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AN INTELLIGENT MONITORING SYSTEM FOR SPORTS MENTAL HEALTH STATUS BASED ON BIG DATA

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Abstract. This provides an effective way to break away from traditional inefficient evaluation methods for monitoring and analyzing the psychological status of a large number of school sports athletes, the author proposes an intelligent monitoring system for sports psychological health status based on big data. Applying big data technology to mental health assessment, using real-time monitoring and analysis of athlete unified EEG waves, dividing athlete EEG waves into frequency bands, and conducting mental health analysis. The author validated the effectiveness of the system through simulation experiments, and the results showed that the psychological states of the subjects were not the same during the early and fatigue stages of training. In the early stages of training, the brainwave frequency band was mainly in the Beta and Gamma bands, accounting for 37% and 41%, respectively. Concentration was greater than relaxation, while in the fatigue stage of homework, the brainwave frequency band was mainly in the Delta and Thata bands, accounting for 43% and 45%, respectively, and concentration was less than relaxation. The psychological monitoring system designed by the author can provide a technical foundation for a series of strategies to promote training efficiency while ensuring the mental health of athletes.

Key words: Big data, Psychological health, EEG signals, Real time monitoring

1. Introduction. In 2021, the General Office of the Ministry of Education issued a notice on strengthening the management of student mental health, emphasizing that mental health management should be strengthened in four aspects: source management, process management, result management, and guarantee management. In addition, the level of emphasis on student mental health education varies among different stages of education [1]. However, many families have significant gaps in mental health education, and vocational and secondary vocational colleges have limitations in understanding the mental health of students.

In order to further improve the pertinence and effectiveness of student mental health work, the General Office of the Ministry of Education issued a notice in 2021 on strengthening student mental health management work (Education and Political Affairs Office Letter [2021] No. 10), and proposed strategies such as "strengthening process management" and "early classification and relief of various pressures" to strengthen professional support and scientific management, and improve student mental health literacy.

According to statistics, about 10% of adolescents in China require mental health interventions. However, the development of psychological counseling is still in its early stages, and the market has shown an explosive growth trend. However, campus psychological counseling services still lack professionalism and systematicity [2]. Despite the establishment of various psychological counseling rooms, the campus is still a place with a high incidence of depression and other mental illnesses, and has not achieved the expected results [3]. With the advent of the big data era, the data reserves and technological concepts related to big data are predicting the development trends of things in an unprecedented way, changing the knowledge system, lifestyle, and mental health level of students [4]. At present, the psychological construction work of schools is only limited to hiring a small number of professional psychological counseling teachers, while class teachers (non psychology professionals) mainly undertake manual intervention and management of students' psychological situations. Sports mental health plays a crucial role in the performance and overall health of athletes. With the development of big data technology, researchers have begun to explore how to use big data technology to monitor and evaluate the mental health status of athletes. The research on this big data based intelligent monitoring system for sports mental health status aims to combine advanced data collection techniques, data analysis methods, and psychological principles to provide comprehensive and timely psychological health monitoring

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and intervention support for athletes. In traditional sports mental health monitoring, athletes usually rely on self-report or professional psychological assessment tools, which has problems such as strong subjectivity and untimely information acquisition. A monitoring system based on big data can comprehensively and objectively understand the psychological state of athletes through the collection and analysis of multi-source data such as daily training data, competition data, physiological parameter data, and social media data. This system can identify the psychological health status and changing trends of athletes, such as anxiety, stress, confidence, etc., by analyzing a large amount of data. At the same time, by combining with the personal characteristics and historical data of athletes, personalized psychological health intervention suggestions can be provided to help athletes better cope with challenges and stress.

Overall, the research on an intelligent monitoring system for sports mental health status based on big data can not only provide athletes with more comprehensive and objective mental health monitoring services, but also provide personalized psychological support and intervention, thereby improving their competitive performance and overall health level.

2. Literature Review. Wang, K. et al. advocate for early intervention in mental health disorders, particularly among adolescents and children. They emphasize the importance of establishing various positive psychological education frameworks for individuals grappling with mental health issues. Consequently, the development of effective mental health education leveraging big data is crucial to fostering positive thinking and support systems, especially within school environments.Ultimately, this innovative mental health education model enhances individuals' learning experiences and contributes to a reduction in mental illness, depression, and stress within communities[5]. Wang, S. et al. introduced an innovative empirical framework that harnesses the power of social media to systematically evaluate, quantify, map, and monitor a nation's mental health status. This framework is structured to enable ongoing surveillance and scalability to other countries as needed. By tracking regions where individuals express heightened levels of negative mental health indicators via social media, valuable insights are gleaned to strategically allocate limited mental health resources. This approach facilitates intelligent resource allocation, ensuring targeted interventions where they are most needed based on real-time data analysis of digital expressions of mental well-being[6]. Liu, X. et al. conducted a comprehensive study involving two rounds of data collection and organization, followed by rigorous statistical analyses such as descriptive analysis, unbiased t-tests, chi-square tests, variance assessments, and SNK-q tests using validated data. They investigated the evolution of mental health among students experiencing negative psychological symptoms over a two-year period and assessed the associated impacts. Employing advanced machine learning techniques, they developed models to identify susceptibility factors and analyze their contribution to mental health outcomes. The findings from testing and data analysis confirm the efficacy and viability of their approach[7]. Bakare, A. et al. explored the processes involved in gathering, monitoring, managing prescriptions, and analyzing real-time health data. They employed a network simulator to evaluate the effectiveness of their proposed system and compared it with various communication protocols to identify optimal techniques for health monitoring[8].

By applying big data technology to the monitoring and analysis of the psychological health of sports students, corresponding training allocation plans can be formulated based on work characteristics and the psychological status of sports students. Real time tracking of the psychological status of sports students can be carried out during the training process, and intervention can be given at appropriate time points, thereby achieving the effect of improving the experience of sports students while ensuring efficiency. Therefore, by combining big data monitoring and analysis technology with the theory of EEG psychological feedback for sports students, a psychological health evaluation system for real-time monitoring and analysis of the psychological state of sports students is designed, providing a new practical path for related fields.

3. Research Methods.

3.1. Establishment of a data-driven system for brainwave monitoring and analysis . The author designs an automatic monitoring system for psychological health evaluation data based on big data perception technology, which collects different EEG signals using big data perception technology to automatically monitor and analyze human psychological health [9]. The author mainly understands the essence of mental health from two aspects. On the one hand, it evaluates the subjective state and direct indicators of work and learning ability. On the other hand, it analyzes the indirect indicators of work and learning ability. Compared with direct indicators, indirect indicators can more accurately reflect the psychological health of testers. The method used needs to monitor the initial symptoms of the tester when their mental health is relatively good. For fluctuations in their mental health that conform to normal conditions, an appropriate sensitivity range should be set for the monitoring indicators.

The electrical signals of the brain are generated by the stimulation of ion movement by neurons, and all reactions and actions in the human body are completed by the potential changes generated by synapses between countless neurons in the brain [10]. EEG changes can be divided into evoked potential response and self generating activity. Spontaneous EEG is similar to sinusoidal signals, and it changes over time without specific external stimuli. Due to the fact that the time-domain waveform of spontaneous EEG waves does not have specific patterns, but it conforms to specific patterns in the frequency domain, it is generally classified based on the frequency domain of EEG waves. EEG waves are divided into five different rhythms based on frequency, including Y waves (31 Hz to 100 Hz), β waves (14 Hz to 30 Hz), α waves (8 Hz to 13 Hz), θ waves (4 Hz to 7 Hz), δ waves (1 Hz to 3 Hz). The voltage amplitude value of Y wave is detected as 1 $\mu V \sim 5\mu V$. Indicates that the tester is currently highly mentally tense and generates EEG pulses when stimulated, with intermittent buffering between them [11]. The voltage amplitude value of β waves is detected as 5 uV-20 uV, with a high frequency, indicating that the tester is currently relatively nervous and has a high level of perception of the surrounding things. The voltage amplitude value of waves is detected as 20uV-100 uV, and its frequency is relatively stable in the absence of external stimuli, indicating that the tester's brain is currently clear and relaxed, with more focused attention, and in a brain state suitable for work and learning.

The voltage amplitude value of θ waves is 50 $\mu V \sim 150\mu V$. The amplitude of EEG waves is relatively stable, indicating that the tester's current mental state is relatively relaxed and their attention concentration is poor, gradually entering a state of fatigue. When exposed to external stimuli, their attention will be focused. The voltage amplitude value of δ wave is 20 $\mu V \sim 200\mu V$. Indicates that the tester is currently in a state of extreme fatigue. When the tester gradually wakes up due to external stimuli, there may also be discontinuities δ wave, θ wave sum δ wave.

In the actual detection of EEG signals, the collected signals are presented as superimposed time-domain waveforms of EEG signals with different rhythms, making it difficult to obtain EEG information that can describe the psychological health of the tester. Therefore, it is necessary to convert the time-domain signals into frequency-domain signals and analyze them. Calculate using the eSense index based on the proportion of brain wave energy with different rhythms obtained [12]. This index is mainly used to describe the focus and relaxation of testers in reflecting their mental health status during the work and learning process. Y wave and β when the proportion of waves in the energy of EEG signals is relatively high, it indicates that the tester is focused and mentally tense; θ wave sum δ when the proportion of waves in the energy of EEG signals is high, it indicates that the tester has poor concentration and relatively relaxed mental state. The formula for calculating focus is shown in equation 3.1.

$$P_1 = (mY + n\beta + t\alpha) \times 100 \tag{3.1}$$

In equation 3.1, Y,β and α represent Y waves, respectively, β wave sum α proportion of waves in the energy of EEG signals, where m, n, and t represent Y waves, respectively, β weight coefficients of wave and α wave. The calculation formula for relaxation is shown in equation 3.2.

$$P_2 = (x\theta + y\delta + z\alpha) \times 100 \tag{3.2}$$

In equation 3.2, θ δ and α represent separately θ wave δ wave sum α proportion of waves in the energy of EEG signals, represented by x, y, and z, respectively θ wave, δ wave sum α weight coefficient of the wave. Set a rating range of 1-100 for the focus and relaxation of the tester, and evaluate their current thinking and mental state [13,14].

3.1.1. Design of Big Data Brain Wave Analysis System. When designing an automatic monitoring system for mental health assessment data, the author mainly divided the system into two parts, the first part being the big data monitoring part and the second part being the big data analysis part. The big data monitoring

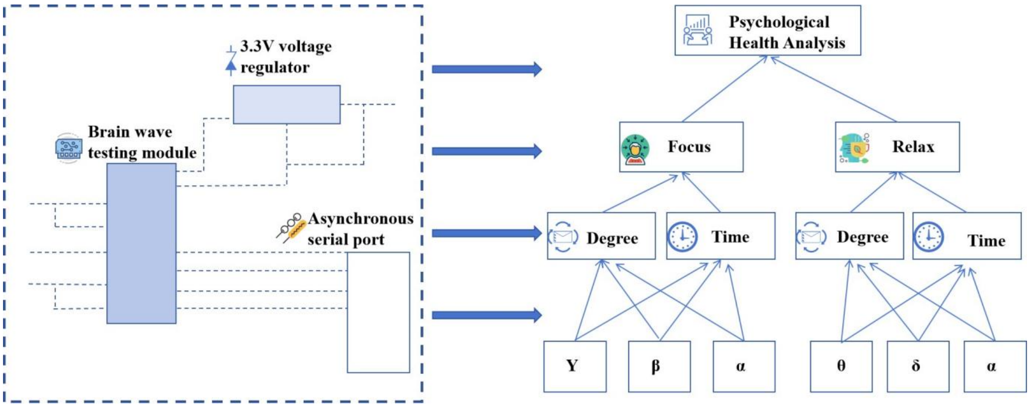

Fig. 3.1: Architecture of Big Data Brain Wave Monitoring and Analysis System

part mainly adopts cluster based EEG monitoring as the main monitoring method, and the uploading of EEG signals is also in the form of cluster uploading. The big data analysis part is responsible for cluster analysis of EEG data and ultimately forming psychological health analysis results. The system structure is shown in Figure 3.1.

From Figure 3.1, it can be seen that the monitoring part of the system is mainly composed of a brainwave testing module, equipped with 3 A 3V voltage regulator and asynchronous serial port, this module can complete functions such as brain wave signal acquisition, signal filtering, signal scaling, and signal conversion [15]. In the process of information collection, subjects do not need to undergo traumatic monitoring, but only need to use a head mounted contact point, which is more suitable for the scenario of work psychological monitoring.

In the big data analysis section, combined with the established brain wave monitoring and analysis data-driven system, the system strictly analyzes the changes in different bands of brain waves under external stimuli through big data hierarchy analysis, transforming brain wave performance into two dimensions of psychological focus and psychological relaxation, among them, the bottom level brain wave judgment of psychological focus is based on Y waves, β wave sum α three types of EEG signals are used as the basis, while the bottom level EEG judgment of psychological relaxation is based on θ wave, δ wave sum based on three types of EEG signals. In the scenario of considering work efficiency, the ratio of worker's focus to focus time and the ratio of relaxation to relaxation time is 2, and the matrix is shown in equation 3.3.

$$A_a = \begin{bmatrix} 1 & 2 \\ 1/2 & 1 \end{bmatrix} \tag{3.3}$$

The focus judgment matrix obtained from the analysis is shown in equation 3.4.

$$B_1 = \begin{pmatrix} 1 & 2 & 3 \\ 1/2 & 1 & 3/2 \\ 1/3 & 2/3 & 1 \end{pmatrix} \tag{3.4}$$

The focus duration judgment matrix is shown in equation 3.5.

$$B_2 = \begin{pmatrix} 1 & 1/3 & 1/2 \\ 3 & 1 & 3/2 \\ 2 & 3/2 & 1 \end{pmatrix} \tag{3.5}$$

The relaxation judgment matrix is shown in equation 3.6.

$$C_1 = \begin{pmatrix} 1 & 1/4 & 1/2 \\ 4 & 1 & 2 \\ 2 & 1/2 & 1 \end{pmatrix} \tag{3.6}$$

The relaxation time judgment matrix is shown in equation 3.7.

$$C_2 = \begin{pmatrix} 1 & 1/2 & 1/3 \\ 2 & 1 & 2/3 \\ 3 & 3/2 & 1 \end{pmatrix} \tag{3.7}$$

On this basis, the maximum eigenvalue of the judgment matrix is determined by judging the matrix, and consistency testing is carried out using the eigenvectors and the random consistency indicators found in the query. The results are represented according to the overall ranking, and the dual hierarchical overall ranking of psychological focus and psychological relaxation is finally obtained as shown in equation 3.8.

$$\begin{cases} W_1 = \begin{bmatrix} 0.89 \\ 0.74 \\ 0.50 \end{bmatrix} \\ W_2 = \begin{bmatrix} 0.32 \\ 1.01 \\ 0.75 \end{bmatrix} \end{cases} \tag{3.8}$$

In equation 3.8, W_1 represents the weight coefficient result of psychological concentration, and W_2 represents the weight coefficient result of psychological concentration. Through big data hierarchical analysis, it is possible to analyze the changes in brainwave rhythms of workers in batches, and to make automated judgments on the psychological changes of workers through a combination of quantitative and qualitative methods in a hierarchical and three-dimensional manner [16].

4. Result analysis. The research data comes from the fatigue assessment of sports athletes in a certain school in S Province. The author used wearable EEG detection together, the instrument used dry electrode collection form, and optoelectronic coupling isolation sensor technology to achieve noise reduction [17]. In terms of connection form, the study adopts a unipolar lead form, with the back of the tester's earlobe as the reference electrode. The fixed electrode is placed on the scalp, and the potential difference between the two is recorded. The research designed system can conduct unified real-time testing and big data perception analysis on the psychological concentration and relaxation of subjects. Through two-dimensional decomposition analysis of the psychological state of subjects, dynamic real-time warning can be achieved when the psychological concentration or relaxation of subjects reaches the warning value during the work process, thereby avoiding unnecessary errors caused by psychological problems during the training process. Before conducting actual experimental analysis, the author first conducted brainwave testing analysis on the system, and the specific analysis results are shown in Figures 4.1 and 4.2.

From Figures 4.1 and 4.2, it can be seen that the author divides the different rhythmic segments of EEG waves into different frequency bands from low to high, namely Delta waves (0 Hz to 3 Hz), Thata waves (4 Hz to 7 Hz), Low alpha waves (8 Hz to 10 Hz), High alpha waves (11 Hz to 13 Hz), Low beta waves (14 Hz to 22 Hz), High beta waves (22 Hz to 30 Hz), Low gamma waves (31 Hz to 46 Hz), and Midgamma waves (above 46 Hz).

Different bands display different wavelengths and rhythmic energy amplitudes in the same interval, indicating that the system can clearly distinguish their overlapping and differential parts when facing different wavelengths. The special band peaks formed by Delta waves (0Hz∼3 Hz) and Thata waves (4 Hz∼7 Hz) are also perfectly restored. After conducting big data monitoring and input, analyze the concentration and relaxation status of the subjects [18]. It can be seen that although the noise generated by the subject's own body can have a significant impact on the system's band detection, it still has a good analytical effect on the patient's psychological focus or relaxation during the system detection process. Among them, the band of psychological relaxation is significantly lower than that of psychological attention, and the fluctuation range is larger. There is a clear intersection between the two. Although the noise band of the subjects is similar to the fluctuation area of the psychological attention band, it can be seen that the psychological attention band is not affected, and the energy proportion of different rhythm stages is successfully extracted. It can be seen from this that

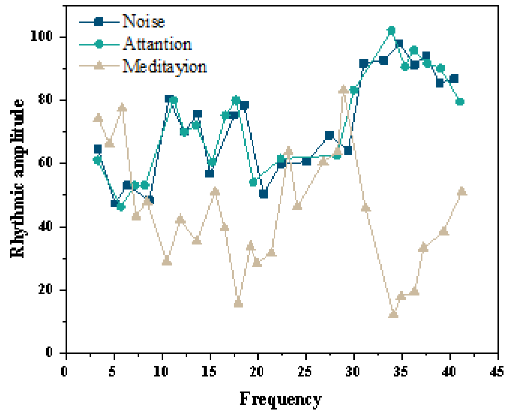

Fig. 4.1: Brain wave rhythm spectrum test chart

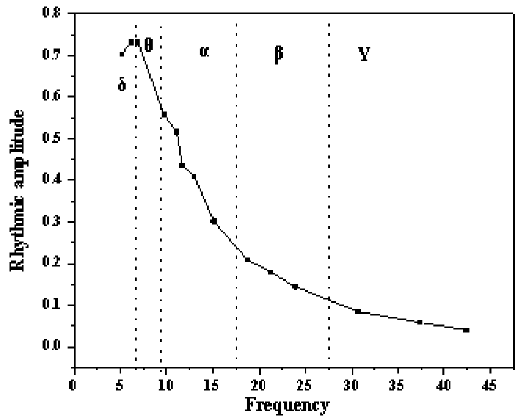

Fig. 4.2: Brain wave rhythm spectrum test rhythm spectrum

the psychological health evaluation data automatic monitoring system designed in the study is effective. The brainwave big data monitoring and analysis results of the subjects in the early stage of training are shown in Figures 4.3 and 4.4.

From Figures 4.3 and 4.4, it can be seen that the proportion of energy in the EEG rhythm spectrum of the subjects is relatively high in the Beta and Gamma bands of the subjects during the early training stage, among them, the energy proportion of the Beta band is 37%, while the energy proportion of the Gamma band is 41%. The Delta band and Thata band have the lowest proportion in the subjects' EEG waves, with the Delta band accounting for 8% and the Thata band accounting for 9%.

At the same time, observing the changes in the brainwaves of the subjects, it can be seen that the overall state of the subjects is relatively stable, and there are few cases of severe fluctuations, indicating that at the current stage, the subjects are in a highly focused state of attention. In this state, even under external stimuli, the subjects can still maintain their high concentration, that is, even if there are stimulating fluctuations in the brainwaves, they can quickly return to a normal and stable state. At the same time, from the comparison between the psychological concentration and psychological relaxation of the subjects, it can be seen that the psychological concentration line of the subjects is basically above the psychological relaxation line in the current situation, indicating that compared to psychological relaxation, the psychological concentration of the subjects is higher and maintains a relatively stable fluctuation range for a long time, showing a gradually decreasing

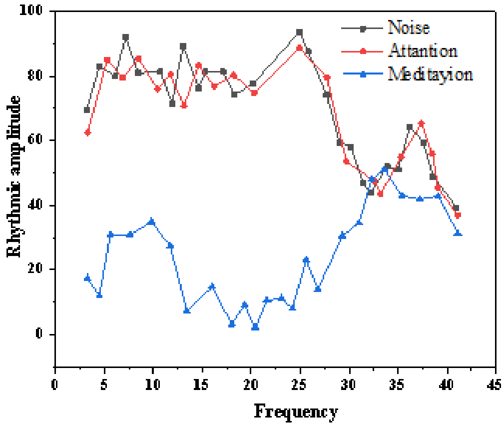

Fig. 4.3: Test chart of analysis results in the early stage of training

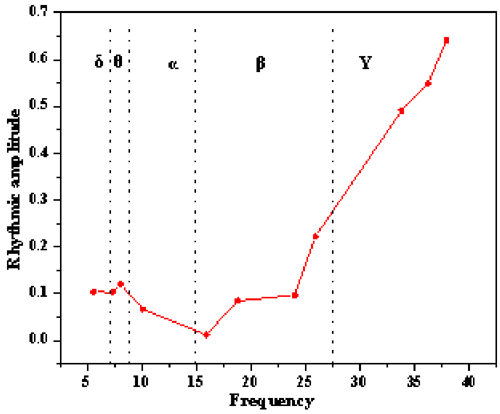

Fig. 4.4: Rhythm Spectrum of Analysis Results in the Early Training Stage

trend overall. On the other hand, the psychological relaxation line is opposite to the psychological concentration line, showing a gradually increasing trend. This indicates that with the increase of training time, the patient's psychological concentration gradually decreases, but the psychological relaxation gradually increases, and the two intersect in the later stage. From this, it can be seen that this stage is the stage in which the overall mental health status of the subjects is relatively good during the homework stage, and there is no need to intervene too much in the psychological status of the subjects [19,20]. But as the training time increases, the subjects will gradually shift from a more focused state to a more tired state during the training process, which is often the main interval for fluctuations in their mental health status.

The monitoring and analysis results of the subject's brainwave big data in this interval are shown in Figures 4.5 and 4.6.

From Figures 4.5 and 4.6, it can be seen that from the perspective of the proportion of energy in the EEG rhythm spectrum of the subjects, during the training fatigue stage, the energy proportion of the Delta and Thata bands in the EEG of the subjects is relatively large, with the Delta band accounting for 43% and the Thata band accounting for 45%. The Beta band and Gamma band have the lowest proportion of EEG waves in the subjects, with the Delta band accounting for 3% of energy and the Thata band accounting for 2% of energy. It can be seen that compared with the early stage of training, the proportion of brainwave energy in the subjects shows a completely opposite state, indicating that at this time, the subjects are generally

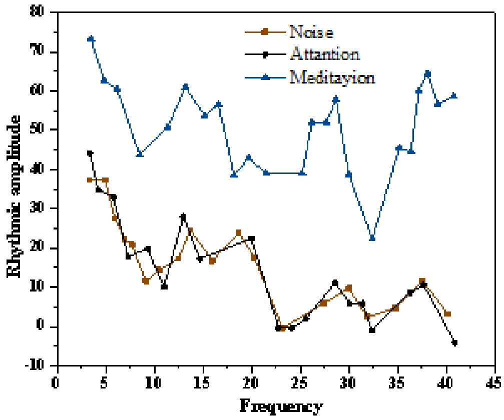

Fig. 4.5: Test chart of training fatigue stage analysis results

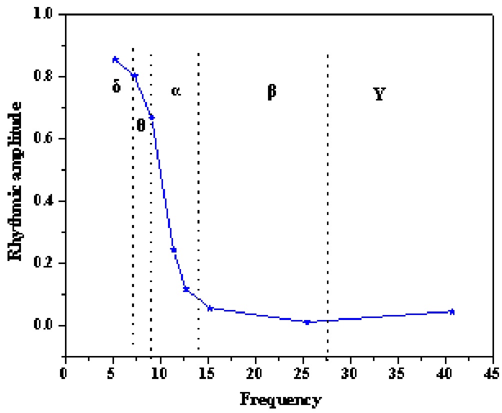

Fig. 4.6: Rhythm spectrum of training fatigue stage analysis results

in a state of fatigue and it is difficult to effectively concentrate their psychological attention. Observing the changes in the brainwaves of the subjects at the same time, it can be seen that compared to the early stage of training, the overall psychological state of the subjects at this stage is more unstable, prone to frequent and intense psychological fluctuations, and easily stimulated by the external environment. Moreover, once external stimuli are generated, the psychological state of the subjects is difficult to immediately recover, the frequency of being influenced by external stimuli is also constantly increasing. From the comparison between the psychological concentration and relaxation of the subjects, the psychological relaxation line is basically located above the psychological concentration line, indicating that compared to psychological concentration, the subjects have higher psychological relaxation, that is, their concentration is continuously decreasing and they are more relaxed. In this situation, the psychological concentration line of the subjects still shows a continuous downward trend, and the gap between their psychological concentration level and their level of psychological relaxation continues to widen. It indicates that the patient's psychological focus is generally in a declining state after the initial stage of training, but the level of psychological relaxation gradually increases in the early stage and stabilizes in the later stage. At this stage, the subjects are relatively tired and require external psychological intervention [21,22].

5. Conclusion. In order to address the issue of real-time and dynamic psychological health assessment for school sports athletes during training, the author combines big data real-time monitoring and analysis technology with brain wave detection technology. Through batch and unified monitoring and big data analysis of the changes in athletes' brain waves during training, the author aims to understand the psychological health of the staff. The author used simulation experiments to test the effectiveness of the technology.

The research results show that in the early stage of training, the energy proportion of the Beta and Gamma bands in the brainwaves of the subjects is relatively large, accounting for 38% and 40% respectively. At this time, the subjects have a greater psychological focus than their psychological relaxation, and can still quickly recover under external stimuli. During the fatigue stage of training, the energy proportion of the Delta and Thata bands in the brainwaves of the subjects is relatively high, accounting for 44% and 46% respectively. At this time, the subjects have a lower psychological concentration than their psychological relaxation, making it difficult for them to recover their focused state under external stimuli and are extremely susceptible to external factors. From this, it can be seen that the athlete mental health detection system designed by the author can effectively detect and analyze the psychological health changes of athletes during the training process, helping athletes improve their training experience while ensuring their own training efficiency.

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