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RESEARCH ARTICLE

Personalized Recommendation Method of "Carbohydrate-Protein" Supplement Based on Machine Learning and Enumeration Method

XIANGYU WANG[1], ZIHAO LI[2], AND HAO WU[1]
[1]School of Kinesiology and Health, Capital University of Physical Education and Sports, Beijing 100191, China
[2]Institute of Physical Education and Training, Capital University of Physical Education and Sports, Beijing 100191, China

Corresponding author: Hao Wu (shoudutiyuan1@163.com)

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Ethics Committee of the Capital University of Physical Education and Sports under Application No. 2022A57.

ABSTRACT Carbohydrate-protein supplement (CPS) intake is a well-established strategy for enhancing athletic performance, promoting glycogen replenishment, maintaining a positive nitrogen balance, and minimizing muscle damage in endurance athletes. Current CPS intake recommendations often rely solely on weight, lacking personalization. This study aimed to develop a machine learning-based personalized CPS intake recommendation system for endurance sports enthusiasts. We recruited 171 participants and collected 45 indicators from 12 diverse aspects, including lifestyle, psychological state, sleep quality, demographics, anthropometrics, physical activity levels, exercise capacity, blood parameters, central nervous system parameters, cardiovascular metrics, meal timings, and beverage composition. Additionally, we assessed each subject's performance in the Jensen Kurt's 60-minute rowing ergometer distance race. Utilizing back propagation (BP) neural networks, we employed 5-fold cross-validation to optimize the learning rate and identify the relationship between the 45 indicators and the 1-hour rowing distance. Based on this optimized learning rate, we trained a well-fitted model on the training dataset. We further employed an enumeration method to tailor the CPS intake protocol for each individual. Our results demonstrate the feasibility and potential of using machine learning to deliver personalized CPS intake recommendations. Future work will focus on expanding the dataset's dimensions to iterate, update, and enhance the model's robustness.

INDEX TERMS Artificial intelligence, carbohydrate-protein supplement, machine learning, sports nutrition, sports performance.

I. INTRODUCTION

The intake of carbohydrates (CHO) mixed with protein (PRO) has been traditionally applied by endurance and strength athletes to enhance athletic performance, promote glycogen replenishment and positive nitrogen balance, and minimize muscle damage [1], [2]. The consumption of PRO along with CHO enables endurance athletes to exercise for a longer duration than when CHO is consumed alone [3], [4]. Existing approaches to carbohydrate-protein supplement (CPS) intake recommendations often overlook inter-individual variability. Studies have shown that general recommendations often propose the same dose of CPS for different individuals or differentiate recommendations based only on individual body weight [5], [6]. The human body is a complex system, and different individuals have unique variations in their lifestyles [7], [8], gut flora [9], [10], hormone secretion levels [11], and psychological states [12]. These variables affect each person's processes for acquiring nutrients and controlling their energy levels, which eventually results in varying rates

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of utilization of the same amount of sports supplements and varying improvements in athletic performance.

Robergs et al. [13] first reported in 1998 that the ingestion of food supplements containing CHO, PRO, and fat produced glycemic, metabolic, glucoregulatory hormones, and exercise performance responses similar to those following ingestion of CHO beverages. In the past 20 years, several studies have further demonstrated that PRO supplementation during exercise increases the rate of myogenic glycogen synthesis and improves the exercise performance of endurance athletes [14], [15]. Despite the differences in exercise regimens across these studies, comparative analyses have suggested that the rates of CHO and PRO intake might be the main factors responsible for the varying findings. Many studies have focused on beverages with a CHO-to-PRO ratio of approximately 4:1 [2], [14] and a CHO intake rate of above 0.50 g/kg/h [14], [15] but not exceeding 1.2 g/kg/h. This is primarily because several studies have reported that when CHO intake rate is equal to or above 1.2 g/kg/h, additional PRO supplementation does not provide any further nutritional benefits or exercise performance gains for the subjects [16], [17].

Compared to traditional statistical methods, machine learning techniques like artificial neural networks are capable of identifying nonlinear relationships between complex indicators, facilitating the construction of regression or classification models. Recently, these methods have been widely used in the medical field for target drug development [18], [19], [20], compound screening [21], [22], drug crystal type prediction [23], [24], and imaging diagnosis [25], [26]. Given the complexity of the human body, it is logical to apply artificial intelligence methods to the field of sports nutrition. Furthermore, the feature importance functionality of machine learning methods could be utilized by professional or amateur athletes (with the assistance of trainers and experts) to improve their fitness and health levels.

In this study, we recruited 171 endurance sports enthusiasts and conducted endurance exercise experiments. Based on the data collected, we propose a machine learning-based personalized CPS recommendation method. We integrated a total of 45 indicators from 12 aspects (Fig. 1) pertaining to participants' daily life and health status: lifestyle, psychological status, sleep quality, demographics, anthropometrics, physical activity levels, exercise capacity, blood parameters, central nervous system (CNS) parameters, cardiovascular system (CS) parameters, meal timings, and beverage composition. Unlike traditional CPS recommendation methods, our approach considers multiple factors related to individual exercise performance and energy acquisition, making it more personalized. The results of the test set also demonstrated the feasibility of this method.

II. METHODS

A. STUDY DESIGN AND OBJECTIVES

The primary objective of this study is to leverage machine learning for personalized CPS intake recommendations tailored to endurance sports enthusiasts. In this study, we integrated 45 indicators across 12 diverse domains, including lifestyle, psychological state, sleep quality, demographics, anthropometrics, physical activity levels, exercise capacity, blood and CNS parameters, cardiovascular metrics, meal timings, and beverage composition. We employed a back propagation (BP) neural network model, using 5-fold cross-validation to optimize the learning rate for analyzing the relationship between these multidimensional indicators and the 1-hour rowing distance. Subsequently, a well-fitted model was trained on the training dataset based on the optimized learning rate. Subsequently, the fitted BP neural network model is used with the enumeration method to provide individualized CPS intake protocols. The focus of this research is on innovatively applying the BP neural network model for personalized recommendations.

B. PARTICIPANTS

A total of 171 male subjects were classified as "low risk" according to the American College of Sports Medicine risk stratification [27]. These subjects were considered endurance exercise enthusiasts, engaging in aerobic exercises three to six times per week on average, for more than one hour per session. The participants were familiar with rowing exercises, with most of them having rowing experience of at least 1 year. For the purpose of this study, we assumed that all participants had a similar level of rowing experience, allowing us to focus on developing a BP neural network model based on the collected participant data and implementing personalized CPS recommendations using enumeration method. Prior to exercise testing, all participants received a detailed explanation of the goal and clinical implications of this experiment, including the instructions of strategy throughout the trial. All participants read and signed an informed consent form, which was approved by the Ethics Committee of the Capital University of Physical Education and Sports, Beijing, China. The physical attributes and endurance exercise data of the subjects are summarized in Table 1.

TABLE 1. Physical attributes and endurance exercise data of the subjects.

Parameters	Value
Age	22.78±2.43
Height	179.24±6.93
Weight	76.06±9.85
Body fat percentage	17.39% ± 4.83
1-hour rowing distance (m)	11997.19±1002.04

C. EXPERIMENT

1) DIET SUPPLEMENTS

The PRO and CHO supplements used in the experiment consisted of commercially available products from ALL STARS,

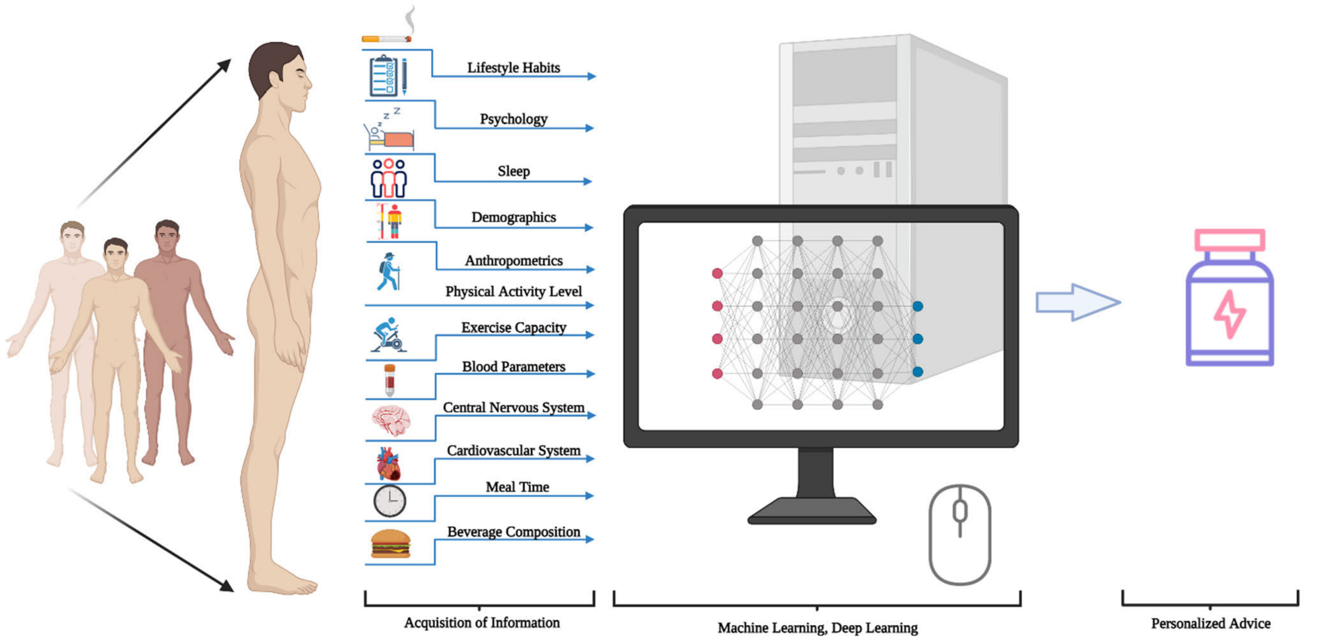

FIGURE 1. A machine learning-based approach to CPS intake recommendation.

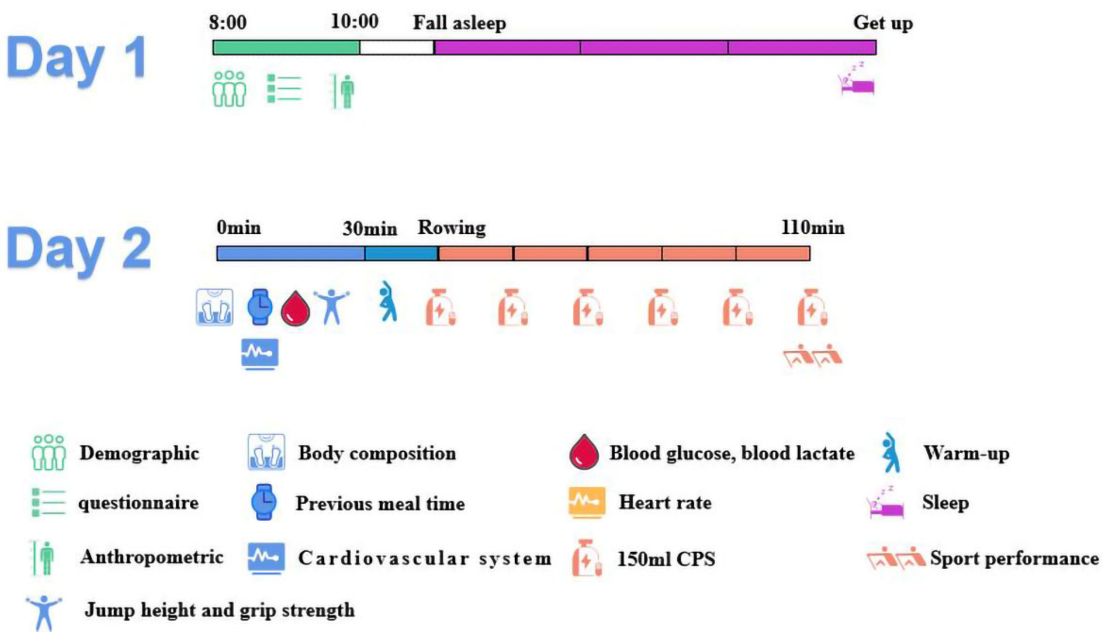

FIGURE 2. Experimental procedure and indices data collected.

Germany, including whey PRO powder and CHO supplement powder. The whey PRO powder provided the protein content, while the punch powder supplied the CHO component. Additional elements in the supplements, such as fat, sodium, magnesium, and calcium, were also included as part of the modeling indicators. The effective CHO intake range, as established in prior CHO-PRO studies [28], [29], [30], was subdivided into eight intake regimens, each differing by 0.1 g/kg/h, ranging from 0.5 to 1.2 g/kg/h, while maintaining a CHO to PRO ratio of 4:1. This mixture was then formulated into a 900 ml drink for the test subjects to consume at a rate of 150 ml every 15 minutes during exercise. All subjects consumed their respective drinks at the same time of the day and at the same room temperature. The eight established CPS intake protocols were coded '1' through '8', in an order different from the increasing order of the CPS intake protocol. The order in which the subjects participated in the experiment was also random, with each of the eight subjects being randomly assigned to one of the eight codes the day before the formal experiment. The subjects as well as the personnel in charge of dispensing the CPS were unaware of the intake protocol represented by each code.

2) SELECTION OF INDICATORS

In this study, the BP neural network model was used to estimate the endurance sports performance (rowing distance). The model utilized 46 indicators (Table 2), with 45 serving as input indicators and one as an output indicator (rowing distance).

Endurance sports performance is a multifaceted phenomenon influenced by various physiological, psychological, and environmental factors. Over the years, extensive research has shed light on the myriad of elements that can directly or indirectly influence athletic performance. The input indicators chosen for this study have been previously demonstrated by researchers to have a tangible impact on sports performance, either directly or indirectly. These factors include:

a: AGE

With aging, individuals often experience a noticeable decline in physical capabilities, which in turn affects athletic performance. This decline is largely mediated by a decrease in the intensity and volume of physical activity [31].

b: UNHEALTHY LIFESTYLE HABITS

Practices such as smoking [32], excessive alcohol consumption. [33], staying up late [34], and disordered eating [35] may adversely impact physical capabilities and thus affect endurance performance.

c: INDICATORS RELATED TO SYSTEMS AND FITNESS

Parameters related to the CS, blood system, muscular fitness, body composition, and physical activity levels are integral components of the comprehensive health fitness evaluation conducted by the American College of Sports Medicine (ACSM). These indicators reflect an individual's readiness for physical activities, and their significance is underscored by numerous scientific studies [36].

d: ELECTRICAL SIGNAL INDICATORS

Metrics such as the brain's direct current potentials and HRV offer insights into an individual's fatigue levels [37] and have implications for performance. These indicators have found extensive application in sports science.

e: NUTRITIONAL TIMINGS AND BEVERAGE COMPOSITION IN SPORTS

An individual's metabolic rate spikes dramatically during physical activity. Factors such as meal timings before the activity and nutritional supplementation during the activity play pivotal roles [38], [39]. They play a role in determining the concentration of metabolic substrates and energy supply during endurance sports, ultimately impacting performance.

3) EXPERIMENTAL PROCESS

a: FAMILIARIZATION

The subjects were required to visit the laboratory one week before the formal experiment to familiarize themselves with the exercise regimen and the timing of CPS supplementation. The beverage consumed by the subjects during the familiarization program was water, and no indicators were collected during the process. In addition, the subjects were asked to maintain a stable dietary intake, physical activity level, and sleep schedule for 48 hours prior to the familiarization as well as formal experiment and to maintain a record of the same. On the day of the formal experiment, the records were examined to ensure that the subjects had maintained a stable pattern of diet and exercise.

b: FORMAL EXPERIMENT

Each subject participated in the formal experiment on the seventh day following the familiarization program. The sequence of indicator collection is depicted in Fig. 2.

First Day:

- ✧ Subjects were asked to arrive at the laboratory by 8:00 a.m.
- ✧ Upon arrival, participants completed a demographic questionnaire, intuitive eating scale-2 (IES-2) [40], Physical Activity Ranking Scale (PARS-3) [41], Pittsburgh sleep quality index (PSQI) scale [42], and a survey detailing their smoking and alcohol consumption over the past 30 days [43].
- ✧ Laboratory staff then recorded specific morphometric data, including:
  - ✧ Circumference measurements of the upper arm, waist, hip, subgluteal thigh, mid-thigh and calf.
  - ✧ Skinfold thickness readings from the triceps, subscapular, suprailiac and abdomina.
- ✧ Participants were then provided with a sports bracelet to track that night's sleep data, capturing metrics such as the duration of deep sleep, light sleep, and rapid eye movement sleep.

Furthermore, each subject was randomly assigned a numeric identifier, ranging from 1 to 8, which corresponded to a specific CPS intake protocol.

Second Day:

Prior to the initiation of the exercise experiment, the staff gathered comprehensive data encompassing multiple domains:

- ✧ Body composition metrics were collected, specifically differentiating between the percentages of body water and body fat.
- ✧ Data pertaining to the time elapsed since the participant's last meal was recorded.

- ✧ CS indicators were collected, including resting heart rate, systolic and diastolic blood pressure, as well as heart rate variability (HRV), were measured.
- ✧ Key blood parameters such as glucose concentration, lactate levels, and hemoglobin count were evaluated.
- ✧ CNS parameters were assessed with particular emphasis on Direct Current (DC) Potential.
- ✧ Finally, staff collected subjects' two-handed grip strength and average vertical jump height.

These collected indices served as input variables for the regression modeling.

4) EXERCISE PROTOCOL

The Jensen Kurt's 60-minute rowing ergometer distance race. [44], originally designed to evaluate the aerobic metabolic capacity of athletes based on the glide distance of the rowing ergometer, was adapted as the exercise protocol for this experiment. The subjects were required to perform two 30-minute rowing ergometer sessions with a 15-minute rest period in between. The resistance factor was set to 120 for all subjects, and they were recommended to maintain a stroke rate between 16 and 24. Additionally, subjects were advised to exercise at a constant power level that could be sustained throughout the test.

To ensure maximal performance, participants were instructed to perform at their highest capacity and were verbally encouraged throughout the trial. Several measures were taken to ensure the tests were equitable between groups:

a) The resistance factor was set to 120 for all subjects, ensuring a consistent level of difficulty across participants.
b) All participants received the same instructions and encouragement from trained personnel to minimize variability in motivation.
c) The rowing ergometer's display was blocked during the test, preventing participants from comparing their performance or adjusting their pacing based on the glide distance.

The subjects were required to perform two 30-minute ergometer sessions with a 15-minute rest period in between. The rowing ergometer (Concept II, Type D) was equipped with a fixed 30-minute exercise program, automatically stopping the count after 30 minutes to ensure the consistency of participation time among all subjects. During the exercise, the subjects were verbally encouraged to row the longest distance possible. The rowing ergometer is capable of recording the rowing distance of the subjects, and the data will be exported by the staff after the exercise experiment.

To ensure the effectiveness as well as safety of the experiment, the experiment termination criteria that were determined prior to commencement included the subject displaying any of the following symptoms: 1) heart rate less than 40% of maximum heart rate reserve at least three times during the experiment [2], [45]; 2) Angina; 3) shortness of breath, croup, or muscle cramps; 4) mild headache, confusion, ataxia, pallor, cyanosis, nausea, or clammy skin; 5) conveying or showing extreme fatigue; or 6) the subject requesting to stop the experiment; or 7) the test equipment breaking down.

D. MACHINE LEARNING APPROACHES: BP NEURAL NETWORK VS. GRADIENT BOOSTED REGRESSION TREES (GBRT)

1) BP NEURAL NETWORK MODEL

In this study, we apply the BP neural network in combination with enumeration to develop a personalized CPS intake recommendation system for participants. Compared with traditional statistical methods, machine learning techniques such as artificial neural networks can identify nonlinear relationships between complex indicators and facilitate the construction of regression or classification models.

BP neural networks are an essential type of neural network [46], [47]. As shown in the Fig. 3, the network consisted of three parts: input, hidden, and output layers. The input signals propagate forward through the network on a progressive basis. This type of network is essentially input-to-output mapping. It can learn many mapping relationships between the input and output without any precise mathematical expressions between the two.

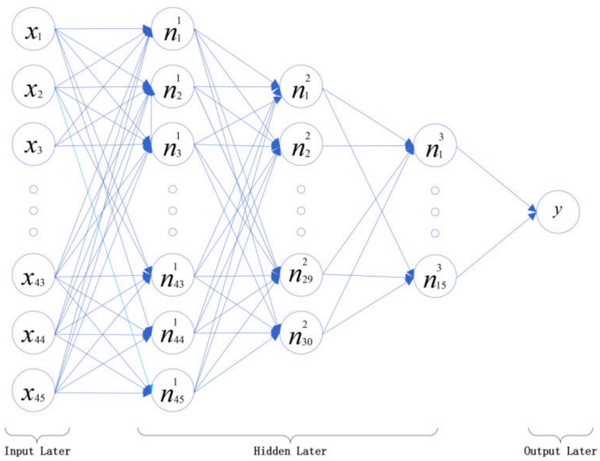

FIGURE 3. Structure of the network. $x_1 \sim x_{45}$ denote the input variables, which are listed in the Table 2. The output variable y denotes the rowing distance. Terms n_1^1, n_1^2, and n_1^3 denote the first node in the first, second, and third layer, respectively. $W_{1,1}^1$ denotes the weight value from the first node in layer 0 to the first node in layer 2.

The network used in this study is known as the BP algorithm. When an input mode is provided, transmission of the input signal from the input layer to the output layer is a forward propagation process. If the output signal is different from the expected signal, there is an error. It then turns into a process of error back propagation, and the weight value of each layer is adjusted according to the error of each layer.

Each node of the hidden layer in the network has a nonlinear function. The nonlinear function used in this test is a sigmoid function [48], [49], as follows:

$$S(x) = \frac{1}{1 + e^{-n_p^k}} \tag{1}$$

where n_p^k denotes the input of p node in the layer k.

The specific steps of the BP algorithm used were as follows:

Step 1: Perform random assignment on each weight term $W_{p,q}^{k}$ and intercept term $b_{p,q}^{k}$,

where $W_{p,q}^{k}$ denotes the weight from the p node in layer k-1 to the q node in layer k.

Step 2: Normalization

To remove the unit limit of the data, the data are normalized, and the input and output data are uniformly mapped between [0, 1]. The conversion formula is as follows:

$$Y = \frac{(X - X_{min})}{(X_{max} - X_{min})} \tag{2}$$

where X represents the original value, $X_{\min}$ the minimum value in the original data, and $X_{\max}$ the maximal value in the original data.

Step 3: Input the 'input' and 'output' indices into the model;

Step 4: Calculate each node in the training set;

a) Calculate the input and output of each node in the first layer as follows:

$$n_q^1 = \sum_{6} W_{p,q}^1 X_P + b_q^1 \tag{3}$$

$$O_q^1 = sigmoid\left(n_q^1\right) = \frac{1}{1 + e^{-\left(\sum\limits_{6} W_{p,q}^1 X_P + b_q^1\right)}} \tag{4}$$

b) Calculate the input and output of each node in the second layer as follows:

$$n_q^2 = \sum_{l} W_{p,q}^2 O_p^1 + b_q^2 \tag{5}$$

$$O_q^2 = sigmoid\left(n_q^2\right) = \frac{1}{1 + e^{-\left(\sum\limits_{l} W_{p,q}^2 O_p^1 + b_q^2\right)}} \tag{6}$$

c) Calculate the input and output of each node in the third layer as follows:

$$n_q^3 = \sum_{i} W_{p,q}^3 O_p^2 + b_q^3 \tag{7}$$

$$O_q^3 = sigmoid\left(n_q^3\right) = \frac{1}{1 + e^{-\left(\sum\limits_{i} W_{p,q}^3 O_p^2 + b_q^3\right)}} \tag{8}$$

d) Calculate the input and output of the output layer as follows:

$$n_1^4 = V = \sum_{m} W_{p,1}^4 O_p^3 + b_1^4 \tag{9}$$

From the presented equations, p and q denote the orders of nodes, whereas O denotes the output of nodes. For instance, O_p^k denotes the output of the p node in layer k.

Step 5: Calculate the error between the expected output and network output:

For the output layer of the network, the error between the output O_p^k of its p node and expected output d_p^k is expressed as follows:

$$E_p = \frac{1}{2}\left(O_p^k - d_p^k\right)^2 \tag{10}$$

Then, the total error of the network is obtained as follows:

$$E = \sum_{j} E_p = \frac{1}{2}\sum_{j}\left(O_p^k - d_p^k\right)^2 \tag{11}$$

where j denotes the number of nodes in the output layer.

Because there is only one node in the output layer of this network, the total error of the network is obtained as follows:

$$E = \frac{1}{2}(V - d)^2 \tag{12}$$

Step 6: Reverse calculate and correct the network weight value.

The purpose of learning and training the BP network is to minimize E by adjusting the model parameters. The gradient descent method was used to reduce the weight value along the negative gradient of the error when adjusting the weight value. The adjustment formula is as follows:

$$\Delta W_{p,q}^k = -\eta\delta O_p^{k-1} \tag{13}$$

where η denotes the learning coefficient, and $W_{p,q}^k$ denotes the weight value from the p node in layer k-1 to the q node in layer k. Term $\Delta W_{p,q}^k$ denotes the adjustment quantity of the weight value.

When k is the output layer.

$$\delta = (V - d) \cdot sigmoid'^{\left(n_1^4\right)} \tag{14}$$

When k is not the output layer,

$$\delta = \left(\sum_{t} \frac{\partial E}{\partial n_t^{k+1}} \cdot W_{q,t}^{k+1}\right) \cdot sigmoid'^{\left(n_q^k\right)} \tag{15}$$

where t denotes the order of the node in layer k+1.

When the learning coefficient η is larger, the learning speed is higher, but the convergence is poor, and oscillation may occur. However, if the learning coefficient η is excessively small, the learning speed will be affected. Therefore, the value of η is typically determined experimentally. In addition, in practical use, the momentum term α is usually added to the equation as follows:

$$\Delta W(t+1) = -\eta\delta O_p^{k-1} + \alpha\Delta W(t) \tag{16}$$

where ΔW (t) denotes the adjustment quantity of the weight value during the last learning. This is conducive to accelerate the learning process, such that the training efficiency of the model has a significant relationship with the learning coefficient and momentum term.

Step 7: Transfer to step 4 and repeat.

The convergence of the BP algorithm cannot be generally proved. Moreover, there is no clearly defined stopping criterion. The weight value must be made the error surface for the weight gradient vector, which is zero. Therefore, we proposed the following stopping criterion:

Stop criterion 1: When the Euclidean norm reaches a sufficiently small gradient threshold, the BP algorithm is considered to have converged.

Stop criterion 2: When the change rate of the mean square error reaches a sufficiently small value, the BP algorithm is considered to have converged.

a: MODEL EVALUATION, DATA SPLITTING, AND PERFORMANCE METRICS

In the machine learning modeling process, it is common practice to divide the data into training and test sets. The test set is independent of the training data and does not participate in the training process, but is used to evaluate the model's final performance. In our study, we carefully split the data into training and test sets, ensuring that the test set provides an accurate and unbiased evaluation of the model. By evaluating our model on this independent test set, we were able to demonstrate its effectiveness and avoid issues related to overfitting.

To rigorously assess the predictive performance of the BP neural network model, we employed Mean Absolute Error (MAE). MAE is used to gauge the average magnitude of the prediction errors, without taking into account the direction of the discrepancies. It is computed as the arithmetic mean of the absolute differences between the predicted and ground truth values. The MAE offers an intuitive metric for the mean prediction error, with lower values signifying superior model performance.

We employed 5-fold cross-validation on the training data to fine-tune the learning rate, thereby enhancing the model's parameter reliability. This approach facilitated a robust performance evaluation across multiple training subsets. By analyzing validation loss and mean absolute error (MAE) across variable learning rates, we identified optimal hyperparameters, deepening our insights into the model's capabilities. This strategy provided a rigorous and transparent assessment of the BP neural network model, aligning closely with our research objectives.

b: PERMUTATION FEATURE IMPORTANCE ANALYSIS

After building and training the BP neural network model, we assess the contribution of each input variable to the model's predictive performance using permutation feature importance. This model-agnostic method provides insights into the importance of individual features by measuring the decrease in model performance when a single feature is randomly shuffled.

2) GRADIENT BOOSTED REGRESSION TREES (GBRT)

In this study, we also chose Gradient Boosted Regression Trees (GBRT) as a comparison model. GBRT is a powerful supervised learning technique that builds a strong predictive model by combining multiple weak predictive models. We chose GBRT as a comparison to fully evaluate the performance and applicability of BP neural networks in specific scenarios.

E. ENUMERATION METHOD

Enumeration. [50] is a method of proving a proposition by listing all the (finite) possible cases involved in the proposition and then eliminating the impossible cases one by one to obtain the result of the proposition. In our study, we used the enumeration method based on the fitted BP neural network model to identify the optimal CPS supplementation intake rate for each individual.

After fitting the BP neural network model, we entered the existing CPS intake rate interval (0.5–1.2 g/kg/h) data into the network model in increments of 0.01 g/h. These intake rates were combined with the other 44 indices of the subjects and then input into the BP neural network model again. This allowed us to identify the CPS intake rate that resulted in the best prediction distance, which was considered to be the optimal intake level for the individual.

By leveraging the fitted BP neural network model, the enumeration method could effectively determine the optimal CPS supplementation intake rate for each subject, providing valuable insights for personalized nutrition strategies in sports.

III. RESULTS

A. DESCRIPTIVE STATISTICS

The main objective of this study is to construct a personalized CPS recommendation method based on BP neural network with enumeration. For a nuanced understanding of the data, comprehensive descriptive statistics, such as mean and standard deviation, have been meticulously calculated for each specific indicator. These detailed statistics are presented in the Supplementary file.

B. MODEL COMPARISON AND CONFIGURATION DETAILS

1) BP NEURAL NETWORK MODEL

In this study, three hidden layers and 136 nodes were proposed in the network (Fig. 3). The number of nodes in the three hidden layers sequentially decreased from input to output, with counts of 45, 30, and 15, respectively. The model utilized the Adam optimizer for efficient gradient-based optimization.

This study utilized 5-fold cross-validation on the training dataset specifically to optimize the learning rate for our BP neural network model. This process enabled us to identify a learning rate that yielded more consistent and reliable performance across different subsets of the training data.

We trained the model with learning rates of 0.001 and 0.01, respectively, observing the validation loss (MAE) for each fold. The detailed results are as follows:

Learning rate 0.001:

- ✧ Fold 1: Validation loss 0.0209
- ✧ Fold 2: Validation loss 0.3306
- ✧ Fold 3: Validation loss 0.0274
- ✧ Fold 4: Validation loss 0.0250
- ✧ Fold 5: Validation loss 0.0431

Learning rate 0.01:

- ✧ Fold 1: Validation loss 0.0172
- ✧ Fold 2: Validation loss 0.0393

TABLE 2. Modeling indicators for the BP neural network model.

Model Structure	Classification of indicators	Specific indicators
Input Indicators	Living Habits	Smoking frequency in the last 30 days, Alcohol use in the last 30 days
	Psychological status	IES-2
	Sleep quality	Deep sleep, light sleep, rapid eye movement, PSQI
	Demographics	Age
	Anthropometry	Height, weight, Triceps skinfold, subscapular skinfold, suprailiac skinfold, abdominal skinfold, upper arm circumference, waist circumference, hip circumference, subgluteal thigh circumference, mid-thigh circumference, calf circumference, Body water percentage, body fat percentage
	Physical Activity Levels	PARS – 3
	Athletic ability	Left- and right-hand grip strength, average vertical jump height before exercise
	Blood Parameters	Blood glucose, blood lactate, hemoglobin (non-invasive test)
	CNS parameters	DC Potential
	CS parameters	Resting heart rate, high blood pressure, low blood pressure, HRV (HF, LF, total power, SDNN, RMSSD, SDSD)
	Meal Time	Previous meal time
	Beverage Ingredients	CHO, fat, sodium, magnesium, calcium
Output Indicators	Sports Performance	Rowing distance

- ✧ Fold 3: Validation loss 0.3532
- ✧ Fold 4: Validation loss 0.0250
- ✧ Fold 5: Validation loss 0.0343

The optimal learning rate was determined to be 0.01, which yielded the lowest average validation loss during the cross-validation process.

As can be seen in the Fig. 4, which represents the test loss, the network, when iterated 151 times, reached a point where the test loss showed a sufficiently small value with minimal fluctuations. This indicates that the model achieved the desired stability, meeting the aforementioned "Stop criterion 2", suggesting that the BP algorithm had effectively converged on the test data. The performance of the best BP neural network model was evaluated on the test set, yielding a MAE of 470.77.

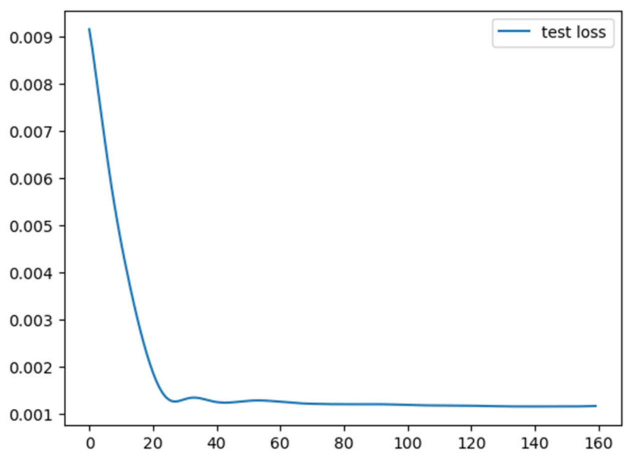

FIGURE 4. Test Loss Iteration of BP Neural Network (160 times). The abscissa is the number of iterations of BP neural network, and the coordinate is the model loss value. This model achieved its best performance at the 151st iteration.

2) GBRT

This study utilized the default settings provided by the scikit-learn library, which includes trees with a maximum depth of 3 and a minimum sample split of 2. However, the learning rate was fine-tuned to optimize the model's performance.

The GBRT model's performance was evaluated across different learning rates through a 5-fold cross-validation process to ensure the stability and reliability of the model. The learning rates were selected to be 0.001 and 0.01 for this analysis. The detailed validation loss (MAE) for different learning rates are as follows:

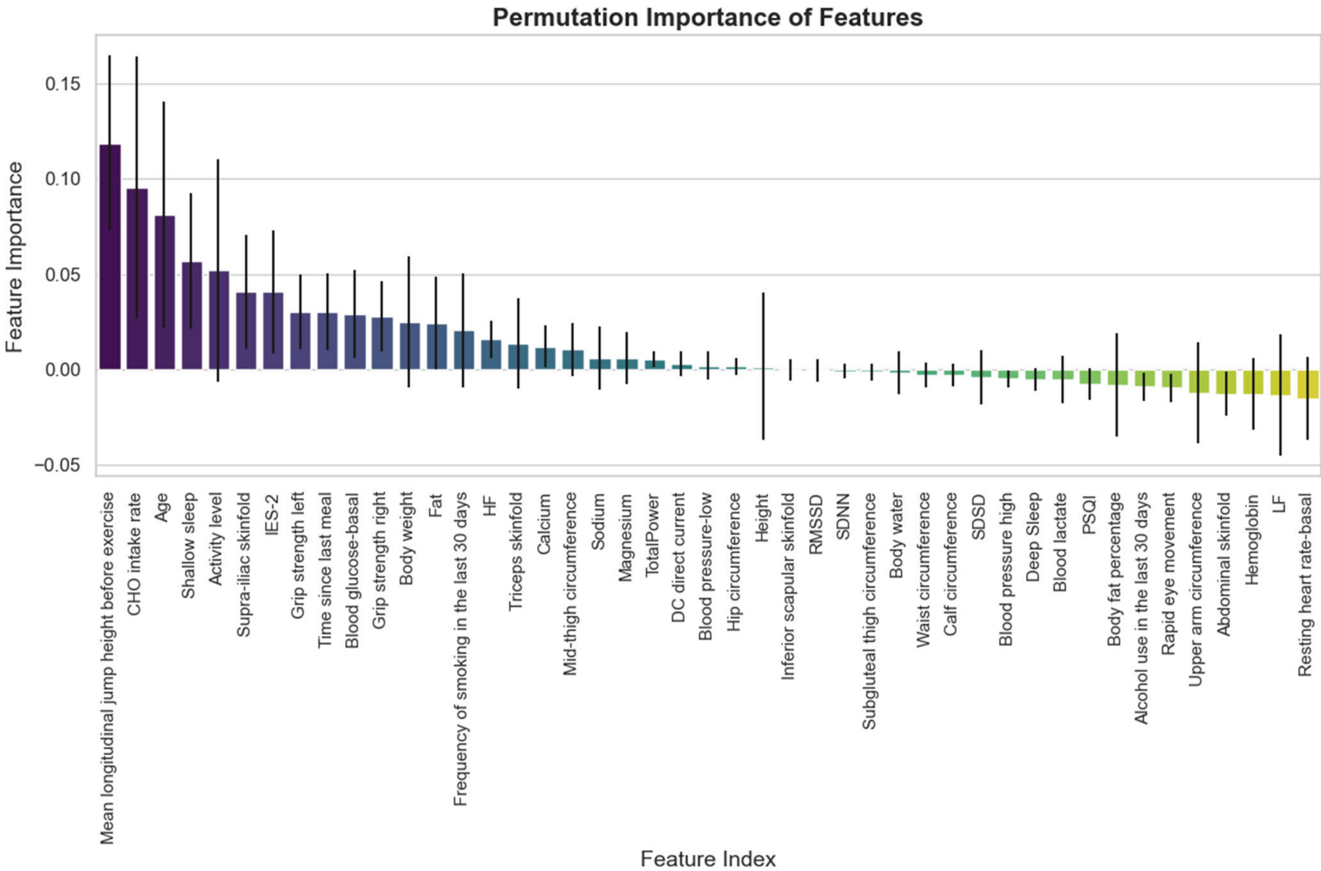

FIGURE 5. **Permutation Importance of Features.**

Learning rate 0.001:

- ✧ Fold 1: Validation loss 0.2248
- ✧ Fold 2: Validation loss 0.1474
- ✧ Fold 3: Validation loss 0.1640
- ✧ Fold 4: Validation loss 0.1674
- ✧ Fold 5: Validation loss 0.1579

Learning rate 0.01:

- ✧ Fold 1: Validation loss 0.1996
- ✧ Fold 2: Validation loss 0.1370
- ✧ Fold 3: Validation loss 0.1348
- ✧ Fold 4: Validation loss 0.1422
- ✧ Fold 5: Validation loss 0.1468

The optimal learning rate was determined to be 0.01, which yielded the lowest average validation loss during the cross-validation process. Subsequently, a model trained with this learning rate was evaluated on the test set, where it produced a denormalized Mean Absolute Error (MAE) of 500.84.

Both the BP neural network and GBRT models demonstrated robust performance in predicting the target variable. The models were optimized using 5-fold cross-validation to select the best learning rate, ensuring stability and reliability. However, based on the observed Mean Absolute Error (MAE) in both validation and test sets, the BP neural network model displayed marginally superior performance. This may indicate a better fit to the underlying patterns in the data.

3) PERMUTATION FEATURE IMPORTANCE

The ability to predict 1-hour rowing distance using the BP neural network model relies on the integration of 45 distinct variables. Understanding the relative importance of these variables provides insights into their individual contributions to the model's predictive accuracy. To this end, we employed permutation feature importance analysis to evaluate the significance of each feature.

The results of this analysis are depicted in Fig. 5 and reveal the hierarchical importance of the different variables.

The five most impactful features include "Mean Longitudinal Jump Height Before Exercise" (average importance 0.1188), "CHO Intake Rate" (average importance 0.0953), "Age" (average importance 0.0813), "Light Sleep" (average importance 0.0570), and "Activity Level" (average importance 0.0520). These features likely encompass physical, lifestyle, and physiological factors that affect rowing performance.

Conversely, the five least impactful features are "Upper Arm Circumference" (average importance -0.0124), "Abdominal Skinfold" (average importance -0.0128), "Hemoglobin" (average importance -0.0128), "LF" (average importance -0.0136), and "Resting Heart Rate-Basal" (average importance -0.0153). This suggests that these indicators may add noise rather than meaningful information to the model, and thus they appear to have a weaker role in predicting rowing distance.

These findings underscore the complexity of endurance performance and highlight individual characteristics that may influence rowing distance. By understanding the importance of these features, we provide the foundation for a personalized approach to optimizing CPS supplement intake.

C. PERSONALIZED CPS INTAKE PROTOCOL RECOMMENDATION THROUGH BP NEURAL NETWORK AND ENUMERATION METHOD

The ultimate goal of our study is to provide personalized CPS intake rate recommendations. To achieve this, we employed a two-stage process involving the BP neural network and enumeration method [51]:

1) BP NEURAL NETWORK MODELING

CPS Intake Protocol Random Assignment 171 subjects were randomly assigned one of the 8 intake rates (0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.1, 1.2g/kg/h).

- *Individual Indicator Collection*

After the CPS intake rate assignment, 44 other individual indicators were gathered for each subject.

- *Rowing Distance Measurement*

Subsequently, the rowing distances were recorded.

- *Regression Model Establishment*

A BP neural network was employed to create a regression model that aims to elucidate the relationships between the 45 individual indicators and rowing performance.

- *Model Training*

Using the collected data, the BP neural network was trained to understand these relationships.

2) PERSONALIZED CPS INTAKE RATE RECOMMENDATION

The BP neural network serves as the foundation for identifying the relationship between the 45 individual indicators and rowing distances. The enumeration method is used to explore the best CPS intake protocol.

- *Enumeration of Intake Rates*

We divided the range of 0.5g/kg/h–1.2g/kg/h into 71 intake rates with a step of 0.01.

- *Combination with Other Indicators*

As can be seen in the Fig. 6 using the enumeration method, we combined each of the 71 CPS intake rates with the other 44 indicators, inputting them into the BP neural network model.

- *Prediction of Rowing Distances*

This resulted in 71 predicted rowing distances, each corresponding to a specific CPS intake rate.

- *Selection of Optimal Rate*

The intake rate corresponding to the longest rowing distance was considered the best one for the individual, thus completing the personalized CPS intake rate recommendation.

This intricate process ensures that the recommended CPS intake rate is tailored to the individual's unique characteristics, maximizing their exercise performance.

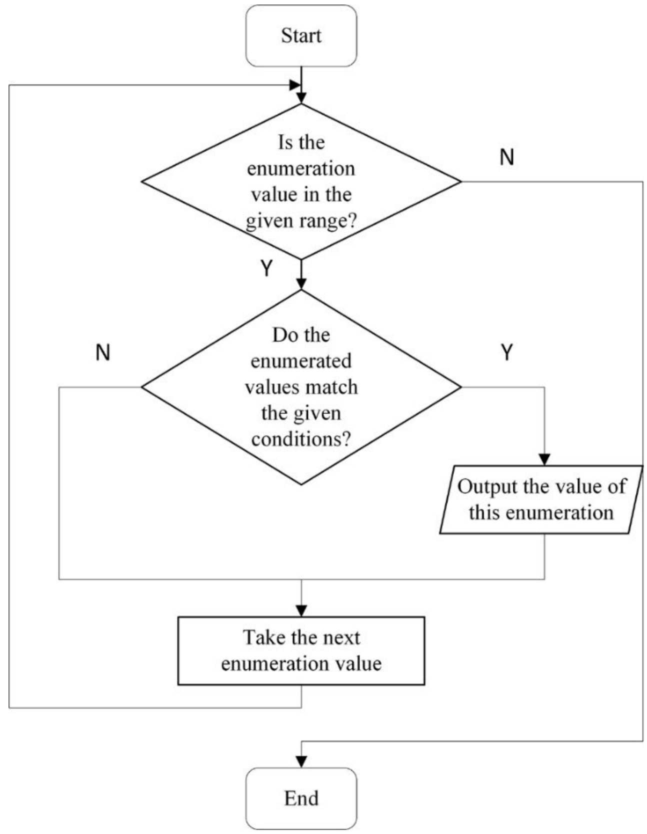

FIGURE 6. Steps in the enumeration method.

IV. DISCUSSION

In this study, we introduced a novel method for recommending a personalized CPS intake regimen for endurance exercise enthusiasts. The method consists of two main parts: 1) a BP neural network to find relationships between exercise performance and various indicators, including lifestyle, psychological state, sleep quality, demographics, anthropometrics, physical activity levels, exercise capacity, blood parameters, central nervous system parameters, cardiovascular metrics, meal timings, and beverage composition; 2) an enumeration method to identify the most suitable CPS intake strategy for individual subjects. Our findings will offer insights into personalized CPS supplementation intake strategies in sports.

A. MODEL COMPARISON AND CONFIGURATION DETAILS

In our study, we conducted a comparative analysis between the BP neural network and the GBRT model. Both models were carefully tuned, focusing on selecting the best learning rate through 5-fold cross-validation to ensure stability and reliability. The BP neural network was designed with three hidden layers, utilizing the Adam optimizer, and was trained with a learning rate of 0.01 over 151 iterations. In contrast, the

GBRT model was employed with default settings, including trees with a maximum depth of 3 and a minimum sample split of 2.

The results revealed that both the BP neural network and GBRT model demonstrated robust performance in predicting the target variable. Specifically, the BP neural network achieved a MAE of 470.77, whereas the GBRT model yielded a MAE of 500.84. Although both models were effective in capturing complex patterns in the data, the BP neural network displayed slightly superior performance. This indicates that the BP neural network may offer a better fit to the underlying patterns in the data, potentially making it a more suitable choice for this particular application. The comparative analysis enhances our understanding of the modeling choices and provides valuable insights for future research in personalized CPS supplementation intake strategies.

B. PERMUTATION FEATURE IMPORTANCE

The permutation feature importance analysis conducted in our study sheds light on the intricate relationship between various input indicators and the 1-hour rowing distance. By evaluating the decision-making behavior of the BP neural network model, this analysis enhances trust in the model and provides a nuanced understanding of the underlying factors affecting rowing performance.

The five most impactful features identified, including "Mean Longitudinal Jump Height Before Exercise", "CHO Intake Rate", "Age", "Light Sleep", and "Activity Level", reflect a combination of physical capabilities, nutritional factors, age-related considerations, sleep quality, and overall activity levels. These attributes capture essential aspects of an individual's fitness and lifestyle, and their significant influence on rowing distance underscores the multifaceted nature of endurance performance. Their prominence in the model suggests potential areas for targeted interventions and personalized strategies to optimize CPS supplement intake.

The most impactful features identified, such as "Mean Longitudinal Jump Height Before Exercise" and "CHO Intake Rate", are consistent with prior research emphasizing the role of physical strength [52] and nutritional factors [3] in endurance performance. Sergio et al. [52] found that the power output of deep squat jumps and countermovement jumps were related to the performance of rowers. This implies that the vertical jumping ability of rowers may be one of the important factors affecting their performance in the rowing ergometer. Endurance sports are long in duration and require adequate metabolic substrates to energize the body, with CHO and PRO being the main sources of energy. When performing high-intensity exercise, CPS can provide the body with a large amount of energy to maintain exercise performance. Existing studies have shown [53] that CPS promotes the storage and recovery of muscle glycogen [54], which improves exercise performance and the rate of recovery of the body.

'Age,' identified as another significant factor, aligns with studies highlighting age-related physiological changes that can influence exercise capacity [55]. Meanwhile, the importance of 'Light Sleep' and 'Activity Level' resonates with emerging research on the interconnectedness of sleep quality, daily activity, and athletic performance [34], [36].

On the other hand, the discovery of the least impactful features, such as "Upper Arm Circumference", "Abdominal Skinfold", "Hemoglobin", "LF", and "Resting Heart Rate-Basal", provides insights into the variables that may not contribute meaningfully to the predictive power of the model. The negative values in permutation feature importance for these variables intriguingly indicate that their permutation might enhance the model's accuracy. This could be a signal that these features introduce some degree of noise into the model, a finding that warrants further exploration and may lead to model refinement.

The 'Upper Arm Circumference' and 'Abdominal Skinfold,' might seem counterintuitive given their common association with body composition assessment. However, some studies have found mixed results regarding these variables' influence on endurance activities [56], [57], which may explain their limited impact in our model.

The negative values in permutation feature importance for indicators like 'Hemoglobin,' 'LF,' and 'Resting Heart Rate-Basal' present an intriguing observation. While these parameters have been explored in various contexts [58], [59], [60], our findings suggest that they may not be universally applicable or may even introduce noise into the model. This highlights the complexity of individualized performance prediction and calls for further research to elucidate these unexpected results.

Overall, our analysis contributes to the growing body of literature on personalized CPS supplementation, drawing on and extending previous research to offer a nuanced understanding of the factors influencing endurance performance.

C. THE ROLE AND VALUE OF THE ENUMERATION METHOD IN PERSONALIZED CPS INTAKE PROTOCOL RECOMMENDATION

The enumeration method employed in this study, in conjunction with the BP neural network, represents a significant advancement in the field of personalized CPS intake rate recommendations. By dividing the effective range of CPS intake into 71 distinct levels and integrating them with 44 individual indicators, this approach ensures that each recommendation is uniquely tailored to maximize exercise performance.

The integration of the enumeration method with the BP neural network demonstrates a novel and flexible modeling strategy. This combination not only enhances the model's accuracy but also offers a scalable framework adaptable to diverse sports environments and populations.

D. DISCUSSION OF MODEL LIMITATIONS AND FUTURE DIRECTIONS

Despite its success, our model may have limitations in terms of potential underperformance in specific scenarios. Future work could explore more advanced models or techniques, such as deep learning or ensemble methods, to overcome these challenges. Additionally, the inherent challenges of data collection and preprocessing remain complex tasks in sports science, requiring consideration of time investment and economic aspects.

The human body's complexity, marked by individual variations in lifestyles, gut flora, hormone secretion levels, and psychological states, affects the utilization of sports supplements and improvements in athletic performance [7], [8], [9], [10]. In this study, we addressed these intricacies by using 45 indicators as input indices for the BP neural network, enabling it to uncover relationships with exercise performance. While neural networks such as CNN [61], DCNN [62], [63] and RNN [64] offer strong fitting abilities, their requirement for large sample sizes often restricts their application, primarily to image recognition. In contrast, BP neural networks, with their lesser data volume requirements, have been widely applied in similar studies, thus representing a fitting choice for our research.

In conclusion, our study lays the groundwork for future advancements in the field of personalized CPS supplementation intake strategies. While acknowledging certain limitations, we open new avenues for more effective and practical solutions, contributing to the ongoing innovation in sports nutrition and performance optimization.

V. CONCLUSION

In this study, we developed a machine learning-based personalized CPS decision-making method tailored to endurance exercise enthusiasts. This approach integrated 45 indicators across 12 diverse aspects, including lifestyle, psychological status, sleep quality, demographics, anthropometrics and body composition, physical activity levels, exercise capacity, blood and CNS parameters, CS parameters, meal timings, and the composition of consumed beverages. Utilizing 171 samples, we applied the BP neural network to uncover the relationship between these 45 indicators and endurance exercise performance. Subsequently, we implemented personalized CPS recommendations using an enumeration method.

Our findings indicate that this novel method can effectively recommend CPS use protocols, drawing on multidimensional individual information. The results affirm its practicality and feasibility in the sports science domain. As we look to the future, expanding the dataset and continuing to iterate and update the machine learning model will be essential. Such efforts can further enhance the model's robustness and accuracy, contributing to more precise and personalized CPS supplementation strategies for athletes and fitness enthusiasts.

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XIANGYU WANG was born in Shandong, China. He received the bachelor's degree in physical education from Anhui Normal University, China, in 2016, and the master's degree in physical education teaching from Shandong Normal University, China, in 2019. He is currently pursuing the Ph.D. degree in youth physical sports training with the Capital University of Physical Education and Sports, China. He is also a significant contributor to three patents related to physical endurance testing methods and a training method for massage robotic arms based on deep reinforcement learning. He is the coauthor of a book *Integrated Sports Pharmacology* and an article titled "Artificial Neural Network-Based Model for Evaluating Maximum Oxygen Uptake from the Incremental Squatting Test in Young People." His research interests include physical endurance testing, deep reinforcement learning applications in sports, and youth physical sports training. He is a member of the Sports Artificial Intelligence Committee. He has also demonstrated his commitment to community service as a lifeguard of the Beijing Red Cross Society. He is a member of the China Lifesaving Association. In addition, he is a Swimming Lifeguard and a Social Sports Instructor (Swimming). He is proficient in Mandarin Chinese, with a Second Grade A level in the National Putonghua Proficiency Test, and has also achieved the College English Test Band 6. He holds the Teacher Qualification Certificate, demonstrating his dedication to fostering the next generation of sports science researchers and practitioners.

ZIHAO LI is currently pursuing the Ph.D. degree in education with the Capital University of Physical Education and Sports. He is a Lecturer with the Capital University of Physical Education and Sports and is renowned for his dedication to education and remarkable athletic achievements. His credentials extend beyond academia, revealing a competitive spirit in athletics. He holds the title of a Level One Coach from the International Association of Athletics Federations (IAAF), a testament to his expertise in the field. In his role as a Lecturer, he primarily focuses on the study of physical functional training, sports training science monitoring, promotion of health through sports, and athletics teaching and training. During the Ph.D. degree, he has cultivated his academic and athletic prowess during his undergraduate and master's studies. He is passionate about combining his love for athletics with his commitment to education, making significant contributions to the field of sports science. His work is not only shaping the future of athletic training but also promoting a healthier and more active lifestyle. His athletic prowess is further demonstrated by his victories at various national competitions, including the National Collegiate Athletics Championship, the National Physical Education Institutions Athletics Championship, and the Beijing Universities Athletics Championship. His contribution to the preparations for the 2020 Tokyo Olympics was recognized with an award, highlighting his role in the advancement of athletics on a global stage.

HAO WU is currently a Ph.D. Mentor. He is an Eminent Scholar in the field of exercise physiology. He is a Professor at the School of Kinesiology and Health, Capital University of Physical Education and Sports. He has established himself as a high-level sports academic and technical talent within the National Sports Bureau, as well as an Olympic Technology Expert. He is the Leader of the Beijing's Talent Empowers Education Academic Innovation Team. In addition to his academic pursuits, he is the Founder and Curator of the Spiral Culture Museum and the Co-Founder of the China Rural Development Foundation. Through years of theoretical research and applied research practice, he has accumulated a wealth of experience in the fields of exercise physiology, biochemistry, and sports nutrition. During the preparation for the 2008 Beijing Olympics, he was the Head of the National Team's Research Team and was a member of the Olympic Plateau Training Technology Expert Group under the National Sports Bureau. In universities, he undertakes bachelor's, master's, and Ph.D. courses, including sports nutrition, a professional direction course in sports human science, teenage physical function training and nutrition recovery, and a bilingual course, in health promotion and weight control. He has mentored and guided nearly 50 master's and doctoral students. He has undertaken numerous projects funded by the Ministry of Education Doctoral Fund, the National Sports Bureau Olympic Technology Attack, the Ministry of Science and Technology Support Plan, and the National Philosophy Social Science Project. He has completed nine monographs and translations and obtained three national invention patents and one utility model patent technology in sports nutrition. He is also an esteemed member of the International Society of Sports Nutrition (ISSN) and a Standing Committee Member of the Sports Physiology and Biochemistry Branch of the Chinese Sports Science Society. His extensive roles and responsibilities extend to being a member of the Science Popularization Committee, the Secretary-General of the International Exchange Committee, and the Vice Chairperson of the Beijing Sports Science Society. For his exceptional contributions, he earned recognitions such as the 2008 Beijing Olympic Games Special Contribution Advanced Individual Award from the National Sports Bureau and the Chinese Olympic Committee, the Olympic Merit Award and the May 1st Labor Medal from Beijing, and the Beijing Advanced Worker (2010) Title. His contributions led to a historic breakthrough for China's rowing project, which secured a gold medal at the Olympics.