

Artificial Intelligence-Driven Personalized Learning Models for Special Education

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ABSTRACT:

Learning personalized through the use of AI is gaining importance in special education since there is a need for learners who require special attention to receive personalized learning. Predictive machine learning can be used to analyze learning patterns from participation data. This study aimed to develop and evaluate AI-driven personalized learning models for predicting academic outcome categories using learner-related educational variables. A quantitative machine learning design was applied to a dataset containing 14,003 observations and 16 variables. After preprocessing, the ExamScore variable was removed to prevent target leakage. The data were divided into training and testing subsets using an 80:20 stratified split. Decision Tree and Random Forest classifiers were trained and evaluated using accuracy, precision, recall, weighted F1-score, confusion matrices, ROC-AUC analysis, and feature importance. The Random Forest classifier substantially outperformed the Decision Tree model. Random Forest achieved 84.33% accuracy, 85.04% precision, 84.33% recall, and an 84.29% weighted F1-score, while Decision Tree achieved 32.42% accuracy and a 29.49% weighted F1-score. The Random Forest model also produced strong multiclass ROC-

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AUC performance, with a macro-average AUC of 0.961. Assignment completion, attendance, study hours, online course participation, and age were the most influential predictors. The ensemble-based method will help to apply personalized AI learning based on detecting engagement patterns of students and predicting their performance. It can be concluded that it is possible to apply this learning technique in special education programs.

Keywords: artificial intelligence, personalized learning, special education, machine learning, Random Forest.

1. Introduction

AI has been revolutionizing the education sector, with the emergence of intelligent systems that can assist with adaptive learning, predictive analytics, and personalized learning experiences. AI has enhanced the efficiency of education and provided personalized learning support by leveraging data-driven decision-making processes (Chen et al., 2020). As the demand for flexible and personalized learning environments to support the needs and behaviours of diverse learners increases, AI-based technologies are now being used increasingly in educational institutions. Yet, as AI continues to shape the teaching and learning landscape, the development of intelligent platforms that can automate assessment, track learner engagement, and optimize instruction has further revolutionized the field (Harry & Sayudin, 2023). Therefore, with the popularity of personalized learning, the unified teaching model has been broken, and the general model has been shifted to the personalized teaching model, in which the learners are the subject of the teaching and learning process. The vision of personalized learning environments is to tailor the learning content, the pace and the learning method according to the behavior, engagement, preferences and learning outcomes of the learner. This transition is vital, as Artificial Intelligence can handle large volumes of data in the field of education, and adaptive learning pathways can be provided in real-time (Tapalova & Zhiyenbayeva, 2022). Adaptive Learning Systems (ALS) with AI

also help to make education more flexible by adaptively adjusting the learning content based on the interaction of learners (Gligorea et al., 2023). AI-driven adaptive learning systems have demonstrated great potential in supporting the transformation and engagement of learners in digital learning environments. With the advent of intelligent educational systems, it is now possible to identify trends and patterns in student progress, student behaviour and participation, providing assistance and support in education and personalized learning (Strielkowski et al., 2025). AI in personalized learning environments has also been used to improve the autonomy and engagement of learners by providing personalized learning recommendations and adaptive content delivery (Pratama et al., 2023). This is even more relevant with learners who have educational and learning challenges. Individuals with learning disabilities may need unique methods of teaching and learning that take into account their cognitive, behavioral and academic differences. However, traditional education systems often find it challenging to deliver continuous adaptive support due to limited flexibility in instruction and resources. The necessity of targeted educational strategies and individual support systems for better outcomes and participation of learners with learning disabilities has been consistently highlighted in the research field (Grigorenko et al., 2020). AI can play a significant role in overcoming these obstacles by facilitating adaptive learning interventions and intelligent

monitoring with the ability to adjust to learners' educational needs.

The predictive and analytical capabilities of machine learning have made it one of the most influential approaches in the field of AI in education. In the field of precision education, machine learning algorithms have been frequently used to analyze the behavior of learners, predict the risk of failure and provide personalized education decision-making processes (Luan & Tsai, 2021). The introduction of AI into educational systems has brought new research areas, including adaptive learning environments, learner analytics and intelligent educational support mechanisms (Hwang et al., 2020). In the field of e-learning, AI-based adaptive learning systems have proven to be very promising in enhancing the learning level of learners by supplying personalized learning strategies to boost the level of engagement and assessment accuracy. The AI-assisted cognitive and behavioral analysis enables educational systems to adapt in real-time to students' needs, thus improving educational accessibility and effectiveness (Halkiopoulou & Gkintoni, 2024). The application of educational data mining techniques is also a valuable part of this, as they can be applied to the prediction of academic performance based on the learner-related behavioural and engagement variables. The use of algorithms such as Decision Tree or Random Forest classifiers has proved beneficial for educational performance analysis and learner classification problems in terms of prediction (Yağcı, 2022). The incorporation of AI in inclusive education has also been a much-talked-about area of academic research in recent years. AI systems have proven to be highly promising in the field of special education for aiding students with special educational needs through adaptive learning technologies, intelligent communication devices, and personalized teaching strategies (Fitias, 2025). AI-powered adaptive learning systems have the potential to support more inclusive education by detecting learning challenges for each learner and enabling the implementation of individualized learner

support strategies (Habib et al., 2022). While the literature on AI in education has been growing, there are still some research gaps to be noted. Prior research has mainly been centered on general educational prediction systems and adaptive e-learning environments, which failed to investigate the role of learner engagement variables in the prediction of personalized learning based on AI. Lots of studies focus on prediction accuracy, with little interpretation of how predictors of behavior and patterns of educational engagement are interpreted. Also, there is limited comparative analysis between interpretable machine learning models and ensemble learning models in the context of adaptive educational prediction.

To overcome these limitations, this study aims to build and test personalized learning models for education based on educational engagement and behavioral variables with the help of AI. The predictive results of the Decision Tree and Random Forest classifiers for academic outcome categories and the comparative importance of the learner-related variables for educational prediction are compared. The study shows how machine learning techniques can be used in predictive educational modelling, which serves as a basis for AI-supported personalized learning.

2. Methodology

2.1 Research Design

The approach of this research was quantitative machine learning to develop and test personalized learning prediction models based on artificial intelligence. A comparative classification framework was adopted to analyze the prediction accuracy of the Decision Tree and Random Forest algorithms to find patterns that can be used to predict academic outcomes of students. The methodological process comprised data preprocessing, exploratory analysis, model development, performance evaluation and feature importance analysis.

2.2 Data Source

For this study, the data have been retrieved from an openly accessible educational dataset from a

project that has been developed for learning analytics research (Pavlidis & Perifanis, 2024). The data includes learner-level variables pertaining to learner behavior, educational engagement, participation patterns and academic achievement. The data set contained 16 variables, including one target variable that represented the categorization of the final academic grade, and 14,003 observations.

2.3 Data Preprocessing

Data was checked for missing data and inconsistencies in structure before analysis. There were no missing values found. All variables were numerically coded, and therefore, no transformations of categorical variables were needed. The ExamScore variable was dropped before training the model, as it was highly correlated with the target variable to avoid target leakage. All the other variables were kept as predictors. The data was then randomly split into 80% training data and 20% testing data based on stratified sampling. The StandardScaler technique was used to normalize the numerical variables.

2.4 Exploratory Data Analysis

An exploratory analysis was conducted to examine variable distributions, class balance, and relationships among educational variables. Descriptive statistics and correlation analysis were used to evaluate the characteristics of the dataset and identify potential multicollinearity.

2.5 Machine Learning Models

In this study, two supervised machine learning algorithms were chosen: the Decision Tree and the Random Forest classifiers. The Decision Tree model was chosen due to its interpretability in the context of educational prediction tasks, and the Random Forest classifier was chosen for the purpose of improving predictive stability and

classification performance using ensemble learning. The Decision Tree model was trained with a limited-depth model to prevent overfitting. The Random Forest model was constructed from several estimators in order to enhance the model's generalization ability.

2.6 Model Evaluation

The performance evaluation of the model was done using accuracy, precision, recall, weighted F1-score, confusion matrix analysis, and multiclass ROC-AUC. Overall prediction performance was evaluated using accuracy, while precision, recall and weighted F1-score reflected the effectiveness of the classification in the four target classes. Class-level prediction behavior and misclassification patterns were studied and analyzed using confusion matrices. Additionally, Multi-class ROC curves and AUC scores were calculated for the Random Forest model to assess discriminative ability. Feature importance analysis was also carried out to determine the most influential variables that affect the prediction result.

3. Results

3.1 Dataset Characteristics and Class Distribution

The data set included 14,003 student observations and 16 variables, 15 of which were predictors and one was the target, the final academic grade category. Preprocessing did not reveal any missing values, suggesting the dataset is complete and suitable for machine learning analysis. The dataset also included 4 target classes for the development of the framework of predictive learning for a multiclass problem. Table 1 shows the general characteristics of the dataset and indicates that the dataset was large enough and of a proper structure to be used for supervised educational prediction tasks.

Table 1. Dataset Description

Characteristic	Value
Total Observations	14,003

Total Variables	16
Predictor Variables	15
Target Variable	Final Grade
Missing Values	0
Target Classes	4

There was a relatively even distribution of the target classes with respect to each grade level, which helps to minimize model bias when the

classes are classified. The target class distribution by the four academic outcomes is shown in Figure 1.

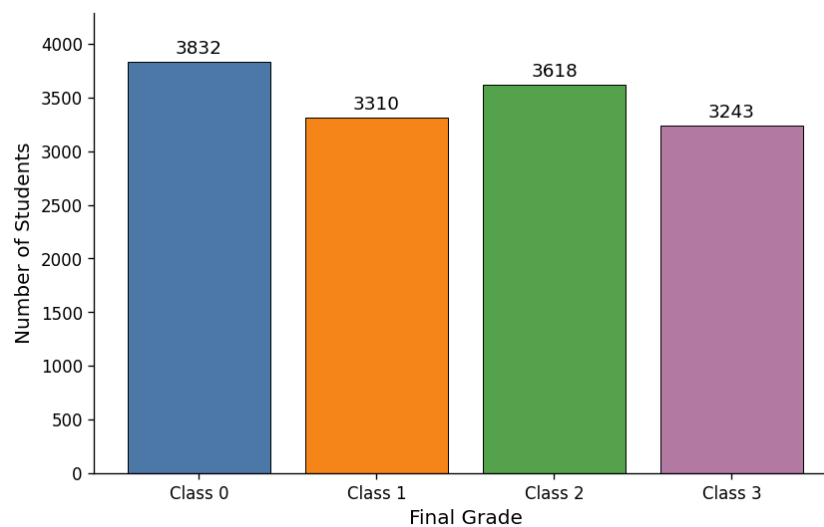


Figure 1. Target Class Distribution

The figure illustrates that the frequency of the four grade classes remained fairly even, with the maximum class frequency being 3,832 students (Class 0) and the minimum class frequency being 3,243 students (Class 3). The lack of class imbalance is a good indicator of the reliability of the machine learning evaluation that follows.

3.2 Correlation Analysis of Educational Variables

A correlation analysis was performed on the remaining variables of the learner engagement to investigate the relationships between these variables without the influence of the target leakage effect brought by ExamScore. This correlation matrix showed that most of the variables were generally not highly correlated with each other.

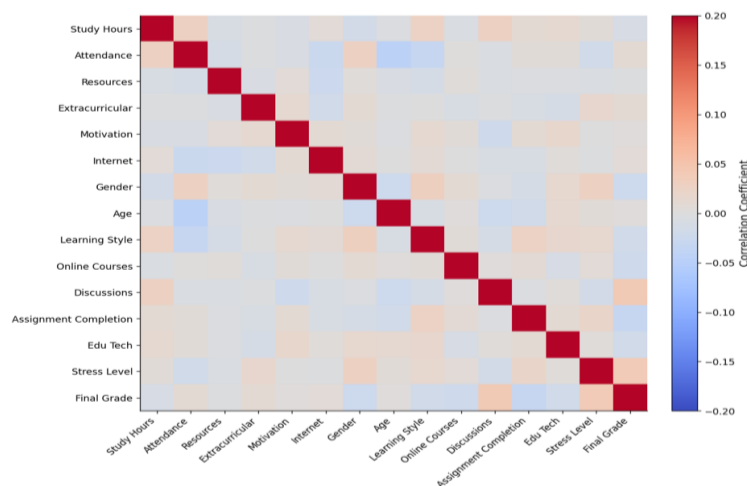


Figure 2. Correlation Matrix of Learning and Engagement Variables

As seen in Figure 2, the correlation magnitudes for most of the educational variables were low, suggesting that there was no severe multicollinearity between variables. Moderate relationships were found between variables and final grade outcomes (assignment completion, discussions, stress level), while demographic and resource-related variables had comparatively weaker relationships. The overall low levels of correlation found indicate that the educational outcome is a result of nonlinear combinations of factors, rather than individual factors alone. This finding is helpful for choosing the ensemble

learning methods that can model multidimensional educational patterns.

3.3 Comparative Performance of Machine Learning Models

In this study, two machine learning algorithms, namely Decision Tree and Random Forest classifiers, were evaluated. They were evaluated based on accuracy, precision, recall, and weighted F1 score for their prediction. The comparative performance results of both models are summarized in Table 2

Table 2. Model Performance Comparison

Model	Accuracy	Precision	Recall	F1 Score
Decision Tree	0.3242	0.3400	0.3242	0.2949
Random Forest	0.8433	0.8504	0.8433	0.8429

The Decision Tree classifier showed low prediction performance with an accuracy of 32.42% and a weighted F1 score of 29.49%. Such findings suggest that there is still a lack of generalization abilities and that there are limitations in reflecting more complicated patterns of educational behaviors. Random Forest classifier, on the other hand, showed significantly better results in all the evaluation

metrics such as accuracy (84.33%) and weighted F1-score (84.29%). Results show that ensemble learning methods offer greater stability in prediction and better multiclass discrimination in prediction for educational applications. This is further demonstrated in Figure 3 with comparative differences between the two machine learning models.

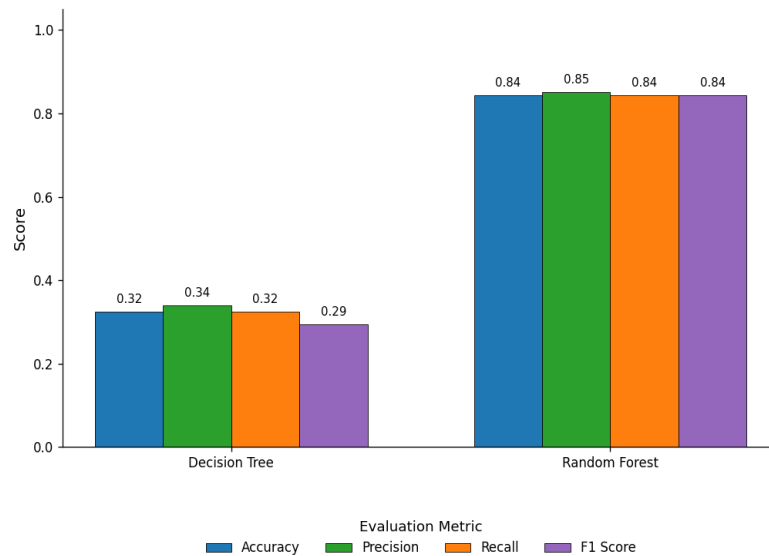


Figure 3. Comparison of Machine Learning Model Performance

It is clear from the visualization in Figure 3 that the Decision Tree model has demonstrated a huge difference in performance for all evaluation metrics compared to the Random Forest model. For AI-driven personalized education prediction, the accuracy, precision, recall, and F1-score of the Random Forest model consistently surpass the Decision Tree classifier, showcasing its superior performance across various metrics.

3.4 Classification Error Analysis

The confusion matrix was also generated for both the machine learning classifiers for further evaluation of model behaviour. As seen in Figure 4(a), the classifier Decision Tree had a large

number of classes misclassified, especially between class 0 and class 2. There was also a poor classification capability where the model was unable to correctly classify some of the Class 3 cases. As seen on the other hand, Figure 4(b) shows that the Random Forest classifier exhibits high diagonal dominance, which implies that it has a much higher prediction accuracy for all of the target classes. The Random Forest model could correctly classify 702 students of class 0, 519 students of class 1, 640 students of class 2 and 501 students of class 3. The rather small off-diagonal errors suggest that this ensemble model is capable of capturing this complicated learning engagement pattern with academic outcomes.

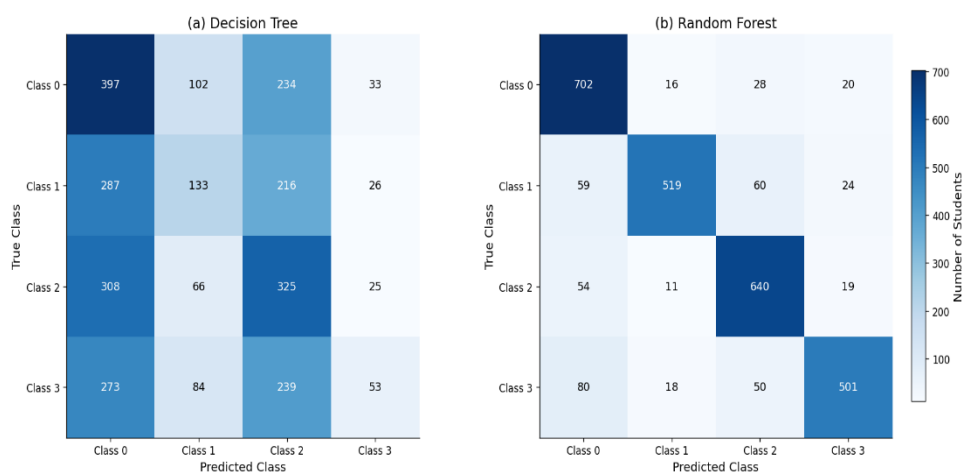


Figure 4. Confusion Matrix Comparison of Decision Tree and Random Forest Models

3.5 Feature Importance Analysis

A random forest classifier was used to implement feature importance analysis, which helps identify the most important factors affecting educational

outcomes. All predictor variables ranked by importance score are shown in Table 3.

Table 3. Random Forest Feature Importance

Rank	Feature	Importance
1	Assignment Completion	0.1644
2	Attendance	0.1585
3	Study Hours	0.1419
4	Online Courses	0.1397
5	Age	0.1168
6	Learning Style	0.0685
7	Stress Level	0.0515
8	Gender	0.0357
9	Edu Tech	0.0329
10	Discussions	0.0305
11	Motivation	0.0199
12	Resources	0.0196
13	Extracurricular	0.0127
14	Internet	0.0074

The most predictive factor was completion of assignments, followed by attendance, study hours, and online course participation. The results indicate that the learner engagement behaviors affect a significant contribution to the prediction of academic performance. The relative distribution of the scores of importance of

features shows that the Random Forest was not dominated by a feature but rather by an educational combination of features. This makes the proposed personalized learning model more interpretable and educationally relevant. The contributions of predictor variables to the model are shown in Figure 5.

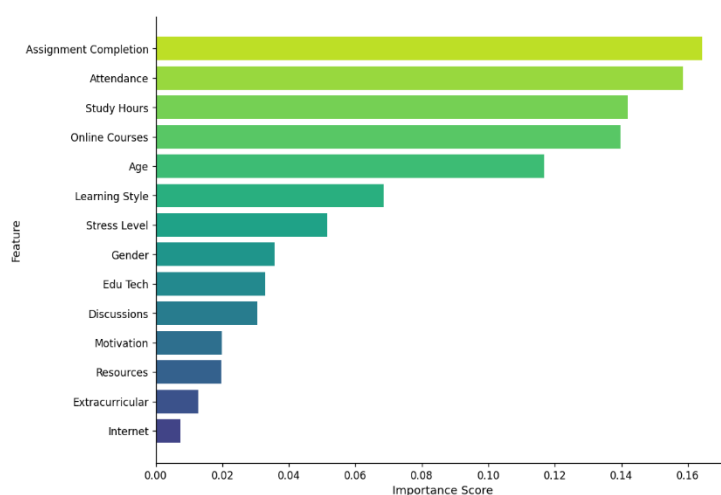


Figure 5. Random Forest Feature Importance

It shows that behavioural and engagement-related variables were more influential on the

predictive performance than were the demographic and infrastructural variables.

Importantly, assignment completion and attendance scores had significantly higher importance values than Internet access and extra-curricular involvement, highlighting the need for active engagement of learners in AI-powered education systems.

3.6 ROC-AUC Evaluation of the Random Forest Model

Multiclass ROC-AUC analysis was then used to assess the discriminative ability of the Random Forest classifier. As shown in Figure 6, all ROC curves were significantly above the diagonal, indicating strong classification capability for all the grade categories. The area under the curve (AUC) values for the four classes were 0.966, 0.955, 0.963, and 0.959, respectively.

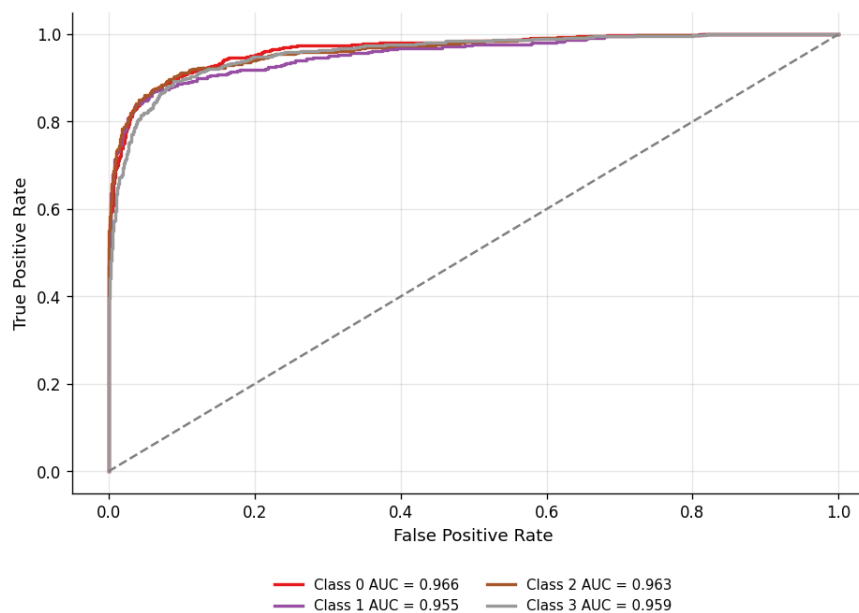


Figure 6. Random Forest Multiclass ROC Curves

The macro-average AUC of about 0.961 validates the high level of predictive reliability of the Random Forest classifier. The high ROC-AUC for each class also confirms that ensemble learning techniques are effective for AI-based personalized educational prediction systems.

4. Discussion

The results show that machine learning can be used as a valuable foundation for a prediction of personalized learning by AI. The classification accuracy of the Random Forest was 84.33%, which was significantly higher than the classification accuracy of the Decision Tree (32.42%). The weighted precision, weighted recall and weighted F1 score of the Random Forest was 85.04%, 84.33% and 84.29%, respectively, which were also significantly higher than the weighted precision, weighted recall and

weighted F1 score of the Decision Tree. Meanwhile, the Decision Tree model had much lower accuracy and a weighted F1 score of 32.42% and 29.49%, respectively. There seems to be a gap that the one-to-one tree model was unable to capture the complex relationship among learning behaviour, engagement and learning outcomes. This is further demonstrated with the results of the confusion matrix. The Decision Tree model had high diagonal misclassification and cross-classification errors, and the Random Forest model had high misclassification among the grade levels. The Random Forest AUC for each class and macro-average also further confirmed good performance of this model with values of 0.955 – 0.966 and 0.961, respectively. The overall discriminative ability of the model was good for all the academic outcome categories, based on

these results. The feature importance analysis shows that assignment completion, attendance, study hours, online course participation and age are the most important features. These are not just demographic factors, but they are variables that are a reflection of learner engagement and participation. The significance of this discovery is that it demonstrates that AI prediction can be used to identify behavioral indicators that can be used as a basis for timely support of learning.

This result of the Random Forest model is aligned with previous studies on educational prediction that indicate ensemble methods can enhance the classification of the students' performance by utilizing multiple decision structures to form a more stable predictive model (Nafea et al., 2023). Other comparative machine-learning research highlights that ensemble classifiers can improve simpler classifiers when learning educational outcomes are based on several interacting variables (Chen & Zhai, 2023). The significance of these engagement-related predictors corresponds to recent studies on personalized learning with AI, which attribute the influence of learners' behavior, participation and psychological engagement to the improvement of their learning outcomes (Wang et al., 2025). The outcomes also resonate with studies on AI-driven personalized learning systems for students with special needs, which highlight the importance of ongoing tracking of student progress as a key component of personalized learning support (Baumuratova et al., 2025).

This is further illustrated by the research on special educational needs in which learners need flexible pacing, targeted feedback, and to be taught in their own way (Hamid, 2025). The results in the present study also align with the wider literature that demonstrates how integrating learning analytics into teaching and learning decisions with the assistance of AI can improve engagement and prediction of student outcomes (Tariq, 2025). The focus of the study on educational equity and adaptive prediction aligns with the recent discussions about the use of AI in personalized learning to overcome barriers in education (Gokhe et al., 2024). The

importance of intelligent architectures that adapt and respond to the needs of learners is also highlighted in emerging research on agentic and multi-agent tutoring systems (Gupta & Heggond, 2026). The shift from general AI-directed learning to one that is personalised to the learner further underscores the need for models that can understand trends across individual behaviours, not just in groups of learners (Kyambade et al., 2025).

The results have implications for applying AI in personalised learning in special education scenarios. Predictive models can help identify pupils who are showing signs of needing extra teaching and learning, especially when they are making less of an effort at assignments, attendance and study time. This may involve models to support teachers in transitioning from a reactive support to more proactive planning for intervention. Results also show the applicability of explainable prediction. This knowledge of the significance of features in the behaviour of learners enables the teacher and the system designer to know which behaviour is the most significant to be classified. This is very important in the special educational arena where decisions must be clear, educationally sound and responsive to the needs of the learners. The results indicate that, in terms of systems design, it is important to focus on engagement tracking, participation monitoring, and providing feedback in a timely manner for a platform that supports adaptive learning. AI models should not only predict performance but also provide insights that can help teachers adjust their teaching, adapt content, and provide better support to students.

But there are some caveats to take note of. A single secondary data set was used in this study, which could result in findings not being transferable to other educational settings. Some learner variables were used in the analysis as well, and more detailed information in relation to cognitive profile, intervention history and classroom context would also be helpful in future modelling. Just two classifiers, the Decision Tree classifier and the Random Forest classifier, were compared. For future work, other algorithms,

hybrid models, and explainable AI techniques could be explored to further enhance the predictive power and interpretability of the models. Additional validation with larger and more heterogeneous special education data also would be useful in establishing whether there are similar response trends among the various groups of learners and instructional contexts.

5. Conclusion

Personalized learning based on AI is an effective way to enhance educational prediction and adaptive assistance in special education. The results indicated that the Random Forest outperformed the Decision Tree classifier by having excellent accuracy, weighted F1 score, and ROC – AUC scores. This suggests that ensemble learning is more successful in modelling relationships between learner engagement, learner participation and academic outcomes, which are complex. The feature importance

results also revealed that assignment completion, attendance, study hours, online course participation and age were the most important features. The results indicate that behavior and engagement should be emphasized in personalized learning systems for detecting students who might need extra support from instructional systems. The study is intended to support personalized education using AI by showing how machine learning can be applied to personalized education decision-making in an interpretable way, in addition to prediction. While the analysis relied on just one secondary data set and two machine learning models, this analysis gives a good basis for future research. These results should be validated with more diverse special education data on a larger scale and other explainable AI approaches.

References

- Baumuratova, D., Zhukabayeva, T., Baumuratova, S., & Nurbekova, G. (2025, September). Design of an Adaptive Educational Platform for Special Needs Students Using Artificial Intelligence. In *2025 10th International Conference on Computer Science and Engineering (UBMK)* (pp. 80-85). IEEE.
- Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. *IEEE access*, 8, 75264-75278.
- Chen, Y., & Zhai, L. (2023). A comparative study on student performance prediction using machine learning. *Education and Information Technologies*, 28(9), 12039-12057.
- Fitias, R. (2025). Inclusive education with AI: Supporting special needs and tackling language barriers. *AI and Ethics*, 5(6), 5729-5757.
- Gligorea, I., Cioca, M., Oancea, R., Gorski, A. T., Gorski, H., & Tudorache, P. (2023). Adaptive learning using artificial intelligence in e-learning: A literature review. *Education Sciences*, 13(12), 1216.
- Gokhe, S., Ulhe, P., & Bhasme, M. (2024, November). AI-Powered Personalized Learning for Advancing Educational Equity. In *2024 2nd DMIHER International Conference on Artificial Intelligence in Healthcare, Education and Industry (IDICAIEI)* (pp. 1-6). IEEE.
- Grigorenko, E. L., Compton, D. L., Fuchs, L. S., Wagner, R. K., Willcutt, E. G., & Fletcher, J. M. (2020). Understanding, educating, and supporting children with specific learning disabilities: 50 years of science and practice. *American psychologist*, 75(1), 37.
- Gupta, N., & Heggond, S. (2026). Agentic artificial intelligence-driven tutoring: A multi-agent cognitive architecture for personalized adaptive learning in Education. *International Journal of Applied Resilience and Sustainability*, 2(2), 572-598.
- Habib, H., Jelani, S. A. K., & Najla, S. (2022). Revolutionizing inclusion: AI in adaptive learning for students with disabilities. *Multidisciplinary Science Journal*, 1(01), 1-11.
- Halkiopoulos, C., & Gkintoni, E. (2024). Leveraging AI in e-learning: Personalized learning and adaptive assessment through cognitive neuropsychology—A systematic analysis. *Electronics*, 13(18), 3762.

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- Hamid, S. M. (2025). Optimizing AI-Based Adaptive English Language Learning for Students with Special Educational Needs. *INTERACTION: Jurnal Pendidikan Bahasa*, 12(4), 957-981.
- Harry, A., & Sayudin, S. (2023). Role of AI in Education. *Interdisciplinary Journal and Hummanity (INJURITY)*, 2(3), 260-268.
- Hwang, G. J., Xie, H., Wah, B. W., & Gašević, D. (2020). Vision, challenges, roles and research issues of Artificial Intelligence in Education. *Computers and Education: Artificial Intelligence*, 1, 100001.
- Kyambade, M., Namatovu, A., & Male Ssentumbwe, A. (2025). Exploring the evolution of artificial intelligence in education: From AI-guided learning to learner-personalized paradigms. *Cogent Education*, 12(1), 2505297.
- Luan, H., & Tsai, C. C. (2021). A review of using machine learning approaches for precision education. *Educational Technology & Society*, 24(1), 250-266.
- Nafea, A. A., Mishlish, M., AL-Ani, M. M., Alheeti, K. M. A., & Mohammed, H. J. (2023). Enhancing Student's Performance Classification Using Ensemble Modeling. *Iraqi Journal For Computer Science and Mathematics*, 4(4), 16.
- Pavlidis, N., & Perifanis, V. (2024). FLAMENCO Learning Disabilities Dataset [Data set]. Zenodo. <https://doi.org/10.5281/zenodo.10492892>
- Pratama, M. P., Sampelolo, R., & Lura, H. (2023). Revolutionizing education: harnessing the power of artificial intelligence for personalized learning. *Klasikal: Journal of education, language teaching and science*, 5(2), 350-357.
- Strielkowski, W., Grebennikova, V., Lisovskiy, A., Rakhimova, G., & Vasileva, T. (2025). AI-driven adaptive learning for sustainable educational transformation. *Sustainable development*, 33(2), 1921-1947.
- Tapalova, O., & Zhiyenbayeva, N. (2022). Artificial intelligence in education: AIED for personalised learning pathways. *Electronic Journal of e-Learning*, 20(5), 639-653.
- Tariq, M. U. (2025). AI-driven personalized learning-enhancing student engagement and outcomes. In *AI and learning analytics in distance learning* (pp. 151-178). IGI Global Scientific Publishing.
- Wang, J., Hussain, Y., & Mao, C. (2025). Artificial intelligence-driven personalized learning: Psychological implications and educational outcomes. *International Journal of Education, Humanities and Social Sciences*, 2(1), 24-39.
- Yağcı, M. (2022). Educational data mining: prediction of students' academic performance using machine learning algorithms. *Smart Learning Environments*, 9(1), 11.
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