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Comprehensive mental health assessment and graded intervention pathways supported by large-scale optimization algorithms in competitive sports

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Abstract This paper focuses on the assessment method of athletes' mental health and explores the effective path of intervention for athletes with abnormal mental health status. A BP neural network model was established to realize the assessment of athletes' mental health status, and a genetic algorithm (GA) was used to optimize the limitations of BP neural network in training. Athletes were selected as subjects, and the mental health status of athletes was assessed by the symptom self-assessment scale (SCL-90) combined with the GA-BP neural network assessment model in this paper. Further, the athletes whose model assessment results showed the existence of abnormal mental health status were taken as research subjects, and psychological intervention experiments were conducted for them by using positive thinking training, and the experimental results were analyzed by visualization. The study shows that the GA-BP neural network assessment model can reach 86.67% of the assessment accuracy on the test set. After adopting this paper's positive thinking training intervention, the athletes' five-factor positive thinking questionnaire (FFMQ) scores, attention level and sports performance level were improved to different degrees, and the follow-up experiments showed that the continuation of the intervention effect was more significant overall. The research results of this paper can provide an effective reference for timely grasping the mental health status of athletes and taking scientific intervention measures.

Index Terms BP neural network, genetic algorithm, positive thinking training, FFMQ, mental health assessment

I. Introduction

The 2020 Tokyo Olympic Games gymnastics competition is in full swing, but the Rio Olympic Games 4 gold and 1 bronze medalist, the United States gymnastics famous Biles, due to their own mental health reasons have announced their withdrawal from the women's team final, the women's individual all-around final and the women's vault, uneven bars and floor gymnastics individual finals, public opinion suddenly an uproar. People inside and outside the competition have to look again at the increasingly serious mental health problems of athletes [1], [2]. Looking back, there are not a few athletes who have attracted intense attention because of psychological issues that have plagued them, such as Naomi Osaka who withdrew from the 2021 French Open due to depression and anxiety. Women's basketball player Cambage announced her withdrawal from the 2024 Olympic Games due to psychological issues. U.S. swimmer Phelps revealed that he struggled with depression for more than a decade and even had thoughts of suicide. An even more extreme example is Germany's former national goalkeeper Enke, who was overwhelmed by depression and eventually chose to commit suicide by lying on the rail [3]-[6]. These experiences of the world's top athletes only represent the tip of the iceberg, and there are many more athletes who suffer from mental health problems that go unrecognized.

In view of the critical situation and the long-term plan to protect the mental health of athletes, organizations such as the International Olympic Committee (IOC), the International Association of Sport Psychology (IASP), and the European Association of Sport Psychology (EASP) have issued statements in recent years calling for increased attention to the mental health of athletes [7]-[10]. On the one hand, the competitive level of the competitive sports athlete group is higher, the competition they face will be more intense, and the slightest slack may be surpassed by their descendants, so the outside world and the athletes themselves have less tolerance for mistakes or injuries in their careers, as well as over-training of the athletes and other factors, which leads to an increased risk of psychological problems and the emergence of psychological problems, such as anxiety, depression and other psychological problems [11]-[14]. On the other hand, inside and outside the field of play also keep a strong focus on athletes' training, competition, and even personal life, resulting in a lack of sufficient privacy space for athletes, especially when the hype and focus of mass media reports are more likely to form a huge external pressure, which further increases the level of athletes' anxiety, resulting in more serious psychological consequences, thus affecting the competition performance [15]-[18]. In addition, Fiedler et al [19] found that excessive use of social media by athletes affects athletes' performance, with social comparisons mediating cognitive behaviors, sleep quality, and psychological well-being resulting from social media use, thus affecting performance. However, Fazenda et al [20] reported that professional soccer players were influenced by the media as spontaneous behavior to influence their own emotions, opinions, and performance, and did not have a direct effect on the outcome of the game. While Olive et al [21] learned that although the overall level of psychological well-being of disabled and non-disabled athletes in competitive sports is similar, there is a difference between the two at the gender level, and non-disabled athletes have lower self-esteem. Academics have gradually realized the seriousness of the reality, and more and more scholars are exploring from the theoretical and practical levels.

In the long run, mental health services for competitive athletes are promising, but not much work has been done at the practical level, and there are fewer experiences that can be directly learned from. Early psychological assessment can help early detection and resolution of mental health problems, and if it is normalized, it can be followed up in the long term [22]-[24]. The concurrent assessment process is also a good opportunity to disseminate mental health knowledge to athletes, coaches, and sports team managers, which can help reduce discrimination and stigmatization of mental problems in sports teams [25]-[27]. In order to carry out psychological screening smoothly and efficiently, the first task is to find or develop a mental health assessment method that is in line with the sports context, so that we can accumulate experience based on the practice of mental health screening and continue to explore new modes of targeting the implementation of relevant psychological interventions, and finally, form a perfect mental health service system for athletes.

In the assessment of athletes' psychological well-being, Shannon et al [28] described the effectiveness of the Athletes' Psychological Stress Questionnaire designed by the International Olympic Committee (IOC), which is also one of the core tools for assessing athletes' psychological well-being, in the psychological diagnosis, assessment, and guidance of psychological disturbances in athletes. Sore et al [29] used the Sport Mental Health Assessment Tool as a source of data on athletes' psychological well-being and reported differences between female and male athletes in psychological disorders of anxiety, depression, alcohol use, ADHD, and PTSD with higher probability of occurrence in females under a variety of statistical analysis tools. Donohue et al [30] narrated and validated the validity and utility of the screening tool for mental health disorders in athletes in assessing the measurement of the level of psychological well-being of athletes, which is also valid in the assessment of groups of athletes. Matsuura and Ochi [31] suggested that the heart rate variability assessment method during arousal, the Athletes' Psychological Depression and Fatigue Index assessment are recognized methods of assessing psychological well-being in athletes, and that the results of repeated assessments of both may have a role in preventing the deterioration of the level of psychological well-being in athletes. Si et al [32] introduced the negative psychopathology and positive well-being dimensions of the psychological assessment method for athletes, and proposed three dimensions of screening, intervention, and education for the management of athletes' psychological well-being, and the combination of the two could contribute to the large-scale screening of athletes' psychological problems.

In terms of psychological well-being interventions for athletes, Grilli Cadieux et al [33] synthesized the results of several studies and analyzed the effective role of yoga interventions in athletes' psychological well-being and athletic performance, but the role needs to be corroborated by more studies. Shannon et al [34] concluded that a positive thinking program that includes family guidance and teaching exploratory sessions in conjunction with an appropriate mental health competency enhancement program is effective in relieving stress and enhancing the physical and mental health of athletes. Dehkordi and Chtourou [35] considered the individualized context of athletes' needs, training programs, and cultural influences, and the psychological interventions of cognitive-behavioral therapy, positive thinking, relaxation techniques, and motivational interviewing could substantially reduce athletes' psychological anxiety. Vella-Fondacaro and Romano-Smith [36] intervened in the psychological well-being of five-a-side soccer players through ten phases of mental skills training and positive thinking interventions, which were effective and found that athletic performance was better in game-experienced players.

It is not difficult to find that the above studies lacked the assessment of athletes' dynamic psychology, the indicators of measurement also showed solidification, and the cycle of assessment and intervention was mostly based on the unit of months, which did not combine with the physiological data of athletes to assess and intervene, and other problems. These problems lead to the solidification and one-sidedness of the assessment and intervention tools, detachment from the event schedule, lack of personalized programs, and assessment lag and intervention lag. With the development of artificial intelligence, large-scale optimization algorithms contribute to the cause of competitive sports by capturing changes in physiological data and behavioral performance of athletes during competition and training, integrating multi-source data, comprehensively evaluating the psychological state, and exploring the optimization path of psychological interventions as a means of realizing the assessment of athletes' mental health and the design of intervention paths [37].

In this paper, the BP neural network is used to construct the assessment model of athletes' mental health status, and the genetic algorithm is used to solve the slow convergence speed of the algorithm that exists in the process of training the BP neural network with the gradient descent algorithm. The basic information and mental health data of student athletes of the class of 2023 from all colleges and universities in a province were collected by means of questionnaires and scale surveys, and the data were processed such as feature extraction and normalization. The trained GA-BP neural network assessment model was used to analyze and assess the mental health status of the athletes, combined with the results of filling out the athletes' symptom self-assessment scale (SCL-90). A single-subject experimental method was used to carry out the psychological intervention of positive thinking training for six athletes whose model assessment results were abnormal mental health status. The experimental data of the athletes in the pre-test, intervention and tracking stages were collected through the Five-Factor Positive Thinking Questionnaire and other measurement tools, and the results were visualized to show the effectiveness of the Positive Thinking Training method on the athletes' psychological interventions, so as to provide useful references for the rational assessment of the athletes' mental health status and the scientific interventions.

II. GA-BP Neural Network Evaluation Model Construction

II. A. BP Neural Network

BP neural network is a multilevel feed-forward neural network trained according to the error back propagation algorithm with good mapping ability, which is one of the most widely used learning algorithms [38]. In terms of hierarchy, the neural network is structured with 3 layers, which are input, output, and implicit. In order to realize the transfer function of the network, the neurons between different layers are connected two by two, i.e., the input and implied neurons are connected by weights, the implied and output neurons are connected by weights, and the neurons in the same layer have no connection.

Let the input layer of the BP neural network has n nodes, the hidden layer has q nodes, the output layer has m nodes, the connection weights when passing from the input layer to the hidden layer are v_{ik}, the connection weights when passing from the hidden layer to the output layer are w_{kj}, and the mathematical model of the BP neural network is:

(a) Forward propagation calculation. (b) Hidden layer output:

$$O_k = f_1\left(\sum_{i=1}^{n} v_{ik} x_i - \theta_k^{(1)}\right) \tag{1}$$

where, x_i is the input data. $\theta_k^{(1)}$ is the threshold at the node of the implied layer. $f_1(\cdot)$ is the transfer function of the implicit layer.

Output layer output:

$$z_j = f_2\left(\sum_{k=1}^{q} w_{kj} O_k - \theta_j^{(2)}\right) \tag{2}$$

where, $\theta_j^{(2)}$ is the threshold at the output layer node. $f_2(\cdot)$ is the transfer function of the output layer.

(b) Backpropagation calculation. In the BP neural network, when the calculation error of the network output result and the expected value is too large, the feedback adjustment process is carried out, and the weights and thresholds in the model are constantly adjusted by the gradient descent algorithm, and in the cycle of repeated adjustments, the following four parameters can be obtained:

$$v_{ik}(t+1) = v_{ik}(t) + \Delta v_{ik} = v_{ik}(t) - \eta^{(1)} \frac{\partial E}{\partial v_{ik}} = v_{ik}(t) + \eta^{(1)} \delta_k^{(1)} x_i \tag{3}$$

$$w_{kj}(t+1) = w_{kj}(t) + \Delta w_{kj} = w_{kj} - \eta^{(2)} \frac{\partial E}{\partial w_{kj}} = w_{kj} + \eta^{(2)} \delta_j^{(2)} O_k \tag{4}$$

$$\theta_k^{(1)}(t+1) = \theta_k^{(1)}(t) + \Delta\theta_k^{(1)} = \theta_k^{(1)}(t) + \eta^{(1)} \frac{\partial E}{\partial \theta_k^{(1)}} = \theta_k^{(1)}(t) + \eta^{(1)} \delta_k^{(1)} \tag{5}$$

$$\theta_j^{(2)}(t+1) = \theta_j^{(2)}(t) + \Delta\theta_j^{(2)} = \theta_j^{(2)} + \eta^{(2)} \frac{\partial E}{\partial \theta_j^{(2)}} = \theta_j^{(2)} + \eta^{(2)} \delta_j^{(2)} \tag{6}$$

The BP neural network model based on the gradient descent algorithm belongs to a single algorithm, and the limitations of the algorithm are found in the cyclic adjustment: (1) The cyclic calculation leads to the slow convergence of the algorithm. (2) The direction of this back-propagation calculation is not adjusted along different directions, which ultimately results in a locally optimal calculation. In order to make up for this defect of BP neural network, this paper chooses genetic algorithm to adjust the network and construct GA-BP neural network evaluation model.

II. B.Genetic algorithms

Genetic algorithms (GA) apply the survival properties of heredity and evolution in biology to the field of system optimization computation [39], which provides a general framework for solving the optimization of complex systems in the field of machine learning research. The main idea of genetic algorithm optimization network is to optimize the initial value of BP neural network. The specific steps are as follows:

(1) Coding. Coding refers to the transformation of sample data into a language that can be recognized by the genetic algorithm. The three commonly used types of encoding methods are mainly binary encoding methods, symbolic encoding methods and floating point encoding methods.

(2) Fitness function. The degree of adaptation is used to measure the degree of excellence of an individual who is more likely to obtain an optimal solution during the computation process, and this function that can measure the degree of adaptation is called the fitness function. At the same time, in order to make a correct calculation of the fitness, the conversion method between the objective function value $f(X)$ and the fitness function value $F(X)$ is introduced, and the conversion rules of $f(X)$ and $F(X)$ are usually determined well according to different types of problems.

(3) Selection. The purpose of selection is to eliminate the individuals that are unfavorable to the optimal solution finding and retain the individuals that are favorable to the algorithm. Usually the roulette method is used for selection, i.e., the selection operation is performed by calculating the probability of an individual being selected. The formula is as follows:

$$P_k = \frac{F_k(x)}{\sum_{i=1}^{K} F_i(x)} \tag{7}$$

where, K is the number of individuals. $F_k(x)$ is the fitness value of the k th individual.

(4) Crossover. Simply put, crossover is to randomly select two individuals as crossover objects from the individuals screened by selection, select a certain part of these two individuals to be exchanged with each other in accordance with certain rules, and the individual crossover parts are reorganized to produce a new individual. Crossover is a key step in the genetic algorithm to generate new individuals.

(5) Mutation. Mutation refers to the operation of substituting a segment of an individual with an allele, which generates a new individual.

II. C.Construction of the GA-BP assessment model

GA-BP neural network essentially uses genetic algorithm to find the optimal parameter values, optimizes the randomness of BP neural network in the initialization of weights and thresholds, improves the operational efficiency of the combination algorithm and the accuracy of the final evaluation results, and reduces the risk of BP neural network falling into the local optimum during the operation. The specific steps are shown in Figure 1.

III. Mental health assessment of athletes

In this section, the GA-BP neural network assessment model constructed in the previous section is used to assess the mental health status of athletes. Firstly, the athlete data are collected and processed, and then the collected data are used to train the GA-BP neural network model. Finally, the trained model is applied to the athletes' mental health assessment scenario to verify the effectiveness of the model in this paper.

III. A. Data collection and processing

III. A. 1) Subject of the study

In this study, the data were collected by organizing athletes to fill out questionnaires by the method of class whole group sampling with all the colleges and universities in a certain province with the class of 2023 college athletes as the subjects. In this study, a total of 3,748 copies were recovered, excluding 13 copies of invalid data, and 3,735 copies of valid data were actually recovered, with an effective recovery rate of 99.65%.

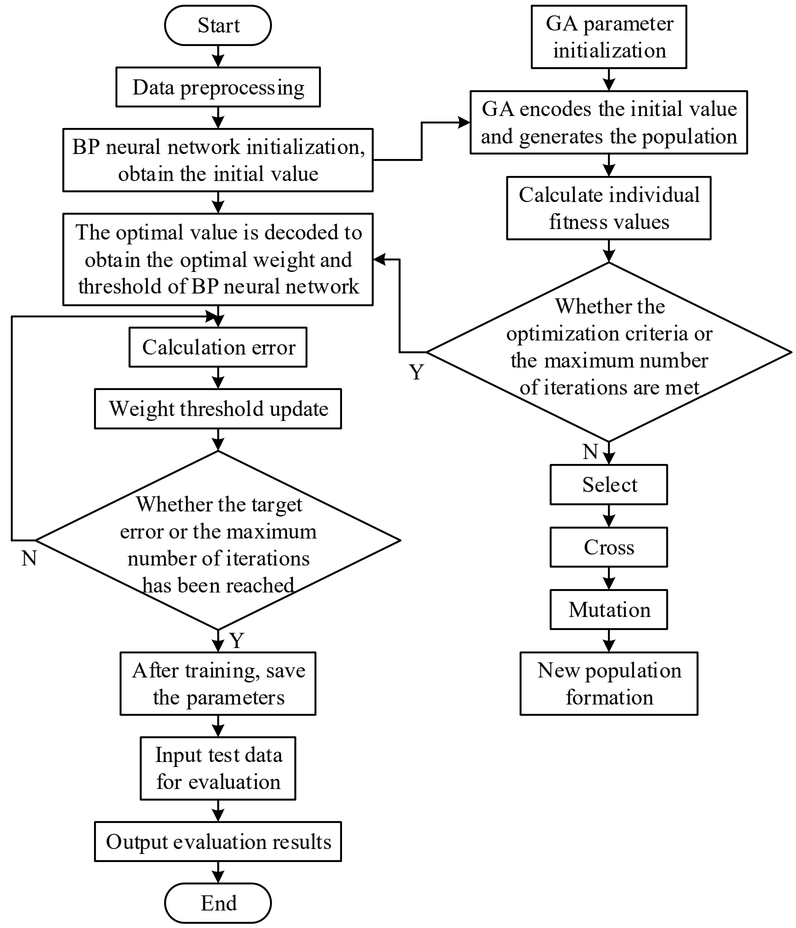


Figure 1: GA-BP neural network algorithm flow

III. A. 2) Survey instruments

(1) Basic situation questionnaire

In this study, a self-developed basic situation questionnaire was used to collect the basic background information of college athletes in the class of 2023, including school number, gender, age and so on. The basic background information was collected as long as it was convenient for data analysis after the psychological census, as well as timely intervention for athletes with abnormal mental health status.

(2) Symptom self-assessment scale (SCL-90)

The Symptom Self-assessment Scale (SCL-90) used in this study consists of 90 items, which are scored based on the actual feelings in the past week, and comprehensively assesses the individual's recent mental state from daily life, emotional changes to thinking consciousness, etc. Each item of the SCL-90 is scored on a 5-point scale (1 = “none” ~ 5 = “severe”), and the results can be divided into 10 factors, which can clearly show whether an individual has psychological symptoms and the severity of psychological symptoms. In this study, the Cronbach's alpha for the SCL-90 was 0.971.

III. A. 3) Data pre-processing

(1) Data feature extraction

This study is mainly based on the results of SCL-90 measurements for feature learning and assessment, thus firstly, the irrelevant data in the basic situation questionnaire should be cleared, and the data of 10 factors should be put forward, including F1: somatization, F2: obsessive-compulsive, F3: interpersonal, F4: depression, F5: anxiety, F6: hostility, F7: horror, F8: paranoia, F9: psychoticism, and F10: others. Then, mean scores were made for the total scores of the scale and the total scores of the factor items to reflect the level position of the individual's mental health level. Finally, this paper graded the mean scores as normal, mild, moderate, severe, and serious, which were labeled as A, B, C, D, and E, and their corresponding limit ranges were (1, 1.5], (1.5, 2.5], (2.5, 3.5], (3.5, 4.5], and (4.5, 5].

(2) Data normalization

Because the original data collected for the study have large distributional differences and more dimensions, but in order to reduce the impact of distributional differences and dimensions on the experimental results, this paper adopts the mean normalization method to process the experimental data, and scales the data to the range of [-1, 1] interval.

III. B. Model Training

III. B. 1) Parameter setting

In terms of parameters, after many experiments, the learning rate is set to 0.001, the error is set to 10-5, the number of training times is 200, the input layer neurons are 10, the output layer neurons are 1, and the trial-and-error method obtains the smallest error value of the model when the hidden layer neurons are 8. The population size in the genetic algorithm is set to 20, the maximum number of iterations is set to 50, the crossover probability is set to 0.7, and the variance probability is set to 0.3. In terms of experimental error selection, this paper adopts the relative indexes, such as R2 (decidable coefficient) and Mean Absolute Percentage Error (MAPE), to assess whether the training results of the GA-BP neural network are accurate.

III. B. 2) Analysis of training results

In this paper, Matlab software is used to simulate and train the sample data. The processed data are divided into training set, validation set and test set according to the ratio of 6:2:2, the data are input to the model for training to derive the training results, and the error is calculated by comparing the output results with the real values.The change curve of the GA-BP neural network adaptation is shown in Fig. 2. It can be seen that the change is faster in the process of 1~5 iterations, and the optimal solution is reached in the 5th time, which indicates that the model can quickly jump out of the local optimal solution, and has a good global search ability, and it can be found through the adaptation change curve that the GA-BP neural network model reaches the optimal adaptation in the 5th generation.

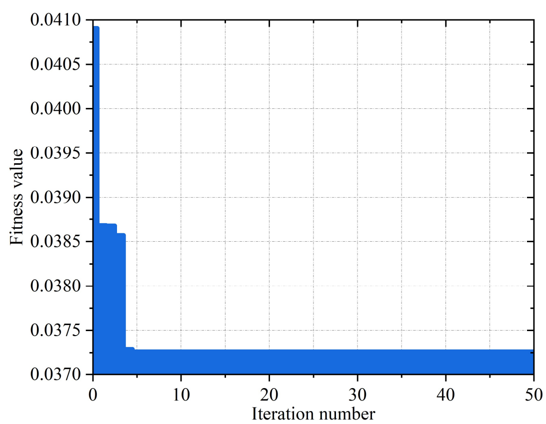


Figure 2: Optimum fitness curve

The training results of the GA-BP neural network model are shown in Figures 3 and 4, and Figures 3(a)-(d) represent the training results of the model on the training set, validation set, test set, and the whole dataset, respectively. Generally the decidability coefficient above 85% can be considered as a better training effect, and from the neural network regression graph, it can be seen that the decidability coefficients of the training set, validation set, and test set are 97.03%, 93.28%, and 98.67%, respectively, and the decidability coefficient of the overall data is 96.02%, which meets the precision requirements, indicating that the training effect of the GA-BP neural network model is better, and the degree of model training fit is stronger. Figure 4 shows the comparison of the overall trend of the evaluation values of the training set of the GA-BP neural network model with the real values, from which it can be seen that the overall trend of the predicted values of the training set of the model is consistent with the real values, and the error is very small in most of the prediction samples, which indicates that the two are well fitted and belong to the high-precision evaluation.

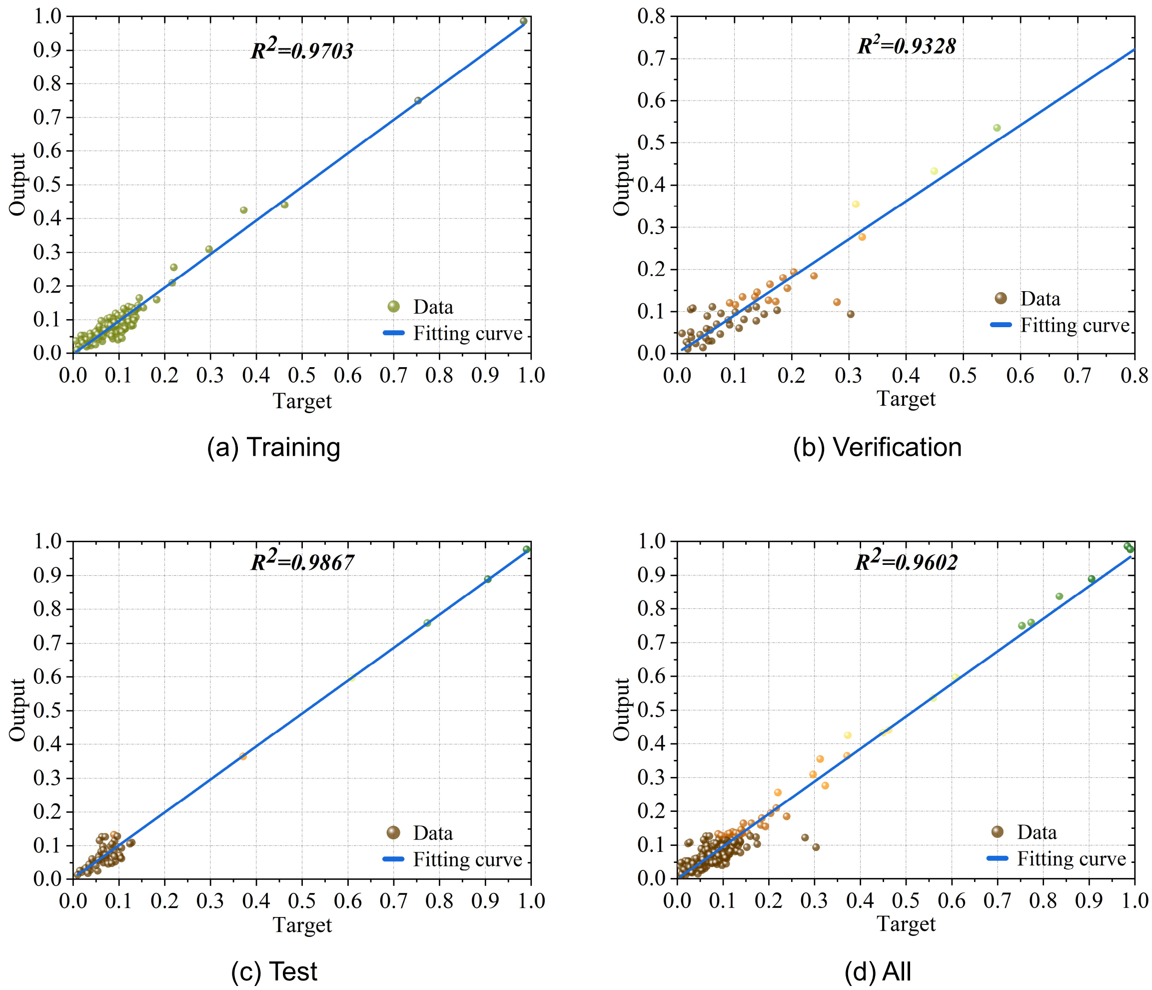


Figure 3: The GA-BP neural network model returns results

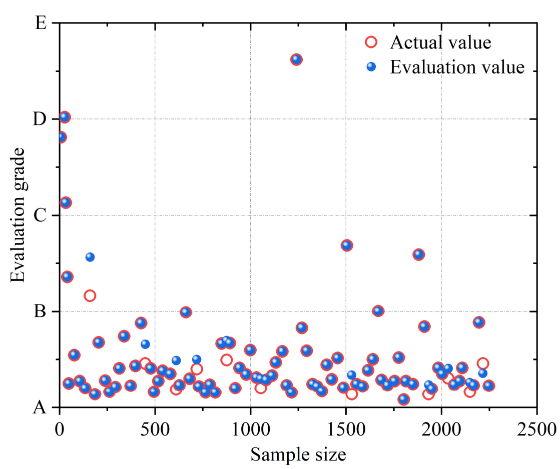


Figure 4: Comparison of the results in training set

III. C. Mental Health Assessment Results and Analysis

III. C. 1) Results of the experimental dataset

Of the 3735 data collected, the number of detections of normal, mild, moderate, severe and serious levels of mental health were 2069, 1368, 243, 38 and 17 respectively. A total of 44.61% of the athletes who might have a psychological crisis indicated that the overall mental health of athletes was not too optimistic. Figure 5 shows the distribution of the number of positive SCL-90 factors. From the results of the SCL-90 survey, it can be seen that the athletes' mental health problems are mainly concentrated in the dimensions of compulsion, interpersonal relationship and depression.

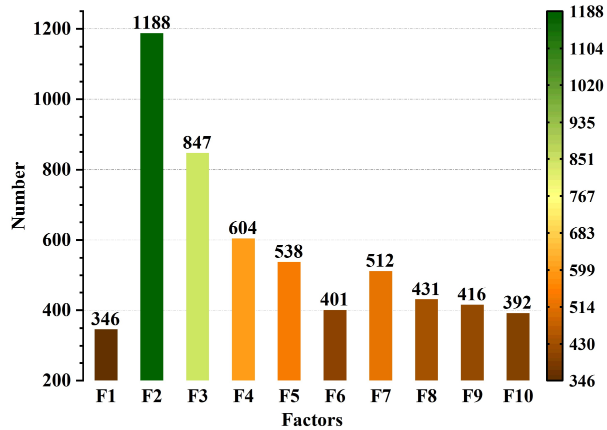
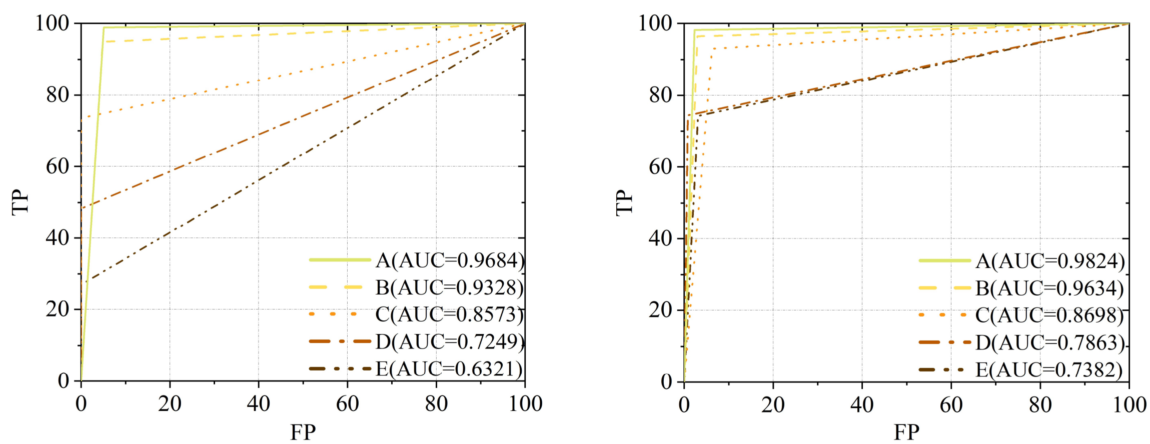


Figure 5: SCL-90 factor positive population distribution

III. C. 2) Experimental modeling results

In order to be able to see the classification effect of the grades of mental health level in the training set, this study analyzes the classification effect of the five rating criteria in the training set and the test set by using ROC curves and AUC indexes respectively, and the results are shown in Fig. 6, (a) and (b) are the ROC curves of the model in the test set of the training set respectively, and TP and FP in the figure denote the true rate and the false-positive rate respectively. The highest AUC value of 0.9684 for rating A (normal) among the five grades of mental health level in the training set indicates that the model is the most effective in identifying the normal level of mental health in the training set. And the lowest AUC value of 0.6321 for rating E (severe) indicates that the model is the least effective in recognizing the severe level of mental health in the training set. In the test set, the same five levels of mental health level had the highest AUC of 0.9824 for rating A (Normal) and the lowest AUC of 0.7382 for rating E (Severe.) In comparison the model had a higher AUC in the test set, indicating that the model performed better in the test set as a whole.



(a) Training set (b) Test set

Figure 6: The ROC curve of GA+BP model in training and test set

In order to observe the evaluation effect of the model in this study more objectively, the study compares and examines the true values of the data in the test set with the predicted predictive values predicted by the model. Because of the large amount of test data in this study, it is not convenient to show all the comparisons, so 15 sets of data were selected from the first and last of the test set, and a total of 30 data comparisons were plotted in a table as shown in Table 1. From the table, it can be seen that among the 30 data in the test set, only 4 (bolded) predicted values do not match the actual values, indicating that the model's mental health level assessment is effective.

Table 1: Comparison between true and prediction value in the test set

ID	True	Prediction	ID	True	Prediction	ID	True	Prediction
1	A	A	**11**	**D**	**C**	**21**	**A**	**B**
2	B	B	12	C	C	22	A	A
3	A	A	13	A	A	23	D	D
4	A	A	14	B	B	24	B	B
5	A	A	15	A	A	25	A	A
6	**A**	**B**	16	E	E	26	A	A
7	C	C	**17**	**A**	**B**	27	C	C
8	D	D	18	C	C	28	A	A
9	A	A	19	B	B	29	C	C
10	B	B	20	D	D	30	B	B

IV. Mental health interventions for athletes

Based on the predictive assessment results of the GA-BP neural network assessment model in this paper, some athletes with mental health problems in the assessment will be selected in this section and psychological intervention will be provided to them by using positive thinking training, so as to explore the effective psychological intervention path for athletes with mental health problems.

IV. A. Subjects of study

Through consultation with coaches and teammates, the subjects of the mental health intervention experiment in this study were determined to be the six athletes with abnormal mental health status in the assessment results of the GA-BP neural network model in the previous article, and their basic information is shown in Table 2. These six research subjects were selected as the experimental subjects of this paper during the same period of time, and received the mental health intervention of positive thinking training according to the same way and duration.

Table 2: Basic information of the subjects

Sample	Gender	Age	Height	Weight	Training time
1	Male	18	176cm	63kg	5
2	Male	19	178cm	68kg	7
3	Female	21	167cm	57kg	10
4	Male	20	178cm	67kg	9
5	Female	18	165cm	54kg	5
6	Female	19	168cm	61kg	7

IV. B. Experimental design

The experimental design methodology used in this study was a single-subject experiment through a pre-test, intervention, and follow-up ABA experimental design. This experimental design is used to evaluate the changes in the athletes' level of positive thinking, level of acceptance, and level of each data by comparing them before and after applying the positive thinking training intervention.This experimental design must contain three aspects: determining the measurement tool and repeated measurements on the sample. Second, the independent variables must have systematic rules introduced and withdrawn. Thirdly, the data of each stage is built through professional data analysis to analyze the effect.

IV. B. 1) Single-subject experimental strategy

The research strategy adopted in this study is an ABA design based on multiple baseline levels, representing the three phases of the experiment, i.e., pre-test phase, intervention phase, and follow-up phase. The logic and order of these three phases cannot be reversed and must be executed in strict accordance with this sequence.

(1) Pre-test phase

Before using positive thinking training intervention, it is necessary to go through a long period of pre-measurement, and repeat the measurement for a specified period of time, so as to obtain a basically stable baseline, which can provide a basic reference for the comparison of data in the intervention phase.

(2) Intervention phase

In the intervention phase, the main measurement methods are basically the same as those in the front phase, except that some training contents and measurement methods are added compared with those in the front side phase, and the measurement tools are also basically the same. Then by comparing the data with each other and the data of the pre-test stage, so as to find out the psychological changes of the sample athletes, as well as to evaluate the corresponding utility of the test effect and the effect of positive thinking training.

(3) Tracking stage

The main purpose of the tracking stage is to test the effect of six synchronized swimmers six times after the completion of the positive thinking intervention training for one month. The tests were conducted in much the same way as the front side phase. The purpose of the follow-up tests was to obtain graphical lines of tracking data to test the continuation effect of the intervention.

IV. B. 2) Experimental measurement tools

(1) Five-Factor Mindfulness Questionnaire

The Five-Factor Mindfulness Questionnaire (FFMQ) is a measurement tool for self-assessment of mindfulness training in an individual sample [40], which consists of 39 questions, using a five-point Richter scale, (scoring 1-5 in order from conformity to non-conformity), with some questions positively scored and some negatively scored, with the higher the score the more pronounced is the effect of the mindfulness training, and vice versa, the lower the score.

The five elements of the Five-Factor Positive Thinking Questionnaire are consistent and logical. The Five-Factor Positive Thinking Questionnaire has been used in other fields, and there is a certain correlation with various aspects such as experience avoidance and emotional intelligence.

(2) WT-Attention Test Software

“WT-Attention Test Software” is a computer application that focuses on measuring the quality of attention. After starting the test program, the test subject will see 99 irregular shapes on the computer, each of which is labeled with a serial number. Starting from 1, the participant will find and click on the irregular shapes corresponding to the serial numbers until they are exactly in the right position. In the test layer, once there is an error, the system will be prompted, and prompted to continue the subsequent test. Through the test of this software, the validity of the exercise level of the exercise performance and other samples can be effectively tested.

(3) Athlete Training Quality Record Sheet

The main purpose of the athlete training quality record sheet is to score the athlete's status of each training, and evaluate and analyze it at a certain stage, and supervised by the coach. This ensures the real validity of the record evaluation. Moreover, in order to train the data more accurately, more able to reflect the individual training status, so it will generally be combined with the training land line to carry out in-depth research, through different levels of records and verification, to ensure the accuracy and fairness of the data. The scoring standard of the table has three main parts, the difficulty standard of the training session, the quality and quantity of the movement, and the collective cooperation standard, and in the table, each item is rated with 10 points, and the scoring is carried out through these three dimensions. Athletes' training quality rating scale can reflect from the side of the athletes in the state of positive thinking training intervention, whether the level of sports performance is improved.

IV. B. 3) Experimental steps

The steps of the experiment in this study are still in accordance with the single-subject experiment involved, before the experiment, the first step is to give the sample athletes the test methods that need to be used in this test, firstly, the demonstration and training on the use and testing of WT-Attention Test Software, and secondly, the use of the “Athletes' Quality of Training Record Sheet” to inform the coaches, to make sure that the methods are correct, and the data are accurate.

The first step was the pre-test phase. The main purpose was to collect baseline data from the subjects and then calculate a stable baseline for each subject. The time period was from August 1, 2023 to August 20, 2023, and the tests were conducted on August 1, August 5, August 9, August 13, August 15, August 17, and August 20, respectively. Through these seven tests and data collection, a stable baseline was successfully obtained for each of the six subject athletes.

Step 2, Intervention Phase. The main focus was to train the 6 athletes in positive psychology and to collect and organize the training data within 1 week of attending the training after the completion of the intervention course, to form the relevant intervention data, and to form the relevant charts for analyzing the intervention data,. The course time is from October 21, 2023 to December 7, 2023.

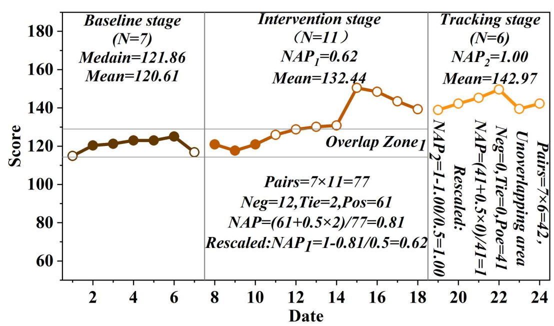
Step 3, Follow-up test. Conducted one month after the intervention training, and did six times in 18 days to collect and organize the data, mainly to test the analysis of its subsequent functioning after the training of positive thinking intervention, and to obtain the graph line of the post-intervention data.

The fourth step, social validity test. The main purpose is to let the athletes and coaches recognize the intervention effect at the same time, so it is usually carried out after the end of the positive thinking intervention training, through the form of interviews, so as to evaluate and analyze the social validity of this experiment.

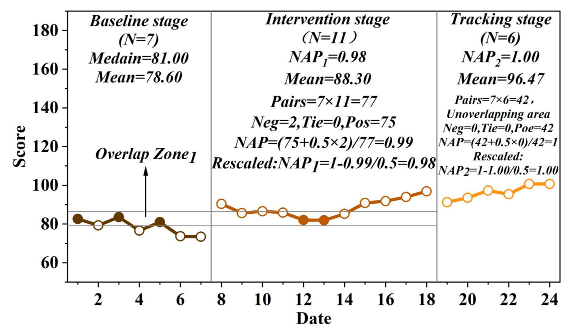
IV. C. Analysis of intervention results

IV. C. 1) Analysis of changes in FFMQ scores

Figure 7(a)-(f) shows the changes in the FFMQ scores of the six subject athletes, and the solid circles in the figure indicate the overlapping areas located in the baseline and intervention phases, the same below. From the figure, it can be seen that the intervention mean values of FFMQ scores of the six subjects are higher than the baseline mean values, indicating that the intervention can increase the “overall level of positive thinking” of the subject athletes. Subject 1 had the smallest standardized NAP1 value of 0.62, indicating a moderate effect of the intervention. Subject 3 had the highest standardized NAP1 value of 1.00, indicating a significant effect of the intervention. The other subjects had standardized NAP1 values of 0.98, 0.98, 0.98, and 0.90, in that order, indicating a significant effect of the intervention.The follow-up means for the six subjects were higher than the baseline means, and the standardized NAP2 values were all 1.00, suggesting a significant effect of the intervention in terms of continuity. Overall, the “overall level of positive thinking” of each athlete improved significantly after the intervention, and the continuation of the intervention was significant.



(a) Test 1



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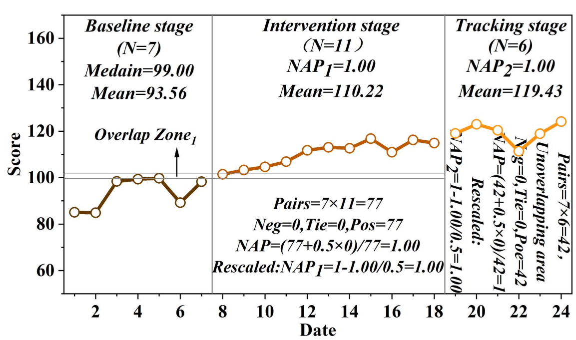

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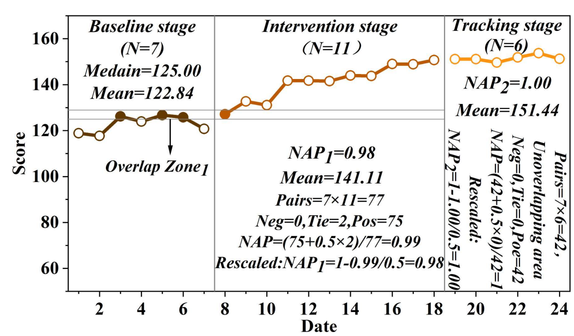
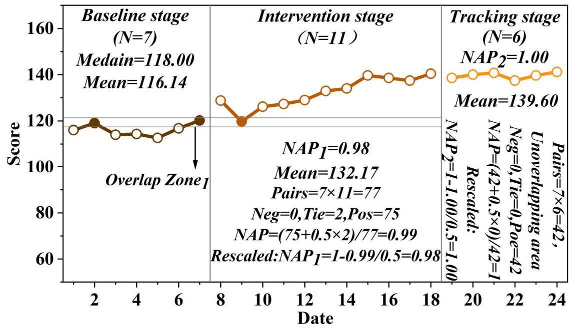
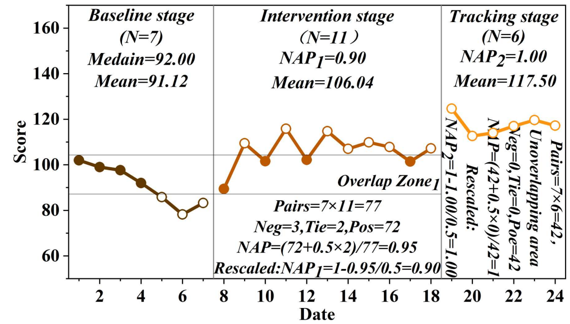


(d) Test 4



(e) Test 5

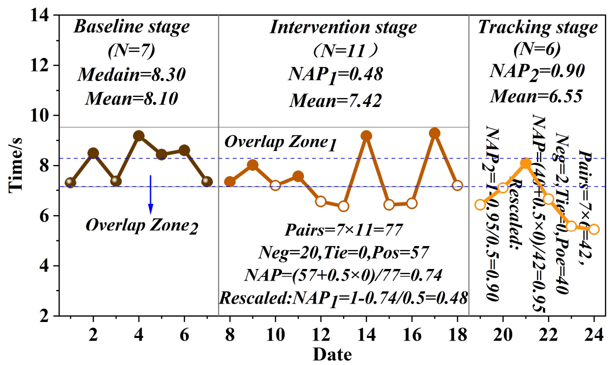


(f) Test 6

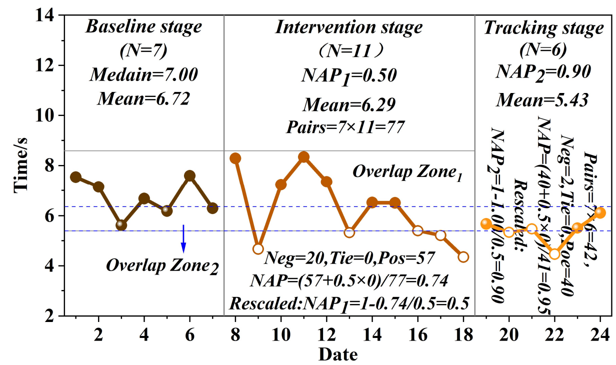
Figure 7: Changes in FFMQ scores of the tested athletes

IV. C. 2) Analysis of changes in attention levels

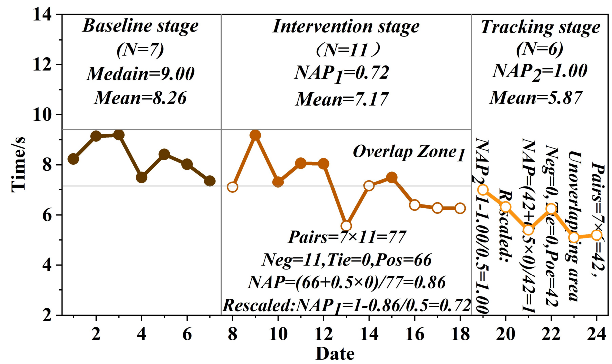
Figure 8(a)-(f) shows the changes in the attention level scores of the six athletes, in which the round balls indicate the overlapping area between the baseline stage and the tracking stage, the same as below. From the figure, it can be seen that the intervention mean values of the attention time scores of the six athletes were lower than the baseline mean values, indicating that the "attention level" of the athletes was improved after the intervention. Among all subjects, subjects 1 and 5 had the smallest standardized NAP1 value of 0.48, indicating that the effect of the intervention was weak. Subject 3 had the highest standardized NAP1 value of 0.72, indicating a moderate effect of the intervention. The other subjects had standardized NAP1 values of 0.50, 0.66, and 0.62, respectively, indicating a moderate effect of the intervention.The follow-up means of the six subjects decreased further from the intervention mean, with subject 5 having the lowest standardized NAP2 value of 0.38, indicating a weak effect of the intervention's continuation effect, and subject 3 having the highest standardized NAP2 value of 1.00, indicating a continuation effect of the intervention significant, and the other subjects had standardized NAP2 values of 0.90, 0.90, 0.76, and 0.72 in that order, indicating a significant or moderate continuation of the effect of the intervention. Overall, the "attention level" of the athletes improved after the intervention, and the continuation of the intervention was significant.



(a) Test 1



(b) Test 2



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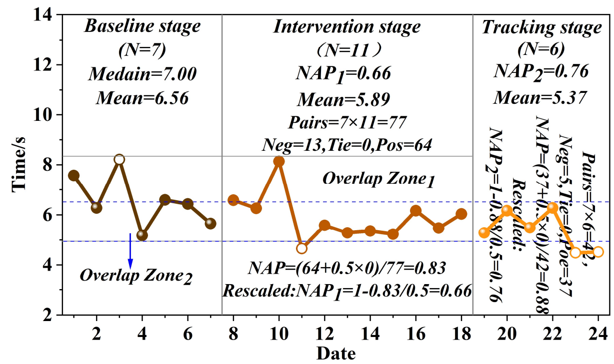

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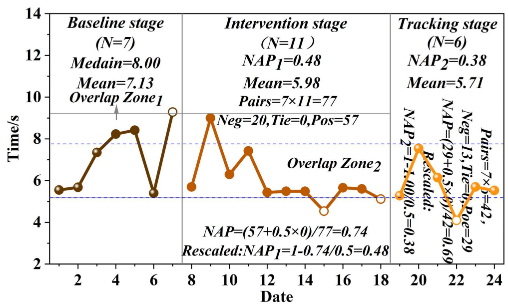
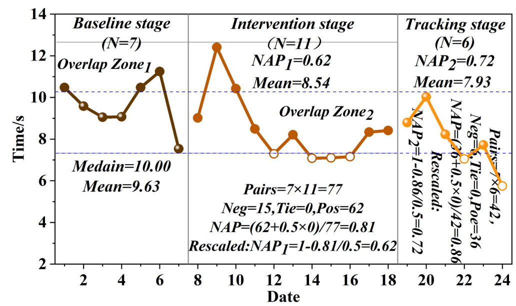


(e) Test 5

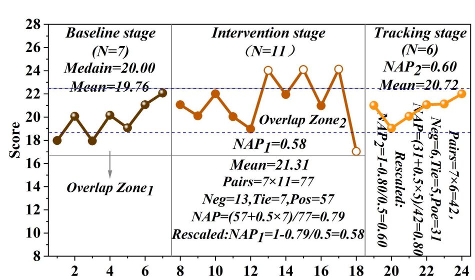


(f) Test 6

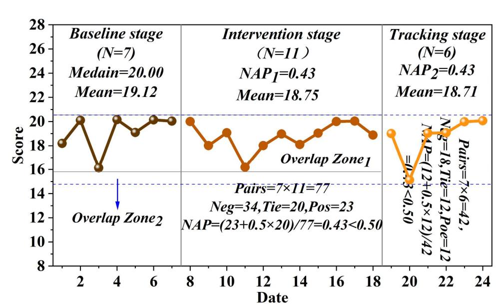
Figure 8: Changes in attention time of the tested athletes

IV. C. 3) Analysis of changes in levels of athletic performance

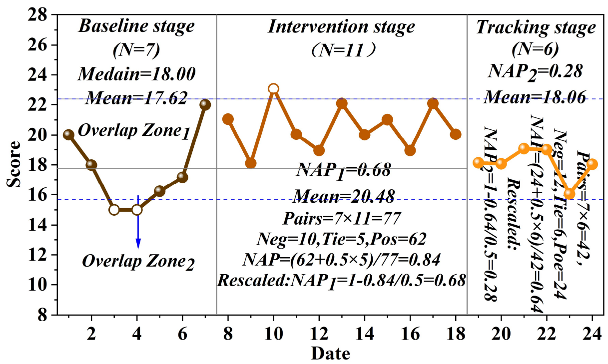
Figures 9(a)-(f) show the changes in attention level time spent scores of the six athletes. As can be seen from the figure, except for subject 2, whose intervention mean of motor performance level score was slightly lower than the baseline mean, the intervention mean of motor performance level score of the other athletes was higher than the baseline mean, which indicated that the "motor performance level" of these athletes was improved after the intervention. The raw NAP1 score of subject 2 was 0.43 (<0.50), indicating that the intervention had no effect on the improvement of the subject's "sports performance level". Of all the subjects, subject 5 had the highest standardized NAP1 value of 0.80, indicating that the intervention had a significant effect on improving this athlete's "level of athletic performance". The standardized NAP1 values of the other subjects were 0.58, 0.68, 0.66 and 0.68, respectively, indicating that the effect of the intervention was more significant. In the follow-up phase, the raw NAP2 values of Subject 2, Subject 3, Subject 4, Subject 5 and Subject 6 were all lower than 0.50, which indicated that the athletic performance level of these athletes decreased after the intervention. Subject 1's standardized NAP2 value was 0.60, indicating that the intervention had a continuing effect on the athlete's performance level.



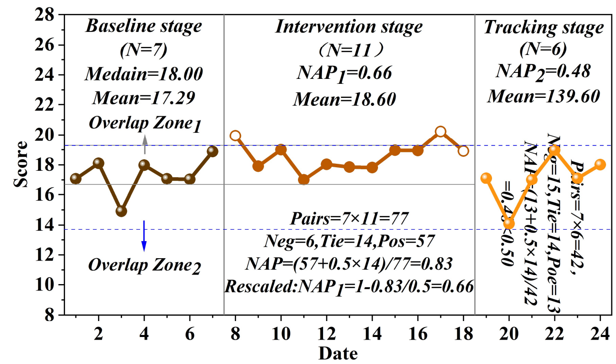
(a) Test 1



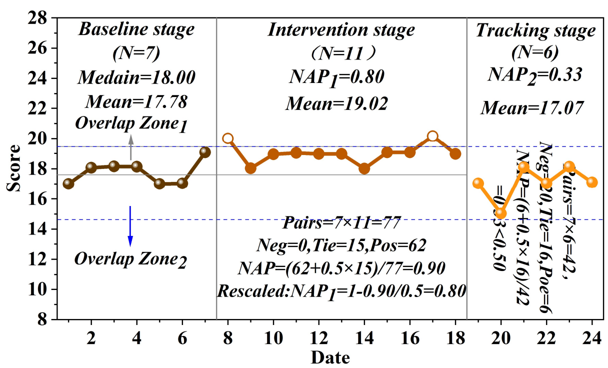
(b) Test 2



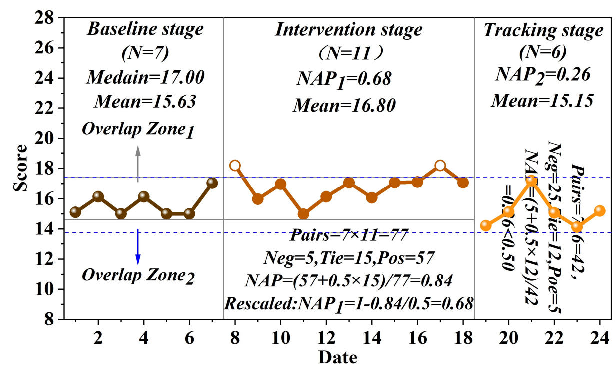
(c) Test 3



(d) Test 4



(e) Test 5



(f) Test 6

Figure 9: Changes in performance levels of the tested athletes

V. Conclusion

In this paper, a GA-BP neural network assessment model is constructed by optimizing BP neural network through genetic algorithm to assess the mental health status of athletes. Based on the assessment results, positive thinking training is used to intervene in athletes with psychological problems and explore effective psychological intervention paths for athletes. The experimental results show that:

(1) Among the collected athletes' data, the total number of athletes with abnormal mental health status is 1,666, accounting for 44.61%, and their mental health problems are mainly concentrated in the aspects of compulsion, interpersonal relationship and depression. Using the GA-BP neural network model to assess the mental health status of athletes, the assessment prediction value on the training set is highly consistent with the overall trend of the true value, and the prediction accuracy rate is up to 90% or more, which has a good training effect. And the assessment results of the model on the test set can reach 86.67% as well. It shows that the GA-BP neural network model can effectively realize the accurate assessment of athletes' mental health status.

(2) Positive thinking training was used to intervene in athletes with mental health problems, and after the experiment, the FFMQ scores, attention levels and sports performance levels of the six subjects increased significantly, and the tracking results showed that the continuation of positive thinking training for athletes to carry out psychological interventions had a significant effect. The results of the follow-up experiment showed that the positive thinking training method can be applied to the mental health management of athletes as an effective path for athletes' psychological intervention.

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