Evaluation and Prediction of Sports Health Literacy of College Students Based on Artificial Neural Network

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Abstract

Sports health literacy (SHL) is an important indicator of the all-round development of college students. However, the existing studies have not constructed a systematic and complete evaluation index system (EIS) or diversified the index weighting method. To solve the problem, this paper tries to evaluate and predict college students' SHL based on artificial neural network (ANN). Firstly, an EIS was designed for college students' SHL, including 4 goals, and 19 primary indices, and the structure of the evaluation and prediction system was presented for college students' SHL. Next, college students' SHL was comprehensively evaluated through analytic hierarchy process (AHP). Finally, a backpropagation neural network (BPNN) was established to predict college students' SHL, and the initial weights were optimized by genetic algorithm (GA). The proposed EIS and prediction model were found scientific and effective through experiments. To sum up, the SHL of college students were evaluated and predicted in the following aspects: EIS construction, evaluation model establishment, and evaluation system design. The proposed model and system can comprehensively rate college students' SHL. The statistical analysis of the ratings reflects the gaps between indices, and identifies those doing well and poorly on each index. Then, pertinent intervention can be implemented to satisfy the actual needs of improving college students' SHL.

Keywords: sports health literacy of college students (college students' SHL); back propagation neural network (BPNN); evaluation index system (EIS)

Introduction

Sports health literacy (SHL) is the most indicator of the all-round development of college students (Balalavi et al., 2021; Blazheska-Tabakovska et al., 2019; Parisod et al., 2018; Widiyawati et al., 2018). College students' SHL emphasizes the physical and mental health of college students over the mastery of sports rules and skills (Mayer, 2017; Montagni and Tzourio, 2017; Rachmani et al., 2019). In actual teaching, few colleges teach and cultivate the awareness and ability of lifelong exercise, good living habits, and a tough mind (Faria et al., 2019; Jamal et al., 2020; Kuo and Tsai, 2020; Saho et al., 2021; Subiantoro and Mutiarani, 2021; Teixeira Lopes and Ramos, 2020). As a result, it is meaningful to explore the SHL of contemporary college students.

In recent years, many developed countries have formulated action strategies and evaluation tools for improving the health literacy of their citizens. The focal points of SHL research gradually extends from patients to ordinary people. Kim et al. (2020) constructed an evaluation index system (EIS) for youngsters' SHL, which includes four primary indices (i.e., sports and health skills, knowledge, behaviors, and morality) and 25 secondary indices (e.g., treatment of other common injuries, and parameter test), and weighs each evaluation index. The students can nurture healthy behaviors through the SHL instruction by teachers in physical education (PE) classes. Therefore, the SHL level of PE teachers has a major impact on the formation of healthy behaviors among students (Bartlett et al., 2019; Levin-Zamir and Baron-Epel, 2020; Nair et al., 2020; Pleasant et al., 2020; Thapa-Chhetry and Keck, 2019; Willis et al., 2019).

Through statistical analysis and questionnaire survey, Ike et al., (2019) studied six qualities among PE majors and teachers in a region, namely, health literacy, healthy behavior and lifestyle, health skills, etc., and proposed rectification measures like promoting publicity, providing targeted health skill training, and perfecting health education system. Christie and Ratzan, (2020) designed a physical health monitoring bracelet based on wearable technology. The bracelet relies on radio frequency identification (RFID) chips and sensors to check the identity and physical data of students in real time, transmit the data to the teacher terminal via Wi-Fi communication, and enable teachers to monitor students' exercises, thereby improving the physical fitness of students. Peterson et al., (2019) carried out multistage stratified random sampling on the cognitive attitude and practice ability of college students for the basic knowledge, concepts, skills, and qualities of environment and health, and conducted an on-site questionnaire survey based on the Technical Guide for Environmental and Health Literacy Assessment of Citizens. Finally, the index data were statistically analyzed through logistic regression.

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College health education is the most effective way to promote the health literacy of college students (Bocevska et al., 2018; Duckhorn et al., 2019; Hirvonen et al., 2018; Parnell and Agris, 2020; Peyton et al., 2019). Dellinger et al. (2019) identified a series of problems in various links of health education, e.g., higher education teaching mode, classroom teaching contents, after-class Q&A (question and answer)/counseling, and course appraisal, and suggested that the teaching mode and classroom teaching contents should be flexibly designed based on the actual situation of students; the health education teachers should be more professional; an online health system should be established for college students, covering the society, colleges, and families.

So far, the SHL cultivation strategies for students are largely theoretical, rather than empirical. There is not yet a systematic and complete EIS for students' SHL, or diversified means to weight the evaluation indices. By virtue of the advantages of neural network in data processing, this paper aims to evaluate and predict college students' SHL based on artificial neural network (ANN) (Ouchtati et al., 2019; Sbargoud et al., 2019; Wang, 2020). Section 2 designs an EIS for college students' SHL, which includes 4 goals, and 19 primary indices, and clarifies the structure of the evaluation and prediction system; Section 3 completes the comprehensive evaluation of college students' SHL through analytic hierarchy process (AHP) (Wang, 2019); Section 4 predicts college students' SHL with backpropagation neural network (BPNN) (Jiang, et al., 2020; Li et al., 2020), and optimizes the initial weights of indices by genetic algorithm (GA) (Özyurt et al., 2020; Saraiva, A.A., 2019). Finally, the proposed EIS and prediction model were found scientific and effective through experiments.

EIS Construction

AHP facilitates flexible decision-making of complex, multilayer EISs. This paper chooses this method to quantify the indices of the qualitative evaluation of college students' SHL. A hierarchical evaluation model was constructed, including a goal layer, a primary index layer, and a secondary index (alternative) layer. The goal layer is the final solutions to college students' SHL evaluation, i.e., the problems to be solved through fuzzy AHP. There are four goals on this layer: sports health knowledge, sports health beliefs, sports health behaviors, and sports health skills. There are four primary indices in the intermediate layer, which are based on the four goals in the goal layer. They provide the instructions on the evaluation of how much college students' SHL could achieve the four goals. The secondary indices refer to the direct measures or necessary skills for improving college students' SHL. The indices in goal layer and primary index layer are as follows:

Layer 1 (goal layer):

$SH=\{SH_1, SH_2, SH_3, SH_4\}$ = {sports health knowledge, sports health beliefs, sports health behaviors, sports health skills}.

Layer 2 (primary indices)

$SH_1=\{SH_{11}, SH_{12}, SH_{13}, SH_{14}, SH_{15}, SH_{16}\}$ = {diet, exercise, psychology, disease, drug, adolescent health care};

$SH_2=\{SH_{21}, SH_{22}, SH_{23}\}$ = {behavioral intentions, behavioral habits, behavioral beliefs};

$SH_3=\{SH_{31}, SH_{32}, SH_{33}, SH_{34}, SH_{35}\}$ = {personal health, regular diet, physical exercise, mental health, preventive behaviors};

$SH_4=\{SH_{41}, SH_{42}, SH_{43}, SH_{44}, SH_{45}\}$ = {exercise health, environmental adaptation, health hazard identification, health hazard aversion, first-aid technology}.

There are many secondary indices in our EIS. According to the nature of college students' SHL evaluation, the relationship between primary and secondary index layers is essentially the hierarchical correlations between every primary index on the superior layer and every secondary index on the inferior layer.

Specifically, sports health knowledge on diet SH_{11} covers three aspects: nutritional composition SH_{111}, good eating habits SH_{112}, and identification and treatment of common food poisonings SH_{113}; sports health knowledge on exercise SH_{12} covers four aspects: exercise effects SH_{121}, exercise methods SH_{122}, types of sports damages SH_{123}, and treatments of common sports damages SH_{124}; sports health knowledge on psychology SH_{13} covers five aspects: types of negative emotions SH_{131}, influence of negative emotions on physical and mental health SH_{132}, self-cognition and understanding SH_{133}, features of adolescent psychological changes SH_{134}, and regulation of negative emotions SH_{135}; sports health knowledge on disease SH_{14} covers three aspects: harms of infectious diseases SH_{141}, transmission pathway SH_{142}, and prevention methods SH_{143}; sports health knowledge on drug SH_{15} covers three aspects: types of drugs SH_{151}, harms SH_{152}, and rejection methods SH_{153}; sports health knowledge on adolescent health care SH_{16} covers four aspects: hygiene during menstruation SH_{161}, principle of opposite sex interaction SH_{162}, correct ways of losing weight SH_{163}, and healthy work and rest habits SH_{164}. Sports health beliefs about behavioral intentions SH_{21} covers two aspects: benefits of physical and mental health SH_{211}, and severity of physical and mental sickness SH_{212}; sports health beliefs about behavioral habits SH_{22} covers four aspects: exercise habit SH_{221}, healthy work and rest habit SH_{222}, healthy dietary habit SH_{223}, and the habit of caring for own physical and mental health SH_{224}; sports health beliefs about behavioral beliefs cover two aspects: active maintaining habits SH_{231}, and acquiring own health information SH_{232}.

Sports health behaviors about personal health SH_{31} covers four aspects: taking bath frequently SH_{311}, changing clothes frequently SH_{312}, washing hands frequently SH_{313}, cutting hair frequently SH_{314}; sports health behaviors about regular diet SH_{32} covers four aspects: eating on time SH_{321}, balanced nutrition SH_{322}, moderate diet SH_{323}, and healthy diet SH_{324}; sports health behaviors about physical exercise SH_{33} covers four aspects: regular daily exercise SH_{331}, outdoor activities SH_{332}, morning exercise SH_{333}, PE class and health class SH_{334}; sports health behaviors about mental health SH_{34} covers three aspects: keeping optimistic SH_{341}, kind treatment of other students or teachers SH_{342}, and maintaining the environment of public health SH_{343}; sports health behaviors about preventive behavior SH_{35} covers three aspects: no pornography, gambling, and drug abuse SH_{351}, no drug abuse SH_{352}, and no game addiction SH_{353}.

Sports health skills about exercise health SH_{41} covers two aspects: mastering exercise methods SH_{411}, and reasonable control of exercise load SH_{412}; sports health skills about environmental adaptation covers three aspects: climate change SH_{421}, changes in indoor/outdoor environment SH_{422}, and maintaining normal interpersonal relationship SH_{423}; sports health skills about health hazard identification covers four aspects: common frauds SH_{431}, hazards of natural disasters SH_{432}, hazards of campus violence SH_{433}, and hazards of traffic accidents SH_{434}; health hazard aversion SH_{44} covers four aspects: resisting common frauds SH_{441}, avoiding hazards of natural disasters SH_{442}, coping with hazards of campus violence SH_{443}, and hedging hazards of traffic accidents SH_{444}; first-aid technology SH_{45} covers three aspects: treatment of minor injuries SH_{451}, cardiac resuscitation SH_{452}, and emergency treatment of bone fractures SH_{453}.

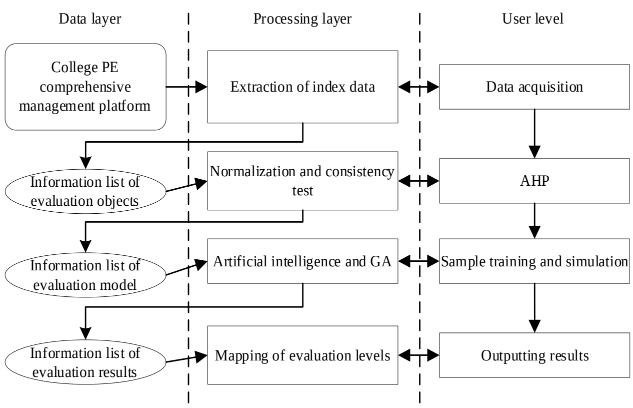


Figure 1. Structure of the evaluation and prediction system for college students' SHL

In our evaluation and prediction system for college students' SHL, the core modules are the AHP module and the BPNN module. The structure of the system is explained in Figure 1. Our system firstly extracts the data related to college students' SHL evaluation from the college PE comprehensive management platform and saves the college students participating in the evaluation. Then, the post-AHP index data are processed on MATLAB, using the normalization and consistency test modules. The processing results are saved in the information list of evaluation model. After initializing the parameters of BPNN, the index data are imported to the neural network for training. The trained network parameters are saved. Finally, the evaluation results are mapped to evaluation levels, and saved for display to observers.

AHP of College Students' SHL

In the proposed hierarchical model for college students' SHL evaluation, the relative importance and independence of the indices on different layers can be determined based on the membership between superior and inferior indices. Let MT be the overall evaluation goal; $F_i \in MT$ be an index on the i-th layer. Then, the relative importance v_{ij} of F_i to F_j can be organized into a judgment matrix V:

$$\begin{pmatrix} v_{11} & v_{12} & \cdots & v_{16} \\ v_{21} & v_{22} & \cdots & v_{26} \\ \vdots & \vdots & \vdots & \vdots \\ v_{61} & v_{62} & \cdots & v_{66} \end{pmatrix} \tag{1}$$

Next is to quantify the relative importance of indices between the goal layer and the primary index layer, and those between the primary and secondary index layers. Through the quantification, a single weight vector can be calculated $\omega = (\omega_l, \omega_2, \ldots, \omega_i, \ldots, \omega_m)^r$, i.e., the eigenvector corresponding to the maximum characteristic root γ_{max} of V. The normalized result can be expressed as:

$$\frac{\sqrt[m]{\prod_{j=1}^{m} v_{ij}}}{\sum_{j=1}^{m} \sqrt[m]{\prod_{j=1}^{m} v_{ij}}} \tag{2}$$

After all the indices on the superior layer are ranked by importance, the weights of these indices can be described as $q_l, q_2, \ldots, q_n$. Then, the inferior indices $W_l, W_2, \ldots, W_m$ corresponding to q_l can be ranked by importance as $w^i_l, w^i_2, \ldots, w^i_m$. If W_j is independent of Q_j, then $w^i_j=0$. Then, we have:

$$\sum_{j=1}^{m} \sum_{i=1}^{n} q_i w_j^i = 1 \tag{3}$$

To ensure the reasonability and accuracy of the evaluation results on college students' SHL, this paper tests the consistency of the judgement matrix V. Let ON and AO be the consistency index of the judgement matrix, and random consistency index AO. Then, ON can be calculated by:

$$ON = (\gamma_{max} - m)/(m-1) \quad (4)$$

The maximum characteristic root γ_{max} of V can be calculated by:

$$\gamma_{max} = \sum_{i=1}^{m} \frac{(V \cdot \omega)_i}{m\omega_i} \quad (5)$$

The ratio of ON to AO is the consistency ratio NA of V:

$$NA = \frac{ON}{AO} \quad (6)$$

If NA<0.10, the selected evaluation indices for college students' SHL are consistent. There is no need to rescale V. Furthermore, it is necessary to calculate the weights of secondary indices to the indices in the goal layer. Let N be the number of classes of primary indices; M be the number of secondary indices in each class; $OA' = (OA_l', OA_2', \ldots, OA_M')$ r be the normalized fitness of goal layer indices; $FA_j = (FA_{lj}, FA_{2j}, \ldots, FA_{Mj})^T$ be the fitness of all secondary indices relative to the class of the j-th primary index. Then, the weight of each secondary index to a goal layer index can be obtained by:

$$OA_i = \sum_{j=1}^{N} OA_j' \times FA_{ij}$$
(7)

Multi-layer fuzzy comprehensive evaluation (FCE) was adopted to evaluate college students' SHL. The specific steps are as follows:

Step 1. Divide the set of primary indices $SHS = (SHS_l, SHS_2, \ldots, SHS_n)$ into several subsets according to the classification of goals. Assume that the subsets need to satisfy three conditions: $\Sigma^l_{i=1} SHS_i = SHS$, $SHS_i \cap SHS_j = \phi$, and $i \neq j$. Then, each subset of secondary indices SHS_i (i=1, 2, …, l) contains the following elements $V_i = \{v_{il}, v_{i2}, \ldots, v_{in}\}$.

Step 2. Comprehensively evaluate the m_i elements in each SHS_i of secondary indices. Let $C = (c_l, c_2, \ldots, c_n)$ be the set of comments; $\delta_i = (\delta_{il}, \delta_{i2}, \ldots, \delta_{in})$ be the weight of each index in SHS_i; E_i ($E_i = a_{ijt}/M_S$) be the comprehensive evaluation matrix, where M_S is the number of experts, and a_{ijt} is the number of times that index Q_{ij} receives the comment c_t. Then, the composite evaluation vector can be defined as:

$$CEV_i = \delta_i \circ E_i = (CEV_{i1}, CEV_{i2}, \ldots, CEV_{in}) \quad (i = 1,2,\ldots,l) \quad (8)$$

Step 3. Comprehensively evaluate each subset of each primary index. Treat subset SHS_i as an evaluation unit and adopt the composite evaluation vector CEV_i of secondary index layer for the single-factor evaluation of SHS_i. Let $\delta = (\delta_l, \delta_2, \ldots, \delta_l)$ be the weight vector of each subset. Then, the corresponding composite evaluation matrix can be described as:

$$E = \begin{bmatrix} CEV_1 \\ CEV_2 \\ \vdots \\ CEV_l \end{bmatrix} = (\delta_{ij})_{l \times n} \quad (9)$$

The composite evaluation vector of college students' SHL can be described as $CEV = \delta \circ E = (CEV_1, CEV_2, \ldots, CEV_l)$. If $\Sigma^n_{i=1} CEV_i$ does not equal 1, normalize the results of comprehensive evaluation. Through expert scoring and the membership derived from fuzzy statistics, the evaluation matrix E can be obtained as:

$$E = \begin{bmatrix} e_{11} & e_{12} & \cdots & e_{1m} \\ e_{21} & e_{22} & \cdots & e_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ e_{m1} & e_{m2} & \cdots & e_{mn} \end{bmatrix} \quad (10)$$

Prediction Method for College Students' SHL

BPNN-based prediction

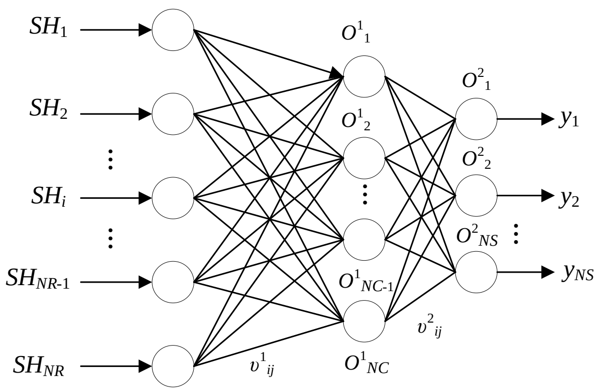


Figure 2. BPNN structure

Figure 2 presents the structure of the BPNN. The proposed prediction model for college students' SHL includes an input layer, a hidden layer, and an output layer. Based on the BPNN, the SHL of college students can be evaluated in the following steps:

Step 1. Determine the number of nodes on the input layer N_R, the hidden layer N_C, and the output layer N_S. Define the top-30 optimal index values in terms of importance as N_R and set N_S to 1. Then, N_C needs to be determined after optimization.

Step 2. Let υ^1_{ij} be the connection weight between the input layer and the hidden layer, and υ^2_{ij} be the connection weight between the hidden layer and the output layer. Then, initialize the two weights.

Step 3. The input layer receives the values of the trained index samples for college students' SHL evaluation. Describe the received values as a vector $[SH_1, SH_2, \ldots, SH_{NR}]$. Based on the vector and υ^1_{ij}, the input to hidden layer nodes can be calculated by:

$$O_j^1 = \sum_{i=1}^{n} \upsilon_{ij}^1 SH_i \quad (11)$$

Take hyperbolic tangent function as the activation function of the hidden layer. Then, the output of hidden layer nodes can be calculated by:

$$O_j^2 = g(O_j^1) = \frac{exp(O_j^1) - exp(-O_j^1)}{exp(O_j^1) + exp(-O_j^1)} \quad (12)$$

Step 4. Correct the network weights by the commonly used gradient descent method. The adjustment of the weight matrix K_1 of the input layer can be calculated by:

$$\frac{\partial K_1}{\partial v_{ij}^1}=\frac{\partial K_1}{\partial O_i^1}\cdot\frac{\partial O_i^1}{\partial v_{ij}^1}=SH_i\cdot\frac{\partial K_1}{\partial O_i^1} \tag{13}$$

The adjustment of the weight matrix K_2 of the hidden layer can be calculated by:

$$\frac{\partial K_2}{\partial O_j^1}=\sum_{i=1}^{l}\frac{\partial K_2}{\partial O_i^2}\cdot\frac{\partial O_i^2}{\partial O_j^1}=g\left(O_j^1\right)\cdot\sum_{i=1}^{l}\frac{\partial K_2}{\partial O_i^2}\cdot v_{ji}^2 \tag{14}$$

The adjustment of the weight matrix K_3 of the output layer can be calculated by:

$$\frac{\partial K_3}{\partial O_i^2}=\frac{\partial\sum_{j=0}^{l}\frac{1}{2}\left(\overline{b_j}-b_j\right)^2}{\partial O_i^1}=\overline{b_j}-b_j\cdot g\left(O_i^2\right) \tag{15}$$

Step 5. Repeat Step 4 to complete the training of the BPNN until the number of iterations reaches the maximum, or the model error falls below the preset error threshold.

The index data for college students' SHL evaluation have different units of measurement. The normalization function of MATLAB was selected to normalize the data. Let SH_{ik} be the data of the i-th index for the k-th college student; min (SH_{ik}) and max (SH_{ik}) be the minimum and maximum of the index, respectively. Then, the normalization formula can be established as:

$$\mathrm{b_{ik}}=\frac{\mathrm{SH_{ik}}-\min(\mathrm{SH_{ik}})}{\max(\mathrm{SH_{ik}})-\min(\mathrm{SH_{ik}})} \tag{16}$$

GA optimization of initial weights

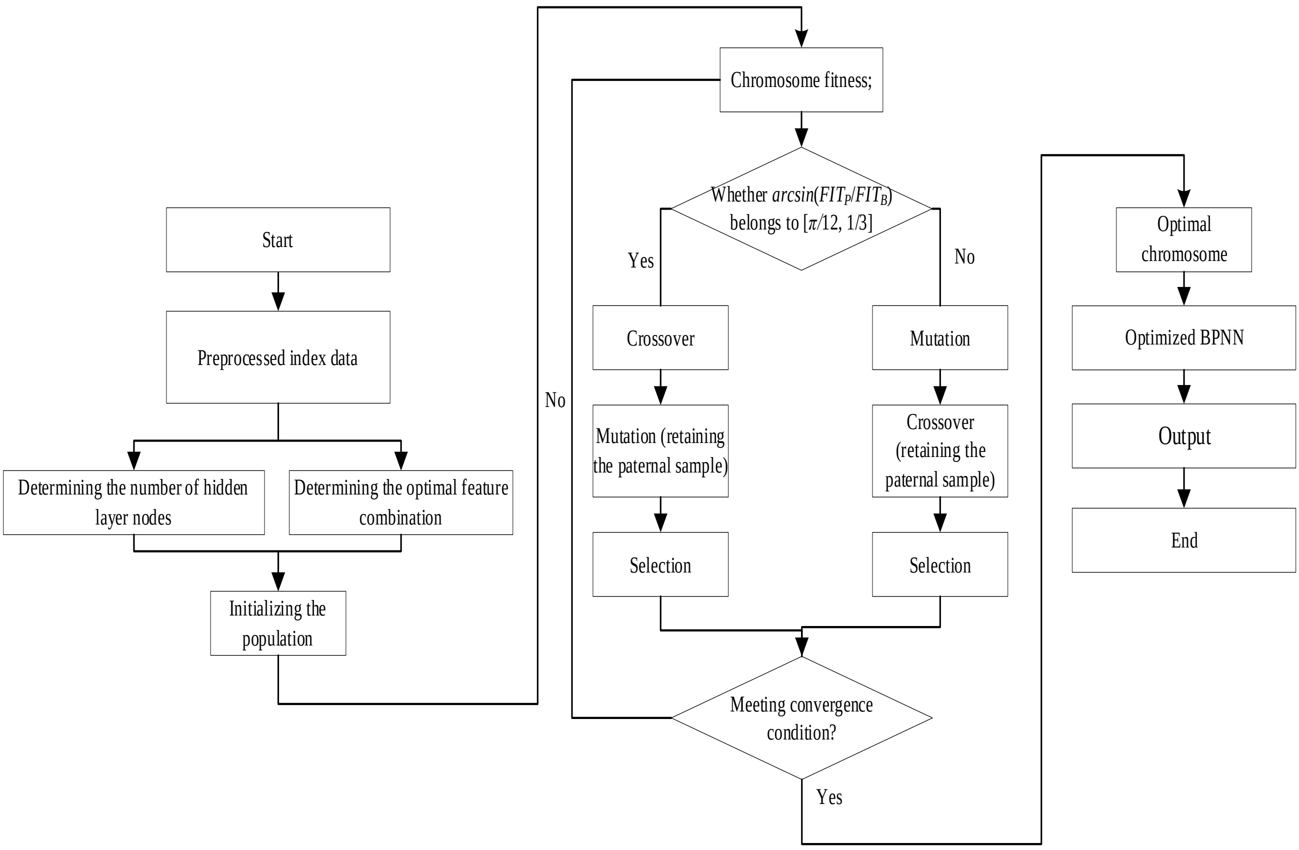


Figure 3. Prediction flow of college students' SHL

The neural network might fall into local optimum, if the initial weights are not adjusted properly. To prevent this problem, the improved GA was selected to optimize the initial weights of the BPNN, in view of the algorithm's superiority in global search. Figure 3 illustrates the prediction flow of college students' SHL with the aid of the optimization algorithm. Let θ and u be the selection probability and serial number of chromosomes, u=1, 2, 3, …, $M_P/2$; ψ be the optimal selection probability; M_P be the population size; φ be the current number of iterations. Then, the selection probability of a chromosome in the population can be calculated by:

$$\begin{cases}\theta_{M_P}^{\phi}=\Psi^{\phi}\left(1-\psi^{\phi}\right)^{M_P-1}\\ \Psi^{\phi}=\frac{\psi^{\phi}}{1-\left(1-\psi^{\phi}\right)^{M_P/2}}\end{cases} \tag{17}$$

To maximize the selection probability for chromosomes with a high fitness, the chromosome difference and ψ value should be relatively large in the initial phase of genetic evolution. As the population shrinks through evolution, it is important to keep small chromosome difference and ψ value. Let ψ_{max} and ψ_{min} be the selection probabilities of the optimal and worst chromosomes, respectively; N_I be the total number of iterations. Then, the ψ value can be calculated by:

$$\psi^{\phi} = \psi_{max} - (\psi_{max} - \psi_{min}) \times \frac{\phi - 1}{N_I - 1} \quad (18)$$

To prevent the local optimum trap of traditional adaptive Gas, this paper improves the crossover and mutation of the GA. Let FIT_P and FIT_B be the mean fitness and maximum fitness of chromosomes, respectively. The improved crossover probability η_A can be expressed as:

$$\eta_A = \begin{cases} u_1 \frac{arcsin(FIT_P/FIT_B)}{\pi/2} & \arcsin(FIT_P/FIT_B) < \pi/6 \\ u_1 \left(1 - \frac{arcsin(FIT_P/FIT_B)}{\pi/2}\right) & \arcsin(FIT_P/FIT_B) \geq \pi/6 \end{cases} \quad (19)$$

The improved mutation probability η_H can be expressed as:

$$\eta_H = \begin{cases} u_2 \frac{arcsin(FIT_P/FIT_B)}{\pi/2} & \arcsin(FIT_P/FIT_B) \geq \pi/6 \\ u_2 \left(1 - \frac{arcsin(FIT_P/FIT_B)}{\pi/2}\right) & \arcsin(FIT_P/FIT_B) < \pi/6 \end{cases} \quad (20)$$

where, arcsin (FIT_P/FIT_B) changes quickly with the mean fitness FIT_P. Therefore, it is reasonable to measure the dispersion of population fitness with arcsin (FIT_P/FIT_B). If $\arcsin(FIT_P/FIT_B) \geq \sin(\pi/6) = \pi/6$, and $FIT_P/FIT_B \geq 1/2$, FIT_P is close to FIT_B. Further, if $\arcsin(FIT_P/FIT_B)$ falls in [π/12, 1/3], the crossover should be implemented prior to mutation; otherwise, the mutation should be implemented prior to crossover.

Experiments and Results Analysis

The experimental data were obtained from SHL samples on the Comprehensive Management Platform of Physical Education for College Students, Jiangsu Province, China. The samples come from 20 colleges in Jiangsu. The sample size needs to be determined scientifically and effectively. By the principle that the sample size should be 5-10 times that of the number of variables, the final sample size was determined as >3,600. Each sample contains 64 attributes, which correspond to the 64 secondary indices. Four thirds of the samples were allocated to the training set, and one third to the test set. The top 30 optimal indices in importance ranking were taken as the input layer nodes in the BPNN. The number of hidden layer nodes was determined as 15 through GA optimization. To optimize the initial weights of the BPNN, the population size and maximum number of iterations of the improved GA were set to 100 and 300, respectively. The crossover and mutation probabilities of the chromosomes were set to 70% and 30%, respectively. The experiments were conducted on simulation software.

Figure 4 compares the mean squared error (MSE) of the BPNN before and after GA optimization. It can be observed that, after GA optimization, the BPNN performed more stably and accurately in the evaluation of college students' SHL.

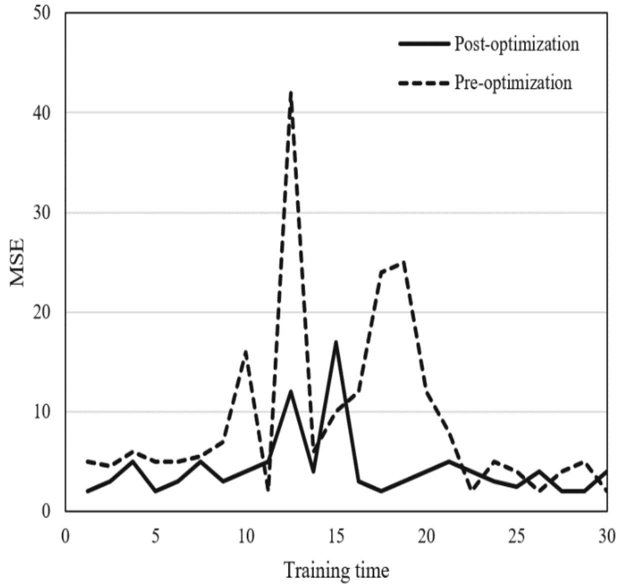


Figure 4. MSE curves

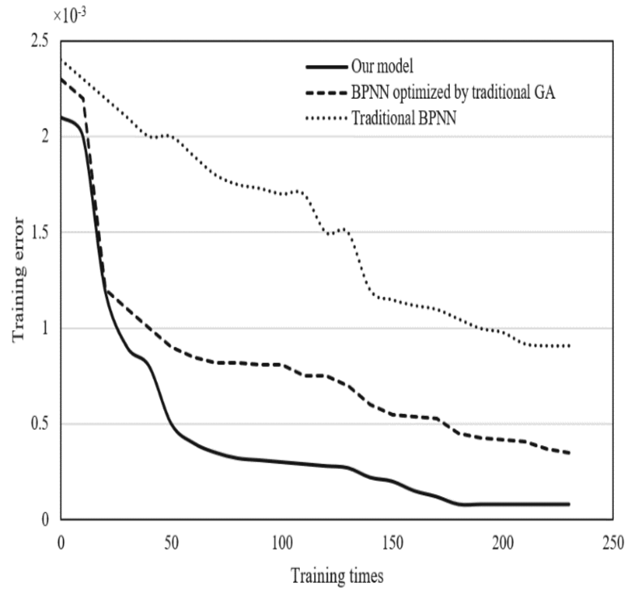


Figure 5. Training error convergences of different models

Figure 5 compares the training error convergences of traditional BPNN, the BPNN optimized by traditional GA, and our model. Figures 6 compares the prediction errors of the three models. It can be seen that the errors of the traditional BPNN and the BPNN optimized by traditional GA tended to be stable since the 130th iteration. The traditional BPNN had a greater error than the BPNN optimized by traditional GA. In contrast, our model started to converge since the 100th iterations, and realized the minimum error among the three models after convergence. The results verify that our model overcomes the defect of the traditional BPNN: proneness to local optimum trap.

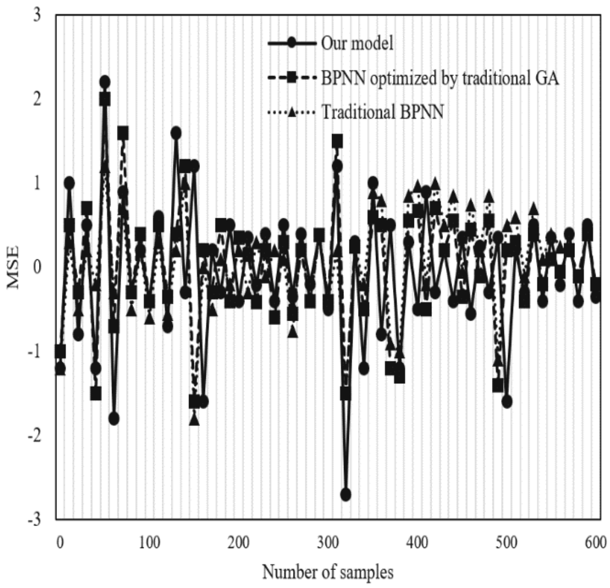


Figure 6. Prediction errors of different models

Tables 1 and 2 compares the difference between prediction accuracy and prediction error of the three models above. It can be seen that the traditional BPNN and the BPNN optimized by traditional GA achieved a prediction accuracy of 57.61% and 75.32%, respectively, while the mean prediction accuracy of our model was as high as 98.15%. The prediction error of our model was 36.8% better than that of the BPNN optimized by traditional GA, and 58.7% better than that of the traditional BPNN. Therefore, our model boasts better prediction accuracy, and lower MSE and root-mean-square error (RMSE) than the other two models.

Table 1

Comparison of prediction accuracy of different models

Model	Our model	BPNN optimized by traditional GA	Traditional BPNN
Accuracy	98.15%	75.32%	57.61%

Table 2

Comparison of error of different models

Model	Our model	BPNN optimized by traditional GA	Traditional BPNN
MSE	0.2751	0.3765	0.4367
RMSE	0.3435	0.4122	0.6350

Figure 7 compares the generalization ability of the three models above. The generalization ability of our model was 89.8%, while that of traditional BPNN and the BPNN optimized by traditional GA was 63.2%, and 82.1%, respectively. Hence, our model has stronger generalization ability than the other two models.

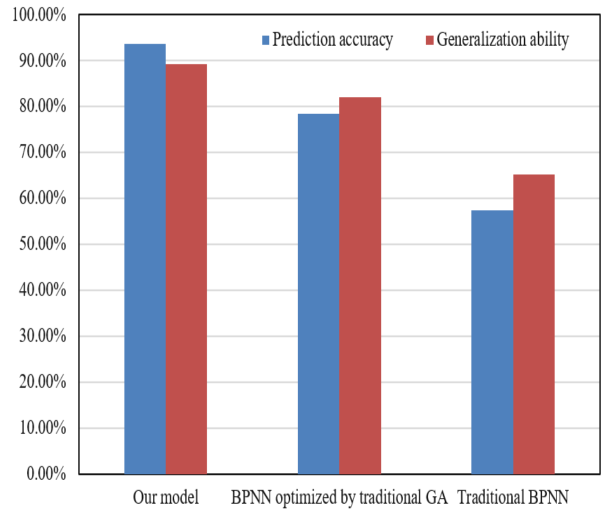
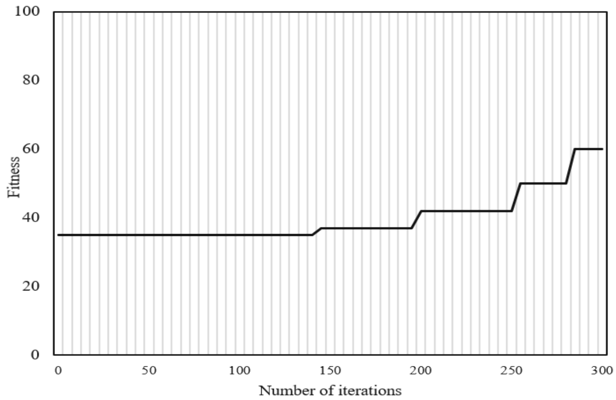
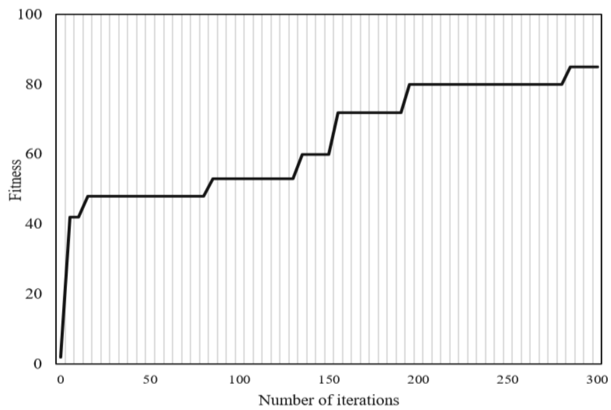


Figure 7. Comparison of generalization ability of different models



(a) BPNN optimized by traditional GA



(b)Our model

Figure 8. Fitness curves of

Figure 8 compares the fitness curves of our model before and after being optimized by the improved GA. After 300 iterations, the improved GA could quickly optimize the initial weights of the BPNN. The traditional GA could not stabilize the maximum fitness of chromosomes before the 250th iteration, while our improved GA tended to converge as early as the 150th iterations. Compared with the BPNN optimized by traditional GA, our model, i.e., the BPNN optimized by improved GA, has a higher optimal fitness of the population for the college students' SHL evaluation experiments, a faster convergence, and better initial weights and thresholds of the BPNN. The trained BPNN in our model can evaluate college students' SHL more accurately than the BPNN optimized by traditional GA.

Conclusions

This paper attempts to evaluate and predict college students' SHL based on ANN. Specifically, the authors designed an EIS for college students' SHL, which includes 4 goals, and 19 primary indices, and established the structure of the evaluation and prediction system. Next, the college students' SHL was comprehensively evaluated through AHP. Finally, a BPNN was established for the prediction of college students' SHL, and the GA was improved to optimize the initial weights of the network. Through experiments, our model was compared with traditional BPNN, and the BPNN optimized by traditional GA in terms of training error convergence, prediction error, prediction accuracy, and generalization ability. The comparison shows that our model achieved the best prediction accuracy, MSE, and RMSE, and generalization ability. Furthermore, the authors obtained the optimal chromosome fitness curves of the BPNN before and after GA optimization. The results confirm that our algorithm can improve the initial weights of the BPNN, and the trained BPNN can evaluate college students' SHL with a high accuracy.

This paper successfully optimizes the BPNN evaluation model for college students' SHL, and then tries to overcome the defects of GA. The original and improved neural networks were compared through simulation to reveal their difference in the evaluation of college students' SHL. The results show that the proposed neural network opens a promising research direction. Apart from the evaluation of college students' SHL, our network is expected to achieve a good application effect in other fields.

There are several outstanding issues in the improvement of BPNN for the evaluation of college students' SHL: What is the influence of the number of hidden layers on training result? How should we optimize crossover and mutation probabilities of GA? Whether the primary indices are comprehensive and objective? How should we reduce the sample size of our network? Are there better algorithms for the evaluation of college students' SHL? These issues will be further investigated in future research.

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