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Evaluation of the Recommender and Predictive Algorithm in Learning Management System

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This study evaluates the accuracy of a predictive algorithm and the effectiveness of a recommender system integrated into a Learning Management System (LMS). The LMS was used by 387 second-year Information Technology students taking Object-Oriented Programming. The model utilized demographic and academic data—such as age, gender, class schedule, and previous programming grades—as predictors to forecast student performance. Students identified as at-risk of failing were divided into two groups: one receiving targeted content recommendations from the LMS, while the other received no intervention. The study measured the model's performance through a confusion matrix, showing an accuracy of 86% and a kappa value of 0.61, reflecting substantial agreement between predicted and actual outcomes. Furthermore, an independent t-test revealed a statistically significant improvement ($p = 0.002$) in the final grades of students who received recommendations, with an average increase of 2.01 points compared to those who did not. The findings highlight the practical benefits of integrating predictive analytics and personalized learning interventions into LMS platforms. The study underscores the system's ability to provide meaningful support to at-risk students, improve performance, and reduce variability in academic outcomes. Future work will focus on refining the algorithm to better identify failure risks and optimize the distribution of educational resources.
Keywords: learning management system, prediction model, recommender system, educational data mining, analytic model evaluation.

1. Introduction

The incorporation of technology in education has resulted in a substantial paradigm change in the learning process. Historically, the responsibility of knowledge transfer was exclusively on teachers, who acted as the primary source of information, while students remained passive recipients (Byers et al., 2018). This dynamic has transformed; education now surpasses the limitations of the classroom, with extensive learning material accessible at any time and anywhere. As a result, students have assumed active roles in their education, positioning themselves at the core of the learning process, while teachers have evolved into facilitators and evaluators (Sailer et al., 2021).

This transformation highlights a shift from a teacher-centered model to a student-centered approach that prioritizes the "needs, skills, and interests" of individual learners. This method has demonstrated greater effectiveness and sustainability; however, it poses additional challenges for instructors (Groos et al., 2021). Educators are now responsible for cultivating interactive learning environments that promote autonomous learning and discovery (Hockings et al., 2018; Zhang et al., 2018). They are also anticipated to expand learning beyond conventional limitations of time and space by utilizing technology to provide instructional resources.

The growing dependence on technology-driven resources and online services in educational institutions, especially in universities and colleges globally, signifies a notable transformation in instructional delivery. Information and communications technology has emerged as a crucial instrument in contemporary education (Karatza, 2019). The worldwide health crisis induced by the COVID-19 pandemic has expedited this transformation, radically changing education and leading to the consensus that schooling "will never be the same again" (Bleske, 2020; Legg, 2020). The academic sphere, alongside diverse corporate and governmental sectors, has adjusted to a "new normal," requiring modifications in operations and procedures to survive the post-pandemic landscape (Eberstadt, 2020).

In this changing environment, Learning Management Systems (LMS) have become essential instruments that facilitate collaboration and knowledge growth. Multiple studies have evidenced the advantages of LMS, such as heightened student engagement, improved collaboration, adaptability in instructional methods, streamlined tracking and reporting of student data, centralized information management, and facilitated evaluation processes. The benefits are especially evident in underdeveloped nations (Hetsevich, n.d.; Top 5 LMS Benefits for Students Infographic, e-Learning Infographics, 2019; Owen et al., 2017).

Recently, the capacity to deliver personalized learning experiences has emerged as an added advantage of LMS. This personalized learning allows the LMS to suggest resources customized to each student's proficiency, prior knowledge, current abilities, learning preferences, and requirements. This is achieved by the integration of Recommendation Systems or RS (Kurniadi et al., 2019; Imran et al., 2016; Syed et al., 2017). Recommendation systems are algorithms developed to forecast a user’s or learner’s future preferences based on a collection of available materials, thus improving the educational experience by rendering it more customized and personalized.

In 2016, the researcher conducted the first phase of this study. The initial phase successfully developed an LMS with a prediction model and course-content recommendation module to enhance the learning process for students, particularly those enrolled in a Java Programming course. The primary aim was to address the diverse needs of learners by leveraging educational data mining to predict student performance and offer personalized recommendations based on their predicted outcomes, learning styles, and prior knowledge. The system's analytics model was developed using the Fayyad knowledge discovery process for data mining and the evolutionary prototyping method for system development. The five-year historical data (2010–2015) of students in Java programming was analyzed, and the J48 decision tree algorithm emerged as the best predictor for students' performance, particularly based on attributes such as age, gender, class schedule, and grades in previous programming courses. The results showed a prediction accuracy of 93%, validating the effectiveness of the LMS in identifying students likely to pass or fail. Moreover, the system generated personalized recommendations to help students focus on weak areas in Java programming, improving their overall learning outcomes (Evale, 2016).

The researcher performed a pilot implementation of that LMS with a prediction model and course-content recommendation module for selected sections of students taking a Java programming subject at the College of Information and Communications Technology at Bulacan State University. The system has been used for two years but hasn't been subjected to any actual evaluation process. Evaluation is vital to implementing any electronic learning platform to ensure quality assurance; we can measure its significant impact and implications for the learners (Zlatkovic et al., 2019). Various approaches can be used to evaluate LMS; most of the studies conducted aimed to evaluate the technical aspects or functionalities and usability of the system; however, assessing the effectiveness and user satisfaction towards the system is also of equal importance (Daniela et al., 2021). In machine learning technologies, evaluating the success and failure of recommendations generated by a recommender system is a challenging task (Silveira et al., 2019). However, it is the only way to measure the validity of its performance.

Therefore, now that enough data has been collected, the researcher wishes to evaluate the performance of the two primary components of the implemented LMS – the recommender system and the prediction model.

2. Methodologies

Data Collection

Data for this research was gathered from the LMS used by 387 second-year Bachelor of Science in Information Technology students taking Object-Oriented Programming. The LMS, with an integrated analytics model for predicting students' performance, stored relevant student demographic data (age, gender, class schedule, location), previous academic records (grades in three prior programming courses), and an index of learning style. Data was collected over two academic years (2016-2018). Those data were used to determine the actual accuracy of the prediction algorithm and the effectiveness of the recommender system.

Using the LMS, all students were first asked to take a standardized assessment from Dr. Richard Felder, a Professor Emeritus from North Carolina State University, to identify their Index of Learning Style (ILS). Right after the ILS evaluation, students can get feedback about their learning style.

Afterward, they took a multiple-choice pre-test about Java programming topics. Based on the results of their exam, in combination with their demographic and academic profile, the system can predict whether they would pass or fail in the subject. The result of the exam is only visible on the teacher's screen to avoid discouragement of the students who were predicted to have a high probability of failing. Finally, 50 percent of the students who were predicted to fail were randomly selected to take recommendations (intervention) from the LMS on what specific programming topics they should focus on and how they should study based on their index of learning style in order to increase the probability of passing the subject at the end of the semester. This group is called the Intervention Group in this study.

Data Preparation

Since all significant predictors of performance are mandatory requirements upon registration in the system, there have been no problems in handling missing values. No duplicate records were also generated due to the presence of a unique student identification number, which is also required from the users. The system also ensured the consistency of data formats to avoid non-standard inputs.

Should there be outliers in the datasets, capping will be used, but no outliers were detected upon visualization of data using a boxplot.

Statistical Treatment

The researcher utilized several statistical methods to assess the precision of the prediction model and the efficacy of the recommender system incorporated within the LMS.

Confusion Matrix

A confusion matrix was created to evaluate the efficacy of the predictive model. This matrix encompassed four metrics essential to assess the model's accuracy, precision, recall (sensitivity), and specificity, which are all significant indicators of the model's dependability.

Independent T-Test

An independent t-test was performed to compare the performance of students who receive recommendations via the LMS with those who do not. This test will ascertain whether a statistically significant difference exists in the final grades between the two groups. The p-value will ascertain the importance of the results, with a threshold established at 0.05.

Levene's Test for Equality of Variances

Levene's test was utilized to assess the assumption of homogeneity of variances between the two groups (with and without intervention).

Descriptive Statistics

Means and standard deviations were computed to determine the general performance of students in both groups. The histograms and boxplots will visually show the grade distributions, facilitating a straightforward comparison of variability and core tendencies among the groups.

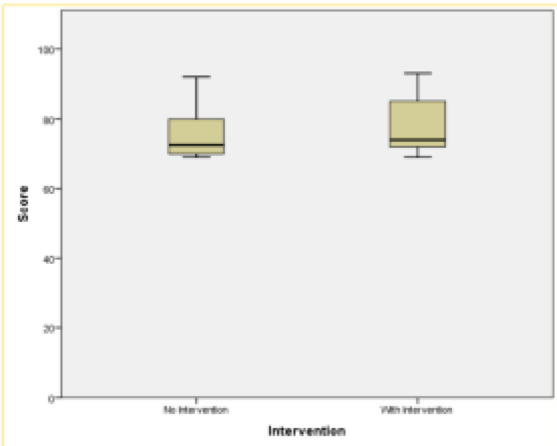
3. Results and Discussion

Effectiveness of the recommendation model

Checking for Outliers

The effectiveness of the recommendation model is illustrated through the box-and-whisker plot shown in Figure 1, which displays the distribution of student grades before and after the implementation of the LMS. The plot reveals a notable improvement in performance, with the intervention group demonstrating a higher median score compared to the no-intervention group. Specifically, students who received tailored recommendations achieved an average grade of 75.67, while the control group averaged 73.66. This significant difference, with a p-value of 0.002, underscores the positive impact of personalized learning interventions on student performance.

Figure 1 Box-And-Whisker Plot Used to Determine the Presence of Outliers in the Dataset



Research supports these findings, indicating that tailored recommendations can lead to improved academic outcomes. For instance, Dwivedi and Roshni (2017) found that collaborative filtering-based recommendation strategies significantly enhanced students' course selections and overall performance. Similarly, Islam et al., 2022 demonstrated that decision-tree-based recommender systems led to marked improvements in student grades, reinforcing the notion that personalized educational interventions can facilitate better learning experiences.

The box-and-whisker plot further indicates reduced variability in grades among the intervention group, as evidenced by a narrower interquartile range (IQR). This suggests that the recommender system not only helped struggling students but also aided higher-performing students in maintaining their success. The moderate standard deviation of 2.584 reflects the model's effectiveness in promoting a more uniform level of achievement, thereby fostering a fairer learning environment.

In a boxplot, outliers are typically depicted as separate points situated beyond the whiskers. The image demonstrates the absence of outliers in both groups, supporting the concept of a uniform data distribution without notable deviations.

Overall, these findings affirm that the recommendation model effectively enhances student performance by guiding learners toward relevant resources tailored to their individual needs.

Comparing the performance of two groups through T-test

The t-test result shows a significant difference between the two groups regarding grade, assuming equal variances. The p-value is 0.002, which is less than the significance level of 0.05. This means we can reject the null hypothesis, which is that the two groups have the same mean grade. T-test was used to compare the final grades of students who received intervention (targeted recommendations) from the LMS versus those who did not. Figure 2 shows the results of the T-test.

Figure 2 T-Test Results Generated From SPSS

T-Test

[DataSet0]

Group Statistics

	Intervention	N	Mean	Std. Deviation	Std. Error Mean
Grade	without intervention	35	73.66	2.363	.399
	with intervention	27	75.67	2.448	.471

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Grade	Equal variances assumed	.140	.709	-3.268	60	.002	-2.010	.615	-3.240	-.779
	Equal variances not assumed			-3.252	55.042	.002	-2.010	.618	-3.246	-.771

A p-value of 0.002 indicates a statistically significant difference between the two groups, with the intervention group achieving a higher average score. This finding aligns with Dwivedi and Roshni (2017), who found that collaborative filtering-based recommendation strategies enhanced student course choices. The recommender system in the present study effectively guided students toward improved performance. The average grade difference of 2.01 points shows that students who received the intervention obtained higher grades than those who did not. This result is consistent with Islam et al. (2022), who demonstrated that decision-tree-based recommender systems significantly improved student grades, thereby supporting the practical benefits of integrating predictive analytics with personalized recommendations in LMS.

The 95% confidence interval for the difference in averages ranges from -3.240 to -0.779, suggesting the likely range of the actual difference between the two groups. The t-test results confirm that the recommendations provided by the LMS, based on individual student performance, significantly enhanced the students' final grades. Specifically, the average grade for students who received the intervention was 75.67, compared to an average of 73.66 for those who did not. The statistically significant p-value (0.002) indicates that the grade disparity is unlikely to be due to random chance, with the intervention group achieving an average score 2.01 points higher than the control group.

However, despite the statistically significant difference, the intervention's effect size of 2.01 points is relatively low. While this improvement might seem minimal, it is critical for students on the cusp of passing or failing, where even a slight enhancement in performance can mean the difference between success and failure. For students whose final grades are just below the passing criteria, the tailored suggestions from the LMS could provide the necessary support to achieve a passing grade. The implications of successfully completing a course are significant, as it prevents the need for retakes—saving time and costs—and improves a student's overall academic progress and retention.

For borderline students, the incremental improvement offered by the LMS may be vital for sustaining progress toward graduation. Although a 2.01-point increase may appear insignificant in isolation, its cumulative impact across multiple courses or an entire academic career can be substantial. Students who consistently receive targeted recommendations might experience significant incremental improvements, enhancing their overall general average and increasing their chances for scholarships, internships, or honors programs.

In various educational settings, especially at the university level, students who fail essential courses early in their academic journey are more likely to withdraw or disengage from their studies. The LMS can enhance student retention, particularly for those at risk of dropping out, by providing a modest yet statistically significant improvement in academic performance. A small intervention can prevent academic failure from escalating into broader educational disengagement.

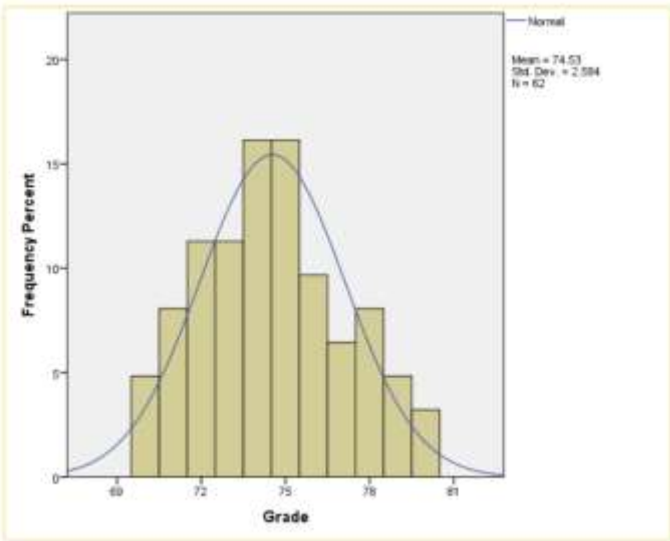
Variability and Reliability

Levene's test for equality of variances was conducted to assess the variability of student performance and the reliability of the predictive model. The results yielded a p-value of 0.709, indicating that the assumption of equal variances is valid for this dataset. This finding enhances the reliability of subsequent statistical analyses, including the t-test, by confirming that any observed differences in means are attributable to the intervention rather than inherent variability in student performance.

Levene’s test is particularly significant in educational research as it helps ensure that the assumptions underlying many parametric tests, such as the t-test, are met. According to studies by Nordstokke et al. (2019) and Chukwudi et al. (2019), violating the assumption of equal variances can lead to inaccurate conclusions regarding the effectiveness of educational interventions. Furthermore, research by Ishwaran and Lu (2019) emphasizes the necessity of conducting variance tests to validate the robustness of statistical findings, particularly in contexts involving diverse student populations.

Recognizing the function of the histogram for illustrating distributions of data (Cooper, 2018), it was used to present the distribution of student grades following the implementation of the LMS. As shown in Figure 3, there is a normal distribution centered around a mean grade of 74.53 and a standard deviation of 2.584. This bell-shaped curve indicates that most students scored near the mean, with fewer achieving scores at the extremes. Such a distribution aligns with anticipated outcomes in educational environments, where performance typically exhibits symmetry.

Figure 3 T-Test Results Generated From SPSS



The close aggregation of grades in the 73–76 range suggests that the recommender system integrated into the LMS effectively enhanced or maintained student performance. By directing students toward relevant topics through tailored recommendations from predictive algorithms, the system likely assisted lower-performing students while enabling higher performers to sustain or elevate their achievements.

The limited grade range (approximately 69 to 81) illustrates the LMS's contribution to stabilizing student performance and reducing extreme outcomes. Most students scored near the mean, while fewer received exceptionally low or high marks. The LMS's interventions promoted uniformity, ensuring that performance levels remained comparable across the student population.

Low performers, typically vulnerable to failure, often fell within the 69-72 grade range. The clustering of grades toward the mean and the lack of significant outliers suggest that the LMS positively influenced these underperforming students through individualized recommendations, enhancing their grades and preventing failures.

Overall, the LMS's effectiveness as an early intervention tool underscores its potential to support various student groups while contributing to a more equitable academic environment. Future enhancements could focus on advanced modules for high-achieving students to further enrich their educational experience.

Measuring Accuracy of the Predictive Model Through Confusion Matrix

The confusion matrix, as cited by Amin and Mahmoud (2022), provides essential insights into the performance of the predictive model by categorizing predictions as True Positives (TP), True Negatives TN), False Positives (FP), and False Negatives (FN). While TP and TN are accurate predictions FP and FN represent errors that need to be minimized to optimize the model.

The confusion matrix presented in Table 1 is an evaluation of the predictive accuracy of the LMS integrated with a predictive algorithm. It compares the predicted outcomes of student performance (pass or fail) as determined by the model with the actual results of the students. This analysis provides insights into how effectively the model was able to predict student success or failure in the course.

Table 1. Confusion Matrix Showing the Values of the Actual and Predicted Data

		ACTUAL	
		PASSED	FAILED
PREDICTED	Passed	271	25
	Failed	29	62

Key Metrics from the Confusion Matrix

The model accurately forecasted that 271 students would pass, and they did (True Positive). This denotes the students whom the model projected would pass and who subsequently did pass their course. The methodology accurately identified these students as self-assured for success without the need for further assistance. This group illustrates the algorithm's predictive capability in recognizing students who are inclined to succeed independently.

On the other hand, the model accurately forecasted that 62 students would fail, and they did fail (True Negatives). These students may be classified as the "at-risk" demographic that should benefit from educational intervention. Thus, among this group are the students who were given recommendations. Recognizing True Negatives is essential for early warning systems in education.

Twenty-five students were forecasted to succeed but ultimately did not (False Positives). These are erroneous forecasts in which the model overstated its performance. Identifying false positives is significant, as it may lead to overlooked possibilities for assistance. Due to the inaccurate prediction of their success, these students did not obtain the necessary assistance, resulting in potential failure.

Lastly, there are 29 students who were forecasted to fail but ultimately passed (False Negatives). These are erroneous predictions, too, in which the model undervalued their performance. False negatives, although less concerning than false positives, signify excessive involvement. These students have received unnecessary additional resources or attention, resulting in resource misallocation. This may not be as crucial as offering further assistance to students who ultimately achieve is improbable to detriment their educational experience. Nonetheless, enhancing the system in the future to minimize False Negatives could further optimize resource allocation and enable instructors to concentrate on students who genuinely require assistance.

Balancing false positives and false negatives is essential due to the differing implications of these errors in practice. In education, false positives are typically more alarming, as they entail neglecting students in need of assistance, while false negatives result in excessive involvement without necessarily adversely affecting student outcomes.

Evaluation of Model Accuracy

The confusion matrix provides a basis for calculating key metrics related to the model's performance, such as accuracy, precision, recall, and specificity.

Accuracy: It is the overall proportion of correct predictions (both TP and TN) to the total number of predictions.

The accuracy of the predictive model was calculated using the following formula:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{FP} + \text{FN} + \text{TP} + \text{TN}}$$

For this study, the formula was applied as follows:

$$\text{Accuracy} = \frac{271 + 62}{271 + 62 + 25 + 29} = \frac{333}{387} \approx 0.86$$

The model exhibits an accuracy of 86%, signifying that the algorithm effectively predicts student outcomes with considerable reliability. Alsariera et al. (2022) documented the same results, indicating that neural networks attained equivalent accuracy rates, hence reinforcing the efficacy of predictive algorithms in detecting at-risk students.

Precision: It is the proportion of true positive predictions (students predicted to pass who actually passed) to the total number of positive predictions made (both TP and FP).

The Precision of the predictive model was calculated using the following formula:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

The same formula was applied to get the precision of the model, the result is shown below:

$$\text{Precision} = \frac{271}{271 + 25} = \frac{271}{296} \approx 0.916$$

The precision rate identified in this study corresponds with Li & Liu (2021), who emphasize the necessity for accurate predictions to prevent excessive intervention in students at risk. The accuracy of 91.6% indicates that when the model forecasts a student's success, it is true in most instances, resulting in fewer false positives. The model accurately predicts a student's passing status 91.6% of the time.

Recall: It is also known as sensitivity, it is the proportion of true positive predictions to the total number of actual positives or the students who actually passed.

The Recall of the predictive model was calculated using the following formula:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

To calculate the recall in this study, the formula was applied as shown below:

$$\text{Recall} = \frac{271}{271 + 29} = \frac{271}{300} \approx 0.903$$

In accordance with Alsariera et al. (2022), this study similarly concludes that attaining elevated sensitivity while preserving enough specificity is essential for recognizing both successful and at-risk students. The recall of 90.3% indicates that the model effectively identifies students likely to pass. However, it overlooks a small segment of students who may pass but are expected to fail. A high sensitivity rate indicates that the LMS can accurately identify students who will succeed academically, allowing instructors to concentrate on those students truly at risk.

Specificity: This is the proportion of true negative predictions to the total number of actual negatives or those students who actually failed.

The Specificity of the predictive model was calculated using the following formula:

$$\text{Specificity } = \frac{\text{TN}}{\text{TN} + \text{FN}}$$

The above formula was used to compute the Specificity of the model in this study:

$$\text{Specificity } = \frac{62}{62 + 25} = \frac{62}{87} \approx 0.713$$

The model's specificity of 71.3% indicates effectiveness in predicting student failure, though it does produce some false positives by inaccurately forecasting passing students as failing. While the specificity is acceptable, there is room for improvement in identifying students truly at risk of failure. Enhancing specificity would allow the system to better target those needing interventions like tutoring or individualized feedback, reducing unnecessary over-intervention.

Achieving a balance between sensitivity and specificity is crucial; refining the predictive algorithm to harmonize these aspects could lead to better early detection and support, ultimately improving student outcomes.

4. Conclusion

This research highlights the significant impact of predictive algorithms and recommender systems integrated into LMS on enhancing student performance and academic outcomes. The study shows that the LMS effectively meets students' learning needs by using educational data to predict success or failure and deliver personalized recommendations.

The predictive model within the LMS demonstrated high accuracy, correctly identifying 86% of student outcomes. This precision emphasizes the ability of machine learning models to facilitate timely interventions, with a recall rate of 91.6% for students predicted to pass. The recommender system has proven effective in providing tailored support to at-risk students, resulting in a statistically significant grade improvement ($p = 0.002$) with an average increase of 2.01 points. This enhancement, though modest, can be crucial for students near the passing threshold, where even slight gains can determine academic success.

The study also reveals that the LMS promotes a more equitable learning environment by reducing performance disparities and stabilizing student outcomes. While the model successfully predicts achievement, the presence of false positives indicates a need for refinement in identifying students at risk of failure.

In conclusion, the integration of predictive analytics and recommender systems in LMS platforms serves as a powerful tool for improving student performance and fostering academic equity. As educational institutions adopt these technologies, further refinement will enhance support for diverse student populations, ensuring that all learners can achieve their full potential.

5. Recommendations

1. Augment the Dataset for Enhanced Generalizability

To enhance generalizability, the dataset should include students from diverse academic levels, disciplines, and institutions. This will facilitate identifying varied patterns and predictors across different educational environments, strengthening the prediction model.

2. Integrate Supplementary Predictive Variables

Incorporating additional intrinsic variables such as motivation, cognitive abilities, self-efficacy, attendance, and social factors like peer connections will provide a more comprehensive understanding of determinants affecting student performance. This may enhance model precision and minimize false positives and negatives.

3. Evaluate Various Machine Learning Algorithms

Assessing different machine learning algorithms, including Random Forest, Gradient Boosting, and Neural Networks, will help determine the most effective method for improving accuracy, specificity, and recall in predicting student outcomes and optimizing recommendations.

4. Improve the Recommender System for High-Achieving Students

Developing advanced modules for high-achieving students will ensure the recommender system accommodates all performance levels. Enhancements should provide enrichment activities to promote ongoing advancement for every student.

5. Conduct Longitudinal Studies to Assess Long-Term Effects

Implementing longitudinal studies will evaluate the lasting effects of LMS interventions on academic achievement and retention rates, clarifying the influence of sustained LMS use on student performance and motivation.

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Declaration of interest

There are no perceived conflicts of interest for all authors.

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Author contribution statement

Digna Evale performed data preparation and analysis, while Reylan Evale performed the installation of the LMS in the networked environment and facilitated data collection. Both have equal contributions in writing the paper.

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