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Retraction

Retracted: Psychological Motivation of Athletes' Physical Training Based on Deep Learning Model

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret 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 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] Y. Yang, "Psychological Motivation of Athletes' Physical Training Based on Deep Learning Model," *International Transactions on Electrical Energy Systems*, vol. 2022, Article ID 1962461, 11 pages, 2022.

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Research Article

Psychological Motivation of Athletes' Physical Training Based on Deep Learning Model

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In the field of sports training, two methods of physical and psychological monitoring are usually used to monitor the training process. Physiological index monitoring can objectively reflect the physical function of athletes, and there are many monitoring constraints. Psychological indicators can subjectively reflect the athlete's own state, and the monitoring is simple and easy. This paper mainly used the subjective perception of effort (RPE) and the profile of mood state (POMS) scales to track and monitor 20 nonprofessional athletes in a university track and field team. Based on the change of the same training volume, the change law and relationship between RPE and POMS, and the change law and relationship between RPE, POMS, heart rate, and blood pressure were analyzed. Finally, it was concluded that the athletes are feeling more and more about the amount of training, and the minimum value $P < 0.01$ showed a very significant difference, reflecting that the increase of training volume has a significant impact on the t-test value. The training volume has an impact on both the positive and negative dimensions of POMS, but the negative dimension reflects the training volume more clearly. There was a linear relationship between RPE and POMS subscales. RPE was not significantly correlated with positive emotions but positively correlated with negative emotions and TMD. The change trend was the same and the RPE grade increases; the blood pressure and systolic blood pressure also increased accordingly, and vice versa. The POMS negative dimension and TMD were the same as changes in blood pressure increase or decrease, and TMD was not related to heart rate. Scientific training has a large impact on the training of nonprofessional athletes, and whether the training volume is reasonable or not directly affects the qualitative change of athletes' physical functions. Therefore, it is particularly important to monitor the physiological and psychological indicators of nonprofessional athletes. The improvement of sports performance is the goal, and the improvement of physical function is the guarantee.

1. Introduction

The change of training volume not only has an impact on the physical indicators of athletes, but also has a corresponding impact on psychology. RPE is a person's subjective feeling, and POMS is a person's state of mind. Both of them can reflect the size of the training volume and have been applied in a large number of experiments. Different from the application of heart rate and blood pressure, it is rare to use the two for psychological monitoring and study changes in a period of time, and it lacks the aspect of monitoring the subjective factors of athletes themselves. Increasing the continuous time monitoring of the athlete's psychological level makes great theoretical sense. At present, there are many studies on subjective effort perception and mood state profiles in the field of sports in China, but they are mainly used as means and tools for experimental research. It is mainly used in only one experiment and reflects the subjective feeling of effort and state of mind of the subjects at all times. The amount of training in sports training is one of the elements in formulating a training plan, and it is also the fundamental content of the implementation of the training plan. Scientific arrangement of training volume is the basic guarantee for the improvement of athletes' athletic performance.

Physical training can improve the physical fitness of athletes. Chronic dietary protein deficiency significantly alters the composition and content of polyunsaturated fatty acids in tissues and body fluids. Aneta et al. believed that the nutritional factor that may reduce the negative impact of protein malnutrition is vitamin B2 because of its greater impact on lipid metabolism [1]. The purpose of the study by Grier et al. was to determine the effect of physical activity and physical fitness on the risk of running-related injuries in physically active young adults. Data on personal characteristics, PT, military fitness test scores, and injuries were collected through questionnaires [2]. The purpose of the LCBC study was to analyze morphological and functional changes in recruits following 12 weeks of physical activity. The exercise program includes running, strength, agility, and flexibility exercises. Finally, descriptive statistical processing was performed using mean, standard deviation, difference, and percentage [3]. Couto et al. believed that iodinated contrast media is the main cause of acute kidney injury in hospitals, and contrast media-induced acute kidney injury (CI-AKI) referred to the decline in renal function caused using iodinated contrast media. This was increasingly common in populations with risk factors [4]. Although all above believe that physical training is necessary, no specific experimental process is shown.

Deep learning is an important category in machine learning. Litjens et al. believed that convolutional learning networks with deep learning algorithms are rapidly gaining popularity as a method of medical image analysis. They reviewed the applications of deep learning in tasks, such as image classification, object detection, segmentation, and alignment, and provide an overview of the research in each application area [5]. Deep learning is rapidly becoming the state of the art, leading to improved performance in various medical applications. Shen et al. introduced the basics of deep learning methods and reviewed successful experiences in image alignment, anatomical and cellular structure detection, tissue segmentation, computer-aided diagnosis, and disease prediction [6, 7]. Oshea and Hoydis presented and discussed several new applications of deep learning at the physical level. They would develop a fundamentally new approach to designing communication systems as a holistic reconstruction project. The aim was to jointly optimize the transmitter and receiver elements in a single process [8]. The above scholars have relatively thorough research on deep learning, but they have not studied a certain aspect in a targeted manner.

Psychological monitoring and physiological monitoring are two necessary means to monitor training, but for nonprofessional athletes, physiological monitoring is very difficult to implement. In psychological monitoring, a paper psychological scale can be used to complete the monitoring of athletes. The psychological state has the characteristics of recall, and the monitoring time point is more flexible. Therefore, in the process of monitoring nonprofessional athletes, it is particularly important to find the relationship between psychological indicators and physiological indicators so that the two can complement each other. The innovation of this study is to determine the law and relationship between psychology and physiology by using the training volume as a medium.

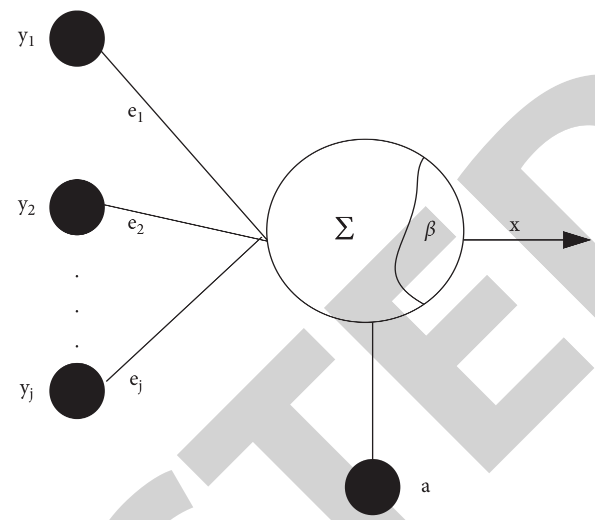

Figure 1: Perceptron cell model.

2. Human Motion State Recognition Based on Deep Learning

2.1. Classical Neural Networks. Various neural network structures can classify motion states, and their accuracy is the key to judge whether the network model can be applied in practice. Figure 1 shows the perceptron unit model, which is the basis of a type of artificial neural network [9].

Formula (1) shows the final result of the output, where y_j is the input of the jth perceptron and e_j is the connection weight of the jth neuron. It is a real constant; a is an offset to better control the output result [10]. β is the threshold, when the sum of the inputs needs to exceed a certain value, there would be a data output, and β is the condition used to judge whether the excitation is reached.

$$g = h\left(\sum_{j=1}^{m}\left(e_j y_j + a\right) - \beta\right). \tag{1}$$

Common activation functions include Sigmoid, Tanh, and ReLU, as shown in Figure 2.

It can be seen from Figure 2(a) that the sigmoid function maps the input value to the output value and compresses it between 0 and 1. In recent years, the sigmoid function has been used less and less, mainly because it has a great influence on the descending gradient of the function. The other is the ReLU function, whose graph is shown in Figure 2(b), and its Chinese meaning is the modified linear unit. Its mathematical definition formula is shown in formula (2). Compared with the sigmoid function and the Tanh function, the gradient descent obtained by the ReLU function converges faster [11].

$$h(y) = \max(0, y). \tag{2}$$

2.2. Convolutional Neural Networks. The convolutional neural network is also the first network structure to be successfully trained with multiple layers, which can share the

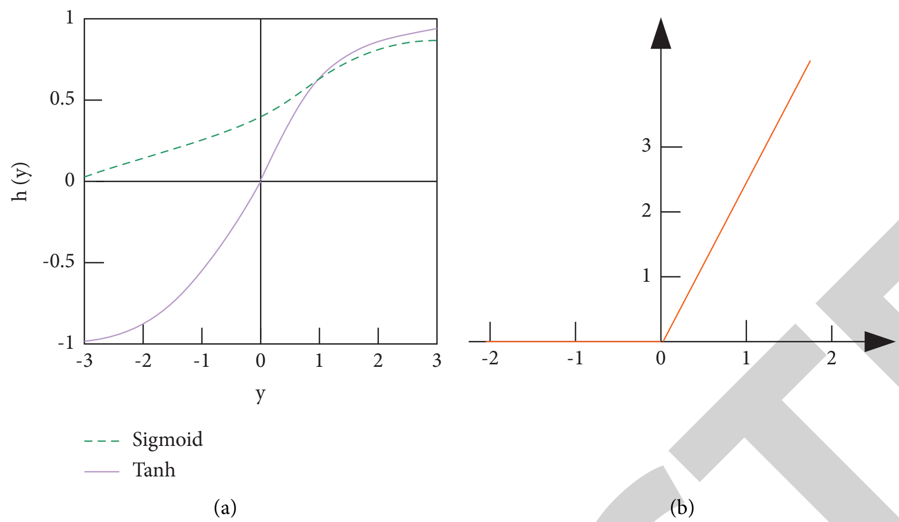

Figure 2: Three function images. (a) Sigmoid-Tanh function image. (b) ReLU function image.

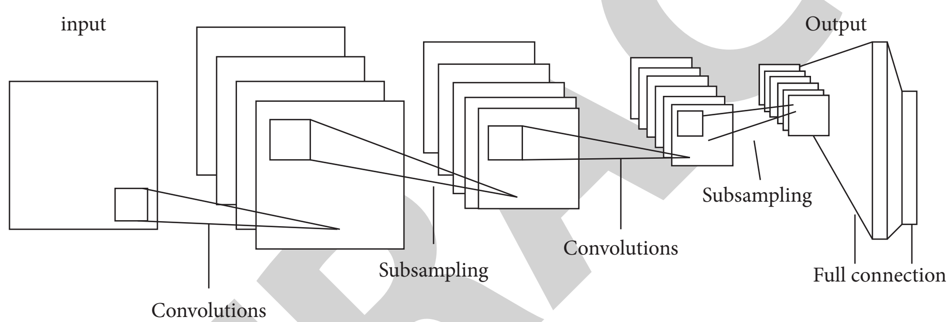

Figure 3: Convolutional neural network architecture.

number of parameters learned by using the spatial structure. Thus, the learning efficiency of the backpropagation algorithm is improved, and the complexity of the algorithm is reduced. Figure 3 shows the general structure of a convolutional neural network. There is no explicit requirement on the order of convolution and clustering, it can continue after the first convolution layer, or clustering can be done.

Of course, convolutional neural network also needs the support of mathematical theory, Formulas (3) and (4) show its learning process.

$$d_j = \alpha\left(\sum_{j=0}^{m} e_j * y_j + a\right), \quad (3)$$

$$q_j = \max(d_j). \quad (4)$$

Among them, e_j represents the weight of the jth layer, y_j represents the input of the jth layer, a represents the bias term, q_j represents the output of the jth layer, and α represents the activation function.

2.3. LSTM Neural Network. RNN performs well in signal processing, audio processing, and natural language processing, especially for time series data processing. Each neuron can save the previous input information through internal components [12]. The structure diagram of RNN is shown in Figure 4; Figure 4(a) is the structure diagram of the RNN neural network, and Figure 4(b) is a schematic diagram of the expanded RNN neural network.

The gate structure and operation process of LSTM are shown in formulas (5)–(10). Formula (5) calculates the j_r of the value of the input gate at time r, and formula (6) calculates the memory state of the LSTM unit at time r.

$$j_r = \alpha_j\left(e_j \cdot \left[f_{r-1}, y_r\right] + a_j\right), \quad (5)$$

$$G_r = \alpha_d\left(e_d \cdot \left[f_{r-1}, y_r\right] + a_d\right). \quad (6)$$

The following formula calculates the h_r of the forget gate value at time r:

$$h_r = \alpha_h\left(e_h \cdot \left[f_{r-1}, y_r\right] + a_h\right). \quad (7)$$

The following formula calculates the D_r of the new state value of the state information at time r:

$$D_r = h_r * D_{r-1} + j_r * G_r). \quad (8)$$

Formulas (9) and (10) calculate the output values u_r and f_r of output gate and hidden layer information at time r.

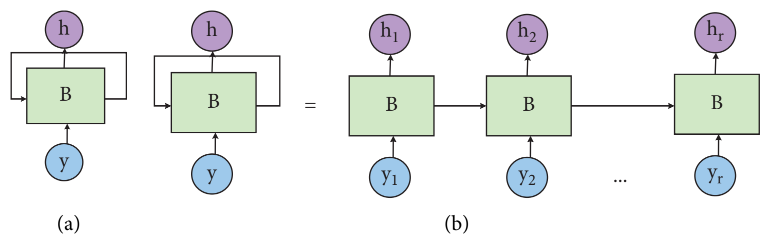

FIGURE 4: Structure diagram of RNN. (a) RNN neural network structure. (b) Schematic diagram of RNN neural network expansion.

$$u_r = \alpha_u\left(e_u \cdot \left[f_{r-1}, y_r\right] + a_u\right), \tag{9}$$

$$f_r = u_r * \alpha_r\left(D_r\right). \tag{10}$$

Among them, D_r represents the state of information transfer, f is the value of the hidden layer, α represents the activation function, and a represents the bias term.

2.4. Bi-LSTM Neural Network. Bi-LSTM, like LSTM, is also a variant of RNN. It is a bidirectional RNN neural network. This structure allows the information in the neural network to be used more effectively. The calculation process in two directions is shown in formula (11) and formula (12).

$$\overrightarrow{\text{forward}}_r = h\left(N_h Y_r + W_h \overrightarrow{f_{r-1}} + \overrightarrow{a}\right), \tag{11}$$

$$\overleftarrow{\text{backward}}_r = h\left(N_a Y_r + W_a \overleftarrow{f}_{r-1} + \overleftarrow{a}\right), \tag{12}$$

$$\text{output}_r = k\left(N\left[\overrightarrow{\text{forward}}_r V_h + \overrightarrow{g}; \overleftarrow{\text{backward}}_r V_a + \overleftarrow{g}\right] + d\right). \tag{13}$$

Among them, W, N is the weight matrix; a is the bias term; $\longrightarrow$ and $\leftarrow$ represent the forward and backward transfer directions of the neural network, respectively, and h represents the activation function. Formula (13) represents the output result, V represents the weight matrix; g and d represent the bias term. N represents the joint function; k represents the new activation function; the value of $output_r$ is the score result, which is the score of a certain class. Since the LSTM unit is a variant of the RNN unit, one can directly replace the RNN unit with an LSTM, and the same is true for bidirectional RNN [13].

2.5. Bi-GRU Neural Network. In the bidirectional RNN neural network, for each neural network unit structure selection, this paper proposes two types, one is LSTM, and the other is GRU. The unit structure of the GRU is shown in Figure 5.

Formulas (14)–(17) show the calculation process of GRU. The process of taking a linear sum between the existing state and the newly computed state is similar to an LSTM cell. However, the GRU does not have any mechanism to control how exposed its state is, and the entire state is displayed every time.

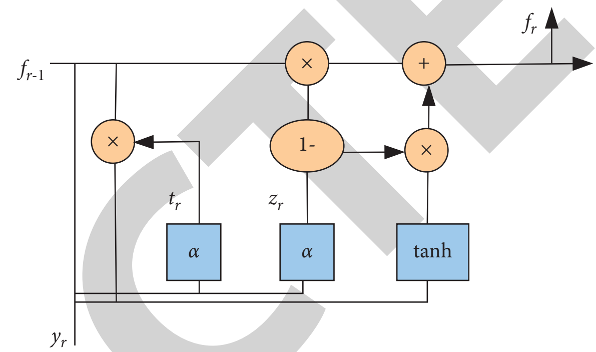

FIGURE 5: GRU neural network unit structure.

$$z_r = \alpha\left(e_z \cdot \left[f_{r-1}, y_r\right]\right), \tag{14}$$

$$t_r = \alpha\left(e_t \cdot \left[f_{r-1}, y_r\right]\right), \tag{15}$$

$$\tilde{f}_r = \tanh\left(e \cdot \left[t_r * f_{r-1}, y_r\right]\right), \tag{16}$$

$$f_r = \left(1 - z_r\right) * f_{r-1} + z_r * f_r]). \tag{17}$$

e represents the weight, and t_r represents a set of reset gate values.

After using various neural networks to extract features, the next step is to classify the data, and the following formula is the softmax function.

$$q = \text{argmax}_d q(x = d|y) = \text{argmax}_d \frac{\exp\left(\text{output}_r\right)}{\sum_{g=1}^{g} \text{output}_r}, \tag{18}$$

where d is the class label, y is the sample feature, x is the label variable, g is the total number of classes, and $output_r$ is the output of each layer. It can be seen from this that softmax classification is a probability-based classification result [14]. The final result of softmax is the probability of identifying a certain data as each class in the current data, and the sum of the probability of classification results for a piece of data is added to 1.

There are two forms of regular expressions, $L1$ and $L2$ regular expressions, as shown in the following formulas for details.

$$D = D_0 + \frac{\eta}{n} \sum_e |e|, \tag{19}$$

$$D = D_0 + \frac{\eta}{2n} \sum_e e^2. \tag{20}$$

When using $L1$ regularization, the weight is reduced to 0 by a constant, and $L2$ is reduced by an amount proportional to e.

3. Psychological Analysis Based on Physical Fitness Training of Athletes

3.1. Objects and Methods

3.1.1. Research Objects. This paper selects 20 members of a university track and field team, namely, 10 boys and 10 girls.

3.1.2. Research Methods

Measurement Methods. RPE: the subjective feeling of effort directly monitors the subjects' subjective feelings. POMS: Mood Profiles can monitor the mood state of subjects over a period of time. Heart rate: the most sensitive indicator of training intensity; it is simple and easy to implement. Blood pressure: it monitors blood pressure changes before and after training to reflect training volume.

3.1.3. Measurement Steps

(1) Psychological monitoring of RPE and POMS for 12 weeks was carried out on 20 athletes using RPE scale and POMS scale.

(2) RPE is monitored every day from the beginning of training. The specific time of the test is to be completed within 10 minutes after the end of the training every day. The test is completed by me throughout the whole process.

(3) POMS is monitored weekly from the 1st week to the 8th week of training; the test is carried out before the start of the next training week, and every Wednesday and Saturday from the 9th week to the 12th week. The scales were distributed by me half an hour before training on the day of monitoring. The athletes fill in the form based on their first feelings, and then they receive the scale and archive it.

(4) Heart rate and blood pressure were monitored every Wednesday and Saturday from the 9th week to the 12th week. The heart rate and blood pressure test time are to complete two monitorings within 10 minutes before and after training.

(5) Weeks 9 to 12 are 4 weeks before the competition. The main purpose of increasing the number of monitorings in the 4 weeks before the competition is to fully grasp the psychological and physiological changes of the athletes throughout the training week through the monitoring in the middle and end of the last 4 training weeks.

(6) Sports performance is tested monthly, the training plan is formulated according to the monthly plan, and the 1-month plan is 4 weeks.

(7) During the monitoring period, no psychological and physiological intervention is required.

3.1.4. Mathematical Statistics. Using SPSS19.0 statistical software as a data statistical tool, the RPE and POMS of different training cycles were compared. The F-test was used to conduct an overall test on the psychological and physiological indicators of male and female athletes. t-test was used to compare the differences of RPE values from weeks 1 to 12. Differences were compared between the four subscale values, total and TMD values of POMS in weeks 1–12; heart rate was compared between weeks 9 and 12. Differences in blood pressure changes were compared between weeks 9 and 12; differences in RPE values were compared between weeks 9 and 12. Differences were compared between the four subscale values and total and TMD values of POMS tested in weeks 9–12. Pearson's coefficient was used to analyze the regularity of heart rate variability, RPE, and POMS in weeks 9–12. The regularity analysis of blood pressure changes, RPE, and POMS in the 9th to 12th weeks was carried out in the experiment. Regularity analysis was performed on the four subscale values and total and TMD values of RPE and POMS from 1 to 12 weeks.

3.2. Results

3.2.1. Difference Test of Psychological Indicators. Table 1 is the test table for the differences of POMS components and RPE of male and female athletes.

As can be seen from Table 1, the differences between the four subscale values of POMS, the total score, the TMD value, and the RPE value of 10 boys and 10 girls in the untrained state were tested respectively. Among them, stress, fatigue, and total score in POMS were $P < 0.05$. Therefore, in the data analysis, the total score of stress, fatigue, and POMS cannot be compared for the overall value of 20 subjects. Other values can be analyzed and compared for a population [15].

3.2.2. Comparison of Differences in RPE Grades from Weeks 1 to 12. Table 2 is the test table of the difference before and after RPE measurement.

As can be seen from Table 2, by comparing the difference between the weekly measurement value of RPE and the measurement value on March 31, there was a significant difference in the weekly measurement value from April 18 to June 7 ($P < 0.01$). This shows that when the training volume increases, the subjective feeling of athletes is obvious, and some subjects have the highest value of 17 (very difficult), and the impact of training volume increase on individual subjects may reach the limit [16]. There was no significant difference in the other weeks, indicating that the athletes have adapted to the training volume.

3.2.3. Comparison of the Correlation between RPE and POMS in Weeks 1–12. Table 3 shows the correlation statistics between RPE and POMS subscales.

It can be seen from Table 3 that the correlation between RPE and POMS subscales is compared, and RPE is strongly correlated with depression and panic ($0.6 < r < 0.8$). There was a

Table 1: Difference test table of POMS components and RPE for male and female athletes.

Index		Male M ± SD	Female M ± SD	F	P
POMS	Nervous	2.33 ± 1.85	5.50 ± 3.71	0.211	0.021
	Fatigue	3.22 ± 2.13	4.00 ± 3.90	0.175	0.012
	Energy	10.67 ± 5.87	12.00 ± 3.98	1.819	0.222
	Panic	2.56 ± 1.95	4.38 ± 3.31	0.287	0.051
	Total score	30.33 ± 7.53	47.00 ± 18.29	0.166	0.010
	TMD	97.00 ± 17.59	106.50 ± 18.89	0.680	0.299
RPE		11.44 ± 0.84	11.67 ± 1.1	0.778	0.365

Table 2: Difference test table before and after RPE measurement.

Date	RPE M ± SD	t	P
3.31	11.52 ± 0.95		
4.18	12.96 ± 1.05	5.469	0.310
5.6	13.29 ± 1.73	5.149	0.000
5.21	13.33 ± 1.37	5.599	0.000
6.7	11.96 ± 0.67	1.589	0.000
6.21	11.11 ± 0.85	−1.809	0.078
7.5	11.94 ± 0.68	1.341	0.188

Table 3: Statistical table of correlation between RPE and POMS subscales (Pearson's coefficient r).

	Anger	Depression	Energy	Panic	Mood	TMD	RPE
Anger		0.41	0.31	0.56	0.43	0.50	0.31
Depression			0.43	0.76	0.49	0.78	0.65
Energy				0.26	0.70	0.20	0.12
Panic					0.35	0.68	0.60
Mood						0.18	0.11
TMD							0.58

Table 4: Test table for differences in heart rate and blood pressure between male and female athletes.

6.14	Male M ± SD	Female M ± SD	F	P
Heart rate before training	77.90 ± 11.03	73.42 ± 8.79	2.057	0.196
Heart rate after training	104.90 ± 14.68	102.43 ± 10.88	1.424	0.344
Systolic blood pressure before training	124.90 ± 14.47	119.86 ± 8.86	2.822	0.109
Diastolic blood pressure before training	84.20 ± 15.38	74.00 ± 6.13	4.766	0.035
Systolic blood pressure after training	126.70 ± 17.72	122.28 ± 8.37	9.737	0.005
Diastolic blood pressure after training	77.90 ± 10.04	79.43 ± 4.56	4.502	0.040

moderate correlation with TMD of $0.4 < r < 0.6$, a weak correlation with anger of $0.2 < r < 0.4$, and a very weak correlation with energy and mood of $0 < r < 0.2$. The correlation between TMD and POMS subscales was compared. Among them, TMD was strongly correlated with depression and panic ($0.6 < r < 0.8$), moderately correlated with anger ($0.4 < r < 0.6$), and weakly correlated with energy and mood ($0.2 < r < 0.4$). The rest of the subscales are highly correlated with the same attribute and generally less correlated among different attributes [17].

3.2.4. Values and Comparison of Indicators in Weeks 10–12

(1) Difference Test of Heart Rate and Blood Pressure. Table 4 is a test table about the difference in heart rate and blood pressure between male and female athletes.

It can be seen from Table 4 that the difference test is carried out through the physiological indicators of male and female athletes. Among them, the diastolic blood pressure before training, systolic blood pressure after training, and diastolic blood pressure after training $P < 0.05$ cannot be used as a regular analysis of the overall data of men and women. Other groups of data can be compared as a whole.

(2) Comparison of Heart Rate Differences in Weeks 10–12. Figure 6 is a comparison chart of changes in heart rate before and after training. As shown in Figure 6(a), the weekly measurement of heart rate before training was compared with the measurement value on June 14, and there was no significant difference. The average was about 79 times/min, showing a downward-up-down trend, and the change range was small.

As shown in Figure 6(b), the weekly measurement of heart rate after training was compared with the

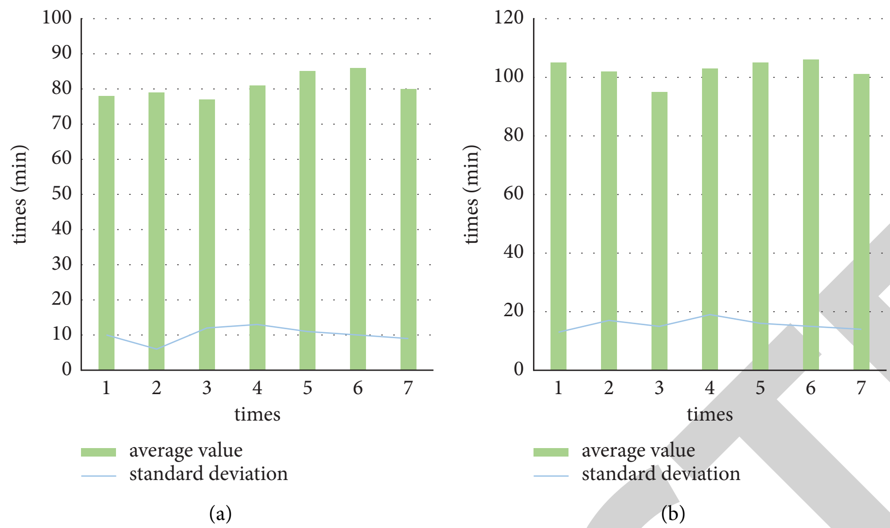

FIGURE 6: Comparison of heart rate changes before and after training. (a) Change trend of heart rate before training in weeks 10–12. (b) Change trend of heart rate after training in weeks 10–12.

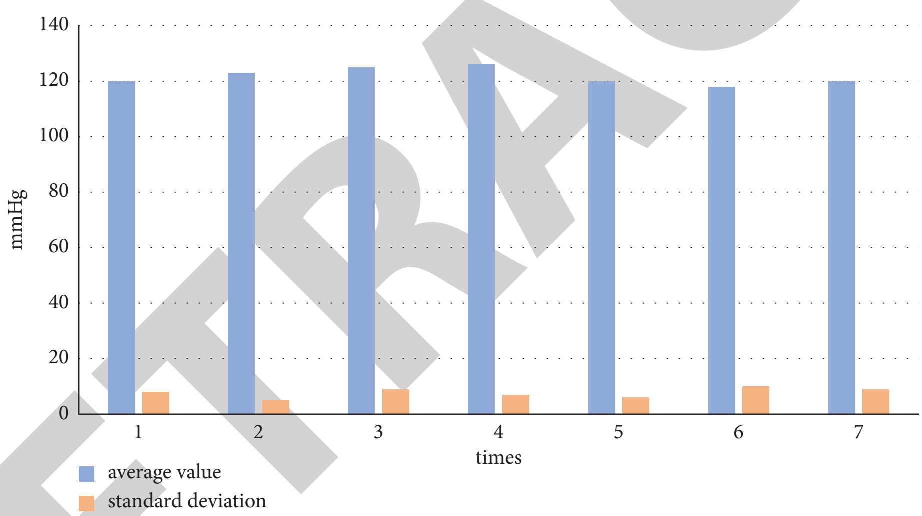

FIGURE 7: Trend of systolic blood pressure before training in weeks 10–12.

measurement value on June 14, and there was a significant difference on June 21 ($P < 0.05$). There was no significant difference in the rest, and the average value was around 104 times/min, showing a downward-up-down trend with a small change.

(3) Comparison of Blood Pressure Differences in Weeks 10–12. Figure 7 is the trend chart of systolic blood pressure before training in weeks 10–12. The weekly measurement of systolic blood pressure before training was compared with the measurement value on June 14, and there was no significant difference. The overall value was within the normal range, but the individual data fluctuated greatly, and the blood pressure value of the throwing athletes was higher. The systolic blood pressure before training showed an increasing-decreasing trend [18].

(4) Comparison of RPE Grade Differences in Weeks 10–12. Figure 8 is a graph of the change trend of the P value of RPE from weeks 10 to 12, and the weekly measured values of RPE are compared with the measured values on June 14th. The significant difference on June 25 was $P < 0.01$, indicating that the impact of training volume on RPE became greater, and there was no significant difference at other times.

(5) Comparison of the Correlation between Psychological Indicators and Physiological Indicators. As shown in Table 5, the correlation analysis is carried out through psychological indicators and physiological indicators. The positive and negative values only represent the size of the determined basic indicators, and the absolute value of the numerical value represents the degree of correlation. Among them, heart rate before training was strongly correlated with TMD

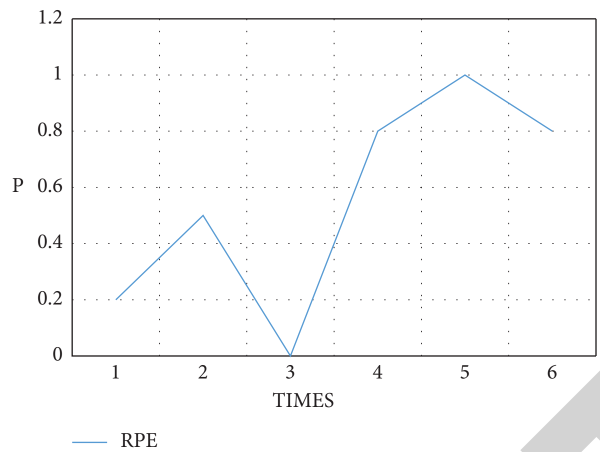

Figure 8: Trend of P value of RPE in weeks 10–12.

Table 5: Statistical table of correlation between physiological indicators and psychological indicators in the 10th to 12th weeks (Pearson's coefficient r).

	Anger	Depression	Energy	Panic	Mood	TMD	RPE
Heart rate before training	0.53	0.53	−0.60	0.15	0.42	0.62	−0.14
Heart rate after training	−0.39	−0.01	0.08	0.09	−0.52	−0.15	−0.16
Systolic blood pressure before training	0.79	−0.53	0.09	−0.51	−0.55	−0.52	0.61

$(0.6 < r < 0.8)$, and systolic blood pressure before training was strongly correlated with RPE and anger $(0.6 < r < 0.8)$. There was a moderate correlation between heart rate and anger, depression, and energy before training $(0.4 < r < 0.6)$ and a moderate correlation between heart rate and emotion after training $(0.4 < r < 0.6)$. Pretraining systolic blood pressure was moderately correlated with depression, panic, mood, and TMD $(0.4 < r < 0.6)$.

3.2.5. Comparison of the Influence of Training Volume on Sports Performance in Weeks 1–12. Sports performance is an objective indicator that reflects the training effect of athletes, and it can also reflect the changes in the physical function of athletes after training for a certain period of time. Physical performance changes with the amount of training in each phase of the training program. When evaluating the impact of training volume on the subscales of RPE and POMS, the impact of changes in an athlete's physical function on changes in athletic performance should be considered [19].

The sports performances of 4 athletes were randomly selected, 1 for men's 100 m, 1 for men's 400 m, and 2 for women's 400 m. Sports performance improved with the increase of training volume in the first eight weeks but did not decrease with the decrease of training volume in the last four weeks. It shows that with the continuous deepening of sports training, the physical function of athletes has improved, and the sports performance has also made breakthroughs. The results are shown in Table 6.

The results in March are the sports results before training, the results in May and June are the sports results in training, and the results in July are the results of participating in the Provincial University Games. The first three

Table 6: Statistical table of changes in sports performance of 4 athletes.

Project	3.31	5.26	6.28	7.20
Men's 100 m	11″45	11″36	11″40	11″21
Men's 400 m	56″21	53″92	54″50	53″ 67
Women's 400 m (1)	1′13″60	1′11″67	1′09″ 80	1′09″65
Women's good 400 m (2)	1′22″50	1′21″00	1′14″50	1′12″20

results are hand-timed, and those of the Provincial University are electronic-timed.

3.3. Data and Discussion

3.3.1. Analysis of the Regularity of Training Volume and RPE and POMS in Weeks 1–12. The training program is based on a 4-week 1-month cycle. The first 4 weeks are the intervention period, the training volume is moderate and the intensity is medium and small, the weekly training load changes are small, and the weekly training content is similar. The purpose is to allow the athlete to develop their own adaptation to the training. The second 4 weeks is the strengthening period, the training volume is large and the intensity is large, the weekly training load changes greatly, and the training content is similar. The purpose is to improve the performance of the athletes; the third 4 weeks is the maintenance period, the training volume is reduced to the middle, and the intensity is moderate, and the weekly training load changes are moderate. The purpose of training is to keep the athlete in physical condition to participate in the competition. Therefore, the trend in overall training volume is medium-high-medium-high. The training schedule is designed to fluctuate in training volume within each monthly cycle of training to prevent overfatigue. There are also changes in the training volume in the weekly training plan to ensure that the athletes are in the best physical and psychological state [20].

(1) Analysis of Training Volume and RPE Law in Weeks 1–12. Variations in training volume are performed strictly in accordance with the arrangements of the training plan. It can be seen from the change trend of the average value and standard deviation of RPE that the value of the first 4 weeks from the beginning of training gradually increased and then decreased, and the highest value was around 12. This shows that the athletes themselves feel that the training volume is gradually increasing, but the training volume is not large. In the second 4 weeks, the value has been kept at around 13.5, and the athletes themselves feel that the training volume has always maintained a certain height, but there is tension and relaxation. There is a gradual adaptation process. In the last 4 weeks, the value decreased significantly but maintained a certain level of about 11.5. The athletes felt that the training volume was reduced and maintained a certain level. The change trend of the average RPE is basically the same as the change trend of the training volume in the training plan, and the change of the training volume can affect the change of the average RPE.

Beginning in the first 4 weeks of training, the *t*-test value is a process from high to bottom, and the decline is very obvious. The athletes are feeling more and more about the amount of training, and the minimum value $P < 0.01$ shows a very significant difference, reflecting that the increasing process of training volume has a significant impact on the *t*-test value. The second 4-week *t*-test value was a process of steady and then rising, and the steady value was always less than 0.01. Athletes have a very large degree of perception of training volume, reflecting that the process of continuous large training volume has a more significant impact on the *t*-test value. The third 4-week *t*-test value was a process of increasing and then decreasing, but there was no difference in the value, and the impact of training volume on the *t*-test value became smaller. The change of training amount in the training plan reflects the change of *t*-test value, and there is an inherent law between the change of training amount and the change of *t*-test value.

From the above comparison, it can be seen that the change of training amount can have an impact on the change rule of the average value of the RPE grade and the change trend of the *t*-test value [21]. The change law of the influence of training amount on the *t*-test value can better reflect the overall change law of RPE, and the degree of reflection is obvious, and the numerical expression is comprehensive, but the change range is general.

The reflection of RPE is subjective, and it can directly reflect the athlete's tolerance to a certain training volume. At the beginning of training, although the training volume is not large, the general reactions of athletes are relatively strong. This is due to the fact that during the transitional stage from no training to training, the stimulation of the training volume to the athlete is very obvious, so the RPE level would change significantly. In the mid-term stage, when the training volume is the largest, the value of RPE is generally high but tends to be stable. It shows that athletes have adaptability to training, and the increase of training volume is also the process of athletes improving their own abilities. Athletes' physical function is at a high level, and this stage is also the fastest stage of sports performance improvement. In the early stage of the game, the RPE is also in a stable state. Although the training volume is larger than that at the beginning, the RPE level is similar to it. This also shows that the athletes have adapted to the current training volume, the level of physical function has improved, and the feeling of the increase in training volume is not obvious.

(2) Analysis of Training Volume and POMS Law in Weeks 1–12. The positive dimension of POMS can reflect the athlete's enthusiasm for training, and the change of training volume has an obvious effect on the change of the positive dimension. At the beginning of the training, the overall value was very low and the range of changes was large, while the value was higher and more stable when the training volume increased in the mid-term, and the decrease in the value in the early stage of the game was also very stable. This shows that changes in training volume can cause changes in the positive dimension. However, athletes' attitude towards training is proactive. From no training to excessive training, the athlete's initiative declines rapidly, and oppositional emotions appear, which recover after a period of adaptation.

The negative dimension of POMS is the main indicator reflecting the mental fatigue of athletes, and it is also the main factor of TMD change. The value of negative dimension is generally high when the training volume is not large in the early stage of training. In the middle of the training, the training volume is the largest, but the negative dimension value decreases slightly, and the change range is small and stable. It can be seen that from no training to overtraining is the most prone to fatigue stage. The fatigue response is not obvious when the training volume is the largest, and the influence of the training volume before the competition on the mental state of the athletes is not a decisive factor. The stress of the game is the main factor, which has a great influence on the performance of the game.

(3) RPE and POMS Relationship in Weeks 1–12. Changes in training volume can affect the values of each subscale of RPE and POMS, and the changes in the mean and standard deviation of the two have the same place. The change trend of RPE is almost the same as that of POMS negative sentiment and TMD and partly the same as that of positive sentiment. Although changes in values can be found in the trends, they do not fully reflect the overall values. Therefore, the *t*-test values of each subscale of RPE and POMS were used to compare the relationship between the two. Through the comparative analysis of the relationship between the subscales of RPE and POMS, the relationship between the two is very close. Using the relationship between the RPE and the negative dimension subscale at various stages of training can directly show the impact of training volume on athletes. Changes in RPE values can reflect changes in the negative dimension of POMS.

3.3.2. Analysis of the Regularity of Training Volume and Physiological Indicators and Psychological Indicators in the 10th to 12th Weeks. The last 4 weeks are 4 weeks before the competition, and the training volume is medium to high in the training plan, but the training volume is different every week. The arrangement is a small amount of training before a large one. The main purpose is to keep the athletes in the state to cope with the competition, maintain their personal best results, and be able to further improve.

(1) Analysis of Training Volume, Heart Rate, and Blood Pressure in Weeks 10–12. From the mean and standard deviation of the data, it can be seen that the heart rate before training is a process of increasing and decreasing slowly, and the athletes' basal heart rate fluctuates. After training, the heart rate is also a process of increasing and decreasing slowly, and the recovery of the athlete's heart rate is slower. Systolic blood pressure increases and then decreases before training. The average values of the above physiological indicators can reflect the changes in training volume.

It can be seen from the overall t-test value that the heart rate first decreased and then increased before training, and the heart rate increased and decreased after training. The change trend of the two in the second two weeks was clearly opposite, indicating that the training volume played a great role in the change of heart rate. The systolic blood pressure decreased before training and then gradually increased, indicating that the impact of training volume on blood pressure is also more significant. The degree of change is as follows: heart rate after training > heart rate before training > systolic blood pressure before training.

The change of heart rate before and after each training can objectively explain the change of the athlete's physical function and reflect the athlete's physiological fatigue state. The heart rate changes before and after training hours are synchronous, and the changes in heart rate before and after training become larger, and vice versa. When the training volume is large, the two change in opposite directions; one becomes larger and the other becomes smaller. This also shows that there is a large gap between the heart rate changes before and after each training, and the heart rate changes when the training volume is small, and the body recovers quickly. When the training volume is large, the heart rate change increases and the body recovers slowly.

Blood pressure is another physiological indicator that effectively reflects the changes of athletes' physical functions, and the impact of training volume on blood pressure is also significant. The change trend of systolic blood pressure before training is the same, indicating that the physical function is in good condition and recovers quickly without fatigue. When the training volume is large, the trend of systolic blood pressure before training is opposite, which means that the recovery of body function is slow and prone to fatigue.

(2) Analysis of Training Volume and RPE Law in Weeks 10–12. The training volume also changed in the last 4 weeks, showing a trend of more and then less. The change trend of the mean and standard deviation of RPE can be seen from the influence degree of training volume, and the change range is small. In the case of medium and high training volume, the RPE of athletes did not change significantly, indicating that most athletes have adapted to the current training volume.

The t-test value changed from a small fluctuation in the tenth week to a large fluctuation in the last two weeks, and the change trend was obvious and the change range was large. This can clearly reflect the size of the training volume, which is proportional to the same trend as the training volume. The main factor is that the value of the basic index is too large, but it does not affect the comparison of the change law.

The prematch RPE changes closely with the training volume. The reason for the small change is that after the physical function of the athlete is improved, the response to the stimulation of the training volume is not so strong, which indicates that the athletic ability of the athlete is also improved.

(3) Analysis of Training Volume and POMS Law in Weeks 10–12. The effect of training volume on POMS value can be seen such that the average value of each subscale of negative emotion in the last 4 weeks is too large. In particular, the average value of TMD is obvious, the average value of positive emotion is small, and the standard deviation changes greatly. It shows that the athletes' state of mind tends to be fatigued in the last 4 weeks and further indicates that the main factor affecting the athletes' state of mind is the stress of competition when the training volume is not the largest.

The overall change trend of the t-test value of each subscale of POMS and TMD was the same, which was a process of recovery from insignificant to significant, but the change of positive emotion was small. This shows that the athletes maintain a good positive state, and the negative emotions and TMD change greatly. This shows that the precompetition mood reflects the training volume mainly from negative emotions. The change range of each subscale is as follows: panic > depression > TMD > anger > energy > mood.

4. Conclusion

Psychological monitoring and physiological monitoring are two necessary means of monitoring training. Based on the scientific arrangement of training volume, this study conducted a 12-week psychological monitoring on 20 athletes and analyzed the changes in RPE, POMS, heart rate, and blood pressure during the entire training process. Through comparative analysis, it is concluded that the RPE grade can clearly reflect the impact of training volume on athletes. Only when the physical function of the athlete is not significantly improved, can it accurately reflect the athlete's tolerance to the regular changes in training volume. The t-test value is a process from high to bottom, and the decline is very obvious. The athletes are feeling more and more about the amount of training, and the minimum value $P < 0.01$ shows a very significant difference, reflecting that the increasing process of training volume has a significant impact on the t-test value. The regularity of POMS can be used for mental monitoring throughout the training process. In particular, the positive relationship between the negative dimension and the amount of training is highly reliable. Under the same training volume, there was a linear relationship between RPE and POMS subscales, and RPE was significantly related to negative emotions and TMD. In particular, there is a strong correlation with the two subscales of depression and panic. There is an internal relationship between psychological indicators and physiological indicators, and RPE and POMS can reflect both psychological and physiological changes.

Data Availability

The data underlying the results presented in this study are available within the paper.

Conflicts of Interest

The author declares that there are no conflicts of interest regarding the publication of this paper.

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