RESEARCH ARTICLE

Innovative pedagogies in physical education integrating technology to enhance learning outcomes

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The incorporation of technology into education has transformed teaching methods across multiple disciplines. Physical education (PE) that relies on conventional approaches is undergoing a paradigm shift with the adoption of creative pedagogies supported by technological tools. This shift seeks to tackle various learning styles, increase engagement, and improve results in PE. Although technology has the potential to transform PE, its influence on learning achievements is unclear with gaps in engagement, personalization, and measurable progress. This research created a new method that combined innovative pedagogies and technology to improve PE learning results by concentrating on student-specific requirements to investigate how technology interventions could be allocated and improved for enhanced engagement and efficiency. A technology-driven physical education dataset (TechPE-Data) was developed, which included features like age, fitness level, learning style, engagement level, and preferred technology. The proposed algorithm, technology-driven physical education enhancer (TechPE-Enhance), preprocessed data using K-nearest neighbors (KNN) imputation, one-hot encoding, and min-max normalization. A hybrid filter-wrapper ensemble (HFWE) was used for feature selection, which included mutual information, chi-square, ANOVA F-test, and recursive feature elimination (RFE). Soft voting was used to train an ensemble classification model that included a random forest, support vector machine (SVM), and gradient boosting machines (GBM) to allocate the best technology interventions. Furthermore, a random forest regressor predicted learning results depending on specific features. Model performance was assessed utilizing metrics like accuracy, precision, recall, F1-score, mean absolute error (MAE), and R^2. The results showed that the proposed method had a classification accuracy of 92.5% with precision, recall, and F1-score of 91.8%, 92.1%, and 92.0%, respectively. The regression model achieved a MAE of 2.4 and an R^2 score of 0.89, indicating high predictive capacity. Key factors such as fitness, engagement, and learning style influenced the outcomes. The study focused on technology's role in transforming PE, specifically the TechPE-Enhance algorithm for personalized and measurable learning.

Keywords: physical education; pedagogies; feature selection; classification; regression.

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Introduction

Physical education (PE) has long been a staple of academic curricula, encouraging physical fitness, motor skills, teamwork, and overall well-being [1, 2]. Traditionally, PE depends on structured exercises, skill development activities, and instructor-led training. However, the advancement of technology in education has created new opportunities for improving learning experiences. Digital tools like motion tracking, wearable fitness devices, gamification, and virtual simulations are increasingly being used in PE programs to increase student engagement, track performance, and tailor instruction [3]. These innovations are consistent with current educational tactics that prioritize data-driven decision-making and personalized learning [4]. Recent advances in educational technology have allowed for significant progress in PE [5]. Mobile applications offer immediate feedback. Smart wearables track fitness metrics and virtual reality (VR) platforms simulate sports scenarios to improve training [6]. Artificial intelligence (AI) and machine learning (ML) are also being investigated to personalize exercise suggestions and forecast student performance. Technology-driven PE programs have been confirmed to improve motivation, engagement, and knowledge retention. However, efficient deployment of technological interventions remains a challenge as current implementations frequently fail to account for individual variations in learning styles, fitness levels, and engagement preferences. Despite the promising incorporation of technology into PE, numerous major problems remain, which include the absence of a structured framework for optimizing the selection and application of technological tools according to individual student requirements, inconsistent engagement with some students benefiting from gamified learning and others requiring data-driven insights to enhance performance. Furthermore, existing research provides limited quantifiable evidence of the direct influence of technology on PE learning results. Without an organized method to tackle these issues, the full potential of technology-enhanced PE goes unrealized.

Previous attempts to include technology in PE have mainly concentrated on generic tools like fitness trackers and fundamental tracking devices. These solutions often adopt a uniform approach to monitor metrics like step count, calories burnt, or heart rate without considering the unique needs and objectives of individual students. While these devices may offer helpful data regarding a student's physical activity, they do not tackle wider learning aspects that are necessary for PE, like student engagement, motivation, and personal growth. Rusmitaningsih *et al*. investigated the role of fitness tracker apps in increasing students' involvement and motivation in PE, emphasizing their ability to improve activity levels but avoiding customization for individual goals [7]. Similarly, Koryahin *et al*. incorporated information systems to track heart rates in PE classes and found that, although these systems provided useful real-time data, they lacked adaptive feedback tailored to individual students [8]. Reis *et al*. found that targeted PE interventions could boost children's physical fitness and activity levels through the PROFIT pilot study. However, the study highlighted the significance of aligning these interventions with individual learning styles [9]. Furthermore, Abdupattayevich and G'ayratovich proposed strategies to improve teaching methodologies, integrate modern technologies, and encourage student engagement to enhance the efficiency of the training process [10]. Several studies have used sophisticated methods such as VR and smartphone apps to improve PE. Muntaner-Mas *et al*. developed a smartphone app for university students that measured fatness and fitness, resulting in increased engagement but lack of personalized feedback in real time [11]. Similarly, Bae investigated the impact of a VR-based PE program on elementary students' fitness levels with positive results but restricted adaptability to various student requirements [12]. Anthony assessed the incorporation of technology in American schools, noting enhancements in student fitness results while emphasizing the need for systems to tackle wider learning objectives [13]. Additionally, Krause and Jenny applied exergaming in PE and found challenges in its implementation and teachers' confidence [14], while Vilchez *et al*. studied online PE during the COVID-19 pandemic and found limits in student involvement and interaction [15]. Hassan *et al*. highlighted the importance of structured and authentic evaluations when incorporating technology, advocating data-driven methodologies to improve outcomes [16]. The main drawback of current technological interventions in PE is the lack of personalization. While fitness apps and wearable devices provide useful information regarding student achievement, they frequently fail to account for the wide range of learning styles, fitness levels, and activity choices among students. Each student's distinctive features such as their background, motivations, and learning styles can have a significant effect on their participation and success in PE. However, existing systems rarely consider these factors, offering a general solution that may not be efficient for all students. Additionally, many existing systems fail to assess educational results other than physical activity, like skill development, engagement, or cognitive learning. Scalability is another issue as noted by Vilchez and Krause *et al*. [14, 15]. Numerous systems are intended for small-scale use and require extensive customization, which limits their adoption in larger educational institutions. This gap emphasizes the need for scalable, adaptable solutions that can cater to various student populations while remaining efficient.

To address these issues, this study proposed a machine learning framework based on technology-driven physical education enhancer (TechPE-Enhance) that aimed to effectively integrate innovative pedagogies and technological tools to improve PE learning outcomes by transcending the limitations of contemporary systems and creating personalized, data-driven interventions for student PE. The research systematically evaluated student features like age, fitness level, learning style, and engagement preferences by using TechPE-Data that included various features pertinent to PE learners. K-Nearest Neighbors' (KNN) imputation was employed for the handling of missing values, while one-hot encoding for categorical data and min-max normalization for feature scaling. This research outlined a structured, data-driven framework for incorporating technology into PE. The proposed TechPE-Enhance algorithm was a novel method for personalized learning in PE that tackled individual differences while enhancing engagement. The results of this study could have implications for educators, policymakers, and developers looking to improve PE programs using intelligent and adaptive machine learning technologies. Additionally, this study laid the foundation for future research into AI-powered personalization, real-time performance analytics, and adaptive learning in PE.

Materials and methods

Dataset construction and data collection

A TechPE-Data dataset, which contained a variety of features that represented both the demographic characteristics of students and their engagement with technological tools, was meticulously designed to capture the important attributes that influenced learning results in PE when combined with technology. The data for TechPE-Data was collected by a series of anonymized structured surveys with parental consent acquired for minors, activity logs, and teachers' observations of students enrolled in a PE program with each participant being assigned a unique student ID to ensure privacy and confidentiality. Each participant was asked to provide age, fitness level (from 1 to 10), preferred learning style (visual, auditory, kinesthetic), preferred technology tools (fitness app, smartwatch, VR), and participation in PE sessions with various physical exercises like cardio, yoga, and tennis. The weekly technology utilization of each student recorded in hours as 0 to 10 and learning results assessed on a scale of 1 (poor) to 100 (excellent) were tracked throughout the study. Data was obtained utilizing standardized forms and electronic records to ensure consistency and accuracy. All data were stored in a safe database. The TechPE-Data model was developed utilizing data gathered from 350 students enrolled in a PE program from January 2023 to June 2023 with 180 males and 170 females aged from 13 to 17 years old.

Data storage and organization

All collected data were kept in a relational database management system (RDBMS) in a tabular format for ease of access, querying, and manipulation. Each student's data was separated into individual records with student ID as the main key for record identification. The dataset was consistently updated with feedback on technology interventions, guaranteeing ongoing enhancement and improvement of the technology allocation model. Students initially completed a survey that collected demographic information, fitness levels, learning styles, and technology choices. Throughout the study, students used weekly logs to track their engagement and technology usage, while teachers recorded participation levels. At the end of the study, students completed evaluations to assess their learning results, which ranged from 1 to 100. Based on the characteristics and preferences, each student was allocated a particular technology intervention like a fitness app, smartwatch, or VR headset to maximize learning results. This process guaranteed that the data set captured both baseline features and the impacts of technology interventions, helping to create the TechPE-Enhance algorithm for customized technology allocation in PE.

Data preprocessing

(1) Handling missing values:

K-Nearest Neighbors (KNN) Imputation was employed to handle numerical missing values by approximating missing values using the values of *k* closest data points in the feature space. The imputed value x_i was determined as the weighted average of *k* closest neighbors below.

$$x_i = \frac{1}{k}\sum_{j=1}^{k} x_j \tag{1}$$

where x_j was the values of *k* nearest neighbors. *k* was the number of neighbors. For categorical missing values, the most common category was chosen to replace the missing data, guaranteeing that the imputation was consistent with the current distribution of categorical variables.

(2) Encoding categorical variables:

One-hot encoding was used to transform categorical variables like learning style, preferred tech, and activity type into numerical representations, which generated a binary feature for each category in the original variable. If learning style had the categories "Visual", "Auditory", and "Kinesthetic", one-hot encoding would change this feature into three separate binary columns as follows.

$$\begin{aligned} &Visual \rightarrow (1,0,0) \\ &Auditory \rightarrow (0,1,0) \\ &Kinesthetic \rightarrow (0,0,1) \end{aligned} \tag{2}$$

This conversion was also applied to other categorical attributes including preferred tech and activity type to ensure that no ordinal relationship was presumed between categories.

(3) Normalization:

Min-max normalization was performed on numerical features like fitness level and engagement level to ensure that all numerical variables were on a consistent scale of [0, 1]. This conversion was carried out utilizing the following formula.

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{3}$$

where x was the original value. $\min(x)$ was the minimum value in the feature. $\max(x)$ was the maximum value. This normalization step guaranteed that features were comparable, contributing equally to the model's effectiveness. These preprocessing methods were essential to guarantee that the dataset was properly cleaned, converted, and standardized before further examination and modeling.

Feature selection

Feature selection is essential for decreasing dimensionality, enhancing model performance, and discovering the most important variables. In this study, key features from the dataset were selected using the hybrid filter-wrapper ensemble (HFWE) approach, which integrated filter methods for ranking features and a wrapper approach for iterative evaluation to ensure reliable and data-driven feature selection. Statistical methods were employed to rank features according to their relevance to the target variable.

(1) Mutual information:
Mutual information (MI) measured the relationship between a feature (X) and its target variable (Y). Higher MI values suggested a stronger relationship. MI was calculated as below.

$$I(X;Y) = \sum_{x \in X} \sum_{y \in Y} P(x,y).\log\left(\frac{P(x,y)}{P(x)P(y)}\right) \quad (4)$$

where $P(x,y)$ was the joint probability of X and Y. $P(x)$ and $P(y)$ were their marginal probabilities.

(2) Chi-square test:
The Chi-square test assessed the independence of categorical features and the target variable as follows.

$$x^2 = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i} \quad (5)$$

where O_i was the observed frequency. E_i was the expected frequency under the assumption of independence. Features with maximum x^2 values were more important.

(3) ANOVA F-test:
The ANOVA F-test determined whether the mean values of a numerical feature differed substantially between groups of the target variable. The F value was determined as follows.

$$F = \frac{Variance\ Between\ Groups}{Variance\ Within\ Groups} \quad (6)$$

Features with maximum F values were considered more influential.

(4) Wrapper method
The recursive feature elimination (RFE) technique was used as the wrapping technique. RFE worked by iteratively eliminating the features that contributed the least to the model's efficiency. In this study, RFE was incorporated with gradient boosting machines (GBM) as the foundation model. At each stage, the model's effectiveness was assessed utilizing the remaining features, and the least important features were removed. RFE mathematically chose the subset (S) of features that improved the model's predictive efficiency as below.

$$S = \arg\max_{S'} ModelPerformance(S') \quad (7)$$

where S' was a subset of features. ModelPerformance was a scoring metric like accuracy or F1-score.

(5) Majority voting
The outcomes of the filter techniques including mutual information, Chi-square test, and ANOVA F-test and the wrapper technique (RFE with GBM) were combined using a majority voting system. Each feature's ranking across all techniques was combined, and the features with the most votes were chosen as the final subset.

(6) Final selected features
The final features chosen in this research included age, fitness level, learning style, engagement level, and tech usage. These characteristics were deemed most influential in determining learning results in PE, offering a solid basis for further evaluation and modeling.

Model training and prediction
The TechPE-Enhance algorithm was created to accurately classify and predict the results of technology-based interventions in PE. The algorithm used ensemble learning methods to guarantee high accuracy and resilience in classification and regression tasks. The TechPE-Data dataset was divided in an 80:20 ratio with 280 students' data (80%) utilized for model training and 70 students' data (20%) for validation and testing.

(1) Ensemble classification model
The algorithm used an ensemble classification model to identify and assign the best technological intervention, which included three

powerful base classifiers of random forest (RF), support vector machine (SVM), and gradient boosting machines (GBM). These models were selected for their complementary advantages as RF for its capacity to manage high-dimensional datasets, SVM for its robustness in dealing with non-linear decision boundaries, and GBM for its capacity to detect complex patterns in data. Predictions from the base classifiers were integrated using a soft voting method, in which the predicted probabilities of each model were averaged to determine the most likely technology intervention. This method guaranteed that the final classification decision was balanced and representative of the advantages of all three models, enhancing overall accuracy. The classification model in the TechPE-Enhance algorithm selected the best technology intervention (fitness app, smartwatch, or VR headset) for each student depending on factors such as age, fitness level, learning style, engagement level, and tech utilization. By combining the ensemble classification model with soft voting, the algorithm guaranteed that the chosen intervention was in line with the student's preferences and requirements, optimizing engagement and learning results in physical education.

(2) Regression model

The numerical learning outcome with a score ranging from 1 to 100 was predicted using a random forest regressor. This regression model estimated each student's learning result using chosen features like age, fitness level, learning style, engagement level, and technology utilization. Random forest was selected for its capacity to manage non-linear relationships while preventing overfitting by averaging predictions from numerous decision trees. The integration of these classification and regression models within the TechPE-Enhance algorithm enabled both precise allocation of technology interventions and dependable prediction of learning results, rendering it a strong solution for improving physical education experiences.

Experimental setup

The experiments were carried out on a Windows 11 system equipped with an Intel Core i7 processor, 16 GB of RAM, and a 512 GB SSD. The development environment used Anaconda with the Spyder IDE for Python (version 3.9) coding. NumPy and Pandas were utilized for data preprocessing and manipulation, while Scikit-learn was used for machine learning implementation, and Matplotlib and Seaborn for visualization. The HFWE approach was employed for feature selection, while cross-validation was used to train classification and regression models. The outcomes were analyzed and provided in tables and charts to evaluate the efficacy of the TechPE-Enhance algorithm. The machine learning models of RF, SVM, GBM, and logistic regression were executed utilizing Scikit-learn (https://scikit-learn.org). The TechPE-Enhance algorithm's efficiency was assessed utilizing a variety of important metrics for classification and regression tasks. Metrics like accuracy, precision, recall, and F1-score were used to evaluate the model's capacity to correctly classify the allocated technology interventions. The accuracy of the model measured its overall correctness, whereas precision assessed the proportion of true positive predictions among all positive predictions, and recall assessed the model's capacity to correctly identify positive instances. The F1 score determined a balance between precision and recall. The mean absolute error (MAE) and R^2 score were employed in regression analysis to evaluate the model's ability to explain learning outcomes. These metrics provided an extensive assessment of the algorithm's efficiency, and high values indicated strong prediction precision and efficacy.

Results and discussion

Comparison of proposed algorithms with other machine learning models.

The comparison results showed that the TechPE-Enhance algorithm functioned better than other machine learning models in both classification and regression tasks with the maximum classification accuracy, precision, recall, and F1-

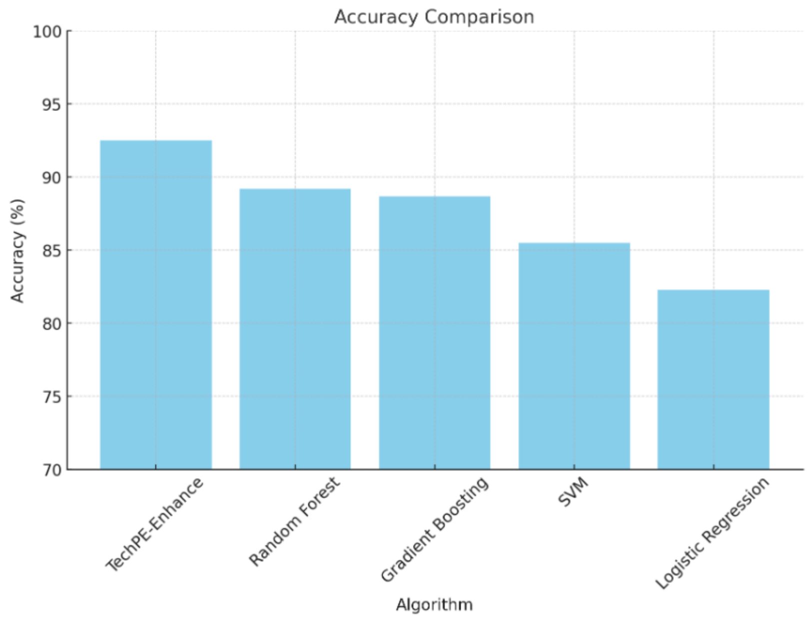

Figure 1. Accuracy comparison.

score, demonstrating its ability to assign the best technology interventions and predict learning outcomes. The regression model outperformed other models in terms of MAE and R^2 score, indicating strong predictive capacity. In comparison, RF and GBM functioned well but fell short of TechPE-Enhance in terms of overall accuracy and regression metrics. SVM and logistic regression performed poorly, especially in classification accuracy and capacity to explain variance in learning results. The results suggested the robustness and efficacy of the TechPE-Enhance algorithm for improving technology interventions in PE.

Accuracy

The TechPE-Enhance had the highest accuracy of 92.5%, surpassing all other algorithms in the study (Figure 1). This superior accuracy confirmed its ability to correctly classify students using their learning characteristics and allocate the most appropriate technology intervention for improving PE outcomes.

Precision

The model's high accuracy reflected its ability to leverage HFWE feature selection and soft voting ensemble classification, resulting in precise predictions. Furthermore, the enhanced classification performance indicated that the model had successfully identified important factors impacting engagement and learning in technology-enabled PE. The results showed that TechPE-Enhance surpassed all alternative models with a precision of 91.8% (Figure 2). This high precision suggested that the model correctly detected and allocated the most pertinent technology interventions while reducing false positives. TechPE-Enhance guaranteed that the interventions allocated to each student were well-suited to their specific needs by efficiently differentiating between various learning styles, engagement levels, and technology preferences. The model's high precision score reflected its ability to decrease misclassification, which improved the efficacy of personalized learning in physical education.

Recall score

The comparison results of recall scores across all models showed that TechPE-Enhance demonstrated better performance in rendering precise and meaningful technology allocations with 92.1% recall, which outperformed all other

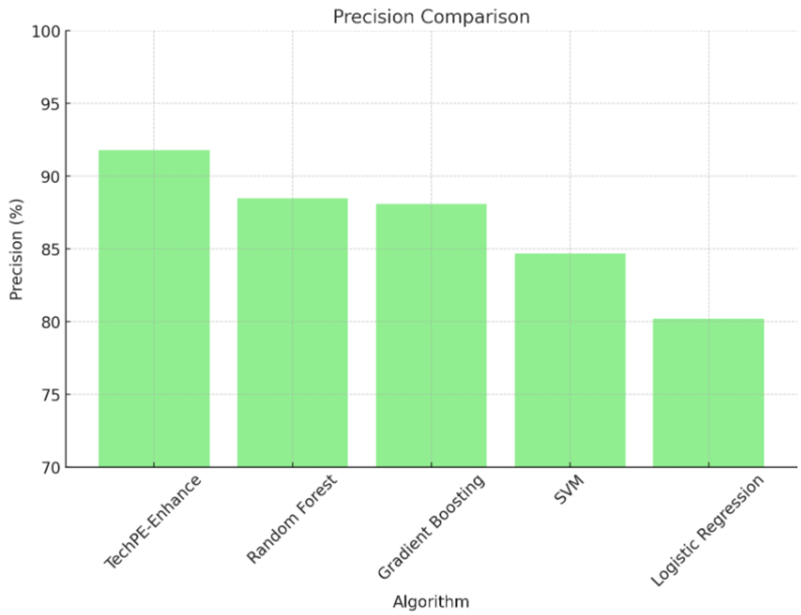

Figure 2. Precision comparison.

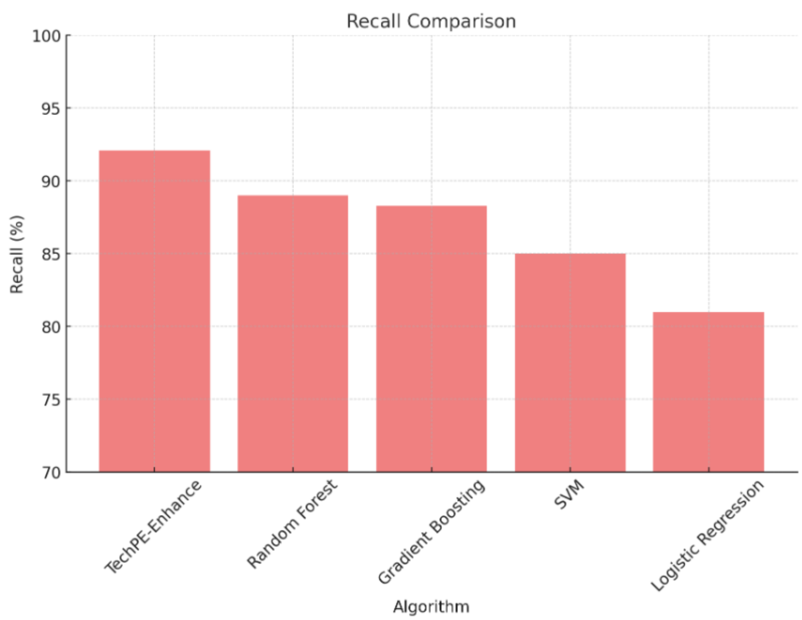

Figure 3. Recall comparison.

approaches, demonstrating its excellent capacity to accurately identify and recommend the most suitable technology interventions for students (Figure 3). A high recall score suggested that the model efficiently captured all pertinent instances, guaranteeing that students who needed a specific intervention such as a fitness app, smartwatch, or VR tool were correctly classified and not overlooked. This effectiveness reduced missed opportunities and ensured that each student obtained the most appropriate technology to improve their PE learning experience. The superior recall score proved TechPE-Enhance's ability to handle a wide range

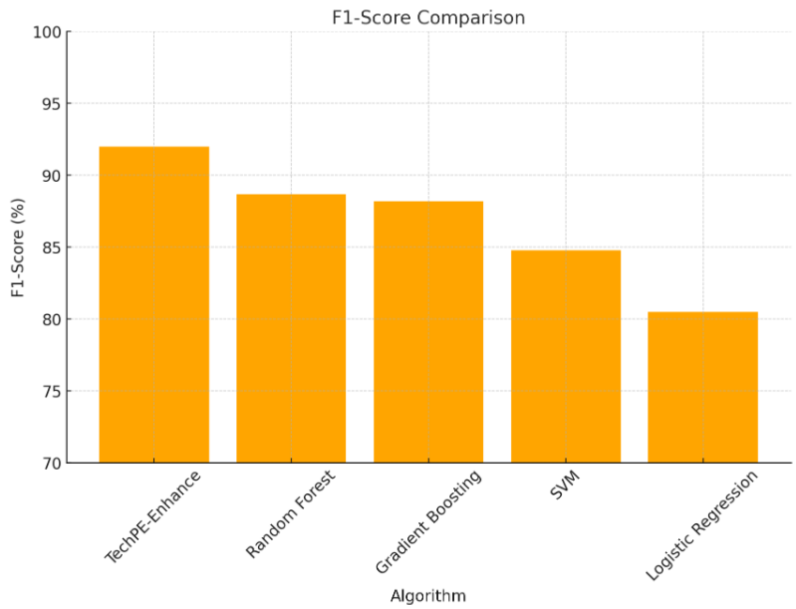

Figure 4. F1-score comparison.

of learning features, engagement levels, and technological preferences.

F1 scores

The results demonstrated that TechPE-Enhance had an F1-score of 92.0%, indicating that it was a reliable and efficient classification model for assigning the most appropriate technology interventions in PE (Figure 4). The F1-score, which balanced precision and recall, confirmed that the model made precise forecasts while also minimizing false positives and false negatives. This guaranteed that students were given the most suitable technology based on their learning styles, engagement levels, and fitness characteristics. The high F1 score reflected the TechPE-Enhance algorithm's ability to consistently make well-informed decisions, which improved personalized learning experiences in PE.

Mean absolute error (MAE)

With the lowest MAE of 2.4, TechPE-Enhance outperformed other regression models in terms of predictive accuracy when predicting learning results (Figure 5). A lower MAE suggested that the model's predictions were closely aligned with actual learning outcomes, reducing deviation and guaranteeing high accuracy in estimating student performance, which was especially important for personalized technology interventions as it allowed educators to better assign technological tools based on individual student needs. By decreasing errors in learning result predictions, TechPE-Enhance guaranteed a data-driven strategy for improving student engagement and performance in PE.

R^2 scores

The results demonstrated that TechPE-Enhance had the highest R^2 score of 0.89, indicating a strong capacity to explain variance in learning results and better predictive capacity (Figure 6). The TechPE-Enhance algorithm consistently surpassed other approaches on all key metrics, making it the best option for technology-driven PE improvement. Its high classification accuracy and resilient regression performance demonstrated its capacity to allocate appropriate technology tools while precisely forecasting learning results. These findings highlighted its practical application in enhancing student engagement and learning efficiency.

This study demonstrated the potential for combining technology and innovative

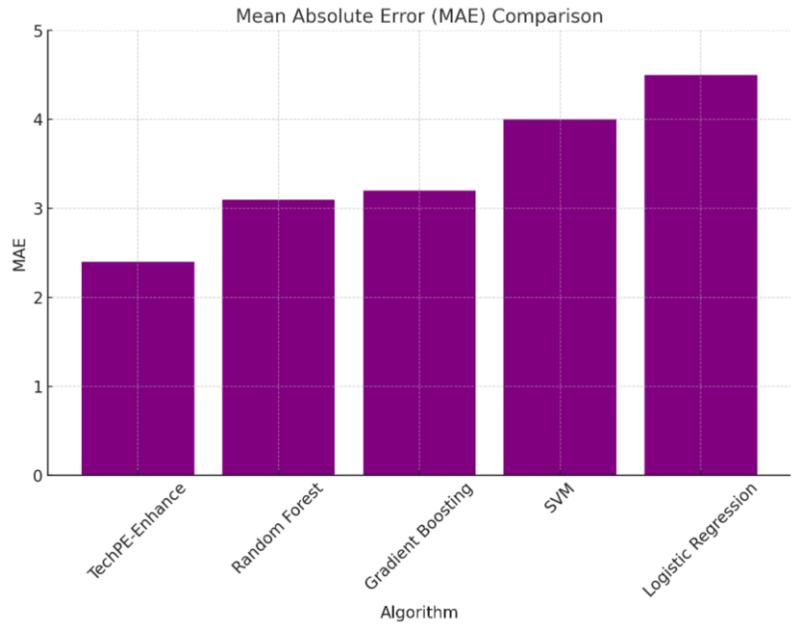

Figure 5. MAE comparison.

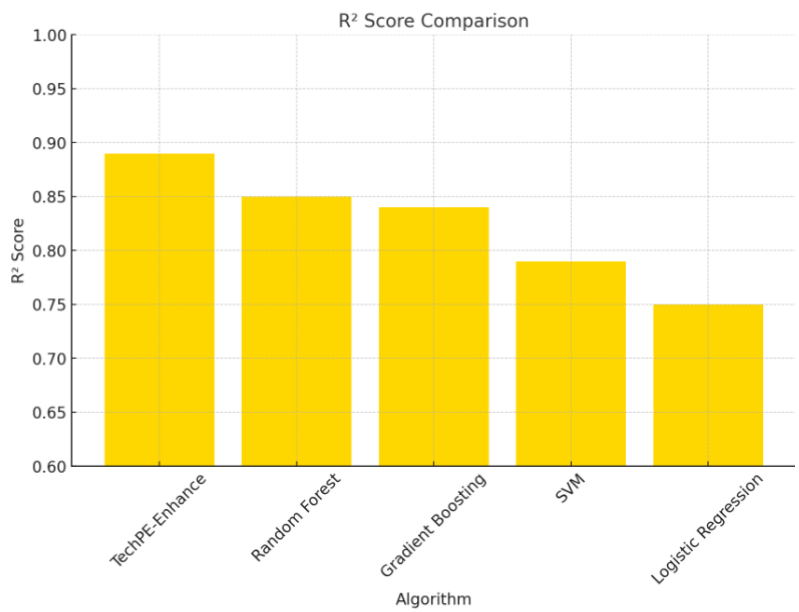

Figure 6. R^2 score comparison.

pedagogies to substantially improve learning results in PE. The proposed TechPE-Enhance algorithm outperformed expectations with high classification accuracy and predictive capacity, efficiently distributing technological interventions based on student requirements. However, some drawbacks existed in this research, which included the dependence on self-reported data and the need for a more diverse dataset to generalize the findings across various populations and educational settings. Future work could include broadening the algorithm's scope by incorporating new technologies, assessing its efficiency in realworld scenarios, and investigating its application to other educational disciplines. Additionally, future research could investigate the long-term effect of technology-driven interventions on student engagement and learning results, providing valuable insights for continual enhancement in educational practices.

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