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Article

Unraveling the threads of adaptability: Analyzing key determinants influencing student success in online learning environments

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Abstract: This study evaluated the performance of several machine learning classifiers—Decision Tree, Random Forest, Logistic Regression, Gradient Boosting, SVM, KNN, and Naive Bayes—for adaptability classification in online and onsite learning environments. Decision Tree and Random Forest models achieved the highest accuracy of 0.833, with balanced precision, recall, and F1-scores, indicating strong, overall performance. In contrast, Naive Bayes, while having the lowest accuracy (0.625), exhibited high recall, making it potentially useful for identifying adaptable students despite lower precision. SHAP (SHapley Additive exPlanations) analysis further identified the most influential features on adaptability classification. IT Resources at the University emerged as the primary factor affecting adaptability, followed by Digital Tools Exposure and Class Scheduling Flexibility. Additionally, Psychological Readiness for Change and Technical Support Availability were impactful, underscoring their importance in engaging students in online learning. These findings illustrate the significance of IT infrastructure and flexible scheduling in fostering adaptability, with implications for enhancing online learning experiences.

Keywords: machine learning algorithms; student adaptability classification; SHAP analysis; online learning environments; adaptability factors

1.Introduction

The application of machine learning to model and describe real-world phenomena has significantly enhanced efficiency and resilience across various sectors. From public health (Kooptiwoot et al., 2024) and telemedicine (Kooptiwoot et al., 2024) to food science (Kooptiwoot and Javadi, 2022), machine learning plays a transformative role in driving advancements and optimizing processes. The rapid evolution of educational technologies has transformed the learning landscape, particularly with the growing prevalence of online learning platforms (An and Oliver, 2021). While online learning provides flexibility, accessibility, and a wealth of educational resources, students' adaptability to this mode of learning varies greatly (Qiao et al., 2021). Understanding the factors that influence students' adaptability to online learning is essential, particularly as educational institutions increasingly integrate online education with traditional onsite learning environments (Idrisoglu and Javadi, 2024; Kooptiwoot et al., 2024).

Several key factors impact a student's adaptability to online learning. These include digital literacy, self-regulation, time management skills, and access to reliable technology (Besser et al., 2022). Furthermore, learning styles, levels of motivation, and the ability to engage in self-directed learning play pivotal roles in determining how well students adjust to the online format (Mushtaha et al., 2022). Environmental factors, such as having a quiet study space and support systems, also contribute to students' ability to thrive in online learning (Kooptiwoot et al., 2024). In contrast, onsite learning environments often provide more structured interactions with peers and instructors, which can be a challenge for students transitioning to the relatively independent nature of online education (Vieira, 2024).

Machine learning algorithms offer powerful tools to analyze and predict how these factors affect students' adaptability to online learning (Essa et al., 2023). Machine learning algorithms can process large datasets to identify patterns related to students' adaptability to online learning (Kaddoura et al., 2022). They can analyze various factors such as learning styles, engagement levels, and external conditions (Alhothali et al., 2022). By training on historical data, these algorithms can predict which students may struggle or excel in online environments (Barbosa et al., 2024). This predictive capability enables educators to tailor support and resources effectively. Ultimately, leveraging these tools can enhance student outcomes and foster a more personalized learning experience.in particular after modeling the adaptability of student with machine learning models, SHAP (SHapley Additive exPlanations) can provide clear insights into the importance of individual features in the specific machine learning models (Belle and Papantonis, 2021). In the context of education, SHAP can be applied to evaluate the specific factors contributing to student success or difficulty in adapting to online learning (Fiok et al., 2022). By quantifying the influence of features like digital proficiency, time management, and motivation, SHAP can help educators better understand which students are more likely to succeed in an online environment.

This paper explores the educational factors that influence students' adaptability to online learning and utilizes machine learning classification models to evaluate these factors. SHAP was employed to interpret the contributions of different features, providing a clear understanding of the key determinants affecting students' ability to adapt to both online and onsite learning. By gaining these insights, educational institutions can better tailor their support strategies to enhance students' adaptability, improve learning outcomes, and create a more effective online learning experience.

2. Materials and methods

2.1. Survey design and data collection

A survey was designed to collect data on various factors influencing students' adaptability to digital learning. This survey included 14 features: Gender-GND (boy, girl), Digital Tools Exposure-DTE (1–6 years), Education Level-EDU (first, second, third year of university), Technical Support Availability-TSA-(institution, friends), IT Skills-ITS (yes, no), Psychological Readiness for Change-PRC (yes, no), Digital Literacy-DLT (low, high), IT Resources in the University-ITR (poor, mid-level, rich), Access to Reliable Internet-ARI- (mobile, Wi-Fi), Network Infrastructure-NET (4G, 5G), Class Scheduling Flexibility-CSF (good, poor), Self-Learning Habits-SLH (yes, no), Device Ownership-DVC (computer, mobile), and the Adaptability classifier (moderate, low, high). These questions were structured to gather demographic, technical, and behavioral data, helping to provide a comprehensive view of factors impacting adaptability to digital learning environments. The survey was distributed to university students, with data collected over four weeks. Responses were recorded using a standardized format and processed for analysis. The adaptability score (moderate, low, high) was treated as the primary target variable, while the other features served as independent variables. The survey data was anonymized, preprocessed, and validated to ensure completeness and accuracy, particularly focusing on missing data and inconsistencies.

2.2. Data preprocessing and feature engineering

Data preprocessing involved encoding categorical features and standardizing numerical values. Missing values were imputed using a mode-based imputation approach for categorical features and mean imputation for numerical features. Additionally, feature engineering was conducted by converting ordinal variables into numerical values, facilitating compatibility with various machine learning algorithms.

2.3. Machine learning models

To classify students' adaptability levels, several machine learning models were evaluated, including Decision Trees, Random Forests, Naïve Bayes, and Support Vector Machines (SVM), Logistic Regression, Gradient Boosting and K-Nearest Neighbors. Each model was trained and tested using a k-fold cross-validation approach ($k = 5$), allowing for a robust evaluation of model performance. Key metrics such as accuracy, precision, recall, and F1-score were recorded for comparison. Decision Tree Classifier was chosen for its ability to handle categorical data and provide interpretability through its tree structure, which displays the importance of each feature in predicting adaptability (Sachan and Saroha, 2022). Random Forest model as an ensemble of decision trees, provides improved accuracy and robustness against overfitting by averaging multiple decision trees. It also allowed for feature importance ranking, highlighting key predictors of adaptability (López et al., 2021; Alhothali et al., 2022). Naïve Bayes, that is a probabilistic classifier based on Bayes' theorem, assumes feature independence and performs well with categorical data, making it suitable for classifying adaptability levels with a simple, interpretable model (Gligorea et al., 2023). Support Vector Machines (SVM) was included for its effectiveness in high-dimensional spaces and its ability to find the optimal hyperplane that best separates classes, providing an alternative approach to decision-tree-based methods (Su et al., 2022). Other machine leaning models (Logistic Regression, Gradient Boosting and K-Nearest Neighbors) were applied for comparison the results and finding the best model performances (Rastrollo-Guerrero et al., 2020).

2.4. Interpretability with SHAP

To better understand the contribution of each feature to the adaptability predictions, SHapley Additive exPlanations (SHAP) was applied. SHAP values provide insights into the impact of each feature on individual predictions, allowing for a transparent understanding of how each factor influences adaptability classification. SHAP analysis helped reveal the most significant predictors across models, shedding light on the most influential factors affecting students' adaptability in a digital learning environment (Jin et al., 2022).

3. Results

The performance metrics of seven machine learning models—Logistic Regression, Decision Tree, Random Forest, Gradient Boosting, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Naive Bayes—were evaluated using accuracy, precision, recall, and F1-score. The results are summarized in **Table 1**.

Table 1. The performance metrics of seven machine learning models.

Machine learning models	Accuracy	Precision	Recall	F1-score
Logistic Regression	0.791667	0.541667	0.541026	0.535121
Decision Tree	0.833333	0.554779	0.582051	0.567766
Random Forest	0.833333	0.562963	0.574359	0.566416
Gradient Boosting	0.75	0.536111	0.515385	0.521164
Support Vector Machine	0.75	0.521008	0.507692	0.501961
K-Nearest Neighbors	0.75	0.521008	0.507692	0.501961
Naive Bayes	0.625	0.634259	0.746154	0.560705

The Decision Tree and Random Forest classifiers achieved the highest accuracy at 0.833, with comparable performance in precision, recall, and F1-scores. Decision Tree demonstrated a precision of 0.5548, recall of 0.5821, and F1-score of 0.5678, while Random Forest had a slightly higher precision at 0.5630, recall of 0.5744, and an F1-score of 0.5664. Logistic Regression showed a lower accuracy of 0.792 but achieved balanced values for precision (0.5417) and recall (0.5410), resulting in an F1-score of 0.5351. Gradient Boosting, SVM, and KNN models each recorded an accuracy of 0.750. Gradient Boosting yielded a precision of 0.5361, recall of 0.5154, and F1-score of 0.5212, slightly outperforming SVM and KNN, which shared identical values for precision (0.5210), recall (0.5077), and F1-score (0.5020). Notably, Naive Bayes achieved the lowest accuracy at 0.625, yet it excelled in recall with a value of 0.7462, indicating its strength in identifying positive instances, although this model had a lower precision of 0.6343 and a modest F1-score of 0.5607. While accuracy provides a primary benchmark, the trade-offs between precision, recall, and F1-score reveal deeper insights into each model's suitability for various scenarios. For instance, Naive Bayes, despite its lower accuracy, demonstrates a high recall, making it advantageous in contexts where capturing positive instances is critical. In contrast, the Decision Tree and Random Forest models balance accuracy with robust performance across all metrics, suggesting their effectiveness for balanced classification tasks. These findings suggest that Decision Tree and Random Forest classifiers provide optimal accuracy and balanced performance across all metrics in this context, whereas Naive Bayes, despite lower accuracy, may be preferred when higher recall is required.

3.1. Random forest classification

A representation of a decision tree derived from a random forest model was presented in **Figure 1**. The root node is defined by the condition Class Scheduling Flexibility (CSF ≤ 0.5), with a Gini impurity of 0.504, encompassing 64 samples and yielding a distribution of class values represented as [4, 32, 57]. Upon evaluating the branches, the true outcome of the root condition leads to a terminal node characterized by a Gini impurity of 0.0, which is composed of 80 samples and displays a class distribution of [0, 14, 66]. This indicates a high purity in this subset. Conversely, the false outcome branches to another node defined by the feature Gender (GND ≤ 0.5), which has a Gini impurity of 0.425. This node consists of 53 samples with a class distribution of [4, 18, 57], suggesting moderate impurity and variability among classes. Subsequent nodes reveal additional features and criteria, illustrating the tree's hierarchical structure. Each node provides Gini impurity values and sample distributions, which reflect the effectiveness of the splits in classifying the data. As traverse deeper into the tree, the Gini impurity values typically decrease, indicating improved classification as the model narrows down potential outcomes. In summary, this random forest decision tree serves as a crucial component of the random forest model, elucidating the decision-making process and the underlying structure of the data. The analysis demonstrates how features interact to influence predictions and the resulting class distributions at each node.

The decision tree representation provides a visual interpretation of the model's decision-making process, illustrating how features interact to classify data. At the top of the tree, the root node displays the first feature (Class Scheduling Flexibility, Technical Support Availability, IT Resources in the University and IT Skills) used for splitting the data, along with its corresponding Gini impurity and sample size. The Gini impurity quantifies the impurity of a node, with lower values indicating a higher likelihood of homogeneity among the classes. The top square in **Figure 2** identifies the initial feature (Class Scheduling Flexibility), which serves as the primary decision point for splitting the dataset. This feature (Class Scheduling Flexibility) is crucial for determining the path taken through the tree. Accompanying the feature is the Gini impurity value (0.531) indicates the effectiveness of the split. A Gini value closer to 0 suggests that the resulting groups are predominantly composed of a single class, enhancing classification certainty. The number of samples (117) at the root node provides context for the decision, indicating the amount of data contributing to the analysis. This is essential for understanding the representativeness of the split. As presented in **Figure 2**, move down the tree, each subsequent node represents additional splits based on other features, demonstrating how the model progressively narrows down classifications. The tree culminates in terminal nodes, or leaves, which contain the final predictions. These nodes indicate the predicted class label for the data points that reach that endpoint. The sequence of features from the root to the leaves reveals the hierarchy of importance. Features such as Class Scheduling Flexibility, Technical Support Availability, IT Resources in the University and IT Skills that appear earlier in the tree generally hold more significance in the decision-making process. The branching structure of the decision tree enhances clarity, making it easy to follow the decision paths and understand how different features contribute to predictions. Each node is associated with a specific condition (e.g., feature value thresholds) that determines how data is divided, reflecting the model's logic. The overall design emphasizes the model's ability to classify data accurately by leveraging significant features while discarding irrelevant ones. Insights gained from the decision tree can inform future feature engineering efforts, suggesting which features may warrant further exploration. The decision tree showed that the students with better Class Scheduling Flexibility and more technical support and IT skills had more adaptability to online learning. The decision tree model segments the data based on a series of encoded features, creating an interpretable classification structure. The initial split is determined by Class Scheduling Flexibility (CSF), which divides the data into two primary branches at a threshold of 0.50. Subsequent splits further segment the branches based on features like Technical Support Availability (TSA), IT Skills (ITS), and Device Ownership (DVS), each guided by specific thresholds. Notably, complex rules that combine features such as Access to Reliable Internet (ARI), University Resources (ITR), and Education Level (EDU) capture detailed class distinctions, ultimately leading to final class assignments (0, 1, or 2) at the terminal nodes. This hierarchical structure reflects conditional dependencies among features, where each path from root to leaf forms a unique rule set that contributes to precise classification outcomes.

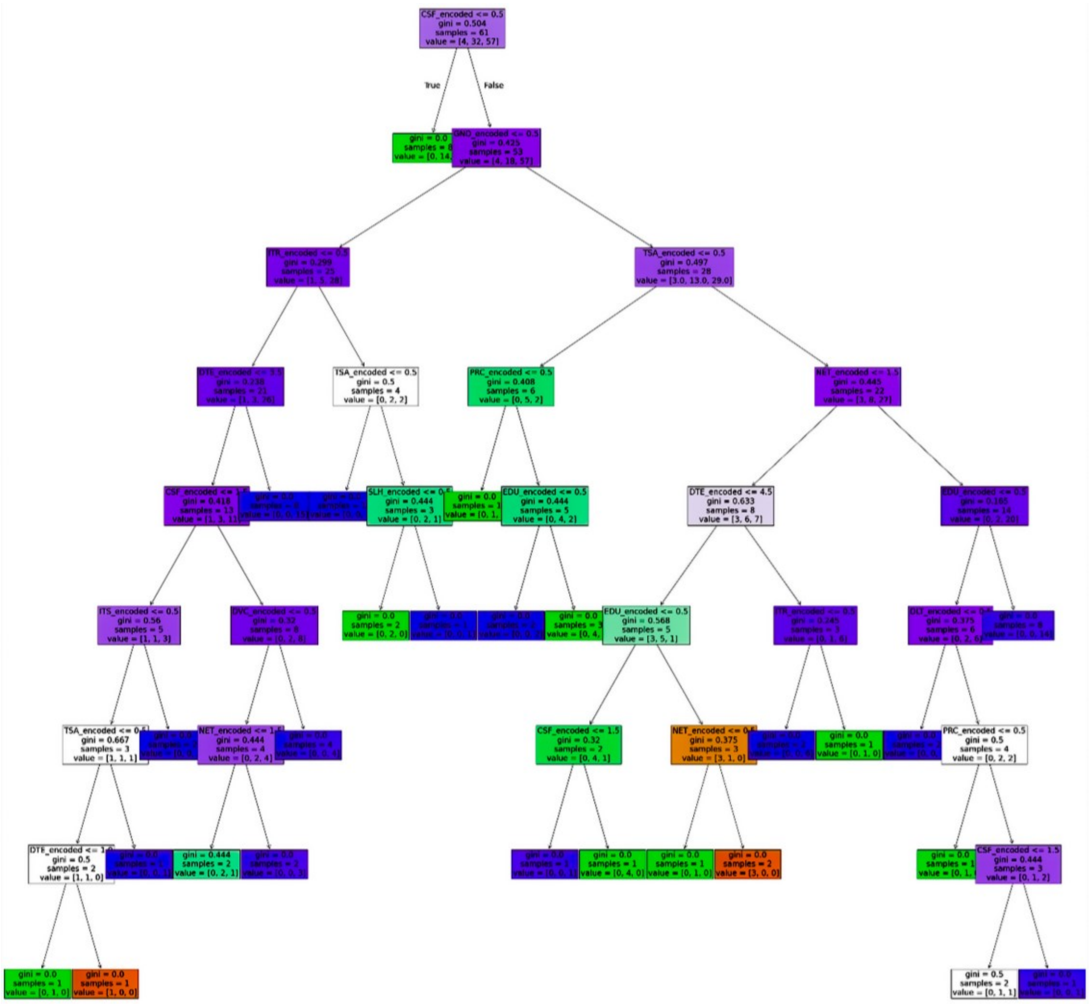

Figure 1. Representation of a decision tree derived from a random forest model.

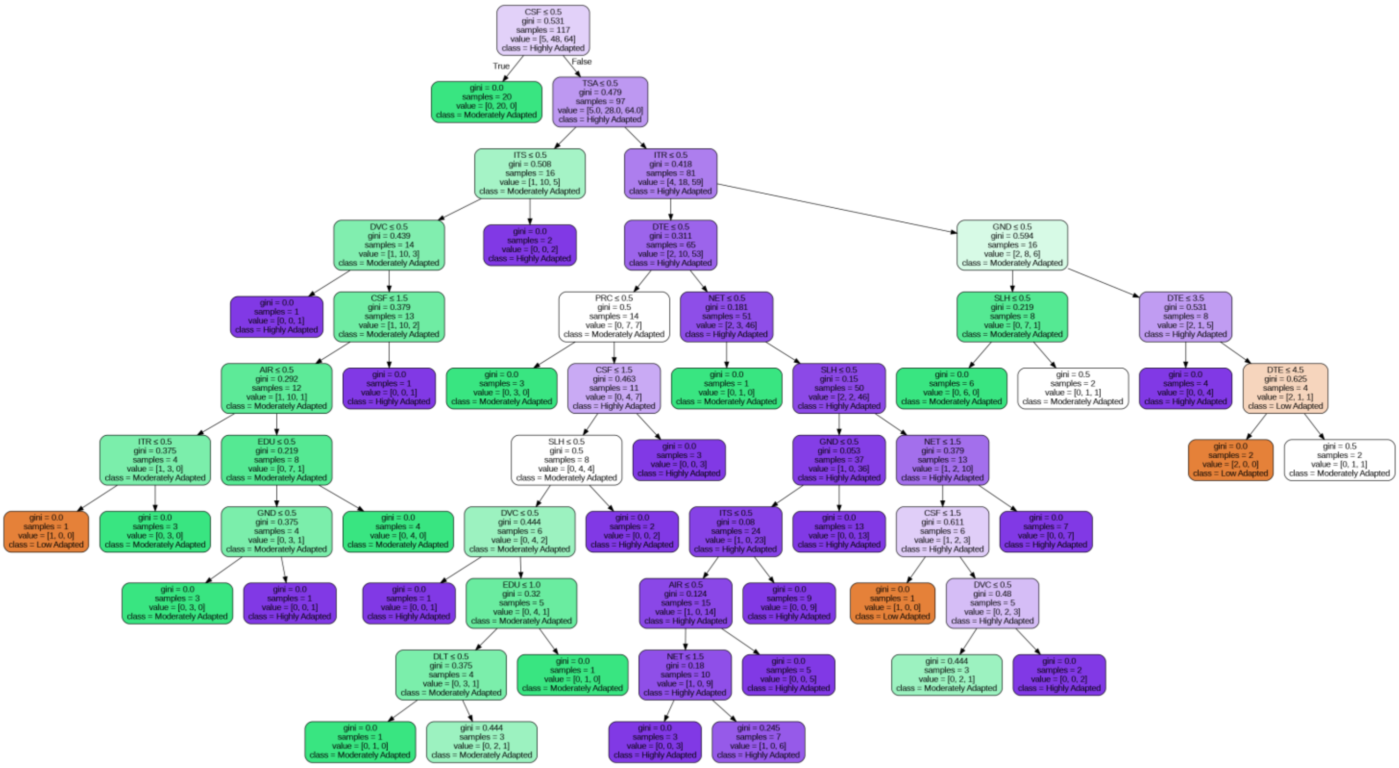

Figure 2. Decision tree representation.

3.2. Permutation importance analysis

Permutation importance is a technique used to assess the contribution of individual features to the predictive performance of a model. It measures the effect of randomly permuting the values of a feature on the model's accuracy. If permuting a feature significantly decreases the model's performance, that feature is considered important. This method provides an intuitive understanding of feature significance across various modeling approaches. In our analysis, we evaluated the permutation importance of features across multiple modeling techniques: logistic regression, decision trees, random forests, gradient boosting, support vector machines (SVM), k-nearest neighbors (KNN), and naive Bayes. Each model presents a unique perspective on feature importance, reflecting the underlying mechanics and assumptions of the algorithm used.

The visual representations include vertical bars indicating the permutation importance for each feature, plotted on a horizontal axis. Features with higher bars signify greater importance, while those without bars indicate minimal or negligible contribution to model performance. In Logistic Regression, features such as Class Scheduling Flexibility and Access to Reliable Internet displayed with significate permutation importance, suggesting a linear relationship with the target variable. Notably, these top features show a clear impact on model accuracy, while some features (such as Network Infrastructure) had negligible importance, reflecting their limited predictive value. Decision tree-based model illustrates a more varied importance distribution among features. Several features such as (Class Scheduling Flexibility, Access to Reliable Internet and IT Resources in the University) exhibit high importance, indicating their decisive role in the splits of the tree structure, while others are less influential. In Random Forest, similar to decision trees but with a broader range of feature importance values. The ensemble approach averages the importance scores across multiple trees, resulting in a more robust estimate. Key features are prominently ranked, underscoring their predictive strength. It should be noted here that Class Scheduling Flexibility and IT Resources in the University again had a significant impact on the model. Gradient Boosting model highlights a few key features with significant importance, showcasing the iterative nature of boosting (Class Scheduling Flexibility and IT Resources in the University). Some features stand out dramatically, while others reveal lower importance scores, suggesting their role in refining model predictions. The SVM analysis presents a unique importance profile, with certain features (Technical Support Availability and Class Scheduling Flexibility) showing relatively high importance, potentially reflecting their role in defining the decision boundary. However, many features remain unimportant, indicating a more complex relationship with the target variable. Other models (K-Nearest Neighbors (KNN) and Naive Bayes) permutation importance was presented in **Figure 3**. Overall, the permutation importance analysis across these models provides valuable insights into which features are most influential in predicting outcomes. It clearly showed that Class Scheduling Flexibility and Technical Support Availability are among the significant features with high impact on student adaptability towards online learning. The variations in feature importance across different algorithms underscores the necessity of considering multiple modeling approaches to fully understand the underlying data structure and feature contributions. This comprehensive evaluation not only enhances interpretability but also guides feature selection for future modeling endeavors.

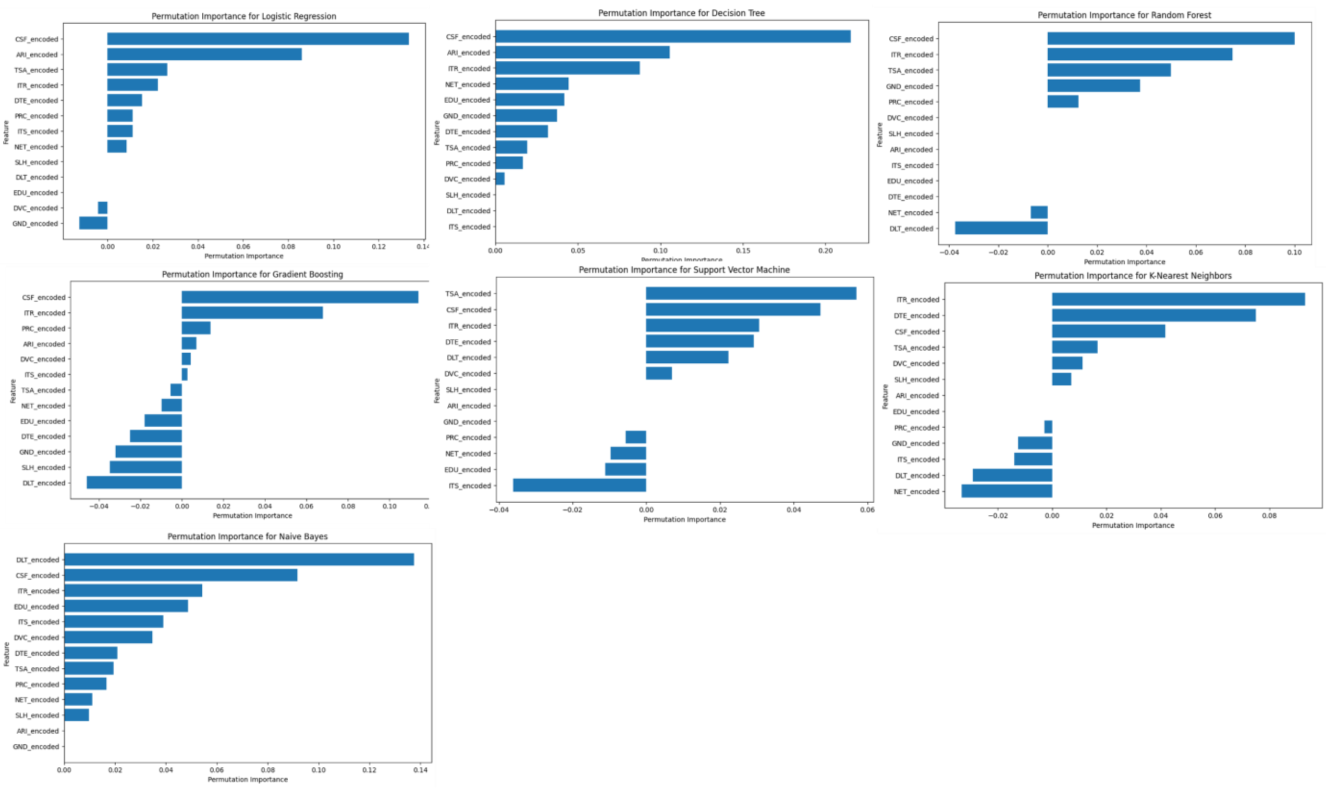

Figure 3. Permutation importance analysis of different machine leaning models.

3.3. ANOVA *F*-Value Representation

The ANOVA (Analysis of Variance) *F*-value is a statistical measure used to assess the significance of differences between group means. It quantifies how much of the variance in the dependent variable can be attributed to the independent variable(s). A higher *F*-value indicates a greater likelihood that the group means are significantly different from each other, suggesting that the feature has a strong relationship with the target variable. In the context of feature importance, ANOVA *F*-values provide insight into which features contribute most to explaining the variance in the outcome. The representation typically displays features on the vertical axis, with their corresponding *F*-values plotted on the horizontal axis. The ANOVA *F*-value representation ranks features based on their importance, allowing for easy identification of the most significant predictors. Features with higher *F*-values are prioritized **Figure 4**.

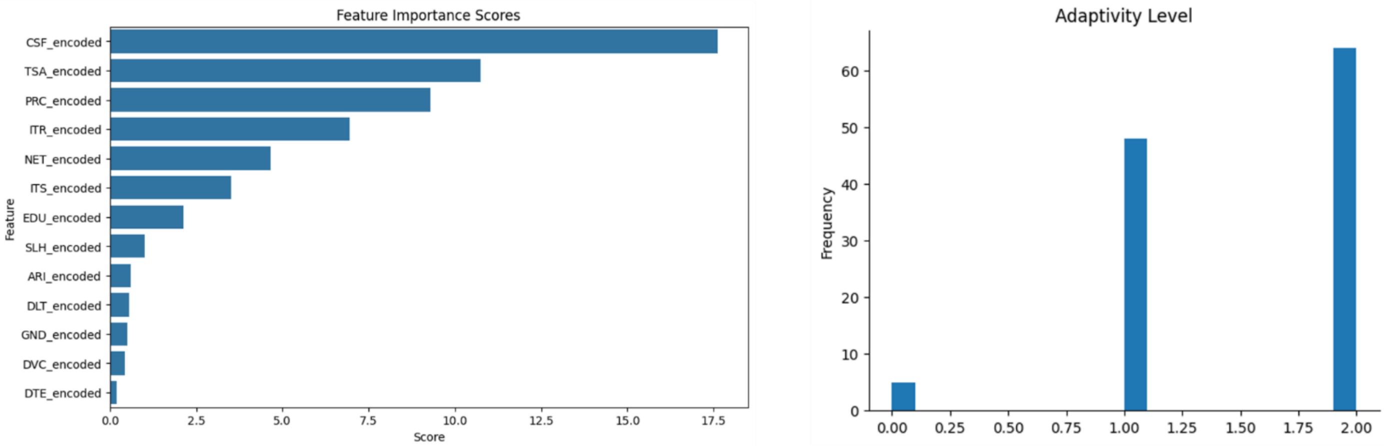

Figure 4. Representation ANOVA *F*-Value and classifier features frequency.

The SHAP (SHapley Additive exPlanations) analysis revealed the following features as influential in the classification of online and onsite learning adaptability. IT Resources in the University (ITR) feature emerged as the most significant factor influencing adaptability, suggesting that IT resources provided by your university play a crucial role in students' learning experiences. The second feature was Digital Tools Exposure which indicated the years of working with digital tools showed considerable importance, indicating impact students' adaptability. Class Scheduling Flexibility was highlighted as a significant factor, suggesting that good scheduling of the online class can influence access to and engagement with online learning. Furthermore, the Psychological Readiness for Change was another important feature impacting on adaptability. Technical Support Availability showed impact on engaging with online learning platforms. Other features represented in **Figure 4** with less impact on the random forest modeling **Figure 5**.

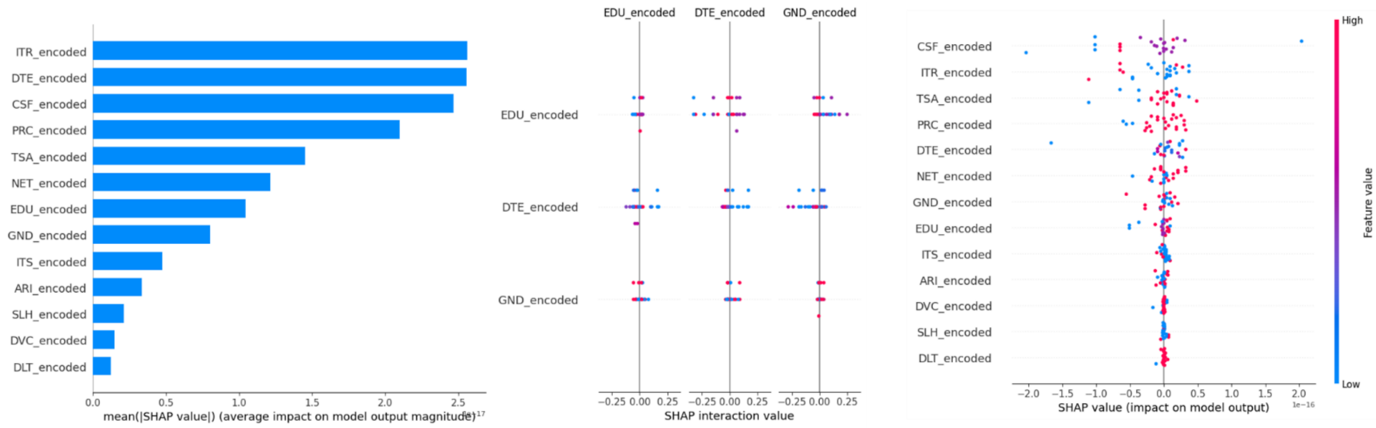

Figure 5. Representation of the SHAP (SHapley additive exPlanations) analysis.

4. Discussion

The finding of this study serves as an effective visual tool for understanding the model's classification process and the interaction between various features impacting students' adaptability to online learning (Chaddad et al., 2023). As indicated at the root of the decision tree, the initial split based on Class Scheduling Flexibility is significant, as it demonstrates the primary factor influencing students' experiences in online environments. The accompanying Gini impurity value of 0.531 indicates a moderate level of impurity, suggesting that while the split provides some clarity, there is still room for improvement in distinguishing between classes (Fiok et al., 2022).

As we navigate through the branches of the tree, additional features such as Technical Support Availability and IT Skills further refine the classification. Each subsequent node illustrates how these factors contribute to the overall adaptability of students, with the hierarchy of features revealing their relative importance (Sachan and Saroha, 2022; Okoro, et al., 2024). Features appearing earlier in the tree, such as Class Scheduling Flexibility, are paramount in determining pathways through the model, emphasizing the critical nature of scheduling in online education (Dutta et al., 2024). The Gini impurity measure at each node plays a crucial role in evaluating the effectiveness of these splits. Lower Gini values in later nodes indicate a more homogeneous grouping of classes, enhancing the model's predictive accuracy (Chitti et al., 2020). The terminal nodes, or leaves, present the final predictions for adaptability based on the conditions set by previous nodes, allowing for straightforward interpretation of the results (Baigarayev et al., 2021; Sachan and Saroha, 2022). Moreover, the decision tree's structured branching enhances clarity, making it accessible for educators and researchers alike. This transparency allows participants to trace the decision-making process, fostering a better understanding of how specific features impact student outcomes (Wangoo and Reddy, 2021). Each decision point reflects the model's logic, grounded in data, enabling informed discussions around interventions to enhance online learning experiences (Arun Kumar et al., 2022). The insights garnered from the different machine learning model analysis underscore the importance of targeted support mechanisms (da Silva et al., 2021). Students with greater Class Scheduling Flexibility, along with robust Technical Support and IT Skills, exhibit a marked adaptability to online learning environments.

These findings not only validate the significance of these features but also highlight potential areas for improvement in educational practice. Considering these results, future feature engineering efforts should prioritize the exploration of Class Scheduling Flexibility and support systems to further enhance model performance. The insights gained can drive strategic initiatives aimed at fostering adaptability among students, ultimately leading to improved educational outcomes. This approach aligns with the growing emphasis on personalized learning experiences in online education (Zhang and Zhang, 2021), suggesting a pathway for institutions to better support their students in navigating digital learning landscapes. Moreover, the SHAP analysis provides a comprehensive understanding of the factors influencing adaptability to online learning. The interplay between institutional characteristics and individual traits emphasizes the need for a holistic approach to educational reform. By addressing these multifactorial elements, we can better equip students for success in increasingly digital learning landscapes. The decision tree model in this study reveals key insights for the education sector, particularly in understanding factors that influence students' adaptability to online learning. By highlighting "Class Scheduling Flexibility" as the primary split, followed by critical features like "Technical Support Availability," "IT Skills," and "Device Ownership," the model emphasizes the importance of flexible and supportive online learning environments. Additionally, features like "Access to Reliable Internet," "University Resources," and "Education Level" indicate that adaptable, well-resourced, and technically supported settings are essential for student success in virtual learning. This suggests that educational institutions can improve online adaptability by prioritizing flexibility, robust technical support, and resource accessibility. This study has limitations, including a narrow focus on specific demographic groups. Future research should explore a broader range of populations and examine additional factors influencing online adaptability, such as psychological aspects and learning preferences.

5. Conclusion

In conclusion, this study highlights the critical factors influencing students' adaptability to online learning, with Class Scheduling Flexibility, Technical Support Availability, IT Resources in the University and IT Skills emerging as the most significant determinants. The interplay between these variables underscores the necessity for tailored educational strategies that consider individual and contextual differences. By prioritizing resource equity and infrastructural support, educational institutions can enhance student engagement and success in digital learning environments. Educational institutions should prioritize flexible class scheduling and enhanced technical support to improve students' adaptability to online learning. Additionally, investing in resources that ensure reliable internet access and bolster IT skills can significantly boost student engagement and success in online environments.

6. Future work

Future research should focus on longitudinal studies that track the adaptability of students over time, exploring how their experiences evolve as online education becomes more integrated into mainstream learning. Additionally, investigating the specific barriers faced by marginalized groups can provide deeper insights into developing inclusive educational practices. Finally, examining the impact of technological advancements on adaptability will be crucial in refining educational methodologies.

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Ethical approval: The Ethical Committee has granted approval for this study (Ref. No. COE.2-012/2024). All procedures performed in this study involving human participants were in accordance with the ethical standards of national research committee. Informed consent was obtained from all individual participants included in the study.

Informed consent: Informed consent was obtained from all subjects involved in the study.

Conflict of interest: The authors declare no conflict of interest.

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