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Retraction

Retracted: Establishment and Optimization of College Students Physical Health Standard Test System Based on Neural Network Reliability Evaluation Model

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

In addition, our investigation has also shown that one or more of the following human-subject reporting requirements has not been met in this article: ethical approval by an Institutional Review Board (IRB) committee or equivalent, patient/participant consent to participate, and/or agreement to publish patient/participant details (where relevant).

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] J. Zhang, S. Zhang, and D. Li, "Establishment and Optimization of College Students Physical Health Standard Test System Based on Neural Network Reliability Evaluation Model," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 8642707, 12 pages, 2022.

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Research Article

Establishment and Optimization of College Students Physical Health Standard Test System Based on Neural Network Reliability Evaluation Model

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At present, the physical condition of college students is declining day by day, and the relevant sports departments pay more and more attention to the daily physical exercise of college students. To deeply understand the physical health status of college students and further adjust the health intervention measures, this paper constructs a neural network reliability evaluation model and carries out the physical health standard test on 50 college students from the sports department of Nanchang University and analyzes the physical health test data by using the neural network error reverse evaluation method; to optimize the physical health test system, the accuracy of physical health test is fitted in parallel. Then, according to the fitting degree of the test results, the direction of health intervention is predicted, and some specific suggestions are made for college students' health indicators such as running and vital capacity. The research shows that the fitting degree of the neural network reliability evaluation model is 86%, and the accuracy of the neural network model is high. In the 50 college students' physical health project, the fitting degree of 50 m running and vital capacity is higher than that of long distance running. Therefore, the neural network reliability evaluation model is feasible for college students' physical health tests and can rank the intervention items, which has great practical significance for the improvement of college students' physical health.

1. Introduction

The survey object can conduct self-assessment in a better secretive environment, which can reduce their physical pressure. At present, the popular Internet software, including QQ, WeChat, microblog, and online forums, will record the user's status in varying degrees. These software data can also help experts judge the user's physical health. Therefore, to explore the relationship between the level of social development and physical health of college students whether there are some mediating variables and regulatory variables, which has a certain theoretical significance for an in-depth understanding of the impact model of social development on physical health and also has a certain practical significance for the physical health education of college students.

At present, there are few direct studies on the influence of social development level on college students' physical health at home and abroad, especially the specific process of social development on physical health and the factors that affect their relationship. Ziaee and Choobineh analyze the data reflecting the user's physical health status hierarchically and fuse the user's physical data in different ways [1]. Vivek Kumar et al. carefully analyze the needs of users and divide the system into different functional categories; Pan Fang selected the elderly as the research object. Different theoretical models were used for physical health tests to evaluate the advantages and disadvantages of different models, and a physical health evaluation method was proposed by combining the advantages of various theoretical models, but the accuracy needs to be improved, according to this group [2]. Xiang et al. have studied the detection technology of the physique of the elderly, and through the algorithm; they have established a physical health assessment framework for the elderly [3]. To further improve the performance of the current physical health evaluation system, Yuan et al. designed an intelligent evaluation system for college students' physical health based on multifeature fusion [4]. The experimental results show that the designed system has good application performance. Liu and Wang's research also found that college students' social development level can promote their physical health level [5].

In the research of physique monitoring, Liu et al. pointed out that the identification, expression, and adjustment of the physique are an important component of the level of individual social development. The higher the level of individual social development, the stronger the identification and regulation ability of physique [6]. Li et al. also pointed out that one of the manifestations of individual social cognitive impairment is physical disorder [7]. Li et al.'s research directly found that the level of social development of college students can significantly negatively predict the level of their physical barriers [8]. Cox also found that the use of social interaction group counseling can effectively improve the physical health of people with physical disorders, and the effect can be maintained for more than 3 months. Therefore, the level of social development may indirectly affect the level of physical health through physical barriers [9]. Katzman et al. point out that the satisfaction of self-expansion can be achieved through two paths, namely, "relationship expansion" and "personal expansion." "Relationship expansion" is to achieve self-expansion through the development of good and valuable social relations, and "personal expansion" is to achieve self-expansion through their efforts to obtain new material resources [10]. The above research shows that the pace of people's life is gradually accelerating, which makes college students face more and more pressure of study, employment, and life, leading to prominent physical problems. However, when the need for self-expansion is met, the individual can hardly experience a positive physique and will not promote their physical health.

This paper constructs a neural network reliability evaluation model and carries out the physical health standard test for 50 college students in the department of physical education of Nanchang University. This paper randomly selects from various colleges of Nanchang University and randomly generates the student numbers of 50 students in the student number database of the educational administration system and uses these 50 students as samples. The neural network error reverse evaluation algorithm is used to analyze the physical health test data. By adjusting the error range, the physical health test accuracy is fitted in parallel, to optimize the physical health test system. Then, according to the fitting degree of the test results, the direction of health intervention is predicted, and some specific suggestions are made for college students' health indicators such as running and vital capacity.

2. Experiment and Method of Physical Health Test System

2.1. Research Content. This paper designs an evaluation system for college students' physical health, which needs to have the functions of user management, evaluation content, data analysis, result query, etc. According to the system design requirements, the intelligent evaluation system architecture for college students' physical health is constructed, as shown in Figure 1.

As shown in Figure 1, the college students' physical health intelligent evaluation system uses the principle of the Internet of Things to link the students' health monitoring equipment with the cloud computing center, so that the data transmission can be completed in real time. Feature analysis module information query and storage module college student user information management module test module physical health evaluation module college student physical health evaluation system [11, 12]. Physical health disease is an important cause of depression and other problems, which will have a certain impact on the healthy development of students and the stable operation of the school [13, 14]. Therefore, the physical health problems of college students have attracted the attention of all walks of life in society. Early detection of whether college students have physical health problems will help to put forward treatment or auxiliary prevention programs in time, help students develop healthily, and promote the stable operation of the school, which also has important social significance [15]. Physical disorder refers to the inability of individuals to process and supervise physical information, and its main symptom is the difficulty of physical identification and processing [16]. The identification, expression, and control of physique are a kind of social interaction behavior, so it is bound to be affected by the level of individual social development [17, 18]. Because the development and progress of society bring people a better material life, and the improvement of material living standards will improve the physical quality of individuals.

2.2. Physical Health Test Model. The social development of college students may have a certain impact on their physical barrier level. At the same time, the physical disorder can cause the decline of individual physical health level. Previous studies have pointed out that physical disorders can cause damage to the process of physical perception and regulation, which makes individuals more prone to panic attacks, drug abuse, eating disorders, and other diseases and reduces the clinical efficacy. Moreover, physical barriers not only lead to many physical health problems but also affect the effect of physical health intervention [19]. Then, the reliability function w of the constitution can be written as

$$\Delta W^{l} = -\eta \frac{\partial E}{\partial W^{l}} = \eta \left(X^{l}\right)^{T} \delta^{l}. \quad (1)$$

When the j subsystem has w failures in X tests, the maximum likelihood estimation of system reliability SR is as follows:

$$\Delta \mathrm{SR}^{l2} = -\eta \delta^{l2} X^{l2} = \eta \delta^{l3} \left(W^{l3}\right)^{T} f' \left(X^{l2} W^{l2}\right) X^{l2}. \quad (2)$$

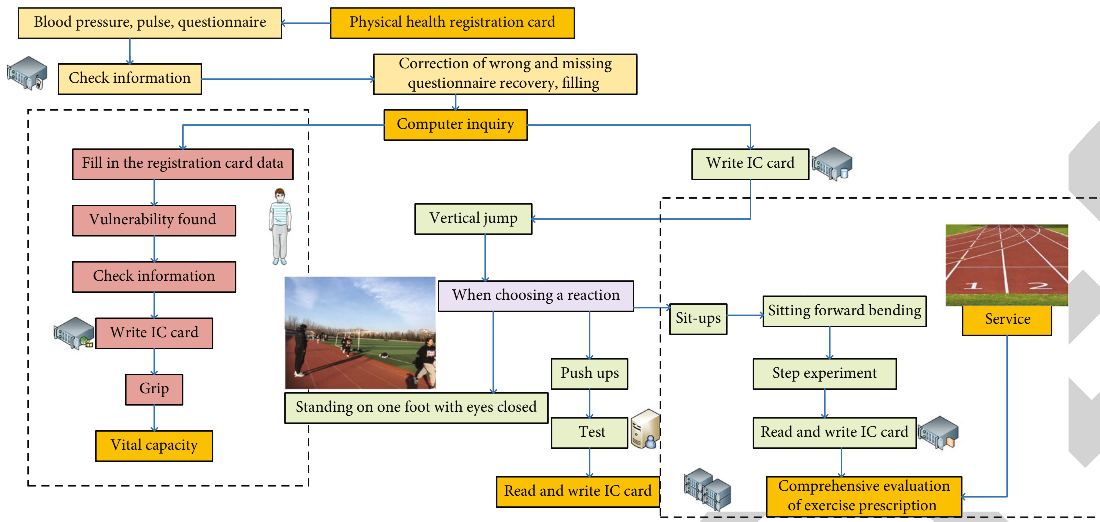

Figure 1: The framework of the intelligent evaluation system for the physical health of college students.

Then, it is equivalent to the number of "virtual" tests N and the number of successful tests x at the system level

$$\log_2 n + 1 \leq X \leq \log_2 n + 2, \tag{3}$$

$$X(\sigma, g) = e\left(\prod_{i=s_1}^{s_l} H(v\|i)^{v_i} \cdot u^{\mu}, v\right). \tag{4}$$

Because of the problem of "different population" between different historical samples and field samples, the similarity coefficient is introduced to characterize the closeness of historical samples to field samples. Then, formula (4) can be further characterized as follows:

$$Y^{l2} = \delta^{l3}\left(W^{l3}\right)^T f'\left(X^{l2}W^{l2}\right), \tag{5}$$

where WL is the uncertainty of X when y is known. It can be seen that information entropy describes the uncertainty of information by quantitative means, and conditional entropy describes the residual uncertainty of the information when certain information is known [20]. Information entropy and conditional entropy models can be used to quantify the uncertainty of reliability r without historical samples and with historical samples. The difference between the two kinds of uncertainty is the contribution value of the introduction of historical samples to eliminate the uncertainty of reliability R. The greater the proportion of the contribution value to the original uncertainty value, the greater the contribution value is; it shows that the closer the reliability characteristics of the historical samples are to the field samples, that is, the higher the similarity coefficient [21]. Then, we make them equal to the first and second moments of the beta distribution, and we can get the values of the super parameters a and B. Based on the field samples, it is easy to deduce the posterior distribution as follows:

$$R = \frac{1}{2}\left(\frac{t-y}{a-b}\right)^2. \tag{6}$$

Then, the formula of conditional entropy R is

$$\frac{u_{(j|i)}}{R} = w_{ij}A_i, \tag{7}$$

where A is the uncertainty value of reliability r in the presence of class I historical samples, and the specific expression is as follows:

$$\Delta R^{l3} = -\eta\delta^{l3}X^{l3} = \eta(t-y)f'\left(X^{l3}W^{l3}\right)X^{l3}. \tag{8}$$

Because the prior information of the l source is obtained, the loss ratio of information entropy of parameter r is as follows:

$$R = P - \frac{\left(2\mu_x\mu_y + C_1\right)\left(2\sigma_{xy} + C_2\right)}{\left(\mu_x^2 + \mu_y^2 + C_1\right)\left(\sigma_x^2 + \sigma_y^2 + C_2\right)}. \tag{9}$$

Obviously, the larger the C is, the greater the contribution of the prior information of the C source to eliminating the uncertainty of reliability R is. As the inheritance factor, the value of Y is

$$Y_{ij} = \frac{e^{b_{ij}}}{\sum_k e^{b_{ik}}} * X, \tag{10}$$

$$N_{(j|i)} = \frac{w_{ij}A_i * \mathrm{t}}{n}, \tag{11}$$

$$R^L = (t-y)f'\left(X^L W^L\right), \tag{12}$$

where n is the total number of categories of historical samples. The above process brings the multisource prior information into the unified framework, which lays the foundation for constructing the Bayesian multisource mixed prior function of reliability R. The problem of Bayesian inference is the problem of conditional probabilistic inference. The discussion in this field has important theoretical and practical significance for revealing people's cognitive processing process and laws of probability information, and guiding people to conduct effective learning and judgment and decision-making. Bayesian statistical inference of reliability characteristic quantity in the process of reliability identification, the results of the field test are "success" and "failure," which obey binomial distribution. For binomial distribution, when the random variable is success probability (i.e., reliability R), it is conjugate prior distribution is beta distribution. The probability density function of cloth is as follows:

$$R^l = \delta^{l+1}\left(W^{l+1}\right)^T f'\left(X^l W^l\right), \tag{13}$$

where R is a random variable and a and B are superparameters. The superparameters can be solved based on the prior moment method, which will not be discussed here. The premise of using Bayesian theory for statistical inference is that the samples come from the same population, so Equation (13) can not be directly used as the prior distribution function of the constitution reliability r in this paper. In the Bayesian fit theory, the premise is that the samples come from the same space, but as can be seen from Equation (13), the probability density of the cloth is not a standard normal distribution, so the samples cannot be in one dimension. The determination of inheritance factor solves the problem of quantitative description of "different populations" between historical samples and field samples, so a multisource weighted mixed prior distribution function $f : F$ can be constructed based on beta distribution and inheritance factor:

$$F_1^{ij} = \cos\left(S_1^i, S_2^j\right), \tag{14}$$

$$2\left\lceil \frac{S}{2} \right\rceil^{d-2} \times \left\lceil \frac{S}{2} \right\rceil \le n \le S^{d-1} \times S, \tag{15}$$

where n is the number of historical sample categories. The joint distribution of sample X and parameter r is as follows:

$$R^{l3} = (t-y)f'\left(X^{l3} W^{l3}\right). \tag{16}$$

Equation (16) integrates three kinds of available information: general information, sample information, and prior information. Y is decomposed as follows:

$$Y = \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{TN}+\mathrm{FP}+\mathrm{FN}}, \tag{17}$$

$$\frac{e^x - e^{-x}}{e^x + e^{-x}} = \frac{x*}{1+|x|}, \tag{18}$$

where $x*$ is the marginal density function of X, i.e.,

$$\begin{cases} \sigma = \prod_{i=s_1}^{s_l} \sigma_i^{\;v_i} = \prod_{i=s_1}^{s_l} H(v\|i)^{v_i} u^{v_i s_i}, \\ \mu = \sum_{i=s_1}^{s_l} v_i f_i, \end{cases} \tag{19}$$

$$\mathrm{Y}_{ij} = \frac{e^{b_{ij}}}{\sum_k e^{b_{ik}}}. \tag{20}$$

It can be seen that only the conditional distribution RX can be used to infer R, and its solution formula is as follows:

$$\mathrm{RX}_i = \left(H(f_i) \in u^{f_i}\right)^x \left|\sigma_i \in G, i = 1, 2, \cdots, n,\right. \tag{21}$$

$$\frac{\partial E}{\partial \mathrm{R}^l} = \frac{-\left(x^l\right)^T}{X}\delta^l. \tag{22}$$

Given the sample x, formula (22) is the probability density function of the posterior distribution of R. For physical reliability evaluation, engineering circles generally pay more attention to the lower confidence limit of reliability [22]. The lower confidence limit of the given single side confidence C and reliability R can be solved by the following formula:

$$C_{\mathrm{R}} = \begin{cases} \dfrac{n}{\Delta}\sqrt{\sum_{s=1}^{n} (x(\varepsilon)\text{-}x(\varepsilon))^2 \Delta(\varepsilon)}, & \Delta > 0, \\ 0, & \Delta < 0. \end{cases} \tag{23}$$

Thus, the comprehensive evaluation of the reliability of a high-value constitution is completed. In the engineering prototype evaluation stage, the ground reliability evaluation test of simulated field test was carried out for the two newly developed components, and the success or failure data was converted from the metrological data. Now, it is necessary to formulate the reliability assessment scheme of this type of constitution to be identified in the finalization stage.

3. Results and Analysis

3.1. Reliability Analysis of Physical Fitness Evaluation. In this paper, the reliability index is defined as follows: under the confidence level of 0.9, the unilateral lower confidence limit of reliability is greater than or equal to 0.9. Before the known type test, except for two newly developed electronic components, the rest are mature products using the basic constitution. Based on the method presented in this paper, the curves of the lower confidence limit (confidence 0.9) of the reliability of this type of constitution with the amount of ammunition used are obtained in the case of zero failure and one failure, respectively.

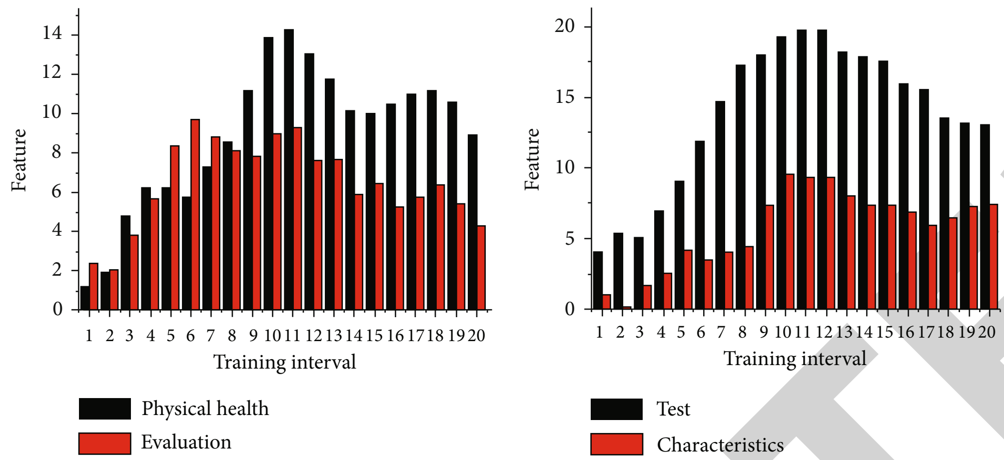

Figure 2: Bar graph of reliability changes with ammunition volume.

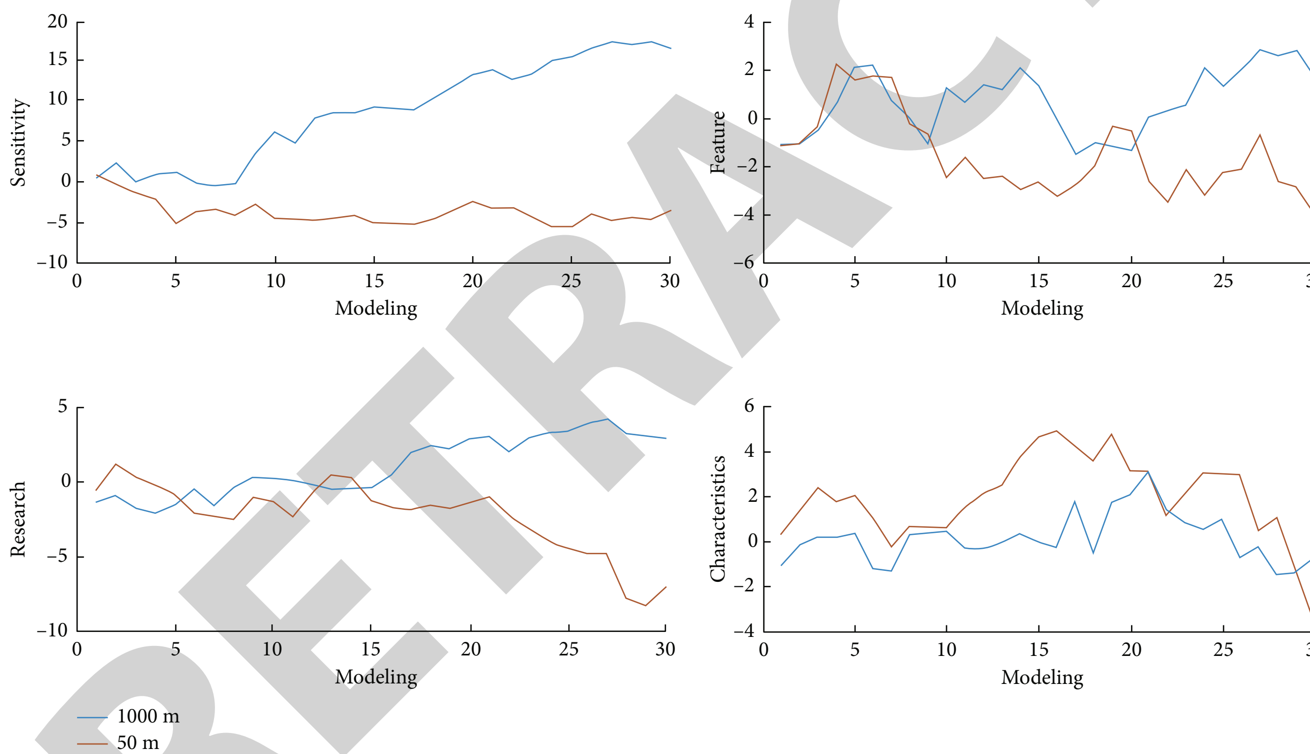

Figure 3: Statistical chart of test results for 50 m and 1000 m.

The column chart of reliability with the change of ammunition consumption under the reliability evaluation method is shown in Figure 2.

As shown in Figure 3, the evaluation system designed in this paper includes five modules: user information management, testing, feature analysis, physical health evaluation, and information query and storage. The user information management module of college students is mainly responsible for completing the user test. In the testing module, the physical fitness test is carried out through the scale to collect the user's physical data and simultaneously collect the user's information, the collected data is input into the feature analysis module for feature extraction and classification, and then, the evaluation module is used to fuse different feature data to obtain the user's physical health status, which is output through the information query module and synchronously stored in the system. As the next user's physical analysis auxiliary information, it can also be used as students' physical files.

As shown in Figure 4, in the design process of college students' physical health intelligent evaluation system, it is important to design scale parameters to collect user information more accurately. In addition, the analysis and evaluation of physical health characteristics are also very

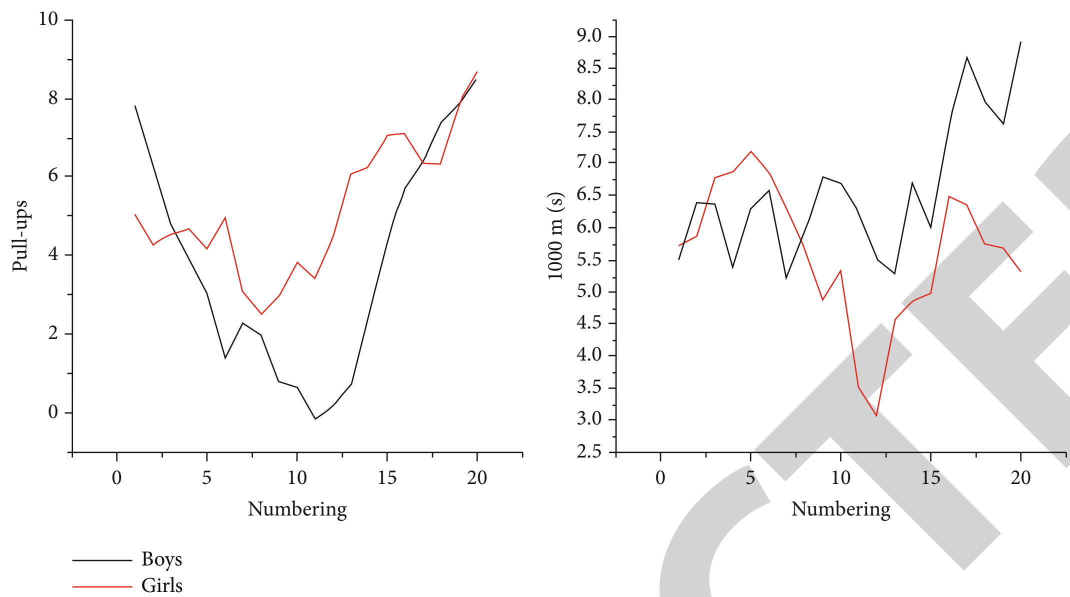

Figure 4: The design process of physique health intelligent evaluation system.

important. In this process, the data of college students' physical health status needs to be extracted, and the feature data needs to be deeply studied in the way of multifeature fusion, complete the physical health intelligent evaluation. The evaluation module uses a combination of scale tests and social software data analysis to conduct research. The scale test results include test topic, content, test time, and user information. The field settings are shown in Table 1. As shown in Table 1, each item has little difference in value, but the feature is the highest in value and the warehouse is the lowest.

As shown in Table 2, the administrator is responsible for the content management of the integer evaluation scale. Only the administrator has the rights of content modification, question attribute setting, answer option management, and whether the scale is open. Only when the equivalent scale is open can the scale data be collected. College students' physical health characteristics mainly include behavior characteristics, attribute characteristics, content characteristics, and social relationship characteristics. Behavior characteristics refer to users' behavior on social networks, including likes, comments, and online browsing traces. Attribute feature refers to the user's personal information, including name, age, gender, occupation, and hobbies. Content features include users' chat content on social software and posting.

3.2. Artificial Intelligence College Students' Physique Test System. As shown in Figure 5, the relationship between students' physical health data is shown in the number of mutual attention and fans. Firstly, we infer whether the collected data information is valid or not. If it is valid, the collected data information will be transformed into the data form directly processed by the system, which needs to introduce the concept of the time window to extract the physical health characteristics of college students. Batch conversion scale data and using social network data, divided into different samples, a sample corresponding to a window, using the time window data to complete feature extraction, and the feature extraction results are classified and marked. The time window selected here is 24 hours, to obtain more comprehensive information of college students' physical health data.

To further explore the physical health status of college students and obtain more accurate physical characteristics of users, multifeature fusion analysis is carried out on the physical health data of college students. As shown in Figure 6, the multichannel physical health data are analyzed as a whole to provide the basis for intelligent evaluation. A neural network is an effective nonlinear data fusion method, which can transform the input space into the hidden space, and it is more convenient to analyze the data in the hidden space. Therefore, the neural network has strong data processing ability and meets the needs of large-scale data processing, which is suitable for multifeature fusion analysis. By inputting the extracted college students' physical health feature data and calculating the radial basis function according to the above formula, the multifeature fusion can be realized and the college students' physical health intelligence evaluation can be completed. The experimental results show that the method in this paper has a good effect on a large sample. Compared with the traditional method, the method designed in this paper is more suitable for the analysis of the physical fitness data of college students.

Student life and reach-out online forum post data are employed as data sources, as indicated in Figure 7. Dartmouth College conducted study on the Student Life Data Set, which included academic data, online physique test data, questionnaire survey data, and other information on 49 students' perceptions of their bodies over the course of 20 days. The user post information, post time, liked number, and browse number are all included in the reach out online forum post. Each of the two data sets yielded five million data sets, for a total of ten million data sets. The data set is

Table 1: The evaluation module uses scale testing and social software data analysis.

Item	Sensitivity	Feature	Advisory	Research	Modeling
Characteristics	9.43	13.05	7.63	10.07	9.75
Physical health	7.97	11.76	7.69	10.86	9.57
Evaluation	7.35	10.14	5.95	9.65	9.06
Information	7.38	10.02	6.37	7.97	9.54
Inquire	6.9	10.46	5.25	6.23	10.41
Storage	5.92	11.02	5.72	5.24	8.47

Table 2: Physical fitness and health behavior characteristics of college students.

Item	Characteristics	Physical health	Evaluation	Information	Inquire	Storage
Sensitivity	1.37	3.7	3.41	3.75	6.21	4.13
Feature	3.29	3.33	3.3	6.36	5.96	5.83
Advisory	5.52	6.29	5.15	8.37	7.98	8.53
Research	6.4	8.61	4.38	10.24	8.06	7.82
Modeling	8.6	8.04	4.98	12.2	8.22	10.73

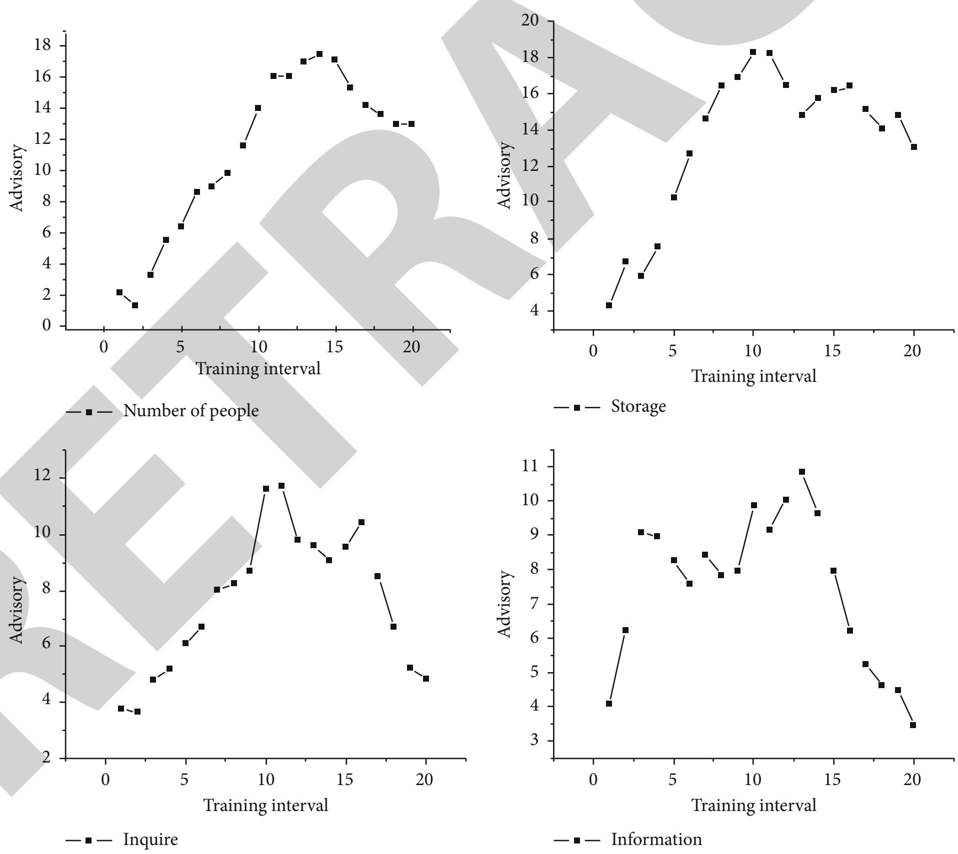

Figure 5: Characteristics of physical health data obtained through multiple channels.

separated into ten equal portions, six of which are used to train neural network models and four of which are utilized for experimental testing.

The accuracy of feature fusion is directly connected to the accuracy of system assessment outcomes, as illustrated in Figure 8; hence, this index was chosen for analysis. Recall rate is the ratio of the information retrieved from a system query to the entire quantity of system information. Test the system's recall rate to ensure that it is working properly.

Figure 9 depicts a comparison curve of the feature fusion accuracy rate of several methods. The accuracy rate of the method in this study is consistently the greatest, averaging

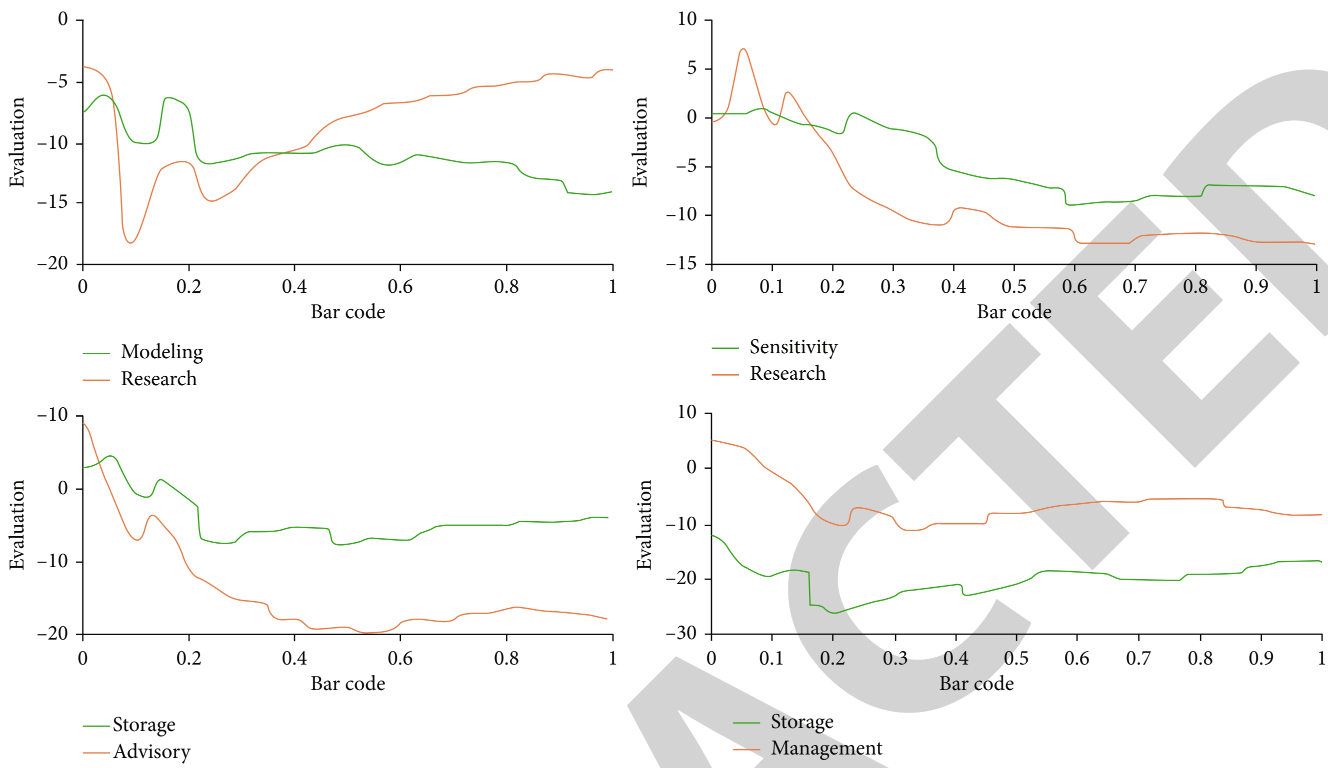

FIGURE 6: The system achieves fluid quality health data results.

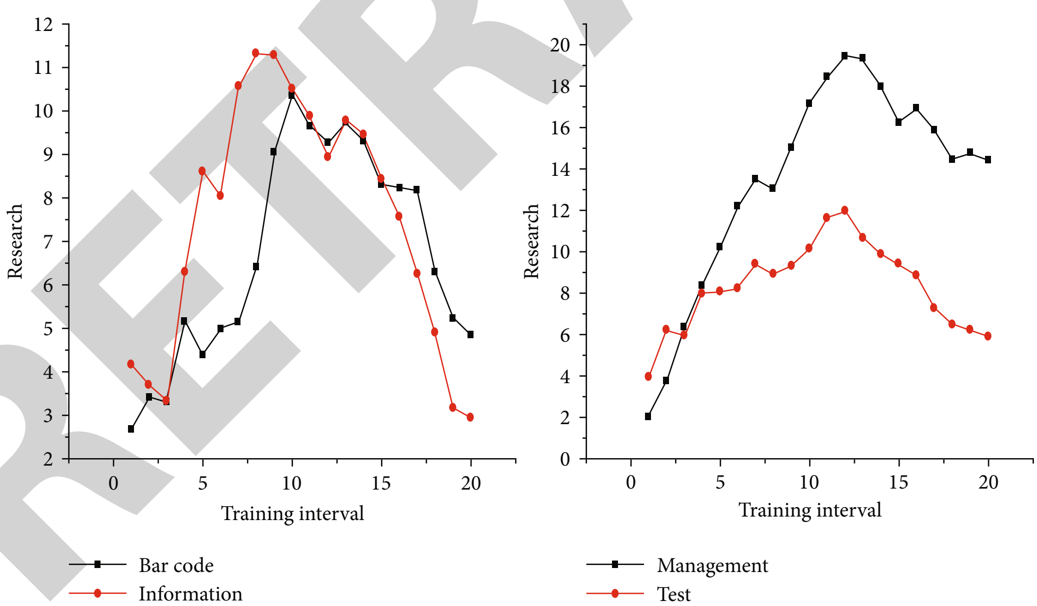

FIGURE 7: Physical perception data for 20 consecutive days.

about 90%. The literature has a larger feature fusion accuracy rate, up to 80%, than the other three literature outcomes, and the accuracy rate of literature and literature is low. It can be seen that multifeature fusion based on neural network in this paper makes full use of the parallel processing ability of the neural network and achieves high accuracy of feature fusion effect. The higher the recall rate is, the higher the recall rate is, and the better the system performance is. The results of the recall comparison are shown in Table 3.

As shown in Figure 10, the running time of the system in this paper increases to about 30s when the number of experiments reaches 200, but the running time of the ordinary neural network system is much higher than that of the

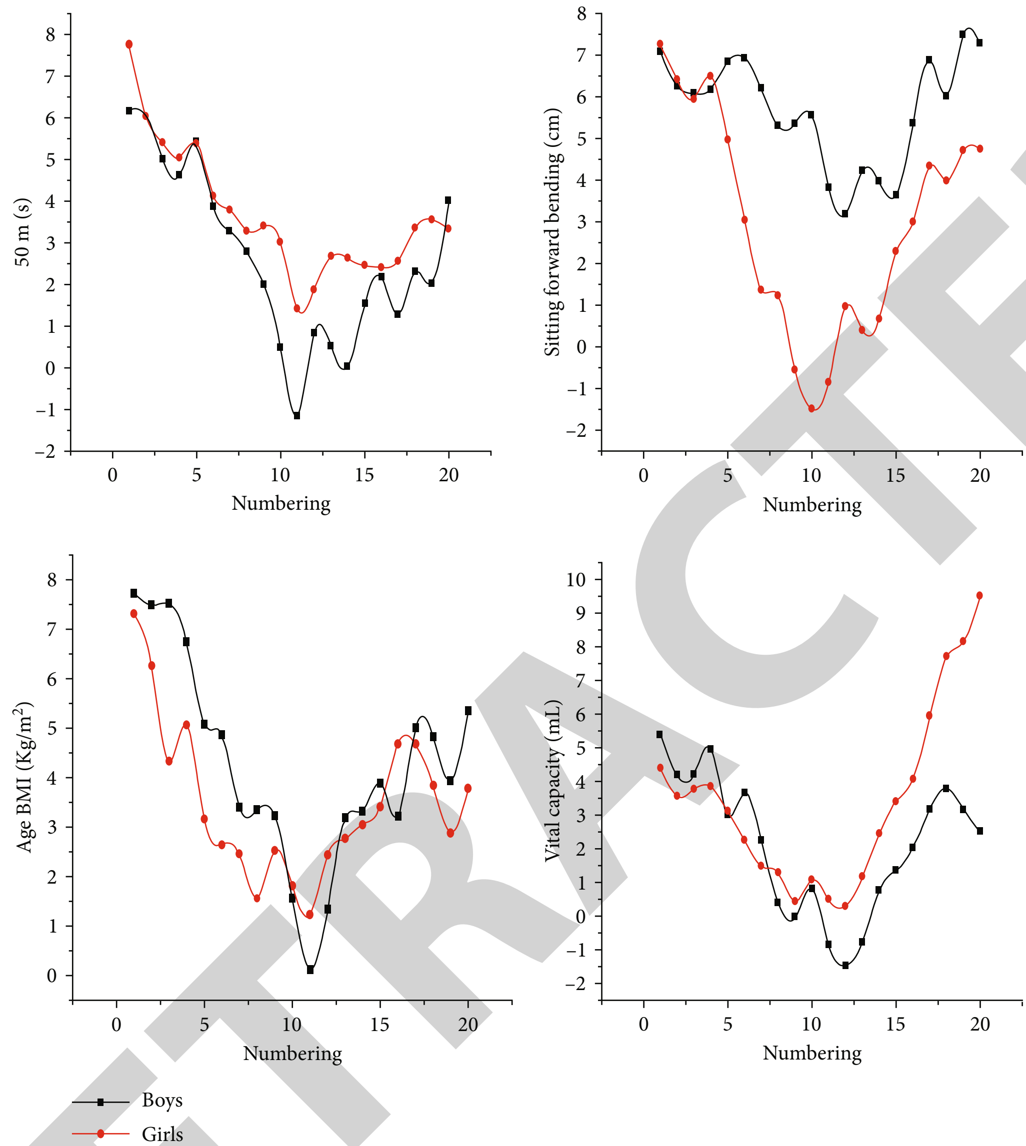

FIGURE 8: The accuracy of the results of the boys and girls system.

system in this paper. It can be seen that the intelligent evaluation system designed in this paper has strong practical applicability, because the neural network is used to fuse the characteristic data in the system design, and the running speed is fast, and the running speed of the system is improved.

As shown in Table 4, although the order of the minimum cut set is not high, it does not affect the accuracy of this method. The purpose of the parameter optimization stage is to obtain the parameters of the important sampling probability density function. When the parameters are calculated, the real reliability index calculation stage of the large physical fitness test is entered, that is, the main sampling stage. When the number of samples is limited in the main sampling stage, the calculation accuracy is often measured by the variance coefficient of reliability index statistics. In the parameter optimization stage, different methods are used to obtain the important sampling function parameters, which will lead to the difference of the calculation cost in the parameter optimization stage, and further, affect the calculation time of the reliability evaluation of the whole physical fitness test (including the parameter optimization and the main sampling stage), but it does not affect the calculation accuracy of the reliability index in the main sampling stage, because the accuracy of calculation is determined by the variance coefficient given in the main sampling stage.

4. Discussion

Under the influence of COVID-19, college students return to collective life, and the change of interpersonal communication makes them feel uncomfortable, even contrary to and exclusion, and then appear or aggravate physical problems. It may also be that after returning to school life and studying, the pressure of college students on learning or employment increases abruptly. Some students feel anxious because

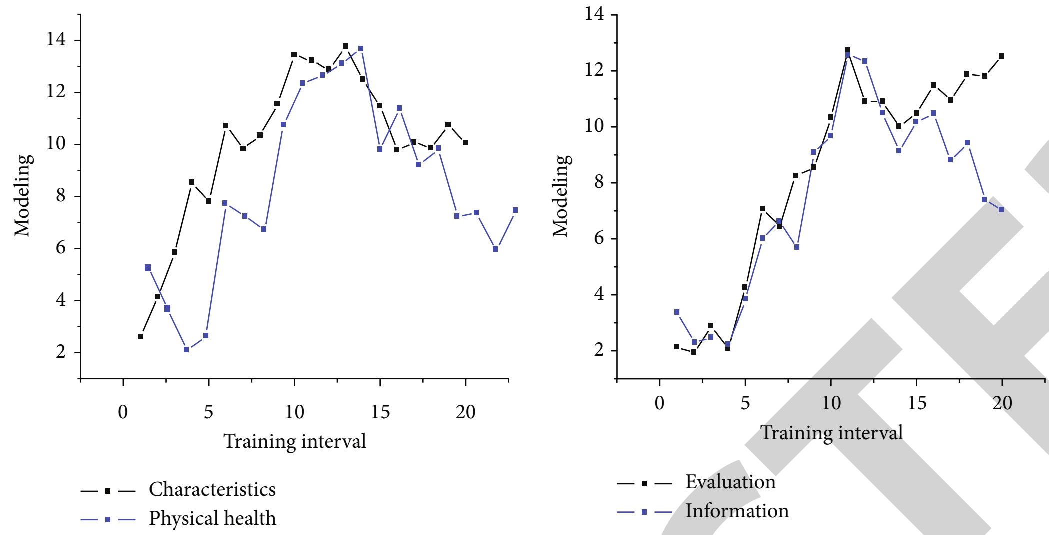

Figure 9: Comparison curve of feature fusion accuracy rate of different systems.

Table 3: The system's physical health data recall rate.

	Vital capacity	50 m	Standing long jump	1000 m	Pull-ups
Sensitivity	3.19	7.27	0.18	0.14	2.43
Feature	4.23	8.51	0.75	0.36	2.77
Advisory	3.97	9.55	2.56	1.3	3.05
Research	3.64	10.56	4.31	3.29	3.41
Recall rate	5.37	12.49	5.72	4.75	4.68

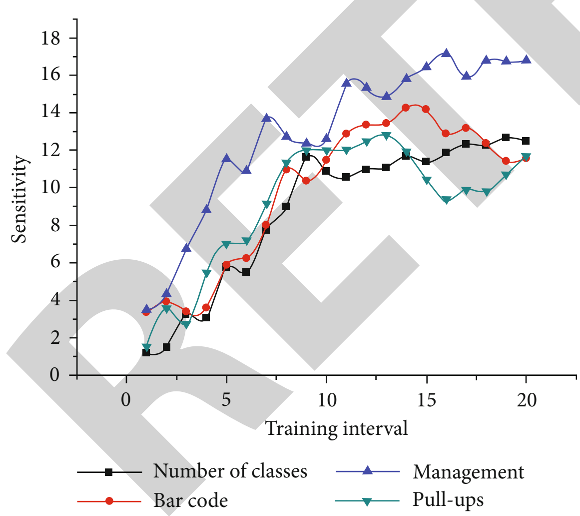

Figure 10: The actual test degree of the intelligent evaluation system in the high jump.

they cannot concentrate on online learning and their state cannot be adjusted after the class resumption, which leads to the disconnection with the progress of the school. Some graduates feel confused and uneasy because the economy of some industries is still difficult to recover after the impact of the epidemic, and the employment competition is more intense. Using the likelihood function and trust function of D-S evidence theory to express the upper and lower bounds of the probability of the bottom event of the test system tree, the probability interval of the top event plunger pump test system can be determined according to the interval operator. To more accurately describe the degradation process of the test system phenomenon, and determined the system reliability and the importance of the bottom event through the minimal path set method. However, the above models only solve the limitations of traditional test system tree analysis methods from one point of view. It has unique advantages in expressing the fuzzy relationship between the bottom event and the superior event, describing the event polymorphism and uncertainty, and has been gradually applied to the reliability analysis of complex systems .

In this paper, the intelligent evaluation system of college students' physical health is designed based on the multifeature fusion method. By introducing the multifeature fusion method to process the physical data, the accuracy of the evaluation system is improved, and the feature fusion analysis is carried out with the help of the advantages of neural network fast processing data, which improves the operational efficiency of the system. Since different items have different data in the monitoring projects of college students' physical health, and there are dimensions in the calculation of data, it is necessary to integrate the characteristics of the data. The recall rate is an indicator to measure the success of a retrieval system in detecting relevant documents from a document collection, that is, the percentage of relevant

Table 4: The likelihood function of physical health.

	Sensitivity	Feature	Advisory	Research	Modeling
Age BMI	6.38	2.78	7.69	4.85	5.44
Vital capacity	7.76	4.65	6.88	5.34	4.7
50 m	7.99	6.16	7.98	5.04	4.02
Sitting forward bending	9.44	6.64	8.64	5.69	5.63
Standing long jump	10.77	6.01	7.87	6.94	6.08
1000 m	12.35	7.31	9.16	6.64	6.65
Pull-ups	11.49	6.92	10.72	7.9	6.56
Consolidated results	10.98	7.4	10.72	9.15	8.09

documents detected and all relevant documents.In the experiment, two data sets are used to test the system, and the results show that the overall performance of the designed system is good. This system has a high data recall rate. Under the condition of different amounts of test data, the recall rate is high, which is far higher than the results of other kinds of literature. It can be seen that this system has certain advantages.

The higher the order of the minimum cut set, the faster the convergence of the main sampling stage, but it also brings two effects: first, the number of system states that need to be enumerated and analyzed in the parameter optimization stage increases exponentially, the calculation cost increases sharply, and the efficiency of the whole quality test reliability evaluation decreases. Second, when the order of the minimum cut set is too high, the parameter changes of the importance sampling function will enter the saturation stage, that is, the calculated value of the parameter only changes slightly with the increase of the order of the minimum cut set. It can be seen that the higher the order of the minimum cut set is, the better. At the same time, considering that the components that have an important impact on the system reliability can be reflected in the low order cut set events, the ineffectiveness of the components in the low order cut set events can be optimized to highlight the probability of their occurrence, and the reliability index calculation can be significantly accelerated in the subsequent main sampling stage.

Considering the factors of economy and reliability, this paper establishes a bilevel multiobjective optimal allocation model of the regional comprehensive fitness test system, which combines planning and operation. In the model, the sequential Monte Carlo method is used to quantitatively evaluate the reliability of the allocation scheme. Through the analysis of the optimal configuration results of the regional comprehensive physique test system, for the two-level and multiobjective optimal configuration of the regional comprehensive fitness test system proposed in this paper, there is a certain contradiction between reducing the expected value of comprehensive energy shortage and reducing the comprehensive annual cost. The Pareto optimal solution set of the former has some advantages in reliability and economy compared with the optimization results in the case of considering 50 m, 1000 m storage, high jump, and not considering the above equipment. By combining the lower-level optimization operation model with the sequential Monte Carlo simulation method, it can simulate the time-series state change and operation of each equipment in the regional comprehensive fitness test system, to realize the quantification of the operation reliability of the configuration scheme in the iterative process of the algorithm.

5. Conclusions

Compared with the previous single-objective optimization method, the multiobjective optimization method can provide more diversified and refined choices for planners and help them make the final decision according to their actual needs. In the test data of college students' physical health standard using the neural network reliability evaluation model, the fitting degree is 86%, and the accuracy of the neural network model is high. In the 50 college students' physical health project, the fitting degree of 50 m running and vital capacity is higher than that of long-distance running. Therefore, the neural network reliability evaluation model is feasible for college students' physical health tests and can rank the intervention items, which has great practical significance for the improvement of college students' physical health. In the follow-up research work, the sequential Monte Carlo simulation method will be improved, and the influence of the test system recovery strategy on reliability will be considered in the model. At the planning level, in addition to the optimal configuration of a single regional comprehensive fitness test system, we will also carry out more in-depth research on collaborative planning among multiple systems. Since this paper selects relatively fine experimental objects and adopts a relatively complete measurement method for testing, the results of this paper have good generality.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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