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Artificial Intelligence-Based Prediction of Student Academic Performance: An Explainable Machine Learning Approach to AI-Assisted Learning

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ABSTRACT
Artificial intelligence-assisted learning is increasingly influencing higher education, creating a need for predictive approaches that can identify academic-performance patterns while remaining interpretable. This study aimed to develop and explain machine-learning models for predicting student academic performance using demographic and learning-related characteristics. Secondary data from 257 students were analyzed, with CGPA as the outcome and age, gender, academic level, location, Creative Thinking, GenAI Literacy, Digital Literacy, and GenAI use frequency as predictors. Elastic Net, Random Forest, Gradient Boosting, and support vector regression were compared using five-fold cross-validation and a held-out 20% test set. Random Forest achieved the lowest mean cross-validation RMSE (0.489) and was retained as the final model. On the test set, it achieved R^2 = 0.382, RMSE = 0.420, and MAE = 0.299. Creative Thinking and Age emerged as the most influential predictors, while GenAI Literacy also contributed meaningfully to prediction. SHAP analysis identified positive contributions for Creative Thinking, a nonlinear pattern for Age, and an inverse conditional pattern for GenAI Literacy. The findings demonstrate that explainable machine learning can provide moderate predictive performance while revealing distinct predictor contributions, supporting transparent academic-performance analytics in AI-assisted learning environments.

Keywords: academic performance, explainable artificial intelligence, machine learning, generative AI literacy, creative thinking

1. Introduction

AI is transforming higher education, moving digital learning beyond the conventional online space to systems that can produce content, facilitate inquiry, give feedback and assist students with complex academic tasks. Generative AI has fast-tracked this shift as students can now directly interact with tools that generate explanations, summaries, ideas and other learning resources. However, the educational value of AI is dependent on pedagogically appropriate and ethically responsible use, not merely access, and students' ability to engage critically with AI is increasingly relevant to learning outcomes (Nguyen, 2025). Thus, higher education institutions are challenged to harness the educational potential of generative AI while addressing concerns about reliability, assessment, academic integrity, and evolving learning practices (Michel-Villarreal et al., 2023). The broader growth of AI in higher education has also expanded the role of educational data and predictive analytics. Current applications include learning support, assessment, personalization, institutional decision-making, and increasingly sophisticated forms of student-technology interaction (Zawacki-Richter et al., 2024). These shifts expand the competencies necessary for successful participation in digital learning environments. Digital literacy remains important, but in the case of systems powered by AI, users need to know how intelligent tools work, how to assess what they produce, and how to make smart choices about using them. This change has caused a transition from traditional digital competence to skills appropriate for interaction with AI-powered assistants (Naamati-Schneider & Alt, 2024). Evidence from technology-supported education, however, suggests that the use of technology does not lead to uniform learning benefits, as effects vary across cognitive, affective and behavioral outcomes and depend on how technologies are embedded in learning activities (Wang et al., 2023).

Hence, student academic performance in such environments is influenced by more than technological access. The interaction between individual characteristics, technology, learning tasks, and learning environments could influence performance via behavioral, emotional, and cognitive engagement (Liu et al., 2023). Gradient boosting is a type of artificial intelligence (AI) that may be used to solve regression and classification problems. As a prediction model, it provides a set of overall prediction models and decision trees. It builds models in a stage-savvy approach, similar to previous improvement strategies, and summarizes them by permitting arbitrarily distinguishable unpleasant work (Ghulab Nabi 2022) This is especially true for creative thinking, as AI-assisted learning may require students to articulate problems, evaluate information that is generated, consider alternatives, and turn technology outputs into meaningful academic work. Research into the use of generative AI in design-thinking pedagogy has proposed its potential connections to creativity, critical thinking, and ethics when purposefully incorporated in higher education (Rana et al., 2025). Therefore, Creative Thinking, Digital Literacy, and GenAI Literacy may represent complementary dimensions of students' ability to function within AI-assisted learning environments. Machine learning provides a data-driven way to study how these characteristics contribute to variation in academic performance. More and more algorithms are being used to predict student performance by capturing patterns that may be hard to express using traditional linear relationships alone. The comparative applications have shown that it is possible to use machine-learning algorithms to model educational results from student-related data (Ahmed, 2024). Likewise, classification and prediction studies have demonstrated that different algorithms can lead to varying degrees of performance when used on educational data, emphasizing the significance of systematic model comparison rather than simply using one technique (Pallathadka et al., 2023). Machine learning approaches have also been used to predict achievement in secondary and intermediate educational contexts, demonstrating their applicability to modeling academic performance across different student populations (Hussain & Khan, 2023).

Predictive modeling is particularly useful where it does not merely describe retrospectively, but actually identifies patterns associated with academic outcomes. Research on early prediction in higher education has provided evidence on how student data can be integrated into machine-learning models to forecast future performance (Alhazmi & Sheneamer, 2023). Educational data mining has extended this approach to include computational methods for analyzing academic performance and identifying informative attributes in student datasets (Sarker et al., 2024). However, predictive accuracy alone does not tell us why a model makes particular estimates. This problem is interesting in the setting of nonlinear ensemble models where good predictive performance might be achieved at the expense of ease of interpretability. This limitation can be mitigated by using explainability techniques that quantify the feature contributions. SHAP and permutation feature importance offer complementary views, with the former explaining feature contributions to predictions and the latter assessing model performance changes when feature information is perturbed (Mamba et al., 2024). Yet, significant gaps in the prediction of academic performance in AI-assisted learning contexts persist. Most existing machine-learning studies have focused on demographic, behavioral, engagement, or traditional academic variables, and the combined predictive relevance of Creative Thinking, Digital Literacy, and GenAI Literacy is not well studied. Emerging work on generative AI has deepened understanding of its educational opportunities, but relatively little attention has been given to the role of GenAI-related competence in forecasting models considering wider digital and cognitive characteristics. The second gap is interpretability. Knowing which algorithm is accurate does not tell us which student features are driving its predictions, nor whether these effects are linear or nonlinear. Thus, the combination of machine learning with explainable artificial intelligence can provide predictive and interpretable evidence at the same time, without treating the relations derived from models as causal effects. Digital media now have enhanced provenance tracking methods. Collaborative repositories provide global access to cultural data that encourages transdisciplinary research and alternative access for public engagement. Furthermore, Augmented Reality (AR) technologies are increasingly employed to provide interactive visualization and immersive experiences of heritage artefacts, enhancing public engagement and education (Srivastava ,2026)

Artificial Intelligence has found its way on educational ecosystems, museum experiences, and informal cultural learning settings, providing the opportunities of adaptive, interactive and user-centered knowledge interaction. In the formal education process, AI can aid automatic grading, profile-specific tutoring, content recommendation, and multimodal analytics that will match the instructional content with the cognitive profile and development patterns of learners. (Vanishree Kavi Mahesh 2026)

The present study attempts to fill these gaps by applying an explainable machine-learning framework to student academic performance based on CGPA. The study aims to: (1) investigate the relationships between Creative Thinking, Digital Literacy, GenAI Literacy and academic performance; (2) develop and compare machine-learning models to predict academic performance based on demographic and learning-related characteristics; (3) explain the contribution and prediction patterns of major academic performance predictors using explainable artificial intelligence methods.

2. Methodology

2.1 Research Design

This study used a quantitative secondary-data design to predict student academic performance and explore the contribution of AI-assisted learning characteristics. The continuous outcome was CGPA, and the predictor variables included demographic characteristics, Creative Thinking, Digital Literacy, and GenAI Literacy. The analysis was carried out with descriptive statistics, correlation analysis, supervised machine learning regression and explainable artificial intelligence techniques.

2.2 Data Source

The data were obtained from the secondary dataset published by Setsoafia et al. (2026). It consisted of pre-service visual art teachers in Ghana. It included demographic, academic, Creative Thinking, Digital Literacy, and generative AI-related measures. These variables were used to analyze variation in student academic performance.

2.3 Data Preparation and Variable Construction

The data were screened for duplicate records, missing values, invalid responses and implausible observations. One duplicate was excluded. 257 participants were analyzed. One invalid Digital Literacy response was coded as missing. An age value of zero was coded as missing. Composite scores were calculated for Creative Thinking, GenAI Literacy, and Digital Literacy from their respective questionnaire items. Cronbach's alpha was used to assess internal consistency. CGPA was retained as the academic performance outcome.

2.4 Predictor Specification and Preprocessing

The predictors were Age, Gender, Academic Level, Location, Creative Thinking, GenAI Literacy, Digital Literacy, and GenAI use frequency. Continuous variables were assessed using Pearson and Spearman correlations. Multicollinearity was determined using variance inflation factors. Median imputation and standardization were used for numeric predictors, while for categorical variables, the most frequent category was imputed and one-hot encoding was used. These preprocessing procedures were included in the modeling pipeline.

2.5 Machine-Learning Modelling and Evaluation

The data set was split into 80% training and 20% test subsets, corresponding to 205 and 52 observations respectively. Elastic Net, Random Forest, Gradient Boosting and support vector regression were tried. Hyperparameter tuning was performed by five-fold cross-validation on the training set. Model performance was evaluated using R^2, root mean squared error (RMSE) and mean absolute error (MAE). The final model was selected based on the cross-validation performance and stability, and Random Forest was kept for subsequent interpretation.

2.6 Explainable Artificial Intelligence Analysis

Permutation importance and SHapley Additive exPlanations (SHAP) were employed to interpret the final Random Forest model. Permutation importance quantified the impact of individual predictors on predictive performance, and mean absolute SHAP values provided a summary of the overall contribution of individual predictors to model predictions. SHAP dependence plots were used to investigate the direction and pattern of contributions for the major continuous predictors. These explanations were treated as properties of the fitted prediction model rather than as causal relations.

3. Results

3.1 Participant Characteristics and Descriptive Profile

The data screening yielded 257 retained participants and valid age information was available for 256 participants. The mean age was 23.59 ± 4.06 years (range 17–46 years). The average CGPA was 3.02 ± 0.56. The average scores of Creative Thinking, GenAI Literacy, and Digital Literacy were 4.04 ± 0.59, 5.12 ± 0.87, and
5.24 ± 1.05, respectively. Table 1 presents the continuous academic and learning-related characteristics of the sample.

Table 1. Continuous Academic and Learning-Related Characteristics of the Study Sample

Variable	N	Mean	SD	Median	Minimum	Maximum
CGPA	257	3.022	0.558	3.090	1.000	4.000
Creative Thinking	257	4.040	0.588	4.160	1.760	5.000
GenAI Literacy	257	5.116	0.873	5.167	2.583	7.000
Digital Literacy	257	5.239	1.050	5.600	1.200	7.000

Gender category 1 was represented by 179 participants (69.65%) and category 2 by 78 (30.35%). The sample percentages of academic level categories 2 and 3 were 40.08% and 38.91%, respectively. The most common category for the frequency of GenAI usage was category 2 (55.25%). Table 2 shows categorical characteristics of the participants.

Table 2. Categorical Characteristics of the Study Sample

Variable	Category	N	Percentage (%)
Gender	1	179	69.65
Gender	2	78	30.35
Academic Level	1	18	7.00
Academic Level	2	103	40.08
Academic Level	3	100	38.91
Academic Level	4	36	14.01
Location	1	166	64.59
Location	2	91	35.41
GenAI use frequency	1	64	24.90
GenAI use frequency	2	142	55.25
GenAI use frequency	3	43	16.73
GenAI use frequency	4	8	3.11

The CGPA distribution was concentrated around 3.0, with similar mean and median values. The distribution of CGPA of the participants is shown in Figure 1A. Figure 1B depicts the general distribution of CGPA values.

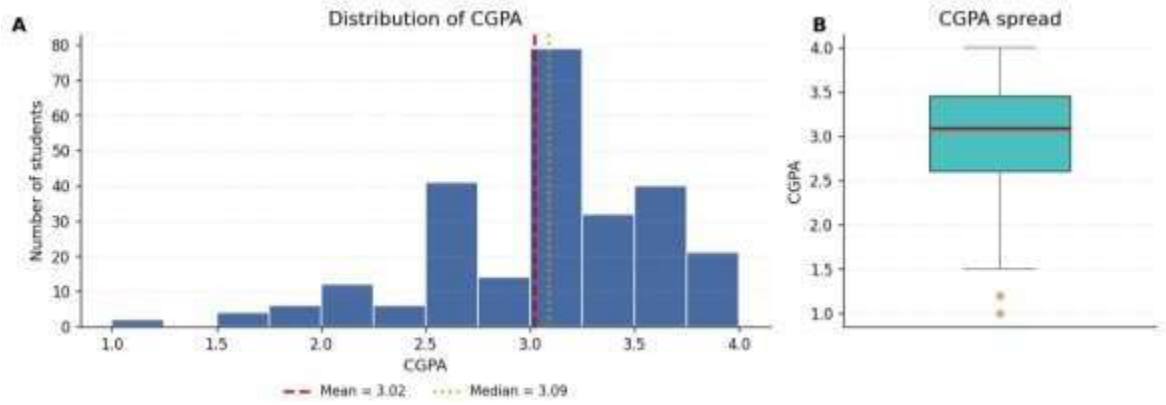


Figure 1. Distribution and Spread of Student Academic Performance: (A) Distribution of CGPA; (B) CGPA Spread.

3.2 Reliability and Associations with Academic Performance

The internal consistency of Creative Thinking and e-literacy were high, and the reliability of GenAI Literacy was acceptable. Creative thinking was positively associated with CGPA by both Pearson correlation ($r = 0.171$, $p = 0.006$) and Spearman correlation ($\rho = 0.139$, $p = 0.026$). GenAI Literacy and e-literacy had weak and insignificant correlations with CGPA. Table 3 presents the reliability estimates and bivariate associations of the three learning-related constructs with CGPA.

Table 3. Reliability and Bivariate Associations of Learning-Related Constructs with CGPA

Predictor	Items	Cronbach's α	Pearson r	p-value	Spearman ρ	p-value
Creative Thinking	25	0.921	0.171	0.006	0.139	0.026
GenAI Literacy	12	0.745	0.057	0.365	0.042	0.506
Digital Literacy	10	0.862	0.044	0.479	0.066	0.292

Age was correlated with CGPA by Pearson correlation $r = 0.103$ ($p = 0.099$) and Spearman correlation $\rho = 0.160$ ($p = 0.010$). The correlation between creative thinking, GenAI literacy and online literacy varied from 0.632 to 0.688. The variance inflation factors ranged from 1.014 to 2.309, showing no serious multicollinearity among the continuous predictors.

3.3 Machine-Learning Model Performance

The Random Forest model had the lowest mean five-fold cross-validation RMSE (0.489), followed closely by the Gradient Boosting model (0.494). Gradient Boosting on the held-out test set yielded $R^2 = 0.394$, RMSE = 0.416 and MAE = 0.293, and Random Forest $R^2 = 0.382$, RMSE = 0.420 and MAE = 0.299. The predictive performance of SVR and Elastic Net was less. Table 4 presents the cross-validation and held-out test performance for the four standard ML models.

Table 4. Cross-Validation and Held-Out Test Performance of Machine-Learning Models

Model	CV R^2 Mean	CV R^2 SD	CV RMSE Mean	CV RMSE SD	CV MAE Mean	CV MAE SD	Test R^2	Test RMSE	Test MAE
Random Forest	0.221	0.083	0.489	0.076	0.363	0.055	0.382	0.420	0.299
Gradient Boosting	0.189	0.153	0.494	0.055	0.379	0.051	0.394	0.416	0.293
SVR	0.034	0.078	0.545	0.085	0.419	0.068	0.099	0.508	0.371
Elastic Net	−0.016	0.078	0.559	0.087	0.438	0.081	−0.027	0.542	0.398

The Random Forest model was selected as the final model due to its cross-validation performance and stability. The mean five-fold cross-validation RMSE and fold-level variability are shown in Figure 2A. Figure 2B presents the RMSE and MAE values obtained on the held-out test set.

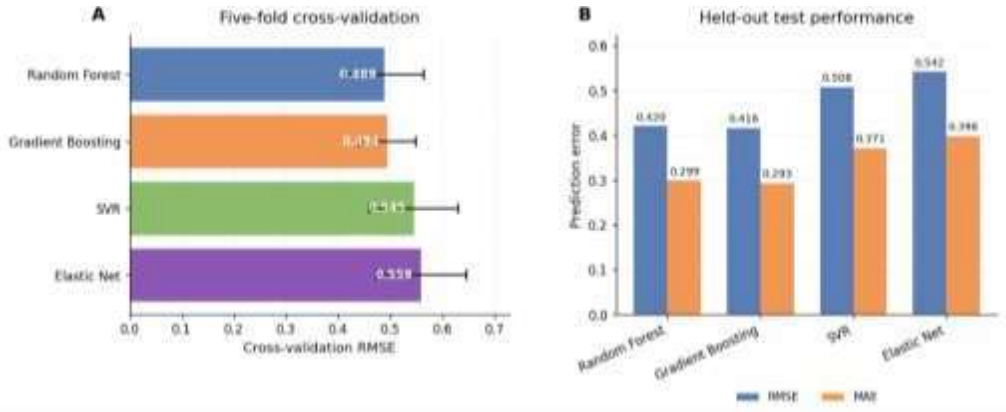


Figure 2. Predictive Performance of Machine-Learning Models: (A) Five-Fold Cross-Validation RMSE; (B) Held-Out Test RMSE and MAE.

3.4 Random Forest Prediction Performance

The final Random Forest model obtained a training R 2 of 0.819, an RMSE of 0.240 and an MAE of 0.185. For the held-out test set, R^2 was 0.382, with an RMSE of 0.420 and an MAE of 0.299. The correlation between observed and predicted test CGPA was 0.621. The residuals averaged 0.025 and 59.6% of the predictions were within 0.25 CGPA units and 78.8% were within 0.50 units of the observed values. The observed versus predicted CGPA is shown in Figure 3A. The residual pattern over the predicted CGPA values is presented in Figure 3B.

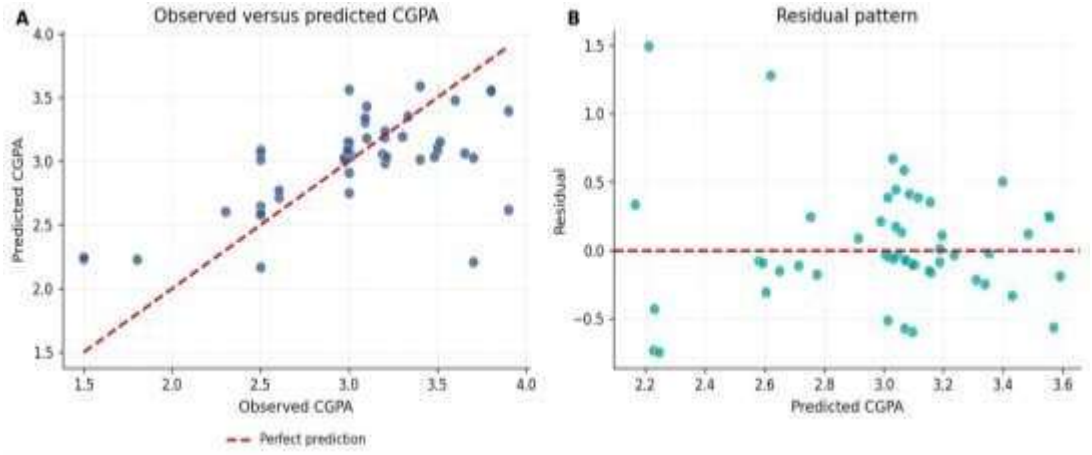


Figure 3. Random Forest Prediction and Residual Diagnostics: (A) Observed Versus Predicted CGPA; (B) Residual Pattern Across Predicted CGPA.

3.5 Explainability of Academic Performance Prediction

The explainability analysis showed that Random Forest predictions were mainly driven by Creative Thinking, Age and GenAI Literacy as continuous variables. Permutation importance showed that age had the highest importance (0.154), while Creative Thinking had the highest mean absolute SHAP value (0.140). In the SHAP analysis, GenAI Literacy remained a prominent feature even with its lower permutation importance, while e-literacy had lower importance estimates. The permutation and SHAP-based

explainability measures for the major continuous predictors are presented in Table 5. Figure 4A shows the permutation-based importance of the major predictors. Figure 4B shows their global importance according to mean absolute SHAP values.

Table 5. Explainability Measures for Major Continuous Predictors

Predictor	Permutation Importance	Permutation SD	Mean Absolute SHAP	SHAP Direction ρ	p-value
Creative Thinking	0.1034	0.0314	0.1395	0.5593	<0.001
Age	0.1537	0.0271	0.1367	0.5678	<0.001
GenAI Literacy	0.0563	0.0155	0.1018	−0.7065	<0.001
Digital Literacy	0.0240	0.0098	0.0375	0.0773	0.586

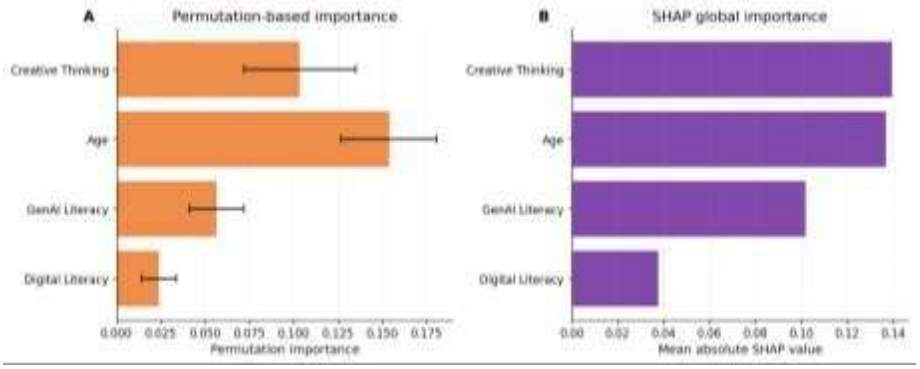


Figure 4. Global Importance of Academic Performance Predictors: (A) Permutation-Based Predictor Importance; (B) SHAP Global Predictor Importance.

3.6 SHAP Dependence Patterns

The SHAP dependence results revealed different contribution patterns for the major continuous predictors. Higher scores on Creative Thinking were generally associated with more positive SHAP contributions (Figure 5A). For Age, its contribution is non-linear (see Figure 5B). In Figure 5C, we observe an inverse conditional SHAP pattern in GenAI Literacy. Smaller and mixed SHAP contributions across Digital Literacy scores are shown in Figure 5D.

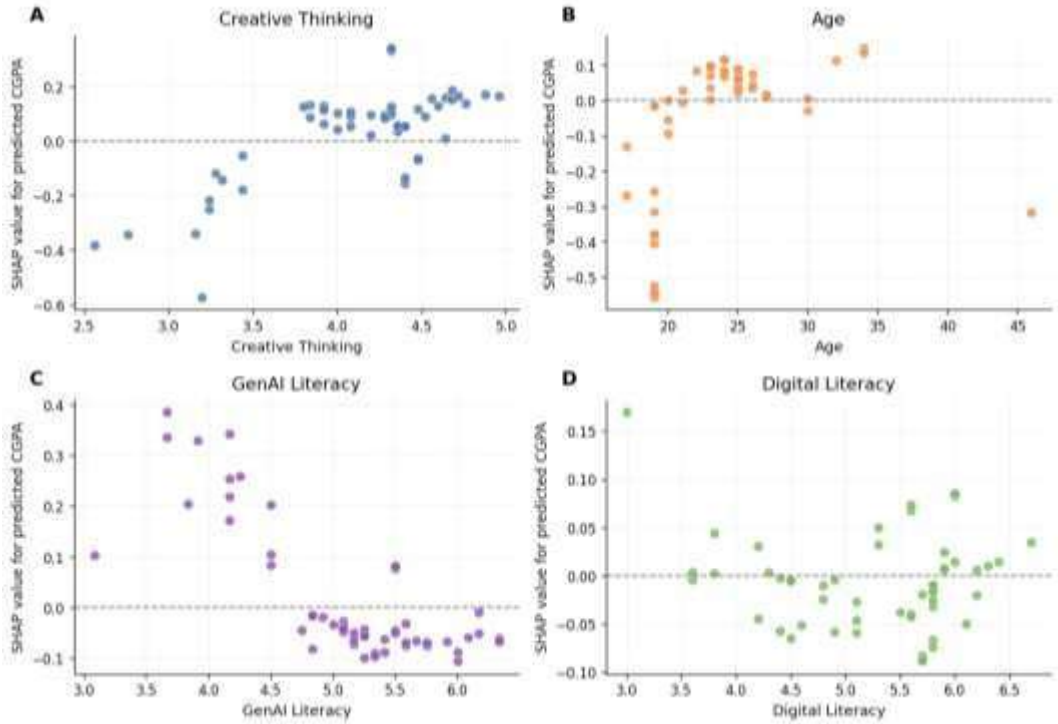


Figure 5. SHAP Dependence Patterns for Major Predictors of Academic Performance: (A) Creative Thinking; (B) Age; (C) GenAI Literacy; (D) Digital Literacy.

4. Discussion

Predictive analysis shows that ensemble machine learning methods were better at capturing variation in student academic performance than SVR and Elastic Net. The Random Forest model was selected as the final model based on its relatively stable performance on cross-validation and yielded the minimum mean five-fold cross-validation RMSE of 0.489. It's held-out test performance was $R^2 = 0.382$, RMSE = 0.420 and MAE = 0.299, indicating moderate predictive ability. The difference between the training and test performance suggests that the model was better able to capture the training data than the unseen observations, but the test predictions still captured a meaningful proportion of CGPA variation. The explainability analysis helped to better understand the variables behind these predictions. Permutation importance showed that Age was the most important variable and Creative Thinking had the largest mean absolute SHAP value. The prevalence of these two variables in two explanation approaches suggests that both variables contributed significantly to the fitted model. Creative Thinking also had a positive bivariate relationship with CGPA and generally positive SHAP contributions at higher scores. Age exhibited a nonlinear SHAP pattern, implying its contribution was not uniform across the observed age range. GenAI Literacy was a different story. It showed weak and non-significant simple Pearson and Spearman correlations with CGPA. However, it came behind Creative Thinking and Age in SHAP analysis. Its inverse SHAP dependence pattern therefore reflects its conditional contribution within the multivariable Random Forest, rather than a direct negative relationship with academic achievement. Digital Literacy had weak bivariate associations and relatively low SHAP and permutation importance values. The results suggest that AI-related and digital competencies were not equally predictive of academic performance, and their roles were contingent on the broader predictor structure.

The competitive performance of Random Forest is consistent with the previous applications of ensemble learning to educational prediction. Kurniasari et al. (2024) showed the usefulness of Random Forest to compare classification approaches for university student grades. The ensemble-based prediction has also been extended by combining Random Forest with Gradient Boosting and XGBoost, showing the usefulness of integrating nonlinear learners for student-performance modeling (Karthika et al., 2025). The present results are in line with this general pattern, with Random Forest and Gradient Boosting clearly outperforming the linear Elastic Net model. Further evidence from learning behavior supports the appropriateness of Random Forest to capture educational outcomes. Chen et al. (2024) utilized the algorithm for student-performance evaluation based on behavioral information, showing its flexibility when considering various characteristics related to academic outcomes. The relevance of Creative Thinking for the present analysis is also in line with a more general perspective in which student achievement is considered to reflect learning and cognitive characteristics beyond standard demographic variables. Bressane et al. (2024) used artificial intelligence to investigate the relationship between study strategies, individual learning characteristics, and academic achievement, emphasizing the necessity to incorporate student-level learning attributes into predictive models. The prominence of Creative Thinking is especially relevant in an AI-assisted learning context. Studies investigating the educational effects of AI have associated the use of AI with academic development, critical thinking, cognitive skills, and learning outcomes, but these associations depend on how AI is integrated into learning processes (Bolarinwa, 2026). Similarly, predictive analytics has been suggested to employ AI for detecting patterns in educational data and assisting with the evaluation of learning outcomes (Tahir et al., 2025). The present findings add to this literature by demonstrating that a cognitive trait such as Creative Thinking can provide very useful information even when GenAI and digital competencies are included within the same predictive model. The comparison with the GenAI Literacy result is more guarded. Dahri et al. (2025) used multimodal machine learning and explainable AI to investigate student satisfaction and performance related to ChatGPT, demonstrating the value of XAI in identifying relationships that were not easily found using traditional analysis methods alone. Research on AI-based learning tools has also shown associations with student performance and engagement in higher education, indicating that educational outcomes are associated with the way students interact with AI-enabled learning environments (Atianashie et al., 2025). The current inverse conditional SHAP pattern is not inconsistent with such findings, as it explains the behavior of GenAI Literacy within the framework of a fitted multivariable model, not a negative direct association with CGPA. The results support the inclusion of cognitive, digital and AI-related features to develop models that predict academic performance. Creative Thinking was a particularly relevant learning-related predictor, suggesting that AI-assisted education should continue to focus on independent reasoning, idea generation and problem-solving in addition to technological proficiency. GenAI Literacy also added to model predictions, but its conditional pattern suggests that it needs to be viewed in conjunction with other student characteristics, rather than interpreted independently. The explainable modeling framework further holds methodological value for educational analytics. Predictive metrics tell us how well a model performs.

SHAP and permutation importance tell us what features contribute to its predictions. Such transparency may help to support more interpretable use of machine-learning outputs in academic monitoring and student-support contexts, without treating model explanations as causal evidence.

There are some limitations to take into account. The sample was relatively small and specific to a student population, which may limit generalization to other educational environments. Some of the measures concerning learning were self-reported and the cross-sectional data do not allow for causal conclusions. The distinction between training and test performance also captures some overfitting present in the final Random Forest model. Future research can evaluate the framework and test predictive performance on independent datasets with larger and more diverse student samples. Longitudinal academic information would allow us to determine whether Creative Thinking, GenAI Literacy and e-literacy keep their predictive contribution over time. Further investigation of the interactions between these characteristics may also shed light on the nonlinear and conditional patterns uncovered by SHAP.

5. Conclusion

The practical frame of reference for predicting student academic performance and explaining the contributions of cognitive, demographic, digital, and AI-related characteristics was provided by explainable machine learning. Random Forest performed the best and most stable in cross-validation, and held-out results showed moderate predictive accuracy for CGPA. The two most powerful predictors were Creative Thinking and Age, and GenAI Literacy contributed meaningfully, although it was weakly and directly correlated with academic performance.

The contribution of e-literacy was lesser in prediction. The findings suggest that there is benefit in combining predictive modeling with SHAP and permutation importance rather than simply viewing metrics for performance. This approach revealed that major predictors did not equally contribute and some relationships were nonlinear or conditional. The results support the use of interpretable AI for academic performance analytics in AI-assisted learning environments, especially when there is a need for transparent identification of influential student characteristics. Future work should apply the framework to larger and more diverse samples, longitudinal data and independent datasets to assess whether the observed predictive patterns are stable across educational contexts.

References

1. Ahmed, E. (2024). Student performance prediction using machine learning algorithms. Applied computational intelligence and soft computing, 2024(1), 4067721.
2. Alhazmi, E., & Sheneamer, A. (2023). Early predicting of student's performance in higher education. Ieee Access, 11, 27579-27589.
3. Atianashie, M. A., Kuffour, M. K., Kyiewu, B., & Amponsah, C. (2025). The impact of artificial intelligence based learning tools on students' performance and engagement in higher education. SAP Social AI, 1, 44-44.
4. Bolarinwa, T. (2026). The impact of artificial intelligence on students' academic development, critical thinking, cognitive skills, and learning outcomes. International Journal of Applied Resilience and Sustainability, 2(2), 1097-1129.
5. Bressane, A., Zwirn, D., Essiptchouk, A., Saraiva, A. C. V., de Campos Carvalho, F. L., Formiga, J. K. S., ... & Negri, R. G. (2024). Understanding the role of study strategies and learning disabilities on student academic performance to enhance educational approaches: A proposal using artificial intelligence. Computers and Education: Artificial Intelligence, 6, 100196.
6. Chen, J., Zhou, X., Yao, J., & Tang, S. K. (2024, March). Evaluation of student performance based on learning behavior with random forest model. In 2024 13th International Conference on Educational and Information Technology (ICEIT) (pp. 266-272). IEEE.
7. Dahri, N. A., Dahri, F. H., Laghari, A. A., & Javed, M. (2025). Decoding ChatGPT's impact on student satisfaction and performance: A multimodal machine learning and explainable AI approach. Complex Engineering Systems, 5(2), N-A.
8. Ghulab Nabi Ahmad, Shafiullah, Hira Fatima, Obaidur Rahman, Imdadullah Mohammed S. Alqahtani (2022) Mixed Machine Learning Approach for Efficient Prediction of Human Heart Disease by Identifying the Numerical and Categorical Features. *Appl. Sci.* 2022, *12*(15), 7449 (28)
9. Hussain, S., & Khan, M. Q. (2023). Student-performulator: Predicting students' academic performance at secondary and intermediate level using machine learning. Annals of data science, 10(3), 637-655.
10. Karthika, K., Balasubramanie, P., Praneash, M. G., Shanmugapriya, P., & Ramya, T. E. (2025, May). Improved Student Performance Prediction Using Stacking Ensemble Learning with Gradient Boosting, Random Forest, and XGBoost. In 2025 6th International Conference for Emerging Technology (INCET) (pp. 1-6). IEEE.

11. Kurniasari, D., Hidayah, R. N., Notiragayu, N., Warsono, W., & Nisa, R. K. (2024). Classification models for academic performance: A comparative study of naïve bayes and random forest algorithms in analyzing University of Lampung student grades. Jurnal Teknik Informatika (JUTIF), 5(5), 1267-1276.

12. Liu, K., Yao, J., Tao, D., & Yang, T. (2023). Influence of individual-technology-task-environment fit on university student online learning performance: The mediating role of behavioral, emotional, and cognitive engagement. Education and Information Technologies, 28(12), 15949-15968.

13. Mamba, S., Djomou, F. R. K., & Awe, O. O. (2024). Explainability of digital wallets' fraud detection algorithms: Comparative analysis of SHAP and permutation feature importance. In Practical Statistical Learning and Data Science Methods: Case Studies from LISA 2020 Global Network, USA (pp. 627-665). Cham: Springer Nature Switzerland.

14. Michel-Villarreal, R., Vilalta-Perdomo, E., Salinas-Navarro, D. E., Thierry-Aguilera, R., & Gerardou, F. S. (2023). Challenges and opportunities of generative AI for higher education as explained by ChatGPT. Education sciences, 13(9), 856.

15. Naamati-Schneider, L., & Alt, D. (2024). Beyond digital literacy: The era of AI-powered assistants and evolving user skills. Education and information technologies, 29(16), 21263-21293.

16. Nguyen, K. V. (2025). The use of generative AI tools in higher education: Ethical and pedagogical principles. Journal of Academic Ethics, 23(3), 1435-1455.

17. Noman Tahir, D. R., Mahmood, S. S., & Malik, D. M. H. (2025). Artificial Intelligence In Education: Enhancing Learning Outcomes Through Predictive Analytics. TPM–Testing, Psychometrics, Methodology in Applied Psychology, 32(4-December), 738-751.

18. Pallathadka, H., Wenda, A., Ramirez-Asís, E., Asís-López, M., Flores-Albornoz, J., & Phasinam, K. (2023). Classification and prediction of student performance data using various machine learning algorithms. Materials today: proceedings, 80, 3782-3785.

19. Rana, V., Verhoeven, B., & Sharma, M. (2025). Generative AI in design thinking pedagogy: Enhancing creativity, critical thinking, and ethical reasoning in higher education. Journal of University Teaching and Learning Practice, 22(4), 1-22.

20. Sarker, S., Paul, M. K., Thasin, S. T. H., & Hasan, M. A. M. (2024). Analyzing students' academic performance using educational data mining. Computers and Education: Artificial Intelligence, 7, 100263.

21. Srivastava, S., Gavhane, S., Itnal, V., M., V., Chate, P. J., and Dr. Anuradha Yadav (2026). AI-Enhanced Cultural Heritage Learning Platforms. ShodhKosh: Journal of Visual and Performing Arts, 7(1s), 368–378 https://doi.org/10.29121/shodhkosh.v7.i1s.2026.7106

22. Setsoafia, P., Essel, H. B., & Tachie-Menson, A. (2026). Dataset on digital literacy, creative thinking disposition, and generative artificial intelligence literacy as predictors of academic performance of pre-service visual art teachers in Ghana [Data set]. Mendeley Data. https://doi.org/10.17632/jz6vbvv5t8.1

23. Vanishree Kavi Mahesh, Lubna Ansari, Aprna Tripathi (2026) Augmented Reality-Enabled heritage preservation using artificial Intelligence, Blockchain, and collaborative repositories Volume 85, article number 248(27) https://link.springer.com/article/10.1007/s11042-026-21372-w

24. Wang, J., Tigelaar, D. E., Zhou, T., & Admiraal, W. (2023). The effects of mobile technology usage on cognitive, affective, and behavioural learning outcomes in primary and secondary education: A systematic review with meta-analysis. Journal of Computer Assisted Learning, 39(2), 301-328.

25. Zawacki-Richter, O., Bai, J. Y., Lee, K., Slagter van Tryon, P. J., & Prinsloo, P. (2024). New advances in artificial intelligence applications in higher education. International Journal of Educational Technology in Higher Education, 21(1), 32.