J. COMBIN. MATH. COMBIN. COMPUT. 127a (2025) 9239--9258

Journal of Combinatorial Mathematics
and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Combinatorial Press

Optimization of the information framework of sports mobilization effect in active health perspective based on particle swarm optimization algorithm

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ABSTRACT

In order to explore and promote the strategy of students' active health behaviors, this paper designs a personalized scientific guidance system architecture for active health promotion based on a three-tier service architecture model, using students' sports literacy big data processing technology to construct a sports mobilization effect information system. Second, a sports prescription generation model is designed. The model adopts a multifactor fusion approach to recommend personalized exercise programs based on the different exercise abilities, different physical conditions, and personal exercise preferences of the exercisers. Under the condition of satisfying multiple constraints such as the physical condition, parameter range and exercise ability of the exerciser, the particle swarm optimization algorithm is used to optimize the exercise parameters, and the topological structure is further used to adjust the broadness of the distribution of the solution set in the objective space. The improved particle swarm optimization algorithm is compared, and the experimental results show that the improved TS-PSO algorithm converges faster, the solution accuracy is higher, and the parameter optimization using this algorithm generates a personalized exercise prescription that is more suitable for the exerciser. The exercise prescription generation model studied in this paper provides a new idea for the improvement of the effect of sports mobilization under the perspective of active health.

Keywords: active health, exercise prescription generation, particle swarm optimization, topology, information system

1. Introduction

Under the modernized life style and concept, the enhancement of people's material conditions is accompanied by a significant increase in chronic non-communicable diseases, sedentary and non-

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Received 05 February 2024; Revised 12 April 2024; Accepted 05 December 2024; Published Online 15 April 2025.
DOI: 10.61091/jcmcc127a-514

exercise mode has become the main way of life of people in today's society, which has seriously threatened people's physical health [1-3]. Exercise for health, "active health", is a developmental, medical model of health governance, through interventions on the human body to promote the body to achieve a good adaptation, thereby slowing down the process of disease, and promote the strengthening of physical fitness [4-6]. At present, the public's understanding of the concept of health is still at a relatively shallow level, and the awareness of "active health" is weak. With the implementation of relevant national health and fitness strategies, people's awareness of chronic disease prevention and understanding of scientific health literacy have gradually deepened, and the concept of "treating existing diseases" has gradually changed to the core concept of "treating non-disease" [7-10]. Under the active health perspective, social mobilization is an important means of conducting grassroots sports governance and is a basic guarantee for the implementation of the national fitness movement in the new era [11-12].

Social mobilization is a unique dynamic activity of human society, which plays a great role in promoting the social practice of human beings to transform the objective world [13-14]. Sport is a social phenomenon with a high degree of social relevance, and sport governance faces a common affair that requires the participation of the whole society and involves the participation of multiple subjects related to the affair [15-16]. The in-depth promotion of sports mobilization will become a powerful complement to a higher level of public service system for national fitness and a basic anchor for the formation of a higher level of grassroots sports governance community [17-18]. Since the purpose of social mobilization is to stimulate more people's enthusiasm for participation and mobilize more social subjects' enthusiasm for participation, it is not only necessary to develop a strong mobilization mechanism to optimize the allocation and integration of a wider range of social capital, but also necessary to assess and feedback the effects of sports mobilization to provide a guarantee for the operation and improvement of the mobilization mechanism [19-22].

This paper investigates a personalized scientific guidance system for sports health promotion, including multi-type sports skills training programs and physical training scientific guidance programs, to achieve the two goals of students' physical fitness level improvement and sports skills mastery. At the same time, a collaborative filtering algorithm based on user preferences is used for the recommendation of sports programs in sports skills. According to the physical condition of the sportsperson and the specification of generating sports prescriptions, the collaborative filtering algorithm is used to determine the sports program by combining the physical condition and comprehensive sports ability of the sportsperson. According to the range of standard exercise prescription parameters corresponding to the exercise program, a multi-objective optimization model is constructed by combining the constraints between the exercise parameters and the exercise expectations of the athletes. Finally, the particle swarm optimization algorithm is used to optimize the parameters, and the algorithm is improved by parameter adjustment and topology adjustment to achieve personalized optimization of exercise prescription parameters.

2. Information system architecture for sports mobilization effectiveness

Combined with active health in medicine and sports science, the concept of active health is given in the field of physical education teaching, and this paper believes that active health refers to a mode of physical education that actively obtains sustained health capacity through sports participation, maintains physical and mental health through physical education and sports, obtains good lifestyle behavior and social adaptation, and has character-driven effects. Under the active health perspective, this paper builds a sports mobilization effect information system to solve the problem of students' active health promotion.

2.1. System technical support

The construction of the personalized scientific guidance system for students' active health promotion requires computers and cognitive and comprehension abilities in the field of physical literacy, and the various support technology engines are interrelated and operate to achieve the functions of system classification, guidance, monitoring feedback and optimization. This system relies on the students' sports literacy monitoring, analysis and wisdom service platform, using most of the big platform technology support engine and part of this system technology support engine. Including sports literacy semantic annotation, sports literacy knowledge mapping, intelligent recommendation, data analysis, deep learning framework integration, sports literacy text processing, image analysis, semantic recognition, action recognition, semantic retrieval, and knowledge expression technology engine, the specific technical support is shown in Figure 1.

1) Knowledge expression is the main technical support engine of this system, which will express students' personal information, sports literacy indexes and guidance programs, etc. into a computer-usable language, and use inference-based rules to achieve automatic matching of students' population classification and personalized guidance programs.

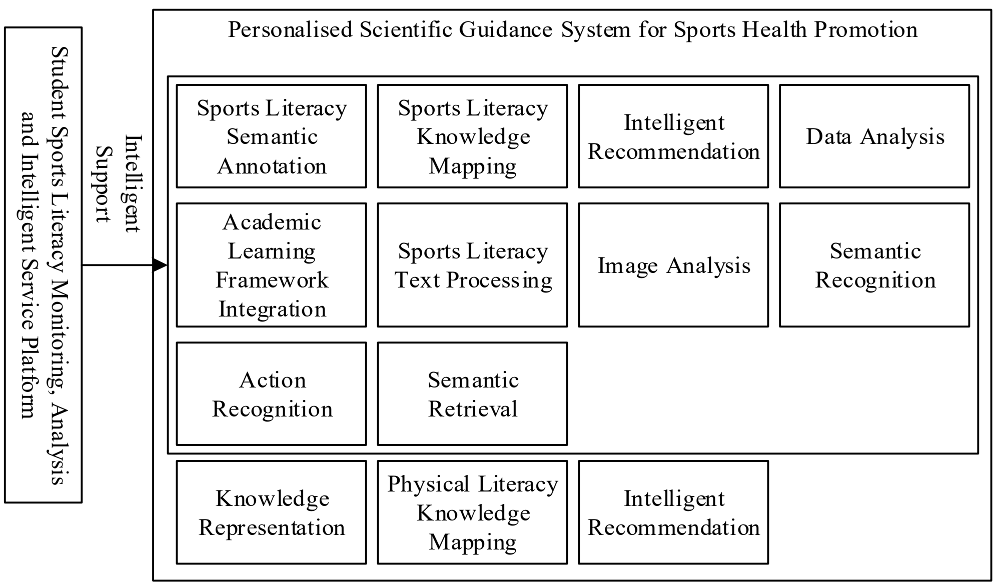

Fig. 1. System technical support framework

2) Intelligent recommendation is based on multi-dimensional data of students' physical literacy, personalized scientific guidance programs, etc., using deep learning and semantic analysis models to build a recommendation engine, which, on the basis of the recommendation of sports prescription and nutritional prescription, adds new personalized physical training and sports skills guidance programs for the improvement of students' physical literacy and realizes the scientific recommendation of sports to meet the service demand of the students' physical literacy sports intervention.

3) The physical literacy knowledge graph is mainly used to extract complete prescriptions such as sports prescriptions and nutritional prescriptions from the corpus of knowledge and rules. On this basis, this system adds new knowledge graphs such as students' sports skills and physical training guidance programs, sports recommendations and sports teaching videos to realize multi-dimensional scientific guidance for students.

4) Data analysis is mainly based on data collected from sports bracelets, intelligent monitoring devices, system questionnaires and mobile applications.

Based on the data collected from sports bracelets, intelligent monitoring devices, system questionnaires and mobile applications, a data analysis engine is provided to support data mining, processing, analysis and visualization.

5) The semantic annotation of sports literacy mainly targets the knowledge base, rule base and database of sports literacy. In order to improve the efficiency of sports literacy data analysis and personalized application, the annotation specification, unified and standard process is formulated, and the quality of annotated data is guaranteed to be reliable.

6) Deep learning framework integration mainly meets the needs of sports literacy in the construction of knowledge graph, intelligent recommendation, data analysis, etc., using deep learning tools and algorithms to provide support.

7) Action recognition mainly captures, tracks, settles and marks students' sports actions, identifies scene content information, realizes the comparison between students' action data and existing or standard actions, and evaluates students' sports.

2.2. System Architecture Model

Based on the three-tier service architecture model, i.e., Infrastructure-as-a-Service (IaaS), Platform-as-a-Service (PaaS), and Software-as-a-Service (SaaS), and combining with the technology of processing big data on students' physical literacy, this study proposes the architecture of a personalized scientific guidance system for students' active health promotion.

2.2.1. IaaS-based data resource layer. The system architecture of the IaaS-based data resource layer is shown in Figure 2, which provides infrastructure services, basic data services, and data collection group services. Infrastructure service is based on hardware, processing, analyzing and storing various data of students through data collection group service, constructing a scientific guidance database for students' active health promotion, and utilizing hardware equipment such as security gateways and firewalls to ensure the safety of information and data, and the normal operation and maintenance of the system. Basic data is based on technical facility resources to realize the management of basic data such as data transmission, data pre-processing, data storage, data calculation, data load balancing, data sharing, and data full-cycle life management. Data collection group service is the collection of student data, including structured data, semi-structured data and unstructured data.

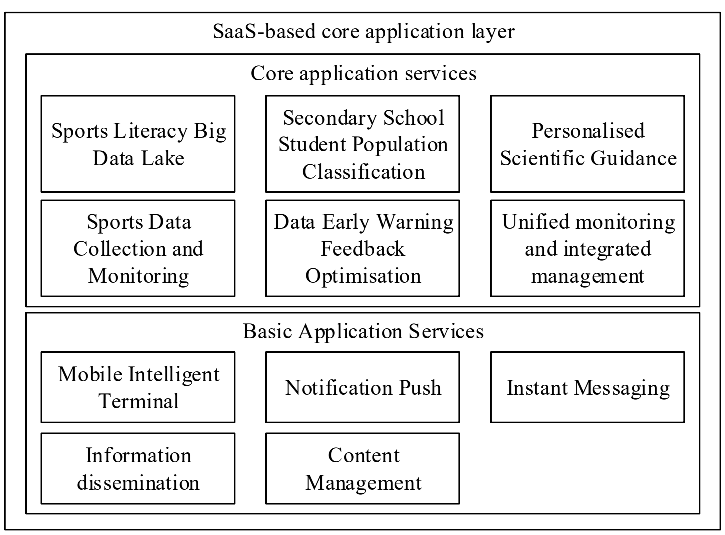

Fig. 2. Data resource layer system architecture based on IaaS

2.2.2. PaaS-based service support layer. The PaaS-based service support layer system architecture is shown in Figure 3, which provides open API data sharing interface services, basic service support, and service engine support. The API interface is to connect the infrastructure and basic services of IaaS with the data docking and sharing of systems in the SaaS application layer. The service engine supports the retrieval, analysis and population classification of data such as students' current physical literacy index, using existing physical fitness and skill knowledge content quantitative model construction and rule reasoning, and then realizing intelligent recommendation and scientific guidance. Computing service support through data collection of IoT devices, intelligent feedback and optimization of the sports guidance process.

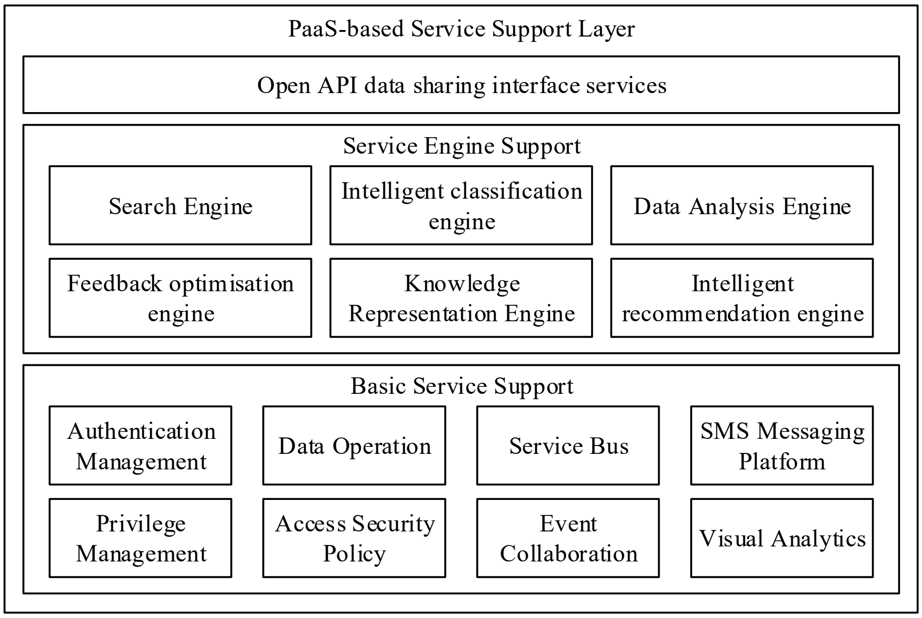

Fig. 3. Service support layer system architecture based on PaaS

2.2.3. SaaS-based core application layer. The core application layer system architecture based on SaaS is shown in Figure 4, which is based on Web Service to provide Internet-based system services. Among them, the basic application service is to build the service application of mobile intelligence and realize the basic application service of interconnection and interaction such as information release, instant communication, information notification and content management. The core application service is to build a scientific guidance system for students' sports and health promotion, a big data lake for students' sports literacy, generation of students' sports prescriptions, sports data collection and monitoring, sports data early warning feedback and optimization, unified monitoring and comprehensive management. The target audience of the service includes students and parents, schools, service organizations and education authorities at all levels.

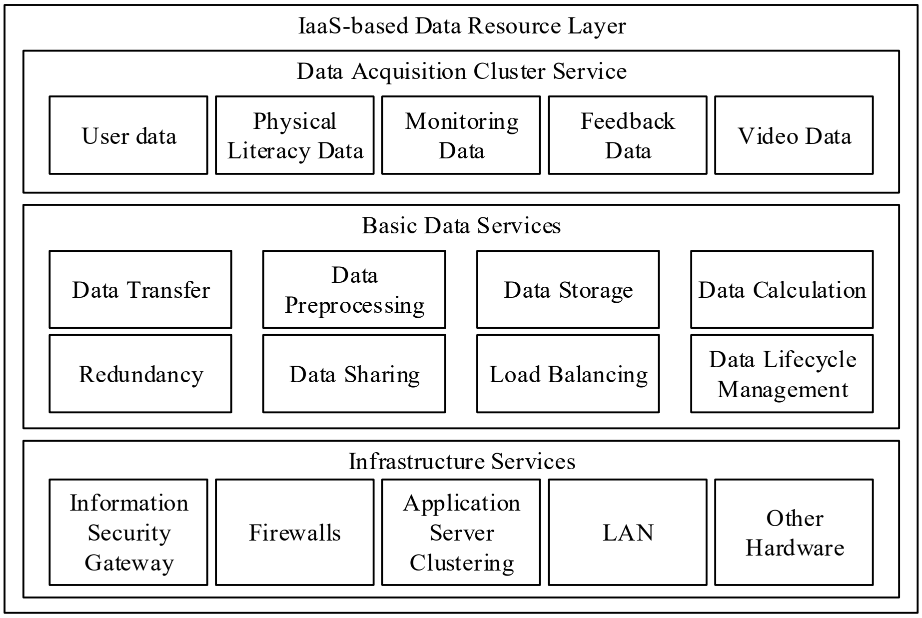

Fig. 4. SaaS-based core application layer system architecture

3. Exercise prescription generation technology in the active health perspective

Sports service health as a major important area of the development of the sports industry in the new era has received a high degree of attention, and exercise prescription, as a theory focusing on the study of sports and physical health, has laid a theoretical foundation for sports health services. Exercise prescription caters to people's demand for active health and exercise, but it is difficult to popularize the manual-based exercise prescription service due to its high cost. Combined with the development concept of "intelligent sports" and the integration of new technologies, sports prescription generation and management system can popularize professional sports and health services, guide people to participate in sports and fitness correctly, avoid sports risks, and realize the application value of sports prescription in active health.

3.1. Exercise prescription generation program design

3.1.1. Calculating similarity. In this paper, based on the principle of relevance in the formulation of exercise prescription and the quantization scheme of exercise programs, we constructed an exercise program screening model based on the improved collaborative filtering algorithm. Based on the quantification scheme of exercise programs, the similarity of exercise programs is calculated from the dimensions of exercise effect, effect site, exercise environment and exercise conditions to discover the potential association between exercise programs and the relationship between exercise programs and exercise needs. In order to accurately calculate the similarity of exercise programs under specific dimensions, this paper improves the collaborative filtering algorithm by incorporating the focusing coefficient matrix to calculate the exercise prescription parameters, and the results of this calculation express the similarity of exercise programs under specific dimensions [23]. Its mathematical expression is:

$$R(i,j)=\frac{\sum_{u\in E_i\cap E_j}\frac{w(u)}{1+p(u)}+\sum_{v\in T_i\cap T_j}f_v}{\sqrt{|E_i||E_j|}+\sqrt{|T_i||T_j|}}\left(1+\frac{1}{\sqrt{\left(\frac{Q_iD_j+D_iQ_j}{2Q_jD_j}\right)^2}}\right)\frac{F_i}{F_j} \tag{1}$$

where, T - quantitative vector of attributes of the sport item effect object.

E - Quantized vector of attributes of the effect of the exercise program.

Q - Exercise intensity required by the exercise program.

D - the required exercise duration of the exercise program.

F - Optimal exercise frequency of the exercise item.

f_v - Focus coefficient of the effect attribute, for the focus of the effect attribute, with a default value of 1.

$p(u)$ - Exercise effect u Distribution rate in the exercise database.

where $w(u)$ denotes the focusing of the movement effects E_i and E_j of the movement programs i and j, calculated as follows:

$$w(u)=1+\frac{\sum_{u\in E_i\cap E_j}f_u}{\sqrt{|E_i||E_j|}} \tag{2}$$

where, f_u - effect attribute focus coefficient, expressing the degree of attention to attribute u, with a default value of 1.

Combined with the quantization scheme of sports items, the similarity between sports items is calculated using an improved collaborative filtering algorithm. Under the action of the focusing coefficient matrix, the focus on the features of certain dimensions is enhanced to improve the calculation accuracy.

3.1.2. Strategies for Screening Campaign Programs. For the generation of exercise prescription, screening suitable exercise programs is the basis for realizing the function of exercise prescription. In this paper, based on the analysis of human physique, we analyze the user's exercise demand and screen the appropriate exercise programs from the demand. Exercise demand mainly expresses the user's expectations for the effect of specific parts of the exercise, so this paper starts from the user's physical analysis to obtain the user's defects in which parts of the body or the system, to determine the user's need to achieve the effect of the exercise, to generate the user's exercise demand, and to establish the search target and screening conditions for the improved collaborative filtering algorithm. The main content of the physical analysis is shown in Figure 5, and the target is divided into body parts and systems, and the effect corresponds to the attribute of the exercise effect of the exercise program.

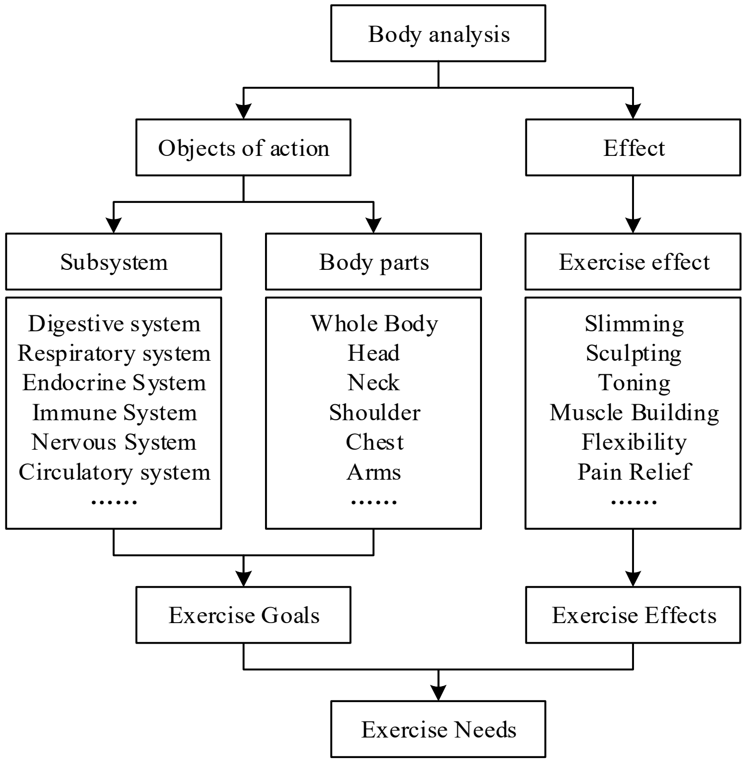

Fig. 5. Obtaining requirements by constitution analysis

Based on the physical analysis to establish the three aspects of exercise demand in terms of exercise purpose, exercise effect and exercise ability, the exercise program recommendation is shown in Figure 6. Among them, the purpose of exercise is subdivided into the type of action and the site of action, based on these two conditions to obtain exercise programs, and then through the correlation analysis to find similar or complementary exercise programs. Exercise conditions are divided into time conditions and exercise facility conditions, which are used to screen and exclude the exercise programs with time conflicts and facilities that cannot be met. Exercise ability analysis is used to determine the upper limit of exercise strength, upper limit of intensity and upper limit of fatigue, and filter the exercise programs that the current users cannot meet the exercise requirements. Ultimately, the acquired exercise programs not only meet the user's exercise requirements, but also satisfy the exercise execution conditions, close to the actual application environment.

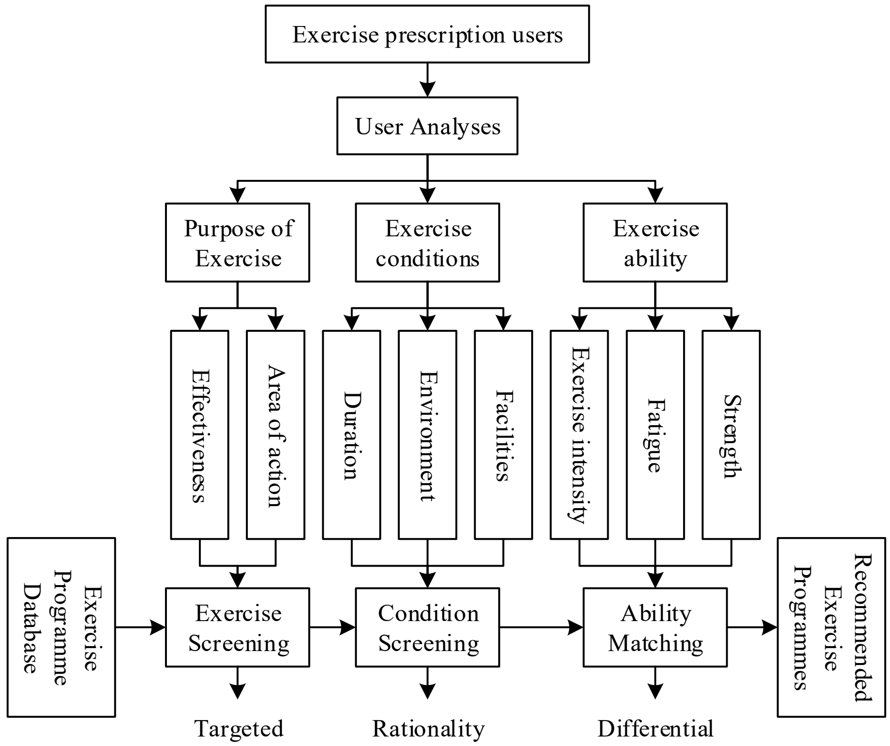

Fig. 6. Sports recommendation chart

According to the above sports item filtering scheme, combine with the improved collaborative filtering algorithm in this paper to construct the sports item filtering model. The ideal sports program model is established from the user analysis, and the similarity of the same type of sports program i is calculated with the ideal sports program model S as the object. And add the user weight matrix, calculate the adaptation degree value $Fitness \in [0,1]$ for the user input, and judge whether the sports project meets the user's expectations. The adaptation degree calculation method is as follows:

$$Fitness(i) = \frac{\sum\sum WE_iE_s + \sum\sum T_iT_s}{\sqrt{|E_i||E_s|} + \sqrt{|T_i||T_s|}} \left(1 + \frac{1}{\sqrt{\left(\frac{Q_id + D_iq}{2qd} \right)^2}} \right) \frac{F_i}{f} \tag{3}$$

where, T - action site vector.

E - Exercise effect vector.

Q - Intensity of exercise program.

D - Exercise duration.

F - Exercise frequency.

d - User input exercise duration.

q - User input exercise intensity.

f - User input exercise frequency.

W - Weights matrix.

The adaptive computing model is used to calculate the degree of conformity of the exercise items in the database to the user's needs, and filter the exercise items that meet the expectations, so as to complete the screening of exercise items in the generation of exercise prescriptions. In order to achieve the accuracy of the screening of sports items, W_{is} weight is introduced to focus on the attributes of user's concern, and the compliant sports items are incentivized to meet the demand for fewer and specialized sports, so as to enhance the robustness of the algorithm, and make the calculation results sparse and accurate.

3.2. Motion parameter calculation based on particle swarm optimization

3.2.1. Particle Swarm Optimization Algorithm. Particle swarm optimization algorithm (PSO) is a population-based meta-heuristic algorithm, PSO in the process of searching for the optimal, each particle, through mutual communication and information sharing between individuals, adjusts the search direction and step size with the historical information of itself and its neighboring particles, and guides the whole population to move in the direction of the optimal solution that may exist [24]. This mechanism based on individual cooperation among particles is a unique advantage of PSO different from other evolutionary algorithms. In PSO, each bird or food to be pursued is treated as a solution to the problem to be optimized, and the information shared among different individuals during the iteration process is used to adjust the search direction so as to fly towards a better area.

Assuming that the search space is a n-dimensional space and the particle swarm consists of N particles, $x_i^t=\left(x_{i,1}^t,x_{i,2}^t,\ldots,x_{i,D}^t\right)$ and $v_i^t=\left(v_{i,1}^t,v_{i,2}^t,\ldots,v_{i,D}^t\right)$ are the position and velocity of the i th particle in the search space at moment t, respectively. $p_i^t=\left(p_{i,1}^t,p_{i,2}^t,\ldots,p_{i,D}^t\right)$ is the individual optimal solution (Pbest) of the i th particle at moment t. $g_i^t=\left(p_{i,1}^t,p_{i,2}^t,\ldots,p_{i,D}^t\right)$ is the global optimal solution (called Gbest) of the i th particle at the t th moment.

The update formulas for the basic PSO can be expressed as respectively:

$$v_{i,j}^{t+1}=\omega v_{i,j}^t+c_1r_1\left(pbest_{i,j}^t-x_{i,j}^t\right)+c_2r_2\left(gbest_j^t-x_{i,j}^t\right) \tag{4}$$

$$x_{i,j}^{t+1}=x_{i,j}^t+v_{i,j}^{t+1} \tag{5}$$

where, ω - inertia weights.

c_1 and c_2 - Learning factors.

r_1 and r_2 - Random numbers in $[0,1]$.

$j=1,2\cdots,D$ - The dimension of the problem to be optimized.

$i=1,2\cdots,N$ - The number of the particle.

The size of the search space is limited to $\left[X_{\min},X_{\max}\right]$. If a particle exceeds the search space during iterative updating, an initialization operation is performed on particles that exceed the limit. In addition, in order to prevent the flight step of the particles from being too large, which leads to premature convergence of the algorithm, a constant $V_{\max}=-V_{\max}=\left(X_{\max}-X_{\min}\right)/2$ is used to limit the speed.

The particle position update method of the basic PSO algorithm is shown in Fig. 7. The particle velocity and position update consists of three parts, including the historical information of the particle velocity, the guidance of the individual optimal position and the guidance of the global optimal position.

In the first part, the particles are influenced by the speed of the individual history to search towards a wider space, avoiding the algorithm to fall into premature convergence. The size of the inertia weights determines how much the particles are affected, with a larger w favoring exploration and a smaller w favoring exploitation.

In the second and third parts, the particles are influenced by the individual optimal information and the global optimal information, and by learning from these two optimal information, it ensures the co-existence of individual diversity and convergence, and the exploration and exploitation go hand in hand to search for the optimal solution with better quality.

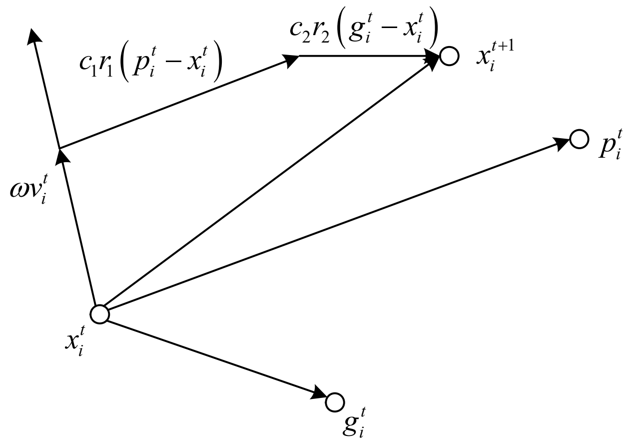

Fig. 7. Location update diagram of particle swarm

3.2.2. Parameter adjustment. From the speed update formula of the particle swarm optimization algorithm, it can be seen that the inertia weight w as well as the learning factors c_1 and c_2 have a great influence on the results of the algorithm. Inertia weight w affects the exploration and exploitation capabilities of the particles, with a larger w favoring exploration and a smaller w favoring exploitation.

Learning factor c_1 affects the perception of a particle's individual previous experience, and c_2 affects the exchange of information between particles. If c_1 is greater than c_2, the algorithm's subsequent search process favors exploration.

If c_1 is smaller than c_2, the subsequent search process of the algorithm favors exploitation.

In order to balance exploration and exploitation, this paper introduces PSO with time-varying acceleration coefficients and inertia weight factors, which applies perturbations to random particles through preset mutation probabilities, and adds adaptive mutation steps to cope with various unexpected situations [25]. It can observe the convergence of the population and the magnitude of the target value of the particles to determine whether it falls into a local optimum or not, and relies on controlling the values of the inertia weights as well as the learning factor to accelerate the population search speed in order to achieve a balance between exploration and exploitation.

3.2.3. Topological adjustment. Topology adjustment is widely used in various particle swarm algorithms, and different topologies correspond to different ways of information exchange. Commonly used topologies, including ring topology, star topology, quad cluster topology and quadrilateral topology [26]. Among them, the ring topology and star topology are more widely used. In the former, each particle exchanges information only with its “neighbors” on both sides, and this local topology is able to form a variety of small habitats, which is conducive to the search for the optimal solution in the neighborhood. The latter belongs to the global topology, in which all particles are in a neighborhood, and all of them share information and update together.

Since the topology of the particle swarm has a great influence on the performance of the PSO algorithm, the PSO algorithm is improved based on the topology, and TS-PSO is proposed, whose velocity and position updating formulas are shown below:

$$v_{i,j}^{t+1} = \omega v_{i,j}^t + c_1 r_1 \left(pbest_{i,j}^t - x_{i,j}^t \right) + c_2 r_2 \left(nbest_j^t - x_{i,j}^t \right) \tag{6}$$

$$x_{i,j}^{t+1} = x_{i,j}^t + v_{i,j}^{t+1} \tag{7}$$

As can be seen from the comparison of the above equation, the difference between the global and local versions of the PSO algorithm is only the different learning samples of the particles. The global version of PSO takes the historical optimal solution of the whole population as the learning sample, so the particles can quickly converge to the neighborhood of an optimal solution. However, it is easy for premature maturity to occur due to too fast convergence, and the local version of PSO takes the optimal solution of the particle's personal neighborhood as the learning sample. As a result, the particles in the population will eventually converge to multiple different optimal solutions, expanding the exploration area of the particles and improving the optimization search accuracy.

3.2.4. Algorithmic steps. The specific steps of particle swarm optimization algorithm are:

Step1, set the population size N, the maximum number of iterations $t_{\max}$, the inertia weights ω, the learning factors c_1 and c_2, etc. Perform initialization operation on the population P and randomly generate N particles.

Step2, calculate the adaptation value of each particle according to the objective function.

Step3, update the individual optimal solution and global optimal solution according to the following equation, respectively:

$$pbest_i^{t+1} = \begin{cases} pbest_i^t & f\left(x_i^{t+1}\right) \geq f\left(pbest_i^t\right) \\ x_i^{t+1} & f\left(x_i^{t+1}\right) < f\left(pbest_i^t\right) \end{cases} \tag{8}$$

$$gbest = \begin{cases} gbest_t^t & f\left(pbest^t\right) \geq f(gbest) \\ x_i^{t+1} & f\left(pbest^t\right) < f(gbest) \end{cases} \tag{9}$$

Step4, iteratively update each particle according to equations (4) and (5).

Step5, determine whether the end requirement is satisfied, if so, output all non-dominated solutions, otherwise go to STEP2.

3.2.5. Calculation of motion parameters. Exercise parameters mainly include exercise intensity, duration and frequency, and the setting of exercise parameters not only needs to consider the requirements of the exercise program itself, but also needs to be combined with the analysis of the athletic ability of the athlete, so as to set the appropriate parameters of the exercise prescription. If you want to achieve the effect of exercise prescription, you can not only rely on the control of the amount of exercise, the enhancement of physical fitness is subject to a variety of factors, the improvement of a single factor can not have a decisive effect on the final effect of exercise. Therefore, it is necessary to comprehensively consider the frequency, duration and intensity of exercise to achieve the optimal exercise state, and fine-tune the exercise prescription according to the implementation of the situation.

In order to solve the optimal solution problem in complex situations, this paper establishes an exercise prescription scheme generation model based on particle swarm optimization algorithm (PSO) solution to find the optimal combination of exercise prescription parameters under various constraints. Setting the amount of exercise per execution of exercise prescription as $f_1(x)$, the cost of execution of exercise prescription as $f_2(x)$, the amount of exercise W must be certain, the time used for exercise each time is not more than T, the frequency of being able to participate in exercise per week is $P<7$, and the maximum intensity of exercise is Q, the exercise prescription model based on Particle Swarm Optimization (PSO) algorithm can be obtained:

$$\min y = F(x) = \left[f_1(x), f_2(x)\right], x \in \left(x_1, x_2, x_3\right) \tag{10}$$

$$s.t. g_1\left(x_1, x_2\right) = \int_0^T x_2 dx_1 > W \tag{11}$$

$$g_2\left(x_1, x_2, x_3\right) = \sum_P \int_0^T x_2 dx_1 > W' \tag{12}$$

$$g_3(x_1) = T_{limit} < x_1 < T \tag{13}$$

$$g_4(x_2) = Q_{timit} < x_2 < Q \tag{14}$$

$$g_5(x_3) = x_3 < P \tag{15}$$

where, x_1 - the parameter of the length of the exercise prescription to be solved.

x_2 - to be solved exercise prescription exercise intensity parameter.

x_3 - Exercise frequency parameter of the exercise prescription to be solved.

W - The minimum amount of exercise to be achieved to complete this exercise prescription.

W' - The minimum amount of exercise required for one exercise cycle.

Q - Maximum exercise intensity.

Q_{limit} - Minimum exercise intensity.

T - Maximum exercise duration.

T_{limit} - Minimum exercise duration.

The two objective functions are constructed as follows:

$$f_1(x) = x_1 \times x_2 \tag{16}$$

$$f_2(x) = \frac{(T - x_1)(x_2 - Q_{\lim it})x_3}{(x_1 - T_{\lim it})(7 - x_3)(20 - x_2)} \tag{17}$$

The calculation of exercise prescription parameters strives to obtain the globally optimal solution, but considering the running time of the algorithm, the number of population iterations is set to be generally no more than 500 times. Combined with the exercise prescription feedback regulation mechanism, the exercise prescription parameters are gradually optimized during the implementation of the exercise prescription to ensure exercise efficiency. In this optimization process, according to the feedback of the exerciser in terms of exercise intensity and duration, the multi-objective optimization constraints are adjusted, and the iteration is continued to calculate the exercise prescription parameters suitable for the new exercise state, and to complete the adaptive adjustment of the exercise prescription parameters.

4. Analysis of the characteristics of sports mobilization and optimization of sports prescription

4.1. *Characterization of sports mobilization*

4.1.1. Types of Active Health Behavior Campaigns. According to the classification information of exercise punch cards in the Active Health Promotion Personalized Scientific Guidance System, the classification statistics of the types of exercise for students' active health are shown in Figure 8. More than half of the users use outdoor running as a fitness activity, and its proportion is 57.1%, while the rest are outdoor walking (14.15%), shaping exercise class (10.08%), indoor training (12.35%), outdoor cycling (5.54%), and yoga (0.78%), respectively. Compared to fitness, running is less costly, and outdoor running and walking, as zero-cost exercise methods, have become the main types of exercise for students' active health behaviors.

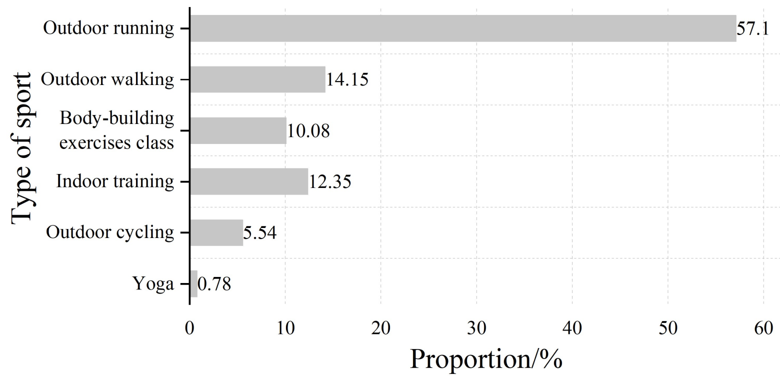

Fig. 8. Types of active health behavior campaigns

The top 30 high-frequency words were extracted based on word frequency by binning word frequency statistics of exercise names in active health behaviors of student users. It was found that the most frequent words in the word frequency were "running", "training", "walking" and "stretching", revealing that the students' exercise forms were mainly the simplest running and walking, revealing that running and walking are the most daily in the type of fitness activities. Activity words are “pamela”, “ballet”, “pull-ups”, “push-ups”, “Yoga” appeared with medium frequency, showing the richness of today's types of fitness activities and the growth of many individualized fitness activities. In the students' feeling vocabulary, “happy”, “relax” and “challenge” are shown, which shows that the students' cognition in active health behavior is positive, and the active health behavior has a positive promotion effect on their psychological state through active health behavior. This shows that students' perception of active health behaviors is positive, and that active health behaviors have a positive effect on their psychological state.

4.1.2. Temporal Characteristics of Active Health Behaviors. Taking one week as a time statistical unit, the number of 24-hour different moments of the clocking logs are summarized and counted, and the time distribution curve of the active health behaviors in one week is drawn, portraying the differences in fitness activities in different time periods between weekdays and days off and the weekly cyclic pattern.

The time distribution of active health behaviors is shown in Figure 9, which shows that the active health behaviors of students on weekdays and rest days show two distinct time periods of concentration, and the graph specifically shows the “saddle-shaped” characteristics of two wave peaks, and the troughs and peaks of the two saddles overlap in the evening. The statistical results of the number of active health behaviors during the week are shown in Figure 10, and the total number of times on rest days reaches more than 70,000 times, which is slightly higher than that on weekdays, indicating that the students have a stronger sense of active health, and maintain a more stable intensity of fitness activities no matter on weekdays or on both rest days.

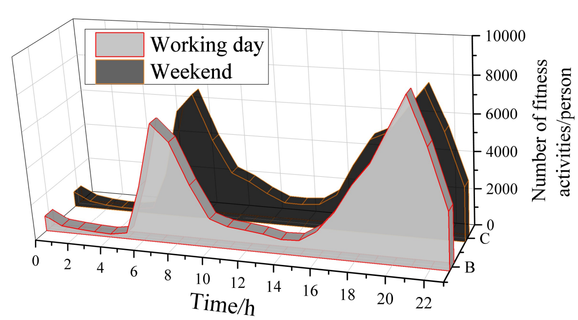

Fig. 9. Time distribution characteristics of hourly fitness activities

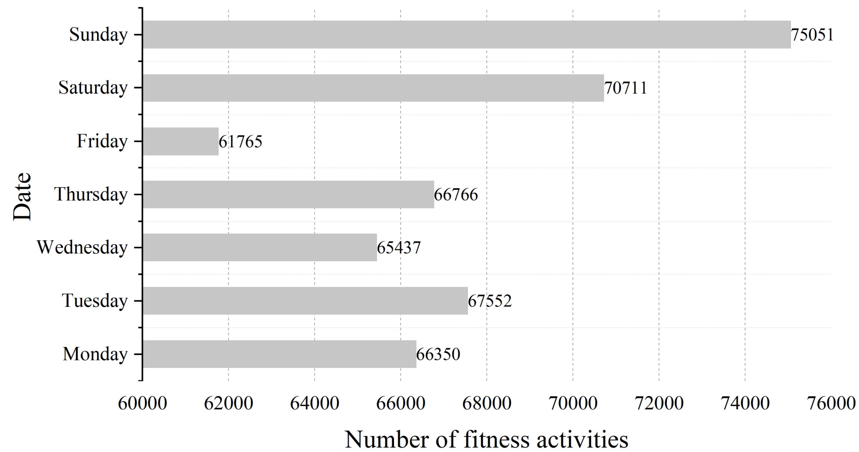

Fig. 10. Time distribution of daily fitness activities in weeks

4.1.3. Characteristics of the duration of a single health event. The duration of the exercise record is divided into equally spaced intervals of 5 minutes, the duration of a single fitness activity is counted, and the corresponding distribution frequency is recorded, and the cumulative frequency curve is drawn as shown in Figure 11. From the perspective of the frequency distribution of the duration of user fitness activities, the distribution of the time duration of fitness activities tends to be generally close to a normal distribution, the average exercise duration of fitness activities is most concentrated in the interval of 30 to 50 minutes, and a small number of marathon enthusiasts exercise for more than 2 hours (0.63%). From the frequency graph of the duration of user fitness activities, the probability of 20 to 50 minutes fitness activities grows significantly, and the distribution of users is higher. More than 60% of the students were within the 50-minute interval for active health duration, performed well in terms of duration of fitness activities, and met the basic requirements for physical fitness improvement in terms of the amount of exercise.

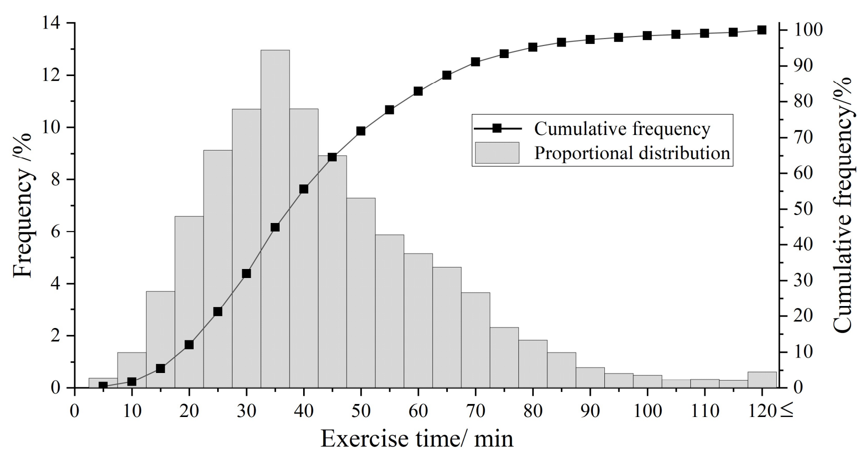

Fig. 11. Distribution of fitness activity duration

4.1.4. Characterization of the length distribution of movement distances. Outdoor running, walking and cycling types of fitness activities are characterized by spatial distance attributes, divided into 2km length intervals, the number and frequency of different exercise distance ranges are counted, and the corresponding distribution frequency is recorded, and the cumulative frequency curve is plotted as shown in Figure 12. The length of the exercise distance reflects the physical activity level of the athletes, i.e., the ability of the human body to self-organize in the unstable "far-from-equilibrium state". The distribution of the exercise distance in general shows the characteristics of nearly normal distribution, and the exercise distance starts from 5km and turns to decay, with the growth of the distance in the process of 11km, 20km, 30km or more at the three outliers, corresponding to the distance of the mini-marathon, half marathon and half marathon, respectively.

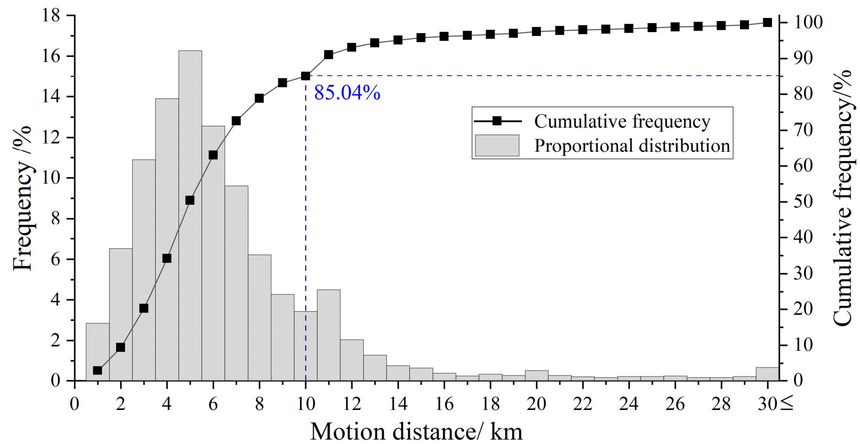

Fig. 12. Motion distance length distribution

Therefore, 10km was used as the demarcation point to divide ordinary types of active health behaviors and positive health activities into two categories:

1) 85% of the residents exercise within a distance of 10km, for the daily ordinary type of active health behavior.

2) 15% of the residents exercise as marathon amateurs with a distance of 10km or more, which is a more active type of fitness activity behavior.

4.2. Experimental analysis of exercise prescription parameter optimization

In order to verify the usability of the particle swarm optimization algorithm through topology adjustment (TS-PSO) in the exercise prescription generation model, TS-PSO is applied to the parameter optimization process of the model, and some cases of exercisers are extracted to validate the effectiveness of the algorithm as well as the usability of the model, respectively. The data used in the experiment come from the Active Health Promotion Personalized Scientific Guidance System (AHPPSG), and the simulation data simulated under various exercise conditions based on the implicit relationship between various attributes, including user data and exercise case data totaling 100,000 items.

The experiment classifies the user data according to the two attribute characteristics of gender and BMI of the student users, and the basic information of the extracted sportsmen cases is shown in Table 1. Gender is divided into male and female, BMI consider the human body normal and overweight two states, $18 \leqslant \text{BMI} \leqslant 25$ (normal), $25 < \text{BMI}$ (obesity), the two attributes of the two ranked combinations of 10 classes of users with different user physique, respectively, from the eight classes of users randomly extracted a sportsman case for experimental analysis.

Table 1. The table of test case basic information

Case	Height (cm)	Weight (kg)	Gender	Age	BMI	Sports level
Case 1	171	75	Male	21	24	1.56
Case 2	165	63	Female	20	27	1.41
Case 3	171	82	Male	21	32	1.45
Case 4	159	56	Male	19	29	1.61
Case 5	161	65	Female	20	23	1.32
Case 6	161	64	Female	20	26	1.37
Case 7	162	69	Male	21	27	1.45
Case 8	177	63	Female	21	23	1.36
Case 9	181	79	Male	20	27	1.52
Case 10	160	64	Female	20	25	1.44

In order to evaluate the performance of the algorithm, the experiments are considered in terms of both convergence speed and stability of the solution accuracy. The experiment sets the population size of the algorithm to $N=20$, the maximum number of iterations to $Iter_{max}=1000$, the maximum number of flows to $F_{max}=5$, and the maximum number of stalls allowed to $S_{max}=10$.

4.2.1. Rate of convergence. In this paper, in the process of model parameter optimization based on the condition of the same number of iterations to compare the speed of convergence, PSO and TS-PSO algorithms are used for experiments, respectively, to find out the results of single optimization of the sportsman and ten optimization of the convergence of the results as shown in Table 2. From the experimental results, it can be seen that the convergence curves of the average fitness value per generation and the highest fitness value per generation (except for case 8) are faster for TS-PSO and its solution accuracy is higher. Therefore, it can be considered that TS-PSO performs better in the parameter optimization process in the exercise prescription generation model and is more suitable for the multi-objective optimization model of exercise prescription generation constructed in this paper.

Table 2. Algorithm convergence result

Case	PSO algorithm		TS-PSO algorithm	
	Convergence rate of single optimization	Convergence rate of ten optimizations	Convergence rate of single optimization	Convergence rate of ten optimizations
Case 1	267	453	**178**	**303**
Case 2	412	423	**378**	**401**
Case 3	543	363	**215**	**222**
Case 4	598	541	**107**	**339**
Case 5	611	527	**343**	**474**
Case 6	131	140	**89**	**118**
Case 7	256	326	**179**	**319**
Case 8	328	**206**	**315**	222
Case 9	434	604	**285**	**553**
Case 10	509	619	**230**	**235**

4.2.2. Solution accuracy. The solution accuracy, i.e., the optimal value found in the algorithm. The experimental statistical results include the obtained negative equilibrium heat distance from the expected negative equilibrium heat ($\min y$), negative equilibrium heat satisfaction (NEHS), exercise intensity satisfaction (EIS), and exercise time satisfaction (ETS), which indicates the degree of compliance of the desired exercise parameters with the generated parameters, portrayed as a percentage. The optimization results were also shown for the mid-exercise intensity (unit, times/min) and mid-exercise time (unit, minutes), which were executed ten times for each test case to find the average optimization results. The specific results are shown in Table 3, where the bolded values indicate the better results obtained. The TS-PSO studied in this paper introduces a topology on the basis of PSO, which increases the algorithm's ability to explore and mine the optimal solution. From the simulation results, it can be seen that compared with PSO, applying TS-PSO to the motion prescription generation model obviously has a stronger exploration capability.

Table 3. The optimization results of test case

Case	Algorithm	min y	NEHS	EIS	ETS	Mid-exercise intensity	Mid-motor time
Case 1	PSO	3.25E-01	68.45%	56.30%	70.02%	151	44
	TS-PSO	**1.51E-01**	**86.04%**	**85.4%**	**90.57%**	149	51
Case 2	PSO	7.33E-01	24.18%	50.33%	53.33%	132	32
	TS-PSO	**1.87E-01**	**85.05%**	**75.61%**	**89.65%**	135	36
Case 3	PSO	5.55E-01	56.23%	50.12%	68.86%	146	35
	TS-PSO	**1.46E-01**	**80.52%**	**78.05%**	**89.33%**	155	45
Case 4	PSO	6.16E-01	37.80%	45.46%	56.54%	141	36
	TS-PSO	**2.23E-02**	**95.05%**	**96.12%**	**87.20%**	158	48
Case 5	PSO	7.45E-01	26.34%	47.78%	61.11%	137	36
	TS-PSO	**2.31E-01**	**78.23%**	**75.05%**	**74.65%**	153	43
Case 6	PSO	4.06E-01	59.99%	62.94%	63.13%	144	38
	TS-PSO	**3.61E-02**	**95.45%**	**97.54%**	**88.06%**	153	45
Case 7	PSO	5.42E-01	41.53%	69.19%	58.17%	147	32
	TS-PSO	**4.35E-02**	**90.52%**	**94.12%**	**91.12%**	162	37
Case 8	PSO	7.72E-01	29.11%	67.78%	54.78%	144	34
	TS-PSO	**2.33E-01**	**87.57%**	**80.86%**	**84.40%**	159	39
Case 9	PSO	4.21E-01	66.90%	57.34%	70.33%	143	44
	TS-PSO	**2.51E-01**	**85.42%**	**87.85%**	**90.52%**	151	52
Case 10	PSO	7.23E-01	23.37%	49.53%	53.31%	112	32
	TS-PSO	**1.45E-01**	**84.52%**	**77.67%**	**89.59%**	136	40

The distance between the negative balance calories obtained from the solution and the expected negative balance calories is smaller, the satisfaction of negative balance calories, the satisfaction of exercise intensity and the satisfaction of exercise time are higher, which is more in line with the exercise expectation of the exercisers. And the negative balance calories required for the exercise purpose of the athletes can be better achieved, which can better achieve the mobilization effect of active health behaviors. And from the experimental results, it can be seen that the exercise prescription optimization model designed in this paper is applicable to all types of users as classified above, which has a certain degree of universality and proves the effectiveness of the model.

5. Conclusion

1) Based on information technology and sports literacy system, a personalized scientific guidance system for students' sports health promotion has been constructed, which integrates the classification of student population, recommendation of personalized scientific guidance program, monitoring and feedback of sports data and optimization of guidance program, and solves the problem of personalized scientific guidance for different categories of students.

2) Based on the big data platform of students' sports literacy, the monitoring, feedback and optimization system of students' personalized scientific guidance is used to realize the improvement of sports mobilization effect and optimization of personalized scientific guidance program under the view of active health through multi-dimensional monitoring and analysis of the effect of exercise implementation.

3) According to the analysis of the demand for personalized exercise prescription service, this paper takes the analysis of exercise demand as the key to the formulation of exercise prescription, establishes the basis of exercise screening from the exercise effect and the parts of exercise exercise, and obtains

the main exercise programs. Moreover, it takes the user's interest preference, physical differences, and differences in the exercise environment as the focus of personalized exercise prescription formulation, and uses the improved particle swarm optimization algorithm to calculate the parameters of the exercise prescription that load the user's physical condition and the exercise environment.

In summary, this paper takes pertinence, reasonableness and applicability as the guidance, based on the different physical state, sports quality and sports preference of the sportsmen, and with the intelligent algorithm as the core, it constructs the personalized sports prescription generation model, which provides the sportsmen with applicable sports and personalized sports parameters, and effectively improves the effect of active health mobilization of the students.

References

[1] Li, J., Wan, B., Yao, Y., Bu, T., Li, P., & Zhang, Y. (2023). Chinese path to sports modernization: fitness-for-all (Chinese) and a development model for developing countries. Sustainability, 15(5), 4203.

[2] Lavie, C. J., Kokkinos, P., & Ortega, F. B. (2017, December). Survival of the fittest—promoting fitness throughout the life span. In Mayo Clinic Proceedings (Vol. 92, No. 12, pp. 1743-1745). Elsevier.

[3] Tan, T. C. (2015). The transformation of China's National Fitness Policy: from a major sports country to a world sports power. The international journal of the history of sport, 32(8), 1071-1084.

[4] Dai, J., & Menhas, R. (2020). Sustainable development goals, sports and physical activity: the localization of health-related sustainable development goals through sports in China: a narrative review. Risk management and healthcare policy, 1419-1430.

[5] Chen, P., Wang, D., Shen, H., Yu, L., Gao, Q., Mao, L., ... & Li, F. (2020). Physical activity and health in Chinese children and adolescents: expert consensus statement (2020). British journal of sports medicine, 54(22), 1321-1331.

[6] Li, F. (2016). Physical activity and health in the presence of China's economic growth: meeting the public health challenges of the aging population. Journal of sport and health science, 5(3), 258-269.

[7] Salvo, D., Garcia, L., Reis, R. S., Stankov, I., Goel, R., Schipperijn, J., ... & Pratt, M. (2021). Physical activity promotion and the United Nations sustainable development goals: building synergies to maximize impact. Journal of physical activity and health, 18(10), 1163-1180.

[8] Saqib, Z. A., Dai, J., Menhas, R., Mahmood, S., Karim, M., Sang, X., & Weng, Y. (2020). Physical activity is a medicine for non-communicable diseases: a survey study regarding the perception of physical activity impact on health wellbeing. Risk management and healthcare policy, 2949-2962.

[9] Chen, S., Guo, L., Wang, Z., Mao, W., Ge, Y., Ying, X., ... & Tang, S. (2019). Current situation and progress toward the 2030 health-related sustainable development goals in China: a systematic analysis. PLoS medicine, 16(11), e1002975.

[10] Tan, X., Wu, Q., & Shao, H. (2018). Global commitments and China's endeavors to promote health and achieve sustainable development goals. Journal of Health, Population and Nutrition, 37, 1-4.

[11] Sabe, M., Chen, C., Sentissi, O., Deenik, J., Vancampfort, D., Firth, J., ... & Solmi, M. (2022). Thirty years of research on physical activity, mental health, and wellbeing: A scientometric analysis of hotspots and trends. Frontiers in public health, 10, 943435.

[12] Cerf, M. E. (2019). Sustainable development goal integration, interdependence, and implementation: The environment–economic–health nexus and universal health coverage. Global Challenges, 3(9), 1900021.

[13] Almeida, P. (2019). Social movements: The structure of collective mobilization. Univ of California Press.

[14] Thorpe, H. (2017). Action sports, social media, and new technologies: Towards a research agenda.

Communication & sport, 5(5), 554-578.

[15] Billings, A. C., Qiao, F., Conlin, L., & Nie, T. (2017). Permanently desiring the temporary? Snapchat, social media, and the shifting motivations of sports fans. Communication & Sport, 5(1), 10-26.

[16] Goodyear, V. A., Armour, K. M., & Wood, H. (2019). Young people and their engagement with health-related social media: New perspectives. Sport, education and society.

[17] Chalip, L., Green, B. C., Taks, M., & Misener, L. (2017). Creating sport participation from sport events: Making it happen. International journal of sport policy and politics, 9(2), 257-276.

[18] Brown, K. A., Patel, D. R., & Darmawan, D. (2017). Participation in sports in relation to adolescent growth and development. Translational pediatrics, 6(3), 150.

[19] Hayes, M. (2022). Social media and inspiring physical activity during COVID-19 and beyond. Managing Sport and Leisure, 27(1-2), 14-21.

[20] Zhou, L., Wang, J. J., Chen, X., Cianfrone, B., & Pifer, N. D. (2020). Community-sport service provision, participant satisfaction, and participation: Experience and perspective of Guangdong, China. International journal of sports marketing and sponsorship, 21(1), 127-147.

[21] Carlisle, C. C., Weaver, R. G., Stodden, D. F., & Cattuzzo, M. T. (2019). Contribution of organized sport participation to health-related fitness in adolescents. Global pediatric health, 6, 2333794X19884191.

[22] Byers, T. (2018). Trends in professional sport organisations and sport management and their market impact. The palgrave handbook on the economics of manipulation in sport, 55-70.

[23] Baiqiang Gan & Chi Zhang. (2020). Design of personalized recommendation system for online learning resources based on improved collaborative filtering algorithm. E3S Web of Conferences01051-.

[24] Haopeng Zhang. (2020). A discrete-time switched linear model of the particle swarm optimization algorithm. Swarm and Evolutionary Computation100606-100606.

[25] Kiani Arooj Tariq,Nadeem Muhammad Faisal,Ahmed Ali,Khan Irfan A.,Alkhammash Hend I.,Sajjad Intisar Ali & Hussain Babar. (2021). An Improved Particle Swarm Optimization with Chaotic Inertia Weight and Acceleration Coefficients for Optimal Extraction of PV Models Parameters. Energies(11), 2980-2980.

[26] Liu Liyang,Wu Junji & Meng Shaoliang. (2019). Analysis and improvement of neighborhood topology of particle swarm optimization. Journal of Computational Methods in Sciences and Engineering(4), 955-968.