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Research on online personalized tutoring strategy of secondary school physical education homework based on cluster analysis in the context of physical education reform of secondary school examination

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Abstract As a special form of extracurricular sports activities, sports homework is an important part of school sports activities, which is an extension of the sports classroom, and can cultivate young people's sports interests and sports habits in a subtle way. This paper proposes to build a personalized sports recommendation system to achieve online personalized guidance for secondary school sports homework. The system is mainly composed of three parts: user model, sports model, and recommendation algorithm. In order to improve the recommendation effect, by weighted integration of differential evolution algorithm and collaborative filtering algorithm, the system can recommend appropriate sports prescription according to students' own characteristics and sports preferences. The recall, accuracy and coverage of the hybrid recommendation algorithm are 0.169, 0.036 and 0.547, respectively, which have obvious recommendation advantages compared with a single algorithm. The system in this paper relies on S Middle School to carry out experimental research, and after the experiment, there is a significant difference ($p<0.05$) between the students' sports quality and physical fitness under the guidance strategies recommended by the system, and the system in this paper ensures the accuracy of the recommendation results compared with manual guidance.

Index Terms differential evolutionary algorithm, collaborative filtering algorithm, weighted fusion, sports homework

I. Introduction

With the development of modern society, homework plays an important role in students' learning life, and physical education homework can provide students with flexible learning time and space as well as enhance students' interest and participation in physical activities [1]-[3]. Students can perform physical activities at home according to their own schedule without being restricted by the time of the school curriculum, which allows students to better utilize their time and perform physical activities according to their own needs [4]-[6]. At the same time, many students may be bored with physical activities due to the limitations of the school physical education program. Through physical education homework, students can participate in physical activities at home in a more relaxed way without being restricted by the vision of their classmates, and they can fully experience the fun and benefits of physical activities, enhance their interest in physical education, and stick to it for a long time [7]-[10].

In the digital era, online teaching has become an important part of the education field, compared with the traditional education model, online education has unique advantages, the most significant of which is the ability to provide learners with personalized guidance programs [11]-[14]. The core of personalized instruction lies in providing customized learning paths for each student's individual differences [15]. Educational technology can acquire students' learning data and interest preferences through data analysis and artificial intelligence, and design personalized learning paths based on this information [16]-[18]. In secondary school PE homework, schools can tailor the learning paths and resources that are most suitable for students according to their characteristics, needs and abilities through personalized learning programs to improve the learning effectiveness and efficiency of PE homework [19]-[22].

In this paper, a personalized sports recommendation system is constructed to realize online personalized guidance for secondary school sports homework in the context of the reform of secondary school sports examination. The system constructs a sports user model and a sports model from the perspectives of users and sports. The differentiated evolutionary algorithm and collaborative filtering algorithm are fused, and the fusion strategy is to weight the recommendation results of each of them by 50%. The two models are recommended by the hybrid algorithm to recommend the sports prescription that suits the students' own characteristics. The recommendation effect of the hybrid algorithm is verified by algorithm performance analysis, and S Middle School is used as the research object to compare the gap between manual guidance and system guidance.

II. Design of an online personalized instruction system for homework in sports

Online guidance for secondary school sports homework must be targeted. Each place has different students, climate, environment and other conditions, when guiding sports homework, we should try to determine the purpose of the homework and the type of homework reasonably according to the physical condition and hobbies and specialties of different students, according to the different occasions of homework, according to the climate of different regions and other conditions. This has two advantages, on the one hand, the teacher to do a scientific selection and arrangement of homework. On the other hand, it is conducive to mobilizing students' enthusiasm and interest. Therefore, this paper proposes a personalized sports recommendation system based on recommendation algorithms, which can recommend appropriate sports prescriptions according to students' own characteristics and sports preferences.

II. A.Key Algorithm Research on Personalized Sports Recommendation System

In this paper, from the perspectives of students and sports, based on the sports user model and sports model, the collaborative filtering (CF) algorithm and the differentiated evolutionary algorithm (DEA) are combined to recommend sports programs to students that meet the students' characteristics. From the user group perspective, the user-based collaborative filtering algorithm (UB-CF) is selected to model the sportsmen. Further, from the perspective of sports, the differential evolution algorithm is used to build a model of recommendation objects based on sports characteristics, and finally the collaborative filtering algorithm and the differential evolution algorithm are combined to form a personalized sports recommendation algorithm, so as to achieve the purpose of personalized recommendation to users.

II. A. 1) Sport user modeling

The degree of construction of the sports user model directly affects the recommendation effect of the entire recommendation system, sports model construction not only consider the user's initial registration system when filling out the basic information, the use of basic information for the user to build a model, but also to take into account the user in the use of the system in the short-term or long-term interest in the change, which has to go to update the user model. Only by building and updating the model in this way can we achieve the purpose of accurate recommendation for the user, the user modeling process is shown in Figure 1.

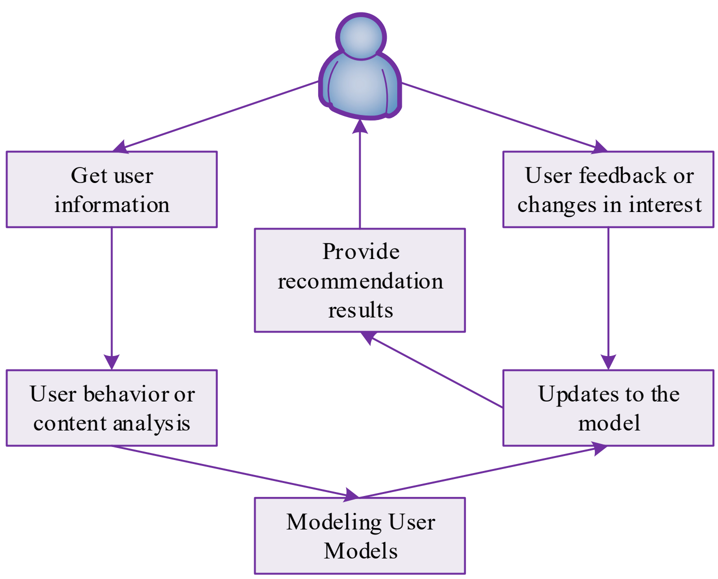

Figure 1: Schematic diagram of the user modeling process

The sports user model includes a model of the user's basic physical characteristics and a model of the user's rating matrix for the program. The basic user characteristics model includes the user's basic attribute information and interests. Here the user keywords are extracted, each keyword is a basic information of the user, the user's basic information are age, gender, BMI, interested in the category of sports, etc., the user model is represented as shown in equation (1):

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

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

II. A. 2) Sport modeling

Because the application domains of recommender systems are different, there is no standard guideline to establish a unified modeling standard for each application, which shows that recommender object modeling has a great impact on recommender systems. In this paper, from the perspective of sports, according to the role of sports can be in the human body can be divided into the upper limbs, trunk and lower limbs. According to the sports itself has the sports quality can be divided into strength, speed, flexibility, endurance, sensitivity five major sports quality. If the sports have both upper limb and lower limb sports, the keyword of the object is set to 1, then the trunk sports is set to 0. If the sports can have the three major sports qualities of strength, speed, flexibility, their weights are set to 1, then the two major sports qualities of endurance and agility are set to 0. Eventually, the model of the sports is as shown in equation (2):

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

where p_u^n represents the n nd keyword, and w_u^n represents the weight of the n th keyword, which is either 0 or 1, that is, whether or not the sport has this keyword.

II. A. 3) Recommendation algorithms

(1) User-based collaborative filtering algorithms

The core of user-based collaborative filtering recommendation algorithm is to calculate the similarity between users, usually using Pearson correlation coefficient or cosine similarity or Jaccard correlation coefficient as the similarity measure [23]. Given user u and user v, let $N(u)$ denote the set of items for which user u has had positive feedback, and let $N(v)$ be the set of items for which user v has had positive feedback. Then, the Pearson correlation coefficient can be defined as:

$$sim(u,v) = \frac{\sum_{i\in N(u)\cap N(v)}\left(r_{ui} - \overline{r}_u\right)\left(r_{vi} - \overline{r}_v\right)}{\sqrt{\sum_{i\in N(u)\cap N(v)}\left(r_{ui} - \overline{r}_u\right)^2 \sum_{i\in N(u)\cap N(v)}\left(r_{vi} - \overline{r}_v\right)^2}} \tag{3}$$

where r_{ui} denotes the rating of item i by user u and $\overline{r}_u$ denotes the average rating of all items by user u. Based on the similarity between users, his rating for an item can be predicted for the target user. The prediction formula is as follows:

$$\hat{r}_{ui} = \hat{r}_u + \frac{\sum_{v\in S(u,K)\cap N(i)} sim(u,v)\left(r_{vi} - r_v\right)}{\sum_{v\in S(u,K)\cap N(i)} \left|sim(u,v)\right|} \tag{4}$$

where $\hat{r}_{ui}$ denotes the predicted score, $S(u,K)$ denotes the set of K users who are most similar to user u, $N(i)$ denotes the set of users who have rated item i, and $sim(u,v)$ is the similarity of users u and v.

The Jaccard correlation coefficient, also known as the Jaccard similarity coefficient, is a metric used to compare similarities and differences between finite sample sets. Its definition is based on the ratio of the intersection of two sets to their concurrent sets. Specifically, given two sets A and B, the formula for the Jaccard correlation coefficient $J(A,B)$ is as follows:

$$Jaccard(A,B) = \frac{|A\cap B|}{|A\cup B|} = \frac{|A\cap B|}{|A| + |B| - |A\cap B|} \tag{5}$$

where $|A|$ denotes the number of elements in set A, the base of set A, and $|B|$ denotes the number of elements in set B, the base of set B.

The Jaccard correlation coefficient has a value between 0 and 1. When the Jaccard correlation coefficient is equal to 1, it means that the two datasets are identical. When the Jaccard correlation coefficient is equal to 0, it means that the two datasets do not have any elements in common. The higher the Jaccard coefficient, the more similar the two samples are.

The Jaccard coefficient correlation metric is called Jaccard distance and is used to describe the degree of dissimilarity between sets. The Jaccard distance measures the degree of differentiation between two sets in terms of the proportion of different elements in the two sets to all elements, the larger the Jaccard distance, the less similar the samples are. The formula is defined as follows:

$$d_j\left(A,B\right)=1-J\left(A,B\right)=\frac{|A\cup B|-|A\cap B|}{|A\cup B|}=\frac{A\Delta B}{|A\cup B|} \tag{6}$$

(2) Recommendation algorithm based on differential evolutionary algorithm

Differential evolutionary algorithm has both genetic algorithm mutation, hybridization and selection operations, through these operations to increase the diversity of the population, while the differential evolutionary algorithm also has the particle swarm algorithm global search capability, can search for the global optimal solution in the global range [24]. Genetic algorithms for high-dimensional problems converge slowly or even difficult to converge, particle swarm algorithms for some optimization of this problem, achieved better results, differential evolution can be a good solution to the high-dimensional optimization problem, convergence speed is very fast and the results are very accurate.

The basic differential evolutionary algorithm is improved according to different application scenarios. Since the differential evolutionary algorithm is designed for the real number domain, it is improved and applied to the field of discrete combinatorial optimization, and the improvement to discrete algorithms is roughly divided into the following three categories: firstly, the real number domain is mapped to the (0,1) interval by a mapping function. Second, direct discrete encoding of the problem solution by performing logical with-or-without operations on the discrete values so that the solution of the problem is in binary form. Third, the problem solution is judged by the strategy to attribute the problem solution to 0 and 1 binary solutions. The discrete discretized evolutionary algorithm is applied to different domains to solve combinatorial optimization problems within the domain with the following algorithmic flow:

1) Initialize the population

Determine the control parameters of the differential evolution algorithm and determine the fitness function. The differential evolutionary algorithm control parameters include: population size NP, scaling factor F and hybridization probability CR.

2) Evaluation of eigenvalues

Evaluate the initial population, that is, calculate the fitness value of each individual in the initial population. Determine whether the termination condition is reached or the number of evolutionary generations is maximized. If yes, terminate the evolution and output the best individual obtained as the optimal solution. If not, continue the evolutionary algorithm.

3) Differential mutation operation

To perform the variation operation, the variation operator is a real constant factor which determines the amplification ratio of the deviation vector:

$$t_{i,j}^{k+1}=x_{ij}^{k}+F\left(p_{ij}-x_{ij}^{k}\right) \tag{7}$$

4) Differential crossover operation

To perform crossover operation, the crossover operator CR is a real number in the range of $[0,1]$. A larger value of CR implies a higher probability of population crossover variability and an increase in population diversity, and conversely a smaller value of CR implies a smaller probability of crossover variability and a decrease in population diversity:

$$U_n=\begin{cases}V_{ij}^{k} & rand>CR\\ 0 & otherwise\end{cases} \tag{8}$$

5) Differential selection operation

A selection operation is performed between the old and new populations to select the population with the better value between the original population and the new population to evolve to the next generation:

$$X_n = \begin{cases} V_{ij}^k & f(U_i) \le f(X_i) \\ X_i & otherwise \end{cases} \tag{9}$$

II. A. 4) Hybrid recommendation algorithms

Today, the existence of intelligent computing website background, in the recommendation method is not only only a recommended mechanism and strategy, the background often use a variety of recommendation algorithms, a few recommendation algorithms are fused with each other, so as to achieve the effect of personalized recommendations for the user. At present, the more popular hybrid recommendation methods are the following:

(1) Weighted hybrid: the recommendation results of each algorithm are combined in accordance with a certain proportion of weights, and finally the results of the two combinations of the set of results in the screening of the first N are recommended to the user [25].

(2) Switching hybrid: In the same project, for different scenarios, there are appropriate recommendation strategies, but in order to achieve better recommendation results, so the switching recommendation strategy is used to switch between different scenarios corresponding to the appropriate recommendation mechanism for the results recommended.

(3) Partitioned hybrid: Commonly found in the front-end interface of websites, different regions display different recommendation results. This recommendation method uses multiple recommendation mechanisms to display different results to the user, who can see comprehensive recommendation results, and it is also convenient for the user to get the goods they want.

(4) Hierarchical mixing: Hierarchical combination of multiple recommendation methods, using the model generated by one recommendation method as the input of another recommendation method, thus combining the advantages of multiple recommendation methods and making the recommendation results more accurate.

(5) Waterfall mixing: Using multiple recommendation mechanisms, the first recommendation method is used to generate approximate recommendation results, and the second recommendation method makes more accurate recommendations based on the results of the previous recommendation.

(6) Feature combination: combining features from different recommendation mechanisms, and then inputting the combined features into a unique recommendation mechanism.

(7) Feature Enhancement: The feature information generated by one recommendation method is embedded in the features of another recommendation method, so as to achieve the effect of accurate recommendation.

In order to recommend personalized sports needs to sportsmen, the system weighted and fused the user-based collaborative filtering algorithm and the recommendation results based on the differentiated evolutionary algorithm each accounting for N*50% to form a personalized sports recommendation algorithm, where N denotes the total number of recommendations.

II. B.Personalized Sports Recommendation System Model

The personalized sports recommendation system consists of three main parts, namely, user model, sports model, and recommendation algorithm. Among them, the user model is used to analyze the user's behavior based on the user's interests, background information, access records and rating records collected during the interaction between the system and the user. The sports model is used by the designer to collect the characteristics of sports. These two models are calculated by the recommendation algorithm to produce results to recommend to the user. The recommendation system model is shown in Figure 2.

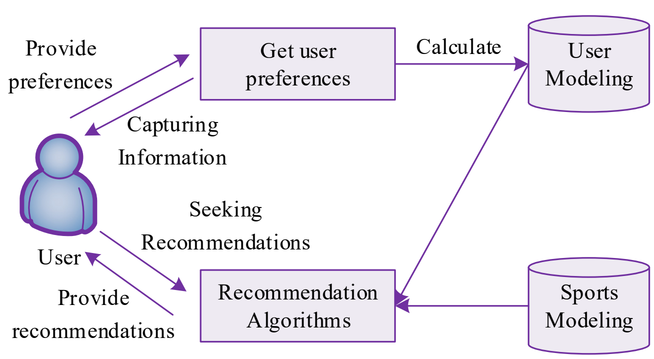

Figure 2: Schematic diagram of personalized sports recommendation system model

III. Experimental analysis of algorithms

III. A. Evaluation criteria

In general systems that provide recommendation services, recommendation is achieved by providing users with a personalized list of recommendations in the form of a recommendation method called Top-N recommendation. In Top-N recommendation, the prediction accuracy is generally measured by recommendation accuracy and recommendation recall.

Recommendation Accuracy:

$$\mathrm{Pr}\,ecision = \frac{\sum_{u \in U} |R(u) \cap T(u)|}{\sum_{u \in U} |R(u)|} \tag{10}$$

Recommended Recall Rate:

$$\mathrm{Re}\,call = \frac{\sum_{u \in U} |R(u) \cap T(u)|}{\sum_{u \in U} |T(u)|} \tag{11}$$

In Eq. (10) and Eq. (11), $R(u)$ represents the recommendation list calculated by the system based on the test data, and $T(u)$ is the list of user access data on the test set. Sometimes, in order to evaluate the recommendation effect of Top-N recommendation in full name, multiple recommendation list lengths are selected and the full recommendation accuracy and recall are calculated for comparison.

The coverage of a recommender system describes the ability of a recommender system to recommend non-popular items, and the coverage also reflects the degree of personalization of the recommender system's recommendation results. There are several ways to define the coverage rate, here the ratio of the set of items recommended by the recommender system to the total set of items is used for the definition.

Coverage ratio:

$$Coverage = \frac{|\cup_{u \in U} R(u)|}{I} \tag{12}$$

where U denotes the set of all users, I denotes the set of all items, and $R(u)$ denotes the set of recommended items for user u.

III. B. Experimental data set

The dataset used in this experiment is a simulation dataset, and its generation process is based on the suggestion of the teacher of the College of Physical Education, which establishes the relationship function between user attributes, such as height, weight, body type, BMI index and athletic ability. Then, a certain amount of randomness was added to the data by introducing Gaussian perturbation, thus making the generated data more realistic and credible. The dataset contains 50,000 data of sportsmen with 28 characteristics for each sportsman.

Such a dataset design enables the model to fully take into account the user's personal characteristics, exercise habits, and health status, so as to more accurately recommend exercise programs. Meanwhile, the large size of the dataset and its rich feature information help to verify the effectiveness and generalization ability of the model in real scenarios.

III. C. Analysis of results

III. C. 1) Influence of the number of similar users on recommendation results

In user-based collaborative filtering recommendation algorithms, different numbers of similar users can also have a significant impact on the recommendation results when a defined similarity metric criterion is chosen. In the following, 10, 20, 30, and 40 similar users of active users in the simulation dataset are compared under 20 extended cosine similarity of recommendation results. The experimental results are shown in Fig. 3. By comparing the data in the figure, it can be found that with the increase of the number of similar users, the recommendation accuracy and recommendation recall increase, but when the number of similar users exceeds 20, the recommendation accuracy and recall do not change significantly. Meanwhile, the recommendation coverage rate decreases significantly as the number of similar users increases.

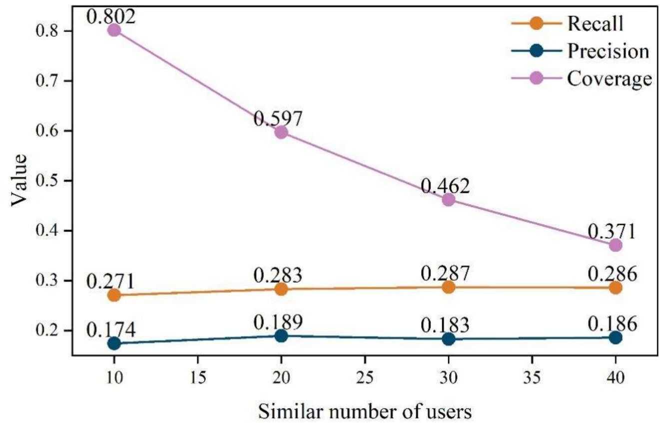

Figure 3: Comparison of recommendation results on different user similarity number

III. C. 2) User preference effect analysis

In this paper, the generalization ability of the differential evolution algorithm is verified on the simulation dataset. The feature attributes of each sportsman in the simulation dataset are 28, so the number of neurons in the input layer and the number of neurons in the hidden layer of the membership neural network are set to 28, and the number of neurons in the output layer is set to one. The software was programmed using MATLAB2008a to randomly initialize the weights and thresholds of the neural network algorithm and train 30 sub-neural networks for integration. To verify the effectiveness and robustness of the differential evolution algorithms, the algorithms were compared with GAE, GASEN, KDE, and AGE. Each algorithm trained the algorithm independently for 10 times, and the mean squared error of the experiment is shown in Figure 4. The mean values of the mean squared errors of the differential evolution algorithm, GAE, AGE, GASEN, and KDE are 0.832, 0.845, 0.861, 0.847, and 0.858, respectively.In terms of the mean squared errors, the best-performing algorithm in the dataset is the differentiated evolution algorithm proposed in this paper, followed by the GAE algorithm, whereas the performance of the GASEN, KDE, and AGE algorithms is relatively unstable and the The average error is not much different. In summary, the differential evolution algorithm proposed in this paper can significantly reduce the mean square error in the training of user preference algorithms, has better generalization ability, and can objectively reflect the user's preferences, thus improving the accuracy of the recommendation.

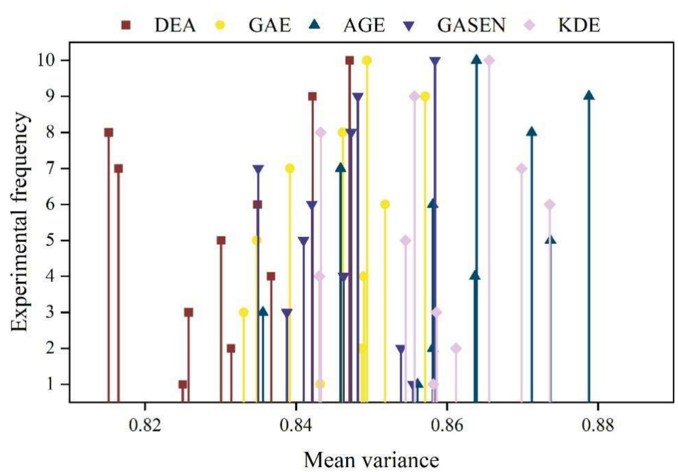

Figure 4: The variance of the experiment

III. C. 3) Comparison of Recommendation Effect of Hybrid Algorithms

In the recommendation effect comparison, the weighted fusion designed in this paper to form a personalized sports recommendation algorithm is compared with the user-based collaborative filtering algorithm and the recommendation algorithm based on the differentiated evolutionary algorithm, and the experimental results on the simulation dataset are shown in Figure 5. The hybrid recommendation has the highest recommendation recall (0.169) and accuracy (0.036), while ensuring a certain degree of recommendation coverage (0.547), and the hybrid recommendation has an obvious recommendation advantage.

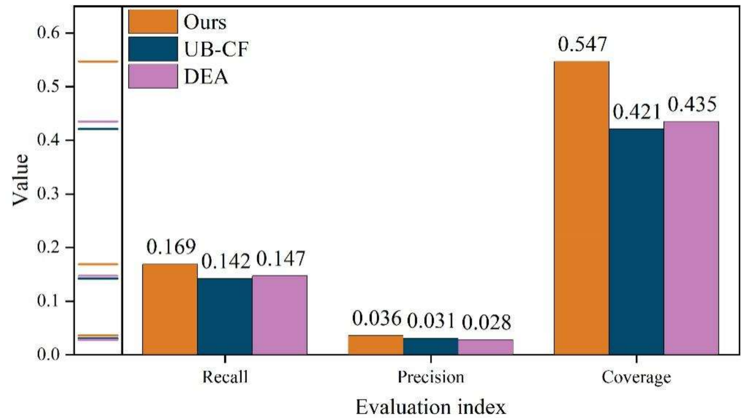

Figure 5: Recommendation result comparison of different recommendation algorithm

IV. System application analysis

In order to accurately grasp the actual effect of the personalized sports recommendation system and promote the intelligent development of the system, this paper relies on S Middle School to carry out experimental research. The experimental subjects are 80 students randomly selected from S Middle School, including 20 students in the male experimental group (Group B2) and 20 students in the control group (Group B1), and 20 students in the female experimental group (Group A2) and 20 students in the control group (Group A1), and we make sure that there is no significant difference between the male and female control groups and the experimental group in terms of their knowledge of sports, athletic ability, sports behaviors, and sports psychology through reasonable division. Differences. The study was conducted over a period of three months in conjunction with the secondary school physical education curriculum.

The control group carried out the exercise prescription experiment under the coordination of the instructor, and the exercise prescription was designed by the instructor according to the students' physical status and in conjunction with the general curriculum, including the purpose of exercise, health care knowledge, types of exercise and loads, exercise frequency, and prevention of sports injuries. During the implementation process, the instructor will adjust the exercise prescription appropriately according to the students' feedback. The experimental group mainly relies on the personalized sports recommendation system to carry out personalized guidance experiments, the system enters the sports quality characteristics of students in the experimental group in advance, and then generates different personalized sports prescriptions for each student based on the rich case base of sports prescriptions and general constraints using the hybrid algorithm designed in this paper.

The experimental results of the evaluation were quantitatively analyzed in terms of students' sports literacy and physical health status, in which students' sports literacy was evaluated using the “Self-measurement Scale of Students‘ Sports Literacy” in the “Construction of Students’ Sports Literacy Evaluation Indicator System and Preparation of Self-measurement Scale”. The scale consists of 4 primary indicators and 17 secondary indicators of sports knowledge, sports ability, sports behavior and sports psychology, and each secondary indicator is assigned a corresponding weight. Students complete the 30 questions in the self-measurement scale, and the formula calculates the score of the primary indicators, which is then summed up to get the total score of students' physical literacy. The assessment of students' physical fitness is based on the evaluation standards of the Student Physical Fitness Monitoring (SPFM), and the common indicators for both boys and girls are lung capacity, 50-meter run, standing long jump, and seated forward bending; in addition, the monitoring indicators for girls are the 800-meter run and one-minute sit-ups, while the monitoring indicators for boys are the 1,000-meter run and pull-ups, with each indicator scored in accordance with the SPFM scoring standards.

IV. A. Comparative analysis of students' physical fitness after the experiment

Comparison of sports literacy between the control and experimental groups after the experiment is shown in Table 1. There were significant differences ($p<0.05$) in sports knowledge, athletic ability, sports behavior and sports psychology between male and female control and experimental groups after the experiment.

IV. B. Comparative analysis of students' physical health after the experiment

The comparative analysis of students' physical fitness after the experiment is shown in Table 2. There were significant differences ($p<0.05$) in lung capacity, 50-meter run, standing long jump, seated forward bending, 800-meter/1000-meter run, and 1-minute sit-up/pull-up between male and female control and experimental groups after the experiment. Although the manual exercise prescription was able to improve students' standing long jump, 800 m/1000 m run, and 1-minute sit-up/pull-up, there was still a gap in physical fitness and health enhancement compared with the exercise prescription recommended by the personalized sports recommendation system.

Table 1: The comparison between the control group and the experimental group

	Sports knowledge	Athletic ability	Physical behavior	Physical psychology
Group A1	0.763±0.076	0.863±0.053	0.936±0.072	0.634±0.117
Group B1	0.776±0.081	0.933±0.041	1.062±0.094	0.723±0.092
P	0.013	0.000	0.002	0.023
Group A2	0.763±0.051	0.926±0.077	0.951±0.063	0.637±0.071
Group B2	0.802±0.088	1.021±0.049	1.055±0.081	0.733±0.084
P	0.036	0.000	0.002	0.001

Table 2: The control group and the experimental group were healthy compared

	Lung capacity(ml)	50m run(s)	Fixed jump(cm)	Preflexion(cm)	800/1000m run(min)	1 minute sit-ups/Laps
Group A1	2511.2±341.2	9.77±0.52	153.2±14.1	15.96±4.33	4.163±0.314	28.6±4.1
Group B1	2763.1±382.3	9.14±0.55	176.3±12.2	22.44±5.21	3.862±0.325	35.6±5.1
P	0.022	0.001	0.000	0.000	0.000	0.003
Group A2	3476.3±514.6	8.21±0.44	207.2±14.2	10.21±11.15	4.364±0.314	5.7±3.1
Group B2	4012.3±526.7	7.63±0.34	234.5±17.8	16.93±5.22	3.621±0.341	17.6±3.9
P	0.002	0.000	0.000	0.022	0.000	0.000

The design and implementation of artificial exercise prescription carries the instructor's more obvious tendency, the teaching content is more likely to dominate the fitness content of exercise prescription, the teaching method is more likely to dominate the implementation method of exercise prescription, which is manifested in the fact that the physical fitness related to the teaching activity improves more quickly, while the other physical fitness improves slowly. At the same time, due to the limited energy of the instructor, when the number of students reaches a certain size, it is almost impossible to achieve accurate docking of each student's fitness needs and continuous tracking and adjustment of student fitness programs. The personalized sports recommendation system will continuously establish a close connection with the students' fitness status, relying on the rich fitness content and continuously optimized matching rules in the sports prescription library, and based on the great advantages of modern information technology in data collection, transmission, processing and sharing, the accuracy, systematicity and real-time nature of the students' sports prescription are fundamentally guaranteed.

V. Conclusion

In this paper, we design a sports recommendation system that can provide personalized guidance based on users' interaction history data and sports characteristics. The system mainly carries out personalized recommendation based on the calculation results of the differential evolution algorithm and collaborative filtering algorithm. The weighted fusion of the two algorithms resulted in a recall, accuracy and coverage of 0.169, 0.036 and 0.547, respectively, with obvious recommendation advantages over a single algorithm. The system was applied to S Middle School for a controlled experiment, and there was a significant difference ($p<0.05$) in students' sports quality and physical fitness after using this paper's system for online personalized instruction of sports homework. The personalized sports recommendation system ensures that the exercise prescription always matches the students' fitness reality and achieves the purpose of recommending personalized and healthy exercise programs for students.

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