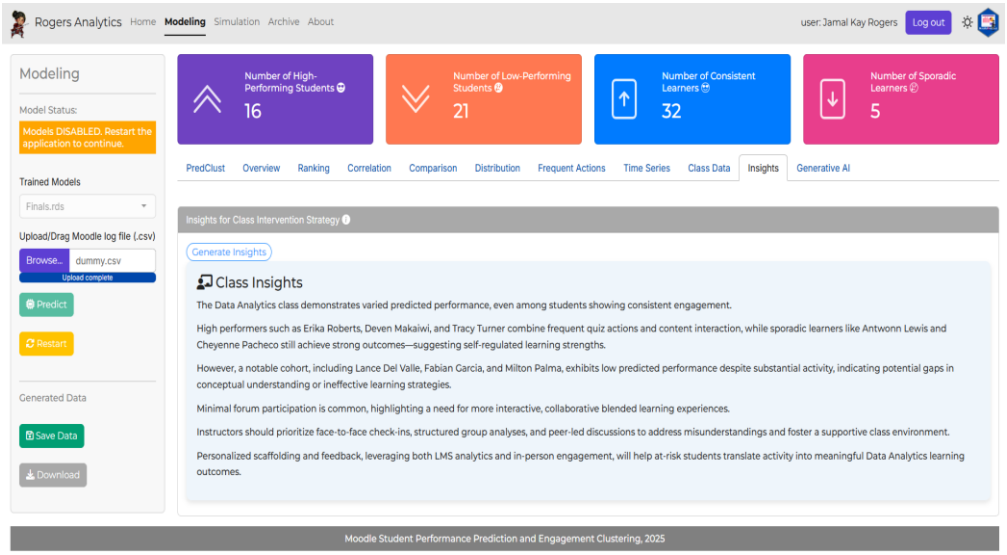



Figure 6. Insights tab of the AI-powered dashboard showing LLM-generated intervention strategies

Table 3 presents the results of the evaluation of the technology's acceptability. The respondents evaluated the AI-powered dashboard through hands-on testing. They responded to the validated and reliability-tested questionnaire based on PU and PEOU. The results show overall mean of 4.34 (SD = 0.57), reflecting a very high level of agreement among faculty members.

Table 3. Results of the technology acceptance evaluation of the AI-powered dashboard

| Item | Question | Mean | SD | Description |
|---|---|---|---|---|
| 1 | I can quickly generate insights about student performance using the AI-powered dashboard. | 4.35 | 0.64 | Very high |
| 2 | I can efficiently use the AI-powered dashboard to monitor student LMS engagement levels. | 4.38 | 0.65 | Very high |
| 3 | I can reduce errors in identifying at-risk students through the AI-powered dashboard's data-driven recommendations. | 4.12 | 0.81 | High |
| 4 | I can complete intervention planning more efficiently in one session with the help of the AI-powered dashboard. | 4.26 | 0.75 | Very high |
| 5 | I can make informed decisions about appropriate interventions for my students through the AI-powered dashboard. | 4.38 | 0.65 | Very high |
| 6 | I can respond to students' needs in a timely manner with the help of the AI-powered dashboard. | 4.29 | 0.84 | Very high |
| 7 | I find the AI-powered dashboard useful in supporting my academic responsibilities. | 4.44 | 0.66 | Very high |
| | Category Mean (items 1-7) | 4.32 | 0.60 | Very high |
| 8 | I find learning to use the AI-powered dashboard easy because of the following: Tooltips, Popovers, Straightforward navigation, and Intuitive layout. | 4.32 | 0.64 | Very high |
| 9 | I find it easy to upload a course log, generate performance predictions and engagement clusters, and seamlessly view results using the AI-powered dashboard interface. | 4.44 | 0.61 | Very high |
| 10 | I clearly understand which button performs which action due to the AI-powered dashboard's layout and icons. | 4.41 | 0.74 | Very high |
| 11 | I find it easy to interact with the AI-powered dashboard when performing tasks such as switching between tabs, adjusting filters to view specific data, and saving or downloading outputs | 4.32 | 0.73 | Very high |
| 12 | I can easily become proficient in using the AI-powered dashboard's features, such as selecting suitable machine learning models, generating performance predictions, clustering engagement levels, exploring insights through data filtering, and interacting with the large language model for personalized support | 4.29 | 0.72 | Very high |
| | Category mean (items 8-12) | 4.36 | 0.62 | Very high |
| | Overall mean (items 1-12) | 4.34 | 0.57 | Very high |

The results show that faculty members rated PU (items 1-7) with a category mean of 4.32 (SD = 0.60), indicating a very high level of PU. This suggests that the faculty members strongly agree with the usefulness of the AI-powered dashboard. The faculty members rated a mean of 4.44 (SD = 0.66), indicating the highest level of usefulness, as they found the AI-powered dashboard to help support their academic responsibilities. Although they rated a mean of 4.12 (SD = 0.81), the lowest, for the AI-powered dashboard to reduce errors in identifying at-risk students through data-driven recommendations, this mean still indicates a high level. The results also show that the faculty members rated PEOU (items 8-12) with a category mean of 4.36 (SD = 0.62), which is a very high rating. This suggests that the faculty members strongly agree with the ease of use of the AI-powered dashboard. The faculty members rated a mean of 4.44 (SD = 0.61), indicating the highest level of comfort, as they found it easy to upload course logs, generate predictions and engagement clusters, and view the results seamlessly. The lowest mean of 4.29 (SD = 0.62) indicates proficiency in using the AI-powered dashboard's features, but still suggests a high level.

### 3.2. Discussion

The study developed an AI-powered learning analytics dashboard based on LMS, integrating multiple supervised and unsupervised machine learning models, along with an LLM, to provide Moodle LMS users with an application for effectively monitoring and enhancing student performance and engagement. The study utilized Moodle course logs from various training courses to compare and evaluate different tree-based algorithms for building predictive models. The study employed the k-means clustering algorithm to construct the clustering model. The models were deployed with the LLM into a dashboard application that is built using the Shiny framework as a progressive web application. A group of faculty members evaluated the technology acceptance of the developed dashboard through PU and PEOU.

The study has demonstrated the effectiveness of the random forest algorithm as the most accurate algorithm for supervised classification, particularly in predicting student performance using Moodle data from course logs. This finding aligns with [36], where random forest emerged as the best model compared

with gradient boosting, k-nearest neighbor (KNN), and linear discriminant analysis (LDA) for predicting alphabetic grades of students and determining whether students pass or fail using 6-week and 10-week Moodle data. Moreover, the finding also aligns with the regression study [37], where random forest was identified as the best model for predicting student grades, compared to KNN, XGBoost, and support vector machine (SVM) models.

The clustering process employed throughout the study is consistent with prior studies that have applied the k-means algorithm to Moodle LMS data to cluster student engagement levels. For instance, the elbow method aligns with [20], [22], in which the technique was employed to determine the optimal value of k. However, their studies yielded different values of k, with three [20] and five for [22], due to the varying features and data sizes used.

The development of the AI-powered dashboard in the study aligns with previous studies, albeit with some differences. For instance, the web development framework used in the study is consistent with [26], which developed a Shiny app to cluster student engagement levels within other LMSs. The study [27] also developed a Shiny app to predict student performance. However, in contrast, it uses data responses from Google Forms. In addition, the machine learning models in this study were integrated within the source code as RDS files, limiting the utilization of the models to the dashboard, in contrast with having the models run via an API or from another source [27], which uses an external server to process the prediction. Furthermore, the study employed a slightly more advanced GPT model than [6], [38], which utilized the GPT 3.5-Turbo and GPT 4.0 versions, respectively.

In comparing TAM constructs, the AI-powered dashboard has a slightly higher mean PEOU score than PU, indicating that the faculty members perceived the dashboard as easier to use than helpful. These findings contradict the study [39], which found that instructors primarily value the tool for its functional benefits rather than its usability. Nevertheless, the PEOU score of the developed AI-powered dashboard can be attributed to the dashboard's user-centered design, which has led to an understanding of PU. The PEOU score of the AI-powered dashboard may have influenced PU, as depicted in the simplified TAM framework in the methodology chapter.

Beyond the descriptive results, a deeper analysis suggests that the random forest model performed best due to its robustness to multicollinearity and its ability to model complex, nonlinear interactions among LMS actions, which are commonly present in student behavioral data. The emergence of two clusters, consistent and sporadic learners, aligns with known engagement archetypes in online learning, indicating that even in varied courses, learner behavioral patterns follow predictable engagement rhythms. Furthermore, the higher PEOU relative to PU implies that user-centered design components, such as tooltips, intuitive navigation, and tab structure, may have had a strong direct influence on educators' perceived value of the technology.

The study was limited to the use of the Moodle LMS as training data and an LMS application. Future studies may consider expanding the training and capability to other LMS. The study was limited to tree-based machine learning algorithms; future research may explore neural network architectures and ensemble deep learning methods for performance prediction, especially for larger and more complex datasets. The study is also limited to the training data. Future studies may also consider other LMS logs or expand the data gathering to other universities as a data source in the machine learning process. The study was limited to k-means clustering; future research can utilize advanced clustering techniques, such as density-based spatial clustering of applications with noise (DBSCAN) or hierarchical clustering, to explore more nuanced groupings. In addition, since the study did not incorporate temporal analysis, incorporating behavioral time patterns as clustering features may yield more profound insights into engagement. Engagement clusters could be evaluated longitudinally to track changes over a semester and validate their relevance for early intervention.

The study employed a direct input-output approach in designing the web application. Further improvements may incorporate adaptive user interfaces that adjust recommendations based on educator feedback or usage patterns. Future iterations of the dashboard may further support student-centered learning through knowledge-tracing mechanisms, enabling learners to monitor their own progress and receive personalized, AI-supported feedback [31]. Integrating knowledge tracing into the dashboard aligns with metacognitive and SRL frameworks by providing students with continuous insight into their evolving knowledge state and personalized study recommendations.

Since the study was limited to the pilot testing stage at a single university, exploring the scalability and deployment of the dashboard across multiple universities can help address institutional adoption challenges. The study was limited to a quantitative evaluation; future research may apply mixed-methods approaches to explore acceptance and its impact on instructional behavior and student outcomes. Additional user studies could assess long-term engagement, trust, and ethical concerns with AI-generated feedback and LLM support. In the context of TAM, the study was limited to the primary TAM constructs PU and PEOU. Future studies may include other constructs, such as behavioral intention and actual use.

Despite some limitations, the development of the AI-powered dashboard offers educators using Moodle a mechanism for identifying students who need assistance early on. Intervention strategies are suggested via the dashboard, and educators can use the recommended interventions based on pedagogical principles. The study contributed to the growing body of literature on the application of AI and IT in education. The integration of predictive analytics and generative AI also positions the dashboard as a catalyst for AI-driven classroom flipping, enabling a shift toward student-centered learning, as outlined in recent research on LLM-enabled personalized learning [30].

This study contributes to strengthening the theoretical discourse on learning analytics and the adoption of AI in education. The integration of predictive modeling, engagement clustering, and LLM-generated interventions aligns with principles of SRL, where timely feedback and actionable insights enhance students' planning, monitoring, and help-seeking behaviors. The behavioral patterns identified in the engagement clusters also correspond with the multidimensional model of student engagement. Furthermore, the results of the technology acceptance evaluation support and extend TAM literature by demonstrating that educators' PU and ease of use remain strong predictors of adoption even in systems augmented by AI-generated recommendations. These findings suggest that traditional technology-adoption theories remain relevant but require expansion to incorporate constructs related to AI trust, transparency, and pedagogical alignment.

## 4. CONCLUSION

The study concluded that random forest is the most effective supervised machine learning algorithm for predicting student performance using Moodle course logs as the training data. The random forest performed best in terms of accuracy, sensitivity, specificity, and ROC-AUC performance metrics compared to XGBoost and decision tree in k-fold cross-validation with hyperparameter tuning. Applying the k-means algorithm in the study enabled the clustering of students' engagement levels based on their Moodle course logs. The unsupervised machine learning classified students as either consistent or sporadic learners based on their engagement. The study developed an AI-powered dashboard by integrating supervised and unsupervised machine learning models into a web-based progressive application using the Shiny framework. An LLM was also incorporated as an added feature that recommends personalized intervention strategies. The faculty respondents rated the AI-powered dashboard very high on usefulness and ease of use, suggesting a potential high level of technology acceptability. The AI-powered LMS-based learning analytics dashboard provides an application for addressing the challenges educators face in monitoring students' performance and engagement in online environments.

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This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

| Name of Author | C | M | So | Va | Fo | I | R | D | O | E | Vi | Su | P | Fu |
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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

## CONFLICT OF INTEREST STATEMENT

The authors have no conflicting interests related to this study.

## DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author (JKBR) upon reasonable request.

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