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Analysis of the mechanism of physical activity enhancing well-being among college students using artificial neural network

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This study explores the impact mechanism of college students' sports behavior on their well-being by constructing an Artificial Neural Network (ANN) model. The study employs an ANN architecture that combines a Long Short-Term Memory (LSTM) network and a Convolutional Neural Network (CNN). A prediction model is established based on the characteristics of sports behavior and psychological indices of well-being, such as psychological resilience, self-efficacy, and subjective well-being. The results show that the proposed LSTM + CNN model has achieved significant improvement on the test set. Its mean absolute error is only 0.072, the mean square error is 0.00596, and the root mean square error is 0.077, which is remarkably superior to traditional machine learning methods such as random forest and support vector regression. The innovative advantages of the proposed model in capturing the nonlinear relationships and deep characteristics of psychological and behavioral data is proved. The analysis of Shapley Additive Explanations (SHAP) values reveals three key factors significantly influencing well-being improvement. These impactful factors include the high-frequency exercise days per week (≥ 4), sustained morning exercise duration, and participation levels in group sports activities. The analysis of the dynamic threshold effect reveals that the critical points of distinct characteristic values exhibit substantial variations in their impact on well-being. Concurrently, the regulatory influence of sports behavior demonstrates differing intensities across diverse conditions. This study provides a new theoretical basis for designing personalized sports interventions and improves the accuracy of predicting psychological measurement data. Thus, it demonstrates the potential of sports behavior in promoting the mental health and well-being of college students.

Keywords Artificial neural network, Psychological resilience, SHAP value analysis, Sports behavior, Well-being

In modern society, college students, as a distinct demographic, confront substantial pressures from academic studies, employment, and social adaptation. While striving for academic excellence remains a priority, their physical and mental health has emerged as an increasingly critical concern. The improvement of mental health and well-being has become a core issue in the research domains of psychology, sports science, and health management[1–3]. Empirical evidence confirms that physical exercise exerts a profound positive influence on mental states, effectively enhancing psychological attributes such as individual resilience and emotional regulation capabilities. Extensive research demonstrates that regular physical exercise improves subjective well-being and strengthens psychological resilience and self-efficacy, fostering a more robust mental health profile[4–6]. Exercise, as a non-pharmaceutical intervention method, improves the physical condition of college students. It also indirectly affects their mental health in terms of cognitive regulation, emotional recovery, and social support.

However, current research on the relationship between exercise and well-being still has obvious limitations. On one hand, existing studies mostly adopt methods such as traditional regression analysis and structural equation modelling. If there is a linear or fixed-path relationship among the variables, it is difficult to reflect the potential nonlinear and multi-order interaction effects between variables[7,8]. On the other hand, most existing models are based on single data sources, such as questionnaires or interviews. There is a lack of systematic characterization of the dynamics and complexity of sports behavior, and a computational model with predictive ability has not

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yet been formed. These limitations restrict the in-depth understanding of the mechanism of college students' exercise well-being. Sarlis and Tjortjis (2020) conducted a systematic evaluation of both contextual and advanced basketball metrics used in the National Basketball Association (NBA) and European leagues. This demonstrated that data-driven approaches played a crucial role in enhancing model interpretability and prediction accuracy[9]. Subsequently, Sarlis et al. (2021) identified key injury-related variables and their impact mechanisms in the NBA through literature review and data analysis methods, proposing viable modeling pathways for sports performance prediction[10]. These studies highlighted the value of parameter identification and data structure integration in complex behavioral pattern modeling. As a powerful data modeling tool, the Artificial Neural Network (ANN) has been increasingly applied in the fields of psychology and health, relying on its excellent ability to handle nonlinear relationships and capture high-dimensional complex data. Recent studies also demonstrated the broad potential of ANNs in sports behavior analysis. Xu et al. (2023) developed a predictive model combining neural networks with anterior cruciate ligament load modeling, which achieved accurate predictions by incorporating fatigue factors[11]. In 2024, they further proposed a novel gait feature selection method based on metaheuristic optimization, identifying optimal subsets from 36 indicators to enhance clinical gait recognition accuracy and efficiency[12]. These studies established a solid theoretical and technical foundation for applying ANNs in sports behavior prediction and psychological modeling.

In terms of deep structure design, Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) shows strong potential in psychological prediction. LSTM is good at modeling temporal dependency information in emotional and behavioral changes, suitable for processing dynamic variables such as exercise rhythms. CNN excels in local pattern recognition and hierarchical feature extraction, capable of automatically learning high-order representations from multimodal behavioral segments. The hybrid architecture of LSTM + CNN forms complementary advantages among feature learning, temporal modeling, and local perception. This has been applied to frontier tasks in behavioral science, such as sleep quality assessment and stress detection, demonstrating excellent generalization and interpretation potential. Given this, this study uses the LSTM + CNN hybrid network to construct a multimodal exercise-well-being prediction model. Meanwhile, it explains the contribution and threshold effects of key exercise features through Shapley Additive Explanations (SHAP).

The objectives of this study are as follows. (1) The wearable devices, campus platform, and questionnaire data are fused to build a high-dimensional feature system; (2) The deep model is used to improve the prediction accuracy of various dimensions of well-being; (3) The nonlinear threshold and interaction mechanism of sports behavior are analyzed to provide a basis for precise intervention. The study's main innovation is the introduction of LSTM + CNN modeling college students' sports behavior and well-being relationship, breaking through the constraints of linear models. This study also constructs a multimodal feature system that integrates data from questionnaires, self-sensing devices, and campus sports platforms. The SHAP method is used to realize the interpretability analysis of feature contribution, and the key influencing mechanism of sports behavior is identified. The dynamic threshold characteristics of key variables in well-being prediction are proposed to provide a basis for personalized intervention strategies. Thus, this study aims to make up for the lack of analysis of the exercise-well-being mechanism in traditional research. Moreover, the study provides theoretical and methodological support for the design of mental health intervention policies and digital health support tools in universities.

Literature review

In recent years, the academic community has paid increasing attention to the relationship between sports behavior and well-being, and related studies have revealed the complex psychological mechanisms between the two from multiple perspectives. Stenseng et al. (2023) explored the role of the two-dimensional escapism model of self-expansion (adaptive escapism) and self-suppression (maladaptive escapism). They found that self-expansion was positively correlated with subjective well-being, while self-suppression was negatively correlated with well-being. Self-expansion and self-suppression played an explanatory role in the inverse relationship between sports dependence and well-being[13]. Zhang et al. (2024) found a significant positive relationship between physical activity and mental health. This relationship was mediated by self-efficacy and stress self-management[14]. Martín-Rodríguez et al. (2024) explored the positive impact of sports on mental health, including emotion regulation, resilience, cognitive function, and the treatment of mental illnesses. It indicated that regular exercise combined with mindfulness practice improved emotions, managed stress, and enhanced social skills[15].

With the extensive application of artificial intelligence (AI) in mental health research, the relevant fields are constantly expanding innovative paths. Gigerenzer (2024) illustrated through two examples how psychological theories could enhance algorithm efficiency. One example to improve the influenza prediction algorithm was to utilize the principle of "recency". The other was to design an algorithm for predicting recallability based on the "paradox effect", showing that psychological AI facilitated developing efficient and transparent algorithms[16]. Khoo (2024) systematically reviewed 184 studies, evaluated the feature extraction, fusion methods, and machine learning methods for detecting mental health disorders from multimodal data. He also pointed out that the application of neural network architectures in model-level fusion and machine learning algorithms was increasing, demonstrating the potential to handle high-dimensional features and modal relationships[17]. Khan et al. (2024) used principal component analysis and ANN models to investigate the relationship between psychological variables and cognitive functions of Indian college students and predicted cognitive performance. They emphasized the importance of addressing the mental health issues of college students and implementing intervention measures to enhance cognitive functions[18].

In the field of motion recognition and human behavior modeling, Sinha and Kumar (2023) developed a novel mechanism based on micro multidimensional local coding convolutional neural networks for human activity recognition from drone videos. This approach significantly improved recognition efficiency through sequential steps, including bounding box generation, clustering, contour segmentation, feature extraction, and encoding[19]. Sinha and Kumar (2024) subsequently proposed an ensemble classification model for human activity recognition comprising four stages: preprocessing, segmentation, feature extraction, and classification. The model achieved substantial accuracy improvements by employing an enhanced balanced iterative reducing and clustering utilizing hierarchies (BIRCH) algorithm for efficient segmentation. Meanwhile, this model combined with gray-level co-occurrence matrix, local gradient threshold patterns, and bag-of-visual-words feature extraction methods, along with an integrated CNN-LSTM classification architecture[20]. These technological advancements established paradigmatic references for high-dimensional perception and modeling of sports behavior. AI applications extended significantly into mental disorder identification and social health domains. Hussain (2024) reviewed the growing economic burden and rising prevalence of global mental health disorders. They examined AI applications in detecting cognitive and developmental conditions such as post-traumatic stress disorder and autism spectrum disorder[21]. Kalita et al. (2025) investigated educational data mining applications over the past decade. They highlighted its positive impacts on learning experience enhancement, educational strategy improvement, and institutional efficiency optimization[22], thereby providing external validation perspectives for student well-being prediction models. Collectively, existing literature demonstrated the significant value of sports behavior in mental health promotion, while confirming the superior capability of AI models, particularly deep learning methods, in extracting complex behavioral features.

Although the above studies have revealed multiple connections among exercise, mental health, and AI applications, there are still three gaps to be filled. First, single-dimensional data: past studies mostly rely on questionnaires or single sensor data, insufficiently integrating multi-source information from wearable devices and campus exercise platforms. This struggles to comprehensively characterize college students' real sports behavior. Second, conservative modeling methods: traditional statistical or single deep architecture show limitations in capturing high-order interactions and temporal-spatial coupling features, leading to insufficient accuracy and stability of well-being prediction. Third, weak explanation mechanism: previous work mostly stays at the macro correlation test, lacking interpretable model outputs for critical points of sports behavior and nonlinear interaction effects. This makes it difficult to provide a quantitative basis for individualized interventions. Aiming at the above gaps, this study innovatively proposes a multimodal feature system integrating wearable, campus exercise big data, and psychological scales. It introduces an LSTM + CNN hybrid network to extract temporal and local patterns synchronously, using the SHAP method to quantify feature contributions. This further clarifies the intensity inflection points of key sports behavior on different dimensions of well-being through dynamic threshold identification. Compared with existing studies, this study significantly improves the prediction accuracy of well-being. The study also provides an operational threshold and interaction interpretation framework for the first time, laying a data-driven foundation for the design of precise intervention programs in colleges and universities.

Research methodology
Research variable setting
The core of this study lies in exploring the complex relationship between the sports behavior of college students and their well-being. In this process, sports behavior serves as the independent variable, influencing the mental health and well-being of individuals; well-being is examined as the main dependent variable of the study. The measurement of sports behavior does not merely stay at the surface level of exercise frequency or duration. Instead, factors such as the intensity, duration, and exercise types are considered more comprehensively[23–25]. According to the Physical Activity Rating Scale-3 (PARS-3), sports behavior is classified into three types of indices: frequency, intensity, and duration[26,27]. Frequency measures the number of times an individual exercises per week, intensity reflects the degree of fierceness of the exercise, and duration focuses on the length of each exercise session.

Well-being, as the dependent variable, involves multiple psychological dimensions. Life satisfaction, positive affect, negative affect, psychological resilience, and self-efficacy are selected to reflect the subjective well-being state of individuals[28–30]. Life satisfaction represents the overall evaluation of an individual's quality of life. Positive affect and negative affect, respectively, indicate the pleasant and unpleasant emotions experienced by individuals in daily life. Psychological resilience and self-efficacy are two key psychological variables. The former shows an individual's ability to withstand and adapt to challenges and pressures, while the latter reflects an individual's confidence in completing specific tasks. Through enhancing psychological resilience and self-efficacy, sports behavior can indirectly promote the well-being of individuals.

Design and construction of ANN model
In this study, ANN is selected as the main modeling tool. Compared with traditional statistical models, ANN has unparalleled advantages in handling multi-dimensional data, capturing nonlinear relationships, and the interaction effects between variables[31,32]. Considering that well-being is a psychological variable with dynamic fluctuation characteristics, and sports behavior also has obvious time series, the constructed ANN model introduces a time-sensitive structure and integrates a local feature extraction mechanism. The structure is displayed in Fig. 1.

Regarding the model structure design in Fig. 1, a hybrid neural network architecture fusing LSTM and CNN is constructed to fully exploit the complex temporal and nonlinear interaction mechanisms between sports behavior and well-being. The model inputs include multi-dimensional feature data, where sports behavior features cover exercise frequency, average intensity, duration, weekly step counts, and common exercise types. Psychological well-being features encompass psychological resilience, self-efficacy, subjective well-being, and life satisfaction scores from psychological scales. Additionally, control variables such as gender, grade, and major are introduced. To enhance model training stability and efficiency, all features undergo standardization and

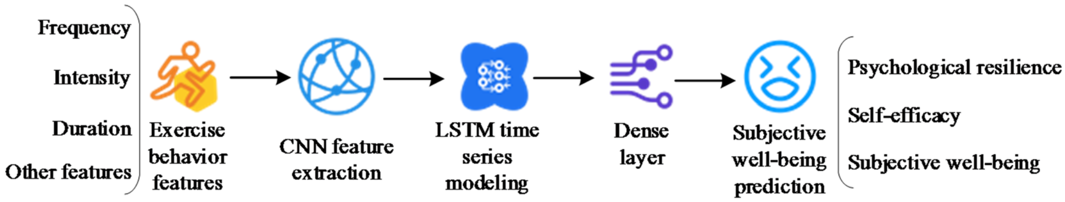

Fig. 1. ANN modeling between exercise and well-being.

normalization processing. For the temporal input structure of LSTM, taking "day" as the unit, sports behavior features for 7 consecutive days are constructed into a time-window sequence. Meanwhile, the well-being scale score on the 8th day is used as the corresponding prediction target, thereby generating temporal samples for supervised learning. This sliding window design not only ensures the integrity of training data but also effectively simulates the potential lagged relationship between "behavior-result".

In terms of the network structure, a layer of LSTM first models the constructed time-series data, with this layer set to 64 memory units to effectively capture long-term dependencies of cross-day behaviors. Subsequently, a one-dimensional (1D) CNN layer is stacked on the temporal representation output by LSTM. This layer sets 32 convolution kernels, the convolution window size is 3, and the activation function is ReLU to enhance the model's perception of local temporal features. Hence, behavioral segments are identified that may have special impacts on well-being, such as "continuous vigorous exercise" or "no exercise on a certain day". After feature extraction, they are flattened into a 1D vector through the Flatten operation and connected to two fully connected layers containing 128 and 64 neurons, respectively. The final output layer is set as a single-output regression node according to the task type for predicting well-being scores, or a multi-category softmax output for well-being grade classification. The entire model uses an Adam optimizer, with the loss function being mean squared error (MSE), and employs an early stopping strategy to prevent overfitting. For ease of understanding and reproduction, the pseudocode of the core model is presented in Fig. 2.

To enhance the model's interpretability and practical guidance, the SHAP method is introduced after model training to conduct feature-level interpretive analysis of the deep network's decision mechanism. As a game theory-based model interpretation framework, SHAP assigns a Shapley value representing the marginal contribution to each input feature. Thus, this reveals the positive/negative impacts and importance of different features on model predictions. A subset of training data is used as the SHAP background reference set. Meanwhile, based on the trained LSTM + CNN model, SHAP value decomposition is performed for the prediction result of each sample in the test set. This process not only yields the ranking of sports behavior variables with the most significant impact on well-being prediction at the global level but also reveals individual-level nonlinear response relationships and key thresholds. For example, results show that variables like "total weekly exercise time" exhibit saturation or even reversal of marginal effects after reaching specific thresholds, indicating an optimal interval for exercise interventions. Additionally, SHAP's visualization tools are employed to plot feature dependency plots and interaction diagrams, assisting in explaining the key exercise-well-being pathway mechanisms identified by the model. Overall, SHAP analysis not only enhances model transparency and trustworthiness but also provides a theoretical basis for formulating personalized exercise recommendations and intervention strategies.

Experimental design and performance evaluation
Experimental materials
The research sample is from a comprehensive university. A combination of random sampling and stratified sampling is adopted, collecting a total of 500 valid data. Stratification criteria include gender, grade, major category, and perceived academic stress level, ensuring the balance and representativeness of data across key demographic variables. To enhance the cultural and social diversity of the sample distribution, participants include students from different majors. Among them, the proportion of science and engineering students is 54%, that of liberal arts and social sciences is 28%, and that of art and sports is 18%. The grade distribution spans from freshman to senior years, with male and female proportions of 49.6% and 50.4%, respectively. Sample information is revealed in Fig. 3.

The sports behavior data are collected by wearable devices. Each subject is required to wear a smart bracelet every day, and the daily sports behavior is continuously monitored for 30 days, including multiple indices such as the daily number of steps, activity duration, heart rate changes, and exercise intensity classification. The exercise frequency is divided into low (≤ 1 time), medium (2–3 times), and high (≥ 4 times) according to the number of exercises per week; the exercise intensity is classified into three levels of mild, moderate, and intense according to the PARS-3 standard. In the data preparation stage, the 500 sample data are divided into a training set and a test set. To adapt to the temporal input requirements of LSTM, 30-day data are partitioned into 4 consecutive weekly windows, with each window containing 7-day data. Five core behavioral features are extracted within each window. (1) High-frequency exercise days are defined as the number of days in the week with daily exercise duration ≥ 30 min. (2) Average daily exercise duration is calculated as total weekly exercise duration divided by 7. (3) Exercise heart rate variability selects daily resting R-R intervals and uses Standard Deviation of the Normal-to-Normal intervals (SDNN) for calculation[33]:

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Input:
    - X: 7-day time-series exercise features (frequency, intensity,
duration, etc.)
    - S: Static features (e.g., demographics)
    - Y: Target well-being score

Preprocessing:
    - Normalize X and S
    - Reshape X into [samples, 7, features]
    - Split into train, validation, and test sets

Model:
    - LSTM Layer (units=64, return_sequences=True)
    - 1D CNN Layer (filters=32, kernel_size=3, activation=ReLU)
    - Flatten
    - Concatenate with S
    - Dense Layer (units=128, activation=ReLU, dropout=0.3)
    - Dense Layer (units=64, activation=ReLU)
    - Output Layer (units=1, activation=linear)

Training:
    - Loss: MSE
    - Optimizer: Adam
    - Batch size: 64, Epochs: 100, with early stopping

Explainability:
    - Apply SHAP after model training
    - Analyze global and local feature contributions
    - Identify key behavioral patterns and threshold effects

Output:
    - Trained model and prediction metrics (MSE)
    - SHAP-based interpretation of key exercise features
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Fig. 2. Pseudocode of the LSTM + CNN model.

$$SDNN = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (RR_i - \bar{RR})^2}. \tag{1}$$

RR_i represents the i-th R-R interval, and $\bar{RR}$ refers to the mean R-R interval within the window. 4) The morning exercise persistence cycle is defined as the longest sequence of consecutive morning (05:00–08:00) exercise days in the window. 5) Group exercise participation index measures an individual's activity level in

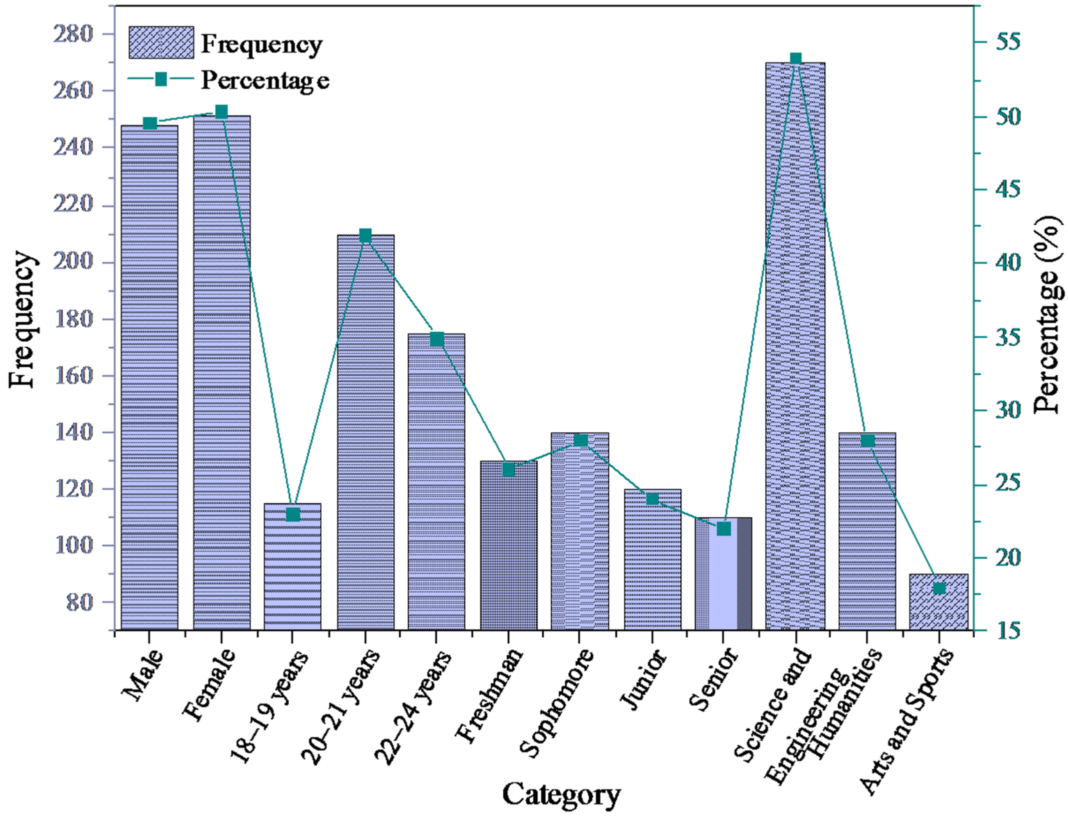

Fig. 3. Descriptive statistics of sample information.

Variable category	Sub variable		Number of entries	Cronbach's α coefficient	KMO value
Psychological resilience	Target concentration		5	0.892	0.936
	Emotional control		6	0.872	
	Positive cognition		4	0.830	
	Family support		6	0.881	
	Interpersonal assistance		6	0.919	
	General psychological resilience		27	0.943	
Self-efficacy			10	0.933	0.905
Subjective well-being	Life satisfaction		5	0.881	0.938
	Sense of happiness	Positive emotion	6	0.908	
		Negative emotion	8	0.919	
	Total table		19	0.926	

Table 1. Psychological measurement tools and reliability and validity indices.

group exercises involving three or more people during the observation period, with values derived from daily exercise records[34]. These behavioral features are rooted in existing literature on sports behavior and mental health, providing strong theoretical support and empirical basis to ensure their interpretability and measurability in LSTM temporal modeling.

The psychological variables of well-being, including psychological resilience, self-efficacy, and subjective well-being, are measured using questionnaires. The results of the reliability and validity tests of each scale are exhibited in Table 1. All psychological scales adopt a five-point Likert scoring system, ranging from 1 point for completely disagree to 5 points for completely agree.

To control for subjective biases in questionnaire measurements, three measures are adopted in the research design. First, questionnaire results are time-aligned and cross-validated with wearable device data to identify abnormal reported values. Second, anonymous filling and online submission are used to weaken social desirability effects. Third, all participants receive a unified instruction document before the study to enhance the accuracy of their understanding and the consistency of their responses. Meanwhile, all participants signed written informed consent forms. The experiment adheres to relevant ethical guidelines throughout, with participant information anonymized and uniformly numbered to ensure irreversible identification. All data undergo complete preprocessing before modeling, including missing value handling, Z-score standardization, and normalization. The training set and test set are divided at an 8:2 ratio, maintaining distribution consistency for each level of psychological well-being. Additionally, to further enhance model robustness and prevent overfitting, 5-fold cross-validation is introduced, with rotational modeling and validation conducted during training. On average, each fold's training and test sets contain 400 samples and 100 samples, with results remaining stable across multiple runs. Cross-validation results and independent test set indices are used to evaluate model generalization. To verify sample balance, distribution consistency tests (χ^2 test and Kolmogorov-Smirnov test) are performed on subvariable distributions, revealing no significant imbalance ($p > 0.05$). Samples are evenly distributed across dimensions such as gender, grade, major, and exercise habits.

The statistical results of weekly exercise frequency, average exercise intensity, and weekly average exercise duration of the sample are shown in Fig. 4.

In Figs. 4 and 82% of the participants engaged in sports more than twice a week, and more than half of the participants tended to engage in high or moderate-intensity exercise. This reflects a high level of sports participation among college students. The distribution of exercise intensity is relatively wide. 46% of the participants have a moderate-intensity exercise, which aligns with the modern fitness trend of pursuing effective exercise results. There are significant differences in the exercise duration of the participants. 45% of the participants exercise for 1 to 3 h per week, and 19% of the participants exercise for less than 1 h. In summary, the sample is well-representative in terms of exercise frequency, intensity, and duration.

Experimental environment and parameters setting

The experimental environment is based on the 64-bit Windows 10 operating system. The experiment is carried out on a computer configured with an Intel(R) Core (TM) i7-7700 3.60 GHz processor, 16GB of memory, and four NVIDIA GeForce GTX 1080 graphics cards. All experiments are developed and implemented using Python version 3.9 and the TensorFlow deep learning framework. To optimize the model's performance, the grid search method is used to adjust multiple hyperparameters of the LSTM and CNN layers. The final model parameter settings are outlined in Table 2.

In the performance evaluation of the model, Mean Absolute Error (MAE), MSE, and Root Mean Square Error (RMSE) are selected as evaluation indices to measure the difference between the predicted and real values. The calculation equation is as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \widehat{y}_i| \tag{2}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y}_i)^2 \tag{3}$$

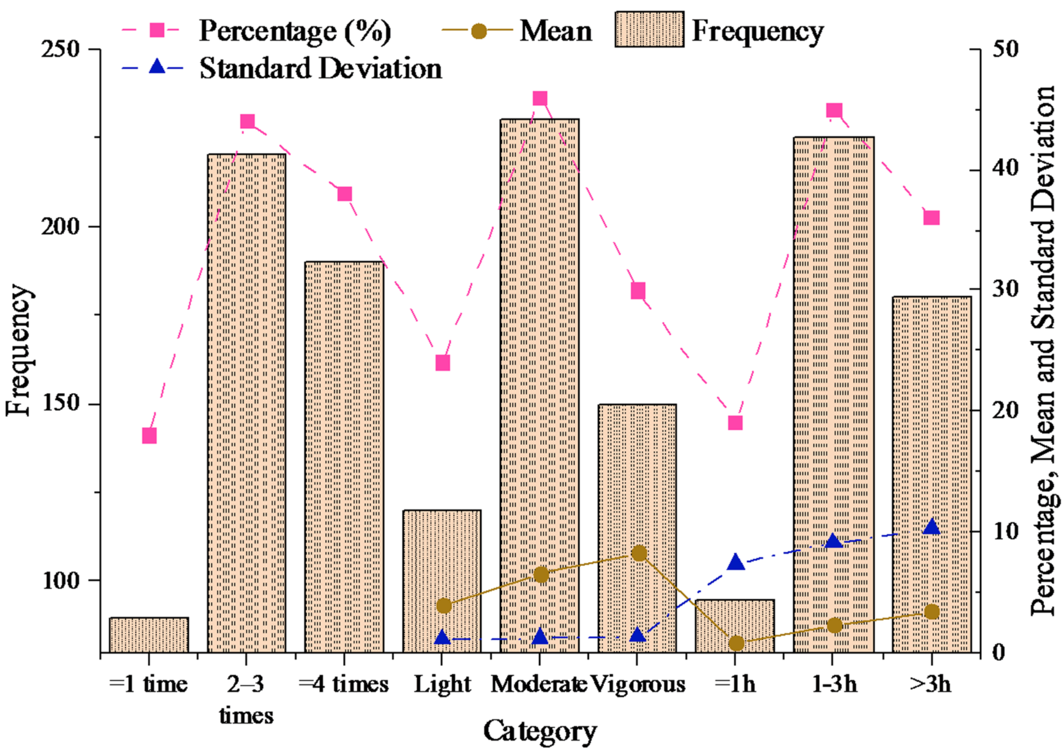

Fig. 4. Statistics of sample motion data.

Parameter	Setting value
Learning rate	0.001
Batch size	32
Optimizer	Adam
LSTM hidden layer unit number	64
CNN convolution kernel size	3 × 3
CNN convolution layer	3
CNN pool layer size	2 × 2
Dropout ratio	LSTM is 0.2, CNN is 0.3
Maximum number of iterations	50
Activation function	ReLU
Loss function	MSE

Table 2. Parameter settings of the ANN model.

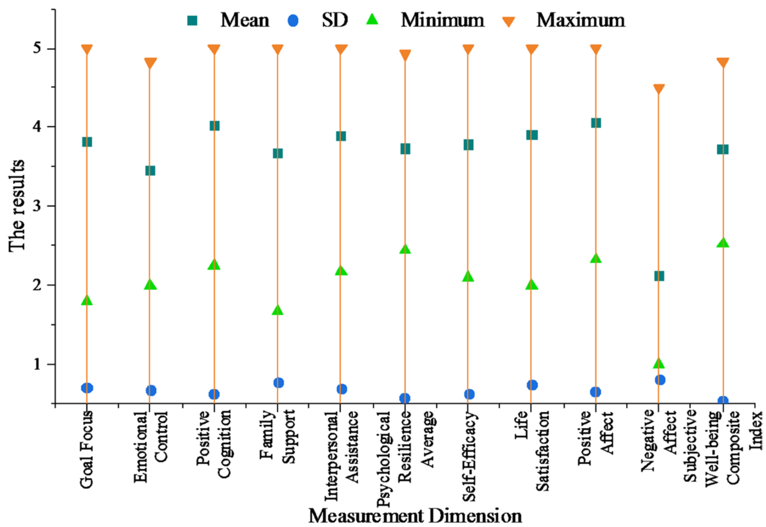

Fig. 5. Descriptive statistical results of sample psychological test variables.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}. \tag{4}$$

n represents the number of samples. y_i and $\hat{y}_i$ refer to the real and predicted value, respectively. According to the interpretable analysis of the model, the importance of each feature is evaluated by combining the SHAP value. SHAP value comes from the concept of Shapley Value in game theory, which aims to distribute the contribution of each feature to the final prediction result fairly.

Performance evaluation

(1) Model accuracy evaluation.

Descriptive statistics are made on the results of psychological measurement tools, and the results of mean and Standard Deviation (SD) are plotted in Fig. 5.

In Fig. 5, there are differences in various dimensions of psychological resilience. The means of goal focus and positive cognition are relatively high, at 3.82 and 4.02, respectively. This indicates that most college students can effectively concentrate their energy and maintain positive thinking when facing challenges. However, the means of emotional control and family support are relatively low, suggesting that some college students have deficiencies in emotional regulation and social support. The mean of self-efficacy is 3.78, illustrating that the sample has strong self-confidence and the ability to cope with challenges. In terms of subjective well-being, life satisfaction is 3.91, positive effect reaches 4.05, and negative effect is 2.12, reflecting the relatively high life satisfaction and positive emotional experience of the participants.

The LSTM + CNN model is compared with LSTM, CNN, Random Forest (RF), and Support Vector Regression (SVR). The prediction results of each model on the test set are suggested in Figs. 6 and 7.

Figure 7 illustrates that the proposed LSTM + CNN model performs outstandingly in prediction accuracy. The MAE is 0.072, the MSE is 0.00596, and the RMSE is 0.077, all of which are superior to other models. This indicates that the proposed model can effectively approach the actual values in predictions of various dimensions and has a

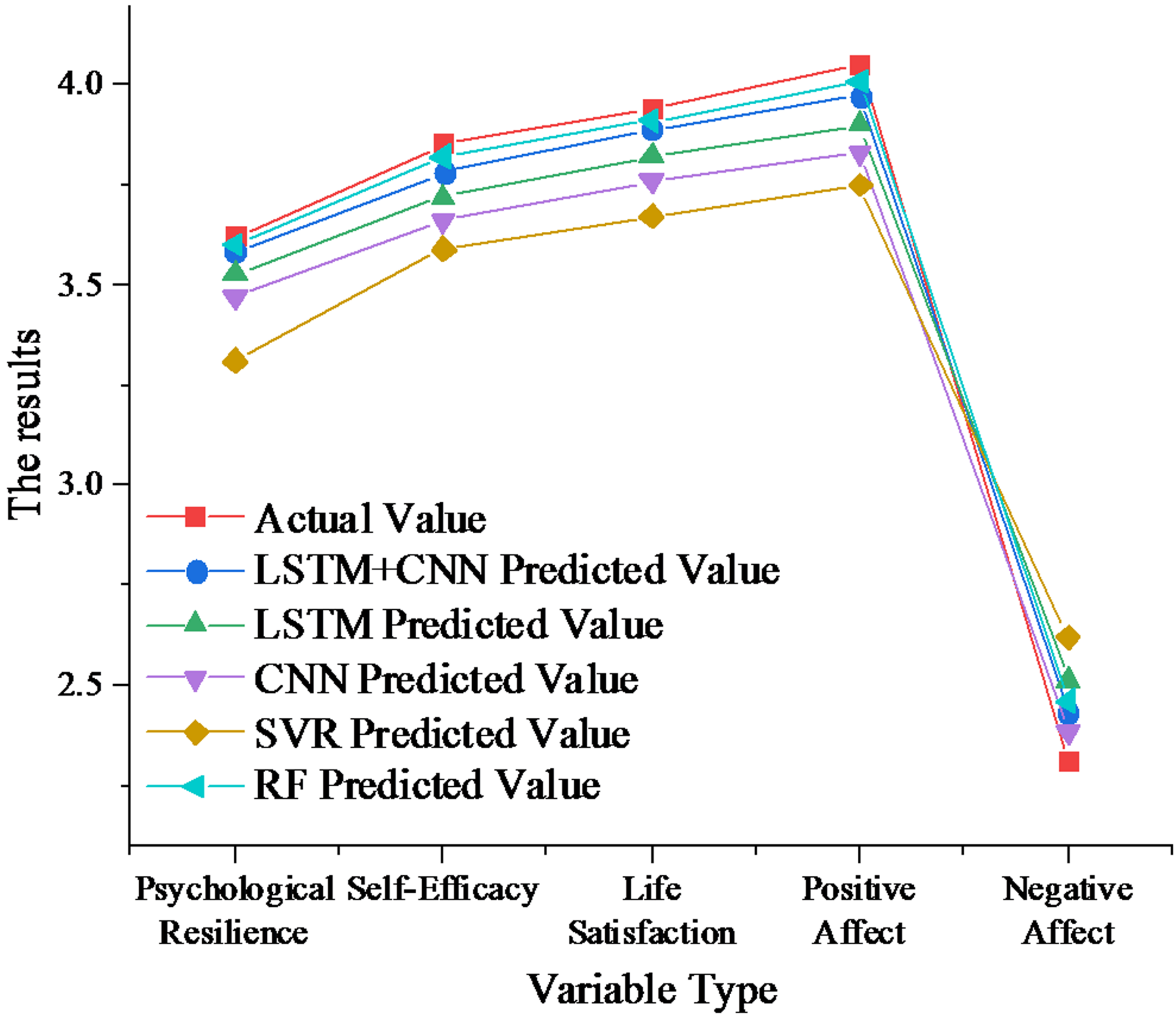

Fig. 6. Comparison between the true mean of psychological variables and the predicted mean of the model.

small prediction error. In comparison, the single LSTM and CNN models have limitations in capturing complex relationships. Among traditional machine learning methods, the SVR has a relatively large error, reflecting its deficiency in modeling nonlinear relationships. The RF is close to the LSTM + CNN in terms of MAE and RMSE, but its MSE is slightly inferior. Overall, the LSTM + CNN, with its stronger advantages in feature extraction and deep learning, demonstrates remarkable superiority in predicting psychological measurement data. To verify the statistical significance of the reported prediction errors and exclude random interference, 5-fold cross-validation is employed to assess the robustness of each model. The LSTM + CNN model achieves an average RMSE of 0.081 (SD = 0.014) in cross-validation, with a 95% confidence interval of [0.074, 0.088]. Additionally, paired t-tests are conducted to examine the significance of RMSE differences between LSTM + CNN and other models. Results show that LSTM + CNN exhibits statistically significant advantages in prediction accuracy over LSTM, CNN, and SVR ($p < 0.01$), while the difference from RF is not significant ($p = 0.09$). These statistical findings further support the prediction stability and superiority of the LSTM + CNN model in the task of this study.

Although the LSTM + CNN model outperforms others in prediction accuracy, practical applications must still consider issues such as model interpretability and computational overhead. The average computational time and interpretability scores of each model during training and prediction are listed in Table 3. The interpretability score adopts a model transparency rating method, where higher scores indicate greater interpretability.

In Table 3, deep learning models indeed require more computational resources during training and prediction. Especially, the LSTM + CNN model has higher computational time and relatively weaker interpretability due to its deeper network structure. This may impose certain limitations on deployment in scenarios with large data scales, high model transparency requirements, or limited computational resources. However, it is emphasized that the LSTM + CNN model demonstrates the most outstanding performance in prediction accuracy, stability, and modeling capability for nonlinear features. Both the paired t-test and cross-validation results show that it

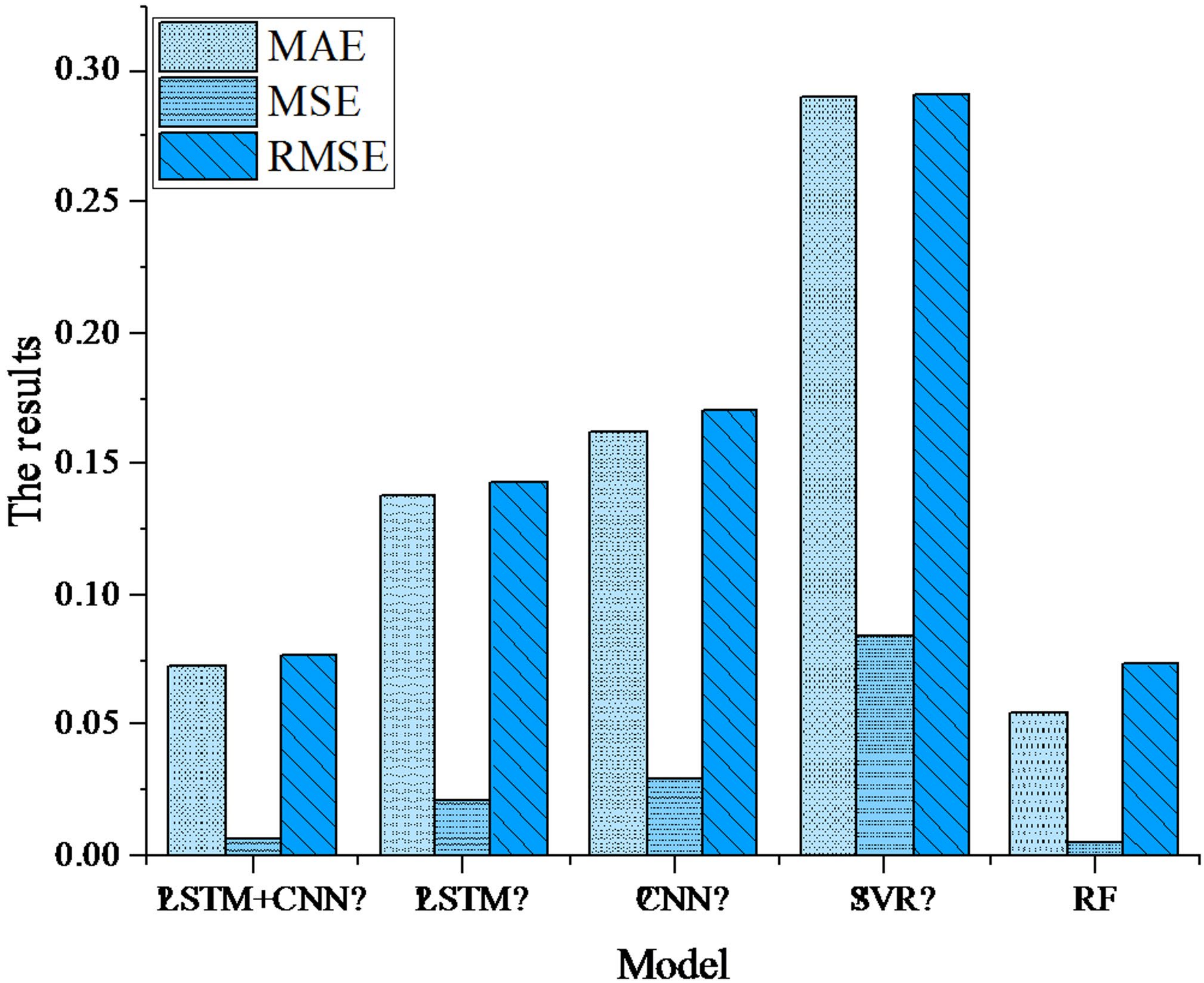

Fig. 7. Comparison of model accuracy evaluation indices.

Types of models	Average training time (seconds)	Time taken for a single prediction (milliseconds)	Interpretability score (out of 10)
LSTM + CNN	78.4	15.2	3
LSTM	51.2	12.5	4
CNN	45.7	10.3	4
RF	12.6	2.3	8
SVR	18.4	3.1	7

Table 3. Comparison of computational resource consumption and interpretability of each model.

has the smallest error and variance. This indicates that although LSTM + CNN is slightly higher in resource consumption, it has obvious advantages in high accuracy and generalization ability. In contrast, traditional models such as RF and SVR, while having higher interpretability and lower computational burden, suffer from insufficient accuracy in handling complex, high-dimensional, nonlinear data. Therefore, in practical applications, the model's accuracy, interpretability, and computational cost should be balanced according to the scenario. When prediction accuracy is the core goal, especially in high-complexity tasks such as individual psychological index prediction, LSTM + CNN is more advantageous. In contrast, in environments with high requirements for model understandability and deployment cost, RF and SVR are more suitable.

(2) SHAP value analysis and feature importance evaluation.

Based on the correlation modeling between sports behavior data and well-being indices, the SHAP method is used to analyze the feature action mechanism of the ANN. The SHAP mean values and interaction effect intensities of the test set are calculated. The nonlinear influence laws of key features on each dimension of well-being are depicted in Fig. 8.

Figure 8 shows the top 5 sports behavior features that affect psychological resilience, self-efficacy, and subjective well-being. The analysis of the SHAP mean values indicates that the high-frequency exercise days per week (≥ 4) have a significant positive impact on psychological resilience, with an interaction effect intensity of 0.092. This suggests that frequent exercise can enhance an individual's psychological resilience. The duration of moderate-intensity exercise and exercise heart rate variability also have a certain impact on psychological resilience, but the interaction effects are weak. In particular, the negative effect of heart rate variability on psychological resilience is relatively obvious. The proportion of nighttime exercise negatively affects psychological resilience, and exercising too late may affect mental health. Key determinants of self-efficacy include the morning exercise persistence cycle and vigorous exercise duration, exerting significant positive impacts. The exercise goal achievement rate and the frequency of recovery after exercise interruption also have an indirect impact on self-efficacy. The group exercise participation index demonstrates the most pronounced effect on improving subjective well-being, highlighting that sports forms with strong sociality can enhance well-being. Exercise-sleep cycle synchronization and the daytime activity energy consumption gradients further contribute positively to well-being, primarily by maintaining energy balance and optimizing rest-recovery dynamics.

To interpret the negative or complex mechanisms, feature contributions are compared with existing physiological and psychological theories. High-frequency exercise days per week (≥ 4) significantly enhance psychological resilience, consistent with stress buffering theory, suggesting that regular exercise strengthens hypothalamic-pituitary-adrenal axis resilience. Conversely, a high proportion of nighttime exercise exerts negative impacts on psychological resilience, potentially due to late exercise-induced sympathetic excitability. This behavior suppresses melatonin secretion, delays sleep, disrupts sleep-wake rhythms, reduces recovery quality, and thereby weakens emotional regulation and stress resistance. The negative interaction effect of exercise heart rate variability can also be explained by short-term autonomic imbalance caused by high-intensity or prolonged exercise. Insufficient immediate recovery leads to decreased heart rate variability (reflecting suppressed parasympathetic activity), temporarily impairing psychological resilience. Regarding self-

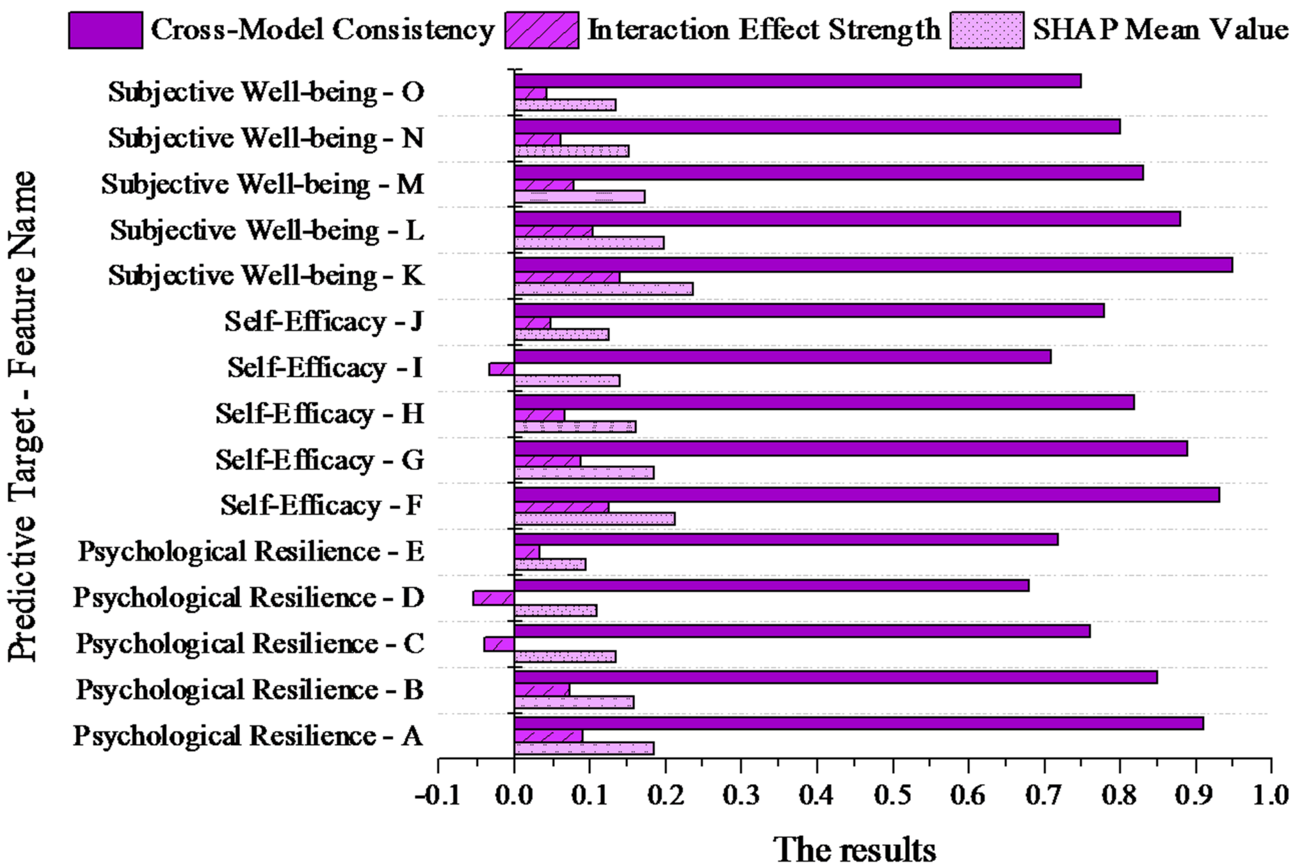

Fig. 8. SHAP contribution degrees of sports behavior features to well-being indices (A: High-frequency exercise days per week (≥ 4); B: Cumulative duration of moderate-intensity exercise; C: Exercise heart rate variability, D: Proportion of nighttime exercise after 20:00; E: Daily step volatility, F: Morning exercise persistence cycle; G: Longest single duration of vigorous exercise; H: Exercise goal achievement rate; I: Frequency of recovery after exercise interruption; J: Density of exercise social interaction; K: Group exercise participation index; L: Exercise-sleep cycle synchronization; M: Daytime activity energy consumption gradient; N: Diversity of exercise scenarios; O: Decline rate of resting heart rate).

Feature name	Target variable	Positive effect threshold	Rate of change of effect intensity	Interactive object
High-frequency exercise days per week	Psychological resilience	≥ 3 days	+ 217%	Exercise heart rate variability (-0.28)
Longest single duration of vigorous exercise	Self-efficacy	≥ 45 min	+ 153%	Morning exercise persistence cycle (+ 0.34)
Group exercise participation index	Subjective well-being	≥ 0.7	+ 329%	Diversity of exercise scenarios (+ 0.41)
Exercise-sleep cycle synchronization	Subjective well-being	≥ 80%	+ 185%	Daytime energy consumption gradient (+ 0.25)

Table 4. Dynamic threshold effect of key features.

efficacy, the positive effects of morning exercise persistence cycles and vigorous exercise duration align with the mastery source hypothesis of self-efficacy theory. Individuals experience mastery in highly self-disciplined and challenging situations, thereby enhancing their confidence in completing tasks. The significant positive contribution of group exercise participation index to subjective well-being accords with the social support-emotional satisfaction model, where collective activities improve well-being through increased belonging and positive emotion amplification. The positive impacts of the exercise-sleep cycle synchronizations and daytime activity energy consumption gradients are attributed to circadian rhythm synchrony theory. Regular exercise-rest patterns maintain energy homeostasis and neurotransmitter balance, thereby enhancing positive affect and life satisfaction. Based on model predictions and SHAP dependency plots, the dynamic threshold effects of sports behavior features are detailed in Table 4.

Table 4 indicates that at the critical points of different characteristic values, the influence of sports behavior on well-being has markedly varied. The positive effect of the high-frequency exercise days per week on psychological resilience is remarkably enhanced when the number of exercise days is ≥ 3. Meanwhile, it has a negative interaction effect with exercise heart rate variability, suggesting that frequent high-intensity exercise may require an appropriate heart rate recovery period to enhance psychological resilience. The positive impact of the longest single duration of vigorous exercise on self-efficacy peaks when it is ≥ 45 min, and it has an obvious interaction effect with the morning exercise persistence cycle. This suggests a synergistic relationship between the exercise duration and an individual's daily persistence cycle. The group exercise participation index demonstrates its most pronounced enhancement effect on subjective well-being when participation levels reach ≥ 0.7. This effect is further amplified through interactions with other features, including diversity of exercise scenarios and daytime activity energy consumption gradients, collectively elevating overall well-being levels.

Discussion

Findings indicate a significant association between college students' sports behavior and well-being, with psychological resilience, self-efficacy, and subjective well-being serving as key mediating factors. Frequent moderate-intensity exercise enhances emotional regulation and psychological adaptation, thereby improving psychological resilience. Morning exercise persistence cycle and vigorous exercise duration correlate positively with self-efficacy, as persistent behavior may foster a sense of control and achievement over behavioral goals. For subjective well-being, group exercise participation, healthy exercise-sleep rhythms, and reasonable daytime energy expenditure may promote emotional stability and life satisfaction. It is emphasized that this study employs predictive modeling and interpretive analysis rather than experimental or longitudinal causal designs. Therefore, the relationships among the variables revealed by this study represent statistical associations rather than strict causal inferences.

This finding is consistent with the results of other studies. Substantial literature has demonstrated that regular physical activity enhances individuals' psychological resilience by improving physical health and psychological stability, enabling them to cope with stress and challenges[35]. In terms of self-efficacy, the positive impacts of the morning exercise persistence cycle and vigorous exercise duration further verify the synergistic effect between morning activities and individuals' daily behavior persistence, which aligns with the research findings of Thapa et al. (2024). Morning exercise arrangements contribute to the formation of long-term stable exercise habits and significantly enhance individuals' self-cognition and sense of control[36]. Regarding the influence on subjective well-being, the role of group sports with strong sociality in improving well-being is particularly prominent, which is consistent with the research of Zhang et al. (2022). Group sports not only promote physical health but also enhance social interaction, improve the sense of social support, and increase emotional satisfaction[37]. The exercise-sleep cycle synchronization and daytime activity energy consumption gradients can effectively improve emotional fluctuations and quality of life. This finding is consistent with the research of Li et al. (2025), and the exercise-sleep synchronization effect is closely related to the improvement of well-being[38]. Through SHAP analysis, this study delves into the complex influence mechanism of sports behavior, revealing nonlinear effects and interaction effects of sports behavior on diverse psychological variables. These insights provide a new perspective for specific sport paths to improve well-being.

However, the study has certain limitations. First, a stratification strategy is adopted during sample sampling to cover different grades and major categories. However, demographic bias may still exist due to variables such as cultural background and personality differences not being included in the control model. Second, some psychological variables rely on self-administered questionnaire assessment, still facing the problem of subjective bias. At the ethical level, this study fully adheres to relevant ethical norms, all participants engage in the study based on informed consent, and data collection strictly follows confidentiality and anonymization procedures. It is worth noting that when using predictive models to analyze psychological variables, special attention should be paid to the boundaries of model interpretation and ethical constraints of usage scenarios. Automatic prediction of psychological variables should not be misused for qualitative judgments in education, employment, or health assessment. In future work, the prudential evaluation of model application ethics should be further strengthened, and interdisciplinary cooperation should be promoted to establish more secure usage norms.

In summary, this study demonstrates potential mechanistic pathways through which sports behavior enhances well-being and reveals complex nonlinear effects via SHAP analysis. However, conclusions require further validation with samples enabling stronger causal inference and higher representativeness. These findings offer new perspectives for understanding the psychological regulatory role of sports behavior. They also emphasize that when using AI models to interpret psychological variables, statistical robustness and ethical controllability must be integrated to ensure scientific validity and social responsibility.

Conclusion

Research contribution

This study proposes a sports behavior—well-being prediction model based on the LSTM + CNN deep architecture. Meanwhile, it reveals key behavioral thresholds and nonlinear interactions through SHAP analysis, providing data-driven intervention ideas for mental health promotion in colleges. Regarding model accuracy and feature importance analysis, the LSTM + CNN model performs excellently on multiple evaluation indices, and its accuracy and low error rate demonstrate the model's advantages in processing psychological measurement data. Through SHAP value analysis, the study reveals the nonlinear influence of sports behavior features on well-being. Moreover, it further clarifies key factors affecting psychological resilience and self-efficacy, such as high-frequency exercise days, vigorous exercise duration, and morning exercise persistence cycles. To transform model outputs into actionable actual behaviors, the following suggestions are proposed. First, based on the thresholds of "≥3 days of moderate-intensity exercise" and "≥45 minutes of vigorous exercise", it is recommended that college physical education courses set Wednesday class hours as intensity-increasing units. At the same time, stratified exercise plans are pushed to students who do not meet the thresholds through campus applications. Second, the positive effect of morning exercise persistence cycles on self-efficacy suggests that a 20-minute "morning-boost" group exercise program can be promoted in dormitory areas. Concurrently, counselors can monitor attendance and heart rate recovery through wearable platforms to form real-time feedback. Third, the coupling effect between group exercise participation index and well-being provides a basis for the "social exercise prescription" of the psychological counseling center. Freshmen are encouraged to give priority to signing up for cooperative projects with more than 3 people, and conducting longitudinal evaluations of well-being improvement rates at the end of the term. Fourth, the model is encapsulated as a RESTful API and embedded into the university's smart sports platform to achieve real-time scoring of students' exercise data and early warning of emotional fluctuations. Online transfer learning can be carried out through rolling data updates in the future. Fifth, follow-up measurements are performed at the half-year and one-year nodes to test the continuous effectiveness of interventions. These data also dock with the school hospital's sleep database to explore the long-term dynamic relationship among exercise, sleep, and emotion. Through the above paths, this study supplements the mechanistic evidence of the relationship between exercise intervention and well-being and provides an implementable action framework for policymakers and educators to promote personalized and precise campus health management.

Future works and research limitations

The limitations of this study are mainly reflected in the geographical and cultural background constraints of the samples, which may affect the broad applicability of the results. Although the LSTM + CNN model performs excellently, it still fails to fully capture the complex dynamic relationship between sports behavior and well-being. Future research can expand the sample scope, combine cross-cultural data, and explore the interaction effects of more types of sports and psychological variables. Meanwhile, by integrating long-term tracking data, the impact of sports interventions on long-term well-being can be further verified, providing more empirical evidence for optimizing personalized intervention programs.

Data availability

The datasets used and/or analyzed during the current study are available from the corresponding author Roxana Dev Omar Dev on reasonable request via e-mail rdod@upm.edu.my.

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Declarations

Competing interests
The authors declare no competing interests.

Ethics statement
The studies involving human participants were reviewed and approved by Department of Sports Studies, Faculty of Educational Studies, Universiti Putra Malaysia Ethics Committee (Approval Number: 2023.022384). The participants provided their written informed consent to participate in this study. All methods were

performed in accordance with relevant guidelines and regulations.

Additional information

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