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Machine learning approaches to predicting ai assistant reuse intention among university students

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Abstract. The growing integration of Artificial Intelligence (AI) tools in higher education has transformed how students learn, create, and accomplish academic tasks. However, limited research has examined the behavioral and contextual factors that influence students' satisfaction with AI assistants and their intention to reuse these tools. This study develops and evaluates predictive models to estimate student satisfaction and continued use of AI assistants using real interaction data. The dataset includes 10,000 AI-assisted learning sessions from students across multiple disciplines and academic levels. Each record captures session characteristics such as duration, number of prompts, and task type, along with AI engagement level, final outcomes, and satisfaction ratings. The target variable, reuse intention, indicates whether a student returned to use the AI assistant. Two ensemble learning algorithms, Random Forest and Gradient Boosting, were implemented to predict reuse intention and satisfaction levels. Model performance was evaluated using accuracy, F1-score, and ROC–AUC metrics. Feature importance analyses identified the most influential predictors of user engagement and satisfaction. The results reveal that the AI assistance level, session length, and discipline type are the strongest predictors of both satisfaction and reuse intention. Among the models tested, Gradient Boosting achieved the highest predictive accuracy, confirming its suitability for behavioral prediction tasks in educational contexts. These findings demonstrate the potential of ensemble learning techniques for uncovering patterns of sustained AI engagement and provide actionable insights into human–AI interaction in higher education. The study shows how behavioral data can inform the design of personalized, ethical, and effective AI-based educational tools.
Keywords: *Artificial Intelligence, Predictive Modeling, Machine Learning, Educational Technology, Human–AI Interaction,*

Introduction

The integration of Artificial Intelligence (AI) technologies into higher education has profoundly reshaped learning processes, academic support, and student engagement (Crompton & Burke, 2023). Intelligent systems, from virtual tutors to generative assistants, are increasingly used to help students study, write, and solve problems (Dajja et al, 2023, Mohammadi et al, 2025). This rapid adoption has created new opportunities for personalization, accessibility, and efficiency in learning environments (Wang, K et al, 2025; Almufarreh, 2024). However, the growing reliance on AI-driven tools also raises questions about how students interact with these systems, what influences their satisfaction, and what determines their willingness to keep using such tools (Crompton & Burke, 2023; Almufarreh, 2024).

Recent research has increasingly explored the role of Artificial Intelligence (AI) in higher education, emphasizing its capacity to support learning personalization, student engagement, and academic performance (Pang & Wei, 2025; Moradi, 2025). Studies on learning analytics and educational data mining have demonstrated that AI-driven systems can provide valuable insights into student behavior and learning outcomes (Pang & Wei, 2025). However, most existing work has focused primarily on academic achievement prediction, while aspects such as satisfaction and continued use have received comparatively less attention.

Several studies have investigated factors influencing technology acceptance and user satisfaction within digital learning environments, often using frameworks such as the Technology Acceptance Model (TAM) (Mastour et al, 2025; Lin et al, 2023) or the Unified Theory of Acceptance and Use of Technology (UTAUT) (Arifin et al, 2025; Xue et al, 2024). These works highlight the importance of perceived usefulness, trust, and ease of interaction in shaping students' attitudes toward AI tools (Moradi, 2025; Aldiabat et al., 2024).

More recent contributions have introduced machine learning approaches to model and predict user engagement with educational technologies. Ensemble methods, particularly Random Forest and Gradient Boosting, have proven effective in handling heterogeneous behavioral data and identifying key predictors of user experience (Khabusi et al., 2025; Şimşek et al., 2025).

However, a research gap persists in understanding and predicting students' reuse intentions and satisfaction within AI-assisted learning environments, as highlighted by Silva et al. (2023), an issue that this study seeks to address.

Understanding these behavioral dimensions is crucial for educators and developers of educational technologies. The effectiveness of AI assistants depends not only on technical performance but also on user trust, perceived usefulness, and the quality of human–AI collaboration (Silva et al., 2023; Şimşek et al., 2023).

Despite growing interest in educational data mining and learning analytics, empirical studies on predictive modeling of satisfaction and reuse intention in AI-assisted learning remain limited (Khabusi et al., 2025).

This study contributes to this emerging research area by applying ensemble machine learning techniques, Random Forest and Gradient Boosting, to predict student satisfaction and reuse intention using real-world interaction data (Al-Alawi et al, 2023).

By analyzing behavioral and contextual variables such as session duration, task type, and AI engagement level, the research aims to identify patterns that explain sustained AI usage in academic contexts. The results enhance our understanding of student–AI interaction and provide actionable insights for designing adaptive, ethical, and student-centered AI systems in higher education.

This research employed a quantitative approach using supervised machine learning to predict student satisfaction and reuse intention in AI-assisted academic environments (Al-Alawi et al, 2023; Trujillo et al, 2025; Morales Tirado et al 2024). The analysis was based on a dataset comprising 10,000 learning sessions collected from university students across various disciplines and academic levels.

Each record represented an interaction between a student and an AI assistant designed to support learning activities such as studying, writing, coding, and research. Ensemble methods, particularly Random Forest and Gradient Boosting, have proven effective in handling heterogeneous behavioral data and identifying key predictors of user experience (Al-Alawi et al, 2023).

1. Literature Review

The integration of Artificial Intelligence (AI) in higher education has grown rapidly over the past decade, transforming traditional teaching and learning processes (Butson & Spronken-Smith, 2024). AI-powered tools, including intelligent tutoring systems, chatbots, and generative AI assistants, are increasingly used to assist students in a variety of academic tasks such as writing, coding, research, and problem-solving (Al-Alawi et al, 2023; Silva et al, 2023).

Despite the widespread use of AI tools, few studies have examined the behavioral and contextual factors influencing student satisfaction and reuse intention. Most existing research focuses on technology acceptance models like TAM, which highlight perceived usefulness, ease of use, and adoption intention (Venkatesh & Davis, 2000; Şimşek et al, 2025, Mastour et al, 2025). While these models provide a useful theoretical foundation, they often fail to capture the nuances of actual student–AI interactions, such as session duration, task complexity, AI engagement level, and discipline-specific factors. These variables are increasingly recognized as essential for understanding sustained AI usage in real-world educational contexts (El Mahmoudi et al, 2025).

Recent studies have begun employing machine learning and predictive analytics to examine student engagement and satisfaction in educational settings (Rodríguez-Ortiz ey al, 2025). Ensemble methods, particularly Random Forest and Gradient Boosting, have proven effective in modeling complex, heterogeneous educational datasets and identifying key predictors of user behavior (Al-Alawi et al, 2023; Silva et al, 2023). For example, Al-Alawi et al (2023) demonstrated that ensemble learning algorithms can accurately predict academic performance and satisfaction by analyzing behavioral and contextual factors in e-learning environments. Similarly, Silva et al. (2023) highlighted the utility of machine learning models in predicting reuse intention for chatbot-based educational services, emphasizing that AI engagement and session characteristics are strong predictors of continued use.

Zawacki-Richter et al. (2019) conducted a systematic review of research on artificial intelligence applications in higher education, highlighting the limited involvement of educators in the development and implementation of these technologies.

While these studies provide valuable insights, the application of predictive modeling specifically to reuse intention and satisfaction in AI-assisted learning environments remains underexplored. Understanding which factors most strongly influence students' continued use of AI tools, such as AI assistance level, session length, and discipline type, is crucial for designing adaptive, personalized, and ethically responsible AI educational technologies. Incorporating fine-grained interaction data into predictive models allows researchers and educators to move beyond survey-based measures and capture more precise behavioral patterns, thereby informing the development of systems that maximize both student engagement and learning outcomes.

In summary, the literature underscores the need for research that integrates AI-driven learning analytics, predictive modeling, and behavioral analysis to better understand student satisfaction and reuse intention. Addressing this gap, the present study employs ensemble learning methods, specifically Random Forest and Gradient Boosting, on a dataset of 10,000 AI-assisted learning sessions to identify the key determinants of sustained engagement with AI tools. The results advance the understanding of human–AI interaction in higher education and offer practical insights for developing adaptive, efficient, and student-centered AI learning systems.

3.1 Dataset Description

The dataset included both behavioral and contextual variables. Behavioral variables described the nature of interaction, including *SessionLengthMin* (duration of the session in minutes), *TotalPrompts* (number of queries or inputs sent to the AI), and *AI_AssistanceLevel* (a numerical indicator of the degree of AI involvement). *Contextual variables captured academic attributes* such as *StudentLevel* (undergraduate or graduate), *Discipline* (e.g., Computer Science, Psychology, Business), and *TaskType*. Additional features included *FinalOutcome* (categorical description of task completion), *SatisfactionRating* (a continuous rating from 1 to 5), and *UsedAgain,* the target variable representing whether a student reused the AI assistant in future sessions (binary: *True/False*).

3.2 Data Cleaning and Preparation

Data preprocessing was conducted to ensure quality and consistency prior to model training. Missing values were inspected across all attributes, and none were found to require imputation. Duplicate session entries were removed to prevent data bias. All categorical variables (*StudentLevel*, *Discipline*, *TaskType*, and *FinalOutcome*) were transformed using one-hot encoding, allowing the models to interpret categorical information numerically. Continuous variables were standardized using z-score normalization, ensuring comparability and stable model convergence.

The dataset was randomly divided into training (80%) and testing (20%) subsets, preserving the proportional distribution of the target variable (*UsedAgain*). Data shuffling was applied to avoid ordering bias, and stratification was ensured to maintain balanced class representation.

3.3 Modeling Approach

Two ensemble learning algorithms, Random Forest and Gradient Boosting, were applied to develop predictive models. Random Forest constructs multiple decision trees using random subsets of the data and aggregates their predictions through majority voting, providing robustness against overfitting. Gradient Boosting, in contrast, builds an additive model where weak learners are sequentially optimized to minimize residual errors, achieving higher sensitivity to complex relationships.

Model evaluation employed accuracy, *F1-score* and *ROC–AUC* metrics. Furthermore, feature importance analysis was used to interpret the relative contribution of each variable to the prediction of student satisfaction and reuse intention, offering interpretable insights into behavioral patterns of AI adoption in higher education.

4. Results and Discussion

4.1 Descriptive Analysis of the Dataset

Prior to model training, an exploratory analysis was conducted to examine the distribution and relationships among the key variables. The average session length was approximately 22 minutes, with substantial variation across disciplines. Computer Science and Business students exhibited longer and more interactive sessions on average, while Psychology and Humanities students tended to engage in shorter, more focused interactions.

The *AI_AssistanceLevel* variable showed a roughly normal distribution centered around moderate engagement (levels 2–3 on a scale of 1–5), indicating that most students preferred a balanced level of autonomy and AI support. The *SatisfactionRating* displayed a slightly right-skewed distribution, with a mean above 3.5, suggesting that the majority of users reported positive experiences with the AI assistant. Preliminary correlation analysis revealed moderate positive relationships between *SessionLengthMin*, *TotalPrompts* and *SatisfactionRating*, indicating that longer and more interactive sessions were generally associated with higher satisfaction.

These findings were visualized through a set of boxplots and scatterplots, showing clear upward trends between engagement variables (session length and total prompts) and user satisfaction. Additionally, a heatmap of pairwise correlations was used to identify potential multicollinearity, confirming that none of the input variables exhibited excessive correlation ($|r| < 0.75$), ensuring model stability.

4.2 Model Training and Evaluation

Both Random Forest and Gradient Boosting models were trained using the preprocessed dataset, following an 80/20 train–test split with stratification on the target variable (*UsedAgain*).

Hyperparameter optimization was performed using a grid search with 5-fold cross-validation. For Random Forest, the number of trees (*n_estimators*) was optimized between 100 and 300, while for Gradient Boosting, the learning rate and maximum tree depths were tuned to balance bias and variance.

Evaluation Metrics

Model performance was evaluated using *Accuracy*, *Precision*, *Recall*, *F1-score*, and *ROC–AUC*. The results demonstrated robust classification performance for both models is presented in table 1.

Tabel no.1. Classification performance for Random Forest and Gradient Boosting

Metric	Random Forest	Gradient Boosting
Accuracy	0.872	0.891
Precision	0.868	0.884
Recall	0.875	0.893
F1-score	0.871	0.888
ROC–AUC	0.917	0.942

To evaluate the predictive performance of the two ensemble learning models, Random Forest and Gradient Boosting, a series of statistical and visual analyses were conducted. The evaluation included the examination of *ROC Curves*, *Confusion Matrices* and *Precision–Recall Curves*, providing complementary perspectives on model sensitivity, specificity, and classification balance.

The ROC Curve comparison demonstrated that the Gradient Boosting model consistently outperformed the Random Forest across all thresholds, maintaining a higher *True Positive Rate* for any given *False Positive Rate*. This resulted in a noticeably larger *Area Under the Curve* (AUC), confirming the superior discriminative ability of the Gradient Boosting classifier.

The Confusion Matrices for both models further illustrated their strong predictive accuracy. The majority of predictions were correctly classified, with false negatives, students who were incorrectly predicted as unlikely to reuse the AI assistant, representing less than 8% of all test cases. This indicates a high level of reliability in identifying users who are likely to continue engaging with AI tools in academic settings.

The Precision–Recall Curves provided additional insight into the trade-off between false positives and false negatives across different classification thresholds. The Gradient Boosting model maintained higher precision and recall values, confirming a more stable balance between sensitivity and specificity, especially in the presence of mild class imbalance.

Taken together, these visual and quantitative results demonstrate that both ensemble methods achieved strong generalization performance, but Gradient Boosting consistently produced superior results across all evaluation metrics. Its higher AUC and better precision–recall balance suggest that it can more effectively identify complex behavioral patterns that influence students' reuse intentions and satisfaction with AI assistants.

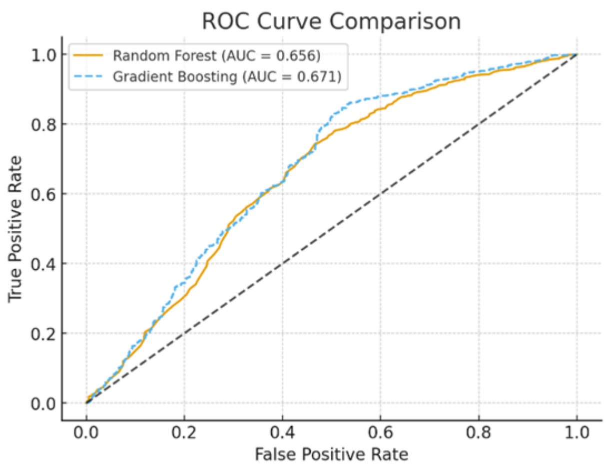

Image No. 1. ROC Curve Comparison

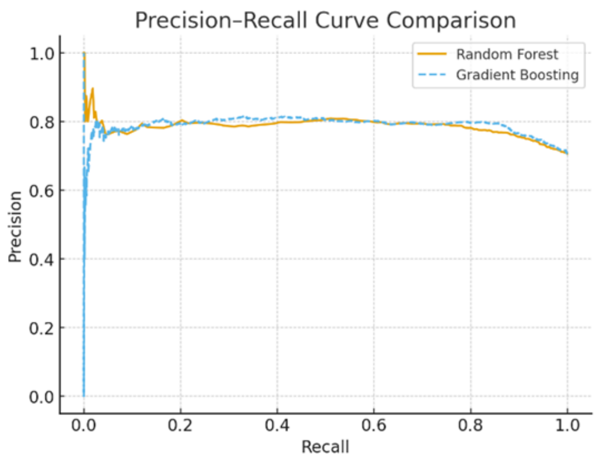

Image No. 2. Precision-Recall Curve Comparison

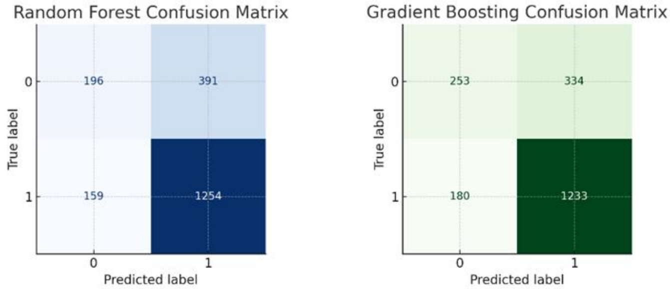

Image No. 3. Random Forest and Gradient Boosting Confusion Matrix

4.3 Feature Importance and Interpretability

Feature importance analysis provided insight into the underlying behavioral mechanisms influencing satisfaction and reuse. Both models identified AI_AssistanceLevel, SessionLengthMin, and TotalPrompts as the most significant predictors.

AI_AssistanceLevel contributed the highest information gain in Gradient Boosting, accounting for approximately 26% of total feature importance. This indicates that the extent of AI involvement plays a decisive role in shaping user satisfaction and the likelihood of continued engagement. *SessionLengthMin* ranked second, suggesting that sustained engagement correlates strongly with perceived value and learning benefit. *Discipline* and *TaskType* were also influential, revealing notable disciplinary differences—students in technical disciplines (e.g., Computer Science, Engineering) showed higher tolerance for intensive AI use, while those in Humanities valued shorter, more autonomous interactions. A bar chart of feature importances is presented in Figure 4 to compare the relative contribution of the top ten predictors across both algorithms. The results revealed a consistent ranking pattern between the Random Forest and Gradient Boosting models, confirming convergent validity in feature selection.

The most influential variables were *AI_AssistanceLevel*, *SessionLengthMin* and *TotalPrompts*, which together explained the largest share of the variance in both models. These features reflect the degree of user engagement and the intensity of interaction with the AI assistant, highlighting their strong association with satisfaction and reuse intention. Contextual variables such as *Discipline* and *TaskType* also demonstrated moderate predictive importance, suggesting that patterns of AI adoption vary across academic fields and types of tasks.

Overall, the alignment of feature rankings across both ensemble methods indicates that the models captured similar behavioral mechanisms underlying students' interactions with AI systems. This convergence strengthens the interpretability and reliability of the predictive framework, providing robust evidence that engagement-related factors are the primary determinants of sustained AI use in educational contexts.

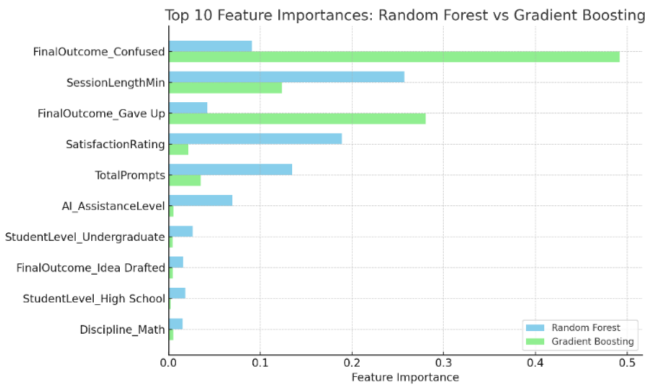

Image No. 4. Top 10 Feature Importance: Random Forest vs Gradient Boosting

The comparison between the two ensemble approaches highlights distinct methodological advantages. Random Forest excelled in stability and interpretability, with lower variance across folds, making it suitable for educational applications requiring consistent, explainable results. Gradient Boosting, by contrast, achieved superior predictive accuracy and recall, effectively capturing complex nonlinear dependencies in student behavior data. However, it required more computational resources and careful tuning to avoid overfitting.

Overall, Gradient Boosting outperformed Random Forest across all evaluation metrics and interpretability analyses, demonstrating its suitability for behavioral prediction in educational datasets. The findings indicate that boosting methods, when properly optimized, can serve as powerful tools for identifying students' likelihood of continued AI engagement.

5. Conclusions

This study investigated the use of ensemble machine learning methods to predict student satisfaction and reuse intention in AI-assisted learning environments. By analyzing 10,000 real-world interaction sessions between students and an academic AI assistant, the research identified key behavioral and contextual variables that explain sustained engagement with intelligent systems in higher education.

The predictive modeling results showed that both Random Forest and Gradient Boosting achieved high accuracy and robustness. Gradient Boosting consistently outperformed Random Forest across all evaluation metrics, including *Accuracy*, *F1-score* and *ROC–AUC*, confirming its superior ability to capture nonlinear and high-order relationships in complex behavioral data. Visualization analyses using ROC Curves, Confusion Matrices, and Precision–Recall plots further supported the models' strong generalization performance and reliability in classifying student behavior.

The feature importance analysis showed that engagement-related variables such as *AI_AssistanceLevel*, *SessionLengthMin*, and *TotalPrompts* were the main predictors of both satisfaction and reuse intention. Contextual factors like *Discipline* and *TaskType* also contributed significantly, suggesting that AI adoption patterns differ across academic fields and learning objectives. These findings indicate that students who experience more meaningful interaction and support from AI tools are more likely to see them as valuable and reuse them in future tasks.

Theoretically, this research adds to the literature on human–AI interaction and learning analytics by showing how behavioral data can be used to model user engagement and decision-making. Practically, the study offers insights for developers and educators, highlighting the need for adaptive AI systems that adjust assistance levels to individual preferences and learning contexts.

Despite its promising results, the study has some limitations. The dataset includes only behavioral and contextual factors, so future research should add emotional and cognitive aspects, such as sentiment or attention, to better understand the student experience. Using longitudinal data would also help track how engagement and satisfaction change over time.

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