Medical Research on the Impact of Sports on College Students Mental Health in the Era of Artificial Intelligence

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Abstract. To explore the influence of sports on the mental health of college students, this paper combines artificial intelligence technology to examine the impact of sports on college students' mental health. It analyzes the definition and calculation methods of two dimensions of college students' behavior data. Moreover, this paper explains the concept of event-related potentials and explores the definition of ERP components and related indicators. In addition, this paper expounds on the machine learning model architecture, hierarchy definition, activation function, and evaluation index used for psychological parameter identification research in detail. The experimental study shows that the correlation between sports and the mental health of college students is relatively significant, and appropriate sports can effectively promote the mental health of college students.

Keywords: artificial intelligence; sports; college students; mental health; Medical Research on the Impact.
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1 INTRODUCTION

At present, most sports are collective and competitive activities. In sports, people's ability, self-cultivation, and charm are displayed so that they can have a more realistic understanding of themselves. [1]. Moreover, physical activity also helps in self-education. Based on a relatively correct self-understanding, people will consciously or unconsciously correct their cognition and behavior, cultivate and improve the psychological quality and various abilities required by society, and make themselves more suitable for social needs and adaptable to society [2].

The mental health benefits of sports have long been noticed. Psychological factors in sports have a significant impact on fitness and medical effects. Especially in competitive games, psychological factors play an increasingly important role. Athletes with mental health issues have quick reactions, concentrated attention, clear appearance, and quick and accurate movements, which are conducive to high-level competitive ability; otherwise, it is not conducive to competitive-level performance. Therefore, in school physical education, people need to maintain a healthy psychology in sports [3].

Physical activity and mental health are closely related. They influence and restrain each other. Therefore, in sports, we should grasp the law of the interaction between mental health and sports, use healthy psychology to ensure the effect of healthy activities, use sports to adjust people's psychological state and promote mental health. Actively carrying out various sports activities in primary and secondary schools, educating students on mental health, and advancing physically and mentally are essential aspects of modern education that cannot be ignored [4].

Sports can enable college students to overcome objective and subjective difficulties and cultivate goodwill continuously. Help college students form good interpersonal relationships. Interpersonal relationships are an essential factor affecting a person's mental health. Physical activity is a good form of increasing human contact. Because sports are carried out in a particular social environment, and there are exchanges and connections between people, increasing the connection with society will bring psychological benefits, coordinate interpersonal relationships, improve college students' social skills, and improve cooperative spirit [5]. Therefore, college students' participation in sports can also meet people's basic needs- the need for activities and the need for interpersonal communication. This need can be met through collective physical activity. Let them practice how to make individuals adapt to other individuals and groups and cultivate good personality and psychological characteristics, which is the key to the success of college students in society [6].

Physical activity is helpful to the development of college students' character. Human character is the synthesis of various psychological characteristics of the human body, embodied in interests, hobbies, talents, temperament, etc. All sports activities are closely related to character and significantly affect cultivating and developing people's character. Regular participation in sports is more likely to form close relationships with others, and interpersonal skills are also more vital [7]. The practice has shown that people who often participate in sports activities have various interests, cheerful personalities, open-mindedness, and generosity. At the same time, sports can help improve college students' sense of self-responsibility, group responsibility, and social responsibility, learn to respect and care for others, and care about the development of themselves, their families, and groups with a positive attitude [8].

In sports, one of the main factors affecting mental health is emotion, which can be regulated through sports. Negative emotions are one of the critical factors leading to physiological and psychological abnormalities and diseases, and sports can bring people happiness and joy. They can reduce tension and anxiety, thereby regulating emotions and improving mental health [9].

The most essential part of a human's psychological adaptation is interpersonal relationships. Interpersonal relationships are an important factor affecting a person's psychological health. Those with good interpersonal relationships are always happy, energetic, and interested in everything. These people live happily and comfortably; those with bad interpersonal relationships are often listless and depressed. Lack of joy, lack of pleasure in life. Sports can change this phenomenon because sports are always carried out in a particular social environment; they interact and make contact with the crowd; people can better overcome loneliness, forget troubles and pains, coordinate interpersonal relationships, expand social interactions, and improve social adaptability [10].

The increasingly fierce social competition and the increase of life troubles may cause many people to feel pessimistic and disappointed, which in turn leads to various psychological disorders such as depression, loneliness, and anxiety. When people participate in a particular sport and keep exercising, their physical skills and physical fitness will be improved, and they will also master and develop some sports skills and techniques accordingly [11]. People will transmit their achievement information to the brain through self-motion feedback to obtain the cognitive and emotional experience of self-achievement, resulting in pleasure, excitement, and happiness. Therefore, appropriate sports can help individuals with psychological disorders get psychological satisfaction and produce a positive sense of achievement [12]. Right sports can give the destructive emotions and psychological depression of college students a reasonable form of release so that the mental state of college students can be balanced and warm, to relieve and eliminate psychological fatigue and depression and promote the mental health of college students to achieve treatment. Effects of mental illness. As an effective means of improving physical health, sports will inevitably promote people's mental health [13]. Among college students, physical exercise can slow down or eliminate symptoms such as anxiety and depression caused by setbacks in learning and other aspects, provide a reasonable and effective means for venting negative emotions, and prevent the occurrence of psychological disorders or diseases [14]. In short, sports can cultivate goodwill quality, effectively promote intelligence development, regulate emotions, enhance self-concept, improve interpersonal relationships, enhance mental health, and enable individuals to exert their optimal psychological performance [15].

Life is only once for everyone. If you don't have a correct outlook on life and health, you will often make your life path full of thorns. By improving people's quality of life and maintaining a good attitude, they can easily cope with the storms and difficulties in life [16]. The quality of life is closely related to the quality of study and work performance. Only with a steady improvement in the quality of one's own life can a solid platform be built for one's intense study life and future work; otherwise, nothing can be discussed. Sports can temper and strengthen college students' self-confidence, self-esteem, pride and self-improvement. Spirit must depend on material to exist, which is Marx's view of dialectical materialism. Believing in oneself and believing in the future is a rational reflection of a person's aggressive attitude toward life [17].

This paper combines artificial intelligence technology to explore the impact of sports on college student's mental health and improve the effectiveness of college student's mental health education.

2 RELATED TECHNOLOGIES AND METHODS

2.1 Behavioral Data

As one of the response variables, reaction time (RT) is widely used in research fields such as psychology, cognitive neuroscience, and brain science. This is due to the inability of the response to co-occur with the stimulus. In most cases, the individual needs to detect the stimuli through the sensory organs, transmit the nerve impulses to the corresponding areas of the brain for processing, and then send the electrical signals to the relevant nerves or effector organs that control the muscles through the targeted response nerve pathways, and finally, the individual appears. The specific behavioral responses are shown in Figure 1.

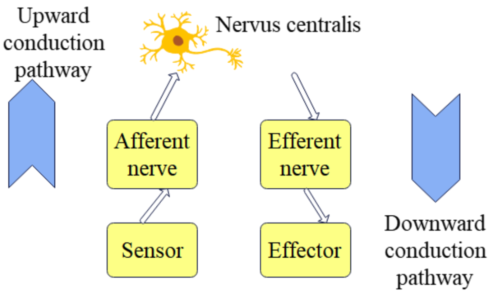


Figure 1: Stimulus-response pathway.

Many factors affect the reaction, and the specific factors are as follows:

1. Stimulus variable: it includes stimulus type, complexity, intensity, and appearance.

2. Body variables include adaptation level, practice effect, set effect, reward and punishment stimuli, age factor, psychological refractory period, etc.

Similarly, there are many ways to study reaction time, as follows:

1. Subtraction method: It subtracts individual responses to stimuli under different conditions and uses the difference to indicate the research goal.

2. Additive factor method: It assumes that the sum of the time required for a series of information processing is the time to complete a task. At the same time, if it is found that multiple factors affect the time required to complete the task in the process of information processing, the researchers can observe the changes in the time needed by combining these factors alone or in pairs to conduct experiments. When, no matter how one of the factors changes, the other factor does not affect the response time, then the effect of the two factors is said to be additive.

3. Windowing experiment: It can directly measure the time required for each information processing stage and can observe the reaction time research method of the characteristics of each information processing stage.

2.2 Event-Related Potential

EEG signals are electrical signals produced by the mutual activity of neurons in the brain. The event-related potential (ERP) is a potential generated in the brain after being evoked by a stimulus, and the stimulus needs to be intentionally given the corresponding psychological meaning.

Common indicators of ERP components include volatility and latency, as shown in Figure 2, and are elaborated as follows:

1. Amplitude: It includes four types: peak-to-peak value, baseline-peak value, average amplitude, and area.

2. Latency period: it includes the peak latency period, the time point corresponding to the maximum peak value; the initial latency, the first time point corresponding to 1/2 the maximum peak; the final latency, the second time point corresponding to 1/2 the maximum peak; and asymmetric peak latency.

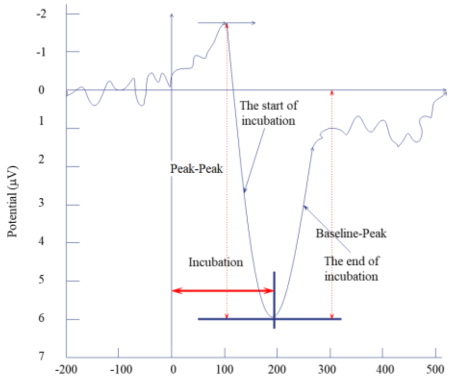


Figure 2: Common ERP component indicators.

2.3 Machine Learning Model

The support vector machine (SVM) is a linear classifier for binary classification based on supervised learning on data. The basic architecture of a linear SVM is as follows:

Data sets $X=\{(x_1),(x_2),\ldots,(x_n)\}$, $Y=\{(y_1),(y_2),\ldots,(y_n)\}$, and class labels $y_i\in\{-1,1\}$ are input. The optimal hyperplane is found, and its formula is as follows:

$$w^T x + b = 0 \tag{1}$$

The decision boundary that satisfies this condition is:

$$\begin{cases} w^T x_i + b \geq 1, y_i = 1 \\ w^T x_i + b \leq -1, y_i = -1 \end{cases} \tag{2}$$

The positive class is above the upper interval boundary, and the negative class is below. The distance between the upper and lower interval boundaries, that is, the margin (margin), is calculated as follows:

$$d = \frac{2}{\|w\|} \tag{3}$$

To solve the maximum-margin hyperplane, it is necessary to satisfy that the distance between the decision boundary and the sample point is not less than 1, which the following formula can solve.

$$max_{w,b}\frac{2}{\|w\|} s.t. y_i(w^T x_i + b) \geq 1 \tag{4}$$

$$min_{w,b}\frac{1}{2}\|w\|^2 s.t. y_i(w^T x_i + b) \geq 1 \tag{5}$$

The decision boundary obtained by the above formula can be used to classify the samples:

$$sign[y_i(w^T x_i + b)] \tag{6}$$

Extreme gradient boosting (XGBoost) is a kind of ensemble learning. XGBoost aims to make the predicted value $\hat{y}_i$ of the tree group as close to the actual value y_i as possible to ensure the generalization ability as much as possible. The big difference from GBDT lies in the calculation of the objective function. The calculation formula is as follows:

$$Obj^{(t)} = \sum_{i=1}^{n} l\left(y_i, \hat{y}^{(t-1)} + f_t(x_i)\right) + \Omega(f_t) + cons\,tan\,t \tag{7}$$

Among them, l represents the loss function, constant represents the constant term, $\Omega(f_t)$ represents the regular term, and the calculation formula of the common term is as follows:

$$\Omega(f_t) = \gamma T + \frac{1}{2}\lambda\sum_{j=1}^{T} w_j^2 \tag{8}$$

Among them, T is the number of leaf nodes, and w_j^2 is the score of leaf nodes.

The original objective function is approximated by Taylor expansion, and the formula is as follows:

$$f(x+\Delta x) \approx f(x) + f'(x)\Delta x + \frac{1}{2}f''(x)\Delta x^2 \tag{9}$$

$$g_i = \partial_{\hat{y}^{(t-1)}} l\left(y_i, \hat{y}^{(t-1)}\right) \tag{10}$$

$$h_i = \partial^2_{\hat{y}^{(t-1)}} l\left(y_i, \hat{y}^{(t-1)}\right) \tag{11}$$

$$Obj^{(t)} \approx \sum_{i=1}^{n} l\left(y_i, \hat{y}^{(t-1)} + g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i)\right) + \Omega(f_t) + cons\tan t \tag{12}$$

Among them, f(x) represents one of the regression trees.

Light Gradient Boosting Machine (LightGBM) is also a type of ensemble learning, similar to GBDT and XGBoost. However, it is better than XGBoost in many aspects, such as higher computing efficiency, accuracy, and processing extensive sample data. In GOSS, according to the descending order of the data gradient, the highest samples are retained as sample subset A, and the remaining samples are randomly sampled. The sampling result is recorded as data subset B of size b, and the formula is as follows:

$$\tilde{V}_j(d) = \frac{1}{n}\left(\frac{\left(\sum_{x_i \in A: x_{ij} \le d} g_i + \frac{1-a}{b}\sum_{x_i \in B: x_{ij} \le d} g_i\right)^2}{njl(d)} + \frac{\left(\sum_{x_i \in A: x_{ij} > d} g_i + \frac{1-a}{b}\sum_{x_i \in B: x_{ij} > d} g_i\right)^2}{n_r^j(d)}\right) \tag{13}$$

Among them, j is the segmentation feature, and d is the segmentation point of j.

A convolutional neural network (CNN) is a feedforward neural network that includes convolution calculation and deep structure and is one of the representative algorithms of deep learning.

Currently, commonly used activation functions include sigmoid, tanh, ReLU, and related variants of RELU, as follows:

1. sigmoid

$$sigmoid(x) = \frac{1}{1+e^{-z}} \tag{14}$$

The sigmoid function is the earliest activation function to convert the input into a value between 0 and 1 for output.

2. tanh

$$tanh(x) = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}} \tag{15}$$

The tanh function is developed after the sigmoid function, and the value range is (-1,1).

3. ReLU

$$Re\,L\,U(x) = \begin{cases} x & \text{ifx} > 0 \\ 0 & \text{ifx} \le 0 \end{cases} \tag{16}$$

ReLU is a modified linear single function with favorable characteristics and can effectively alleviate the gradient disappearance problem of neural networks with deepening depth.

4. PreLU

$$P\,Re\,L\,U(x_i) = \begin{cases} x_i & \text{if} x_i > 0 \\ a_i x_i & \text{if} x_i \le 0 \end{cases} \tag{17}$$

PReLU is a related variant of ReLU. When it is greater than 0, it is consistent with ReLU, but when it is less than 0, i represents different channels, and each channel is multiplied by the corresponding coefficient a.

5. ELU

$$ELU(x) = \begin{cases} x & \text{if} x_i > 0 \\ a(exp(x) - 1) & \text{if} x_i \le 0 \end{cases} \tag{18}$$

ELU is also a related variant of ReLU, which has the same positive value as ReLU, so it can also alleviate the problem of gradient disappearance.

6. SELU

$$SELU(x) = \lambda \begin{cases} x & \text{if} x_i > 0 \\ \text{a}e^x - a & \text{if} x_i \le 0 \end{cases} \tag{19}$$

SELU has further improved ELU so that its output mean is not only closer to 0, but its variance is also closer to unit variance 1, which further achieves the regularization effect and improves the convergence speed of the model. The specific operation is shown in Figure 3.

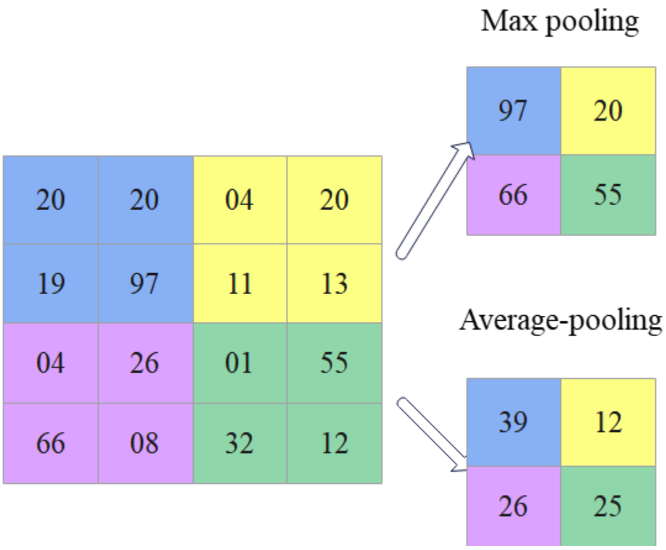


Figure 3: Common pooling methods.

The fully connected layer generally appears in the last layer of the CNN, and all its neurons will have weight connections with all the neurons in the previous layer. The calculation formula is as follows:

$$Y = xw + b \tag{20}$$

The weight is recorded as w, and the offset is b.

An extended short-term memory network (LSTM) is a particular recurrent neural network (RNN). It introduces gates to control the circulation and abandonment of features, which solves the problem of RNNs being unable to learn long dependencies.

The hidden node h_{t-1} has two functions:

1. It calculates the predicted value $\hat{y}_t$ at this moment, and the formula is as follows:

$$\hat{y}_t = \sigma(h_t \times w + b) \tag{21}$$

2. It calculates the hidden node h_t at the next time point.

LSTM consists of a series of LSTM units, the core part of which is the Cell State, which exists in the entire chain system of LSTM. The formula is as follows:

$$C_t = f_t \times C_{t-1} + i_t \times \tilde{C}_t \tag{22}$$

Among them, f_t is called the "forget gate" and is a vector representing which components of C_{t-1} are selected to compute C_t. The information throughput of each element is determined by applying the sigmoid function, whose value range is (0, 1). When the output is 0, no information is allowed to pass, and when the output is 1, all information can pass. The information throughput is f_t, which is as follows:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x] + b_f\right) \tag{23}$$

Among them,h_{t-1} is the previous input, and x_t is the current input.

The updated cell state value must be obtained from the input value and hidden nodes through a neural network, which uses the Tanh function as the activation function. The specific formula is as follows:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{24}$$

$$\tilde{C}_t = tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{25}$$

Among them, $\tilde{C}_t$ represents the updated cell state value, and i_t is called the input gate, which is calculated by applying the activation function sigmoid to $x_t$andh_{t-1}.

Furthermore, the last state value C_{t-1} is updated to C_t, the previous state value is multiplied by f_t to represent the part that needs to be ignored, and then $i_t \times \tilde{C}_t$ is added to the obtained value to obtain a new candidate value, as shown in formula (22).

Finally, it is output based on the cell state. The formula is as follows:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{26}$$

$$h_t = o_t \times tanh(C_t) \tag{27}$$

Among them, o_t is the "output gate," and h_t is the hidden node, which is used to compute the prediction $\hat{y}_t$ and generate the complete input to the next module.

Temporal convolutional network (TCN) is a deep learning model based on temporal features. Compared with various RNN models, it was found that it achieved better performance on multiple tasks. The details are as follows:

1. Causal convolution:

The difference between causal convolution and traditional convolutional neural networks is that their output only relates to previous information and has nothing to do with later details. This causes it to ignore future data and is a strictly time-constrained model, so it is called causal convolution. The architecture is shown in Figure 4. If the filter is $F = \{f_1, f_2, \dots, f_K\}$ and the sequence is $X = \{x_1, x_2, \dots, x_K\}$, the causal convolution at x_t is as follows:

$$x_t = \sum_{K-1}^{K} f_K \, x_{t-K+k} \tag{28}$$

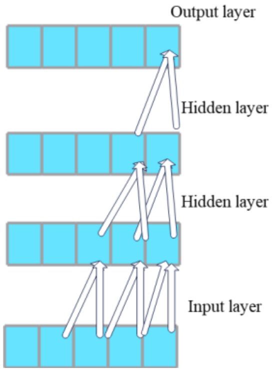


Figure 4: Architecture of causal convolution.

2. Dilated convolution:

Causal convolution still has the common problem of traditional convolutional neural networks; that is, the size of the convolution kernel limits the modeling length of time. If you want to obtain longer dependencies, you need to stack more layers, which will cause the gradient to disappear. Problem occurs. The dilated convolution can solve this problem, as shown in Figure 5. If l_k is the receptive field of the k-th layer, the calculation formula is as follows:

$$l_k = l_{k-1} + \left((f_{k-1}) * {}_{i-1}^{k-1} S_i\right) \tag{29}$$

The current convolution kernel size is f_k, and the stride is S. If d is the dilation rate, the dilated convolution formula is as follows:

$$f_{k\_d} = (d-1) \times (f_k - 1) + f_k \tag{30}$$

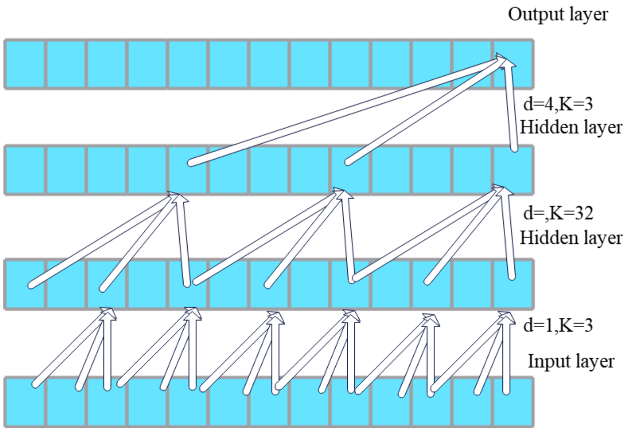


Figure 5: Schematic diagram of dilated convolution.

3. Residual link:

Residual links can effectively train deep networks, and their primary function is to allow the network to pass information across layers.

2.4 Evaluation Indicators of Machine Learning Models

This study uses Six evaluation indicators to evaluate the effect of the machine learning model on severe depression identification. P (Positive) and N (Negative) represent the model's classification result, and T (True) and F (False) mean whether the model's judgment result is correct or not. There are four cases of TP, FP, TN, and FN.

The specific indicators are as follows:

1. F1-score: It is an indicator to measure the accuracy of the binary classification model. It is defined as the harmonic mean of recall and precision. The calculation formula is:

$$F_1 = 2 \times \frac{precision \times recall}{precision + rec} \tag{31}$$

2. ACC: The accuracy rate is the ratio of the number of correct predictions by the model to the total number. The calculation formula is:

$$ACC = \frac{TP+TN}{TP+TN+FP+F} \tag{32}$$

3. Recall: It is the recall rate. That is, in the depressed sample, the proportion that is predicted to be depressed. The calculation formula is:

$$Re\,c\,all = \frac{TP}{TP+FN} \tag{33}$$

4. Specificity: Specificity is also called the actual negative rate. It refers to the proportion of the healthy sample predicted to be healthy. The calculation formula is:

$$Specificity = \frac{TP}{TN+FP} \tag{34}$$

5. PPV: Positive predictive value refers to the proportion of patients predicted to be depressed to the total number of depressed patients. The calculation formula is:

$$PPV = \frac{TP}{TP+FP} \tag{35}$$

6. NPV: Negative predictive value refers to the proportion of individuals predicted to be healthy to the total number of healthy individuals. The calculation formula is:

$$NPV = \frac{TN}{TN+FN} \tag{36}$$

3 RESEARCH ON THE INFLUENCE OF SPORTS ON THE MENTAL HEALTH OF COLLEGE STUDENTS

The model design of this paper is based on the concept of system method, and this paper analyzes and determines the evaluation level, designs the automatic evaluation framework, selects the evaluation strategy, implements the model evaluation, evaluates the model evaluation effect, modifies the model parameters, and applies them. To realize the fusion of various modal data information, the model is designed from the following four parts: data cleaning and preprocessing, text-based affective computing, image-based affective computing, and generation of mental health assessment model, as shown in Figure 6.

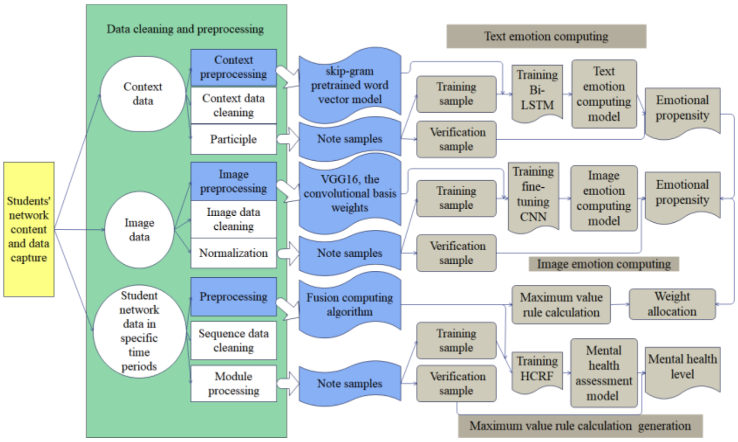


Figure 6: Mental health assessment model.

The developmental relationship of "psychological quality-time" indicates the duration and timeliness of psychological responses under the influence of the environment, as well as the historical process and future development trend of psychological quality formation. The historical relationship of "environment-time" represents the stimuli that significantly affect the psychological growth experience, which are usually some crucial events. The three-dimensional dynamic curve mental image map is a detection map of mental state and a growth trajectory map depicting individual psychological development, as shown in Figure 7.

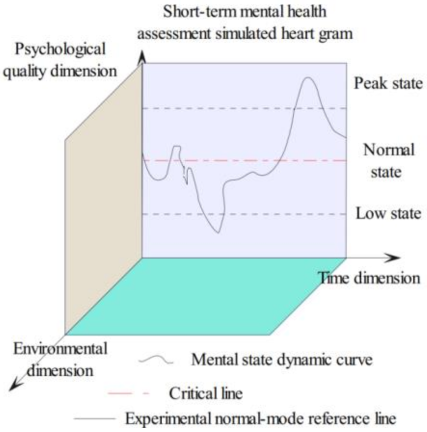
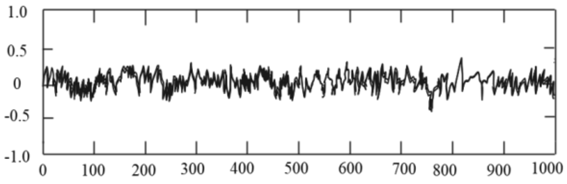
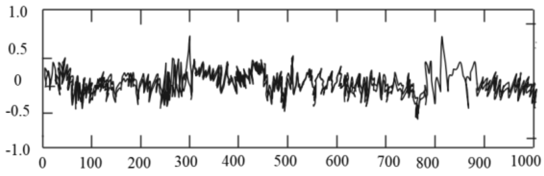


Figure 7: Dynamic curve of mental state.

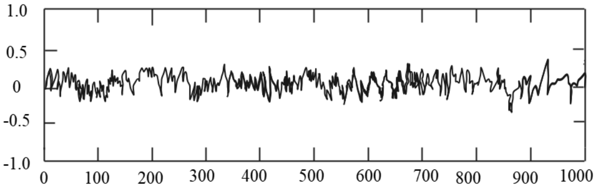
Based on the above, the effect of the model proposed in this paper is tested, and the waveform of the resting state EEG signal is shown in Figure 8. Figure 8 (b) is the original EEG signal waveform collected by this system, and Figure 8 (a) is the EEG signal waveform collected by the MP150 system under the same conditions. It can be seen from Fig. 8(a) and Fig. 8(c) that during the acquisition process, the original EEG signal will be superimposed with the "spurs" caused by the power frequency noise of 50Hz or 60Hz, and the physiological artifacts generated by the EEG, EMG and pulse signals. At the same time, a slight and slowly changing baseline drift caused by impedance changes of the electrodes on the skin surface.



(a) EEG Signals collected by the system



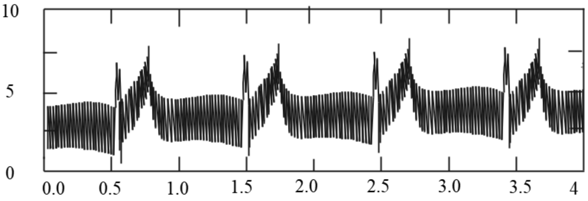
(b) Resting-state primitive EEG signals



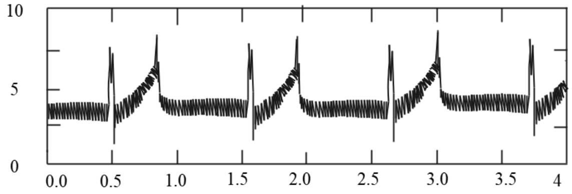
(c) EEG signals after noise removal

Figure 8: Comparison of EEG signal waveforms.

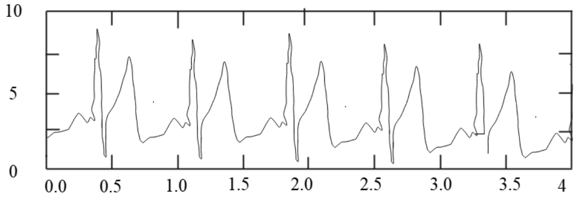
The waveform of the resting state ECG signal is shown in Figure 9. Among them, Figure 9(b) is the waveform of the ECG signal collected by this system, and Figure 9(a) is the waveform of the ECG signal collected by the MP150 system under the same conditions. It can be seen from Figure 9(a) and Figure 9(c) that the original ECG signal is superimposed with frequency interference, EMG noise, and baseline drift during the acquisition process.



(a) Electrocardiosignal collected by the system



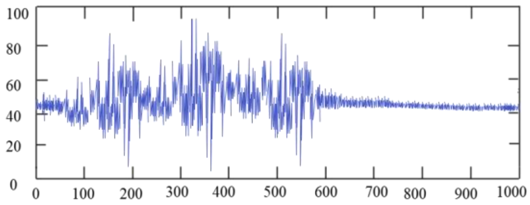
(b) Resting-state primitive electrocardiosignal



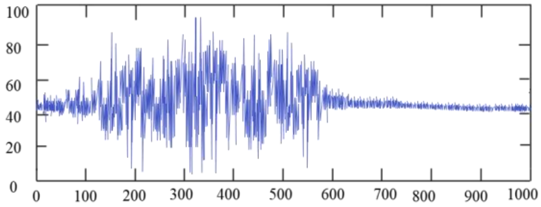
(c) Electrocardiosignal after noise removal

Figure 9: Comparison of ECG signal waveforms.

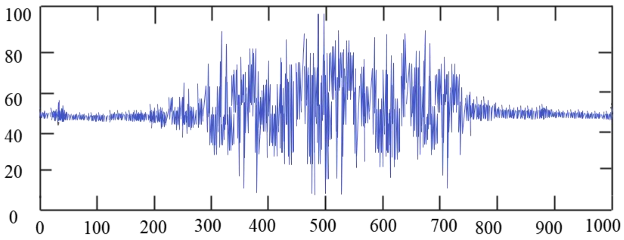
The resting state EMG waveform is shown in Figure 10. Figure 10(b) is the surface EMG signal waveform collected by this system, and Figure 10(a) is the surface EMG signal waveform collected by the MP150 system under the same conditions. Since the amplitude of the surface EMG signal is more significant than that of the EEG signal and the ECG signal, the interference noise with more substantial influence is mainly caused by the motion artifact caused by the movement of the contact surface between the surface electrode and the skin and the crosstalk generated by the surface EMG signal of the non-measured muscle group to the source signal.



(a) Myoelectric Signals Collected by the System



(b) Resting-state primitive myoelectric signals



(c) Myoelectric signals after noise removal

Figure 10: Waveform comparison of surface EMG signals.

The above research proves that this paper's method has a good effect on measuring college students' mental health. Based on this, this paper studies the influence of sports on college students' mental health, analyzes its correlation, and obtains the results shown in Table 1.

Number	*Correlation*	*Number*	*Correlation*	*Number*	*Correlation*
1	*64.723*	*17*	*71.444*	*33*	*64.908*
2	*70.231*	*18*	*64.351*	*34*	*65.942*
3	*67.946*	*19*	*63.072*	*35*	*63.238*
4	*65.887*	*20*	*65.590*	*36*	*67.599*
5	*67.134*	*21*	*71.745*	*37*	*63.442*
6	*66.620*	*22*	*70.295*	*38*	*68.020*
7	*70.182*	*23*	*65.119*	*39*	*71.532*
8	*69.653*	*24*	*66.805*	*40*	*71.501*
9	*66.448*	*25*	*65.803*	*41*	*69.942*
10	*66.370*	*26*	*64.315*	*42*	*63.984*
11	*71.826*	*27*	*65.129*	*43*	*67.932*
12	*66.699*	*28*	*63.393*	*44*	*64.229*
13	*65.610*	*29*	*68.814*	*45*	*63.883*
14	*70.889*	*30*	*69.209*	*46*	*64.405*
15	*69.216*	*31*	*67.996*	*47*	*66.502*
16	*68.699*	*32*	*69.127*	*48*	*63.430*

Table 1: Correlation between sports and mental health of college students.

The above research shows a significant correlation between sports and college student's mental health, and appropriate sports can effectively promote it.

4 CONCLUSIONS

The healthy development of the mind must be based on the normal development of the body, especially the normal and healthy development of the nervous system and brain. Through sports, we can promote the normal and healthy development of the body and provide a solid material foundation for the development of the mind. Moreover, it is an essential condition for psychological development. In addition, sport is an active process in which practitioners must organize their attention, purposefully perceive (observe), remember, think, and imagine. Therefore, regular participation in sports can improve the central nervous system of the human body, improve the coordination of excitation and inhibition of the cerebral cortex, and strengthen the alternating conversion process of excitation and inhibition of the nervous system.

Moreover, it can improve the balance and accuracy of the cerebral cortex and nervous system, promote the development of human perception ability, and improve the flexibility, coordination, and reaction speed of the brain's thinking image. This paper combines artificial intelligence technology to explore sports' impact on college students' mental health. The experimental research shows that the correlation between sports and the mental health of college students is relatively significant, and appropriate sports can effectively promote the mental health of college students. The fusion of medical research and AI-driven analysis in understanding the interplay between sports and mental health offers a pathway to tailor sports programs that holistically support college student's mental well-being. Balancing technological innovation with ethical considerations will be vital in maximizing the potential benefits of this approach in higher education.

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