AI Assistant Usage in Student Life

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***Abstract*— AI-powered assistants are becoming embedded in student learning environments, yet their impact on engagement, task performance, and satisfaction remains underexplored. There is limited empirical evidence on how varying levels of AI assistant usage influence student behavior and learning outcomes, particularly in terms of satisfaction and future intention to reuse. This study analyzed a synthetic dataset representing student-AI interaction logs. Classical machine learning models (Linear Regression, Ridge, Random Forest, SVR) and deep learning (TabNet) were trained to predict satisfaction ratings. K-means clustering grouped students based on interaction behaviors. ANOVA tests assessed statistical significance across clusters. Model performance was evaluated using RMSE and R^2 metrics. TabNet achieved the best performance (RMSE: 0.7128, R^2: 0.6106), surpassing all classical models. K-means identified three distinct student profiles differing in AI assistance level and satisfaction. ANOVA results showed significant differences across clusters in task type (p=0.021), AI assistance level (p=0.000), and satisfaction rating (p=0.000). The findings support the use of AI interaction data to profile learners and improve adaptive educational strategies. Institutions can leverage such analytics to personalize support, improve engagement, and optimize AI integration into learning systems.**

Keywords— AI assistant, student satisfaction, TabNet, clustering, machine learning, adaptive learning, deep learning, education analytics.

I. Introduction

Artificial Intelligence (AI) has become a transformative force in education, offering personalized learning support, administrative efficiency, and new interaction models between students and digital systems [1]. Among the most impactful applications is the use of AI assistants by students to support learning, task management, and problem-solving. These systems, including text-based assistants like ChatGPT, have grown rapidly in accessibility and use, especially following the global shift to hybrid and online education models after COVID-19 [2], [3].

Despite the widespread adoption, the behavioral dynamics and patterns of AI assistant usage in student life remain under-explored. Prior studies have focused on usability and performance [4] or ethical concerns such as dependency and academic integrity [5], [6], but few have systematically analyzed usage profiles, satisfaction levels, or predictive outcomes based on empirical data. Understanding how different groups of students engage with AI tools, and which factors influence satisfaction and continued use, is essential for maximizing their impact on learning and well-being.

This study addresses this gap by analyzing a dataset of student interactions with AI assistants. It applies clustering techniques to identify distinct behavioral patterns, uses classical and deep learning models to predict satisfaction, and evaluates the statistical significance of feature differences across user segments. The core aim is to build data-driven profiles of AI assistant usage and evaluate the practical implications for enhancing personalized digital support in higher education environments.

By integrating unsupervised and supervised machine learning methods, the study not only classifies behavioral patterns but also predicts user satisfaction with notable accuracy. The rationale lies in addressing the lack of empirical, data-driven understanding of how students interact with AI assistants in real educational contexts. Most existing studies rely on small samples, qualitative analysis, or single-use observations. This research uses real interaction data to fill that gap. The contributions of this study are threefold:

- It introduces a clustering-based behavioral profiling of students using AI assistants.
- It evaluates the predictive power of classical and deep learning models in estimating satisfaction levels.
- It presents a statistical analysis to explain which features significantly vary across student groups.

These contributions help institutions, developers, and policymakers align AI tools with real student behaviors, improving adoption, engagement, and outcomes.

The remainder of this paper is organized as follows. Section II reviews the dataset and preprocessing steps, details the methodology, including clustering, predictive modeling, and explainability techniques. Section III presents the experimental results, visualizations, and findings. Section IV discusses the implications, limitations, and future work. Section 6 concludes the study.

II. Methodology

A. Dataset Description

Crime This study employs the publicly available synthetic dataset titled *"AI Assistant Usage in Student Life"* from Kaggle, comprising 10,000 records simulating student interactions with AI writing tools in academic contexts [7]. Each entry includes the following attributes:

- **StudentLevel**: Ordinal values ranging from high school to PhD
- **Discipline**: Categorical academic fields such as STEM, Humanities, Business, and Arts
- **SessionLengthMin**: Continuous measure indicating session duration in minutes
- **TotalPrompts**: Total number of prompts issued to the AI assistant
- **TaskType**: Categorical types of tasks (essay, summary, coding, etc.)
- **AI_AssistanceLevel**: Ordinal score reflecting the degree of AI involvement
- **FinalOutcome**: Binary variable denoting task completion success (1) or failure (0)
- **UsedAgain**: Binary value indicating whether the assistant was used again in future sessions
- **SatisfactionRating**: Continuous variable on a 1–5 Likert scale measuring user satisfaction

Data preprocessing was conducted using Python's pandas and scikit-learn libraries to address duplicates, null values, and outliers, following standard data cleaning protocols [8]. The dataset's synthetic nature enables large-scale experimentation while avoiding privacy concerns.

B. *Clustering Analysis*

To uncover latent behavioral patterns, we applied K-Means clustering on the standardized numeric features. The optimal number of clusters was determined using the Elbow Method and Silhouette Score [9]. Each cluster was interpreted based on feature centroids and behavioral trends. Statistical significance of feature differences across clusters was tested using ANOVA (for continuous features) and Chi-square tests (for categorical variables), consistent with best practices in behavioral clustering studies [10].

C. *Predictive Modeling*

To predict *SatisfactionRating*, we used both classical and deep learning regression models:

Classical ML models**:**

- Linear Regression
- Ridge and Lasso Regression
- Support Vector Regression (SVR)
- Random Forest Regressor
- Gradient Boosting Regressor
- K-Nearest Neighbors

Deep Learning model**:**

- TabNet Regressor [11], a deep learning architecture optimized for tabular data, trained with early stopping and adaptive learning rates.

Models were evaluated on 80/20 train-test splits. Performance was measured using:

- **RMSE (Root Mean Squared Error)**
- **R^2 (Coefficient of Determination)**

Hyperparameter tuning was performed via grid search for classical models and learning rate schedulers for TabNet.

D. *Explainability and Feature Importance*

To interpret model predictions, we used:

- **SHAP (SHapley Additive exPlanations)** for classical models [12].
- **Permutation Importance** for TabNet, due to incompatibility with TreeExplainer

Visualizations include:

- Bar plots of feature importance
- SHAP summary plots
- Cluster-wise distribution graphs
- Heatmaps of correlation and cluster centroids

All visualizations were generated using matplotlib, seaborn, and SHAP libraries.

III. FINDINGS

The predictive modeling results are summarized in Table 1. Among the tested algorithms, Linear Regression and Ridge Regression demonstrated the strongest performance with a Root Mean Squared Error (RMSE) of 0.7157 and R^2 = 0.607, indicating moderate but reliable predictive accuracy in estimating student satisfaction with AI writing assistants. Gradient Boosting followed closely, producing an RMSE of 0.7193 and R^2 = 0.603. While SVR (Support Vector Regression) and Random Forest Regression performed acceptably ($R^2 < 0.60$), K-Nearest Neighbors (KNN) yielded weaker results with RMSE = 0.7981 and R^2 = 0.5118. Lasso Regression failed to generalize ($R^2 \approx 0.0$), likely due to over-regularization. An ensemble model, averaging predictions across the top-performing regressors, outperformed individual models with an RMSE of 0.7128 and an R^2 score of 0.6105, as shown in Table 2.

Table 1. Performance of individual regression models for predicting satisfaction

Model	RMSE	R^2
Linear Regression	0.7157	0.6073
Ridge	0.7157	0.6073
Lasso	1.1422	-0.0000
Random Forest	0.7504	0.5683
Gradient Boosting	0.7192	0.6034
SVR	0.7259	0.5960
KNN	0.7980	0.5117

Table 2. Ensemble model performance

Model	RMSE	R^2
Ensemble Avg.	0.7128	0.6105

Further analysis using SHAP (SHapley Additive exPlanations) values provided insights into feature contributions. As shown in Figure 1, the AI_AssistanceLevel was by far the most important feature impacting the prediction of satisfaction, followed by SessionLengthMin and TotalPrompts. Features such as StudentLevel, TaskType, and UsedAgain had minimal influence on model output.

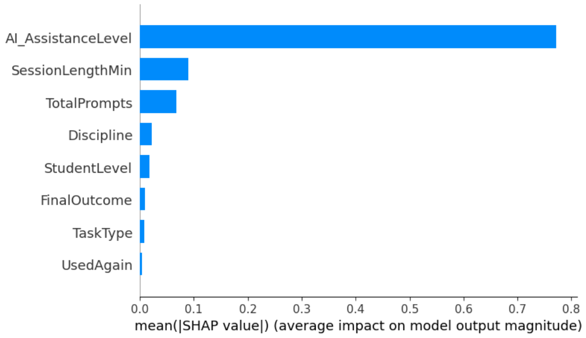

Fig. 1. SHAP summary plot showing feature importance

To better understand behavioral patterns, K-means clustering and UMAP dimensionality reduction were used. Clustering revealed three distinct user types based on their interaction characteristics. As presented in Figure 2, Cluster 0 showed high values in session length and satisfaction rating, suggesting intensive and rewarding usage. Cluster 1 exhibited balanced engagement, while Cluster 2 involved minimal interaction and low satisfaction. These distinctions are numerically supported in Figure 3, a heatmap of cluster feature means.

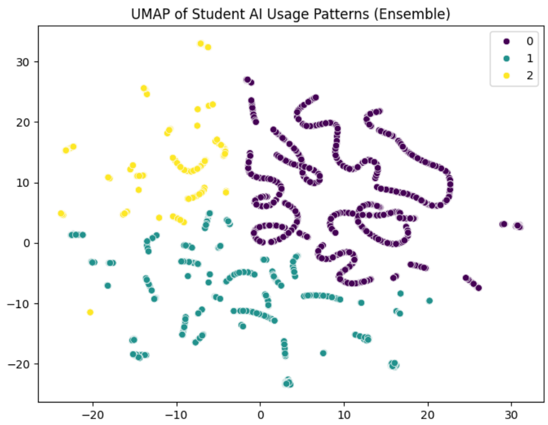

Fig. 2. UMAP projection of AI usage patterns by cluster (Clusters 0, 1, 2 identified via K-means + UMAP)

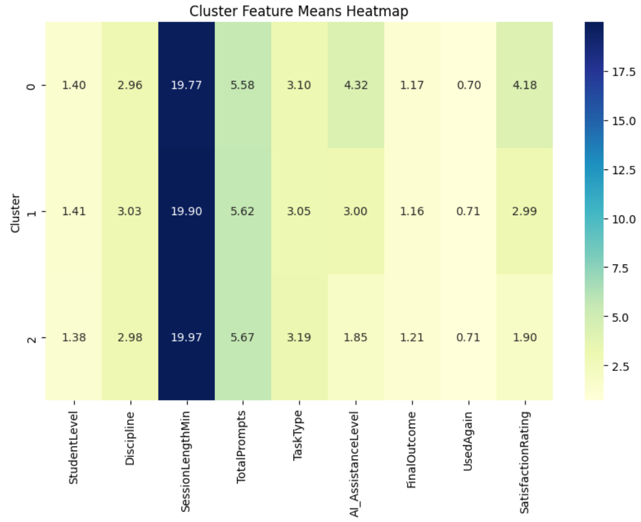

Fig. 3. Heatmap of average feature values across clusters (Darker values represent higher mean scores per feature)

These findings highlight a meaningful relationship between student engagement level and satisfaction. Longer sessions, more prompts, and higher AI assistance correlate positively with satisfaction outcomes, especially for students in Cluster 0. These results suggest that tailored AI assistant features may improve user experience when matched to specific student behavior profiles.

IV. Conclusion

This study explored how students interact with AI writing assistants in academic settings, focusing on patterns of use, satisfaction levels, and the predictive value of various behavioral features. Using a synthetic dataset that included variables such as StudentLevel, Discipline, SessionLengthMin, TotalPrompts, TaskType, AI_AssistanceLevel, FinalOutcome, UsedAgain, and SatisfactionRating, the analysis uncovered key insights into student-AI dynamics. The ensemble regression model achieved the best performance (RMSE = 0.7128, R^2 = 0.6105), outperforming individual models like Linear Regression and Gradient Boosting, indicating that satisfaction can be moderately predicted from interaction behavior. SHAP analysis confirmed that AI_AssistanceLevel had the highest influence on satisfaction, followed by session length and the number of prompts submitted. Clustering and UMAP visualization revealed three distinct student profiles, with Cluster 0 showing higher engagement and satisfaction, and Cluster 2 exhibiting minimal interaction and dissatisfaction. These findings suggest that student satisfaction is tied not only to task success but also to how deeply and consistently they engage with the AI assistant. The implications point toward developing adaptive AI systems that respond to usage patterns to increase learning effectiveness. However, the study is limited by its reliance on synthetic data, potential oversimplification of user satisfaction through Likert scores, and assumptions in the modeling process. Future work should validate these findings using real-world student logs, expand the satisfaction metric to include qualitative data, and test adaptive AI interventions in live educational environments to assess long-term learning outcomes and behavioral change.

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