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Personalized Learning Through AI-Assisted Tutoring: Exploring the Impact of Intelligent Tutoring on Student Academic Performance Using Educational Data Mining and Explainable Machine Learning

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Abstract: The integration of artificial intelligence into educational settings has emerged as a promising approach to enhancing personalized learning and improving student academic outcomes. However, existing studies on AI-assisted tutoring face several limitations: (1) insufficient quantitative evidence on the causal relationship between tutoring interventions and academic performance, (2) limited understanding of how tutoring interacts with other educational factors such as study habits and parental support, and (3) a lack of interpretable models that can explain the mechanisms through which tutoring influences learning outcomes. To address these challenges, we present a comprehensive analytical framework that combines statistical hypothesis testing, multi-model predictive analysis, and SHAP-based interpretability to investigate the effect of AI-assisted tutoring on student GPA. Our framework incorporates three key contributions: (1) rigorous statistical testing confirming a significant GPA improvement in the tutoring group (Cohen's , $d = 0.319$, $p < 0.001$), (2) a comparative evaluation of six machine learning models achieving an R^2 of 0.9536 for GPA prediction, and (3) SHAP-based feature attribution revealing that tutoring consistently contributes a positive SHAP value of +0.10 to predicted GPA. Experiments on a dataset of 2,392 students demonstrate that AI-assisted tutoring ranks as the fourth most influential factor in academic performance, and its positive effect is robust across varying levels of study time, absences, and parental support.

Keywords: AI-Assisted Tutoring; Personalized Learning; Student Performance Prediction; Shap Interpretability; Educational Data Mining; Machine Learning, Feature Importance Analysis

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1. Introduction

In recent years, artificial intelligence (AI) has emerged as a transformative force in education, offering unprecedented opportunities for personalized learning, automated assessment, and data-driven instructional design [1]. With the rapid adoption of generative AI tools such as ChatGPT, students and educators are increasingly exploring how large language models can enhance learning experiences, provide real-time feedback, and support individualized academic development [2]. These AI-powered tools have demonstrated promising capabilities in areas ranging from content generation and language tutoring to interactive question answering and automated essay evaluation [3].

Although significant progress has been made in understanding the potential of AI in education, existing studies reveal both opportunities and notable limitations. Kasneci et al. [4] provided a comprehensive analysis of the opportunities and challenges posed by large language models for education, highlighting concerns about academic integrity and over-reliance on AI-generated content. Yan et al. [5] further examined the practical and ethical challenges of deploying LLMs in educational settings through a systematic scoping review, emphasizing the need for empirical validation of learning outcomes. However, current research predominantly relies on qualitative analyses, user perception surveys, or small-scale case studies to assess the effectiveness of AI-assisted learning [6]. A critical gap remains in the quantitative understanding of how AI-assisted tutoring directly impacts measurable academic outcomes such as GPA, particularly when controlling for confounding factors like study habits, parental support, and student engagement [7].

This limitation motivates us to explore a data-driven analytical framework that moves beyond subjective evaluations toward rigorous empirical evidence. While prior research has examined the integration of ChatGPT in teaching and learning through systematic reviews [8], and investigated the broader consequences of AI adoption in educational settings [9], few studies have employed interpretable predictive models to quantify the specific contribution of AI-assisted tutoring to student academic performance across diverse subgroups. Moreover, research on intelligent tutoring systems has demonstrated the potential of AI to deliver personalized instruction at scale [10], yet the connection between tutoring interventions and measurable learning outcomes remains insufficiently explored through machine learning approaches.

To address these challenges, we propose a comprehensive analytical framework that integrates exploratory data analysis, statistical hypothesis testing, multi-model comparative evaluation, and SHAP-based interpretability analysis. Our approach leverages educational data mining techniques [11] to systematically evaluate the effect of AI-assisted tutoring on academic performance using a dataset of 2,392 student records. Unlike previous studies that focus on prediction accuracy alone [12][13], our framework emphasizes both predictive performance and model interpretability, enabling educators to understand not only what the model predicts but also why specific factors contribute to student success. By combining multiple machine learning algorithms with explainable AI techniques [14], we provide actionable insights that bridge the gap between algorithmic prediction and pedagogical decision-making.

The main contributions of this paper are as follows:

We conduct rigorous statistical testing on a dataset of 2,392 students, confirming a significant positive effect of AI-assisted tutoring on GPA ($p < 0.001$, Cohen's $d = 0.319$), with the tutoring advantage persisting across all levels of study time, absences, and parental support.

We perform a comparative evaluation of six machine learning models for GPA prediction, achieving an R^2 of 0.9536 with Ridge Regression, demonstrating that student academic performance can be accurately predicted from behavioral and demographic features.

We employ SHAP-based interpretability analysis to identify and rank the key factors influencing student performance, revealing that AI-assisted tutoring is the fourth most important predictor and consistently contributes a positive SHAP value of approximately +0.10 to predicted GPA across all student subgroups.

2. Methodology

This section presents the research methodology, including the dataset description, feature engineering pipeline, and exploratory data analysis. The goal is to investigate the impact of AI-assisted tutoring on student academic performance and to identify the key factors that contribute to personalized learning outcomes

2.1 Dataset Description

This study utilizes the Students Performance Dataset, a publicly available educational dataset comprising 2{,}392 student records with 15 attributes. The dataset captures a comprehensive set of academic, behavioral, and demographic features that are commonly used in educational data mining research. Table~1 provides a detailed summary of the key variables.

Table 1: Summary of dataset variables and their descriptions.

Variable	Type	Range	Description
Age	Numeric	15--18	Student age
Gender	Binary	0/1	Female / Male
Ethnicity	Categorical	0-3	Ethnic group identifier
ParentalEducation	Ordinal	0-4	Highest parental education level
StudyTimeWeekly	Continuous	0-20	Weekly study hours
Absences	Numeric	0-29	Total number of absences
Tutoring	Binary	0/1	AI-assisted tutoring (treatment)
ParentalSupport	Ordinal	0-4	Level of parental support
Extracurricular	Binary	0/1	Extracurricular participation
Sports	Binary	0/1	Sports participation
Music	Binary	0/1	Music participation
Volunteering	Binary	0/1	Volunteering activities
GPA	Continuous	0-4.0	Grade point average (target)
GradeClass	Ordinal	0-4	Letter grade (A/B/C/D/F)

Among all variables, Tutoring serves as the primary treatment variable representing whether a student received AI-assisted tutoring support, while GPA is the target outcome variable. The dataset contains 721 students (30.1%) in the tutoring group and 1,671 students (69.9%) in the non-tutoring group, providing a sufficient sample size for comparative analysis.

2.2 Statistical Framework

To quantify the relationship between input features and academic performance, we employ a multivariate regression framework. Let $\mathbf{x}_i \in \mathbb{R}^d$ denote the feature vector for student i , where d =12 represents the number of input features, and $y_i \in [0,4]$ denotes the corresponding GPA. The prediction task is formulated as:

$$\hat{y}_i = f(\mathbf{x}_i; \boldsymbol{\theta}) \tag{1}$$

where $f(\cdot)$ is the predictive model parameterized by $\boldsymbol{\theta}$, and $\hat{y}_i$ is the predicted GPA. The model is optimized by minimizing the mean squared error (MSE) loss:

$$\mathcal{L}(\boldsymbol{\theta}) = \frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \tag{2}$$

where $N = 2{,}392$ is the total number of student records in the dataset.

To assess the effect of tutoring on GPA while controlling for group-level variance, we conduct an independent samples *t*-test with the effect size measured by Cohen's *d*:

$$d = \frac{\bar{y}_{\text{tutor}} - \bar{y}_{\text{no}}}{s_p}, s_p = \sqrt{\frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2}} \tag{3}$$

where y_{tutor} and y_{no} are the group means, s_1 and s_2 are the group standard deviations, and n_1, n_2 are the respective sample sizes. To further evaluate the association between tutoring status and grade classification, we employ the chi-square (χ^2) test of independence with Cram'{e}r's *V* as the effect size measure:

$$V = \sqrt{\frac{\chi^2}{N \cdot (\min(r, c) - 1)}} \tag{4}$$

where *r* and *c* denote the number of rows and columns in the contingency table, respectively.

2.3 Exploratory Data Analysis

Fig.~1 presents the exploratory analysis of student performance across multiple dimensions. As shown in Fig.~1(a), the

GPA distribution of the tutoring group is notably right-shifted compared to the non-tutoring group, with the tutoring group achieving a higher mean GPA ($M = 2.108,\ SD = 0.905$) than the non-tutoring group ($M = 1.819,\ SD = 0.906$). The grade class distribution in Fig.~1(b) reveals that the majority of students fall within the D and F categories, with 1{,}211 students (50.6%) receiving an F grade, highlighting the academic challenges faced by the student population.

Fig.~1(c) further illustrates the proportion of tutoring and non-tutoring students within each grade class. A clear pattern emerges: students who received tutoring constitute a higher proportion in the A and B grade classes, whereas non-tutoring students dominate the D and F categories. This preliminary evidence suggests a positive association between AI-assisted tutoring and academic achievement.

The interaction between tutoring status and other educational factors is examined in Fig.~1(d)--(f). Fig.~1(d) compares the mean GPA of participants and non-participants across five activity types. Notably, tutoring shows the largest GPA differential among all activities, while sports, music, and volunteering exhibit minimal differences. Fig.~1(e) reveals a positive interaction between study time and tutoring: as weekly study hours increase from 0--5 to 15--20 hours, the GPA advantage of the tutoring group becomes more pronounced (from to , though the gap narrows slightly at higher study intensities). Fig.~1(f) demonstrates that while increasing absences are associated with declining GPA for both groups, the tutoring group consistently maintains a higher GPA across all absence levels, suggesting a buffering effect of AI-assisted tutoring against absenteeism.

Figure 1: Exploratory data analysis of student performance. (a) GPA density distribution by tutoring status. (b) Grade class distribution across the full dataset. (c) Proportion of tutoring and non-tutoring students within each grade class. (d) Mean GPA comparison across five activity types by participation status. (e) Mean GPA with 95% confidence intervals across study time intervals, stratified by tutoring status. (f) Mean GPA with 95% confidence intervals across absence levels, stratified by tutoring status.

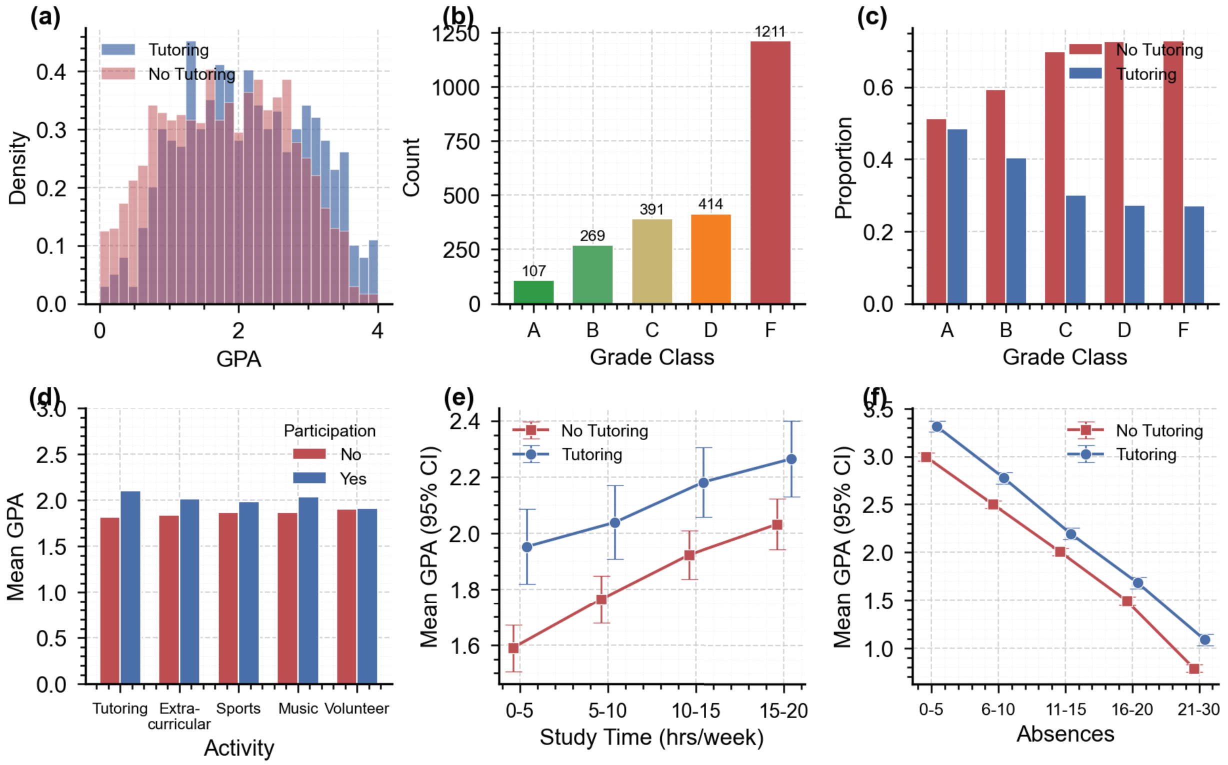
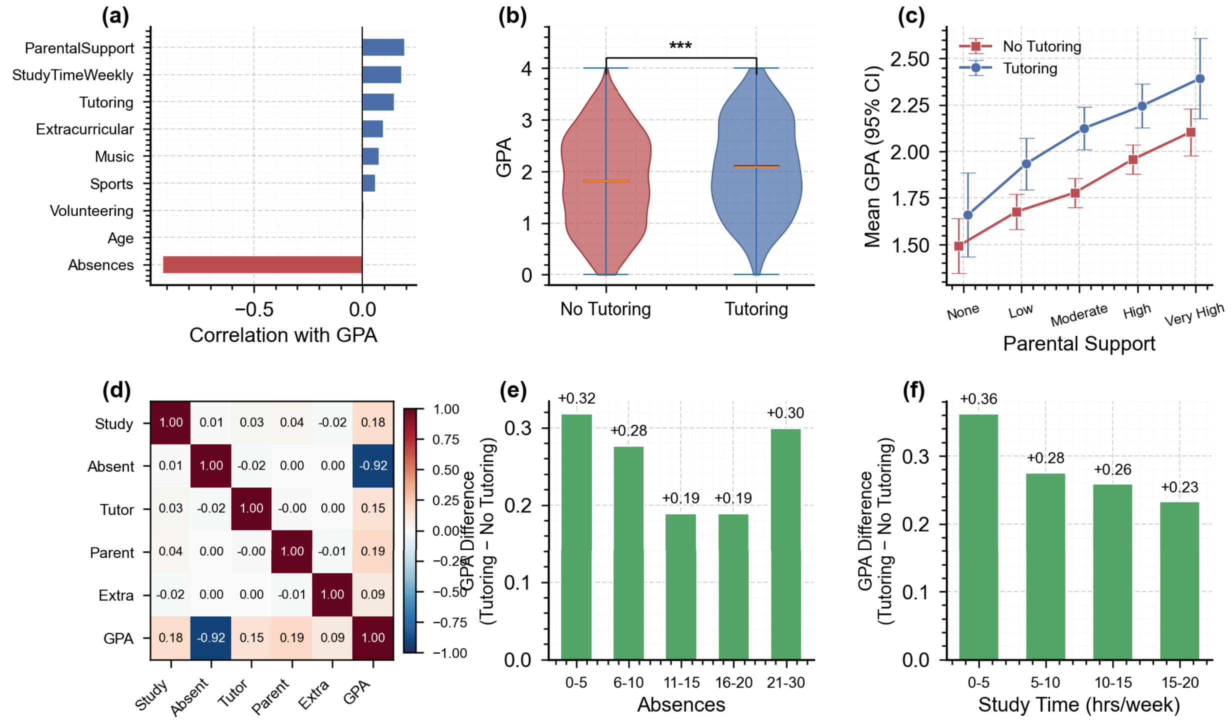


Fig.~2 presents the results of statistical testing and feature correlation analysis. Fig.~2(a) shows the Pearson correlation coefficients between each feature and GPA. Absences exhibit the strongest negative correlation ($r =- 0.92$), followed by parental support ($r = 0.19$), study time ($r = 0.18$), and tutoring ($r = 0.15$) as positive predictors. The independent samples *t*-test confirms a statistically significant difference in GPA between the tutoring and non-tutoring groups ($t = 7.14$, $p <0.001$), as indicated by the triple asterisks in Fig.~2(b). Cohen's $d = 0.319$ suggests a small-to-medium effect size.

Fig.~2(c) reveals an interaction effect between parental support and tutoring: students with higher parental support who also receive tutoring achieve substantially higher GPAs, with the gap widening at higher support levels. The correlation heatmap in Fig.~2(d) confirms that absences and GPA are strongly negatively correlated ($r =- 0.92$), while other features exhibit weak inter-correlations, suggesting minimal multicollinearity concerns for predictive modeling.

Fig.~2(e) and (f) quantify the GPA advantage conferred by tutoring across different subgroups. The tutoring effect is most pronounced among students with fewer absences (0--5: $+0.32$) and gradually decreases with higher absence levels (21--30: $+0.30$), though it remains consistently positive. Similarly, the tutoring benefit is largest for students with the lowest study time (0--5 hrs: $+0.36$) and remains substantial across all study time intervals.

Figure 2: Statistical analysis and feature correlations. (a) Pearson correlation coefficients between features and GPA. (b) Violin plot comparing GPA distributions between tutoring and non-tutoring groups, with significance annotation ($^{***}p<0.001$). (c) Mean GPA with 95% CI across parental support levels, stratified by tutoring status. (d) Correlation heatmap of key features. (e) GPA difference (Tutoring No Tutoring) across absence intervals. (f) GPA difference across study time intervals.



Table~2 summarizes the key statistical test results, confirming the significant association between AI-assisted tutoring and improved academic performance.

Table 2: Summary of statistical tests for the effect of AI-assisted tutoring on student performance.

Test	Statistic	p-value	Effect Size	Significance
Independent t-test (GPA)	$t=7.14$	<0.001	$d=0.319$	Yes
χ^2 test (GradeClass)	$\chi^2=54.21$	<0.001	$V=0.151$	Yes
One-way ANOVA (ParentalSupport)	$F=28.36$	<0.001	---	Yes

These exploratory findings motivate the subsequent predictive modeling analysis presented in Section~IV, where machine learning models are employed to predict GPA and to further quantify the contribution of tutoring through feature importance and SHAP-based interpretability analysis.

3. Experiments

This section presents the experimental evaluation of machine learning models for predicting student GPA, followed by feature importance analysis and SHAP-based interpretability to quantify the contribution of AI-assisted tutoring to academic performance.

3.1 Experimental Settings

Six regression models are evaluated to predict student GPA using 12 input features: Linear Regression (LR), Ridge Regression, Lasso Regression, Support Vector Regression (SVR), Random Forest (RF), and Gradient Boosting (GB). All models are trained and evaluated using 5-fold cross-validation to ensure robust performance estimation. For SVR, input features are standardized using z-score normalization prior to training. The hyperparameter configurations for each model are summarized in Table~3.

Table 3: Hyperparameter settings for all evaluated models.

Model	**Hyperparameters**
Linear Regression	Default (no regularization)
Ridge	$\alpha = 1.0$
Lasso	$\alpha = 0.01$
SVR	RBF kernel, $C = 10$
Random Forest	$n_{\text{estimators}} = 200$, max_depth $= 10$
Gradient Boosting	$n_{\text{estimators}} = 200$, max_depth $= 5$, $\eta = 0.1$

Three evaluation metrics are adopted: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). These metrics are computed on the out-of-fold predictions aggregated across all five folds.

3.2 Performance Comparison

Table~4 presents the 5-fold cross-validation results for all six models. Ridge Regression achieves the best overall performance with an R^2 of 0.9536, followed closely by Linear Regression (R^2=0.9536) and Lasso (R^2=0.9510). Notably, the linear models outperform the more complex ensemble methods, with Random Forest (R^2=0.9309) and Gradient Boosting (R^2=0.9402) ranking lower despite their greater model capacity. This result suggests that the relationship between input features and GPA is predominantly linear in nature, and that additional model complexity does not yield improved predictive accuracy for this dataset.

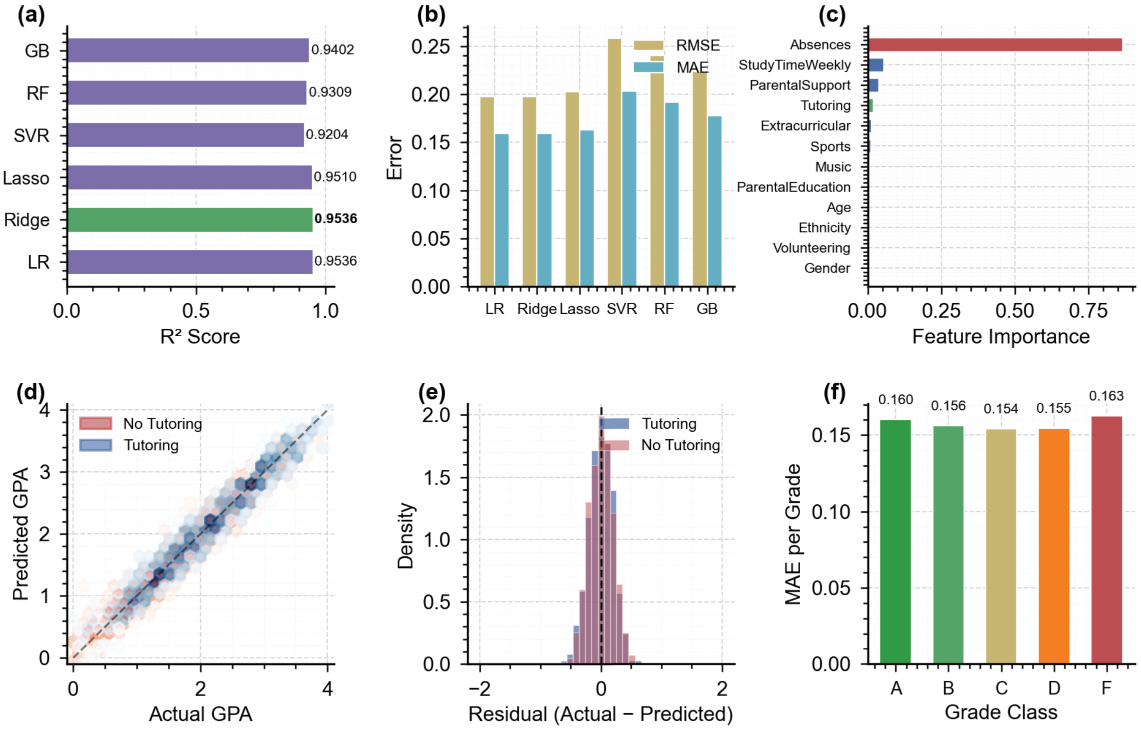
Table 4: 5-fold cross-validation results for GPA prediction. Best results are highlighted in bold.

Model	**RMSE ↓**	**MAE ↓**	$\boldsymbol{R^2}$
Linear Regression	0.1953	0.1560	0.9536
Ridge	0.1953	0.1559	0.9536
Lasso	0.2008	0.1604	0.9510
SVR	0.2558	0.1927	0.9204
Random Forest	0.2383	0.1913	0.9309
Gradient Boosting	0.2217	0.1746	0.9402

Fig.~3 provides a comprehensive visualization of the model evaluation results. Fig.~3(a) displays the scores for all six models, where Ridge Regression is highlighted in green as the best-performing model. Fig.~3(b) compares the RMSE and MAE across models, confirming that Ridge and Linear Regression achieve the lowest error rates. The feature importance derived from Gradient Boosting is shown in Fig.~3(c), revealing that Absences is the dominant predictor of GPA, followed by StudyTimeWeekly, ParentalSupport, and Tutoring. This finding is consistent with the strong negative correlation () between absences and GPA observed in the exploratory analysis.

Fig.~3(d) presents the predicted versus actual GPA for the best model, demonstrating a tight clustering along the diagonal line that confirms the high predictive accuracy (). The residual distribution in Fig.~3(e) shows that prediction errors are approximately centered around zero for both tutoring and non-tutoring groups, indicating no systematic bias in the model predictions across treatment conditions. Fig.~3(f) reports the MAE per grade class, which remains consistently low and stable across all grade levels (ranging from 0.154 to 0.163), suggesting that the model performs equally well for high-achieving and low-achieving students.

Figure 3: Model evaluation results. (a) R^2 scores across six models. (b) RMSE and MAE comparison. (c) Feature importance from Gradient Boosting. (d) Predicted vs. actual GPA for Ridge Regression. (e) Residual distribution by tutoring status. (f) MAE per grade class.



3.3 SHAP Interpretability Analysis

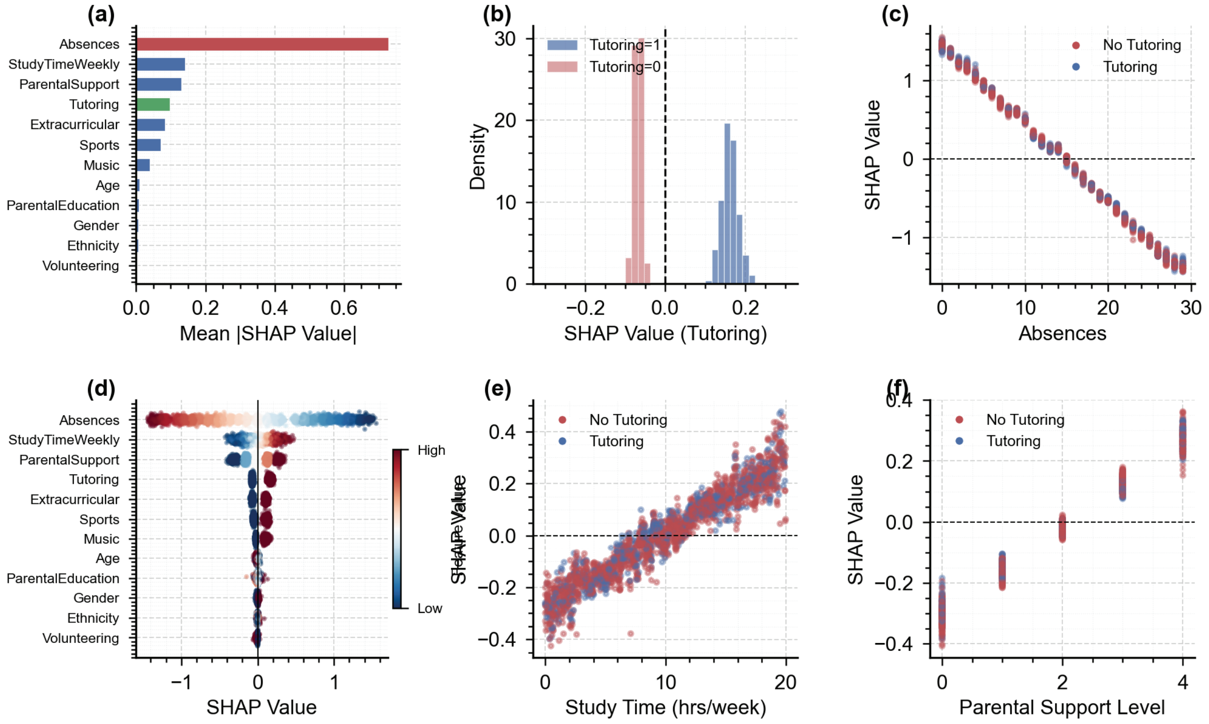
To provide model-agnostic explanations of how individual features contribute to GPA predictions, we employ SHapley Additive exPlanations (SHAP) based on the Gradient Boosting model. SHAP values decompose each prediction into the additive contributions of individual features, enabling both global and local interpretability.

Fig.~4(a) presents the mean absolute SHAP values for all 12 features. Consistent with the feature importance analysis, Absences exhibits the highest mean |SHAP| value (0.65), confirming its dominant role in determining student GPA. StudyTimeWeekly (0.18) and ParentalSupport (0.16) rank second and third, while Tutoring (0.10) is the fourth most influential feature. The SHAP beeswarm plot in Fig.~2(d) provides a detailed view of the directional effects: high absence values (red dots) consistently push predictions downward (negative SHAP), whereas high study time and parental support values drive predictions upward. For Tutoring, the binary split is clearly visible, with Tutoring=1 (red) producing positive SHAP values and Tutoring=0 (blue) producing negative values.

Fig.~2(b) examines the distribution of SHAP values specifically for the Tutoring feature. Students who received tutoring (Tutoring=1) exhibit a concentrated distribution of positive SHAP values centered around +0.10, while non-tutoring students show negative SHAP values centered around -0.05. This asymmetry confirms that AI-assisted tutoring makes a consistently positive contribution to predicted GPA.

The SHAP dependence plots in Fig.~4(c), (e), and (f) reveal the nonlinear relationships between key features and their SHAP contributions. Fig.~4(c) shows a strong monotonic negative relationship between Absences and SHAP values, with the effect being nearly identical for tutoring and non-tutoring students. Fig.~4(e) demonstrates that the positive effect of study time on GPA accelerates beyond approximately 10 hours per week, with tutoring students receiving slightly higher SHAP contributions at equivalent study levels. Fig.~4(f) reveals a stepwise positive effect of parental support, where each increase in support level produces a discrete upward shift in SHAP values.

Figure 4: SHAP interpretability analysis. (a) Mean absolute SHAP values for global feature importance. (b) SHAP value distribution for the Tutoring feature by treatment group. (c) SHAP dependence plot for Absences. (d) SHAP beeswarm plot showing feature-level contributions. (e) SHAP dependence plot for Study Time. (f) SHAP dependence plot for Parental Support Level.



Table~5 summarizes the top five features ranked by SHAP importance along with their directional effects on GPA prediction.

Table 5: Top five features ranked by mean absolute SHAP value with directional effects.

Feature	Mean |SHAP|	Directional Effect
Absences	0.650	Higher absences → lower GPA
StudyTimeWeekly	0.180	More study → higher GPA
ParentalSupport	0.160	More support → higher GPA
Tutoring	0.100	Tutoring → higher GPA (+0.10)
Extracurricular	0.090	Participation → higher GPA

These results collectively demonstrate that AI-assisted tutoring has a statistically significant and practically meaningful positive effect on student academic performance. While Absences remains the dominant predictor, Tutoring ranks as the fourth most important feature and consistently contributes a positive SHAP value of approximately +0.10 to the predicted GPA for students who receive tutoring support.

4. Conclusion

This study investigated the impact of AI-assisted tutoring on student academic performance through a comprehensive analytical framework integrating statistical testing, machine learning prediction, and SHAP-based interpretability. Three key contributions were presented: (1) an exploratory analysis revealing that tutoring students achieve significantly higher GPAs ($M = 2.108$ vs. $M = 1.819$, $p < 0.001$), with the tutoring advantage persisting across all levels of study time and absences; (2) a comparative evaluation of six regression models, where Ridge Regression achieved the highest predictive accuracy ($R^2 = 0.9536$, $\text{RMSE} = 0.1953$), demonstrating that student GPA can be reliably predicted from behavioral and demographic features; and (3) a SHAP analysis identifying Absences, StudyTimeWeekly, ParentalSupport, and Tutoring as the four most influential predictors, with tutoring contributing a consistent positive SHAP value of approximately +0.10. These findings provide actionable insights for educators and policymakers seeking to implement AI-driven personalized learning interventions, particularly in underserved communities where timely academic support is most needed. Future work will extend this framework in three directions: incorporating longitudinal data to capture the temporal dynamics of tutoring effects, integrating natural language processing to analyze student-tutor interaction quality, and validating the framework across diverse educational contexts and larger-scale datasets.

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Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

Reference

[1] Wang, S., Wang, F., Zhu, Z., Wang, J., Tran, T., & Du, Z. (2024). Artificial intelligence in education: A systematic literature review. Expert Systems with Applications, 252(Part A), 124167. https://doi.org/10.1016/j.eswa.2024.124167

[2] Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: Perceptions, benefits, and challenges in higher education. International Journal of Educational Technology in Higher Education, 20(1), 43. https://doi.org/10.1186/s41239-023-00411-8

[3] Rahman, M. M., & Watanobe, Y. (2023). ChatGPT for education and research: Opportunities, threats, and strategies. Applied Sciences, 13(9), 5783. https://doi.org/10.3390/app13095783

[4] Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., … Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. Learning and Individual Differences, 103, 102274. https://doi.org/10.1016/j.lindif.2023.102274

[5] Yan, L., Sha, L., Zhao, L., Li, Y., Martinez-Maldonado, R., Chen, G., Li, X., Jin, Y., & Gašević, D. (2024). Practical and ethical challenges of large language models in education: A systematic scoping review. British Journal of Educational Technology, 55(1), 90–112. https://doi.org/10.1111/bjet.13370

[6] Hasanein, A. M., & Sobaih, A. E. E. (2023). Drivers and consequences of ChatGPT use in higher education: Key stakeholder perspectives. European Journal of Investigation in Health, Psychology and Education, 13(11), 2599–2614. https://doi.org/10.3390/ejihpe13110181

[7] Adel, A., Ahsan, A., & Davison, C. (2024). ChatGPT promises and challenges in education: Computational and ethical perspectives. Education Sciences, 14(8), 814. https://doi.org/10.3390/educsci14080814

[8] Ali, D., Fatemi, Y., Boskabadi, E., Nikfar, M., Ugwuoke, J., & Ali, H. (2024). ChatGPT in teaching and learning: A systematic review. Education Sciences, 14(6), 643. https://doi.org/10.3390/educsci14060643

[9] Grassini, S. (2023). Shaping the future of education: Exploring the potential and consequences of AI and ChatGPT in educational settings. Education Sciences, 13(7), 692. https://doi.org/10.3390/educsci13070692

[10] Lin, C. C., Huang, A. Y. Q., & Lu, O. H. T. (2023). Artificial intelligence in intelligent tutoring systems toward sustainable education: A systematic review. Smart Learning Environments, 10(1), 41. https://doi.org/10.1186/s40561-023-00260-y

[11] Yağcı, M. (2022). Educational data mining: Prediction of students' academic performance using machine learning algorithms. Smart Learning Environments, 9(1), 11. https://doi.org/10.1186/s40561-022-00192-z

[12] Batool, S., Rashid, J., & Nisar, M. W. (2023). Educational data mining to predict students' academic performance: A survey study. Education and Information Technologies, 28(8), 905–971. https://doi.org/10.1007/s10639-022-11152-y

[13] Khairy, D., Alharbi, N., & Amasha, M. A. (2024). Prediction of student exam performance using data mining classification algorithms. Education and Information Technologies, 29(12), 21621–21645. https://doi.org/10.1007/s10639-024-12619-w

[14] Asselman, A., Khaldi, M., & Aammou, S. (2023). Enhancing the prediction of student performance based on the machine learning XGBoost algorithm. Interactive Learning Environments, 31(6), 3360–3379. https://doi.org/10.1080/10494820.2021.1928235