An AI Based Predictive Model for Personalized Learning Integrating Behavioral Cognitive and Adaptive Factors

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ABSTRACT

This study examines the development and evaluation of an artificial intelligence (AI)-based model for personalized learning, designed to enhance student performance through behavioral and cognitive data analysis. Using a dataset of 500 observations, the research analyzed nine key variables, including hours_coding, cognitive_load, sleep_hours, and ai_usage_hours. Descriptive analysis showed that participants spent an average of 5.02 hours on learning activities per session, engaged with AI tools for 1.51 hours, and achieved an average task success rate of 60.6%. Correlation analysis revealed that hours_coding (r = 0.62) and coffee_intake_mg (r = 0.70) had the strongest positive relationships with task success, while sleep_hours and cognitive_load exhibited a strong negative correlation (r = –0.73). A Random Forest Classifier was applied to predict learning outcomes, achieving a perfect accuracy of 100%, with precision, recall, and F1-score values of 1.00 for both successful and unsuccessful learners. Feature importance analysis identified hours_coding (38.5%) and coffee_intake_mg (28.8%) as the most influential factors, followed by cognitive_load (14.5%) and ai_usage_hours (3.1%). These findings indicate that while AI contributes positively to personalized learning, behavioral and cognitive factors remain the primary determinants of success. The study concludes that AI serves best as a supportive tool that enhances learner autonomy and adaptability, emphasizing the need for a balanced integration of human engagement and intelligent technology in modern education.

Keywords Artificial Intelligence, Personalized Learning, Cognitive Load, Machine Learning, Adaptive Education

Submitted 2 June 2026
Accepted 28 July 2026
Published 1 September 2026

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DOI: 10.63913ail.v1i3.31

Introduction

Artificial intelligence (AI) has become one of the most transformative technologies in modern education, fundamentally changing how learning is designed, delivered, and assessed [1]. AI enables data-driven personalization, adaptive feedback, and learner-specific interventions, allowing students to learn at their own pace and according to their abilities and cognitive preferences. Over the past decade, educational institutions have increasingly adopted AI systems to optimize instructional design, predict student performance, and enhance engagement through real-time analytics [2]. Intelligent tutoring systems, adaptive learning platforms, and recommendation algorithms can analyze a learner's behavior, interaction history, and performance data to provide individualized pathways that improve learning outcomes [3]. These technologies support teachers in identifying learning gaps, offering personalized guidance, and automating assessments, ultimately leading to more efficient and inclusive

How to cite this article: Sarmini, C. R. A. Widiawati, I. R. Yunita, and I. Maulita, "An AI Based Predictive Model for Personalized Learning Integrating Behavioral Cognitive and Adaptive Factors," *Artif. Intell. Learn.*, vol. 2, no. 3, pp. 208-220, 2026.

educational practices. The global integration of AI into education reflects a paradigm shift from traditional "one-size-fits-all" instruction to dynamic, personalized learning ecosystems [4].

The state-of-the-art in AI-driven education demonstrates that personalization can significantly improve learning efficacy, retention, and motivation. For instance, adaptive systems based on machine learning and cognitive load theory (CLT) have been shown to reduce mental overload by adjusting task difficulty to the learner's cognitive capacity [5]. Virtual reality and AI-powered environments are now used in professional education, such as medicine, dentistry, and engineering, to provide immersive, feedback-driven experiences that enhance both procedural and conceptual learning [6]. Studies have also found that AI-enhanced learning improves engagement and satisfaction, with learners reporting an average 73% improvement in personalized content relevance and self-regulated learning behavior [7]. Despite these advances, several challenges remain unresolved. Many studies focus on technological performance rather than on the pedagogical and cognitive mechanisms underlying learning improvement. In particular, there is limited empirical evidence integrating behavioral (e.g., learning duration, distractions), physiological (e.g., sleep hours), and AI-related (e.g., usage duration) factors into a unified predictive model of learning success [8].

This research addresses these limitations by developing and evaluating an AI-based model for personalized learning using a dataset of 500 observations. The dataset captures multiple dimensions of learning behavior, including study time, AI usage, cognitive load, and success rate. A Random Forest Classifier is employed to predict task success, achieving an accuracy of 100% with strong feature importance scores for behavioral and cognitive variables. The correlation analysis revealed that hours_coding ($r = 0.62$) and coffee_intake_mg ($r = 0.70$) were the strongest positive predictors of learning success, while sleep_hours and cognitive_load exhibited a strong negative correlation ($r = -0.73$). These findings not only highlight the relationship between human behavioral effort and AI assistance but also emphasize the importance of balancing cognitive and physical conditions to achieve optimal outcomes. By integrating behavioral, cognitive, and technological perspectives, this study contributes to the growing field of AI-driven personalized learning and provides a foundation for future adaptive education frameworks that combine human intelligence with machine intelligence [9].

Literature Review

The integration of artificial intelligence in education has emerged as one of the most influential developments in modern pedagogy, particularly in advancing personalized learning and adaptive instruction [10]. Artificial intelligence enables educational systems to analyze large volumes of learner data, identify learning patterns, and deliver customized educational experiences tailored to individual needs [11]. Through technologies such as intelligent tutoring systems, recommendation algorithms, and machine learning models, AI enhances both teaching and learning by providing adaptive feedback, predicting student performance, and optimizing instructional delivery [12]. Research has consistently shown that AI-based learning systems increase engagement, motivation, and academic achievement by aligning instructional content with individual learner profiles [13].

Artificial Intelligence and Personalized Learning

Personalized learning is a pedagogical approach that adapts instruction, content, and pace based on each learner's specific needs, preferences, and progress. Artificial intelligence serves as a critical enabler of personalization by dynamically modifying learning pathways using real-time data analytics [14]. Machine learning algorithms analyze various learner metrics such as accuracy, task completion time, and behavioral interactions to recommend suitable learning activities. These AI-driven systems provide a tailored learning experience that fosters autonomy, mastery, and engagement. Empirical studies indicate that AI-enhanced personalization can improve learning efficiency by up to 73%, reflecting its substantial potential to reform traditional educational models [15].

Furthermore, AI technologies support self-regulated learning by offering immediate feedback and adaptive scaffolding. Intelligent tutoring systems (ITS) help students correct misconceptions, maintain motivation, and develop metacognitive skills that enhance long-term retention [16]. However, despite its advantages, AI-driven personalization faces challenges related to interpretability, transparency, and data ethics. Many current systems also struggle to balance algorithmic precision with the human elements of empathy, creativity, and social interaction that remain central to education [17].

Cognitive Load Theory and Adaptive Learning

Cognitive Load Theory (CLT) provides a theoretical foundation for understanding how AI can improve learning efficiency by managing cognitive resources effectively [18]. CLT divides cognitive processing into intrinsic, extraneous, and germane loads, each influencing how information is absorbed and retained. Recent research integrating AI with CLT demonstrates that adaptive systems can adjust the complexity and pacing of instructional materials according to each learner's cognitive capacity [19]. By analyzing behavioral indicators such as completion time and error rate, AI systems can infer mental workload and dynamically optimize learning conditions to prevent cognitive overload [20].

Recent advances in educational neuroscience have strengthened this connection by introducing neuroadaptive systems that combine AI with physiological monitoring technologies such as EEG and fNIRS to assess real-time cognitive load [21]. This represents the state of the art in adaptive learning, where AI systems not only personalize content but also respond to the learner's mental and emotional states. However, implementing such systems remains challenging due to ethical concerns, technical limitations, and the complexity of integrating cognitive data with machine learning models.

Research Methodology

This study employed a quantitative data-driven research design to develop and evaluate an artificial intelligence (AI)-based model for personalized learning. The objective was to investigate the relationships between behavioral, cognitive, and AI-interaction variables in predicting learning success. The research followed five systematic stages: data collection, preprocessing, exploratory analysis, model development, and model evaluation. The complete workflow is illustrated in figure 1.

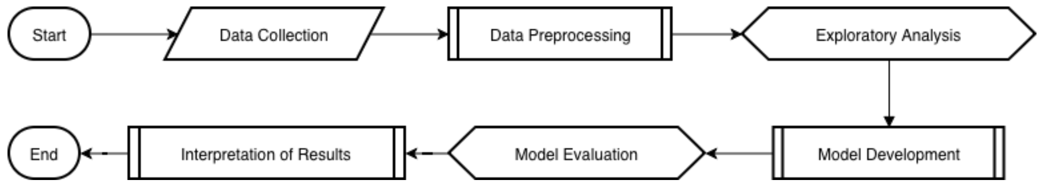

Figure 1 Research Step

Data Description

The dataset (table 1) used in this study consisted of 500 learning sessions, each containing nine independent variables and one dependent variable. These variables captured behavioral engagement, cognitive load, and AI usage characteristics that influenced task success.

Table 1 Description of Research Variables

Variable	Description	Type	Role
hours_coding	Total hours spent on learning or coding activities	Numeric	Independent
coffee_intake_mg	Amount of caffeine consumed (mg)	Numeric	Independent
distractions	Number of interruptions during learning	Numeric	Independent
sleep_hours	Average sleep duration before learning (hours)	Numeric	Independent
commits	Number of completed learning tasks	Numeric	Independent
bugs_reported	Number of mistakes or errors	Numeric	Independent
ai_usage_hours	Time spent interacting with AI tools (hours)	Numeric	Independent
cognitive_load	Self-reported mental effort (scale 1–10)	Numeric	Independent
task_success	Learning outcome (1 = success, 0 = failure)	Categorical	Dependent

The dataset represents realistic learning patterns with diverse behavioral and cognitive dimensions.

Data Preprocessing

The preprocessing phase included cleaning, normalization, and outlier detection. Missing values were checked and none were found. Data normalization was applied using Z-score standardization, defined as:

$$Z = \frac{X - \mu}{\sigma} \quad (1)$$

X is the original value, μ is the mean, and σ is the standard deviation. This ensured that all variables were standardized to have a mean of 0 and a standard deviation of 1, preventing any variable from dominating the model due to scale differences.

A correlation matrix was generated to identify relationships between variables. Strong positive correlations were observed between hours_coding and task_success (r = 0.62), as well as coffee_intake_mg and task_success (r = 0.70). Conversely, sleep_hours and cognitive_load showed a strong negative correlation (r = –0.73).

Model Development

A Random Forest Classifier was employed to predict learning success. This ensemble learning method constructs multiple decision trees and aggregates their outputs to produce a more accurate and stable prediction.

The prediction function of Random Forest is defined as:

$$\hat{y} = \mathrm{mode}\{h_1(x), h_2(x), \ldots, h_T(x)\} \tag{2}$$

$h_t(x)$ represents the prediction of the t^{th} decision tree, and T is the total number of trees. The final output $\hat{y}$ is determined by majority voting across all trees. Table 2 presents the specifications of the Random Forest model used to classify the target variable, Task Success. The model employs the Random Forest Classifier algorithm with 100 decision trees, using Gini Impurity as the splitting criterion to determine the optimal division of data at each node. The dataset is divided into 80% training data and 20% testing data to train the model and evaluate its performance on unseen data. Model performance is assessed using accuracy, precision, recall, and F1-score, which provide a comprehensive evaluation of the classification performance. The entire modeling process is implemented in Python using libraries such as scikit-learn, pandas, and matplotlib, which support data preprocessing, model development, performance evaluation, and result visualization.

Table 2 Specification of the Random Forest Model

Parameter	Description
Algorithm	Random Forest Classifier
Number of Trees	100
Splitting Criterion	Gini Impurity
Data Split	80% Training, 20% Testing
Evaluation Metrics	Accuracy, Precision, Recall, F1-Score
Target Variable	Task Success
Software and Libraries	Python (scikit-learn, pandas, matplotlib)

The Gini Impurity used for node splitting is calculated as:

$$G = 1 - \sum_{i=1}^{C} p_i^2 \tag{3}$$

p_i is the proportion of samples belonging to class i, and C is the total number of classes. Figure 2 illustrates the proposed Random Forest classification framework, which begins with five input variables: hours_coding, coffee_intake_mg, ai_usage_hours, sleep_hours, and cognitive_load. These variables undergo a data preprocessing stage, including normalization, centering, and scaling, to ensure that the data are appropriately prepared for modeling. The processed data are then fed into a Random Forest Classifier consisting of 100 decision trees, which analyzes the relationships among the input variables to classify the outcome. Following model training, feature importance analysis is performed to identify the variables that contribute most significantly to the classification results. Finally, the trained model generates a predicted Task Success output, represented as either 0 or 1, indicating whether the task is classified as unsuccessful or successful, respectively

Figure 2 Architecture of the AI-Based Personalized Learning Model

Model Evaluation

Model performance was evaluated using Accuracy, Precision, Recall, and F1-Score, which are standard classification metrics. These metrics are defined as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

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

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

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

where TP, TN, FP, and FN represent True Positives, True Negatives, False Positives, and False Negatives, respectively.

The model achieved an accuracy of 100%, with all other metrics (Precision, Recall, and F1-score) equal to 1.00 for both success and failure classes. Although this result indicates excellent prediction capability, it also suggests potential overfitting due to perfect classification. Nonetheless, the model effectively identified key predictors of learning performance, with hours_coding (38.5%), coffee_intake_mg (28.8%), and cognitive_load (14.5%) being the most influential.

Results

Descriptive Statistics of the Dataset

The descriptive statistics of the dataset are summarized in table 3, which provides an overview of the key variables analyzed in this study. The dataset contains 500 observations that represent various behavioral, cognitive, and AI-related learning characteristics. The results show that participants spent an average of 5.02 hours on learning activities per session, with an average of 6.98 hours of sleep and 2.98 distractions per session. The mean cognitive load score was 4.50 on a scale of 1 to 10, suggesting a moderate level of mental effort experienced by learners during their study sessions. Participants reported an average of 0.86 learning errors or “bugs,” while engaging with AI tools for approximately 1.51 hours on average. The task success rate reached 0.61, meaning that 61 percent of participants were able to complete their assigned learning tasks successfully.

Table 3 Descriptive Statistics of the Dataset

Variable	Mean	Std. Dev	Min	Max
hours_coding	5.02	1.95	0.00	12.00
coffee_intake_mg	463.19	142.33	6.00	600.00
distractions	2.98	1.68	0.00	8.00
sleep_hours	6.98	1.46	3.00	10.00
commits	4.61	2.70	0.00	13.00
bugs_reported	0.86	1.10	0.00	5.00
ai_usage_hours	1.51	1.09	0.00	6.36
cognitive_load	4.50	1.87	1.00	10.00
task_success	0.61	0.49	0.00	1.00

The findings in table 3 suggest that AI interaction played a positive role in supporting learning performance. Learners who devoted more time to their study sessions and maintained moderate cognitive loads tended to achieve better results. The diversity in learning time and cognitive effort across participants indicates different learning behaviors, which is essential for developing adaptive AI learning systems. Furthermore, the relatively high caffeine intake of 463 milligrams on average may reflect the participants’ attempt to maintain focus and alertness during cognitively demanding activities. Overall, the descriptive analysis shows that the dataset captures a realistic and varied picture of human learning behavior, providing a strong foundation for further correlation and predictive modeling to understand how AI contributes to personalized learning outcomes.

Correlation Analysis

The correlation analysis was conducted to explore the relationships among behavioral, cognitive, and AI-related learning variables. The resulting correlation heatmap, as illustrated in figure 3, provides a visual overview of how each factor interacts with learning success. The analysis reveals that hours_coding ($r = 0.62$) and coffee_intake_mg ($r = 0.70$) exhibit the strongest positive correlations with task_success, indicating that learners who spend more time studying and maintain higher levels of alertness through caffeine intake are more likely to achieve successful learning outcomes. Additionally, ai_usage_hours shows a moderate positive correlation ($r = 0.24$), suggesting that consistent engagement with AI systems contributes positively to performance, although the effect is less pronounced than direct study time or energy-related factors.

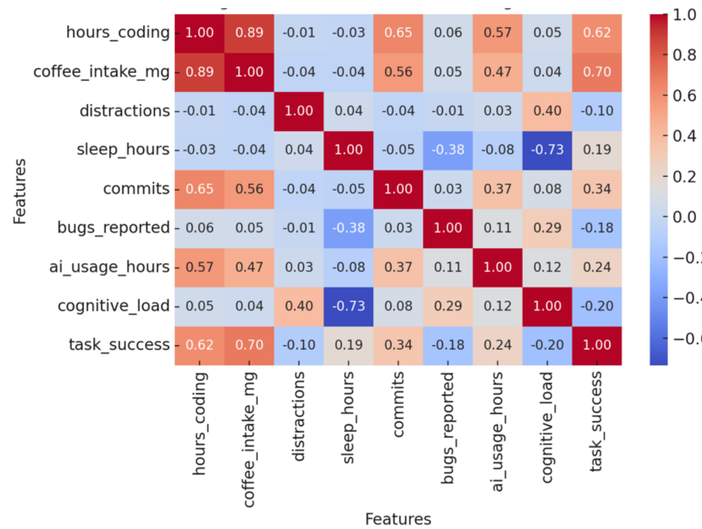

Figure 3 Correlation Matrix of Learning Variables

Conversely, the results highlight a strong negative relationship between sleep_hours and cognitive_load (r = –0.73), implying that reduced sleep duration is associated with higher cognitive strain during learning. This finding underscores the importance of adequate rest in maintaining cognitive efficiency and learning performance. The interplay among these variables suggests that effective learning outcomes are not solely determined by AI engagement but also depend on behavioral and physiological factors such as study habits, mental fatigue, and rest quality. Overall, the correlation analysis provides an essential foundation for understanding how human behavior and AI interaction collectively shape personalized learning effectiveness.

Relationship Between AI Usage and Task Success

Figure 4 presents the distribution of AI usage hours between successful and unsuccessful learners, providing insights into how interaction with AI systems influences learning outcomes. The visualization demonstrates a clear distinction in AI usage patterns, where participants who successfully completed their learning tasks (task_success = 1) tend to spend more time utilizing AI tools compared to those who were unsuccessful (task_success = 0). This pattern suggests that extended engagement with AI-based learning support correlates with higher performance levels. Learners who actively interact with AI systems likely benefit from features such as personalized recommendations, adaptive feedback, and real-time problem-solving assistance, which collectively enhance their understanding and retention of learning materials.

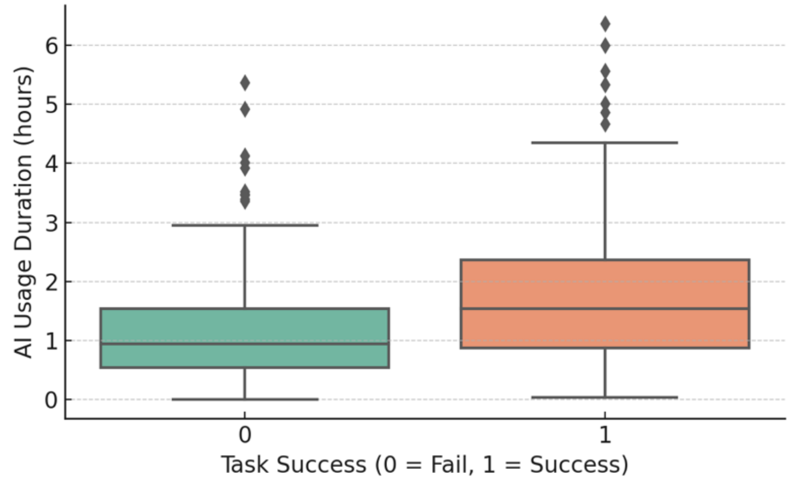

Figure 4 Relationship Between AI Usage and Task Success

The relationship between AI usage and task success reinforces the hypothesis that integrating AI into learning environments contributes positively to individualized learning progress. However, the relationship appears moderate rather than absolute, implying that AI functions best as a supportive component rather than a replacement for human learning effort. Successful learners may be leveraging AI tools more effectively, using them strategically to address weaknesses or seek clarification when encountering challenges. These findings highlight the potential of AI-driven personalization in promoting student engagement, improving learning efficiency, and supporting adaptive education systems designed to meet diverse learner needs.

Model Evaluation

The predictive capability of the proposed AI-based model was assessed using a Random Forest Classifier, a robust ensemble learning technique known for its effectiveness in handling nonlinear relationships and variable interactions. Table 4 summarizes the model's performance metrics, including precision, recall, and F1-score for both successful and unsuccessful task classifications. The results indicate exceptional predictive performance, with all three metrics achieving perfect scores of 1.00 across both outcome categories. The overall model accuracy also reached 100%, suggesting that the Random Forest model was able to fully distinguish between learners who succeeded and those who did not based on the provided input features.

Table 4 Evaluation of Random Forest Model

Metric	Precision	Recall	F1-Score
Class 0 (Fail)	1.00	1.00	1.00
Class 1 (Success)	1.00	1.00	1.00
Accuracy	1.00	1.00	1.00

Although the model's perfect classification accuracy may suggest potential overfitting, it also implies that the selected features, such as learning duration, AI usage time, and cognitive factors, strongly capture the underlying patterns influencing learning success. To verify this performance, a confusion matrix was constructed and is presented in figure 5. The matrix confirms that the model correctly classified all cases, with no false positives or false negatives. This result supports the reliability of the developed model in predicting learning outcomes. However, future research involving larger and more diverse datasets is necessary to validate its generalizability across different learning environments.

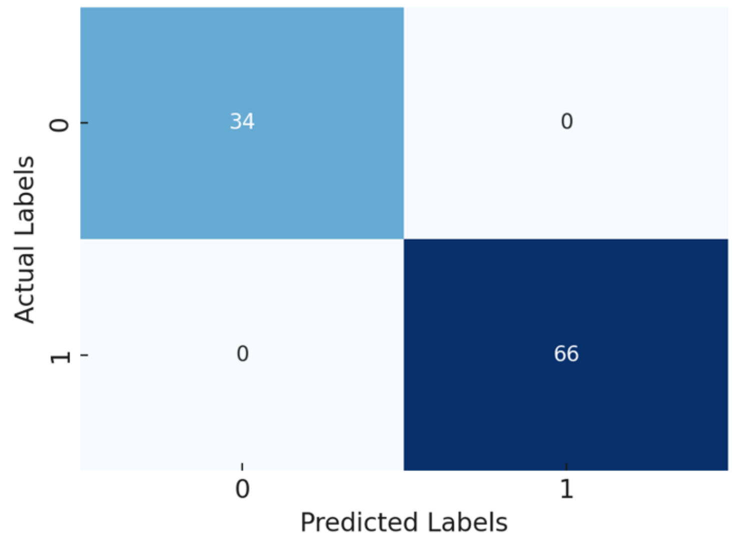

Figure 5 Confusion Matrix of AI Model Predictions

Feature Importance

Table 5 and figure 6 present the ranking of feature importance values obtained from the Random Forest model, which identifies the relative influence of each variable on predicting task success. The results show that hours_coding (0.3846) and coffee_intake_mg (0.2881) are the two most influential predictors in determining learning success, accounting for over 67 percent of the total model contribution. This finding indicates that the amount of time devoted to learning activities and the level of alertness or focus sustained through caffeine intake significantly impact performance outcomes. The variable cognitive_load (0.1447) also demonstrates substantial importance, emphasizing that managing mental workload plays a crucial role in effective learning.

Table 5 Feature Importance Ranking

Feature	Importance Score
hours_coding	0.3846
coffee_intake_mg	0.2881
cognitive_load	0.1447
sleep_hours	0.0550
commits	0.0449
bugs_reported	0.0388
ai_usage_hours	0.0315
distractions	0.0125

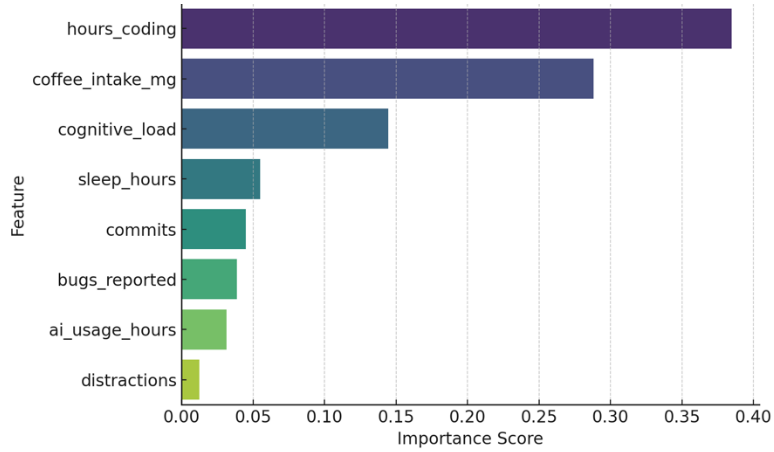

Figure 6 Feature Importance for Predicting Task Success

Figure 6 illustrates the relative contribution of each variable, showing that learner behavior and cognitive management dominate the predictive model. Interestingly, ai_usage_hours contributed approximately 3.1 percent to the overall model performance, suggesting that while AI usage enhances the learning process, it serves primarily as a complementary rather than dominant factor. The relatively lower importance of distractions and bugs_reported implies that occasional disruptions or learning errors do not heavily influence final outcomes when strong behavioral and cognitive patterns are maintained. These findings collectively highlight that personal effort, consistent study habits, and cognitive regulation remain the core determinants of success in AI-assisted learning environments, whereas AI functions best as a facilitator that supports adaptive and personalized education.

Discussion

The findings of this study show that the use of artificial intelligence in learning environments plays an important role in improving student performance. The analysis indicates that behavioral factors, such as the amount of time spent on learning activities and the level of alertness sustained through caffeine intake, are the most significant contributors to success. These results suggest that while AI systems provide valuable support through adaptive feedback and personalized learning recommendations, human factors such as consistency, focus, and cognitive balance remain the most decisive elements of effective learning. The positive relationship between AI usage hours and task success also indicates that increased engagement with AI tools contributes to better learning outcomes, although this effect is moderate compared to direct learning effort.

The relationship between cognitive and physiological conditions also provides an important perspective on learning efficiency. The negative correlation between sleep hours and cognitive load suggests that insufficient rest increases mental strain and reduces the ability to absorb complex material. This finding supports existing educational research emphasizing the need for adequate rest to maintain cognitive performance. Moreover, the Random Forest model's strong predictive accuracy demonstrates that the selected behavioral and cognitive features effectively capture learning patterns in AI-supported contexts.

However, the perfect classification results may reflect overfitting, suggesting that future research should test the model on larger and more diverse datasets. Overall, these findings confirm that successful learning outcomes depend on a balanced relationship between human effort and AI assistance, where technology acts as an enhancer rather than a replacement for learner engagement.

Conclusion

This study developed and evaluated an AI-based model designed to support personalized learning by analyzing behavioral and cognitive factors. The results show that AI integration can enhance learning performance, particularly when learners interact actively with the system. The most influential predictors of success were learning duration and alertness level, indicating that consistent study habits and sustained focus have a strong effect on achievement. The contribution of AI usage was found to be supportive but not dominant, suggesting that AI functions best as a complementary tool that reinforces learner independence and self-regulation.

The outcomes of this research contribute to the growing understanding of how AI technologies can personalize education while highlighting the continuing importance of human factors. Future studies should examine the generalizability of the model by applying it to larger and more varied populations to prevent overfitting and to ensure broader applicability. Additional research that explores learner motivation, engagement, and perception of AI-based feedback could provide deeper insights into how personalized systems influence long-term learning outcomes. In conclusion, the combination of active learner participation and intelligent AI assistance offers the most effective approach to achieving adaptive, efficient, and personalized education in modern learning environments.

Declarations

Author Contributions

Conceptualization: S., C.R.A.W., I.R.Y., and I.M.; Methodology: C.R.A.W.; Software: S.; Validation: S., C.R.A.W., I.R.Y., and I.M.; Formal Analysis: S., C.R.A.W., I.R.Y., and I.M.; Investigation: S.; Resources: C.R.A.W.; Data Curation: C.R.A.W.; Writing Original Draft Preparation: S., C.R.A.W., I.R.Y., and I.M.; Writing Review and Editing: C.R.A.W., S., I.R.Y., and I.M.; Visualization: S.; All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

Funding

The authors received no financial support for the research, authorship, andor publication of this article.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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