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Mathematical Modeling and Integration of Machine Learning-Based Prediction System on E-Learning Platform to Improve Students' Academic Performance

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ABSTRACT

The purpose of this study was to develop and integrate a student academic performance prediction system into an e-learning platform using a mathematical modelling approach combined with machine learning algorithms. The method employed was Research and Development (R&D), encompassing stages of needs analysis, mathematical modelling, development of a machine learning-based prediction system, and implementation and evaluation. The study was conducted at Duta Bangsa University, Surakarta, involving 100 students from the Informatics Engineering study program. Data were collected through the e-learning platform, covering student activity logs such as access frequency, quiz scores, assignment completion time, and forum participation. This behavioral data was then analyzed using supervised learning algorithms, namely logistic regression and decision tree, to build a predictive model for academic performance. The resulting predictive system was integrated into the e-learning platform to deliver risk notifications and adaptive learning material recommendations automatically. To measure the improvement in academic performance, a validated academic achievement test was administered as both a pre-test and a post-test to the experimental group. This test consisted of multiple-choice and short-answer items aligned with the course learning objectives. The results showed that the decision tree model achieved a prediction accuracy of 87.4%, while logistic regression reached 81.2%. Evaluation of the system's effectiveness using the pre-test and post-test scores revealed a significant increase in students' academic performance. Statistical analysis with a paired t-test yielded a significance level of $p < 0.001$, indicating that the adaptive prediction system effectively supports more personalized and impactful learning. This study contributes to the advancement of machine learning-based prediction systems in e-learning by designing and implementing a model that leverages real student activity data. The system enables early detection of academic risks and provides automated, adaptive content recommendations, thus fostering personalized and data-driven learning in higher education. Its practical implementation helps students identify learning weaknesses promptly and receive appropriate supporting materials immediately, promoting proactive and self-regulated learning behavior.

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A. INTRODUCTION

The development of information technology has brought significant impacts across various sectors of life, including higher education. One of the most notable changes is the adoption of online learning systems, or e-learning, as both an alternative and a complement to face-to-face learning. This trend has intensified in the post-COVID-19 era, when distance learning became the primary choice to maintain academic continuity. E-learning enables students to access learning materials anytime and anywhere, thereby increasing the flexibility and accessibility of education in the digital age (Miraz et al., 2018). In line with this, national data shows that the use of e-learning platforms has increased significantly. According to Kurniawan (2019) in (Ruzakki et al., 2024) e-learning has become an essential part of the transformation of higher education in Indonesia. A survey conducted by Wati & Indriyanti (2021) reinforces this finding, showing that e-learning ranks highest in the implementation of distance learning (PJJ) with a usage rate of 26.1%, followed by platforms such as Ruangguru (17.1%) and Rumah Belajar (15.2%).

However, the increasing use of e-learning also brings new challenges. One of the main challenges is the system's limitation in understanding and adapting to each student's individual learning needs. Static e-learning systems often fail to provide timely and adaptive learning interventions, which can ultimately lead to a decline in students' academic performance (Rehman & Butt, 2021). To address these limitations, Artificial Intelligence (AI)-based approaches, particularly predictive systems using machine learning algorithms, offer a promising solution. Machine learning algorithms can leverage student activity data such as access frequency, quiz scores, and participation in discussion forums to build predictive models that can identify academic risks early and provide personalized and adaptive learning recommendations (Deeva et al., 2022).

Support for the effectiveness of this approach is found in the study by Paramita & Tjahjono (2021), which shows that the k-Nearest Neighbors (k-NN) algorithm performs well in processing clearly structured data patterns. However, in the context of more complex data, the Artificial Neural Network (ANN) algorithm has proven to yield more accurate predictions. These findings highlight the importance of selecting machine learning algorithms that are suited to the characteristics of the data. Recent research by Ahmad et al. (2025) also demonstrated that combining decision trees with ensemble techniques, such as Random Forest, can improve prediction robustness in educational data analytics. Similarly, Ghaddar & Naoum (2018) found that Support Vector Machine (SVM) outperformed simple classifiers when dealing with high-dimensional student behavior data.

Nnadi et al. (2024) emphasized that model interpretability must be balanced with prediction accuracy to ensure the results are actionable for instructors and learners alike. A study by (Mu et al., 2022) showed that hybrid models combining multiple algorithms can adapt better to diverse learning behavior patterns. Recent work by Lin et al. (2023) reinforces that algorithm selection and feature engineering play crucial roles in achieving high accuracy and relevant recommendations in intelligent tutoring systems. Furthermore, the implementation of predictive algorithms can be strengthened through mathematical modelling, such as predictive function formulation and statistical analysis, to ensure the validity and reliability of the developed model.

With this approach, predictive systems are not only computationally accurate but also built on a strong theoretical foundation in applied mathematics. Based on this background, the research problem formulated in this study is: How can a mathematical model and machine learning-based predictive system be developed and integrated directly into an e-learning platform to improve students' academic performance? To answer this question, this study adopts a Research and Development (R&D) approach, which includes several stages: user needs analysis, mathematical model design, development and implementation of the machine learning-based predictive system (Dimyati, 2022), and integration of the system into the e-learning platform. The system's effectiveness is then evaluated through pre-test and post-test assessments of students participating in the study.

Although some previous studies have applied machine learning to predict students' academic performance, most have remained exploratory and have not been directly integrated into actively used campus e-learning platforms. Research by Yağcı (2022) emphasizes that ensemble learning models achieve higher accuracy compared to single algorithms. Meanwhile, Chen et al. (2025) demonstrate that machine learning is useful not only for predicting academic performance but also for assessing learning engagement and student self-efficacy. However, studies that combine computational approaches, mathematical modeling, and real-world implementation within e-learning platforms in Indonesia are still very limited.

Thus, the novelty of this research lies in the integration of mathematical modelling and machine learning-based predictive systems directly into the e-learning platforms used by students, as well as the use of actual activity data to generate automatically adaptive learning recommendations. This approach is expected to not only improve the quality of online learning but also support more accurate, data-driven academic decision-making. However, research that actually integrates mathematical models and machine learning algorithms into campus e-learning platforms in Indonesia is still rare. Thus, this study offers a new approach in the form of combining mathematical modelling and machine learning that is directly integrated into the e-learning platform, to detect academic risks early and provide adaptive material recommendations. This is expected to improve the quality of online learning and support more accurate academic decision-making.

B. METHODS

This study uses a Research and Development (R&D) approach to design, build, and integrate an academic performance prediction system based on machine learning algorithms into an e-learning platform. This approach was chosen because it supports a gradual system development process, iterative validation, and direct application in real educational environments (Pugu et al., 2024). In addition, mathematical modelling is applied as a theoretical framework to ensure system reliability (Farida et al., 2020). Figure 1 shows the research flow diagram.

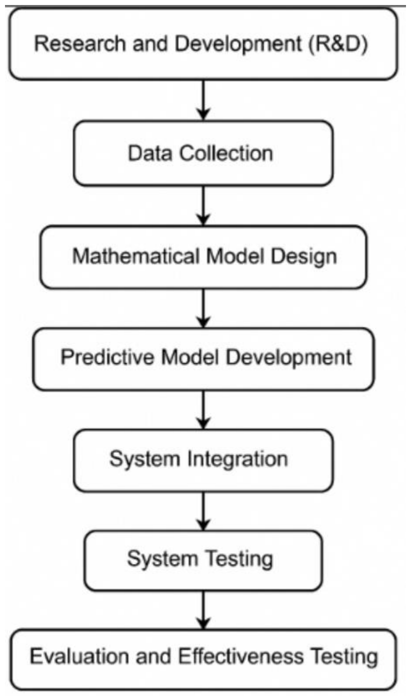

Figure 1. Research method flowchart

The research was conducted in several main stages of R&D as follows:

1. **Needs Analysis**

The purpose of this stage is to deeply understand student learning patterns and system requirements. Data were collected through student activity logs on the e-learning platform (frequency of access, quiz scores, forum participation, assignment completion time), interviews with students and lecturers to identify feature needs, and observations of the online learning process. Qualitative data from interviews and observations were analysed thematically to formulate functional specifications for the prediction system.

2. **Theoretical Model Design and Mathematical Modelling**

This stage aims to build a conceptual model that connects activity variables with academic performance. Numerical data is processed through descriptive and correlational statistical analysis to see the relationship between variables. The prediction model is formulated in the form of a regression function and a decision tree that is adjusted to the characteristics of student data.

3. **Development of a Prediction System Based on Machine Learning**

The predictive model was developed using the Logistic Regression and Decision Tree algorithms (CHEN et al., 2020). The student activity log dataset (n = 100) was divided into training and testing data. Model validation was carried out using the cross-validation method to minimize the risk of overfitting. The performance of each model was measured based on accuracy, precision, and recall.

4. System Integration into the E-Learning Platform

The trained prediction model was implemented through the Application Programming Interface (API) using Python and the Flask framework (Chan et al., 2019). The system was integrated into the campus e-learning dashboard to support automatic academic risk notifications and adaptive material recommendations.

5. System Testing and Reliability Validation

Testing was conducted in two stages: (a) Functionality testing, to ensure that each system feature runs according to design, including validation of data input flow, prediction processing, and recommendation output and (b) User testing, involving students and lecturers to assess ease of use, system speed, and relevance of recommendation results. User feedback was used to improve the interface and integration flow.

6. System Effectiveness Evaluation

To assess the impact of system, use on academic performance, a pre-test and post-test design was conducted on the experimental group. The test results were analysed using a paired t-test, with a significance level of $p < 0.001$, indicating a significant difference between the values before and after using the prediction system. This evaluation proves the effectiveness of system integration in supporting more adaptive and data-driven learning.

C. RESULT AND DISCUSSION

1. Predictive Model Development Results

The training phase involved the application of two well-known supervised learning techniques, namely Logistic Regression and Decision Tree, to analyse activity log data collected from a sample of 100 active students. Logistic Regression, being a parametric method, is appropriate for situations where the target variable is binary; however, it relies on the assumption of a linear link between the predictors and the log-odds of the outcome (Hosmer et al., 2013). In contrast, Decision Trees do not depend on such linearity assumptions and are inherently capable of modelling complex, non-linear relationships and hierarchical data structures, which is particularly beneficial for representing the diverse and often unpredictable patterns in student learning behavior (Zhang, 2021).

To ensure that the models captured meaningful patterns, relevant features such as how often students accessed the platform, their quiz scores, participation in discussion forums, and task completion times were included as input variables. These attributes have been highlighted in previous research Romero & Ventura (2020) as influential factors in predicting students' online academic success. Selecting Logistic Regression and Decision Tree was therefore a deliberate choice to balance transparency and practical use: Logistic Regression produces interpretable coefficients that help educators grasp general behavioral trends, while Decision Trees generate decision rules that can explain individual predictions in a straightforward manner, which is essential for delivering personalized feedback to learners.

Furthermore, the models were assessed based on prediction accuracy, aligning with performance indicators reported in related works (Wang et al., 2021). The evaluation results demonstrated that the Decision Tree outperformed Logistic Regression, achieving an accuracy of 87.4% compared to 81.2%. This difference of 6.2 percentage points underscores the Decision Tree's effectiveness in uncovering intricate interdependencies among behavioral variables. These findings reinforce previous evidence by (Injadat et al., 2020) that tree-based approaches frequently yield superior predictive performance when dealing with the complexity inherent in educational data. The comparison is presented in Table 1.

Table 1. Predictive Model Accuracy

Algorithm	Accuracy (%)
Decision Tree	87.4
Logistic Regression	81.2

The superior performance of the Decision Tree implies that students' learning behaviors exhibit non-linear and conditional dependencies for example, high forum participation may offset low quiz scores for some students but not for others. Such nuanced patterns are not well captured by a linear boundary, validating the choice of using tree-based models in this context. Future iterations could explore ensemble methods like Random Forests or Gradient Boosting, as suggested by Wang et al. (2021), which could further enhance prediction robustness and mitigate overfitting.

2. System Integration Results

The predictive models were embedded into the campus's e-learning platform via a Python-based API using the Flask framework, enabling real-time functionalities such as Academic risk alerts: Automatically notifying students and instructors when performance falls below model-derived thresholds. Adaptive material recommendations: Providing learning resources tailored to individual performance patterns. This approach operationalizes the concept of learning analytics intervention cycles (Chatti et al., 2012), where insights from predictive models directly inform pedagogical action. Initial system trials confirmed that students and instructors received timely alerts, promoting proactive learning management. This aligns with previous implementations like Auto Remind (Chatterjee et al., 2025) and early warning systems by (CHEN et al., 2020), which demonstrate that immediate, personalized feedback increases student engagement and fosters timely academic support.

3. System Effectiveness Evaluation

Effectiveness was assessed through an experiment involving 50 students, using a pre-test/post-test design. The average score increased from 68.3 (pre-test) to 79.6 (post-test), an 11.3-point gain, which is statistically significant ($p < 0.001$, $t = 15.37$). This significant improvement indicates that integrating predictive analytics and adaptive recommendations can meaningfully enhance students' academic outcomes, as shown in Table 2.

Table 2. Average Pre-test and Post-test Scores (Experimental Group)

Phase	Average Score
Pre-test	68.3
Post-test	79.6

To test the effectiveness of the developed system, a trial was conducted on 50 students in the experimental group using a pre-test and post-test design. The average pre-test score of students was 68.3, while the average post-test score after using the predictive system increased to 79.6, indicating an increase of 11.3 points. Statistical analysis using paired t-test showed that the increase was statistically significant. With a standard deviation of 5.2 and a sample size of 50 students, a t-value of 15.37 was obtained with a significance value of $p < 0.001$.

This result corroborates prior research Marienko et al. (2020) that personalized and adaptive learning systems improve not only academic performance but also students' metacognitive awareness and engagement. Notably, this study extends the literature by providing empirical evidence for such improvements within the specific context of a locally developed e-learning platform integrated with real-time predictive analytics. This study demonstrates a clear link between robust predictive model development and improved student performance, supported by a technically justified choice of algorithms and real-time system integration. By critically evaluating limitations and outlining concrete future steps, it provides a solid foundation for scalable, adaptive e-learning solutions grounded in learning analytics best practices.

4. Discussion

The results of this study demonstrate that the integration of mathematical modelling and machine learning algorithms into an e-learning platform not only represents an advancement in educational technology but also provides strong empirical evidence for the effectiveness of adaptive and personalized learning approaches. Specifically, the predictive system developed was able to classify students into low-, medium-, and high-risk groups with an accuracy of 87.4% for the Decision Tree model, outperforming the Logistic Regression model which achieved 81.2% accuracy. Specifically, the predictive system developed was able to classify students into low-, medium-, and high-risk groups based on predefined threshold values derived from the distribution of predicted probability scores. The categorization was determined using percentile-based cut-off points: students with predicted risk scores below the 33rd percentile was classified as low-risk, those between the 33rd and 66th percentiles as medium-risk, and those above the 66th percentile as high-risk. This percentile approach allows for flexible grouping that adapts to the actual data distribution while ensuring balanced group sizes. Such a method is commonly used in educational predictive analytics to differentiate levels of intervention urgency (Larrabee et al., 2019). This categorization then guides the system to deliver tailored risk alerts and recommend appropriate learning materials aligned with each risk level.

This difference confirms the Decision Tree's superior ability to capture non-linear patterns in diverse behavioral data, in line with (Injadat et al., 2020) who emphasize that tree-based algorithms often outperform linear models in complex educational contexts. The classification process relied on meaningful indicators such as platform access frequency, quiz performance, participation in forums, and punctuality in assignment submission variables widely validated in previous studies Romero & Ventura (2020); Wang et al. (2021) as predictors of academic success. The choice to implement both Logistic Regression and Decision Tree was guided by practical and theoretical considerations: while Logistic Regression offers interpretability of coefficients for general trend analysis, Decision Trees enable rule-based classification that aligns more closely with the need for individualized recommendations. To expand on performance validation, additional metrics such as precision, recall, and F1-score could be incorporated in future iterations to assess not just overall accuracy but also the model's sensitivity in correctly identifying at-risk students. This multi-metric evaluation would provide a more robust assessment of predictive quality, as recommended by (Murtaza et al., 2022).

Beyond mere prediction, the system dynamically generated personalized learning material recommendations tailored to each student's risk group and activity patterns. This real-time feedback loop addresses one of the key weaknesses of traditional e-learning: the lack of individualization. Consistent with (Demertzi & Demertzis, 2020), this study shows that integrating machine learning-driven recommendations significantly enhances students' motivation and learning outcomes. Furthermore, by grounding the recommendation logic in explicit mathematical modeling, the system avoids the typical 'black box' pitfall of AI systems, ensuring that educators can interpret and validate how predictions and recommendations are made (Marienko et al., 2020).

The Research and Development (R&D) framework employed here proved effective in translating theoretical constructs into a functional system. The iterative stages including needs analysis, mathematical model formulation, system prototyping, testing, and real-world deployment facilitated continuous refinement and contextual adjustment. This aligns with Vesin et al. (2018), who stress that user-centered and iterative development processes are crucial for ensuring that educational technology aligns with learner needs and institutional contexts.

However, this study is not without limitations. First, the dataset was limited to activity logs from 100 students within a single institution, which may restrict the generalizability of the predictive model to larger or more diverse student populations. Second, only two algorithms were tested, and although Decision Trees showed strong performance, ensemble techniques such as Random Forests or Gradient Boosting Machines could further improve predictive accuracy and reduce overfitting risks. Third, the system currently focuses mainly on behavioral log data; integrating additional student characteristics, such as demographic or motivational factors, could enhance predictive power.

To strengthen external validity, future research should replicate this study across multiple institutions and student cohorts, test a wider range of algorithms, and evaluate long-term impacts on student learning trajectories. Moreover, engaging teachers and students in co-design processes could help refine the recommendation system to ensure it remains practical, relevant, and trustworthy for daily academic use. In conclusion, this study confirms that combining mathematical modeling with machine learning creates not just a digitized but an intelligent, responsive, and highly personalized e-learning environment. This approach aligns with the global trend toward data-driven and AI-enhanced education, ultimately contributing to the goal of raising learning quality and fostering student success at scale.

The findings of this study are in line with previous research highlighting the advantages of tree-based algorithms for complex educational data (Injadat et al., 2020). The high accuracy of the Decision Tree confirms its strength in handling non-linear student behavior patterns better than linear models like Logistic Regression. Additionally, this study supports (Er-radi et al., 2024), showing that machine learning-driven personalization increases student motivation and engagement. The significant learning gains found here echo (Lim et al., 2023), who also reported improved outcomes with adaptive systems. Unlike prior works relying solely on black-box models, this research integrates explicit mathematical modeling, enhancing transparency and trust (Marienko et al., 2020). Overall, these results validate and expand earlier studies by demonstrating how interpretability and predictive power can be balanced. This evidence underscores the value of carefully selecting algorithms and design strategies suited to educational contexts.

D. CONCLUSION AND SUGGESTIONS

This study provides empirical evidence and a concrete technological innovation by demonstrating that integrating mathematical modeling and supervised machine learning algorithms particularly the Decision Tree can effectively enhance predictive accuracy and personalization in e-learning platforms. The primary scientific contribution lies in developing a data-driven predictive system that reliably identifies students' academic risk levels based on real activity data and translates these insights into targeted, adaptive learning recommendations. The statistically significant improvement in academic performance, verified through paired t-tests, confirms that such data-driven adaptive systems support students' learning awareness, self-regulation, and motivation. The structured Research and Development (R&D) approach ensured theoretical soundness, iterative refinement, and practical integration into the campus's real-time e-learning platform. However, limitations such as a relatively small sample size, single-institution scope, and basic algorithm coverage should be addressed in future research. Expanding to ensemble methods, incorporating motivational and demographic data, and conducting longitudinal evaluations are recommended to strengthen external validity and model resilience. In summary, this study affirms that the strategic combination of mathematical modeling and artificial intelligence can transform conventional e-learning into an intelligent, adaptive, evidence-based learning ecosystem, laying a solid foundation for future academic research and practical innovation in the era of data-driven digital education.

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