**Personalized E-Learning with AI-Driven Data Mining for Enhancing Academic Success**

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**Abstract:** This study introduces an AI-driven data mining framework that enhances personalized e-learning by predicting student performance and dynamically adapting content based on learning styles and demographics. By integrating the Felder-Silverman Learning Style Model (FSLSM) with machine learning models, the system provides adaptive learning experiences tailored to individual needs. While following the CRISP-DM process, this paper employs the application of preprocessing data, feature engineering, and model evaluation. KNN, XGBoost, Random Forest, and Neural Networks are compared and compared. XGBoost provides the best predictive accuracy of 92.4%, but KNN is utilized for practical purposes due to its ease of deployment, readability, and computational practicability. This study also brings added force to accuracy-focused methods with the inclusion of FSLSM-based learning styles in suggestions for better personalization. The contributions also move AI for learning ahead by demonstrating model simplicity and deployment feasibility trade-offs. Future studies would do well to pursue hybrid methods, which draw on the simplicity of KNN and predictive power of deep learning to further develop adaptive learning systems.

# Introduction

Differences in learning achievement continue to exist even after education is the main catalyst for economic and social development because heterogeneity of elements like learning personality, socio-economic status, and availability of learning inputs exist [1]. The conventional system of education follows a one-size-fits-all policy, which fails to meet various needs of various learners [2]. With growth in e-learning improving access, yet many existing platforms fail to adapt to the diversity of individual learners' needs, causing disaffection and lower learning performance [3].

The biggest challenge that education is currently facing is diversity in students' learning. While some will learn best through active or visual types of learning, others will require that they hear or have it written down for them to effectively understand information [1]. Moreover, socio-economic status also has a great impact on student performance since disparities in access to the internet, learning environment, and availability of facilities affect learning [4]. Without adaptive learning mechanisms, disadvantaged students will tend to fall behind other students, further exacerbating education inequalities [2].

To address these challenges, this study proposes an AI-driven e-learning framework that utilizes data mining techniques to personalize educational experiences. By combining machine learning algorithms and adaptive learning strategies, the platform keeps updating in real-time the way course content is presented to keep up with unique learners' paths of learning and prediction of academic performance [3]. The framework operates to improve the participation, retention, and performance of the students by way of predictive analytics, offering learning materials as suggestions.

The research is vital in the encouragement of AI adoption within education to enable learners to gain access to customized learning experience that unlocks their potential. By analyzing learning behaviors and academic trends, AI-driven e-learning systems can bridge gaps in educational access and effectiveness, ultimately supporting Sustainable Development Goal 4 (SDG 4) for inclusive and quality education [5].

# Literature Review

Artificial intelligence (AI) and machine learning (ML) have significantly transformed education by enabling personalized learning experiences and predictive analytics for student success. Certain ML algorithms were utilized within predicting academic outcomes, building proposals for individualized learning materials, and increasing engagement. The current literature highlights possible AI-based innovations to education.

Supervised learning techniques such as Decision Trees, Support Vector Machines (SVM), and Neural Networks have been widely applied in student performance prediction. For instance, Nachouki et al. demonstrated the way that Random Forest models produce stable interpretability and predictor importance ranking when examining student success, such that they contribute to the improvement in institutional understanding of learning determinants [6]. Meanwhile, XGBoost has proved highly accurate in predicting students based on learning behavior [7]. Likewise, Deep Neural Networks (DNNs) have also been identified to successfully predict vulnerable students with engagement metrics monitoring and histories of students [8]. But among the most significant disadvantages of DNNs is that they are highly interpretability and computationally complex, which have the potential to compromise model transparency, thus making them unsuitable for real-time educational systems [9].

There have been uses of unsupervised machine learning techniques like K-Means and hierarchical algorithms in clustering students by learning interest. Clustering has been employed to aid adaptive learning through the grouping of students according to features like engagement levels, hence enabling tailored suggestions [10]. Despite these benefits, clustering approaches often struggle with defining optimal cluster sizes and dealing with noisy educational data.

Reinforcement learning has also been studied in learning with the aid of AI where algorithms learn e-learning lessons based on ratings and engagement patterns. Research demonstrated that reinforcement learning models significantly enhance engagement by dynamically adjusting lesson difficulty [11]. However, the largest drawback of reinforcement learning is its requirement for enormous amounts of training data as well as subpar recommendations during early training.

Natural Language Processing (NLP) is another key AI application in education, particularly for intelligent tutoring systems and automated grading. According to research, NLP-enabled chatbots and virtual teaching assistants have the capability to enhance learning engagement as well as provide immediate academic support [12]. Challenges for NLP include the need for large amounts of annotated datasets as well as struggling to comprehend subtly worded questions from students.

Besides that, empirical studies applied to personalization in adaptive learning systems using FSLSM confirm the reality of personalization based on learning style having a heavy influence on learner engagement and satisfaction [13]. AI-based personalization has shown promising results, but several problems are faced. Algorithmic bias, digital exclusion, and data privacy are just some of the ethical concerns that present gargantuan stumbling blocks towards incorporating AI at hitherto unprecedented scales in education [2]. In addition, the incorporation of AI-based models with current education systems demands huge computational power and institutional infrastructure.

This literature review is focused on the application of AI and ML in forming e-learning while highlighting equitable trade-offs between model accuracy, interpretability, and real-time adaptability. While there has been very rich research done on utilizing AI for adaptive learning, incorporating predictive analytics in adaptive learning systems is scarce. This study aims to bridge this gap by combining machine learning models with real-time data-driven personalization techniques, enhancing both the accuracy and adaptability of e-learning systems. By overcoming computational efficiency and ethics barriers, this study helps in building AI-based learning and its implementation in real-world scenarios.

# Methodology

The project utilizes the Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology. CRISP-DM is a common data mining methodology that consists of six phases: business understanding, data understanding, data preparation, modeling, evaluation, and deployment. The processes are executed iteratively to achieve ongoing improvement of data models' performance. CRISP-DM guarantees a systematic and organized process in data analysis and predictive modeling [14].

The Felder-Silverman Learning Style Model (FSLSM) was introduced in 1988 by Richard Felder and Linda Silverman. FSLSM is included within the framework to categorize students based on four dimensions: active/reflective, sensing/intuitive, visual/verbal, and sequential/global learning styles. The framework gives a scientific method towards grasping and adapting with the heterogeneous needs of the students. FSLSM is an effective paradigm for individualizing learning environments within the online platform by categorizing students based on cognitive and perceptual differences [15]. Through correlation of FSLSM types and prediction information, the site can automatically adjust learning materials in real-time according to each individual student, thus improving student motivation and learning by enabling student-individualized learning activities based on unique preferences of students.

This research mainly adopts the CRISP-DM framework to structure the data mining process, along with data based on FSLSM to guide personalized content delivery based on students’ learning styles. The application of the two frameworks ensures that the system not only finds valuable knowledge from data but also interprets it into adaptive learning systems. These identical applications of CRISP-DM and FSLSM have also been proven to be effective in educational contexts, particularly for real-time academic intervention [16].

## Data Collection and Understanding

The dataset used in this study is modeled after an open-access educational data repository, specifically the Open University Learning Analytics Dataset (OULAD), containing anonymized student records from various online learning platforms. For this study, a synthetic dataset of 100,000 student records was generated based on common features found in these public datasets. The independent variables include demographic information such as age, gender, socio-economic background, prior academic performance, engagement metrics (course participation, quiz attempts, time spent on learning modules), as well as FSLSM-based learning preferences. The target variable is the student performance classified into three classes: high, medium, and low achievers. Overall, the dataset comprises 22 features, including categorical and numerical variables, as listed in Table 1.

## Data Preparation

The dataset undergoes rigorous preprocessing before heading into modeling. It first detects for missing values, where if present, imputation techniques such as mean/mode imputation are applied. Data transformation procedures are also necessary, where categorical features are converted using label encoding, and continuous variables are normalized to ensure uniform scale across features.

Additionally, feature selection is also conducted using Principal Component Analysis (PCA). PCA is essential to reduce dimensionality and identify the most significant predictors, retaining the most informative features while minimizing redundancy. The explained variance ratio indicates that 10 principal components account for 92% of the variance, ensuring minimal information loss. These top 10 features identified as the most significant predictors include are shown in Table 2.

These features are selected for modeling as they contribute the most to predicting student performance while reducing computational complexity. After the pre-processed dataset is complete, it is divided into training (70%), validation (15%), and testing (15%) sets to evaluate model performance.

**TABLE 1.** List of features

|  |  |
| --- | --- |
| Variable | Data Type |
| Age | Numeric |
| Gender | Categorical |
| Socioeconomic Status | Categorical |
| Prior Academic Score | Numeric |
| Course Participation | Numeric |
| Quiz Attempts | Numeric |
| Time Spent on Learning Modules | Numeric |
| Preferred Learning Style | Categorical |
| Assignment Score | Numeric |
| Final Exam Score | Numeric |
| Attendance Rate | Numeric |
| Engagement Level | Categorical |
| Forum Participation | Numeric |
| Project Submission Rate | Numeric |
| Study Time per Week | Numeric |
| Device Used for Learning | Categorical |
| Motivation Level | Categorical |
| Course Completion Rate | Numeric |
| Self-Assessment Score | Numeric |
| Preferred Content Format | Categorical |
| Parental Support Level | Categorical |
| Learning Environment Quality | Categorical |

**TABLE 2.** Top 10 features selected for analysis via PCA

|  |  |
| --- | --- |
| Variable | Data Type |
| Prior Academic Score | Numeric |
| Course Participation | Numeric |
| Quiz Attempts | Numeric |
| Time Spent on Learning Modules | Numeric |
| Assignment Scores | Numeric |
| Final Exam Score | Numeric |
| Socioeconomic Status | Categorical |
| Preferred Learning Style | Categorical |
| Attendance Rate | Numeric |
| Course Completion Rate | Numeric |

## Modeling

In this study, four machine learning models are employed for predicting student performance and content personalization.

**K-Nearest Neighbor (KNN):** A distance-based algorithm where it makes predictions based on proximity to similar data point. The optimal value of K is determined using cross-validation. KNN is used as a baseline model due to its simplicity and ease of implementation for classifying student performance, potentially crucial where interpretation and computation time are valued in contexts of education [17]. Since KNN may underperform on high-dimensional datasets, a lower benchmark is set.

**XGBoost (XGB):** A gradient boosting algorithm that performs well with structured data. XGBoost is utilized for its robustness in handling mixtures of categorical and continuous features effectively [18], as well as feature importance analysis. Its high computational efficiency and advanced regularization allows capturing complex interactions within features [19], thus often have promising predictive strength, especially when analyzing student data which usually contains various data types.

**Random Forest (RF):** A tree-based model employed to enhance model generalization and reduce overfitting. Hyperparameters like number of trees and maximum depth are fine-tuned for optimal performance. Since this model works well with both categorical and numerical data, and robust to overfitting, the model could show strong results in predicting student success [20].

**Neural Network (NN):** A deep learning approach leveraging multiple hidden layers, capable of capturing complex, non-linear patterns in student learning behaviors that simpler model may overlook. These models can be beneficial in multi-category performance prediction [21], though adjusting learning rate and dropout regularization is essential to optimize performance.

For each of the four algorithms, base models on default hyperparameters as well as tuned models on optimal hyperparameters, which are obtained through tuning by random search, are built. Table 3 shows the benchmark accuracies for the four models:

**TABLE 3.** Benchmark accuracies of chosen models

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Model | KNN | XGB | RF | NN |
| Benchmark Accuracy (%) | 75 | 90 | 85 | 85 |

# Results and Discussion

Multiple evaluation metrics are used to assess the performance of the predictive models built:

**Accuracy:** The proportion of correctly classified instances.

**Precision:** The proportion of true positive predictions among predicted positives, important for assessing model reliability.

**Recall:** The proportion of actual positives correctly identified, essential for detecting at-risk students.

**F1-Score:** The harmonic mean of precision and recall, balancing false positives and false negatives.

**AUC-ROC Score:** The model’s capability to distinguish between different classes. Values closer to 1 indicate better performance.

Table 4 and Figure 2 presents the results of evaluation metrics and the comparison graph for the base models respectively.

**TABLE 4.** Evaluation results of base models

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Model | Accuracy | Precision | Recall | F1-score | AUC-ROC |
| KNN | 0.820 | 0.805 | 0.789 | 0.797 | 0.843 |
| XGB | 0.886 | 0.875 | 0.852 | 0.863 | 0.912 |
| RF | 0.868 | 0.856 | 0.831 | 0.843 | 0.895 |
| NN | 0.872 | 0.863 | 0.848 | 0.855 | 0.901 |

A graph of different colored bars

AI-generated content may be incorrect.

**FIGURE 1.** Comparison graph of evaluation results of base models

Table 5 and Figure 3 shows the results of evaluation metrics and the comparison graph for the optimized (tuned) models after hyperparameter tuning respectively.

**TABLE 5.** Evaluation results of tuned models

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Model | Accuracy | Precision | Recall | F1-score | AUC-ROC |
| KNN | 0.852 | 0.840 | 0.815 | 0.827 | 0.871 |
| XGB | 0.924 | 0.911 | 0.897 | 0.904 | 0.943 |
| RF | 0.897 | 0.882 | 0.867 | 0.874 | 0.920 |
| NN | 0.910 | 0.897 | 0.885 | 0.891 | 0.932 |

A graph showing different colored bars

AI-generated content may be incorrect.

**FIGURE 2.** Comparison graph of evaluation results of tuned models

The results indicate that hyperparameter tuning increases the predictive capabilities of all the models. Compared to the other base models, XGBoost performed best in terms of all the evaluation metrics with 88.6% accuracy and 91.2% AUC-ROC, demonstrating its high capacity for distinguishing student levels of performance. These results are also consistent with the literature, where XGBoost always achieved higher performance in educational data mining tasks since it is able to handle complex feature interactions effectively [22]. In the context of academic performance prediction, existing studies found similar results, both of which XGBoost obtained the highest predictive accuracy of 97% [23][24]. XGBoost has consistently outperformed simpler and less interpretable models, making it the superior algorithm for reliable learning analytics.

After hyperparameter optimization, XGBoost also maximizes its accuracy to 92.4% and AUC-ROC value to 94.3%. This means optimizing learning rate, tree depth, and regularization increases model generalizability to a very high extent. Neural Networks also show big improvement after their tuning, in which accuracy moves from 87.2% to 91.0%, which suggests deep learning models have the ability to successfully learn complicated learning patterns. However, Neural Networks require higher computational resources and longer training time, making them less efficient for real-time deployment [25].

KNN, while simple and interpretable, shows moderate improvement after tuning, with accuracy increasing from 82.1% to 85.2%. Although useful for simple classification, the dependency of KNN on distances used in calculation makes it relatively less useful for larger datasets with complex relationships. Random Forest also improves upon tuning to 89.7% accuracy. The results are in agreement with (Pan & Dai, 2024)[9], where they also explained that Random Forest also performs extremely well with multi-dimensional education data, although still short of the simplicity of KNN. However, it is still outperformed by XGBoost. Previous research has also been demonstrated to determine that ensemble models like XGBoost are better than Random Forest in learning environments through the application of gradient boosting for allowing more sophisticated decisions [26].

Among the compared models, XGBoost is the highest-performing model with highest accuracy (92.4%), precision (91.1%), recall (89.7%), and AUC-ROC score (94.3%). Such results are congruent with similar studies, e.g., those by Tuama et al.[27], whereby XGBoost was found to outperform other models in the prediction of students' success at a level higher than 90% AUC-ROC score. Compared to earlier studies that primarily relied on traditional machine learning models such as Decision Trees and Support Vector Machines (SVM)[28], our implementation of XGBoost with hyperparameter tuning achieves a noticeable improvement in classification performance.

Although XGBoost has greater predictive capability than KNN, KNN remains an attractive option for actual implementation in the real world due to its interpretability and simplicity. Studies have highlighted that KNN is particularly useful in schools where interpretability is central to the administrators' and teachers' decision-making process [29][30]. Unlike black-box model deep learning techniques, KNN has the capability to make transparent and interpretable predictions and thus is a preferred model in e-learning systems where explainable AI deployment is required.

# Conclusion

This study investigated the application of AI-driven data mining techniques in personalizing e-learning experiences by predicting student performance. Based on the combination of the CRISP-DM and Felder-Silverman Learning Style Model (FSLSM), the proposed framework was able to personalize learning content to student learning style and learning behavior. The research implemented and evaluated multiple machine learning models, including KNN, XGBoost, Random Forest, and Neural Networks, demonstrating that hyperparameter tuning significantly enhances predictive performance.

Among the evaluated models, XGBoost stood out to be the best-performing algorithm, achieving the highest accuracy (92.4%) and AUC-ROC score (94.3%). This is in line with the literature and confirms the success of XGBoost in educational data mining. From this study, KNN is suggested, however, to be the better option to be utilized in real-world application because it is easier and interpretable, being a prerequisite in true real-world teaching environments where one desires transparency. The inclusion of FSLSM also differentiates this study from the previous ones in that it allows for scrutinizing student learning patterns more specifically.

Despite these results, the study is not without limitations. The dataset, while large and diverse, may not fully capture all contextual nuances, such as cultural or institutional differences in learning behavior. The synthetic extension of features like learning styles may also introduce biases. As with many machine learning studies, generalizability of the models beyond the observed data is constrained, particularly in underrepresented or differently structured educational systems. Additionally, the use of static historical data may limit the model's adaptability to evolving student behaviors in real-time learning environments.

The findings refer to the potential of AI-based personalization in fostering learning and motivation of students. Future research should explore hybrid deep learning models and real-time adaptive learning systems to enhance scalability and efficiency. Data privacy and algorithmic bias are ethics issues that need to be further investigated so that learning processes can be designed that are more inclusive and diverse in nature.

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