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Research Article

Scientific Impact of Sports on Human Health and Physique Based on Optimization Big Data Ant Colony Algorithm

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With the continuous improvement of living standards, people began to pay more and more attention to sports, and the impact of sports on human health and physique has been paid more and more attention. This study mainly analyzes the scientific impact of sports on human health and physique under the background of big data. Firstly, the big data analytic hierarchy process is used to construct the comprehensive evaluation structure system of sports on human health and physique. Then, an improved big data adaptive ant colony classification rule algorithm is proposed. Finally, the performance evaluation and physical impact analysis of the improved big data algorithm are carried out. The results show that compared with other algorithms, ACA $*$ (ant colony algorithm) based on big data has more obvious advantages in stability, optimization ability, running time, and convergence speed and is more suitable for practical application. In general, the improvement of the physical fitness level of the association members in 2019 mainly depends on the results of the improvement of the physical fitness level. In the future, we need to strengthen physical exercise, change living habits and traffic habits, and other methods to optimize the overall physical fitness.

1. Introduction

Sports play an important role in promoting human health. This study attempts to use big data to optimize big data ant colony algorithm to analyze the scientific impact of sports on human health and physique. Big data ant colony algorithm has been widely used in various fields because of its strong positive feedback mechanism, self-organization, and distributed computing characteristics [1, 2]. de Santis' team proposed a metaheuristic routing algorithm (FW ACO) based on ant colony optimization (ACO) metaheuristic algorithm and Floyd-Warshall (FW) algorithm. The results show that FW ACO algorithm can provide better results than heuristic algorithm and metaheuristic algorithm and has high computational efficiency, which is suitable for determining the path of selector in real time [3]. Babanezhad and other scholars use the big data ant colony intelligence method to learn CFD data of different parts of BCR. The results show that the algorithm does not need to solve the Navier-Stokes equation and complex solution process but can be used for prediction process [4]. Sutar and other scholars proposed a dynamic energy-saving virtual machine migration method, which applies big data ant colony optimization algorithm to analyze the load on the physical machine and start the sleep mode of an idle physical machine to reduce power consumption, so as to achieve the purpose of energy saving [5]. Kusumahardhini's team proposed to use the K-means method and cross ant colony optimization (ACO) to solve the medium-term strategic planning problem of travel agencies, compared and analyzed the results of the K-means method and cross ant colony optimization, and analyzed the impact of selecting cities as parking lots on the total travel distance [6].

Asghari and Navimipour proposed the inverse ant colony optimization (IACO) algorithm to improve the load balance between nodes. The results show that the IACO algorithm is superior to the ACO algorithm in load balancing, waiting time, and resource utilization [7]. Ji's team combined the heuristic operator of big data ant colony optimization (ACO) with decomposition-based multiobjective evolutionary algorithm (MOEA/D) to propose a

multiobjective community detection algorithm mocd ACO. In the experiment, the performance of mocd ACO is evaluated by using comprehensive network data set and real network data set. The results show that compared with the five most advanced methods, mocd ACO is effective in standardizing mutual information and modularization [8]. Sinwar et al. proposed the application of swarm intelligence (SI) technology based on big data ant colony optimization (ACO) and particle swarm optimization (PSO). Simulation results show that the performance of the ACOP protocol is better than other protocols [9]. Ning and other scholars designed a new pheromone smoothing mechanism to improve the global search ability. When the search process of big data ant colony algorithm approaches a fixed stagnation state, the pheromone matrix is reinitialized. The results show that the improved big data ant colony algorithm is superior to the traditional big data ant colony algorithm in solution diversity and convergence speed [10]. Moeini and Afshar combined ACoA with NLP to optimize the design of sewage pipe network. The results show that acoa-nlp2 is an effective method to solve the problem of optimal design of sewage pipe network [11]. Yuan and other scholars use big data ant colony algorithm to determine the boundary information of the foreground target and fuse different pheromone images at the superpixel level to generate three accurate bitmaps. Experimental results show that the generated three high-quality images effectively improve the performance of the algorithm and achieve accurate segmentation α mask estimation [12]. Wang's team proposed a big data ant colony algorithm based on multiobjective optimization and carried out simulation experiments using cloudsim cloud simulation platform. The results show that compared with other commonly used algorithms, this algorithm has reached a better level in SLA violation rate, power consumption, and resource loss of cloud platform [13]. Yu and other scholars studied the logistics terminal distribution mode and path optimization, combined with the application of big data ant colony algorithm in traveling salesman problem, and analyzed the basic principle and implementation process of big data ant colony algorithm. The results show that the application of big data ant colony algorithm in logistics terminal distribution path optimization is of great significance [14]. Zhao and other scholars proposed a multiobjective optimization model based on cost, carbon emission, and customer satisfaction and designed an improved big data ant colony algorithm (acomo) with multiobjective heuristic function. The results show that acomo algorithm can effectively solve the vehicle routing problem under the multiobjective optimization model, is better than the traditional big data ant colony algorithm, and obtains more Pareto optimal solutions [15]. According to the equipment parameters of the national hot strip mill, the national D team adopted the load distribution optimization method and the max-min big data ant colony algorithm to optimize the load distribution of the rolling mill. After using this method, the compression ratio of upstream and downstream stands gradually decreased, and the change of proportional crown width was less than that of the traditional energy method. The actual fluctuation amplitude is reduced by nearly 50%, which is conducive to shape control, and the total dissipated power is lower than that of the energy consumption method [16].

Based on the above research results, this study will focus on the optimization process based on big data ant colony algorithm, combined with big data analytic hierarchy process to analyze the scientific impact of sports on human health and physique.

This study mainly analyzes the scientific impact of sports on human health and physique under the background of big data. This paper is divided into three parts. The first part constructs a comprehensive evaluation structure system of sports on human health and physique by using big data analytic hierarchy process. In the second part, an improved big data adaptive ant colony classification rule algorithm is proposed. Finally, the performance evaluation and physical impact analysis of the improved big data algorithm are carried out.

2. Construction of the Influence Model of Sports on Human Health and Physique Based on Big Data Ant Colony Algorithm

2.1. Comprehensive Evaluation Structure System of Sports on Human Health and Physique. Under the guidance of the national fitness program, people pay more and more attention to the impact of sports on human health, among which experts and scholars who have been engaged in sports work for a long time have a say. As people participate in sports, the level of physical fitness often has a certain dynamic, so we should consider the actual data and the opinions of experts and scholars. Taking the physique monitoring results of a sports association in Chengdu from 2015 to 2019 as the data sample, this study analyzes the comprehensive physique level of young people aged 20 to 39 and uses the big data analytic hierarchy process (AHP) to construct the evaluation standard of human health and physique after sports, as shown in Figure 1.

Big data analytic hierarchy process (AHP) is a multiobjective decision-making method, which decomposes the problem into different elements according to the nature of the problem and the solving goal and constructs a multilevel structure model by combining the membership relationship between the elements. In the hierarchical structure model of this study, there are three primary indexes in the middle layer: body shape, body function, and physical fitness. The lowest secondary indexes include BMI index, chest circumference index, waist circumference index, vital capacity, quiet pulse, systolic blood pressure, diastolic blood pressure, push up/sit up, grip strength/back strength, vertical jump, and choice reaction time.

After building the hierarchical structure model, it is necessary to allocate the weight and check the consistency of the indicators in the model. The big data analytic hierarchy process (AHP) is to decompose the problem into multiple levels and take the highest level as the decision-making objective of the problem. According to the relative scale, it calculates the weight of the next level relative to the high level, so as to make the best decision. After building the model judgment

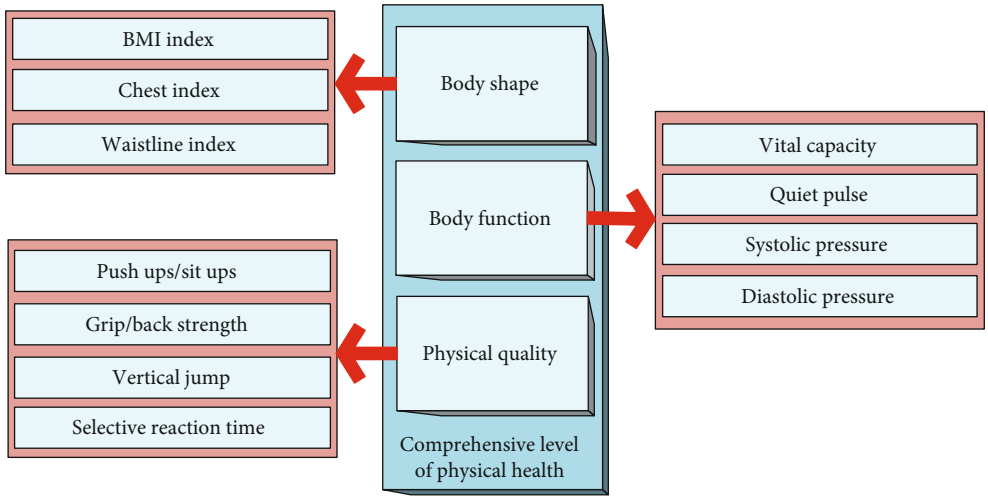


Figure 1: Comprehensive evaluation structure of sports on human health and physique.

matrix, we need to scale the importance of the indicators according to the relative scale, which is to reduce the impact of the differences in the nature of the indicators as far as possible, so as to improve the accuracy of the judgment matrix. By calculating the maximum eigenvalue of the model judgment matrix, we can get the eigenvector of the indicators at the same level. By normalizing the eigenvector, we can get the relative weight of the indicators at the same level. For the judgment matrix A, its maximum eigenvalue can be obtained by the following formula, where n represents the number of indicators in the judgment matrix of this level, and the elements in W represent the weight of indicators after normalization.

$$\lambda_{\max} = \sum_{i=1}^{n} \frac{(AW)_i}{W_i} \cdot \frac{1}{n}. \tag{1}$$

Consistency test is to test the deviation of judgment matrix. The calculation formula of consistency index (CI) is shown in formula (2). When CI = 0, the judgment matrix has complete consistency; when CI is close to 0, the matrix has relatively satisfactory consistency; when the value of CI is larger, the consistency of the judgment matrix is worse.

$$\mathrm{CI} = \frac{\lambda_{max} - n}{n - 1}. \tag{2}$$

Although the consistency index can reflect the inconsistency of the judgment matrix, it can not accurately describe the inconsistency degree of the judgment matrix. Therefore, the consistency ratio of the judgment matrix can be calculated by referring to equation (3), and the judgment matrix can be adjusted in different degrees according to the inconsistency of the judgment matrix.

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}}. \tag{3}$$

Consistency ratio defines the rationality of nonconsistency of judgment matrix. According to the calculation result of formula (3), when $\mathrm{CR} \leq 0.1$, the judgment matrix is considered to be consistent. Since the normalized result of the maximum eigenvalue of the judgment matrix represents the index weight vector of the model, it can be seen that the weight distribution of the corresponding model index of the consistent judgment matrix is reasonable. Therefore, the weight of each indicator relative to the superior indicator is shown in Table 1.

2.2. Adaptive Ant Colony Classification Rule Mining Algorithm Model. This research combines big data ant colony algorithm and classification rule algorithm to get a simplified graph of adaptive ant colony classification rule mining algorithm to find the best path, as shown in Figure 2. Among them, Figure 2(a) shows that the ant colony finds the best path at the starting point and the target two points; Figure 2(b) shows that the number of ants on both sides of the obstacle is almost the same in a short time after placing the obstacle between the starting point and the target; Figure 2(c) shows that with the increase of the time of placing the obstacle, the ants will pass through the path with high pheromone concentration, and the number and number of ants are almost the same. The concentration of pheromone is proportional to the concentration of pheromone; Figure 2(d) shows that most ant colonies can find food in the fastest way after a period of time.

Classification rule algorithm is a data classification technology based on rule classifier. Among them, ant miner algorithm is a traditional classification rule algorithm, which uses information entropy theory to establish heuristic function. The algorithm has high classification accuracy and simple rules [17]. The disadvantage of ant miner algorithm is that the calculation of entropy is complex, the running speed is slow, and it is easy to local stagnation. Based on the original ant miner algorithm, the heuristic factor and pheromone updating method are optimized, and the adaptive mechanism is added to construct the optimization algorithm. For the decision classification problem in the covering algorithm, set k data in the data set, and the attribute variables

Table 1: Comprehensive level of physical health.

Target layer	Criterion layer	Weight	Index layer	Weight
Comprehensive level of physical health	Body shape	0.24	BMI index	0.69
			Chest index	0.20
			Waistline index	0.11
	Body function	0.28	Vital capacity	0.50
			Quiet pulse	0.20
			Systolic pressure	0.16
			Diastolic pressure	0.14
	Physical quality	0.48	Physical quality	0.30
			Grip/back strength	0.30
			Vertical jump	0.12
			Selective reaction time	0.28

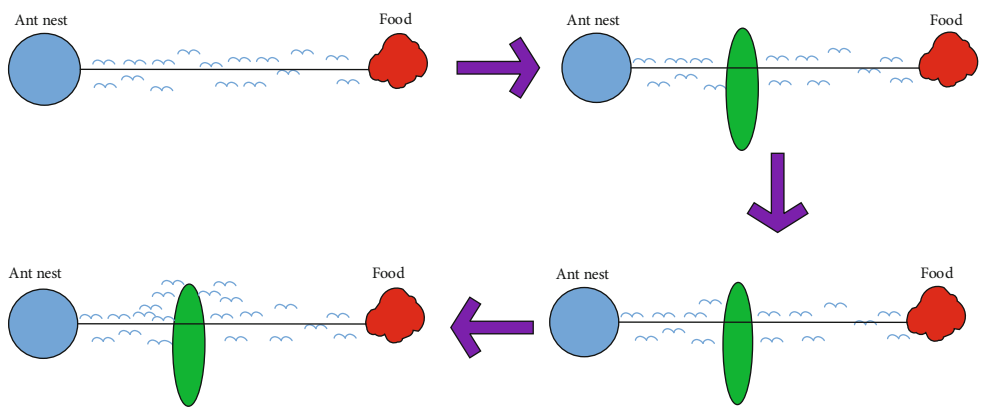


Figure 2: Schematic diagram of big data ant colony algorithm seeking optimal method.

in the data set are A_i, $i = 1, 2, \cdots a$, V_{ij}, and b_i, which, respectively, represent the jth attribute value and the number of A_i attributes. Attribute term$_{ij}$ means that V_{ij} and A_i are the same. In the covering algorithm, the best rule is selected. In the process of rule construction, the term$_{ij}$ selected each time is applied to the current rule. The probability calculation formula of selecting term$_{ij}$ attribute is

$$P_{ij}(t) = \frac{\tau_{ij}(t)^{\alpha} \cdot \eta_{ij}(t)^{\beta}}{\sum_i^a \sum_j^{b_i} \tau_{ij}(t)^{\alpha} \cdot \eta_{ij}(t)^{\beta}}. \quad (4)$$

In equation (4), $\eta_{ij}(t)$ and $\tau_{ij}(t)$ represent pheromone concentration and heuristic factor of t path ij at time, respectively, α and β represent the relative importance of pheromone concentration and heuristic factors, respectively, and α and β are greater than 0. The higher the α value is, the higher the pheromone concentration is. The higher the α value is, the higher the pheromone concentration is. The larger the β value is, the greater the influence of the current attribute of the covering sample on the ant's selection path [18]. In order to accelerate the convergence speed, it is necessary to initialize the information concentration, and the pheromones of all paths are equal at the initial time. After the new classification rules are constructed, the data information attributes need to be updated iteratively, and the method is shown in

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \tau_{ij}(t) \cdot Q. \quad (5)$$

In equation (5), Q is the validity of the rule, ρ is the information exertion factor, and the value is in the interval [0,1]. The relationship between pheromone and rule validity is positive effect. The attribute update method without rules is shown in

$$\tau_{ij}(t+1) = \frac{\tau_{ij}(t)}{\sum_i^a \sum_j^{b_i} \tau_{ij}(t)}. \quad (6)$$

Due to the complexity of the traditional information entropy updating method for attribute items, the heuristic factor based on density is used for calculation, as shown in

$$\eta_{ij}(t) = \frac{|T_{ij}(t)|}{|T(t)|}. \quad (7)$$

In equation (7), $|T_{ij}(t)|$ and $|T(t)|$ represent the number and total number of attribute item data contained in the data set, respectively. Then, the pruning strategy is used to avoid overfitting the rules, and the rules to judge the effectiveness before and after pruning are shown in

$$Q = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \cdot \frac{\mathrm{TN}}{\mathrm{TN}+\mathrm{FP}}. \tag{8}$$

In equation (8), TP refers to the number of data samples that meet the requirements before and after the rule change, FP refers to the number of samples that meet the requirements before the rule change but do not meet the requirements after the rule change, and FN and TN are just opposite to TP and FP. When Q increases after pruning, pruning operation can be carried out, and the rules after pruning are effective rules. To clear the data set contained in the effective rule in the data set, the rule can be added to the rule set only if the number of training set samples of the rule is greater than or equal to the specified number of samples [19]. In view of the existing problems of big data ant colony algorithm, deterministic selection and random selection are applied to optimize, and information volatility is dynamically adjusted. Under the condition of large number of iterations, the gap between the highest and lowest pheromone concentration paths is narrowed, and the probability of random selection is increased. Some scholars pointed out that only setting a small ρ value at the initial stage of path search and increasing the ρ value at the later stage can effectively prevent local stagnation [20]. Therefore, the adaptive adjustment mechanism used in this study is shown in

$$\rho(t) = \frac{3}{2}\int_0^t f(\tau)d\tau. \tag{9}$$

In equation (9), $f(\tau)$ is the normal distribution function with $\mu = 0$, the maximum value of ρ is 0.75, and the standard deviation is 10. Compared with the standard deviation value of 4, the ρ value decreases more smoothly with time, which makes the convergence speed faster and helps to find the best path. The probability expression of path selection is shown in

$$\mathrm{term}_{ij} = \begin{cases} \mathrm{argmax}\left\{\tau_{ij}(t)^{\alpha} \cdot \eta_{ij}(t)^{\beta}\right\}, & \text{if } r \le P_0, \\ \text{select } P_{ij} \text{ according to probability } \mathrm{term}_{ij}, & \text{else}, \end{cases} \tag{10}$$

where $P_0 \in (0, 1)$ and r are random numbers uniformly distributed in (0,1) interval. The improved algorithm is shown in Figure 3, which is divided into three processes: initialization, iterative process, and comparison rule effectiveness. k and m are the number of ants and the total number of ants.

2.3. Construction of Health Constitution Influence Model Based on Improved Adaptive Ant Colony Classification Rule Algorithm. In the process of adaptive classification, the difference of the initial change source will lead to the coupling phenomenon of the algorithm, which increases the difficulty of the optimal classification path [21]. Therefore, an improved adaptive big data ant colony algorithm (ACA*) is proposed in this study. By introducing a guide factor in the probability transfer strategy, the predictability of the big data ant colony algorithm to the target node is improved, the blind selection of ants in the state transition is avoided, and the speed of ant search for feasible solution is accelerated [22]. Let the length from the current node i to the target node E be iE, and the calculation of the guiding factor is shown in

$$\lambda_{iE} = \frac{m-k}{m}\frac{N_{\max}-N}{N_{\max}}\frac{1}{d_{iE}}. \tag{11}$$

In equation (11), m is the total number of ants, k is the current number of ants, N is the current number of iterations, and $N_{\max}$ is the maximum number of iterations. The transition probability of introducing the guidance factor from node i to j is shown in

$$p_{ij}^{k}(t) = \begin{cases} \dfrac{\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}\lambda_{jE}^{\gamma}(t)}{\sum_{s\in \mathrm{allowed}_k}\tau_{\mathrm{is}}^{\alpha}(t)\eta_{\mathrm{is}}^{\beta}\lambda_{jE}^{\gamma}(t)}, & j \in \mathrm{allowed}_k, \\ 0, & \text{otherwise}. \end{cases} \tag{12}$$

In equation (12), $\lambda_{jE}^{\gamma}(t)$ is the guiding function of the current node, $\lambda_{iE}^{\gamma}(t)$ is the guiding function of selecting the next node, η_{ij} is the heuristic factor, that is, the expected degree of ants from node i to node j, and $\eta_{ij} = 1/I_{ij}$. The improved big data ant colony algorithm is used to solve the path optimization problem. In the established change propagation analysis network, the objective function and constraints are defined, as shown in

$$\begin{cases} \min\left(\sum_{1}^{k} I_{ij}\right), & k = 1, 2, 3, \cdots, \\ \text{s.t.} \sum_{i=1}^{p} \rho_i \ge \Delta\rho_u, & p = 1, 2, 3, \cdots, \\ \text{s.t.} \sum_{j=1}^{q} \rho_j \ge \Delta\rho_v, & q = 1, 2, 3, \cdots, \\ \text{s.t.} \sum_{l=1}^{r} \rho_l \ge \Delta\rho_w, & r = 1, 2, 3, \cdots, \\ \cdots. \end{cases} \tag{13}$$

In equation (13), $\Delta\rho_u$, $\Delta\rho_v$, and $\Delta\rho_w$ denote the change impact of the initial change node (ICI), ρ_i, ρ_j, and ρ_l denote the change over absorption capacity of the node they represent, p, q, and r denote the propagation steps of each initial change node, and k represents the sum of the propagation steps of all change nodes. The optimal adaptive optimization algorithm framework based on the improved big data ant colony algorithm is shown in Figure 4 [11].

As can be seen from Figure 4, the first step of the improved adaptive big data ant colony algorithm path is to establish a network model of influencing factors, map different influencing factors to the network as different nodes, and map the relationship between influencing factors to the edges in the network model. The second step

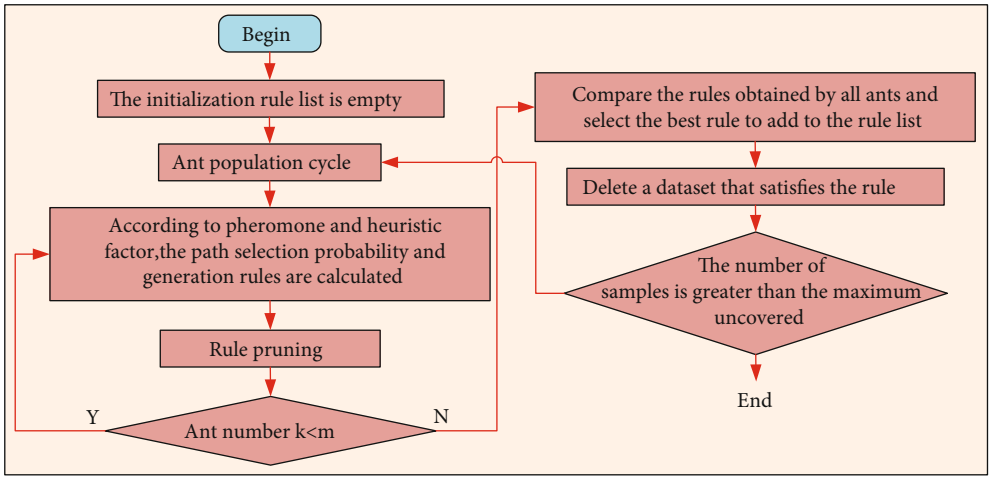


Figure 3: Decision-making model of adaptive ant colony classification rules.

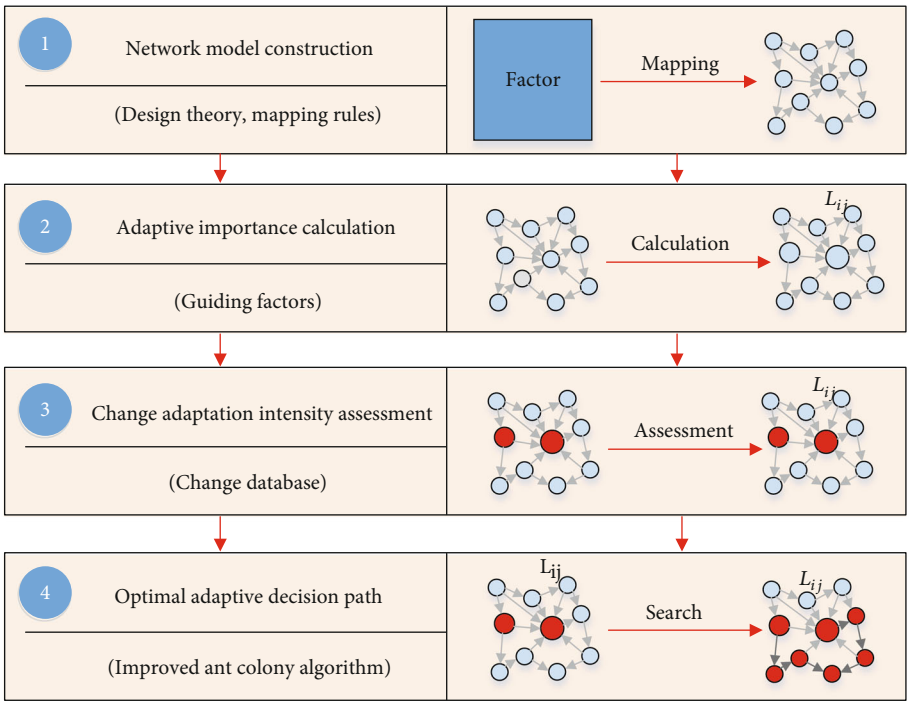
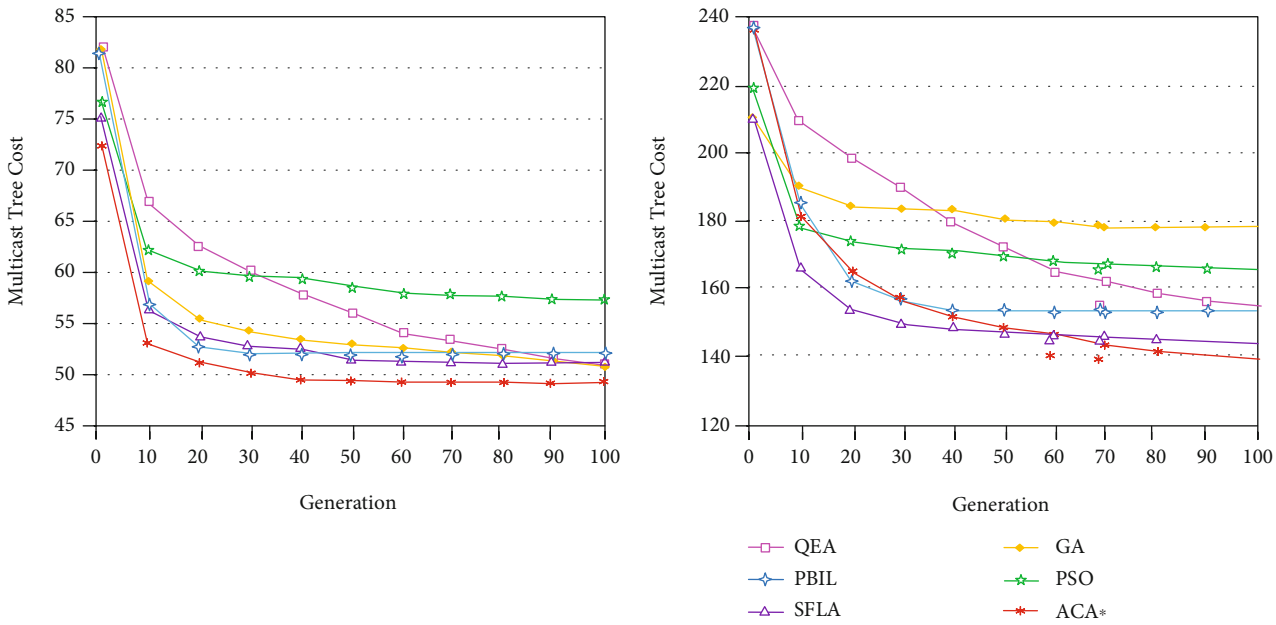


Figure 4: Framework of optimal adaptive optimization algorithm.

is to evaluate the connection importance of each edge by using the guiding factor. The third step is to obtain the data in the historical change database for analysis and calculate the change propagation probability of each side, then calculate the design change index according to the data in the historical change database, finally calculate the node connection importance, and calculate and evaluate the change propagation intensity of each side. The fourth step is to set change nodes of multiple sources. Firstly, the ability of each node to absorb changes is evaluated. Secondly, the ICI of the initial change node is set. Finally, the improved adaptive big data ant colony algorithm is used to solve the path, and the optimal propagation path is obtained.

3. Performance Evaluation and Physique Impact Analysis of Improved Adaptive Big Data Ant Colony Algorithm

3.1. ACA Performance Evaluation and Analysis.* This study uses the route convergence method to evaluate the performance of ACA*. This method refers to the process of route reestablishment, sending, learning, and stability when the topology of the network changes and notifies all related routes of the network of the change. In the experiment, the convergence of ACA* is compared with other five algorithms in eight scenarios. The statistical comparison between scenario 1 and scenario 8 is shown in Figure 5.



(a) Scene 1

(b) Scene 8

Figure 5: Convergence statistics of different algorithms in different scenarios.

It can be seen from Figure 5 that each algorithm tends to converge after iteration to 100 generations. The convergence process of the QEA algorithm is relatively slow, and there is a convergence sign only at 100 generations, while PBIL and SFLA algorithms tend to converge at 40 generations. ACA* is still searching for optimization when most other algorithms begin to converge. Therefore, ACA* can converge to a higher quality solution than other algorithms, and with the increase of algebra, ACA* can find a better solution than other algorithms. This is mainly due to the classification rule strategy used by ACA*, which makes it have stronger path propagation ability.

Figure 6 shows the average running time of several algorithms in the path optimization, and the results retain two decimal places. The running time of GA algorithm is the shortest, while that of ACA* is about twice that of GA algorithm. However, since the time-consuming data of the two systems are of the same order of magnitude, the time difference in actual operation is at most 2 seconds. If the performance of the computer used in the detection is higher, the time-consuming gap between them will be smaller. Combined with the data in Figure 7, the convergence speed of ACA* is significantly faster than GA algorithm, and the quality of the solution is higher. Therefore, ACA* outperforms the other five algorithms.

Figure 7 shows the standard deviation data of ACA* and other five algorithms after 20 times of optimization, with two decimal places reserved. As can be seen from Figure 7, the standard deviation of PSO algorithm is relatively large, while the standard deviation of ACA* in each scenario is lower than other algorithms, and the data difference is large. It can be proved that ACA* has a higher degree of stability.

Figure 8 shows the box chart statistics of ACA* and other five algorithms in each scenario. It can be seen from

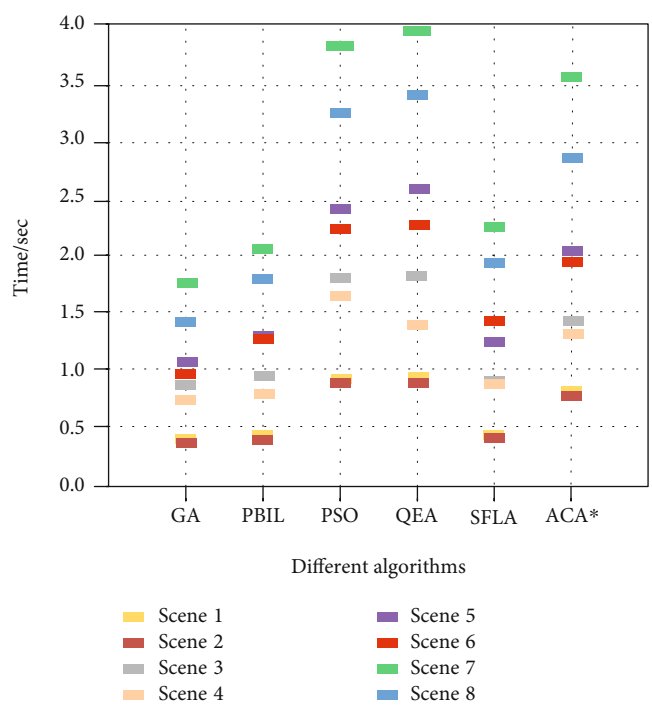


Figure 6: Statistical curve of average running time of six algorithms.

Figure 8 that the "data box block" and nonabnormal data area of ACA* are the narrowest in most scenarios, which proves that the result data of ACA* is relatively concentrated. ACA* has a lot of abnormal data in individual scenarios, mainly because most of the data is too concentrated; in reality, the gap between abnormal data and nonabnormal data of

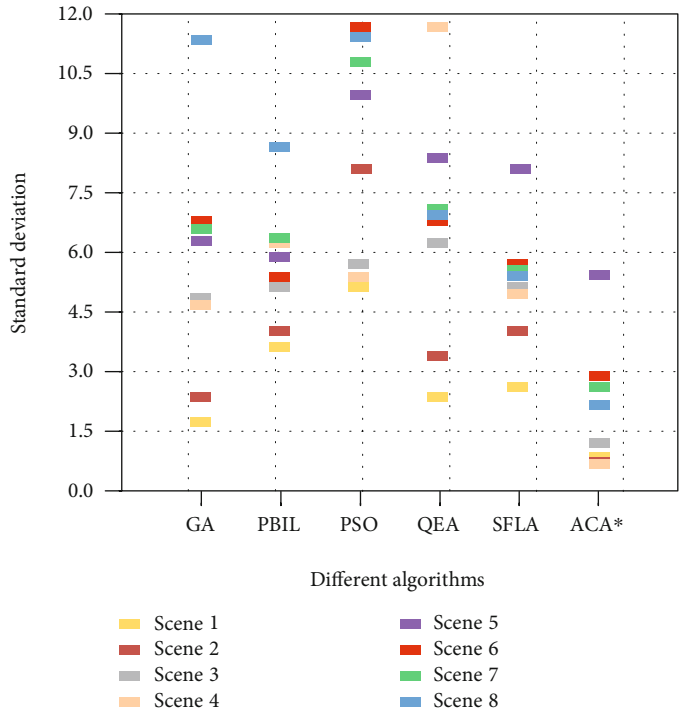


Figure 7: Six algorithms run in each scenario, and the standard deviation of the output multicast tree overhead value is 20.

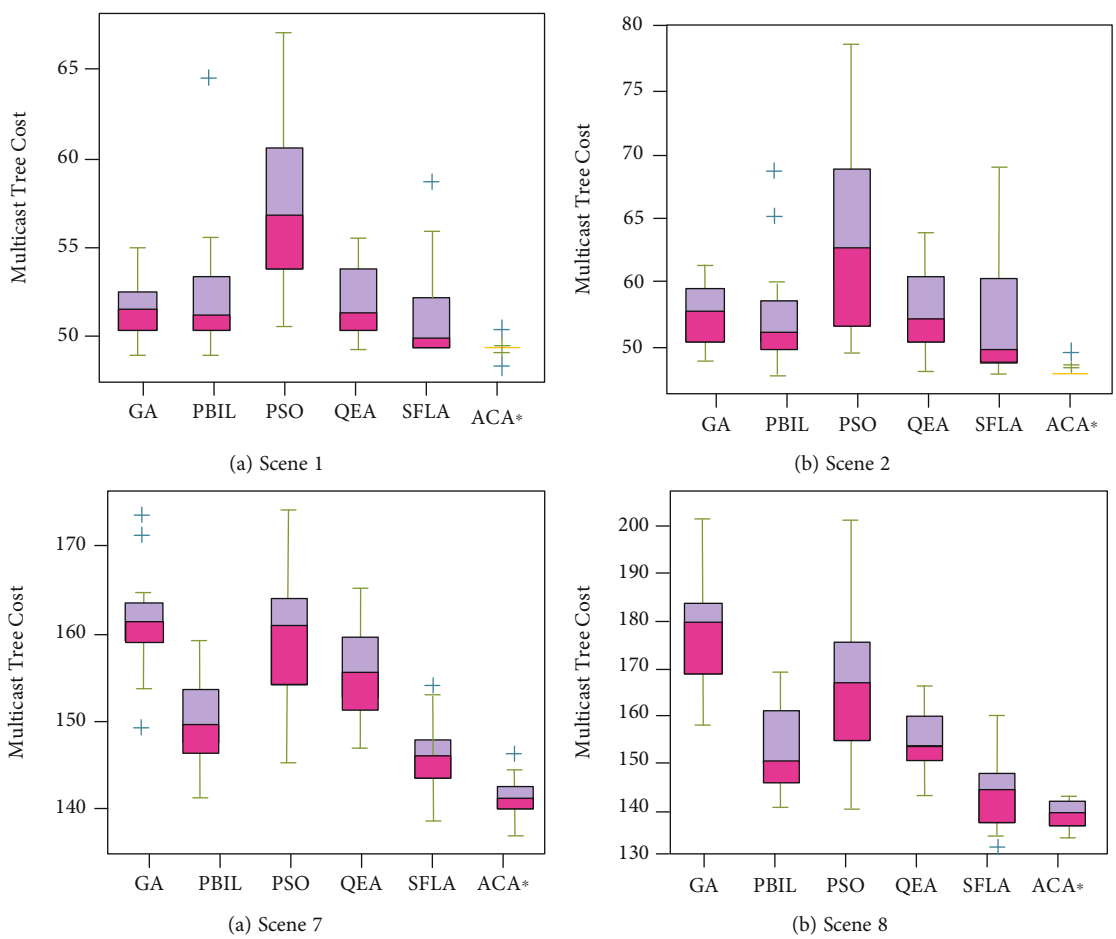


Figure 8: Box-plot statistics of six algorithms in different scenes.

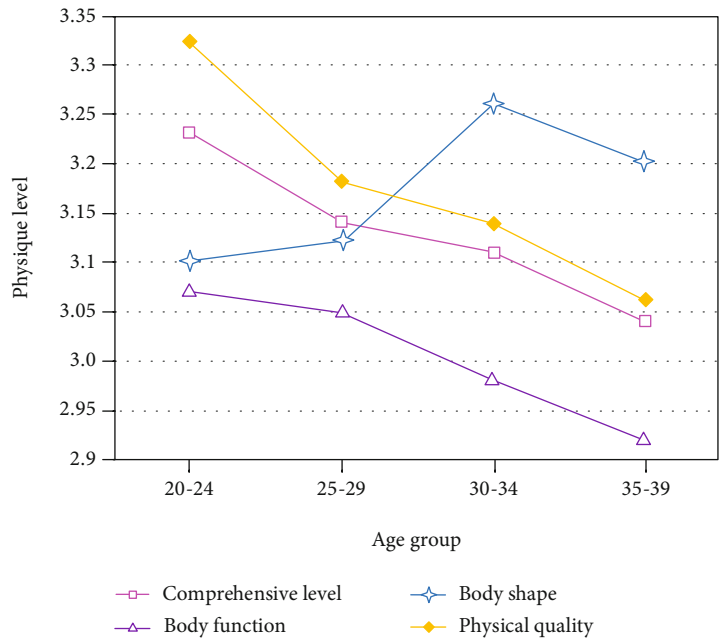


Figure 9: Average level of physical fitness of young people of different ages.

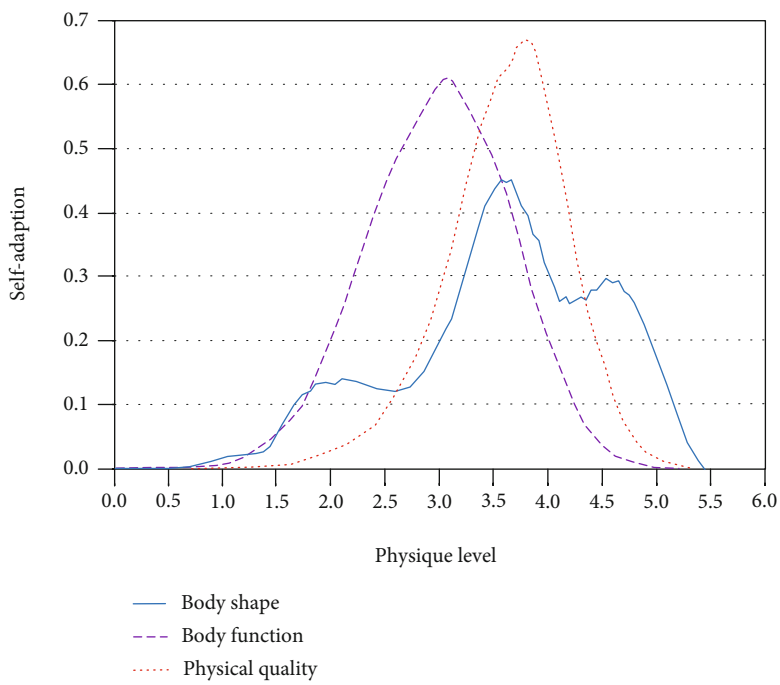


Figure 10: Comprehensive evaluation of physique level of body shape, body function, and body quality.

ACA* is very small. Combined with the data information of standard deviation in Figure 7, it can be concluded that ACA* is more stable than other algorithms.

3.2. Scientific Evaluation of Human Health Constitution. Firstly, the comprehensive scores of body shape, body function, and body quality of the members of a sports association in Chengdu in 2019 are obtained by big data analytic hierarchy process. From the distribution of physical fitness indexes, the skewness of all comprehensive indexes is slightly less than 0, reflecting that less than half of the members' physical fitness level after exercise is higher than the average level; the body shape kurtosis coefficient is also less than 0, and the distribution is steep, reflecting the difference before and after exercise; and the body quality coefficient kurtosis coefficient is not less than 0, and the distribution is flat, reflecting the difference before and after exercise. After that, there are significant differences in the quality level

among individuals, so that there are obvious differences in the comprehensive physique level. Among the members aged 20-39, the physical fitness level of each age group is shown in Figure 9.

With the growth of age, the physical fitness level of young people also continues to decline, mainly due to the greater influence of the law of physiological function development, but also closely related to the corresponding life and work. In terms of body shape, the average level of 20-29 years old youth is low, while the average level of 30-34 years old youth is high; the physical quality and skill level also decrease significantly with the increase of age.

The ACA* proposed in this study is applied to evaluate the comprehensive level of physical fitness of members of a sports association in Chengdu in 2019. The prediction of the physical fitness level of the members in three aspects of body shape, function, and quality in 2019 is shown in Figure 10. On the whole, the distribution of physical fitness reflects a stable trend, while the physical function and shape are on the right and steep, reflecting that the improvement of the physical fitness level of the members of the association in 2019 mainly depends on the result of the improvement of physical fitness level. In the future, we need to optimize the overall physical fitness by strengthening sports, changing living habits, and transportation modes.

4. Conclusion

This study mainly uses the improved big data adaptive ant colony classification rule algorithm to analyze the impact of sports on human health and physique. The results show that under the background of big data, compared with other algorithms, ACA* can converge to higher quality solutions, and with the increase of algebra, ACA* can find better solutions than other algorithms, which is mainly due to the classification rule strategy adopted by ACA*, which makes it have stronger path propagation ability; the convergence speed of ACA* is significantly faster than that of the other five algorithms, and the solution quality is high. The standard deviation of PSO algorithm is relatively large, while the standard deviation of ACA* in each scene is lower than that of other algorithms, and the data difference is large. It can be proved that ACA* has high stability; compared with other algorithms, ACA* has more obvious advantages in stability, optimization ability, running time, and convergence speed and is more suitable for practical application; in general, the improvement of the physical fitness level of the association members in 2019 mainly depends on the results of the improvement of the physical fitness level. In the future, it is necessary to strengthen the physical fitness, optimize the overall physical fitness, carry out sports, and change the living habits and transportation modes. Due to the limitation of time and ability, this study only selects eight scenes as the background to compare the six algorithms. However, this paper does not reflect the scientific impact of the algorithm on human health and physique. In the future, we need to test the performance of ACA* in more scenarios.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The author declares that no competing interests.

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