Application of Biomechanics-Based Data Mining Technology in Personalized Training of Physical Education

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Keywords: Data mining, physical education, biomechanics, personalized training, machine learning, athlete performance

Received: May 29, 2025

In recent years, the rapid development of data mining technology, machine learning (ML) algorithms, and advancements in biomechanics research have provided a new opportunity to realize personalized physical training. This study explores how to apply data mining technology to optimize physical education. By comprehensively considering biomechanical principles, it designs a more scientific and personalized training program that improves the training effect, optimizes the allocation of resources, and effectively prevents sports injuries; this program also enhances the overall athletic performance from a biomechanical perspective. Therefore, this study collects multi-dimensional data covering athletes' physical condition, sports performance, and training feedback. It also analyzes them using various ML algorithms, including but not limited to support vector regression (SVR), decision tree, and support vector machine (SVM) to tailor the optimal training plan for each athlete. Studies show that data-driven personalized training significantly improves athletes' performance, reduces injury frequency, and enhances psychological state scores. At the same time, applying data mining technology has greatly boosted the decision support system's training efficiency and effectiveness. Coaches can now make more informed decisions based on a comprehensive understanding of athletes' physical and biomechanical characteristics. The results of this study provide strong support for future sports training and competitions, highlighting the importance of combining modern data-analysis techniques with biomechanical insights in sports science.

Povzetek: Študija pokaže, da podatkovno rudarjenje in ML (npr. SVR, odločitvena drevesa, SVM) z biomehanskimi vpogledi omogočata personalizirane vadbene programe, ki izboljšajo rezultate, zmanjšajo poškodbe in podprejo odločitve trenerjev.

1 Introduction

With the swift progress of technology, physical education (PE) has ushered in unprecedented changes. Traditionally, the PE teaching mode mainly relies on coaches' experience and intuition to guide training. Although this method has made remarkable achievements in the past, it seems to be inadequate in the face of increasingly complex and personalized athletes' needs [1]. This inadequacy is particularly evident as athletes now require tailored training regimens that cater to their unique physiological and psychological profiles. In recent years, the development of information technology, especially big data and artificial intelligence (AI), has brought new opportunities for PE, which has gradually changed from experience-driven to a data-driven new era. This transition is characterized by the ability to analyze vast amounts of data to derive previously unattainable insights, allowing coaches to make informed decisions based on empirical evidence rather than solely on intuition. In this process, PE is no longer limited to simple physical fitness tests and skill evaluation, but through the integration of various sensors, wearable devices, video capture systems, and other high-tech means to collect massive multi-ž dimensional data of athletes in training and competition. These data not only cover physiological parameters (such as heart rate and blood oxygen saturation), sports performance (such as speed, strength, and endurance), but also include psychological state (such as stress level and mood fluctuation) and social behavior (such as teamwork ability). This comprehensive data collection allows for a more holistic understanding of an athlete's performance, enabling coaches to make informed decisions based on quantitative evidence rather than solely relying on subjective assessments. Massive data provides the possibility to deeply understand the unique characteristics of each athlete, laying a solid foundation for making a more scientific and reasonable training plan [2-5].

Every athlete is unique, and there are significant differences in physical conditions, technical characteristics, and psychological quality. These differences can be attributed to various factors, including genetics, training history, and individual goals. Understanding these variations is crucial for developing effective training strategies. Therefore, the traditional "one-size-fits-all" training method is difficult to meet everyone's needs, and may even cause some athletes to fail to give full play to their potential or get injured due to overtraining. For example, Connor et al. pointed out that although the training plan and training load guided by intuition and experience were suitable for simple goals, when the complexity of planning tasks began to increase, the performance of building the best strategy in the medium and long term would decline exponentially [6]. Injuries can often result from improper training loads or insufficient recovery time, highlighting the necessity for personalized approaches that consider each athlete's unique profile. Developing reasonable training methods through scientific methods has become an important part of the training of coaches and athletes [7]. To achieve the best competitive performance, personalized training comes into being, which emphasizes tailoring the training plan according to each athlete's specific situation to achieve the most efficient promotion effect. This tailored approach enhances performance and fosters a more positive training experience, as athletes feel their needs are being recognized and addressed. However, it is not easy to implement personalized training, and it faces problems such as uneven data quality, lack of pertinence of analysis tools and privacy protection. Ensuring data quality is paramount, as inaccurate or incomplete data can lead to misguided training decisions. These problems require people to find a way to deal with complex data and provide effective solutions to ensure that personalized training can play a role [8-10].

The principles of biomechanics provide underlying theoretical support for sports training. For example, the analysis of joint torque, the optimization of movement trajectories, and the mechanism of energy metabolism can accurately identify the efficiency bottlenecks or potential injury risks in athletes' technical movements. However, traditional biomechanics research mostly relies on analyzing isolated data in a laboratory environment, making it difficult to dynamically capture the complex changes in actual training. The introduction of data mining technology enables the real-time integration of massive biomechanical parameters (such as acceleration, angular velocity, and ground reaction force) with physiological and psychological data. For instance, the gait data captured by inertial sensors, combined with the joint force model in biomechanics, can quantitatively analyze the impact differences on the knee joint caused by different running postures, thus providing a basis for individualized movement correction. This combination not only expands the practical boundaries of biomechanical theory but also, through machine learning (ML) algorithms, uncovers hidden patterns that are difficult to detect by traditional methods (such as the association between minor movement deviations and chronic injuries). The cross-application of biomechanics and data mining essentially constructs a closed loop of "theory-driven data modeling and data-driven theory optimization", providing full-chain support for sports science from microscopic mechanisms to macroscopic decision-making.

This study innovatively integrates biomechanics principles with data mining techniques to build a more personalized and scientific sports training optimization model. Unlike previous studies that mainly relied on single physiological or sports data, this study comprehensively collects multi-source heterogeneous data, including physiological parameters, sports indicators, personal background information, and environmental factors. Based on these multidimensional data, an in-depth analysis is conducted to develop an intelligent training assistant system. This system can accurately identify the key factors affecting athletes' performance and dynamically predict individual sports performance trends. It can then adjust the training plan in real time to achieve personalized training interventions. This study also pays special attention to data security and privacy protection; it adopts advanced encryption technology and strict access control measures to ensure that athletes' personal information is fully protected. Through this method, this study improves the effectiveness and safety of training while providing new ideas and technical support for the future development of PE.

2 Literature review

The application of data mining technology in sports science has become a hot research field in recent years. By integrating data from diverse sources, researchers can better understand athletes' performance patterns, training effects, and potential health risks. The existing literature extensively discusses the application of various data mining methods and technologies, including cluster analysis, classification prediction, and association rule mining. For example, Giles et al. employed cluster analysis to identify athletes with similar characteristics, which is crucial for formulating hierarchical training plans [11]. This method helped coaches to give personalized guidance according to athletes' physical condition and skill level, effectively improving training efficiency. In addition, Wang et al. accurately predicted the athletes' future competition results using the classification prediction model, which provided important decision support for the coaching team [12]. These studies show how data mining technology can help optimize training programs and enhance competitive performance.

In terms of data sources, sensor technology and video recording are the most commonly used methods in sports data analysis [13]. Sensor technology can monitor athletes' heart rate, movement trajectory, and other physiological parameters in real time. For example, Tomaszewski et al. used the data collected by wearable devices and applied ML algorithms to analyze athletes' fatigue levels and recovery time, thereby adjusting training intensity to prevent overtraining [14]. Moreover, video recording technology focuses on capturing the details of sports actions for analyzing techniques and tactical strategies. For instance, Li et al. processed the video data through deep learning (DL) algorithms. They accurately tracked the players' running path and position changes in the football match, which had an important impact on the team's tactical arrangement [15]. These two data sources have their characteristics. The sensor delivers a quantitative and continuous data stream, making it well-suited for evaluating physiological state. Video recording offers qualitative behavior observation, more appropriate for analyzing complex technical movements. The combination of the two can provide comprehensive feedback and support for athletes.

The importance of interdisciplinary cooperation cannot be ignored, especially in applying data mining technology to PE. Truly effective personalized training requires close collaboration among computer scientists, sports scientists, medical experts, and coaches. For example, Alhasani showed that a more intelligent training assistant system could be developed through the cooperation of multidisciplinary teams. The system could predict the athlete's performance trend based on historical data and customize the training content according to individual differences [16]. This cooperative mode ensures that the professional knowledge in all related fields is fully utilized, thus improving the system's practicality and reliability.

Significant progress has been made in the application of deep reinforcement learning (DRL) in energy systems, and relevant research results provide a theoretical basis and methodological inspiration for this study. For example, Giedraityte et al. proposed a hybrid method combining deep neural networks and reinforcement learning (RL) mechanisms to solve the optimal power flow problem in hybrid renewable energy systems. Their method achieved good convergence and robustness in optimizing energy transmission paths [17]. Scarcello et al. further integrated human preferences into the DRL decision-making process. They constructed a "human-driven DRL control strategy" oriented to the balance between thermal comfort and energy conservation, demonstrating high human-machine collaboration potential in home energy consumption optimization [18]. Amer et al., based on the scenario of Home Energy Management Systems (HEMS), proposed a DRL agent that comprehensively considered the dual perspectives of users and grid operators. This effectively improved the responsiveness and fairness of demand response strategies [19]. In addition, Ding et al.'s research applied the DRL method to the collaborative optimization of mobile energy storage and high-penetration renewable grids by constructing a joint scheduling mechanism. This effectively balanced the contradiction between power volatility and resource utilization [20]. Zhang et al. extended this method to the context of multi-energy systems (electricity-heat-gas), constructing a DRL-based low-carbon economic dispatch model; this model promoted the dispatch transformation of integrated energy systems in the context of carbon neutrality [21]. Xu et al. compared the performance of various RL algorithms in multi-objective optimization of residential hybrid energy systems. They pointed out that the trade-off ability of the current model among different optimization objectives still needed to be further improved [22].

It can be found from the above studies that existing work mainly focuses on economic dispatch, equipment control, and carbon emission optimization in energy systems. Although rich achievements have been made in terms of strategy learning efficiency and system integration, most studies still have limitations in the following aspects. (1) Most models focus on power systems or energy load scheduling, lacking exploration of cross-domain applications that deeply integrate DRL with human individual behavioral characteristics (such as motor ability and psychological state). (2) State space modeling tends to focus on physical quantities (such as power, voltage, and temperature), and rarely introduces individual behavior-driven unstructured data (such as emotional indices and action indicators). (3) Although existing models can optimize strategies, their generalization and transfer abilities are insufficient when facing highly individualized training or health scenarios with frequent changes. The personalized training strategy optimization framework based on the proposed Proximal Policy Optimization (PPO) algorithm, building on DRL technology's successful application in energy systems, extends it to complex human factor-dominated sports and training scenarios. It also realizes a strategy learning mechanism driven by a multi-dimensional feedback loop of physiology-psychology-behavior. The study solves the problem of unstructured feature fusion and introduces risk control objectives into the reward function, thereby constructing a decision-making system that balances safety and adaptability. These fill the research gap in the application of DRL in human training with high dynamics and significant individual differences.

3 Method

3.1 Data collection

In the personalized training of PE, the accuracy and integrity of data are very important [23]. During the data collection stage, this study particularly emphasizes the in-depth integration of biomechanical parameters. For example, the tri-axial acceleration and angular velocity data captured by the inertial measurement unit (IMU) describe sports performance and calculate joint torque and power output through biomechanical models (such as inverse dynamics analysis). These parameters, together with physiological indicators (such as heart rate variability) and psychological scores (such as subjective fatigue in training), form a multi-dimensional feature set. For instance, when analyzing the technical movements of throwing athletes, the combination of motion trajectory data and the biomechanical model of the shoulder joint can identify the energy loss problem caused by improper force timing. At the same time, the psychological state data can further explain the distraction of athletes during technical errors. These cross-dimensional features are correlated and modeled through algorithms such as support vector machine (SVM). The final personalized plan optimizes the movement efficiency and reduces the injury risk caused by biomechanical imbalance. This process fully reflects the guiding role of biomechanical theory in data mining and the verification and expansion of biomechanical hypotheses by data-driven methods. The data collection and preprocessing framework is presented in Figure 1:

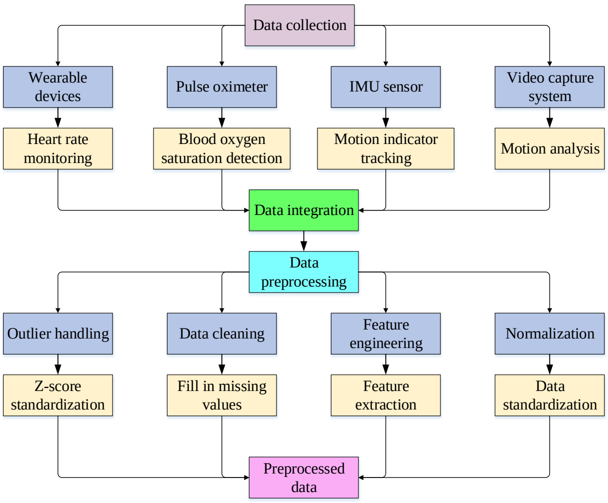

Figure 1: Data collection and preprocessing framework

All wearable devices are standardized and calibrated before training to reduce environmental interference. Baseline physiological parameters (such as resting heart rate and blood oxygen saturation) are recorded in a static environment, and the measured values during exercise are dynamically corrected based on these baselines. For example, the accelerometer data is compensated for the gravitational component to eliminate errors caused by device tilt. At the same time, the subjective feedback mechanism of athletes is introduced. After daily training, athletes fill in the subjective fatigue scale and self-evaluate their technical movements (such as "satisfaction with starting reaction speed") through a mobile application. Combined with the qualitative comments of coaches (such as "insufficient arm swing coordination"), a multi-dimensional verification loop is formed. These subjective data and objective parameters are jointly input into the model to improve the interpretability of decision-making.

(1) Heart rate monitoring: Heart rate is one of the important indicators to measure cardiovascular health and exercise intensity. Wearable devices such as smart watches can continuously monitor athletes' heart rate changes through Photoplethysmography (PPG) [24]. Based on the principle of light absorption, PPG technology uses green LED lights to illuminate the skin surface. When the heart contracts, the blood volume increases, and more light is absorbed. During diastole, the blood volume decreases, and less light is absorbed. This periodic light absorption change reflects the pumping situation of the heart, so the heart rate can be calculated. The PPG sensor in smart watches is usually located on the back and close to the skin to ensure the best signal quality. This technology can provide accurate heart rate readings at rest while tracking heart rate changes in real time during exercise. This is very important for coaches and athletes because it can help them understand whether the current exercise intensity is appropriate and adjust the training plan accordingly to achieve the best results. In addition, long-term recording of heart rate data can identify potential heart problems or signs of overtraining and provide a scientific basis for preventive measures.

(2) Detection of oxygen saturation: SpO_2 refers to the ratio of oxygen in blood to hemoglobin in red blood cells, reflecting the ability of body tissues to obtain oxygen. Maintaining proper blood oxygen levels is critical to sports performance and recovery [25]. It is a noninvasive and convenient method to detect oxygen saturation using a pulse oximeter. In this method, the finger or earlobe is irradiated by infrared light and red light; the blood oxygen saturation is calculated according to the different degrees of absorption of the two kinds of light by blood. Specifically, hemoglobin has different absorption rates for these two kinds of light. Oxygenated hemoglobin absorbs more infrared light, while deoxyhemoglobin is more inclined to absorb red light. By analyzing the attenuation of these two kinds of light after passing through the tissue, people can infer the bleeding oxygen saturation. This technology is vital in high-altitude training, endurance exercise, and rehabilitation training. This is because it can help athletes monitor their oxygen supply status, adjust their breathing rhythm or rest in time, and avoid fatigue or injury caused by hypoxia.

(3) Tracking of sports indicators: To comprehensively evaluate athletes' performance and optimize training programs, accurate tracking of sports indicators is indispensable. The IMU sensor integrates a three-axis accelerometer, gyroscope, and magnetometer, which can capture athletes' movement characteristics in many dimensions [26]. These sensors are installed in smart watches or other wearable devices, enabling portable data collection across diverse environments.

Accelerometers measure the acceleration of objects along three axes, which helps understand the information of athletes' speed change, jumping height, step frequency, and so on. For example, in running training, the accelerometer can record the impact force every time the foot lands, which helps to analyze the running posture and technical movements. A gyroscope detects the angular changes of rotation and translation, such as rotation angle and angular velocity. This is especially useful for sports that require complex physical coordination, such as gymnastics and figure skating, and can record athletes' body posture and rotation accuracy when they complete their movements in detail [27]. Magnetometers are used as electronic compasses to determine the direction of equipment relative to the Earth's magnetic field. This is very useful in outdoor sports, such as cross-country running or mountain climbing, enabling athletes to maintain the correct route while enhancing measurement accuracy through sensor data correction.

The rich data provided by IMU sensors enables coaches to develop precisely tailored training programs based on individual movement patterns and biomechanical profiles. For example, by analyzing the gait data of runners, the coach can suggest adjusting the length or frequency of steps to improve efficiency; For throwing athletes, the coach can optimize the way of exerting force and reduce the risk of injury by monitoring the trajectory of arm swing. For example, the acceleration a can be calculated by equation (1):

$$a = \sqrt{a_x^2 + a_y^2 + a_z^2} \tag{1}$$

a_x, a_y, and a_z represent the acceleration components on the three coordinate axes.

(4) Video capture and motion analysis: The video capture system synchronously collects two-dimensional images of athletes' movements through multi-view high-speed cameras. Combined with the calibration plate and the skeletal key point detection algorithm (such as OpenPose), it realizes the reconstruction of three-dimensional movement trajectories. DL models (such as convolutional neural networks) extract inter-frame features from video data and identify subtle deviations in technical movements (such as insufficient arm swing angles and excessive forward lean of the trunk). For example, in analyzing high jump movements, the model automatically generates movement optimization suggestions (such as increasing the knee flexion amplitude by 5° during the takeoff phase) by comparing the ideal movement template with the captured joint angle sequence. The visual interface on the coach's side presents the analysis results in the form of heat maps and dynamic overlay lines; it intuitively marks the movement defects (such as the direction of the center of gravity shift), and recommends targeted training (such as core stability exercises) in combination with biomechanical models. This process not only improves the objectivity of technical diagnosis but also shortens the feedback cycle of traditional manual analysis.

3.2 Data preprocessing

During the data preprocessing stage, the study focuses on the practical implementation of privacy protection. For instance, all physiological and psychological data undergoes de-identification immediately after collection, with information directly associated with personal identity (such as name and ID number) being deleted. Additionally, differential privacy techniques are employed to add random noise to sensitive features (such as injury records) to prevent the restoration of individual identities through data reverse engineering. Meanwhile, a hybrid cloud architecture is adopted for data storage. Core sensitive data is stored on a local private server, and non-sensitive analysis results are synchronized to a public cloud platform. Zero-knowledge proof technology achieves transparent verification of data usage. In the model training phase, a federated learning approach is adopted, allowing each training node to process data locally and only share encrypted model parameters to avoid the outflow of raw data. This series of measures meets regulatory requirements and constructs a multi-level protection system from a technical perspective, ensuring that athletes' data is protected from infringement while supporting scientific research. The raw data must go through a strict cleaning and standardization process to ensure reliability. Firstly, the Z-score standardization and the Interquartile Range (IQR) rule identify outliers caused by sensor noise or environmental interference (such as invalid records where the heart rate suddenly drops to 0), and a sliding window mean smoothing technique is applied to correct instantaneous fluctuations. For missing data, the Lagrange interpolation method is used for time series to maintain temporal continuity. For non-temporal data, the K-nearest neighbor algorithm is used to fill in the gaps based on similar samples. In the feature engineering stage, the Fast Fourier Transform (FFT) extracts frequency domain features (such as the main frequency of the step rate) from the acceleration signal. Meanwhile, time domain statistics (such as the root mean square value) are combined to construct a high-information feature set. Finally, the maximum-minimum normalization is employed to eliminate the dimensional differences of different sensors (such as the mismatch of units between heart rate and blood oxygen), ensuring the scale consistency of the model input. The time-series data utilizes the FFT to extract frequency-domain features and analyze periodic movement patterns.

$$X_k = \sum_{n=0}^{N-1} x_n \, e^{-j2\pi kn/N} \quad (2)$$

X_k represents the k-th frequency component. x_n is the sample point in the time series. N denotes the total number of samples.

In addition, it needs to be normalized so that data of different scales can be compared in the same range. The commonly used normalization equation reads:

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

Or standard deviation (SD) standardization is used:

$$z = \frac{x-\mu}{\sigma} \quad (4)$$

μ and σ represent the sample mean and SD, respectively.

In terms of sample selection, this study collects data from 40 athletes in their first and second years at a university. This includes 10 sprinters, 10 long-distance runners, 10 throwers, and 10 ball game athletes, covering different training backgrounds and sports types. Additionally, data from 20 non-athletes in the general population are collected to ensure the broad applicability of the research conclusions. The data collection spans six months, with all participants undergoing regular physiological tests and performance assessments to ensure the long-term stability of the data. In the feature selection process, Recursive Feature Elimination (RFE) and Principal Component Analysis (PCA) are used. These methods are applied to identify the most informative features while reducing data dimensions and computational complexity. RFE works by training multiple ML models and progressively removing features that have less impact on training performance. PCA reduces redundant data to improve computational efficiency. Combining these two methods, the following core features are ultimately selected: physiological parameters such as heart rate, maximum oxygen uptake, metabolic enzymes, and injury frequency, as well as relevant kinematic indicators, training performance, and psychological state.

3.3 Model construction and verification

Choosing an appropriate data mining algorithm is the key to realizing a personalized training prediction model. In recent years, DL has demonstrated strong feature learning capabilities in many fields, achieving remarkable success in image and video analysis tasks. However, in this context, the applicability of DL methods is limited by the following factors. First, deep neural networks typically require large amounts of labeled data for training. Given the relatively small sample size, directly training deep models may lead to overfitting. Second, DL models have high computational complexity and require substantial computing resources for parameter optimization. This study, however, focuses on achieving efficient and interpretable personalized training predictions with limited computing resources. In contrast, traditional ML methods perform better in generalization and stability with small sample sizes. These methods provide more interpretable decision rules, optimizing training plans more transparently and intuitively. Additionally, traditional decision tree and linear regression methods were included in the initial comparison. However, decision trees are prone to instability due to data noise, and linear regression struggles with high-dimensional nonlinear features. Therefore, they are not selected as the final models. By comparison, traditional ML model selection prioritizes current data scale and real-time requirements. For example, the SVM can efficiently fit non-linear relationships through kernel tricks for small sample data, and the parallel computing characteristics of the random forest (RF) can meet the requirements of rapid response at the training site. Nevertheless, this study has reserved an interface for DL. When sample sizes exceed tens of thousands, a lightweight network (MobileNet) extracts spatiotemporal features, including video action sequence dependencies. These features integrate with traditional models to form a hybrid architecture balancing computational efficiency and model complexity. The SVM excels in high-dimensional feature spaces and can effectively handle nonlinear classification problems. RF has strong noise resistance and feature selection capabilities. Support Vector Regression (SVR) is suitable for continuous numerical prediction and can capture complex relationships in training data. Considering the strengths and applicability of these models, SVM, RF, and SVR are ultimately chosen for predicting and optimizing personalized training outcomes. Each algorithm has its characteristics and applicable scenarios:

(1) SVM: It is suitable for small sample, nonlinear, and high-dimensional pattern recognition problems. SVM maximizes the interval between diverse classes by finding the optimal hyperplane [28]. In practical applications, SVM can process linearly separable datasets and effectively map data to a higher-dimensional space with the help of kernel techniques; among them, linear decision boundaries can be found even if the original data is nonlinear. This feature of SVM makes it an ideal choice to solve complex classification tasks. It ensures the model's robustness and generalization ability by paying attention to the support vector (that is, the data point closest to the hyperplane). In addition, SVM can effectively deal with high-dimensional data, even if the number of features far exceeds the sample size, and it can maintain good performance. This ability to process complex data efficiently makes SVM widely used in bioinformatics, text classification, image recognition, and other fields, which provides strong support for solving classification and regression problems in the real world. Its decision function form is:

$$f(x) = \sum_{i=1}^{N} \alpha_i y_i K(x_i, x) + b \tag{5}$$

α_i represents the Lagrange multiplier. y_i denotes a label. $K(\cdot,\cdot)$ is kernel function. b refers to a bias term.

(2) RF: It encompasses multiple decision trees, and the final classification result is determined by a voting mechanism. RF effectively suppresses overfitting through a dual mechanism: Firstly, bootstrap sampling is employed to draw subsets with replacement from the original data for training individual decision trees. Samples that are not selected are used for real-time evaluation of the model's generalization error, avoiding excessive dependence on the training set. Secondly, each tree randomly selects only a part of the features for node splitting, reducing the model variance through the diversity of feature subsets. The feature importance is quantified by calculating the decrease in average precision, that is, the degree of decay in the model's prediction performance after shuffling the values of a certain feature, thus screening out key variables (such as maximum oxygen uptake and peak joint torque) that significantly contribute to the prediction of sports performance. This integration strategy, combined with feature evaluation, enables RF to have strong noise robustness and high predictive accuracy [29]. RF demonstrates superior generalization ability. Because each tree is only trained based on some features and samples, this inherently reduces model correlation and prevents overfitting. Even if some trees are sensitive to specific noise, the overall forest can still maintain robust prediction performance. In addition, RF can process high-dimensional data and automatically evaluate the importance of each feature without complicated preprocessing steps. This flexibility makes RF perform well in various application fields, including but not limited to medical diagnosis, financial risk assessment, and image recognition. By combining the wisdom of many trees, RF provides a powerful and reliable ML solution. The splitting node of each decision tree in RF chooses the optimal splitting point according to the Gini coefficient or information entropy. Gini coefficient is defined as:

$$Gini(p) = \sum_{k=1}^{K} p_k (1 - p_k) \tag{6}$$

p_k represents the probability of the k type.

(3) SVR: It solves the regression problem to minimize the prediction error [30]. Different from traditional regression models, SVR aims to reduce the prediction error and find an optimal solution that can tolerate the error within a certain range without punishment. This means that SVR tries to balance prediction accuracy and model complexity, thus avoiding over-fitting. SVR ensures that most data points fall within this boundary by constructing a boundary of support vectors containing all training samples. For points beyond the boundary, penalties are imposed according to the degree of deviation. This method makes SVR more robust to noise and can maintain good generalization ability when dealing with high-dimensional data. In addition, SVR can map the input space to a higher-dimensional space through a kernel function, where a linear regression relationship can be

found even if the original data is nonlinear. This flexibility makes SVR suitable for various complex regression tasks, such as financial time series prediction, energy consumption estimation, and quantitative structure-activity relationship research in bioinformatics. In this way, SVR provides a powerful and effective tool to solve the regression problem in the real world. The SVR balances the model complexity and prediction tolerance through the regularization parameter C and the slack variable (ξ). When the value of C is large, the model strictly fits the training samples (high complexity), and overfitting may occur due to sensitivity to noise. When the value of C is small, more samples are allowed to fall outside the boundary (low complexity), enhancing the generalization ability but possibly ignoring key details. This study uses grid search and cross-validation to optimize the value of C. Combined with the Gaussian kernel function, the low-dimensional non-linear relationships are mapped to a high-dimensional linear space. This captures the complex interactions among the motion parameters (such as the non-linear coupling between heart rate and step frequency); it also controls the complexity of the feature space through the bandwidth parameter γ of the kernel function (a smaller γ corresponds to a smoother decision surface, and a larger γ fits local details). This dynamic balance mechanism ensures the SVR consistently captures global patterns despite sample size constraints. The optimization problem can be expressed as:

$$\min_{w,b,\xi,\xi^*}\left(\frac{1}{2}\parallel w\parallel^2+C\sum_{i=1}^{N}(\xi_i+\xi_i^*)\right) \quad (7)$$

w is the weight vector, which represents the direction of the hyperplane. ξ and ξ^* are slack variables, allowing a certain range of prediction deviation. C is a regularization parameter; b is an offset term, which determines the position of the hyperplane. The process of model construction and verification is displayed in Figure 2:

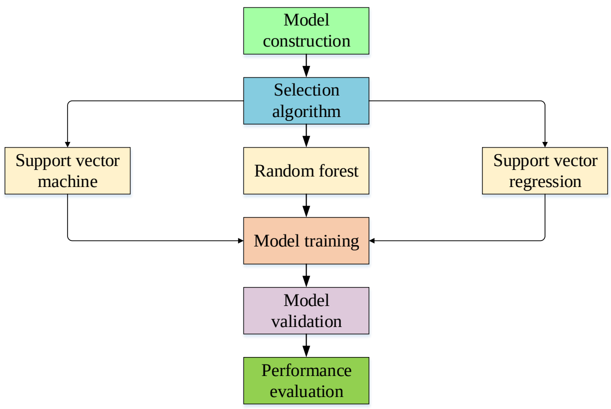

Figure 2: Model construction and verification process

To evaluate the model's performance, the cross-validation method is adopted, that is, the dataset is divided into training and test sets. The model's performance evaluation adopts multi-dimensional indicators. For classification tasks (such as injury risk prediction), accuracy, recall, and F1 score are taken as the core. Among them, the recall focuses on capturing true positive samples (such as the proportion of injured individuals who are correctly warned), avoiding the training risks caused by missed reports. For regression tasks (such as sports performance prediction), the mean squared error (MSE) measures the deviation between the predicted and true values, and the coefficient of determination is combined to evaluate the model's explanatory power for data variation. In addition, class imbalance is a notable issue, such as when the number of injury samples is much smaller than that of normal samples. For this problem, the area under the ROC curve is introduced to evaluate the classifier's robustness under different thresholds. For example, accuracy is defined as the proportion of correctly classified samples to the total number of samples:

$$\text{Accuracy}=\frac{\text{TP+TN}}{\text{TP+FP+FN+TN}} \quad (8)$$

TP, TN, FP and FN respectively represent the number of true cases, true negative cases, false positive cases, and false negative cases.

This study introduces the PPO algorithm from the RL mechanism as the optimization engine to enhance the model's strategy generation capability in personalized training plan recommendation. PPO is a policy gradient algorithm that has performed excellently in continuous action spaces in recent years. By limiting the update range between old and new strategies, it can improve training efficiency while ensuring stable convergence of strategies. This algorithm is particularly suitable for high-dimensional action control scenarios, such as tasks involving exercise intensity and multi-dimensional skill action combinations in personalized training. The model uses a dual-network structure to construct the actor and critic, respectively. The actor network contains three fully connected layers with 128, 64, and 32 neurons in sequence. ReLU is the activation function, and the output layer employs the Tanh function to compress the action space range to [-1,1]. The critic network has a similar structure, but its output layer is a linear function to predict the state value function. The Adam optimizer is selected, with an initial learning rate of 1e-4, a discount factor γ of 0.98, and a Clip parameter ε of 0.2. During training, a mini-batch strategy is adopted, with each iteration batch size of 2048 and 80 update steps.

Training data comes from interactive sampling in the motion behavior simulation environment. To construct an interactive scenario with real physical properties and motion feedback, a "personalized motion task environment" is custom-built based on the OpenAI Gym platform and PyBullet physics engine. This environment simulates the continuous action processes of different sports (such as sprint starts, throwing arm swings, and high-intensity interval training (HIIT)); Meanwhile, it reflects physiological differences among individuals with different body types, genders, and training stages through adjustable parameters of the human skeleton model. All training subjects are human skeleton models built in virtual space, and the simulated individuals have 12-degree-of-freedom joint structures, muscle output parameters, and fatigue recovery functions. To maintain experimental consistency, the initial state of individuals is set to a unified standardized baseline; it has an initial heart rate of 68 bpm, a maximum oxygen uptake of 45 ml/kg/min, and a neutral psychological state score (3/5). Differences among simulated individuals are generated through normal distribution sampling, and training target tasks (such as sprinting, throwing, and strength training) are selected from a fixed task set. Each training action lasts for a 20-minute cycle, with a maximum total training period of 60 days (i.e., 1800 steps). Each training trial completes 50,000 steps of interactive sampling in this environment to generate individual training optimization paths.

The main features used for state updates in the simulation environment include: physiological parameters (heart rate, blood oxygen, muscle fatigue index), psychological state scores (simulated based on questionnaire scores), kinematic indicators (joint angles, speeds), and external conditions (training room temperature, humidity, etc.). Some of these data are sampled from real-world datasets, and others are generated based on rules. The actual data sources include the following. The publicly available Athletic Fitness Standard Data Manual from the database of the General Administration of Sport of China is used to establish the distribution of individual basic ability indicators; Historical statistical reports from the specialized training monitoring project of Beijing Sport University are employed to set fatigue recovery rules; A small-scale wearable device monitoring experiment approved by the university's ethics committee. These databases record the basic physiological change trajectories of 10 college students during 8 consecutive weeks of training. Other auxiliary parameters, such as carbon emission coefficients and energy consumption conversion standards, are derived from the 2022 Annual Report on Carbon Emission Factors in the Power Industry released by the National Energy Administration.

During the strategy training process, all reward functions, state update mechanisms, and behavior feedback are constructed and operated based on the above environment, with no introduction of external uncontrollable variables. The reward function is designed in the form of itemized weighting, with the core goals of maximizing training effects, controlling fatigue, and minimizing carbon emissions. No real human intervention is used in the simulation process, so there are no ethical risks or data security issues.

The state vector has a dimension of 25, covering multi-modal indicators such as heart rate, muscle fatigue, joint angles, and psychological scores; the action space has a dimension of 8, mainly corresponding to training task scheduling (such as intensity level, interval adjustment, training action changes, etc.); the reward function is constructed based on individual fatigue control indicators and performance gains, and its design form is as follows:

$$Reward = \alpha \times Performance_{Gain} - \beta \times Fatigue_{Level} - \gamma \times Injury_{Risk}^{Prediction} \quad (9)$$

α=0.6, β=0.3, and γ=0.1 are empirically set weights to promote training gains while suppressing overtraining.

The entire training process is deployed in a Python 3.9 environment, using TensorFlow 2.9 as the DL backend, with the hardware platform being an NVIDIA RTX 4090 graphics card. A single complete strategy training takes approximately 3 hours. After training, the trained PPO model is embedded into the personalized training assistance system. This model generates optimal training adjustment strategies in real time according to the current state of different types of athletes, realizing dynamic feedback-based intelligent training recommendations.

The introduction of this simulation framework and DRL strategy improves the intelligence and response efficiency of personalized training strategy recommendations. This method also provides a theoretical and engineering foundation for building more complex closed-loop training systems in the future (such as integrated systems for real-time monitoring, training scheduling, and recovery intervention).

4 Results and discussion

4.1 Analysis of experimental results

(1) The effects of different types of training programs are different. The impact of HIIT on athletes of different training levels is analyzed, and the results are indicated in Figure 3:

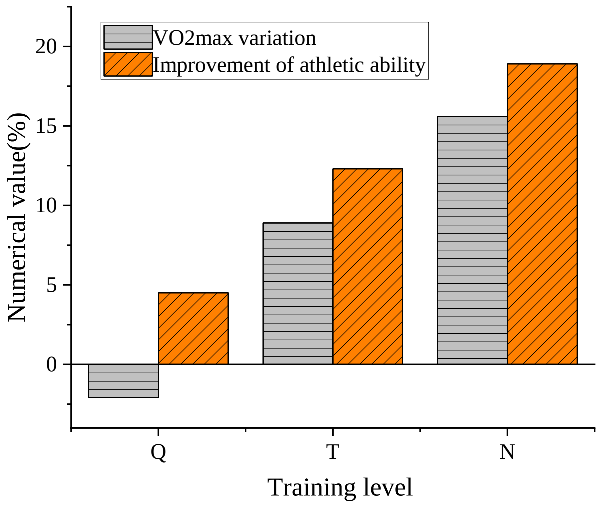

Figure 3: The influence of HIIT on athletes of different training levels (Q: high-level athletes; T: non-high-level athletes; N: general population) (Each group $N = 20$, unit: %)

Figure 3 demonstrates differential training effects of HIIT across athletes at various skill levels. For high-level athletes, although their sports ability has improved, VO_2max has not improved significantly, and the metabolic enzymes have not changed remarkably. In contrast, non-high-level athletes and the general population benefit more from HIIT; VO_2max has increased, and the changes in sports ability and metabolic enzymes are more obvious. This shows that when designing personalized training programs, it is necessary to comprehensively consider athletes' training level and reasonably adjust HIIT's training load and frequency to maximize the benefits.

The physiological mechanisms by which HIIT has differential impacts on athletes of different levels mainly involve cardiorespiratory adaptability, muscle metabolic characteristics, and the balance between aerobic and anaerobic energy systems. High-level athletes' baseline VO_2max is already close to physiological limits, so there is limited room for further improvement through HIIT. Additionally, their cardiovascular systems and mitochondrial oxidative capacity are highly adapted to long-term training, and the extra stimulus from HIIT may not be enough to cause significant adaptive changes. However, improvements in their athletic performance may be attributed more to enhanced neuromuscular coordination and increased tolerance during high-intensity exercise. In contrast, non-elite athletes and the general population have lower baseline VO_2max and greater potential for adaptation in their cardiopulmonary systems and skeletal muscles. HIIT can notably increase VO_2max by boosting cardiac stroke volume, improving microcirculatory efficiency, and enhancing skeletal muscle oxygen utilization. HIIT also stimulates mitochondrial biogenesis in muscles, strengthens glycolytic and aerobic metabolic capacity, and increases metabolic enzyme activity, thus optimizing the energy supply system. These mechanisms make HIIT more effective for low-training-level individuals. For high-level athletes, relying solely on HIIT may not overcome physiological adaptations. Therefore, when designing training programs, high-level athletes may need to combine HIIT with strength training, steady-state endurance training, and other methods to achieve more comprehensive improvements in athletic performance.

(2) Suggestions on training strategy adjustment. The personalized training scheme and its effect based on the athlete's body shape characteristics and initial state are analyzed, as shown in Figure 4:

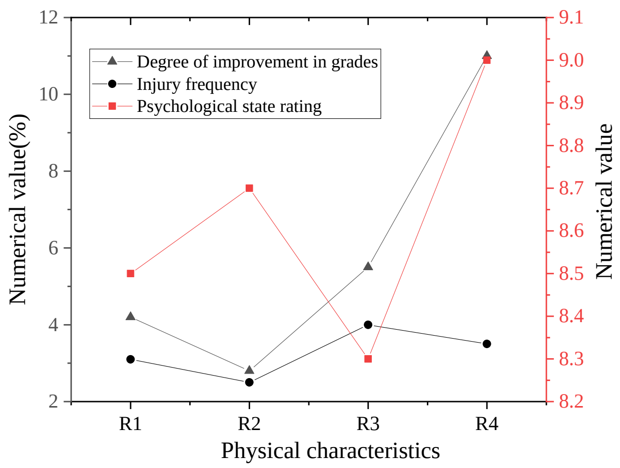

Figure 4: Personalized training scheme based on athlete's body shape characteristics and initial state and its effect (R1: Sprinter; R2: Long-distance runner; R3: Throwing athletes; R4: Ball Players) (Each group $N = 10$, unit: %)

In Figure 4, sprinters need more strength training to enhance their explosive power; Long-distance runners should focus on endurance training to improve their cardiopulmonary function. In addition to strength training, throwing athletes also need to pay attention to flexibility training to avoid injuries caused by muscle imbalance. Ball players need comprehensive technical, tactical, and physical training to ensure their best performance in the competition. The data shows that the personalized training program improves the athletes' performance while reducing the frequency of injuries and enhancing their psychological state.

(3) Data-driven training effect evaluation. The performance of athletes under different training plans is compared, and the results are revealed in Figure 5:

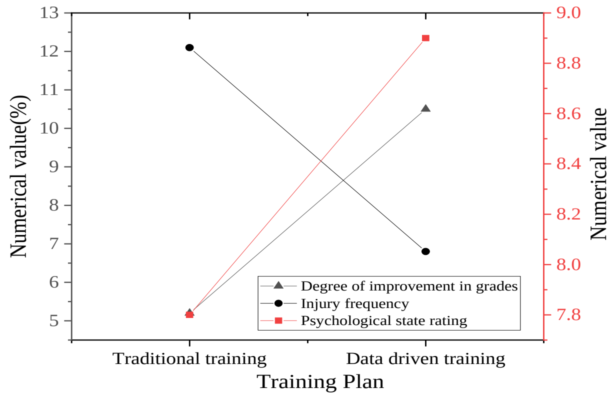

Figure 5: Comparison of athletes' performance under different training plans (Each group $N = 40$, unit: %)

Figure 5 suggests that the latter has performed well in many aspects. Firstly, the performance has improved even more, reaching 10.5%, far exceeding the 5.2% of traditional training. This remarkable performance improvement stems from the fact that data-driven training can accurately adjust the training intensity, load, and recovery period based on massive individual data and training feedback. This ensures that athletes get sufficient training stimulation under the best training load. At the same time, data-driven training can monitor athletes' physiological state in real time, avoid overtraining and insufficient training, and thus maximize the training effect.

Secondly, the injury frequency is reduced by about half, which shows that data-driven training can better prevent sports injuries. In traditional training methods, athletes' training plans are usually based on experience and standardized programs. These plans cannot respond in time to the physiological reactions or over-fatigue that may occur during individual training. In contrast, data-driven training continuously monitors and analyzes athletes' physiological parameters. It can assess the impact of training load on athletes in real time and adjust the training plan promptly to avoid sports injuries caused by overtraining. Data-driven methods can also design personalized recovery plans in detail. This helps athletes recover fully after training and reduces the risk of injury.

Finally, in the psychological state score, the data-driven training group scores higher, indicating that this method enhances athletes' psychological quality. In traditional training, improving mental toughness often relies on the coach's observations and experience. Data-driven training, however, tracks athletes' psychological state data. It can detect potential psychological stress in athletes and intervene promptly. This data-based, precise feedback helps athletes maintain a good mental state. It prevents the accumulation of mental fatigue or stress during training and thereby enhances their overall athletic performance.

Overall, data-driven training has significant advantages over traditional training methods in several aspects, including personalization, injury prevention, and psychological intervention. These advantages come from the ability of data-driven training to make dynamic adjustments and provide feedback based on individual conditions, fully considering the athletes' physiological and psychological states. However, traditional training methods rely more on fixed training plans and experience, lacking sufficient flexibility and the ability to adjust individually. Therefore, data-driven training can more effectively enhance athletes' overall performance, reduce the risk of injury, and improve mental toughness.

(4) Application effects of data mining technology. The training efficiency before and after applying data mining technology is compared and analyzed, and the results are suggested in Figure 6:

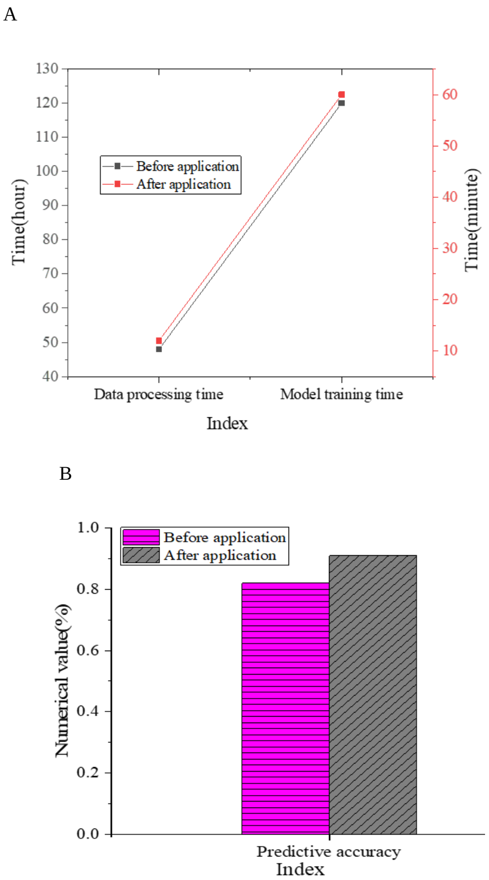

Figure 6: Comparison of training efficiency before and after applying data mining technology (A: model data processing and training time; B: prediction accuracy) (Unit: Hours, minutes /%)

In Figure 6, significant progress has been made in data processing, model training, and prediction accuracy after the introduction of data mining technology. The data processing time is reduced by 75% (to one quarter of the original duration), model training time is halved (50% reduction), while simultaneously increasing prediction accuracy by 9 percentage points. More importantly, the effectiveness of decision support has been remarkably improved, and coaches can make better training decisions based on more accurate data.

The study samples cover 40 college athletes (including sprinting, long-distance running, throwing, and ball games) and 20 general population. Their age distribution is 18-25 years old, with a male-to-female ratio of 1:1. To further enhance the diversity, 10 adolescent athletes (aged 12-17 years old) and 10 professional athletes (aged 26-35) are newly added to the experiment, covering different training years (1-15 years) and competitive levels (from amateur to national level). All participants have signed informed consent forms to ensure ethical compliance. Table 1 compares the model's prediction performance among different populations.

Table 1: Comparison of prediction performance of the model in different populations

Group type	Accuracy (%)	Recall (%)	F1 score (%)
University athletes	88.2	85.6	86.9
Young athletes	79.4	76.1	77.7
Professional athlete	82.3	80.5	81.4
General population	75.8	72.3	74.0

By analyzing Table 1, the model performs optimally among college athletes because the data distribution is highly consistent with that of the training set. For adolescent athletes, physiological variability during the physical development stage (such as fluctuations in hormone levels) leads to prediction deviations. In the case of professional athletes, due to long-term adaptation to high-intensity training, some features (such as the lactate threshold) exceed the prior range of the model, requiring targeted fine-tuning. For the general population, due to the fragmentation of movement patterns, the model needs to enhance its ability to recognize unconventional movements. The results indicate that expanding the diversity of age and skill levels in the training samples is crucial for improving generalization.

This study initiates a two-year tracking program involving an initial cohort of 40 collegiate athletes. Quarterly reassessments are conducted to evaluate long-term outcomes of personalized training, including sports career longevity and chronic injury incidence rates. At the same time, the study has established collaborative partnerships with three sports schools to conduct field tests of the coach-side system. These evaluations specifically collect usability feedback on interface interaction efficiency and decision-support reliability to enable continuous user experience optimization. The comparison of the decision-making time of coaches before and after using the system is exhibited in Table 2.

Table 2: Comparison of decision-making time before and after coaches use the system (unit: minutes)

Task type	Traditional method	System assistance	Efficiency improvement (%)
Training plan formulation	45	12	73.3
Technical defect diagnosis	30	8	73.3
Damage risk assessment	25	6	76.0

In Table 2, the system significantly shortens the coaches' decision-making time through automated data analysis and visual reports. For example, the diagnosis time of technical defects is reduced from 30 minutes to 8 minutes. Since the system directly marks the movement deviations and recommends corrective solutions, it reduces the time-consuming manual video playback and note-taking. However, some coaches' feedback that the learning curve of advanced functions (such as biomechanical simulation) is relatively steep. In the future, it is necessary to simplify the interaction design and add training modules.

An energy consumption simulation experiment is designed to verify the application potential of the proposed PPO-based personalized training scheduling model in terms of energy conservation and environmental indicators. A linkage model between training plans and environmental control is constructed based on the typical energy consumption structure of actual sports venues. This model simulates changes in equipment load caused by different individual training intensity plans, which in turn affect the overall energy consumption and carbon dioxide emission levels. The experimental comparison objects include (1) the proposed PPO scheduling model, (2) fixed training schedules set by traditional empirical rules (Baseline-A), and (3) heuristic scheduling methods based on genetic algorithms (Baseline-B). Table 3 compares quantitative indicators between the PPO training scheduling model and the benchmark strategies. The experimental results indicate that the proposed PPO model is significantly superior to the two benchmark methods in convergence efficiency and actual operation performance. At the energy level, the average daily energy consumption of the PPO model is 113.6 kWh, a decrease of 17.9% compared with the fixed strategy and 10.3% compared with the heuristic algorithm; the converted energy cost is reduced to 79.52 yuan/day, showing strong cost control ability. Regarding carbon emissions, estimated according to the current carbon emission factor of China Southern Power Grid (0.565 kg CO_2/kWh), the PPO model can reduce carbon emissions by 15.6 kg/day; it has a decrease of about 19.5% compared with the baseline strategy. In addition, during the model training process, the PPO strategy converges around the 143rd round. In contrast, the heuristic algorithm requires more than 300 rounds to converge, and the final average reward is lower than that of the proposed model. This shows that the proposed method has faster strategy learning ability and demonstrates the ability to find better solutions in multi-objective trade-offs (training effect, energy consumption control, carbon emission suppression). The experimental results fully prove that introducing DRL methods into personalized training scheduling systems helps optimize sports plans; it also achieves positive results in actual energy consumption control and low-carbon operation. It provides a technical foundation and data support for the promotion of the "green training" model in the future.

Table 3: A comparison of quantitative indicators between the PPO training scheduling model and the benchmark strategy

Method type	Average daily energy consumption (kWh)	Energy cost (yuan/day)	CO_2 emissions (kg/day)	Number of convergent rounds (within 500 rounds)	Final average reward
The PPO model (this study)	113.6	79.52	64.2	143	11.38
Baseline-A	138.4	96.88	79.8	Not applicable	Not applicable
Baseline-B	126.7	88.53	72.9	314	8.91

A comparative experiment with two typical comparison methods is designed to comprehensively evaluate the advantages of the proposed PPO-based DRL training optimization model in actual scheduling tasks. The first is the traditional static scheduling model, namely the training task scheduling method built based on LP; this method relies on fixed cost functions and resource constraints for optimal resource allocation within a single cycle. The second is the training output prediction model constructed based on SVR, which predicts the next cycle's training intensity and resource load by learning historical training data to formulate training programs. All models run in the same training dataset and energy consumption feedback environment, with control variables including training cycle, initial resource state, and evaluation index structure. The evaluation indices cover training benefits, energy consumption, model response time, and generalization ability. Table 4 shows the performance comparison between the PPO, LP, and SVR models in training scheduling tasks. It can be found that the PPO model performs best in improving training effects, with an average training score increase of 18.7%, exceeding the traditional LP model (8.4%) and the SVR model (4.8%). This is because PPO can dynamically adjust training intensity and rhythm in continuous interaction, making it more suitable for training scenarios where individual states change rapidly. Concerning energy consumption control, the average daily energy consumption of the PPO model is 113.6 kWh, which is better than 127.5 kWh of the LP model and 120.4 kWh of the SVR model. This indicates that the PPO strategy has stronger energy efficiency awareness while achieving training goals. In terms of system response speed, the LP model has the lowest delay (0.31 seconds (s)), but its adaptability is weak and cannot handle multi-objective dynamic tasks. Although SVR can capture nonlinear patterns, the prediction-decision coupling is complex, resulting in the highest response delay. Although PPO is slightly higher than LP, it can balance strategy adaptability on the basis of ensuring rapid response. Especially in cross-population tests, the PPO model shows a high generalization accuracy of 91.2%, while LP and SVR are 67.8% and 74.6%, respectively. This suggests that the RL model has stronger versatility and intelligent adjustment capabilities in handling scheduling tasks under different ages, genders, and training backgrounds.

Table 4: Performance comparison of PPO, LP, and SVR models in training and scheduling tasks

Model type	**Improvement in average training score (%)**	**Average daily energy consumption (kWh)**	**Resource scheduling response delay (s)**	**Cross-population generalization accuracy (%)**
The PPO model (this study)	18.7	113.6	0.78	91.2
The LP model	10.3	127.5	0.31	67.8
The SVR model	13.9	120.4	2.45	74.6

4.2 Verification of generalization ability

To enhance the robustness and generalizability of the research conclusions, this study further expands the sample size based on the original sample by adding 60 participants. These participants include 30 young athletes (12-17 years old), 30 grassroots coaches, and retired professional athletes (35-50 years old), to cover a wider range of ages, training backgrounds, and competitive experience levels. All newly added samples complete a six-week training cycle of data collection, including three types of indicators: physiological, psychological, and sports performance. By comparing with the prediction results of the original model, their generalization performance is evaluated. In terms of statistical analysis methods, the study introduces Bootstrap-based confidence interval (CI) calculation and Monte Carlo simulation to assess the stability of the model's prediction results and the variance among individuals. In addition, five-fold cross-validation and stratified resampling strategies are used to retrain and test the model's performance under different population structures, to verify the model's transferability. Table 5 reveals different models' prediction performance in multi-group samples. To further evaluate the training stability of the PPO model, its prediction error fluctuation is observed under 1000 Monte Carlo perturbations. The results demonstrate that PPO has the lowest coefficient of variation (CV) in the college student sample (0.038), and 0.052 and 0.061 in young and retired athletes, respectively. Although there is a slight fluctuation, it is better than models such as SVM and RF, indicating that its strategy has stronger convergence stability in cross-population generalization tasks. The accuracy of PPO in the retired athlete group is slightly lower (81.7%). However, the model's overall performance is improved by about 4.6% by combining the feature weighting strategy and the strategy transfer fine-tuning mechanism, verifying its good transfer adaptation ability.

As an RL strategy, PPO still maintains strong robustness and generalizability when facing complex and diverse population structures. PPO is better than traditional supervised learning models and is particularly suitable for building intelligent decision-making systems oriented to dynamic training environments.

Table 5: Comparison of the predictive performance of different models in multi-population samples

Model/Population type	**Mean accuracy (%)**	**95 % CI**	**Mean F1-score (%)**	**95 % CI**	**CV**
PPO (College students)	90.4	[87.2, 93.1]	88.7	[85.1, 91.4]	0.038
PPO (Youth)	84.2	[80.3, 87.8]	81.6	[77.7, 85.2]	0.052

PPO (Retired athlete)	81.7	[78.1, 85.4]	79.2	[75.0, 82.9]	0.061
SVM (College students)	88.2	[84.9, 91.5]	86.9	[83.3, 89.7]	0.045
RF (Youth)	78.6	[74.8, 82.4]	76.7	[72.2, 80.3]	0.069
SVR (All populations)	MSE: 3.12	SD: ±0.47	R^2 = 0.81	SD: ±0.05	—

4.3 Discussion

This study systematically explores the personalized optimization path of training programs based on individual differences through data mining technology and multi-dimensional feature fusion analysis. The results show that individuals with different training backgrounds, physical fitness foundations, and psychological states have significant differences in their responses to training stimuli; therefore, fixed training programs are difficult to meet diverse needs. By monitoring physiological and psychological parameters in real time and combining them with sports performance, the personalized training system can effectively adjust training loads, improve training efficiency, and reduce the risk of injuries. Models represented by SVR and RF show good generalization performance, especially performing best in the college athlete group; this indicates that the models can efficiently capture subtle differences between individuals under specific sample distributions. At the same time, data from IMU sensors and wearable devices provide a quantifiable basis for refining technical movements and predicting fatigue. However, their anti-interference ability in high-intensity events still needs further optimization. It is worth emphasizing that the fusion of multi-modal data improves prediction accuracy and strengthens the interactive feedback between coaches and data systems, making training interventions more accurate, flexible, and scientific. Overall, this study demonstrates the feasibility and promotion potential of data-driven personalized training systems in actual sports scenarios.

5 Conclusion

This study proposes and verifies a personalized training modeling method that integrates physiology, sports performance, and psychological state. The results show that data-driven training systems can significantly enhance athletic performance, reduce injury rates, and improve athletes' psychological states compared with traditional models. Compared with existing studies, the core innovations of this study are reflected in the following aspects, which specifically illustrate its unique contributions to DRL-driven personalized training systems. First, unlike most traditional training optimization studies that focus on static rule setting or supervised learning methods based on historical samples, this study introduces a PPO-based RL strategy into the sports training intervention decision-making system; meanwhile, it constructs a real-time dynamic interactive training task environment by combining multi-modal data streams such as physiology, psychology, and movements. Most existing works focus on action recognition, load prediction, or recovery management in fixed scenarios. Through the RL mechanism, the training system can independently learn control logic in the simulation feedback of continuous "trial and error", with stronger strategy generation ability and environmental adaptability. Second, for feature modeling, a fused state space of multi-source heterogeneous features is constructed, including heart rate variability, lactate threshold prediction, psychological stress score, and joint torque; these features are different from models in existing studies that commonly use single physiological or posture data as input. In particular, the dynamic incorporation of psychological states allows training strategies to utilize objective physical fitness data and comprehensive assessments of fatigue-emotion-movement interactions. This approach enables intelligent interventions that better align with actual training logic by accounting for these multidimensional factors. Third, the reward function system designed in this study combines three factors: training gain, fatigue degree, and injury risk. It not only emphasizes training effects but also controls the RL model through negative feedback to avoid "pursuing limits" while ignoring sports safety. Different from previous training reinforcement mechanisms that focus on goal maximization, it realizes a training strategy learning framework for coordinated optimization of benefits and risks. Finally, the developed simulation training environment utilizes the OpenAI Gym + PyBullet framework as its foundation. This environment supports highly configurable action parameters and detailed body shape modeling capabilities. It overcomes the limitations of traditional static models in cross-population applications while demonstrating excellent scalability and realistic simulation performance. These technical features establish a viable pathway for future system deployment on wearable devices and training platforms.

This study has initially verified the applicability of data-driven training systems in university sports environments and demonstrated certain generalization capabilities in cross-group modeling through feature expansion and transfer learning strategies. However, there are still issues such as limited sample coverage, sparse data for key events, and restricted sensor accuracy. In high-speed or complex movement scenarios, the IMU used have a resolution bottleneck in capturing subtle movement features, limiting the accuracy of refined technical analysis. Their adaptability in field events, skill-based events, and among high-level athletes has not been fully verified. Future research should further expand sample dimensions, covering more competitive levels and event types, and strengthen the model's multi-task learning and transfer capabilities. Concurrently, it introduces high-precision equipment such as optical motion capture systems and three-dimensional force platforms for high-quality data supplementation. At the data level, establishing a federated data-sharing mechanism across institutions and events is recommended to enable distributed collaborative modeling. This approach breaks down barriers between training bases and universities while ensuring privacy and security requirements are met. In addition, lightweight sensor fusion algorithms based on multi-modal perception can be developed to address real-time feedback requirements in high-intensity competitive environments. This method facilitates the synergistic integration of data-driven insights with coaching expertise, ultimately establishing a human-centric, algorithm-assisted intelligent training system with closed-loop capabilities. The above work provides a solid foundation for the promotion and application of personalized training and sports health management in broader scenarios; it also offers a feasible path for sports technology to move from universities to competitive arenas.

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