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Research on the Application of Artificial Intelligence Technology in Improving Student Participation in Fitness Activities and Personalized Training Effects

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Abstract Breakthroughs in artificial intelligence (AI) technology in the field of health management have enabled personalized support for college students' physical activities. This paper proposes an AI-based personalized exercise prescription system that integrates multi-source data such as physical fitness and health status. A fitness exercise information feedback loop system and a health status assessment model are designed, and a content-based recommendation algorithm (CB algorithm) is employed to dynamically provide personalized exercise prescriptions for college students with varying health levels and exercise preferences. The study reveals that college students can be clustered into four categories based on their physical fitness levels. The performance evaluation metrics of the model's exercise prescription system all exceed 0.9, enabling students to achieve exercise effects ranging from 7.682 to 8.606. The six generated exercise prescriptions keep students' exercise fatigue levels below 12, and students' physical fitness and exercise skills are significantly superior to pre-experiment levels at the 0.01 significance level.

Index Terms artificial intelligence technology, student fitness, information feedback system, CB algorithm, personalized exercise prescription

I. Introduction

College students, as a unique social group, have always been a focus of attention from both the state and society regarding their physical health [1]. Given the large size of this population and the significant individual differences among its members, there is a growing demand for diverse and personalized guidance in physical fitness and exercise. In response to this demand, the intelligent application of exercise prescriptions has become an essential component of efforts to improve the physical health of college students [2]-[4].

In recent years, artificial intelligence (AI) technology has been widely applied across various fields. As the technology becomes increasingly widespread and mature, AI is no longer a concept of the future but has become a powerful driver of the new industrial revolution [5]. Physical fitness, as a mass recreational activity, has also embraced new development opportunities with the evolution of the times and advancements in technology [6], [7]. Digital sports, as an important branch of sports technology, is undergoing a transformation from traditional to modern approaches [8]. As a disruptive technology, AI is reshaping the structure and operational models of sports [9], [10]. From athlete training to competition analysis, from audience experience to venue management, the application of AI is becoming increasingly widespread [11]. Therefore, conducting in-depth research on the application of AI technology in student fitness activities and its future trends is of great significance for promoting the physical health development of the student population.

AI technology can guide training through precise data analysis (such as creating virtual training environments, motion analysis and quantification, and automatic video organization), making the training process more scientific. This not only helps athletes improve training efficiency but also reduces the risk of sports injuries during training [12]-[15]. Literature [16] explores specific methods for using AI technology to develop personalized training plans for basketball players. It employs a novel algorithm (ICO-RNN) to identify athletes' individual strengths and weaknesses, thereby enhancing their performance and decision-making capabilities compared to traditional training methods. Literature [17] evaluates the effectiveness of AI technology in generating personalized exercise plans, finding it has promising applications in strength training and endurance training. Literature [18] developed an AI-based wearable piezoelectric sensor for real-time monitoring of sports activities. This sensor addresses the shortcomings of traditional methods, providing accurate and timely training feedback to optimize athletes' performance. Literature [19] proposed a multimodal framework combining immersive technology with AI, aiming to personalize running training plans by focusing on physical, technical, psychological, and body awareness aspects, thereby providing coaches with tools to design more effective training programs. Literature [20] proposes an intelligent sports training system that utilizes edge-based multi-sensor data processing and lightweight neural networks to generate personalized training plans, thereby improving students' fitness levels and training persistence.

AI can identify users' fitness movements through deep learning and perform real-time tracking and analysis of posture. Literature [21] proposes an automatic motion recognition system for sports training based on multi-source sensor information. This system predicts future motion postures by extracting kinematic features from sensor data, thereby improving training quality. Literature [22] argues that machine learning-based fitness monitoring systems have revolutionized the fitness industry by employing advanced computer vision and posture recognition technologies. These systems provide students with precise motion feedback, personalized guidance, and dynamic exercise experiences. Literature [23] combines wearable sensors with support vector machine (SVM) algorithms to design a motion recognition system aimed at standardizing training processes, improving training efficiency, and reducing the risk of injury in sports such as basketball and racewalking, thereby promoting its practical application. Reference [24] designed and implemented an intelligent fitness training system based on human posture estimation. This system not only provides fitness training courses for students but also offers motion correction feedback, addressing the shortcomings of existing systems and achieving positive results in field trials. Reference [25] proposes a device-free fitness assistance system that utilizes WiFi infrastructure to provide users with personalized fitness guidance, overcoming the limitations of traditional methods by distinguishing individuals, recording exercise data, and assessing dynamic conditions with high precision. In summary, AI-based intelligent fitness can be applied to adolescent student populations, providing them with scientific physical exercise guidance, which is of significant importance for improving their athletic performance and promoting healthy development.

This paper constructs a fitness exercise information feedback system based on AI technology, integrating physical fitness test data with an exercise prescription database. It introduces a three-dimensional health perspective (physical/mental/social health) to build a health assessment model, generating personalized prescriptions for individuals with diseases, sub-health conditions, and healthy populations. Combining user-project dual-dimensional modeling with a CB recommendation algorithm, it calculates the similarity between user physiological feature vectors and exercise feature weights to achieve precise generation and dynamic optimization of exercise prescriptions.

II. Algorithm and model design for improving college students' physical health

II. A. Concept of establishing personalized online exercise prescriptions

II. A. 1) Construction of a fitness exercise information feedback system

The fitness training process for college students is a dynamic system that involves continuous data analysis, implementation of exercise plans, reanalysis, and adjustments. Figure 1 illustrates the information cycle process of the student exercise system. In this system, we utilize artificial intelligence technology to integrate physical testing data, physical movement health diagnostics, the development of exercise plans, the selection of exercise programs, and the implementation and evaluation of exercise plans. By keeping the exercise process and outcomes under the scientific supervision of artificial intelligence, students can clearly feel the tangible progress that scientific exercise brings to their physical development and health maintenance, thereby strengthening their confidence in exercise. This forms a positive feedback loop of "physical fitness assessment – targeted exercise – re-assessment – exercise," ultimately fostering the awareness and habit of self-motivated exercise.

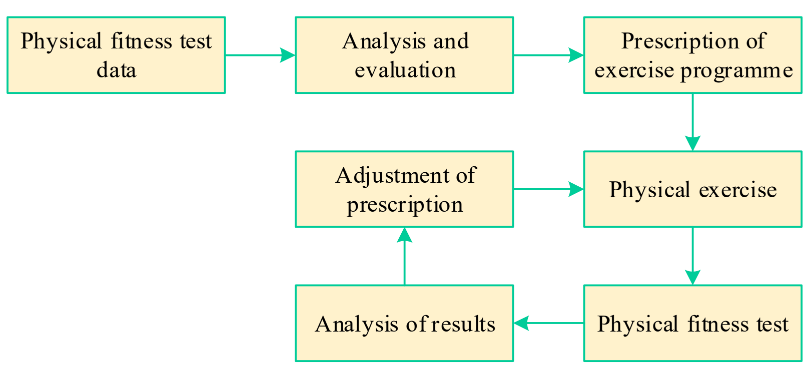

Figure 1: The information circulation process of the student exercise system

II. A. 2) Physical Condition Feedback and Exercise Prescription System Model Structure

Figure 2 shows the structural model of the physical fitness information feedback and exercise prescription system. This system is designed as a multi-level dialogue menu based on an Internet environment. The school's physical fitness testing center first uses online instruments to test students' physical fitness and inputs the test results into the student physical fitness information database. Students input their own information on their personal computers and access their physical fitness information system. The system provides evaluation information based on the students' physical fitness test data, and the exercise prescription database provides corresponding exercise prescriptions based on this evaluation information. This information is output and printed via a computer terminal, allowing students to understand their own physical fitness information and use the relevant exercise prescriptions for scientific and reasonable exercise.

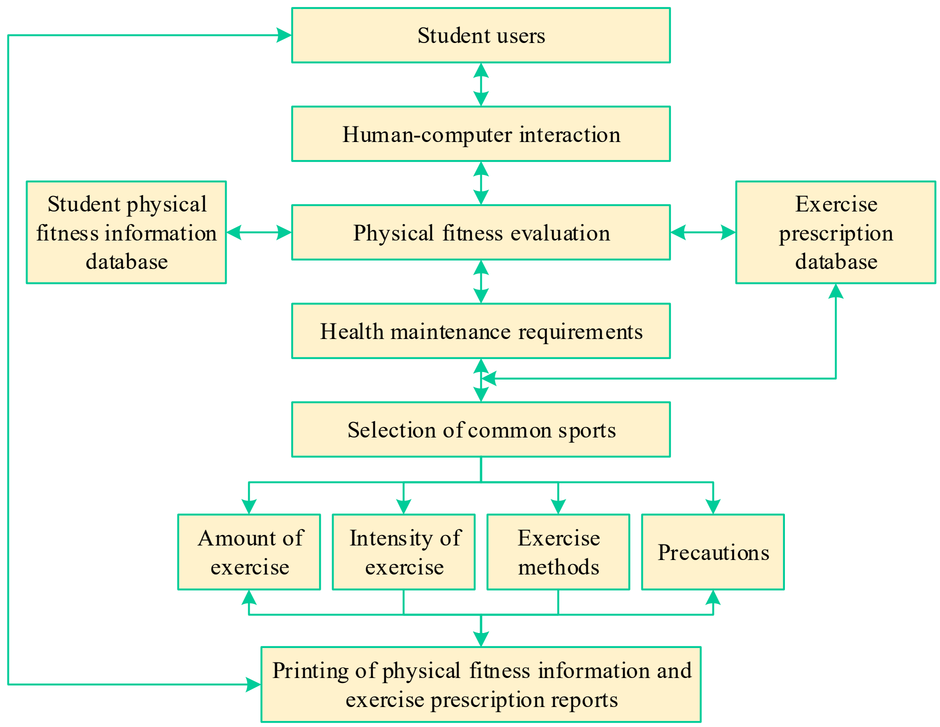

Figure 2: Information feedback and prescription System model

II. B. Analysis of Model Operation Principles

II. B. 1) Overview of Health Assessment Models

Figure 3 shows the health assessment model. The health assessment adopts a three-dimensional health concept, namely physical health, mental health, and social health. Only when all indicators related to physical health, mental health, and social health are normal can the user be determined to be in a healthy state. If one or more indicators are abnormal but there are no symptoms, the person can be determined to be in a sub-healthy state. If the user has been diagnosed by a hospital as having a certain disease, they can be determined to be in a diseased state.

II. B. 2) Assessment of physical health

Physical health status is primarily determined based on physical fitness test reports and medical examination results. Physical fitness test indicators refer to the test scores from the college student physical fitness test, with each test item having corresponding evaluation methods. This paper employs the college student physical fitness test evaluation methods to assess the physical health status of college students. Biochemical indicators refer to the results of tests conducted during hospital physical examinations, including routine tests such as blood routine and urine routine. Each biochemical indicator has corresponding upper and lower limit values, and potential diseases are identified based on the numerical values of these indicators.

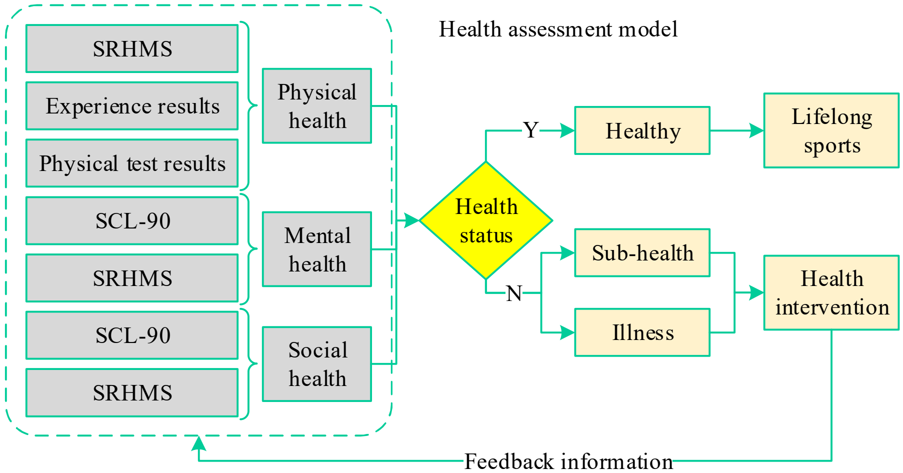

Figure 3: Health assessment model

II. B. 3) Operating mechanism of the exercise prescription model

The operational mechanism of the exercise prescription generation model is based primarily on the criteria identified as suboptimal in physical fitness test data. When multiple suboptimal criteria are present simultaneously, the system follows a principle of addressing issues sequentially, prioritizing physical fitness criteria in the order of cardiovascular, body composition, and physical fitness to formulate exercise prescriptions. Through the cyclical development structure and feedback functionality of the exercise health management system, after an abnormal indicator is improved, the system continues to implement health interventions targeting the next abnormal indicator. Of course, the system also provides feedback on the user's exercise status during the implementation of the exercise prescription, enabling timely updates to the prescription content and achieving personalized design. For exercise prescriptions required by disease populations or exercise-related injury populations, users can directly click on the corresponding disease or injury location to obtain the relevant exercise prescription from the system.

II. C. Personalized Sports Recommendation Algorithm

II. C. 1) Sports User Modeling

The level of sophistication in constructing a sports user model directly impacts the overall effectiveness of a recommendation system. When building a sports model, it is essential to consider not only the basic health information users provide during initial registration but also any changes in their health status or exercise interests over the short or long term while using the system. This necessitates updating the user model. Only by establishing and updating the model in this manner can precise recommendations be achieved for users.

The sports user model includes a user basic physiological model and a user project rating matrix model. The user basic physiological model includes the user's basic health information and interests. Here, user keywords are extracted, with each keyword representing a piece of basic information about the user. Basic user information includes age, gender, BMI, and categories of sports the user is interested in. The user model is represented as shown in (1):

$$\overrightarrow{U_u} = \left\{(k_u^1, w_u^1), (k_u^2, w_u^2), (k_u^3, w_u^3), \cdots, (k_u^n, w_u^n)\right\} \tag{1}$$

In the formula, $\overrightarrow{U_u}$ represents the feature vector of user u, k_u^n represents the n th keyword of user u, and w_u^n represents the weight of the n th keyword of user u.

The user rating matrix model represents the degree to which users like the sports they are interested in, i.e., the rating level. Users' ratings of sports projects include viewing, liking, sharing, and collecting. The rating level is implicitly obtained through users' interface operations to express their preference for recommended sports.

II. C. 2) Sports Modeling

Since the application domains of recommendation systems vary widely, there is no standardized guideline for establishing a unified modeling standard for each application. This highlights the significant impact of recommendation object modeling on recommendation systems. In this paper, we approach the topic from the perspective of sports activities. Based on the body parts involved in sports activities, they can be categorized into upper limbs, trunk, and lower limbs. Additionally, sports activities can be classified into five major physical fitness qualities based on their inherent health attributes: strength, speed, flexibility, endurance, and agility. If a sports activity involves both upper limb and lower limb movements, the keyword for the object is set to 1.0, while the keyword for trunk movements is set to 0.0. If a sports activity can incorporate strength, speed, and flexibility, their respective weights are set to 1.0, while endurance and agility are set to 0.0. Ultimately, the sports activity model is as shown in (2):

$$\overrightarrow{I_u} = \left\{(p_u^1, w_u^1),(p_u^2, w_u^2),(p_u^3, w_u^4),\cdots,(p_u^7, w_u^7),(p_u^8, w_u^8)\right\} \tag{2}$$

In the formula, p_u^n represents the n nd keyword, w_u^n represents the weight of the n th keyword, and the weight of the keyword is either 0.0 or 1.0, which means whether or not the keyword is related to sports.

II. C. 3) Content-based recommendation algorithms

The CB recommendation algorithm requires only one important feature, namely tags. The algorithm needs to break down sports events into a series of features that sufficiently characterize the sports events, and establish relationships between the sports events and users based on user behavior in the system (viewing, sharing, rating, and collecting). Figure 4 illustrates the principle of the CB recommendation algorithm.

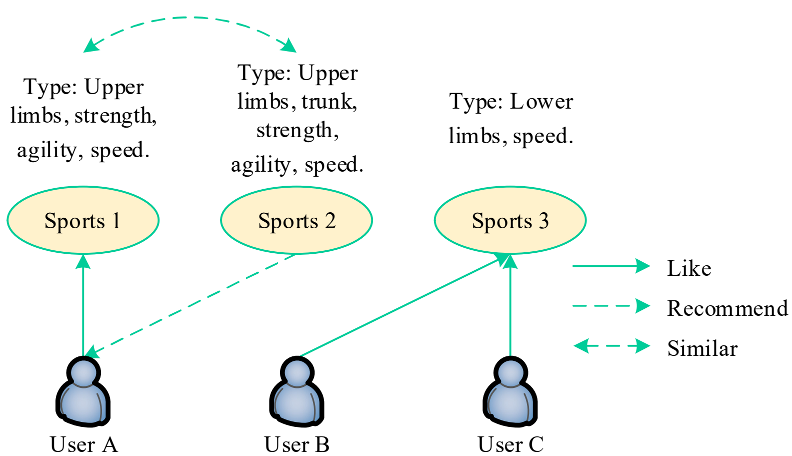

Figure 4: Schematic diagram of CB recommendation algorithm

In Figure 4, User A likes Sport 1, which has the characteristics of upper limbs, strength, agility, and speed. The algorithm calculates the user's preference for these characteristics based on the user's rating of the sport's health level and the characteristics of the sport. Then, by comparing it with Sport 2, it determines that the characteristics with the most overlap are preferred, so Sport 2 is recommended to User A .

The cosine similarity formula for the CB recommendation algorithm is shown in (3):

$$sim(A,B) = \frac{\sum_{i=1}^{n} A_i * B_i}{\sqrt{\sum_{i=1}^{n}(A_i)^2} * \sqrt{\sum_{i=1}^{n}(B_i)^2}} \tag{3}$$

Among them, A_i indicates the user's preference for sports types, and B_i indicates the type of sport to which each sport belongs. This relationship is either 0.0 or 1.0.

Finally, the sports projects are sorted in descending order according to their similarity, and the top N are selected for the user.

III. College students' exercise practices based on personalized recommendation systems

III. A. Classification of Physical Fitness Categories for College Students

A sample of 150 first-year male students from the Computer Network College of a certain university was selected as the research subjects. The physical fitness of these students was tested using the university's online instruments, and the test results were entered into the student physical fitness information database. Cluster analysis was performed on the physical fitness data of these 150 first-year male students. First, all physical fitness indicators were standardized. For high-performance indicators (where higher values indicate better performance), the data was directly Z-standardized. For low-performance indicators (where lower values indicate better performance), the data was Z-standardized and then prefixed with a negative sign. The number of clusters was set to four categories:

excellent, good, passing, and failing, denoted in this paper as Class I, Class II, Class III, and Class IV, respectively. Based on the clustering results, the characteristics of physical health for each category of students are analyzed in detail, and the relevant terms “excellent,” “good,” “average,” and “poor” are used to describe them according to the evaluation criteria. Table 1 summarizes the variance analysis of physical health clustering for first-year male students. Table 2 shows the physical health clustering results for first-year male students. Based on the F-value in the variance analysis of physical health clustering, we can approximately determine which indicator plays a greater role in the clustering analysis. The indicators are ranked in order of importance as follows: lung capacity (244.168) > standing long jump (187.265) > 50m (173.734) > height (142.724) > 1000m (123.635) > weight (118.042) > pull-ups (102.846) > grip strength (73.532) > sit-and-reach (25.674). When sorted by the number of students, the largest group is Category II with 50 students, followed by Category I (45 students), Category IV (35 students), and Category III (20 students); the students with the best physical fitness are those in Category II, followed by Category IV, Category III, and Category I.

Table 1: Summary of variance in the cluster analysis of students' physical health

Physical fitness index	Clustering		Error		F	Sig
	Mean square	Df	Mean square	Df		
Height	178.293	5	0.653	150	142.724	0.001
Body weight	181.094	5	0.349	150	118.042	0.001
Vital capacity	164.735	5	0.561	150	244.168	0.001
50m	98.991	5	0.589	150	173.734	0.001
Standing long jump	185.236	5	0.416	150	187.265	0.001
Sit forward bend	30.761	5	0.862	150	25.674	0.001
Grip strength	90.273	5	0.763	150	73.532	0.001
1000m	118.107	5	0.752	150	123.635	0.001
Pull-ups	184.632	5	0.509	150	102.846	0.001

Table 2: The clustering situation of physical health of freshmen male students

Physical fitness index	I (45)	II (50)	III (20)	IV (35)
Height	-0.243	0.801	0.674	-0.245
Body weight	-0.349	0.632	0.532	-0.357
Vital capacity	-0.541	0.741	0.294	-0.512
50m	-0.278	0.385	-0.518	0.395
Standing long jump	-0.395	0.401	-0.502	0.813
Sit forward bend	-0.297	0.629	-0.105	0.298
Grip strength	-0.352	0.523	-0.291	0.472
1000m	0.002	0.318	-0.193	0.924
Pull-ups	-0.394	-0.264	-0.235	0.641

III. B. Comparison of Model Performance and Motion Effects

III. B. 1) Comparison of the model's exercise recommendation results

Six models—BN, KNN, GRU, LSTM, TT-CF, and UPAT-ARNN—were selected as comparison models. Together with the exercise recommendation model proposed in this paper, personalized exercise recommendations were implemented based on the physical fitness clustering results of 150 male freshmen. Figure 5 shows a comparison of the recommendation results from the seven different models. Table 3 presents the specific statistical data of the recommendation results from the seven models. Among the six evaluation metrics, the metric values of the content-based exercise recommendation model proposed in this paper are: 0.9358, 0.9141, 0.9059, 0.9286, 0.9476, and 0.9336. Compared to the other six comparison models, the metric values of this paper's model are the highest, all exceeding 0.9. This indicates superior exercise recommendation performance, enabling the model to recommend appropriate exercises for first-year male college students based on their physical fitness clustering results.

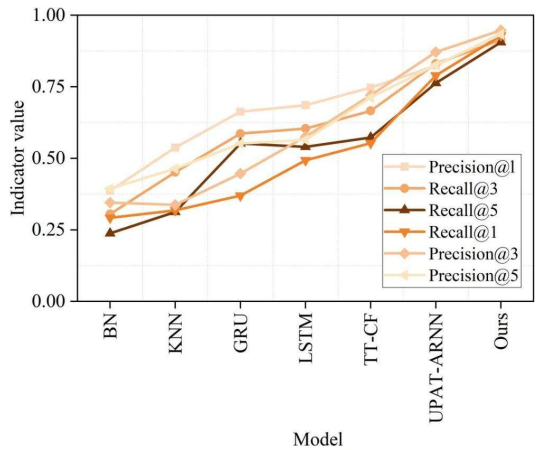

Figure 5: Comparison of the recommendation results of seven different models

Table 3: Data statistics of the recommendation results of the 7 models

Model	Precision @l	Precision @3	Precision @5	Recall @1	Recall @3	Recall @5
BN	0.3869	0.3053	0.2381	0.2922	0.3452	0.3939
KNN	0.5376	0.4516	0.3124	0.3184	0.3374	0.4637
GRU	0.6628	0.5864	0.5522	0.3697	0.4467	0.5521
LSTM	0.6857	0.6041	0.5402	0.4933	0.5758	0.5644
TT-CF	0.7471	0.6659	0.5729	0.5531	0.7205	0.7125
UPAT-ARNN	0.8235	0.8312	0.7628	0.7894	0.8712	0.8262
Ours	0.9358	0.9141	0.9059	0.9286	0.9476	0.9336

III. B. 2) Comparison of exercise effects

Among 150 research students, 15 students were randomly selected as exercisers. Each exerciser was tested under the same experimental conditions, and exercise prescriptions were recommended for these 15 exercisers using BN-based recommendation methods, LSTM-based recommendation methods, and the recommendation method proposed in this paper. Subsequently, these 15 exercisers performed exercises according to the exercise prescriptions, and the exercise effects of the exercisers were verified through testing after the experiment. Figure 6 shows the exercise effects of the 15 participants after implementing the exercise prescriptions under different recommendation models. After applying the exercise prescriptions recommended by the model proposed in this paper, the exercise effects of the 15 participants ranged from 7.682 to 8.606; after applying the exercise prescriptions recommended by the BN method, the exercise effects of the 15 participants only reached 3.125 to 5.113; After applying the exercise prescription recommended by LSTM, the exercise effects of the 15 participants were slightly better than those of BN, reaching 5.246–6.427. The exercise prescriptions recommended by the model in this paper can help students improve their physical health and enthusiasm for exercise.

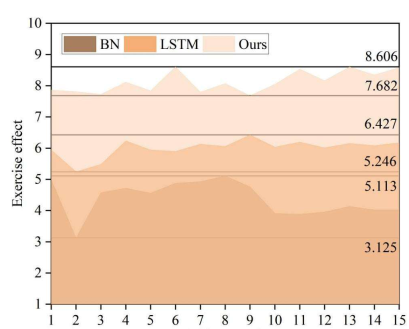

Figure 6: Comparison experiment results of exercise effects

III. C. Exercise experiment for college students based on exercise recommendations

III. C. 1) Analysis of exercise intensity

Using these 150 students as experimental subjects, the football physical education course in the second semester of their first year was selected as the experimental period and exercise improvement target. During this semester, the system provided multiple, dynamic exercise prescriptions, and students were strictly required to complete the exercises according to the prescribed regimens. After the experiment, the students' physical fitness status was collected. Table 4 shows the exercise intensity statistics of the exercise prescriptions. Among the six recommendations, the proportions of low intensity, moderate intensity, high intensity, and maximum intensity were approximately equal. Additionally, the fatigue values (RPE) for each recommendation did not exceed 12, with the highest being 11.42 ± 1.65 and the lowest being 10.25 ± 0.73. This indicates that the exercise intensity based on the exercise prescription recommendations aligns with the students' physical fitness levels and is reasonably appropriate.

Table 4: The exercise intensity of the recommended exercise prescription

Class period	Exercise intensity (%)					RPE
	Minimum strength	Low strength	Moderate intensity	High strength	Maximum strength	
Time 1	18.39	29.38	35.45	10.29	6.49	11.03±1.02
Time 2	14.27	27.83	40.16	12.34	5.40	10.25±0.73
Time 3	16.84	26.46	38.42	12.62	5.66	11.42±1.65
Time 4	20.53	25.17	36.81	11.35	6.14	10.61±0.39
Time 5	18.90	24.61	38.94	10.26	7.29	10.54±0.18
Time 6	16.42	28.34	39.83	11.85	3.56	11.17±1.26

III. C. 2) Effectiveness of exercise prescription applications

Table 5 compares the improvement in students' physical fitness levels before and after the application of the recommendation system for exercise prescriptions. Table 6 compares the improvement in students' soccer skills before and after the application of the recommendation system for exercise prescriptions. In terms of physical fitness levels, after the application of exercise prescriptions, the P-values for all seven indicators except height and weight were less than 0.01, indicating a statistically significant improvement at the 0.01 significance level. In terms of soccer skill levels, after applying the exercise recommendation prescription, the time taken and success rates for five skills were significantly improved at the 0.01 level. This indicates that using artificial intelligence technology to dynamically track physical fitness and provide exercise recommendations for college students can significantly enhance their physical health levels and enthusiasm for group fitness activities, thereby promoting their personalized development.

Table 5: The physical health level before and after the application of the system

Physical fitness index	Before the experiment (N=150)	After the experiment (N=150)	P
Height	178.293	178.293	0.506
Body weight	181.094	183.094	0.593
Vital capacity	164.735	175.018	0.001
50m	98.991	109.274	0.002
Standing long jump	185.236	195.519	0.004
Sit forward bend	30.761	41.016	0.003
Grip strength	90.273	100.556	0.005
1000m	118.107	128.839	0.003
Pull-ups	184.632	194.915	0.004

Table 6: The football skill levels before and after the application of the system

Skill indicators	Before the experiment (N=150)	After the experiment (N=150)	P
Fast dribbling (s)	3.023	2.013	0.001
Success rate (%)	80.462	98.293	0.001
Passing and receiving (s)	4.035	3.084	0.002

Success rate (%)	68.341	99.274	0.002
Dribbling around obstacles (s)	10.384	6.743	0.000
Success rate (%)	35.652	95.693	0.000
Shot (s)	5.304	3.021	0.005
Success rate (%)	37.241	85.034	0.005
Level 1 Test (s)	20.583	15.273	0.001
Success rate (%)	39.518	78.356	0.001

IV. Conclusion

This paper integrates an AI-driven exercise prescription system and CB recommendation algorithms to provide personalized exercise prescriptions for college students, thereby enhancing their participation in fitness activities and training outcomes. The recommendation model achieved scores of 0.9358, 0.9141, 0.9059, 0.9286, 0.9476, and 0.9336 across six performance metrics, outperforming the comparison model. Additionally, after applying the recommended prescriptions, the exercise effectiveness of college students improved to 7.682–8.606. The fatigue values of the six generated exercise prescriptions all remained below 12, and the seven physical fitness indicators and five skill indicators of the students all improved significantly at the 0.01 level. In the future, a psychological intervention module could be introduced into the recommendation system, combining college students' mental health data to optimize the recommendation of exercise prescriptions.

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