

## PAPER

# Predictive Analytics in Mobile Education: Evaluating Logistic Regression, Random Forest, and Gradient Boosting for Course Completion Forecasting

B Herawan Hayadi<sup>1</sup>(✉),  
Taqwa Hariguna<sup>2</sup>

<sup>1</sup>Information Technology  
Education, Faculty of Teacher  
Training and Education,  
Bina Bangsa University,  
Banten, Indonesia

<sup>2</sup>Department of Information  
System and Magister  
Computer Sciences,  
Universitas Amikom  
Purwokerto, Purwokerto  
Utara, Indonesia

[b.herawan.hayadi@gmail.com](mailto:b.herawan.hayadi@gmail.com)

## ABSTRACT

This study aimed to compare the effectiveness of three predictive algorithms—logistic regression, random forest, and GBM—in predicting course completion using user engagement data from online learning platforms. By analyzing engagement metrics such as session duration, session frequency, and quiz scores, the study sought to identify the most effective model for forecasting course completion, providing insights into which aspects of student behavior were most predictive of success. Logistic regression emerged as the best overall performer, achieving the highest accuracy (52.13%) and F1-Score (56.17%), indicating its balanced approach to predicting course completion and non-completion. Random forest and gradient boosting machines (GBM) showed strengths in specific areas; random forest maintained a good balance between precision and recall, while GBM excelled in recall, identifying students likely to complete courses but with lower precision, leading to more false positives. The findings have practical implications for educational technology, particularly in designing personalized learning paths and targeted interventions to support at-risk students. The study also acknowledged limitations, including the dataset's focus on engagement metrics without demographic context and the potential for model-specific biases. Future research should explore additional predictive features, larger datasets, and more advanced algorithms to enhance the robustness and applicability of predictive models in real-time educational settings.

## KEYWORDS

predictive modeling in education, course completion prediction, mobile learning technologies, machine learning models, educational data mining

## 1 INTRODUCTION

Educational technology has quickly changed how we learn by making it easier, more tailored, and based on data. Tools such as educational software, online platforms, and gamification have increased student interest and improved learning results, especially in places with few resources [1], [2]. The COVID-19 pandemic

Hayadi, B.H., Hariguna, T. (2025). Predictive Analytics in Mobile Education: Evaluating Logistic Regression, Random Forest, and Gradient Boosting for Course Completion Forecasting. *International Journal of Interactive Mobile Technologies (IJIM)*, 19(5), pp. 210–232. <https://doi.org/10.3991/ijim.v19i05.52381>

Article submitted 2024-09-28. Revision uploaded 2025-01-08. Final acceptance 2025-01-10.

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further accelerated the adoption of digital learning tools, highlighting their importance for ensuring continuity during disruptions [3], [4], [5]. Data analytics and machine learning have transformed education by studying student behavior, forecasting results, and personalizing experiences. Algorithms such as decision trees and logistic regression help predict grades and dropout rates, leading to adaptive learning environments that enhance motivation and engagement [6], [7], [8], [9]. Mobile learning platforms provide easy access and real-time interaction. They use predictive models to track engagement, such as how long students spend and how often they interact. These models help spot students who might be struggling and offer quick help, improving engagement and supporting different learning styles.

Online learning platforms face challenges such as high dropout rates and inconsistent engagement, which affect learning outcomes. MOOC dropout rates can be as low as 10% due to factors like lack of motivation, poor support, and flawed course design [10], [11]. Inconsistent engagement, spanning behavioral, cognitive, and emotional dimensions, further complicates effectiveness, especially during self-directed learning periods such as the COVID-19 pandemic [12], [13], [14]. Predictive analytics addresses these challenges by enabling data-driven interventions that enhance engagement and retention. By leveraging user interaction data, educators can preemptively identify at-risk students and provide personalized support, such as feedback or adaptive learning paths, to improve course completion rates [15], [16].

Advanced machine learning and predictive modeling are increasingly used to improve decision-making. For instance, random forest regression helps predict the success of animated movies with virtual themes. Structural equation modeling with mediating effects evaluates how people adopt metaverse platforms, providing a detailed understanding of user behavior and costs [17], [18], [19]. Research on decentralized finance in blockchain applications explores its growth and vulnerabilities, complementing studies on decentralized identity management and highlighting blockchains' potential for secure digital identity verification [20], [21]. Machine learning helps predict ad click-through rates in digital marketing using Support Vector Machines, offering insights for better campaigns. MiniBatchKMeans clustering with decision trees is effective for customer segmentation and personalized marketing [22], [23]. Ensemble methods and deep learning have demonstrated machine learning's ability to analyze sentiments in Indonesian hospital reviews and predict congestion [24], [25], [26]. Recent research underscores the pivotal role of online learning environments in higher education, particularly in India and Indonesia, where personalized approaches and accessibility are key to student success [27], [28]. Integrating educational technology tools to enhance learning outcomes is crucial, as evidenced by the significant improvement in students' performance after online lessons [29]. These studies highlight machine learning and predictive models' versatility and impact across diverse fields, emphasizing their relevance to evolving data-driven technologies.

Predictive models are essential for improving educational technology by understanding user behavior. Trust is key in digital adoption, as shown by studies on electronic word-of-mouth, security's role in cryptocurrency purchases, and factors influencing NFT purchase intention through behavioral frameworks [30], [31], [32]. Machine learning techniques such as K-Means clustering have effectively enhanced digital marketing strategies by analyzing engagement patterns [33], [34]. Predictive models are valuable in evaluating consumer perceptions of metaverse shopping and assessing the influence of virtual reality on user engagement, similar to course completion studies in educational settings [35], [36]. Research [37] underscores complex relationships between psychological traits and behavioral outcomes in academic contexts, which aligns with using predictive analytics to identify factors influencing learner success and engagement in online platforms. AI-based models addressing

socio-demographic risk factors and data-driven approaches to sustainable innovation highlight predictive analytics' broad applicability in solving complex problems across diverse domains [38], [39]. The insights from [37] provide a valuable foundation for incorporating behavioral and motivational variables into predictive frameworks, further enhancing the capacity of these models to account for nuanced, human-centered factors in educational technology research. This study uses user engagement data to compare logistic regression, random forest, and gradient boosting machines (GBM) in predicting course completion. It identifies key engagement metrics that impact outcomes. By comparing these algorithms, it provides actionable insights for educational platforms to enhance learning experiences and improve student retention. The findings show the potential of embedding predictive models in mobile learning applications to create adaptive, real-time learning environments for diverse learners.

## 2 LITERATURE REVIEW

### 2.1 Predictive modeling in educational technology

Predictive modeling in education has moved from simple statistical methods to complex machine learning techniques. Early models used linear and logistic regression to find links between student demographics, academic performance, and outcomes. They predicted success based on past grades, attendance, and socio-economic status. Although useful, these models couldn't handle the complexity of non-linear educational data [40]. Traditional statistical models struggled with large and complex datasets. Machine learning improved data handling and interaction modeling using methods such as decision trees, support vector machines, and ensemble models such as random forests and GBM. These algorithms accurately predicted student behavior and performance. Machine learning models are applied to forecast dropout rates, academic performance, and personalized learning paths using real-time data from learning management systems [6], [41]. Machine learning allows educators to make flexible, data-based decisions, meeting students' changing needs. Western research has focused on using predictive analytics in mobile learning settings. For instance, [42] explored how cloud-based technologies facilitate personalized learning through predictive frameworks, offering scalable solutions to support diverse learners. Similarly, [43] examined the evolution of MOOCs, highlighting the critical role of data-driven insights in addressing high dropout rates and enhancing learner engagement. Predictive frameworks from the West must be adjusted for non-Western areas' socio-economic and infrastructural issues. Models focusing on digital metrics might not work well where Internet access is limited or digital literacy is low. They should include factors such as community support and family economic status to be fair and useful in different places. Western predictive analytics for mobile learning offer useful tips for using data effectively. For instance, the scalable cloud-based models discussed by [42] can inform similar applications in developing regions. However, challenges such as low device compatibility and unreliable connectivity necessitate modifications to ensure these models address local needs effectively.

Recent developments in predictive modeling have used deep learning to handle unstructured data such as text, images, and videos. In education, deep learning helps understand student learning habits. It is used for automatic grading and feedback, identifying patterns in video lessons, and suggesting adaptive learning paths. These improvements have made predictive models more accurate and useful in educational settings. Educational technology predictive models use advanced analytics to study student engagement and forecast dropout rates, allowing personalized

learning and tackling issues like student retention and better learning results. For instance, [44] highlight that analytics technologies have emerged as a significant trend in K-12 education, facilitating the identification of student engagement patterns and potential dropout risks. Similarly, [45] emphasize the role of educational data mining techniques in predicting student performance and identifying critical factors that influence learning outcomes. These predictive models allow educators to tailor interventions that meet students' individual needs, enhancing engagement and retention rates. Moreover, [46] discuss using neural network models to predict factors influencing student learning highlights the importance of these technologies in creating effective educational programs. By incorporating predictive analytics, schools can offer personalized learning and tackle student retention and success issues.

## 2.2 Logistic regression

Logistic regression is a fundamental algorithm for educational data classification, especially for binary outcomes such as student completion rates. It models the relationship between predictor and binary dependent variables, providing interpretable results through odds ratios. The logistic regression model follows the formula:

$$P(Y = 1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \dots + \beta_n X_n)}}$$

where  $P(Y = 1)$  represents the probability of the outcome occurring (such as course completion),  $\beta_0$  is the intercept,  $\beta_n$  are the coefficients, and  $X_n$  are the predictor variables. Logistic regression is a preferred method for educational research to predict outcomes such as course completion and student success. It allows researchers to assess the influence of predictors on educational success. This approach provided valuable insights for academic advising, allowing educators to identify students at risk of underperforming and to tailor support strategies accordingly [47]. Logistic regression improves educational outcomes through data-driven decision-making. It predicts course completion rates in online and traditional statistics courses, revealing factors impacting online student completion [48].

## 2.3 Random forest

Random forest, an ensemble learning method, constructs multiple decision trees to improve prediction accuracy and reduce overfitting. It handles large datasets with numerous features, benefiting educational data mining [49]. Random forest algorithm improves prediction robustness by using bagging and feature randomization to create diverse decision trees. This ensemble approach, with the majority voting for classification and averaging for regression, reduces variance and enhances generalization. Mathematically, the prediction for a classification task can be summarized as:

$$\hat{y} = \text{mode}\{T_1(x), T_2(x), \dots, T_n(x)\}$$

where  $\hat{y}$  is the predicted class, and  $T_i(x)$  represents the class predicted by the  $i$ -th tree for input  $x$ . This approach of averaging or majority voting helps random forest achieve high accuracy and robustness, making it an effective method for predictive modeling.

Random forest has been effectively applied in various educational settings to predict academic performance, identify key engagement factors, and manage data with complex interactions. One study [50] demonstrated the utility of random forest

in predicting academic performance within the Computer Science department, achieving an accuracy of 80.29%. This study highlighted how random forest could manage complex interactions among academic factors, providing reliable predictions that could inform academic support strategies. Research [51] also used a random forest model to predict student performance using assessment grades and online activity data. The model outperforms other algorithms, effectively managing high-dimensional datasets and identifying key factors influencing student success.

## 2.4 Gradient boosting machines

Gradient Boosting Machines builds sequential decision trees, focusing on correcting errors in previous trees. Refining predictions by learning from mistakes makes this iterative process effective for complex datasets [52], [53]. GBM uses an iterative approach to improve prediction accuracy by learning from errors. The boosting process involves training decision trees on residuals to reduce overall error, with a learning rate controlling the contribution of each tree. The weight update formula used in GBM is:

$$w_{i+1} = w_i - \eta \frac{\partial L}{\partial w_i}$$

where  $w_{i+1}$  represents the updated weights,  $w_i$  are the current weights,  $\eta$  is the learning rate, and  $\frac{\partial L}{\partial w_i}$  is the gradient of the loss function  $L$  concerning the current weights. This formula shows how the model adjusts the weights of the predictions to minimize the loss function iteratively. A lower learning rate typically leads to more stable and generalized models, ensuring that each tree only modifies the overall prediction. However, a lower learning rate requires more converging iterations, as each tree's contribution is reduced [54], [55]. GBM uses iterative learning and learning rate tuning to capture complex data patterns. This adaptability makes GBM a powerful tool for educational data analysis [56], [57].

Gradient boosting machines excel in educational predictive tasks, particularly student performance prediction and knowledge assessment. It outperforms other models by capturing complex feature interactions and nuanced data. In research [58], GBM outperformed other models in predicting student knowledge assessment and learning outcomes. It also successfully identified key engagement factors impacting academic performance by modeling student behaviors and social influences.

## 2.5 Comparative studies in predictive modeling

Algorithm selection is crucial for accurate predictions, as evidenced by comparative studies of predictive models in various domains. Different models, such as logistic regression, random forest, and GBM, perform differently based on data characteristics and application. One comparative study [48] examined the logistic regression to predict end-of-course outcomes in online and face-to-face statistics courses but struggles with complex data. More robust models such as random forests or GBM are needed to capture student engagement dynamics. Further comparisons have illustrated the strengths of GBM in various contexts. Research [59] demonstrated that GBM outperforms other algorithms in predicting complex outcomes, especially in education where multiple factors influence student performance. Its iterative learning approach and flexibility make it a strong candidate for predictive modeling.

Comparative studies in MOOCs have also highlighted the critical role of predictive modeling in addressing high dropout rates. Research [10] analyzed dropout and retention rates in MOOCs, emphasizing the importance of effective predictive models in identifying at-risk students. Machine learning techniques provide valuable insights into student behaviors and characteristics associated with dropout, enabling timely interventions and improved student retention. However, the transferability of predictive models across different educational systems and cultural contexts remains challenging.

### 3 METHODS

The research methodology followed a systematic approach, as illustrated in Figure 1 below. Data collection, preprocessing, and feature engineering preceded model development. Three algorithms were evaluated using cross-validation for robust performance.

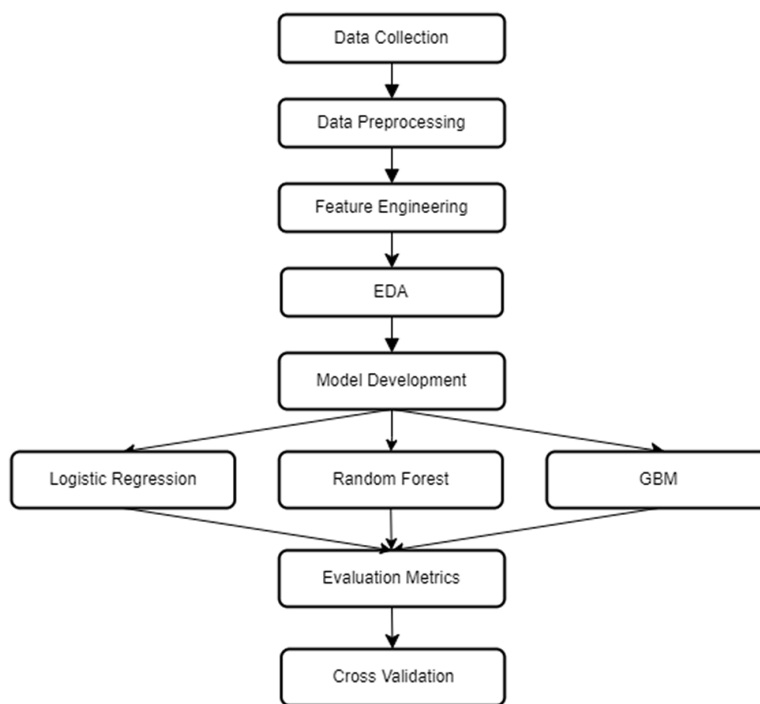


Fig. 1. Research method flowchart

#### 3.1 Dataset overview

The dataset used in this study comprised 2,500 records, each representing an individual student’s engagement and performance data from an online learning platform sourced from Kaggle. The dataset included key features that provided insights into student behavior and interactions with the course content. The primary features were ‘UserID,’ which served as a unique identifier for each student, and ‘Coursename,’ which denoted the specific course in which the student was enrolled. These identifiers were essential for linking engagement metrics to individuals and courses, enabling a detailed analysis of student behavior across different learning contexts. Engagement metrics included ‘SessionDuration,’ which captured the total

time a student spent in each session, and 'SessionsPerWeek,' indicating the frequency of sessions attended by the student each week. These variables were critical for assessing student engagement, as higher session durations and frequencies are often associated with better learning outcomes and increased likelihood of course completion. The target variable, 'Course Completion,' was a binary indicator that specified whether a student completed the course (1 for completion and 0 for non-completion). This variable served as the primary outcome of interest for the predictive models.

The dataset also included 'User Satisfaction,' ratings on a scale of 1 to 5, reflecting the student's satisfaction with the course. This variable provided additional context for understanding how student perceptions of the course might influence their engagement and completion rates. Temporal features such as 'SignUpDate' and 'LastActiveDate' were also included, allowing for calculating metrics like the duration of student activity from enrollment to their most recent interaction. These time-based features offered insights into how sustained engagement over time might correlate with course completion. Performance metrics, such as 'QuizScores,' the average scores of quizzes taken by the students, were included to assess academic performance. Additionally, the dataset contained 'FeedbackComments,' qualitative data that captured student feedback on their learning experiences. While the qualitative nature of 'FeedbackComments' posed challenges for direct inclusion in quantitative models provided valuable contextual information that could inform future qualitative analyses or the development of sentiment analysis tools.

The anonymized dataset used in this study can reveal sensitive student information, such as socio-economic background, learning challenges, and behavioral patterns, through engagement metrics such as session duration and frequency. Personally identifiable information (PII) was removed to ensure privacy, and data protection protocols were followed. However, the dataset may include biases affecting model accuracy and fairness, such as socioeconomic factors, technology access, or prior academic performance. For instance, it may over-represent students with reliable Internet access and higher digital literacy, leading to skewed predictions. Data quality issues, such as missing values or inconsistent data entry, were addressed through standard data cleaning procedures.

### 3.2 Exploratory data analysis

The data preprocessing and feature engineering processes were essential to ensure the quality and robustness of the dataset used in this study. A thorough dataset review revealed missing values in several critical features, including SessionDuration, SessionsPerWeek, and QuizScores. To handle missing data, we applied mean imputation for numerical features. This method involved replacing missing values with the average value of the corresponding feature, helping to maintain the overall distribution of the data while minimizing the impact of missing values on model accuracy. For categorical features, such as Course Completion and User Satisfaction, mode imputation was used, where missing values were replaced with the most frequently observed category. This approach preserved the integrity of the categorical data and ensured that imputed values were representative of the existing dataset.

Outliers were identified using the interquartile range (IQR) method, particularly in features such as SessionDuration and SessionsPerWeek, where extreme values could significantly skew the results. Values outside 1.5 times the IQR were considered outliers. These extreme values were examined further to determine whether they resulted from data entry errors. They were corrected if identified as errors; otherwise, they were retained in the dataset, assuming they represented valid but

extreme observations. This process ensured that the dataset accurately reflected realistic student behaviors while minimizing the influence of anomalous data points.

Feature engineering was carried out to derive additional metrics that would enhance the analysis and predictive power of the models. New features were created by transforming existing data into more meaningful metrics. For example, Days Active Since Signup was calculated by taking the difference between SignUpDate and LastActiveDate. This feature provided valuable insights into the duration of student engagement with the course, helping to capture long-term engagement patterns. To better understand student interaction regularity, a new feature, Frequency of Sessions, was defined as the total number of sessions divided by the number of days active. This metric was crucial for assessing consistent engagement throughout the course.

Additionally, time-based features were engineered to track the recency and intensity of student interactions. Time Since Last Session was introduced to measure how recently a student interacted with the course content, providing insight into recent engagement. Furthermore, the Average Session Duration Per Week was calculated by aggregating session times across weeks, allowing for an analysis of the variability in engagement intensity over time. These engineered features offered a dynamic and more comprehensive view of student engagement, moving beyond raw metrics to capture the behavioral patterns often indicative of student success or dropout.

The validation of these features was an ongoing process to ensure their reliability and relevance for the predictive models. We conducted correlation analysis to check for multicollinearity among the newly engineered features and original variables. Features that showed a high correlation with others were carefully examined and, if necessary, removed to prevent redundancy. Additionally, we used feature importance techniques to validate the most predictive features and ensure that the models relied on the most informative variables, improving the overall performance and interpretability of the models. This transparent and rigorous approach to data preprocessing and feature engineering helped ensure the dataset's quality, strengthening the study's methodological rigor.

Data visualization uncovered patterns and relationships in the dataset. Initial visualizations included histograms and box plots to explore the distributions of key engagement metrics such as 'SessionDuration,' 'SessionsPerWeek,' and 'QuizScores.' Histograms shown in Figure 2 provided an overview of the frequency distributions of these variables, revealing patterns such as skewness, peaks, or gaps that indicated how students typically engaged with the course. As shown in Figure 3, box plots were used to identify the presence of outliers and compare the central tendencies and variability of these features.

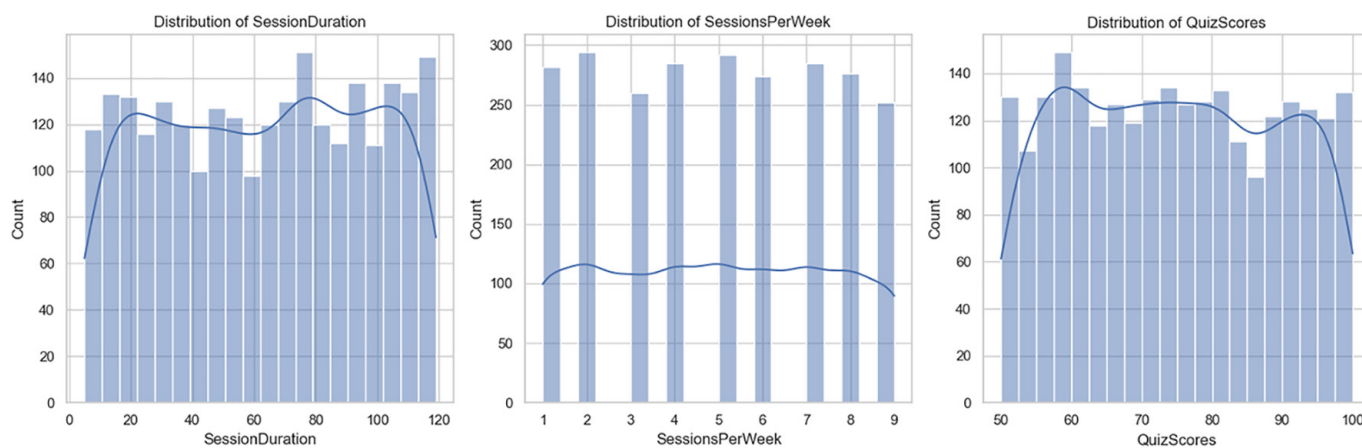


Fig. 2. Frequency distributions of key metrics

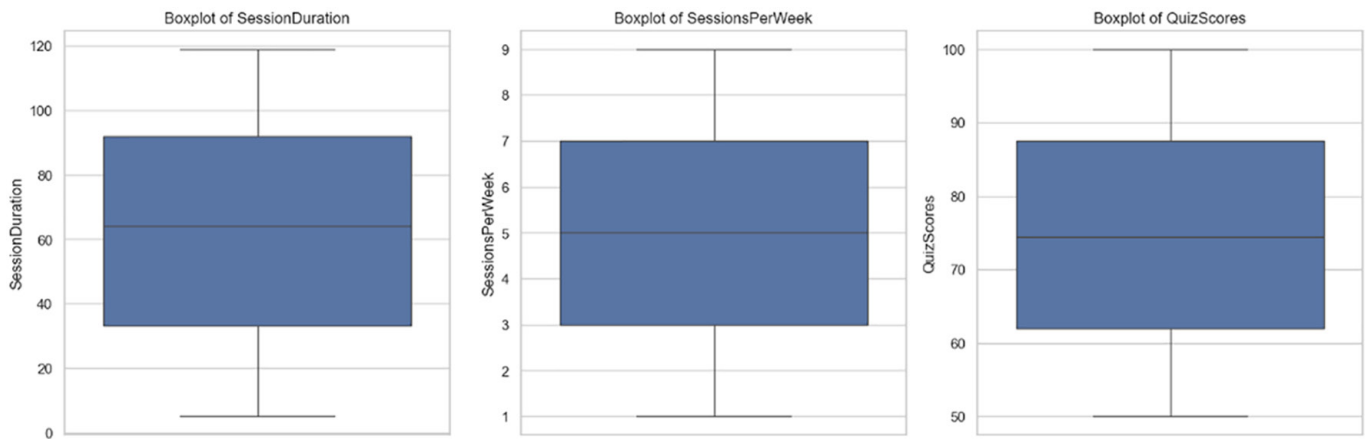


Fig. 3. Box plot of key metrics

Bar charts shown in Figure 4 were employed to compare the counts of completed versus non-completed courses, providing a clear visual representation of the distribution of the target variable, 'Course Completion.' This visualization helped highlight the proportion of students who completed their courses versus those who did not as a preliminary step in understanding the dataset's baseline performance. The imbalance observed in these counts informed subsequent model evaluation strategies, such as the potential need for techniques to handle class imbalance.

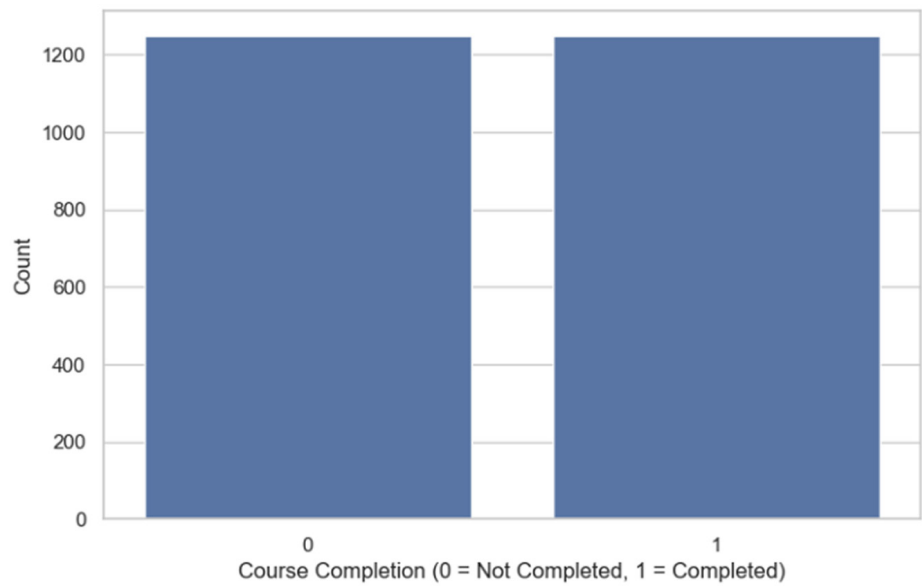


Fig. 4. Count of completed vs. non completed courses

A correlation matrix was also generated to identify relationships between engagement metrics and course completion. This matrix visualized the correlations between features, helping to highlight which engagement variables were most strongly associated with the likelihood of course completion. Strong correlations between variables 'SessionsPerWeek' and 'Course Completion' provided initial evidence of key predictors, guiding the selection of features for the predictive models. This correlation analysis was crucial for understanding the interconnectedness of engagement behaviors and their potential impact on educational outcomes, forming the foundation for building more effective predictive algorithms.

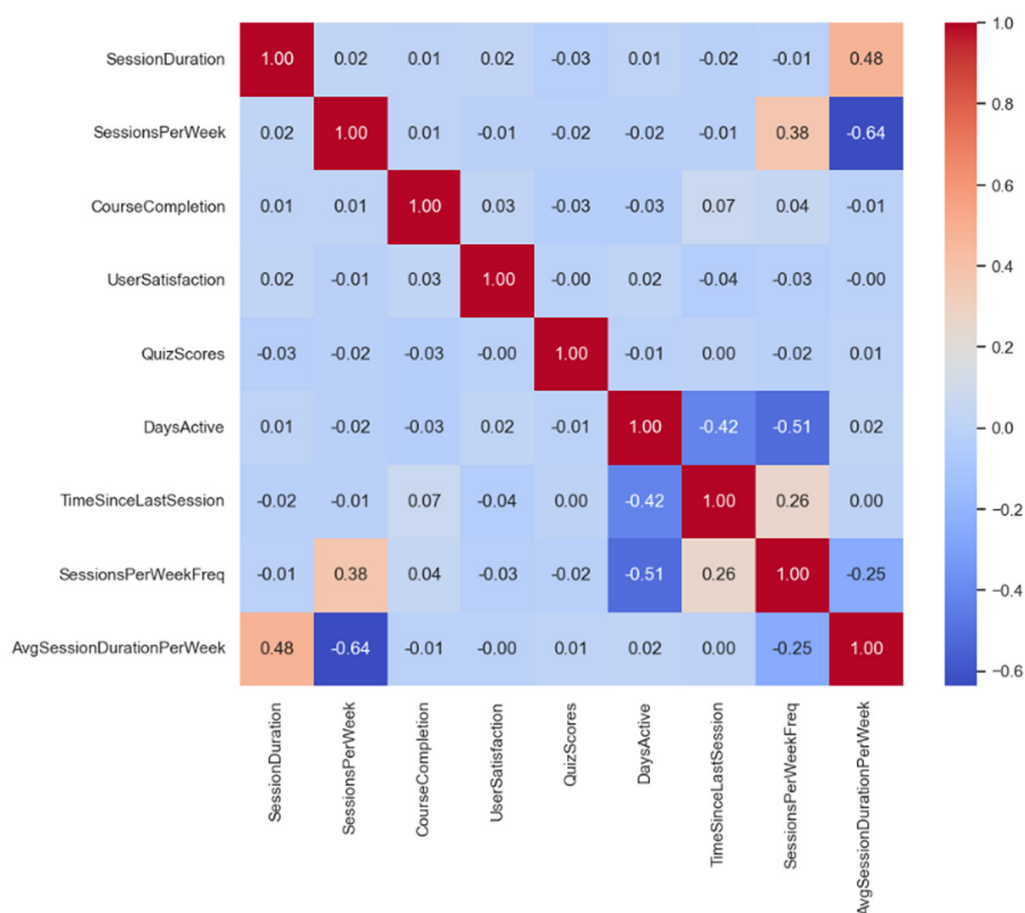


Fig. 5. Correlation matrix of engagement metrics and course completion

### 3.3 Model development

The choice of machine learning models for predicting course completion was guided by the need for both simplicity and interpretability and the ability to capture complex patterns in the data. Logistic Regression was implemented as the baseline model due to its simplicity, interpretability, and suitability for binary classification tasks. Logistic regression uses the sigmoid function to map predicted values to probabilities, making it well-suited for predicting whether a student would complete a course. The model was enhanced with L1 (Lasso) and L2 (Ridge) regularization to prevent overfitting by penalizing large coefficients. L2 regularization, which shrinks coefficients uniformly, was chosen as the default due to its ability to maintain model stability while improving generalization. The model was trained using gradient descent to minimize the binary cross-entropy loss function, a standard approach in logistic regression. Despite its advantages, logistic regression assumes linearity between the log odds of the dependent and independent variables, the independence of errors, and the absence of multicollinearity. These assumptions were validated through diagnostic checks, including variance inflation factors (VIF) for multicollinearity and residual plots for linearity and independence. However, due to logistic regression’s limitations in modeling complex, non-linear interactions in the data, more sophisticated models were tested in subsequent analyses.

Random forest was selected for its robustness in handling high-dimensional data and ability to model complex interactions without overfitting. It builds an ensemble of decision trees, each trained on a random subset of the data using bootstrap sampling. This ensemble approach improves generalization by averaging the predictions of multiple trees. Key hyperparameters tuned during model development included the number of trees ('n\_estimators'), the maximum depth of each tree ('max\_depth'), and the minimum number of samples required to split a node ('min\_samples\_split'). The number of trees was initially set to 100 and then optimized via cross-validation to balance computational efficiency and predictive performance. The 'max\_depth' was adjusted to prevent overfitting, with deeper trees capturing more complex patterns but increasing the risk of overfitting. The 'min\_samples\_split' hyperparameter was set to limit tree growth and reduce variance, ensuring that the model maintained its accuracy while being less prone to overfitting. Random forest also offered the advantage of feature importance ranking, highlighting the key engagement metrics most strongly associated with course completion. This interpretability allowed insights into the factors driving student success, which could be valuable for educators seeking to improve student retention.

Gradient boosting machines were selected as an advanced ensemble method for capturing non-linear relationships and complex interactions within the data. Unlike random forest, which builds trees in parallel, GBM builds trees sequentially, with each new tree attempting to correct the errors of the previous ones. This iterative approach enables the model to focus on the most challenging cases, such as students near the threshold of completing their courses, thereby improving predictive accuracy. Key hyperparameters tuned for GBM included the learning rate ('learning\_rate'), the number of estimators ('n\_estimators'), the maximum depth of each tree ('max\_depth'), and the minimum samples required at each leaf node ('min\_samples\_leaf'). A low learning rate (e.g., 0.01 or 0.1) was chosen to ensure gradual improvement and reduce the risk of overfitting. The number of estimators was optimized based on model performance, as a higher number of trees generally improved accuracy but increased computational cost. The 'max\_depth' was tuned to control tree complexity, balancing the need for capturing intricate patterns with the risk of overfitting. Regularization techniques, such as subsampling and shrinkage, were used to improve model generalization by reducing the impact of each tree's contribution. The combination of these hyperparameters was optimized through grid search and cross-validation, ensuring that the final GBM model was accurate and generalizable.

### 3.4 Evaluation metrics

A set of evaluation metrics was defined to compare the performance of predictive algorithms: logistic regression, random forest, and GBM. These metrics assessed each model's accuracy, reliability, and effectiveness in predicting course completion. The selected metrics included accuracy, precision and recall, F1-score, and ROC-AUC. Each metric offered distinct insights into the model's performance, helping to identify strengths and weaknesses. Accuracy evaluated the proportion of correctly predicted instances, reflecting the algorithm's overall predictive power. However, it could be misleading in cases of class imbalance. Therefore, accuracy was used alongside other metrics for a balanced view.

Precision and recall were used to evaluate trade-offs between true positive and false positive/negative predictions. Precision, the proportion of true positives

out of all positive predictions, highlights the accuracy of positive class predictions (e.g., predicting course completion). High precision indicates that the model is mostly correct when predicting course completion. Recall that the proportion of true positives out of all actual positives reflects the model's ability to identify all completed students. High recall shows that the model captures most completed students but may have more false positives if precision is low. Striking a balance between precision and recall is crucial, as prioritizing one often leads to the other. High recall is valuable in educational contexts for identifying at-risk students, but maintaining balance is important to avoid overwhelming educators with false positives. Both precision and recall provide nuanced insights into model performance predicting course completion.

The F1-score was employed to provide a single metric that balanced precision and recall, making it an ideal measure when both false positives and false negatives were of concern. The F1-score is the harmonic mean of precision and recall, calculated as:

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

This metric offered a more comprehensive evaluation by penalizing extreme values in precision or recall, which could distort overall performance assessments if considered individually. A high F1-score indicated that the model maintained a good balance between precision and recall, particularly relevant in contexts where the cost of false positives and false negatives was significant. In predicting course completion, a balanced F1-Score ensured that the model could reliably identify students at risk of not completing courses without excessively misclassifying those likely to succeed.

The receiver operating characteristic - area under the curve (ROC-AUC) evaluated the model's ability to distinguish classes. The ROC curve plots the true positive rate (recall) against the false positive rate across threshold settings, visualizing model performance across sensitivity and specificity. AUC quantified overall discriminatory power, with values closer to 1 indicating better performance. ROC-AUC captured model performance across all thresholds, offering a holistic view. A higher ROC-AUC indicated better class distinction, making it crucial for assessing predictive accuracy in imbalanced class distributions. This metric helped identify reliable and generalizable algorithms for course completion.

### 3.5 Cross-validation

To ensure robust model evaluation and avoid overfitting, five-fold cross-validation was employed. This method divides the dataset into five equal parts, or "folds," for training and validation. Each fold turns as the validation set, ensuring every data point is used for training and validation. This process provides a more accurate and generalizable estimate of the model's true performance by averaging the performance metrics across the five folds. It also helps mitigate the impact of anomalies or biases present in individual folds, leading to a more robust evaluation of the algorithms.

During each fold, the model's performance was assessed using predefined evaluation metrics, including accuracy, precision, recall, F1-score, and ROC-AUC. These metrics were calculated for each fold and averaged at the end of the cross-validation

process to provide an overall performance estimate for each algorithm. This averaging process ensures the evaluation results reflect the model's general performance rather than being overly influenced by any single fold. Additionally, cross-validation helped fine-tune hyperparameters by allowing for parameter optimization within each fold. This iterative process enabled the selection of hyperparameters that generalized well across all folds, thus enhancing the model's performance when applied to unseen data. Hyperparameter tuning through cross-validation involved selecting the parameter set that maximized the average performance across all folds, ensuring that the chosen model configurations were effective and resilient to variations in the data.

## 4 RESULT AND DISCUSSION

### 4.1 Model performance

The performance of the three predictive algorithms—logistic regression, random forest, and GBM—was compared using key evaluation metrics, including accuracy, precision, recall, F1-score, and ROC-AUC. The results were summarized in Table 1, providing a detailed comparison of each model's strengths and weaknesses across these metrics.

**Table 1.** Model performance result

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Logistic Regression	0.5213	0.4832	0.6706	0.5617	0.5331
Random Forest	0.5133	0.4732	0.5656	0.5153	0.5174
Gradient Boosting	0.4627	0.4434	0.6851	0.5384	0.4802

Logistic regression demonstrated the highest accuracy (0.5213) and F1-score (0.5617) among the models, indicating that it performed relatively well in balancing the trade-offs between precision and recall. Its ROC-AUC score of 0.5331 suggested that it had a modest ability to distinguish between students who completed courses and those who did not. While slightly lower in accuracy (0.5133) and F1-Score (0.5153), random forest offered comparable performance across the board, with a notable advantage in precision and recall balance. The GBM achieved the highest recall (0.6851), indicating its strong performance in identifying students likely to complete courses. However, its lower precision and overall accuracy indicated a higher rate of false positives, reflected in its ROC-AUC score of 0.4802, the weakest among the models.

To further explore and compare the models' abilities to distinguish between completed and non-completed courses, ROC curves were generated for each model, as shown in Figure 6. The ROC curves provided a visual representation of each model's performance across various threshold levels, with the AUC summarizing the overall ability of the model to classify the two outcomes correctly. Logistic regression showed a slightly superior ROC curve with an AUC of 0.5331, outperforming random forest (0.5174) and GBM (0.4802). This result highlighted logistic regression's relatively better, albeit modest, discriminatory power.

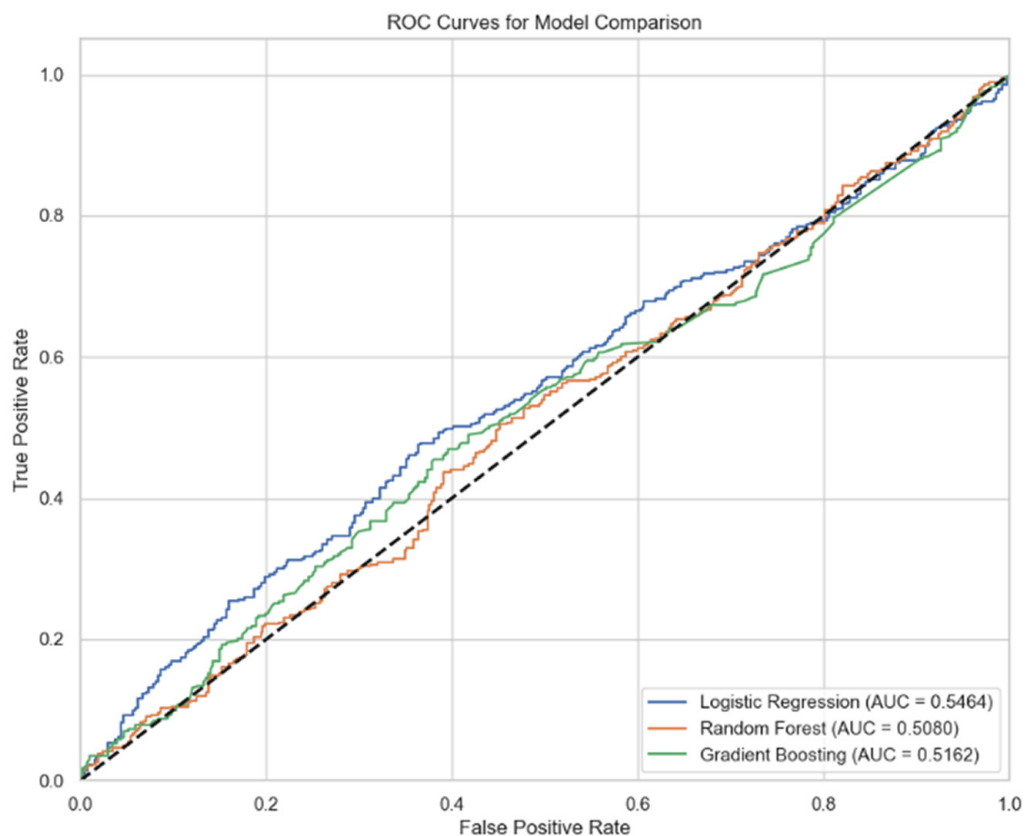


Fig. 6. ROC curves for logistic regression, random forest, and GBM

Additionally, confusion matrices were constructed for each model to illustrate the types of errors made by the algorithms, as shown in Figure 7. These matrices provided insights into the distribution of true positives, true negatives, false positives, and false negatives, helping to identify specific areas where each model struggled. Logistic regression’s confusion matrix revealed a higher rate of correctly predicted completions and a substantial number of false positives, aligning with its higher recall and moderate precision. Random forest exhibited a more balanced distribution of errors, while gradient boosting showed a pronounced tendency towards false positives, as indicated by its high recall but low precision.

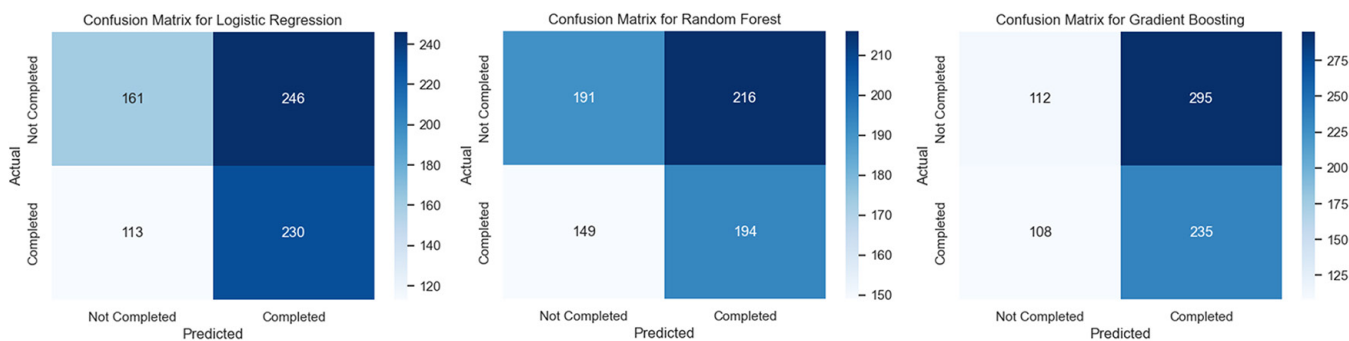


Fig. 7. Confusion matrices for logistic regression, random forest, and GBM

Overall, the performance comparison indicated that while logistic regression provided the most balanced performance across all metrics, random forest and GBM each had unique strengths, particularly in identifying students likely to complete their courses. However, the relatively modest performance of all models suggested that additional feature engineering or the exploration of alternative algorithms might be necessary to achieve more accurate predictions in this educational context. The results underscored the complexity of predicting course completion using engagement data and highlighted the need to refine predictive models in educational technology.

## 4.2 Analysis

Logistic regression, based on evaluation metrics, emerged as the best-performing algorithm. It achieved the highest accuracy (0.5213) and F1-score (0.5617), indicating a balanced model that correctly predicted course completion and non-completion. Though modest, logistic regression's ROC-AUC score of 0.5331 suggests better class distinction. This performance may be due to the data's linear separability, making it suitable for educational datasets with linear relationships. Logistic regression's high accuracy and F1-score suggest robustness in identifying at-risk students and providing actionable insights. Its simplicity and interpretability make it practical for educators and administrators.

The GBM achieved the highest recall (0.6851), indicating strong student completion identification. However, it sacrificed precision and accuracy, with low precision (0.4434) and accuracy (0.4627) due to false positives. The lower ROC-AUC (0.4802) confirmed limited discriminative power. GBM's iterative learning might have focused on complex patterns, potentially hindering generalization. Despite being a powerful ensemble method, it underperformed logistic regression in this task.

Random forest provided moderate performance across all metrics. Its accuracy and F1-score were similar to those of logistic regression but didn't excel in any metric. Random forests' strength is handling complex interactions and non-linear relationships between features. However, it didn't translate into a significant performance advantage in this study. The data's non-linear interactions weren't strong or prevalent enough to give random forest an edge over logistic regression. Additionally, the regularization effect of ensemble methods such as random forest may have controlled overfitting but underestimated the model's discriminative capacity, as seen in its ROC-AUC score.

The results showed that predictive model performance depends on data nature and task characteristics. Logistic regression's strong performance suggests it aligns well with linear decision boundaries, capturing essential patterns. Due to data complexity, complex models such as random forest and GBM didn't show the expected advantages. Logistic regression excelled overall, while random forest balanced precision and recall for equal attention to at-risk and successful students. GBM's higher recall indicated its potential for exhaustive identification of at-risk students, minimizing the risk of overlooking those in need.

Logistic regression offers a transparent approach, making it easy for educators to understand and act on its predictions. In contrast, random forest and GBM require more computational resources and expertise, limiting their applicability in resource-constrained settings. This trade-off emphasizes the importance of aligning algorithm selection with end-user needs. Logistic regression's balanced performance makes it ideal for actionable insights in administrative decision-making,

while random forest supports personalized learning by identifying diverse student engagement patterns. GBM's high recall makes it suitable for early warning systems, even at the cost of false positives. The dataset's linear structure likely contributed to logistic regression's stronger performance, as it captured primary patterns without overfitting. Future research could explore feature engineering or data augmentation techniques to introduce non-linearities that align with ensemble methods.

### 4.3 Feature importance analysis

Feature importance analysis for random forest and GBM models identified the most predictive engagement metrics for course completion. Visualized feature importance charts highlighted the relative influence of each variable on the models' output. For random forest, 'SessionDuration,' 'SessionsPerWeek,' and 'QuizScores' were the top predictors. 'SessionDuration,' the most influential feature, suggested that sustained engagement within sessions is crucial. 'SessionsPerWeek' emphasized consistent participation, while 'QuizScores' linked academic performance to course completion. Both models emphasized engagement quantity (time and frequency) and quality (academic performance). GBM slightly emphasized 'QuizScores,' suggesting it's more sensitive to academic performance variations. 'Time Since Last Session,' capturing recency of engagement, also ranked high, highlighting the relevance of recent interactions.

The findings suggest that fostering consistent and sustained engagement is crucial for improving course completion rates. Educational platforms can implement features such as reminders and gamification to encourage regular participation. Academic performance feedback, particularly, 'QuizScores,' can indicate potential dropout risk, and interventions such as personalized feedback and support for struggling students can mitigate this. 'Time Since Last Session' in GBM highlights the importance of recency in engagement. Students who frequently interact with content are more likely to stay on track, making real-time engagement tracking valuable. Interventions such as targeted notifications and incentives can re-engage students after inactivity. Key engagement metrics, such as 'SessionDuration,' 'SessionsPerWeek,' 'QuizScores,' and 'Time Since Last Session,' can be targeted by educators and platform designers to improve course completion rates. Educational technology can improve student success by increasing engagement. Data-driven interventions can address disengagement and create a supportive learning environment.

### 4.4 Implications for educational technology

Predictive models enhance educational technology by effectively engaging students. Metrics such as 'SessionDuration,' 'SessionsPerWeek,' and 'QuizScores' help predict course completion and personalize learning. Platforms change content based on engagement, offering more interactive material or prompts for less engaged students. These tailored actions boost engagement and address obstacles to finishing courses. Predictive models also shape course design by creating flexible learning environments. Engagement data helps refine the curriculum, adding modular content that meets students' changing needs. Adaptive platforms adjust resources in real time, ensuring materials and support match students' current performance.

Predictive analytics helps at-risk students by identifying those likely to drop out and offering support such as personalized feedback, extra tutoring, or reminders. This data also supports adaptive learning technologies that adjust to student needs. Predictive models assist in institutional decisions by predicting retention risks and effectively using resources. Schools can use these models to add support staff or expand mentoring programs in high-risk areas. Data-driven insights guide strategies to boost graduation rates and create policies to meet student needs. The findings help design courses and content. How often sessions happen and quiz results can improve course optimization. Frequent, shorter sessions and quick assessments with immediate feedback match engagement patterns, leading to more participation and better learning. Educational technology can use these insights in analytics dashboards, giving educators useful data. These tools show detailed student performance, identify at-risk learners, and suggest actions, enhancing course effectiveness and student success.

#### 4.5 Applications in mobile learning

Predictive models in mobile learning platforms change education by studying engagement metrics such as session length and interaction frequency. Mobile apps adjust to individual learning habits, such as sending notifications when engagement drops or recommending extra content to fill learning gaps. These features improve engagement and relevance. Predictive analytics also help educators and developers. Educators get insights into student behaviors, allowing them to intervene quickly to reduce dropout risks or improve learning outcomes. Developers can create smart apps that follow user patterns, optimize resource use, and ensure effective learning tools. This collaboration maximizes educational impact and matches technological investments with learner needs.

This study shows how predictive models connect engagement metrics with personalized learning strategies, especially on mobile platforms. Unlike traditional static methods, these models allow real-time, adaptive feedback, helping learners and educators tackle new challenges. By tackling student disengagement through mobile notifications, personalized content, and adaptive learning paths, the findings highlight the potential to turn passive educational tools into active, interactive systems. Technological advances allow predictive models to be easily added to mobile devices. Cloud computing handles large datasets and runs models without stressing the devices, while edge computing makes quick changes near data sources, cutting down on network use. APIs connect machine learning models to mobile apps, ensuring smooth operation. These technologies support adding predictive features to mobile platforms, expanding across educational settings.

Predictive models' ability to adapt to mobile platforms encourages long-term educational innovation. Institutions can create mobile systems that grow with learners' needs. For example, curricula that adapt based on predictive data can stay current with new trends. This method helps refine educational tools, making mobile learning platforms responsive and proactive in tackling access and outcome issues. Adding predictive models to mobile learning makes quality education more accessible, reducing differences in engagement and outcomes. This vision of mobile learning as a flexible, adaptive system promotes ongoing improvement through data-driven education.

#### 4.6 Practical guidelines for integrating predictive models

This study suggests ways to add predictive models to educational platforms. It emphasizes using engagement metrics, applying predictive models, and incorporating real-time analytics. Engagement metrics such as session length, interaction frequency, quiz performance, and time on course materials show student interest. Gathering this data in real-time via mobile apps or LMS allows quick interventions. Focusing on important metrics provides insights that affect learning outcomes. Customizing predictive models for specific situations increases their effectiveness. Logistic regression is best for understanding, random forest is best for complex data, and GBM is best for spotting at-risk students. Optimizing models through cross-validation and hyperparameter tuning ensures they are strong and adaptable. Predictive analytics in educational platforms, shown in mobile apps and LMS dashboards, allows for personalized learning and targeted student interventions.

A new framework helps systematically implement predictive analytics in education. It has four linked parts: data collection, predictive analytics, intervention, and feedback loop. For instance, an LMS can find at-risk students, inform educators, and offer personalized study advice. This ongoing process ensures flexible and responsive learning experiences, leading to better retention and success. By following these guidelines and the framework, educational platforms can develop adaptive, student-focused learning environments. This integration gives educators useful insights and helps students reach their academic goals with personalized support. These improvements tackle modern education challenges, particularly in mobile and online learning.

#### 4.7 Limitations and recommendations

This study has several limitations. It mainly used one Kaggle dataset focused on behavioral engagement metrics such as session duration and quiz scores, but it lacked important demographic and socio-economic data. This limits the models' ability to understand student engagement successfully. The dataset also focused on specific course types or platforms, making applying to other educational settings hard. The findings may not be universally applicable since they might not represent diverse global educational environments.

Additionally, different levels of student familiarity with online learning platforms could affect the model's accuracy. Students with prior experience might engage differently, potentially skewing the results. The study excluded factors influencing course completion rates, such as technology access, family environment, and socio-economic status, limiting the model's predictive ability for students facing challenges. Including these unmeasured factors would improve the model's accuracy in predicting student success.

Another concern is potential biases in the dataset, which could skew predictions. For example, it over-represents students with consistent Internet access and higher digital literacy, underrepresenting those from rural or economically disadvantaged backgrounds. These biases could affect model fairness and applicability, especially for underrepresented populations. Future studies should use balanced representation techniques or oversampling strategies to reduce biases. A sensitivity analysis can assess how biases impact performance. Ethical data privacy and fairness are also crucial. Although anonymized, engagement metrics could indirectly reveal sensitive aspects of students' socioeconomic backgrounds or learning challenges.

This study adhered to strict data protection protocols, removing all PII and storing data securely. Future research should focus on informed consent, data privacy, and protection transparency.

To improve the study, it's suggested that a wider range of students from different platforms, backgrounds, and locations be included. This helps make the results more applicable to a general population. Also, considering factors such as family background and technology access can provide a better understanding of what helps students finish courses. A long-term study can evaluate how predictive algorithms affect course completion rates over several semesters or years, showing their adaptability and impact on student success. Future research should investigate using new mobile learning technologies, such as adaptive learning systems and AI-driven personalization, to make real-time changes to course content based on predictions. This could boost student engagement and learning results. For instance, using predictive models in mobile apps could offer personalized notifications, assessments, or content suggestions, making learning more interactive.

Using predictive models with real-time learning systems, such as mobile apps or virtual environments, is promising. These systems can improve predictions and offer quick help. For instance, mobile apps can spot disengaged students and give them specific support. Future research should investigate advanced machine learning, such as deep learning and ensemble methods, to better manage complex data. Advanced data preprocessing, like feature engineering and dimensionality reduction, can reveal more patterns and boost model performance. Combining these with adaptive and real-time systems can create strong and scalable predictive models, promoting personalized and inclusive learning. This could greatly enhance mobile learning platforms as tools for lifelong learning and educational fairness.

## 5 CONCLUSION

This study compared logistic regression, random forest, and GBM to predict course completion using user engagement data in educational technology. Logistic regression was the most accurate, with high precision and F1-score. Random forest balanced precision and recall, while GBM had better recall but less precision. Simpler models such as logistic regression are effective when feature-outcome relationships are clear. Integrating these models into mobile learning apps can offer real-time analytics to help identify at-risk students and create adaptive learning environments. Mobile platforms can use engagement metrics to send personalized notifications, suggest resources, or modify learning paths. Real-time feedback systems support educators and learners, encouraging quick decision-making and improving the learning experience.

Mobile apps can provide real-time analytics for both educators and learners. Developers can easily add predictive analytics to mobile learning platforms using APIs and cloud infrastructures, allowing for scalable solutions with personalized insights and efficient resource use. Educators can track student progress, and learners get feedback based on data. These features promote personalized support and manage educational interventions more effectively. However, the study had some limitations. It used a specific dataset with few contextual factors, such as demographic or motivational variables, which might have restricted the models' ability to understand course completion factors fully. Future research should include more predictive features, expand the dataset, and test more advanced algorithms to enhance predictive accuracy.

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## 7 AUTHORS

**B Herawan Hayadi** is with the Information Technology Education, Faculty of Teacher Training and Education, Bina Bangsa University, Banten, 42124, Indonesia (E-mail: [b.herawan.hayadi@gmail.com](mailto:b.herawan.hayadi@gmail.com)).

**Taqwa Hariguna** is with the Department of Information System and Magister Computer Sciences, Universitas Amikom Purwokerto, Purwokerto Utara, 53127, Indonesia (E-mail: [taqwa@amikompurwokerto.ac.id](mailto:taqwa@amikompurwokerto.ac.id)).