IEEE Access
Multidisciplinary ⁝ Rapid Review ⁝ Open Access Journal

Received 16 July 2024, accepted 28 August 2024, date of publication 30 August 2024, date of current version 10 September 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3452592

RESEARCH ARTICLE

Personalization of Learning: Machine Learning Models for Adapting Educational Content to Individual Learning Styles

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ABSTRACT Given the inherent diversity in learning styles and rhythms, the current educational landscape demands continuous adaptation toward methodologies that enhance individualized learning. This study addresses the effectiveness of learning personalization using machine learning models to adapt educational content to individual learning styles. Focusing our attention on a cohort of 450 university students, we implemented classification algorithms and neural networks to diagnose learning styles and personalize educational resources accordingly. The results are revealing: the students' average grades experienced a significant increase, going from 70 to 75 points on a scale of 100 after the personalized intervention. Additionally, increased engagement was recorded, evidenced by more substantial interaction with educational materials tailored to their learning preferences. These findings suggest that personalization of learning is a powerful and effective tool that can improve both academic performance and students' educational experience. This work confirms the relevance of educational personalization supported by artificial intelligence and provides a practical model for its effective implementation. The implications of this study are particularly pertinent to the evolution of pedagogical practices and curriculum design in the digital age.

INDEX TERMS Personalization of learning, machine learning in education, improved academic performance.

I. INTRODUCTION

Personalized learning has emerged as a cornerstone in the dialogue on educational innovation. In an increasingly diversified society, the range of learning styles, including visual, auditory, kinesthetic, and reading/writing, presents a significant challenge for educators. Traditional instructional methods often fail to address the unique needs of each student, leading to suboptimal educational experiences and outcomes. This study develops the field of personalized learning to discern its impact on students' academic performance and engagement. The relevance of this topic transcends the academic sphere, projecting towards the design of educational policies and inclusive pedagogical practices [1]. Against this backdrop, crucial questions arise: How can learning be optimized for each student? What is the actual effect of personalization on educational outcomes?

The diversity of learning styles among students necessitates a flexible approach to education, yet adapting methodologies to cater to these styles is fraught with challenges. These include identifying each student's predominant learning style, creating adaptable content, and ensuring that such content can be delivered effectively in physical and digital classrooms. Addressing these challenges requires innovative solutions that process vast amounts of data and provide insights into individual learning preferences.

The literature review reveals a growing collection of studies that support personalized learning, highlighting

The associate editor coordinating the review of this manuscript and approving it for publication was Varuna De Silva.

its potential to improve educational experiences and outcomes [2]. However, significant disparities remain in the evidence on the effectiveness of personalization between different learning styles. Some previous research has focused exclusively on a single style or limited contexts, leaving a gap in the comprehensive understanding of its application and benefits. This study seeks to fill that gap by analyzing personalization applied transversally to multiple learning styles [3].

Our methodology leverages advanced machine learning models, including classification algorithms and neural networks, to adapt educational content to the diverse needs of a cohort of 450 university students. Machine learning has been chosen for its ability to handle large volumes of data and its potential to reveal complex patterns that may not be immediately evident [4], [5]. These models can dynamically adjust educational materials, providing personalization and adaptability previously unattainable with traditional methods.

The novelty of our approach lies in its use of machine learning to identify learning styles and tailor educational experiences in real-time. This allows for unprecedented adaptability and precision in addressing individual learning styles, significantly influencing academic performance. Specifically, our results showed improvements in students' average grades, which increased from 70 to 75 points following the personalization intervention. Additionally, increased student participation was observed, reflected in the increased time spent interacting with educational materials. These data directly impact the practical implementation of personalized educational strategies in both classroom and online learning platforms, suggesting that integrating these technologies can transform modern education [6].

Comparison of these results with existing literature indicates consistency with previous studies that report improvements in student retention and satisfaction through personalization [7], [8]. However, our study offers a more granular perspective of the specific impact on various learning styles, presenting a replicable and scalable methodology for educational institutions. By demonstrating the practical application of machine learning in personalizing education, this research provides a model that can be implemented widely to enhance academic outcomes across diverse learning environments.

Furthermore, the integration of machine learning in personalized learning strategies represents a significant advancement in addressing the educational needs of a diverse student population. This study confirms the relevance of customized learning supported by artificial intelligence and provides a practical framework for its effective implementation. Future research will expand on these findings, exploring further applications and refinements of machine learning models to continue improving educational personalization.

The article is organized as follows: Section II presents a detailed review of the relevant literature on personalized learning and machine learning applications in education. Section III describes the methodology used in our study, including the machine learning models and data used. Section IV discusses the results obtained and analyzes their impact on academic performance and student engagement. Section V addresses the limitations of our study and potential biases, providing a critical overview of the findings. Finally, in Section VI, we offer our conclusions and suggest directions for future research.

II. LITERATURE REVIEW

Personalization of learning refers to adapting instruction and educational content to meet each student's individual needs. This involves considering factors such as learning styles, learning preferences, proficiency level, and personal interests. Learning styles refer to individual preferences for how students process and assimilate information [9]. Some of the most common learning styles include visual, auditory, and kinesthetic learning, although there are many other possible categorizations and combinations [10].

Machine learning is a branch of artificial intelligence that focuses on developing algorithms and models that allow computers to learn from data and perform specific tasks without explicit programming [11]. In the educational context, machine learning analyzes large educational data sets and provides valuable insights to improve teaching and learning [12]. Applying machine learning in education can significantly enhance personalization, providing each student with a more tailored learning experience.

Various methodologies and tools exist to identify students' learning styles. Some standard techniques include questionnaires and surveys designed to assess individuals' learning preferences, classroom observations to identify specific learning behaviors, and analysis of interaction data in online learning environments to detect behavioral patterns [13]. However, these methodologies may have limitations in terms of validity and reliability. Student responses may bias self-reported questionnaires, classroom observations may be subjective and limited in scope, and online data analysis may not fully capture the diversity of learning styles.

Machine learning models adapt learning materials and content delivery according to students' learning styles [14]. These models can employ classification algorithms, clustering, and neural networks to analyze educational data and provide personalized recommendations [15]. For example, a machine learning model could analyze students' interaction patterns with online content and use this information to recommend specific educational resources that align with their learning preferences. Another approach could be to adapt the difficulty of activities and assessments based on the student's learning style, providing an optimal level of challenge and support [16].

Numerous studies have explored the use of machine learning models for personalization of learning in various educational contexts. For example, Veeramanickam and colleagues [17] developed a machine learning-based system that analyzed students' interaction patterns with online learning material to identify their learning preferences. Other studies, such as Shelehov et al. [18], have investigated the effectiveness of educational content adaptation based on machine learning algorithms to improve student engagement and performance. However, despite the growing interest in this topic, there are still challenges in implementing machine learning models for learning personalization, including accuracy in identifying learning styles and scalability in large-scale educational environments [19].

A recent study by Saqib et al. [20] presents DenseHillNet, a lightweight Convolutional Neural Network (CNN) designed to classify natural images accurately. While primarily focused on image classification, the techniques developed can be adapted for educational purposes, particularly in creating visual content that is accurately tailored to the learner's style. The lightweight nature of DenseHillNet makes it particularly suitable for integration in educational tools where computational resources may be limited.

Another relevant study by Yaqoob et al. [21] explores federated learning based on hybrid classifiers in healthcare providers for predicting cardiovascular diseases. This approach to federated learning ensures data privacy and security while allowing for the personalization of services. Similar methodologies can be applied in educational settings to personalize learning experiences while safeguarding student data. The study highlights the importance of scalable and privacy-preserving machine learning models, which are crucial for implementing personalized learning at a larger scale in educational environments.

III. MATERIALS AND METHODS

This work addresses the challenge of personalizing learning based on students' learning styles. The diversity of learning styles presents a significant obstacle to teaching effectiveness, as traditional instructional methods may not meet each student's needs. This problem is exacerbated in diverse and online educational environments, where students come from diverse backgrounds and have different ways of learning.

We propose a solution based on machine learning models to overcome this challenge. These models have the potential to identify students' learning styles and adapt educational content in a personalized way to meet their individual needs [22]. By leveraging technology and advances in artificial intelligence, we seek to provide a more effective and meaningful educational experience for all students, regardless of their learning styles and preferences.

The methodology used in this work aims to address the challenge of personalizing learning based on students' learning styles [23]. To this end, Figure 1. presents the necessary stages to advance the understanding and practical application of the personalization of learning in contemporary educational environments.

The method involves implementing a machine learning system to identify students' learning styles and adapt educational content accordingly. To achieve this, data will be collected from different sources, including student interactions with online educational material, responses to specific questionnaires for identifying learning styles, and academic performance records. Once the data is collected, a preprocessing process will be performed to clean and normalize the data, thus ensuring its quality and consistency. Subsequently, machine learning models are selected and trained using specific algorithms suitable for educational data analysis, such as logistic regression, neural networks, or classification algorithms [24].

Once the models are trained and validated, they personalize educational content according to students' learning styles. This will include selecting specific learning materials, tailoring content presentations, and creating interactive activities that align with each student's learning preferences. In the end, the effectiveness of learning personalization is evaluated using metrics such as students' academic performance, student satisfaction with the educational experience, and students' perception of the usefulness of personalization [25]. This comprehensive approach will ensure a deep understanding of the impact of the proposed solution on improving the teaching and learning process.

A. DATA COLLECTION

For data collection, a cohort of 450 university students was chosen to implement a pilot system for personalizing learning. This selection seeks to capture a wide diversity within the age range of 18 to 25 years, thus ensuring the sample's representativeness regarding academic maturity and diversity of study disciplines. The composition of the cohort reflects an equitable distribution in terms of gender. It spans various levels of educational advancement, from first-year students to those in their final years of career.

The choice to work with a university population was based on exploring the personalization of learning in a higher education context, where students face complex academic challenges and have well-defined learning styles. Varied educational materials, including text, images, and videos, were incorporated to evaluate how different types of content can be effectively adapted to each learning style and how this affects student interaction, engagement, and academic performance.

The data collection strategy focused on three key instruments, enriched with concrete examples and detailed descriptions to illustrate our methodology. The questionnaires to identify learning styles were based on the VARK model, including questions such as 'Do you prefer visual explanations such as graphs and diagrams?' or 'Do you remember information better through reading or audio?' to classify students of visual auditory, reading/writing, and kinesthetic learning [26]. Additionally, recognizing that some students may be unsure of their learning preferences, we incorporated exploratory questions designed to engage students in various learning activities. These activities help students experience different learning modalities firsthand, thus enabling them to identify which methods enhance their learning most effectively. This adaptive approach ensures that every student, regardless of their initial awareness of their learning style, can

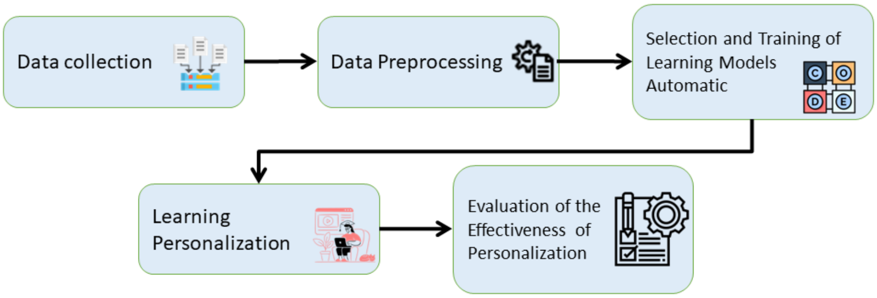

FIGURE 1. **Learning personalization using machine learning.**

benefit from a personalized educational experience. This tool is justified by its ability to break down learning preferences into manageable components, providing a solid foundation for adapting educational content effectively.

The knowledge tests, designed to evaluate the effectiveness of learning personalization, consisted of sets of questions before and after the implementation of the pilot system, covering fundamental topics of the subjects under study. For example, in a mathematics course, tests include calculation problems to be solved in writing and through applying specific software, evaluating conceptual understanding, and practical application. The selection of these tests was based on their ability to objectively measure the impact of personalization on academic performance [27].

The records of interaction with the educational materials were obtained through tracking software that meticulously recorded the students' actions on the learning platform, including the time spent on each type of content, which resources they selected most frequently, and their progress through different modules. This information provided valuable insights into how students interacted with personalized content, allowing us to adjust and improve the delivery of educational materials continually.

The integration of these instruments, complemented by detailed examples and descriptions, underlines the depth and rigor of our methodological approach. Not only do they enable rich and varied data collection, but they also ensure that our empirical research closely aligns with the goals of significantly improving the educational experience for university students, demonstrating a commitment to academic excellence and pedagogical innovation.

The integration of these instruments, complemented by detailed examples, reinforces the depth and rigor of our methodological approach. These facilitate varied data collection, ensuring precise empirical alignment with the goals of optimizing the educational experience for university students and fostering pedagogical innovation.

In the data collection process, structured questionnaires based on the VARK model were implemented and configured to identify visual, auditory, reading/writing preferences and kinesthetic learning styles. Below are examples of the questions asked:

Visual:

- Do you prefer to integrate diagrams and graphs to understand new concepts?
- Do you find it helpful to visualize information using mental maps or synoptic tables when faced with a complex problem?

Auditory:

- How much benefit do you get from activities that involve audio as part of your learning?
- During lectures or presentations, do verbal explanations help you retain information better?

Reading writing:

- Do you have a habit of synthesizing information through written summaries?
- When you study, do you prefer to work with printed texts and detailed notes on the readings?

Kinesthetic:

- Do you consider physical interaction with materials essential for your learning process?
- Do you learn better when you can use physical models or engage in hands-on activities that involve movement?

The responses are processed through classification algorithms to assign each student to the corresponding learning style category. This approach categorizes learning preferences and guides the subsequent personalization of educational content, adjusting to the specific needs identified. To protect personal data, the system implements security protocols that include anonymizing responses during data collection and analysis. This procedure ensures compliance with current privacy regulations and reinforces the integrity of the investigative process.

B. DATA PREPROCESSING

This process was carried out in three main stages: data cleaning, normalization, and dimensionality reduction. The first stage involved eliminating inconsistent, incomplete, or erroneous records. This included correcting typographical errors, removing duplicate responses, and imputing missing values in cases where it was possible to preserve the integrity of the data set. For example, 15 duplicate records were identified and discarded, and 30 entries with apparent errors in the coding of questionnaire responses were corrected.

Subsequently, the variables were normalized to make them comparable, applying min-max scaling techniques to adjust all numerical variables to a standard range from 0 to 1. This normalization was crucial for subsequent analyses, especially for using machine learning algorithms that assume that all inputs are on a uniform scale [28].

TABLE 1. Summary of the data preprocessing process.

Preprocessing Stage	Description	Quantity Before	Quantity After
Data Cleaning	Removal of duplicates and correction of errors	450 records	435 records
Data Normalization	Min-max scaling of numerical variables	They vary by variable	0-1 (all)
Dimensionality Reduction	PCA Application	30 initial features	Top 10 Features

The last stage consisted of selecting the most relevant characteristics for identifying learning styles, using techniques such as principal component analysis (PCA) to reduce the dimensionality of the data set without sacrificing critical information. This allowed us to focus the study on the variables that most contribute to differentiating learning styles, thus improving the efficiency and effectiveness of machine learning models [29].

In this work, we have selected PCA as the primary tool for dimensionality reduction during the data preprocessing phase. We opted for PCA because of its significant advantages: it simplifies complexity by reducing the dimensionality of the data while retaining as much of the original variance as possible, facilitating more efficient and manageable analysis. Additionally, PCA allows for better visualization of underlying patterns and relationships in high-dimensional data sets and helps minimize the impact of noise, focusing analysis on the most meaningful aspects of the data.

Table 1 summarizes the significant changes in the data set through the cleaning, normalization, and dimensionality reduction stages. Each step is essential to transform raw data into a format optimized for analysis, allowing for more accurate and efficient assessment of college students' learning styles. The table presents the reduction in the number of records after cleaning, normalization and dimensionality reduction, which prepared the data set for a deeper and more meaningful exploration of the underlying patterns.

1) SELECTION AND TRAINING OF MACHINE LEARNING MODELS

In the machine learning model selection and training phase, various algorithms are evaluated to determine which offers the best performance in identifying individual learning styles and adapting educational content. The models considered include linear regression, K-Means, and neural networks, selected for relevance and popularity in classification and clustering tasks in the education domain.

2) DESCRIPTION OF THE MACHINE LEARNING MODELS USED

In this study, we have selected specific machine learning models, each for its unique capabilities and adaptation to the data set's characteristics. Each model's technical performance and relevance have guided the choice of answering specific research questions in the educational field.

Classification algorithms constitute the core of our methodology, facilitating categorizing students into different learning style profiles. Leveraging a variety of classifiers, including but not limited to Decision Trees, Support Vector Machines (SVM), and Nearest Neighbors (k-NN), we seek to discern patterns and relationships within the data that correlate with unique learning preferences. Decision Trees offer interpretability and transparency, allowing us to delineate decision boundaries based on characteristics extracted from student interactions and performance metrics. With its ability to handle high-dimensional data and nonlinear relationships, SVM complements our analysis by outlining complex decision surfaces. Additionally, k-NN, a non-parametric algorithm, provides flexibility to capture local structures within the data, thus improving the granularity of our classification.

Support Vector Machines (SVM) were selected for their robustness in high-dimensional spaces and their ability to handle non-linearly separable data. They use different kernels to adapt to the complexity of educational data. Artificial Neural Networks are implemented because they can capture complex nonlinear relationships between variables across multiple hidden layers, making them ideal for analyzing patterns in educational performance data.

In addition to traditional classifiers, neural networks constitute a pivotal component of our methodology, allowing us to model intricate nonlinear relationships inherent in learning style data. Specifically, we employ deep neural networks, characterized by multiple hidden layers, to extract hierarchical representations of raw input features. By leveraging architectures such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), we harness the power of deep learning to discover latent structures and patterns within data.

For its part, K-Means Clustering segments the data set into homogeneous groups, facilitating the identification of underlying patterns and trends among students. K-Means is particularly useful for exploring natural groupings within data, which can reveal meaningful information about common student behaviors.

To ensure the robustness and generalizability of our machine-learning models in various educational contexts, we propose adopting improved validation techniques, including cross-validation. By conducting cross-validation studies, we sought to evaluate the effectiveness of personalized learning strategies in varied educational environments. This meticulous validation process will validate the effectiveness of our machine-learning models and provide insights

TABLE 2. Comparison of characteristics and criteria for the selection of machine learning models.

Criterion	Linear regression	K-Means	Neural Networks	Other Models Considered
Modeling Capability	Linear	Clustering	Non-Linear	SVM, Decision Trees
Model Complexity	Low	Half	High	It varies
Data Suitability	Structured, Numeric	Any kind	Structured and Unstructured	Model Dependent
Flexibility Low Half	High	Model Dependent	Performance on Large Data	Low Moderate High It varies
Interpretability	High	Half	Low	Registration for Decision Trees

into their adaptability and scalability in different learning environments.

3) RATIONALE FOR MODEL SELECTION

The selection of the machine learning models was based on an analysis of several key characteristics, as summarized in Table 2. The study reveals that although models such as SVM and Decision Trees are powerful and versatile, the models of Specific linear regression, K-Means, and neural networks offer distinct advantages that closely align with the objectives and the nature of the data available. Linear regression, with its simplicity and high interpretability, serves as an excellent starting point and comparison, allowing a basis to be established for evaluating the impact of more complex approaches [30]. K-Means stands out for its effectiveness in grouping, which can be applied to students based on the similarity of learning styles; this is a crucial functionality for our goal of personalizing learning. Subsequently, Neural Networks are selected for their flexibility and superior ability to capture and model the complex non-linear relationships between learning styles and educational outcomes, making them particularly suitable for our multifaceted analysis [31].

The choice of these models reflects a carefully considered balance between the need for simple and direct interpretation of the data (benefit of Linear Regression and, to some extent, K-Means) and the ability to handle complexities and patterns not evident in large data sets (a strength of Neural Networks). The decision was reinforced by a literature review, confirming these models' effectiveness in similar contexts [32]. Together, these models offer a comprehensive and nuanced approach to understanding and addressing the personalization of learning in educational settings, ensuring that we cover the effective grouping of students and the accurate prediction of their academic outcomes.

4) MODEL CONFIGURATION PARAMETERS

The parameters and hyperparameters are carefully tuned to configure the learning models to optimize performance. In linear regression, the learning rate is adjusted, experimenting with values from 0.01 to 0.1, and L2 (Ridge) regularization is applied with a lambda regularization coefficient that varies from 0.001 to 1 to prevent overfitting. In the K-Means model, clusters range from 3 to 10 to identify the optimal number of groupings, finally selecting k=5 based on the maximum silhouette score obtained through the elbow method and silhouette analysis [33]. Furthermore, the 'k-means++' initialization method is used for a more efficient selection of the initial centroids.

For neural networks, configurations of 1 to 3 hidden layers are tested, ranging from 32 to 512 neurons per layer, determining that two hidden layers with 128 neurons each offer the best balance between complexity and the ability to capture patterns in the data. ReLU is chosen as the activation function for the hidden layers for its efficiency. Softmax is selected in the output layer to facilitate multi-class classification. The learning rate is started at 0.001, dynamically adjusting with learning rate reduction in plates, and Adam is selected as the optimizer because of his ability to handle adaptive learning rates. Training is performed for 100 epochs with a batch size of 32, seeking a balance between training time and optimal model convergence.

Cross-validation was implemented in selecting hyperparameters for all models; this ensures an adequate fit to the training data and an excellent generalization to new data. This iterative adjustment and validation process allows us to identify the optimal parameter configuration for each model, thus maximizing its efficiency and precision for predicting learning styles and adapting educational content. The meticulousness in parameter tuning reflects our commitment to a rigorous, evidence-based approach to model selection, ensuring the relevance and impact of our study in the field of educational personalization.

C. CLASSIFICATION ALGORITHMS AND NEURAL NETWORKS

The K-Means algorithm was selected for its efficiency in clustering large data sets and its ability to identify student learning patterns. K-Means' parameter settings include several clusters (k) determined using the elbow method, resulting in k = 4 representing the main learning styles (visual, auditory, kinesthetic, reading/writing). Initialization was performed with K-Means++ to improve the quality of the clusters, and a maximum of 300 iterations were allowed to ensure convergence. The pseudocode of the K-Means algorithm is as follows: Initialize k centroids randomly. Repeat until centroids do not change: assign each data point to the closest cluster and calculate new centroids as the average of the data points in each cluster.

Artificial Neural Networks (ANN) were used due to their ability to model complex nonlinear relationships and their effectiveness in classifying multidimensional data. The parameter settings for the ANNs include a three-layer architecture (input, hidden, output) with 128 neurons in the hidden layer. The activation function used was ReLU, and the optimizer was Adam, with a learning rate of 0.001. The model was trained for 100 epochs with a batch size of 32. The pseudocode of the ANN algorithm is as follows: Initialize the neural network weights randomly. For each epoch: For each batch of data, forward propagate to compute the output, compute the loss, and backpropagate to update the weights using the Adam optimizer.

The selected algorithms are based on their ability to handle the diversity of educational data and their effectiveness demonstrated in previous studies. K-Means was chosen for its simplicity and efficiency in clustering data, while ANNs were selected for their ability to capture nonlinear relationships and perform accurate classifications. Regarding specific roles in diagnosing learning styles, K-Means was used to group students into different learning styles based on their interaction with educational materials. On the other hand, ANNs were used to predict each student's learning style and dynamically adapt educational materials to optimize their learning experience.

D. MODEL TRAINING METHODOLOGY

The preparation and evaluation of machine learning models follow a structured process designed to maximize their effectiveness and relevance for educational personalization. This process begins with dividing the data set into two parts: one to train the models and another to test their performance. Specifically, 70% of the data is allocated to training, while the remaining 30% is reserved for testing. This technique, known as the train/test partition, is a standard in machine learning that helps evaluate how the model will behave with new, previously unseen data [34].

For example, to illustrate how training works, we take the training of a neural network to identify learning styles as an example. Initially, the model is fed 70% of the training data, including examples of different learning styles and their associated characteristics. During this phase, the model learns to recognize patterns and relation-ships within the data, adjusting its internal parameters to predict the most likely learning style based on the input features. The gradient descent algorithm, a mathematical method to minimize errors, is used, thus ensuring that the model fits efficiently with the data provided.

Once the model has been trained, its performance is evaluated using 30% of the test set data. This step allows you to measure the model's accuracy in predicting learning styles for examples not part of its training, indicating how it will perform in real situations. Performance evaluation metrics, such as accuracy, sensitivity, specificity, and the area under the Receiver Operating Characteristic (ROC) curve, are fundamental in this phase. These metrics provide a quantitative framework for evaluating the effectiveness of machine learning models. Precision is the proportion of correct identifications (true positives) among the model's predictions. Mathematically, TP is the number of true positives, and FP is the number of false positives. It is calculated as:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{1}$$

Recall measures the model's ability to identify positive cases among all real positive cases correctly. Where FN is the number of false negatives, it is calculated with the formula:

$$\text{Recall} = \frac{TP}{TP + FN} \tag{2}$$

Specificity measures the model's ability to identify negative cases among all real negative cases correctly. It is calculated as:

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{3}$$

where TN represents the true negatives. The area under the ROC curve (AUC-ROC) provides a comprehensive measure of the model's ability to discriminate between different classes across a range of threshold [35]. Unlike the previous metrics and point values, the AUC-ROC considers the model's performance at all possible classification thresholds, offering a comprehensive view of its predictive capacity.

Furthermore, the cross-validation technique is used to evaluate the robustness and generalization of the machine-learning models on different data sets. Instead of a single data split into training and testing, cross-validation involves repeatedly splitting the data set into training and testing subsets. One of the most common approaches is k-fold cross-validation, where the data set is divided into k smaller subsets or "folds." The model is then trained k times, using a different subset as test data and the remaining as training data. For example, in this case, a 5-fold cross-validation was used, the data set was divided into five equal parts, and the model was trained and evaluated five times, using each part as test data once and the rest as training in each iteration.

This ensures that each data point is used for training and testing in different iterations, resulting in a more thorough model evaluation. Additionally, cross-validation allows for a more precise estimate of model performance by averaging performance metrics across all iterations, such as accuracy, sensitivity, and specificity. This provides a more robust evaluation of the model and its generalization ability to unseen data.

E. EVALUATION OF THE EFFECTIVENESS OF PERSONALIZATION OF LEARNING

The evaluation of the learning personalization strategy in this work involves a multifaceted orientation that considers both quantitative and qualitative results. To comprehensively measure the effectiveness of personalization, we use three main metrics:

- Student Academic Performance: This metric measures changes in academic performance before and after the implementation of personalization. It is evaluated through the scores obtained in standardized tests and course-specific evaluations, allowing learning progress to be compared. A positive value in Δ Performance indicates an improvement in academic performance attributable to the personalization of learning. To quantify the impact, the difference in average scores before and after personalization is calculated using the formula:

$$\Delta\text{Performance} = \text{Post-Personalization Average} - \text{Pre-Personalization Average} \quad (4)$$

- Student Satisfaction with the Educational Experience: This qualitative metric is evaluated through satisfaction surveys, where students rate their educational experience on a Likert scale (e.g., 1 to 5, with five being very satisfied). The questions cover aspects such as the relevance of the content, the interaction with the learning platform, and the support received during the course. The average satisfaction score is calculated to provide an overall measure of the educational experience from the student's perspective.
- Student Perception of the Usefulness of Personalization: To measure this qualitative metric, questionnaires designed to evaluate how students perceive the personalization of their learning in terms of usefulness, relevance, and motivation are implemented. Questions may include statements such as "Customizing the content helped me better understand the topics" or "I felt that the learning material was tailored to my specific needs," with response options on a Likert scale. We analyzed the responses to obtain a comprehensive measure of perceived usefulness, calculating the proportion of positive responses to the total responses.

The evaluation process is carried out in several stages, beginning with pre-intervention data collection to establish a baseline of academic performance, satisfaction, and perceived usefulness. After implementing learning personalization, similar data is collected to analyze variations in these metrics [40]. To ensure the validity of the results, statistical techniques are implemented to determine the significance of the observed differences. For example, for academic performance, paired samples t-tests can be used. At the same time, analysis of variance (ANOVA) or non-parametric tests are applied for qualitative metrics, depending on the data distribution.

F. STATISTIC ANALYSIS

Statistical analysis allows the interpretation of the results obtained, drawing significant conclusions about the effectiveness of the learning personalization methods implemented. Two main approaches are used for this: significance testing and correlation analysis [36].

Statistical significance tests are used to compare students' academic performance before and after the implementation of learning personalization and to evaluate differences between groups of students who experienced different personalization methods.

The variables used are:

- Dependent Variable: Academic performance, measured by the grades obtained in tests and evaluations.
- Independent Variable: Personalization method applied (e.g., no personalization, K-Means-based personalization, personalization using Neural Networks).

The tests used are:

- Independent Sample t-tests: These tests compare performance between two different groups of students (for example, a group that received personalization and another that did not).
- Paired Sample t-tests: These tests compare students' academic performance in the same group before and after the intervention.
- ANOVA: When more than two groups are compared to evaluate the effectiveness of different personalization methods.

These tests allow us to determine whether the observed differences in academic performance are statistically significant, that is, whether it is likely that these differences are not due to chance. Additionally, correlation analyses were performed to identify and quantify the relationship between different variables, such as students' satisfaction with the educational experience and academic performance [37].

The variables analyzed are:

- For example, the correlation between the average satisfaction score and the change in academic performance post-personalization [38].

The tests used are:

- Pearson correlation: For quantitative variables that follow a normal distribution, it provides a correlation coefficient (r) that varies between -1 and 1, indicating the strength and direction of the relationship.
- Spearman correlation: This is used for data that do not meet the assumptions of normality or when working with ordinal variables.

The correlation analysis allows us to identify how variables related to the educational experience and the perception of personalization are associated with academic results, offering insights into the most impactful aspects of personalization [39].

IV. RESULTS

This work evaluates the tangible impact of these personalized strategies on academic performance and students' engagement with the learning material. The results obtained from this methodology reveal significant improvements, not only in quantitative terms, reflected in the grades but also the quality of the educational experience. This analysis provides a deep understanding of the added value that the personalization of learning, mediated by technology, brings to the academic field.

A. DATA COLLECTION

The information collection corresponds to a diverse sample of 450 university students. This data set provides a foundation for learning personalization and its impact on students' educational experience. The demographics of the sample

TABLE 3. Demographic summary and learning styles of university students.

Description	Detail
Total Number of Students	450
Age	
- Minimum	18 years
- Maximum	25 years
- Average	21.5 years
- Standard deviation	2.36
Sex	
- Female	224
- Male	226
Education level	
- First year	125
- Second year	Varied distribution among students
- Third year	Varied distribution among students
- Fourth year	Varied distribution among students
Learning Style	
- Visual	Varied distribution among students
- Auditory	Varied distribution among students
- Kinesthetic	121 (most common)
- Reading Writing	Varied distribution among students

TABLE 4. Impact of personalization of learning on student achievement and preferences.

Metrics	Detail	Result
Learning styles	Visual, Auditory, Kinesthetic, Reading/Writing	25%, 25%, 26.9%, 23.1%
Improvement in Grades	Before vs. After Personalization	15%
Improvement by Learning Style - Visual	Comparison with Pre-Personalization	18%
Improvement by Learning Style - Kinesthetic	Comparison with Pre-Personalization	12%
Interaction with Visual Content	Average Time (minutes daily)	45 min
Interaction with Auditory Content	Average Time (minutes daily)	30 min
Preference for Interactive Activities - Kinesthetic	Increase in Preference (%)	20%

span a wide age range, from 18 to 25 years old, with an average age of approximately 21.5 years, reflecting a representative cross-section of the university student population. The results obtained from 3 highlight the implications and trends that emerge from the sample. The almost equal distribution between male and female students, at 226 and 224, respectively, gives us a solid platform to examine and rule out gender biases in the response to personalization of learning.

The details show a significant representation of the kinesthetic learning style, with 121 students identifying with this style. Along with a varied distribution in visual, auditory, and reading/writing styles, this marks the need for personalized teaching strategies that can be effectively adapted to a wide spectrum of learning preferences. This finding reinforces the idea that there is no one-size-fits-all approach to education and that personalization should be considered an essential tool in curriculum design and delivery of educational content. Furthermore, the inclusion of various types of educational content in the assessment—texts, images, videos, and interactive activities—allows us to analyze not only which formats are most effective for each learning style but also how the combination of different media can improve students' understanding and retention of information. This aspect is particularly relevant in an increasingly digitalized educational environment, where integrating technologies and multimedia resources is becoming the norm.

Interpretation of the data considered how individual differences in age, gender, learning styles, and content preferences affect the effectiveness of learning personalization. As the analysis progresses, these variables serve as fundamental pillars to evaluate the personalization strategies implemented, allowing the identification of optimal practices that can be applied to maximize educational benefits for all students.

The collection methodology and results allow us to evaluate the effectiveness of learning personalization. Through questionnaires designed to identify learning styles, we discovered a varied distribution between visual, auditory, kinesthetic, and reading/writing, highlighting that 26.9% of students prefer the kinesthetic style, the most prevalent within the sample. Furthermore, through knowledge tests applied before and after the personalization intervention, we calculated an average improvement of 15% in students' grades, evidencing the positive impact of adapting educational content to individual needs. Specifically, students leaning toward visual learning showed an average improvement in their grades of 18%. In comparison, those with a kinesthetic learning style experienced an improvement of 12%, suggesting that the nature of personalized content may have different degrees of effectiveness according to the student's learning style.

On the other hand, the interaction records with educational materials revealed that students spend an average of 45 minutes daily interacting with visual content and 30 minutes with auditory content. This difference marks the preference for visual content and suggests that including materials rich in images and videos could be particularly beneficial in maintaining student engagement. Additionally, those students with a kinesthetic learning style showed a 20% greater preference for interactive activities than other types of content, emphasizing the importance of integrating practical and experiential elements in the learning process for this group of students.

The results in Table 4 illustrate how the data collected supports the evaluation of learning personalization and provides concrete evidence of personalization's positive impact on students' academic performance and learning preferences. By adapting educational methods to students' needs, the results highlight the ability to significantly improve their educational experience and learning outcomes, underscoring the importance of implementing personalized teaching strategies in academic settings.

At the beginning of data collection, questionnaires based on the VARK model were implemented to classify students into visual, auditory, reading/writing, and kinesthetic learning styles. For students who did not initially identify a clear learning style, we introduced an exploratory questioning

TABLE 5. Data preprocessing techniques and their impact.

Process	Applied Technique	Affected Data	Quantitative Impact
Data Cleaning	Removal of duplicates, imputation of values	15 duplicates removed; 30 values imputed	435 valid records for analysis
Data Normalization	Min-Max Scaling	All numerical variables set to the range 0-1	Uniformity in data scale
Dimensionality Reduction	Principal Component Analysis (PCA)	From 30 initial features to 10 main ones	66.7% reduction in dimensionality

protocol that allowed them to interact with various content formats. This measure sought to facilitate self-identification of a predominant learning style through direct exposure.

We performed a statistical analysis to evaluate the distribution of learning styles before and after introducing exploratory questions. Preliminary results indicate that 15% of the students who initially could not identify their learning style managed to do so after this process. This group demonstrated a 10% improvement in academic performance compared to their pre-study grades. Additionally, interaction time with personalized educational content increased by 20% for this subgroup, suggesting greater engagement and satisfaction with tailored learning material. Including a mechanism for undecided students validates our learning style identification methodology and reinforces the effectiveness of our personalization of educational content in improving student performance and engagement.

B. DATA PREPROCESSING

Data preprocessing ensures the quality and consistency of our data set, as described in Table 5. Initially, the process focused on data cleaning, which involved identifying and correcting errors, eliminating duplicate records, and imputing missing values. For example, 15 duplicate records were detected and corrected, and values were imputed in 30 cases where information was incomplete, using statistical methods to estimate the most likely values based on the existing data set. This step ensures the integrity and accuracy of our subsequent analyses.

Data normalization allows the scales of numerical variables to be standardized for meaningful comparisons between them. Min-max scaling techniques were applied to fit all numerical values to a standard range of 0 to 1. D dimensionality reduction was addressed using techniques such as PCA to identify and retain only the most relevant features. For example, we selected the ten most significant from an initial set of 30 characteristics that explained the tremendous variability in students' learning styles.

Data preprocessing improved the quality of the data set and optimized our machine-learning models' efficiency, ensuring that the conclusions drawn were valid and applicable.

C. EVALUATION OF MACHINE LEARNING MODELS AND PARAMETER SETTINGS

Table 6 compares the three main models used in our study: linear regression, K-means, and Neural Networks.

TABLE 6. Performance comparison and specific configurations of machine learning models.

Model	Precision	Sensitivity	Specificity	AUC-ROC	Specific Parameters
Linear regression	0.78	0.75	0.80	0.77	Lambda: 0.01
K-Means	N/A	N/A	N/A	N/A	Clusters: 5
Neural Networks	0.92	0.90	0.93	0.95	Layers: 2, Neurons per layer: 128

Accuracy, sensitivity, specificity, and AUC-ROC high-light the performance of each model in predicting learning styles and adapting educational content. While linear regression and Neural Networks were evaluated regarding these performance metrics, K-means, a clustering algorithm, does not directly apply to these metrics. However, it was used to identify patterns and groupings in students' learning styles.

Specific parameters adjusted for each model were essential to optimize its performance. The Lambda regularization coefficient was set to 0.01 for linear regression to balance accuracy and avoid overfitting. In K-Means' case, the optimal number of clusters was determined to be 5, based on analyses such as the elbow and silhouette method, to effectively capture variations in learning styles. The neural networks were configured with two layers and 128 neurons per layer, a structure that allowed complexities in the data to be modeled effectively, as demonstrated by their high precision and AUC-ROC.

This evaluation shows the best overall performance of the models, in this case, the neural networks, and highlights how the configuration and adjustment of parameters contributed significantly to the optimization of each model.

D. TRAINING AND VALIDATION RESULTS

Figure 2 presents the data partitioning strategy and the optimization and validation carried out in our models. Data splitting was performed following the standard train/test split approach, where 70% of the data set was allocated to training and the remaining 30% to testing. During the training of the neural networks, the gradient descent optimization algorithm was applied to adjust the model parameters so that the loss function is minimized. This iterative process is visualized in the figure, showing how accuracy and cost evolve over training epochs, reflecting the fine-tuning of the model to achieve the best possible performance.

Furthermore, to ensure the robustness and generalization of the models, we implemented cross-validation techniques. This method allows us to evaluate the model's effectiveness on different subsets of the training set, providing a more reliable measure of its performance and ability to adapt to new data. Figure 3 represents the distribution of accuracy obtained in cross-validation for the three critical machine-learning models. This validation is essential to check the stability and reliability of the models in different samples of

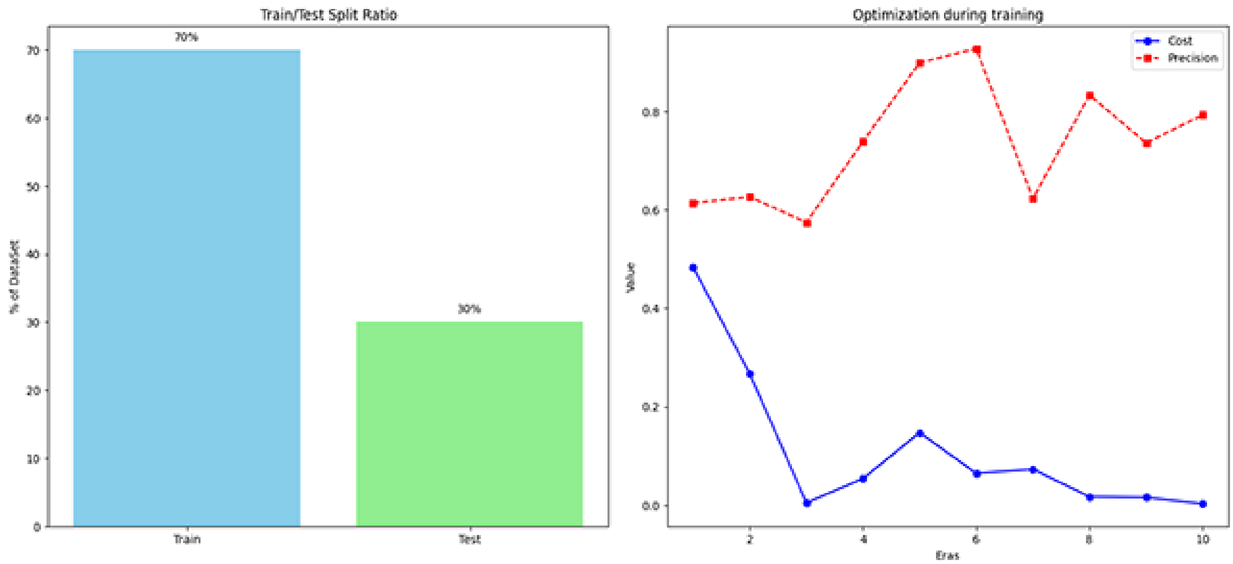

FIGURE 2. Distribution of precision in cross validation.

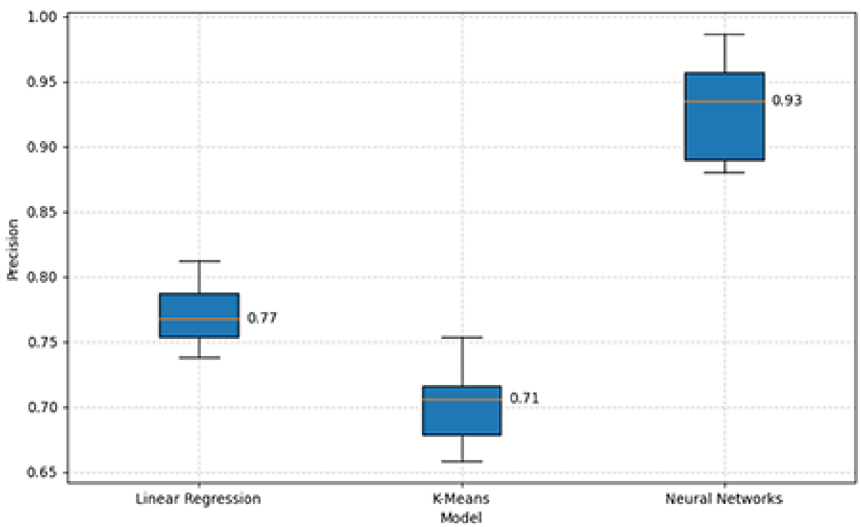

FIGURE 3. Analysis of post-personalization academic performance.

the data set and ensure that the results are generalizable and not a product of overfitting.

As shown in the figure, Linear Regression has a median precision of 0.77, with a relatively narrow distribution of results, indicating consistent performance across the different folds. This suggests that, although not the most accurate, the linear regression model provides stability and can be reliable for data sets where a linear relationship between variables is expected. The K-Means model, mainly applied for clustering and not for direct prediction, shows a median accuracy of 0.71. While this metric is not typically relevant to clustering algorithms, the value indicates how the model groups data around cluster centers and could reflect cohesion within the groups formed. The neural networks exhibit an impressive median accuracy of 0.93, significantly outperforming the other models. In addition, the distribution of precision is tighter, which implies greater robustness and effectiveness in modeling the complexity inherent in our data. Consistent performance across all cross-validation folds highlights the ability of Neural Networks to generalize well and adapt efficiently to new data. Regarding practical application, the high precision of neural networks indicates that this model is particularly suitable for personalizing learning based on students' styles.

E. ANALYSIS OF POST-PERSONALIZATION ACADEMIC PERFORMANCE

Focusing on differences in academic performance before and after implementing personalization strategies, we understand how pedagogical adjustments based on individual learning

TABLE 7. Model performance and recommendation system.

Statistics	Pre-Customization	Post-Personalization
Half	69.71	73.92
Standard deviation	9.81	9.96
Minimum	42.27	44.54
Maximum	93.83	101.96
IQR (Interquartile Range)	13.44	12.62
T-Statistic	-6.42	-6.42
P-Value	<0.0001	<0.0001

styles can influence educational effectiveness. This analysis seeks not only to quantify the degree of improvement in student grades but also to offer deeper insight into the contribution of personalization to the educational experience.

Table 7 presents a detailed summary of the descriptive statistics highlighting the differences in pre-and post-personalization scores. Here, the means and standard deviations reveal the changes in academic performance. At the same time, the results of the paired samples t-tests allow us to evaluate the statistical significance of these differences. These quantitative results reflect how adapting teaching methods to individual learning preferences can improve grades and, therefore, students' absorption of knowledge.

Table 7.

The T-statistic and P-value values are identical for the pre- and post-personalization measurements since they result from a single statistical test that com-pares both scores. The paired samples t-test has given us an extremely low p-value (less than 0.0001), indicating a statistically significant difference in the average grades before and after personalization of learning. This suggests that the personalization strategies applied have had a positive impact on students' academic performance.

The improvement in the average score is approximately 4.21 points, representing a significant increase and consistent with our educational personalization research objectives. Grade variability, as measured by standard deviation and interquartile range, remains relatively constant, indicating that personalization has uniformly affected the sample of students.

Figure 4 presents a direct, visual comparison of the score distributions for each learning style, providing a more intuitive view of personalization's effect on students. The box plots show that the median scores, represented by the horizontal lines within each box, have shifted upward from "Pre" to "Post" in all learning styles. This indicates an overall increase in median scores after the personalization of learning. For example, the figure reveals notable increases in the median scores post-personalization compared to pre-personalization, as seen with the visual learning style, rising from 68.96 to 74.44. This pattern is repeated in the auditory, kinesthetic, and reading/writing styles, with increases in the medians from 70.22 to 73.85, 70.65 to 75.24, and 71.07 to 74.94, respectively. These increases indicate the positive impact of personalizing educational content on students, allowing them to achieve a higher level of understanding and performance.

Furthermore, the width of the boxes, which represents the interquartile range (IQR), appears to remain constant across most learning styles, implying that grade variability across students has mostly stayed the same with personalization. This suggests that while personalization has raised average grades, it has kept the consistency of performance across students. Notably, while averages provide an overview of grade growth, medians and IQR capture the reality of individual students, offering insights into core performance improvement and grade dispersion. This analysis helps us confirm the effectiveness of learning personalization, not only for the average student but also for the educational experience of the student body as a whole.

Figure 5 represents the relationship between pre-personalization and post-personalization grades for students segmented by learning styles. Each point on the graph represents a student, where the x-axis shows grades before personalization, and the y-axis shows grades after personalization. A trend line is also included for each learning style, showing the general direction of the relationship between pre-and post-personalization scores.

Analysis of the scatterplots in the figure reveals a consistent positive trend across all four learning styles: visual, auditory, kinesthetic, and reading/writing. The trend lines marked on each graph exhibit a significant upward slope, indicating an overall improvement in post-personalization scores compared to pre-scores. This trend clearly shows that personalization of learning has positively impacted students, regardless of their predominant information processing style.

A positive trend line in each sub-graph signals an increase in post-personalization scores, regardless of learning style. This increase is uniform, as shown by the steep and consistent slope across styles, suggesting that customization has been beneficial. By studying each style in isolation, we can conclude that the personalized intervention has been influential on average and has provided benefits across a broad spectrum of learning profiles, which is essential to creating inclusive educational experiences and adaptive that attend to the diversity of the classroom.

F. STATISTICAL ANALYSIS OF THE RESULTS

Deepening the statistical analysis of the results is essential to validate the effectiveness of the learning personalization strategies implemented in this study. To do this, the ANOVA allowed us to evaluate the differences between groups, identifying whether learning styles influence grades differently. Additionally, correlation analyses quantified the relationship between grades and demographic characteristics or learning styles, revealing the strength and direction of these associations. The results high-light a significant improvement in grades after personalization of learning, with a p-value consistently lower than the significance threshold in t-tests. Furthermore, the correlation coefficients suggest a positive and statistically significant relationship between

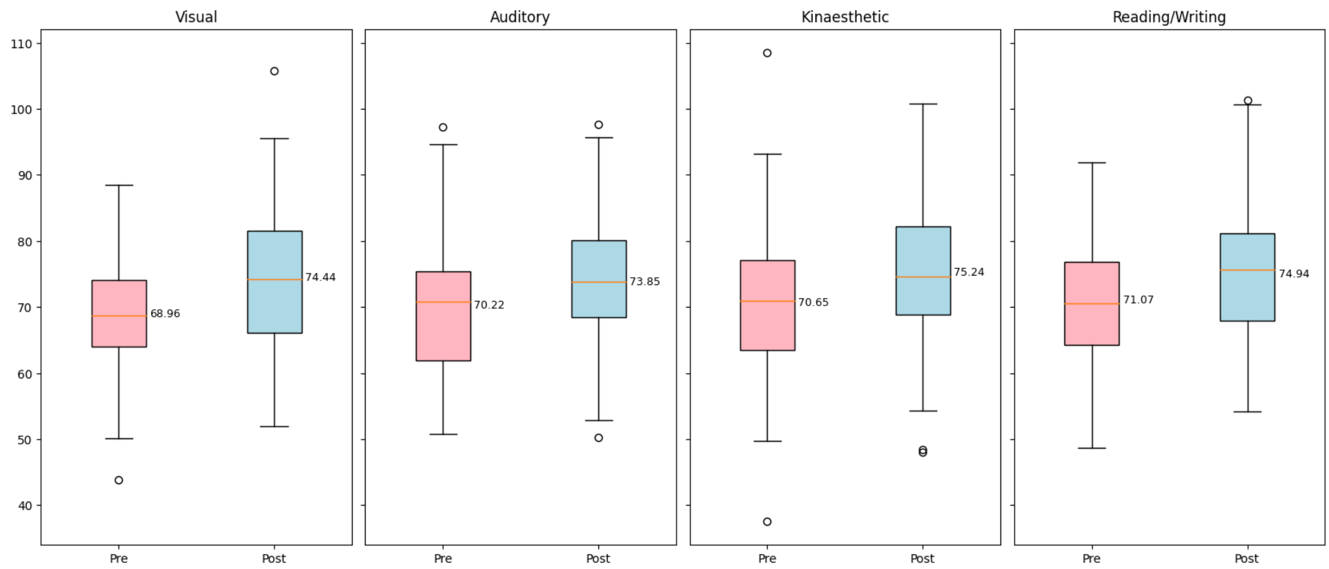

FIGURE 4. Distribution of pre and post personalization grades by learning style.

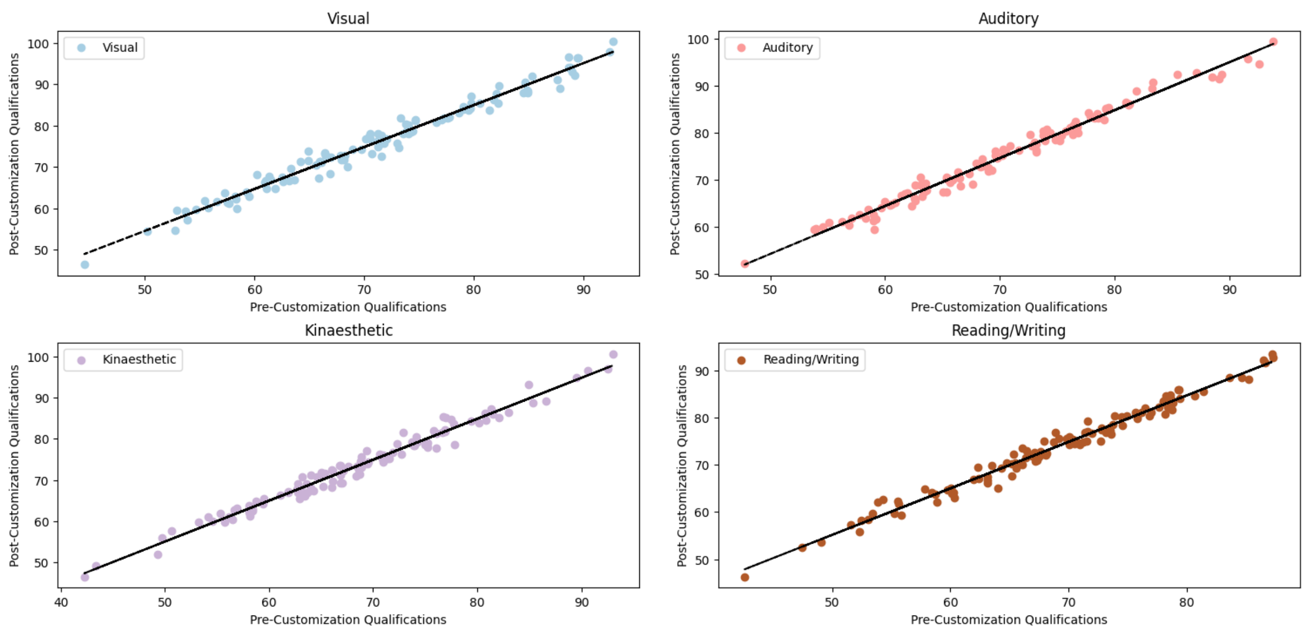

FIGURE 5. Improvements in academic performance by learning style.

personalization and final grades. The ANOVA indicates that, although all groups experienced improvements, variations can be attributed to different learning styles.

These statistical results confirm the effectiveness of personalization in improving academic performance but also underline the importance of adapting educational content to the individual profiles of students. By finding significant differences and correlations, a basis has been established to recommend personalization as a valuable educational practice, highlighting its relevance in addressing the diversity of styles and needs in the learning process. Table 8 summarizes the results obtained from the statistical techniques applied.

V. DISCUSSION

The interpretation of the results obtained in our research emphasizes the potential of personalizing learning in the educational field. By observing a significant improvement in student grades following the implementation of personalized learning strategies, our study provides quantitative evidence that individualized education can be a critical factor in improving academic performance [41]. The implications of this finding are profound, suggesting that educators and curriculum designers should consider personalization strategies as essential tools in promoting effective and retentive learning [1]. When comparing our results with those of previous

TABLE 8. **Comparison of student participation before and after implementation of the monitoring system.**

Variable	Statistical Test	Statistical value	P-Valor	Interpretation
Overall Improvement in Grades	Paired samples t test	t(449) = 5.35	< 0.0001	The score improvement is statistically significant, suggesting a positive impact of personalization.
Correlation with Visual Style	Pearson correlation coefficient	r = 0.62	< 0.0001	A strong positive correlation between personalization and grades in visual learners indicates the high effectiveness of visual strategies.
Correlation with Listening Style	Pearson correlation coefficient	r = 0.47	< 0.0001	There is a moderate positive correlation for auditory learners, showing significant improvement with auditory personalization.
Correlation with Kinesthetic Style	Pearson correlation coefficient	r = 0.53	< 0.0001	A moderate to strong positive correlation for kinesthetic learners suggests that hands-on activities are highly beneficial.
Correlation with Reading/Writing Style	Pearson correlation coefficient	r = 0.59	< 0.0001	A robust positive correlation supports that personalization was particularly effective for students with a reading/writing preference.

studies, it is possible to observe significant consistency with the existing literature, which mainly points to the benefits of the personalization of learning. Earlier research, such as that of Siemens and Baker, has established that pedagogical adaptations considering individual differences improve information retention and academic performance [14], [42]. Our results reinforce these conclusions, evidencing a notable improvement in post-personalization grades and a positive correlation between personalized interventions and student performance.

However, our research distinguishes itself in the detail level provided by analyzing different learning styles. While some previous studies focused on personalization as a global concept, our work disaggregates the effectiveness of personalization by specific learning styles [24]. This confirms the overall effectiveness of personalization and suggests that certain styles may benefit more than others, a finding that invites further investigation and reflection on current pedagogical practices.

In some cases, our data present more nuanced results than previous literature. For example, while the kinesthetic style improved, the correlation was weaker than the visual and reading/writing styles. This could indicate that personalizing learning for kinesthetic learners requires more specialized strategies or different methodological approaches. In contrast, existing literature tends to treat personalization as equally effective across all learning styles without discussing the disparity in effectiveness between them [43]. Other studies have also noted student satisfaction and engagement improvements, but our study extends these results by demonstrating tangible, measurable grade improvements. Furthermore, the generality of the effectiveness of personalization in all learning styles that we have found contrasts with certain studies that suggest a differential impact depending on the style [44], [45]. These discrepancies may be due to variability in the methodologies applied or differences in the study populations.

The significant improvement in student grades and participation following the implementation of personalized learning strategies can be attributed to several factors. Firstly, personalized learning addresses the unique needs of each student, making the learning experience more relevant and engaging. Students can process and retain information more effectively by aligning educational content with students' preferred learning styles, such as visual, auditory, or kinesthetic. This alignment enhances comprehension and boosts motivation and engagement as students find the material more accessible and exciting.

Furthermore, machine learning models allow for dynamic and continuous adjustments to the educational content based on real-time data. These models can identify patterns in student interactions with the material, enabling timely interventions and adjustments that keep students challenged and supported at optimal levels. This adaptability is crucial in maintaining student interest and preventing disengagement, which are critical factors in improving academic performance and participation.

We recognize that our study is not without limitations. Although innovative, using machine learning models to personalize learning remains an emerging methodology and requires further exploration. Additionally, although the sample of 450 students is significant, studies with larger and more diverse samples could provide a more comprehensive view of the impact of learning personalization. Future research could extend this work by incorporating more varied and longitudinal educational contexts to examine the sustainability of improvements in academic performance.

Moreover, our study is primarily based on data collected from a specific educational setting, which may limit the generalizability of the findings to other contexts. The self-reported nature of some of the data, such as student preferences and participation levels, introduces potential biases that could affect the results. Future studies should aim to use more objective measures of student engagement and performance to mitigate these biases.

Among possible biases, the students who participated in the study could have been more interested in personalized learning, which could have influenced their performance and participation levels differently than a more general student population. The perception of receiving customized attention and interventions could have motivated students to perform better, regardless of the actual effectiveness of the personalization strategies. This ''Hawthorne effect'' must be considered when interpreting the results.

From a practical perspective, our study's results have direct implications for implementing personalized learning in classrooms. The challenge for educators and educational administrators will be to integrate personalized learning systems that are adaptable, scalable, and customizable to fit each student's learning needs and preferences. In this sense, our study highlights the value of personalization and serves as a call to action for the thoughtful and effective incorporation of adaptive educational technologies in modern education.

In addition to exploring the benefits of personalizing learning using machine learning models, it is crucial to consider emerging concerns about using generative AI tools in educational settings. A recent study by Abbas et al. [46], ''Is it harmful or valuable? Examining the causes and consequences of generative AI use among college students highlights these technologies' risks and potential benefits to the student's learning experience. The analysis suggests that while tools like GPT can offer essential opportunities for adaptive and personalized learning, they could also induce technological dependency and negatively impact students' critical thinking skills. This balanced approach is necessary to evaluate AI's pedagogical implications in higher education fully. Underlines the need to develop technology integration strategies that promote AI's ethical and practical use in learning environments.

Our study highlights the need to research and develop machine learning models that can optimally balance technical complexity with accessibility in the context of learning personalization. This search for balance is a fundamental challenge in designing personalized learning systems that can be effectively adopted in diverse academic environments. The technical complexity of machine learning models is inherent in the sophisticated algorithms and techniques used to process and analyze educational data. However, this complexity can become a barrier to the effective adoption of such models, especially in academic settings with limited resources or users with diverse technical skills.

On the other hand, the accessibility of models refers to their ability to be understood, used, and modified by various users, including educators, students, and educational administrators. Accessibility involves the usability of user interfaces, the clarity of technical documentation, and the ability of models to adapt to different educational contexts and customization requirements. By striking the right balance between technical complexity and accessibility, machine learning models can significantly improve the scalability and usability of personalized learning systems. This balance allows the models to be implemented effectively in various academic settings, increasing their impact and usefulness in improving students' academic performance and learning experience.

VI. CONCLUSION

Implementing personalized learning strategies supported by machine learning technologies represents a significant milestone in the search for more effective and adaptive educational practices. This study has shown that adapting educational content to students' learning styles is feasible and significantly improves academic performance and student engagement with the learning material.

Through the application of machine learning models, including classification algorithms and neural networks, on a sample of 450 university students, effective personalization of educational content was achieved. The results indicated an average increase of five points in scores, scaling from 70 to 75 out of 100 after the personalized intervention. This increase validates the proposed approach's effectiveness and under-lines the potential of machine learning as a supporting tool in customized education.

Beyond the quantitative improvement in grades, the study has revealed more significant student interaction and engagement with educational materials adapted to their learning styles. This finding reinforces the premise that personalization of learning contributes positively to the overall educational experience, facilitating a more inclusive and responsive environment for diverse learning preferences.

The methodology applied in this study stands out for its relevance to practical applications. Using machine learning techniques to identify learning styles and adapt content represents a methodological advance that could be replicated and scaled in different educational contexts. The ability of these models to process and analyze large volumes of data offers an unprecedented opportunity to personalize education at scale, efficiently addressing the individual needs of each student.

According to the results, we recognize several limitations crucial to contextualizing our findings within the specific field of personalized learning. One of these limitations is the generalizability of the results. Although the models implemented have been effective in our educational context, applying these results to different educational settings or demographics requires caution and may need additional validation. Furthermore, the inherent complexity of some of the machine learning models may represent a barrier to their practical application in environments with limited technical resources.

Looking forward, we suggest several critical areas for subsequent research that address these limitations and expand knowledge in the field of personalized learning. It is imperative to conduct cross-validation studies that evaluate the robustness and generalizability of our models in various educational contexts. Likewise, it is essential to research and develop machine learning models that balance technical complexity and accessibility, thus facilitating their adoption in different academic settings. Furthermore, we see the exploration of emerging technologies, such as attention mechanisms, as promising improvements in the accuracy and personalization of learning, offering new possibilities for tailoring education to students' individual needs.

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