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Evaluating the Quantitative Effectiveness of Cultural Nurturing Background Music Therapy on College Students' Mental Health in a Machine Learning Framework

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ABSTRACT

Music therapy is the treatment of college students' psychology through various techniques and methods of music, and this paper focuses on researching and analyzing the improvement effect of music therapy on college students' mental health in the context of cultural education. Students' physiological data are collected and denoised, and machine learning models are used to realize the multimodal fusion of all kinds of physiological signal features to obtain the objective psychological state assessment values of college students. The subjective assessment results of the mental health assessment scales were then combined to analyze the improvement effect of mental health of college students in the music therapy intervention. The analysis of the psychological health status of the students before and after the intervention experiment revealed that the objective assessment values of the psychological state of the college students in the intervention group gradually tended to be positive with the music therapy, and the subjective assessment results of the psychological health scales of the students in the intervention group were significantly better than those of the non-intervention group after the experiment ($P<0.05$). Music therapy has a significant role in intervening in the mental health of college students and resolving their psychological malaise, which is of great practical and guiding significance in improving the psychological tolerance and health of college students.

Keywords: Physiological data, multimodal fusion, machine learning, mental health, music therapy

1. Introduction

In today's fast-paced social environment, college students are facing pressures from academics, employment, socialization and other aspects, and mental health problems are becoming more and more prominent [1-2]. Music therapy, as an emerging psychotherapeutic method, is gradually gaining

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attention. It affects the psychological state of college students in a unique way and provides an effective aid for their mental health [3-5].

First of all, music therapy can help college students relieve stress and anxiety. College life is full of various challenges and uncertainties, examination pressure, interpersonal relationship troubles and so on may lead to students' anxiety [6-8]. Soothing music can encourage the human body to secrete neurotransmitters such as endorphins, which can bring pleasure and relaxation, thus reducing the tension of the body. Music therapy can help students to free themselves from nervousness [9-12]. Secondly, music therapy helps to improve college students' emotional regulation ability. Music has a strong ability to express emotions, and different types of music can evoke different emotional experiences [13-14]. Through contacting and experiencing various kinds of music, college students can sense their emotional changes more acutely and learn to adjust their emotions through music. The cultivation of this ability to perceive and regulate emotions is important for college students to cope with emotional fluctuations in daily life [15-18]. Furthermore, music therapy can enhance college students' self-knowledge and self-expression ability. In the process of music composition and performance, students need to show their inner feelings and thoughts through the form of music. This requires them to think deeply about their emotions, values and personal experiences, thus promoting the deepening of self-knowledge [19-22]. At the same time, music, as a non-verbal way of expression, can help students who have difficulties in verbal expression to express their inner feelings and thoughts more freely, so that their inner world can be better released and understood [23-26].

Literature [27] examined the significance of music therapy for college students' mental health and proposed the orientation and implementation of mental health education. It emphasized the importance of music therapy in eliminating college students' bad emotions, cultivating a healthy mental state, and establishing a correct outlook on three things. Literature [28] and literature [29] explored the impact of music therapy on the mental health of college students during the New Crown epidemic, pointing out that music therapy is an effective way to effectively improve the mental health of students, and it can reduce the psychological pressure and depression of students. Literature [30] analyzed the effects of improvisational music therapy on college students' emotion regulation ability and depressive symptoms. It revealed that improvised music therapy had a positive impact on improving the emotion regulation and reducing the depression symptoms of college students. Literature [31] discussed the impact of music education on college students' mental health, emphasizing that music education not only has a positive impact on students' mental health, but also has multiple physiological effects. Literature [32] studied the effects of mental health rehabilitation interventions for college students by combining self-regulated music psychotherapy. The effectiveness and robustness of mental health rehabilitation methods based on self-regulated music psychotherapy were revealed. Literature [33] explored the effectiveness of group and individual music therapy interventions on college freshmen's social adjustment and negative coping styles, demonstrating that both treatments positively impacted the students, with no significant difference in the degree of impact.

Literature [34] discusses numerous proactive strategies that can be implemented by faculty and relevant staff to support the mental health status of music therapy students. The aim is to help teachers create a safe atmosphere that leads to positive outcomes for students. Literature [35] noted the prevalence of depression among college students and examined the use of music therapy in alleviating depression. It revealed that music therapy alleviates depressive symptoms and improves the emotional state of college students. Literature [36] developed a big data-driven evaluation model of the effectiveness of music education in colleges and universities to make up for the shortcomings of the results of the evaluation of the effectiveness of music education. It illustrated that music systematic desensitization therapy had a positive impact on college students' speech anxiety and shyness, which was conducive to improving interpersonal communication skills. Literature [37] pointed out that anxiety and depression are common mental health disorders among college students and analyzed the efficacy of music therapy, emphasizing its obvious effect in relieving students' anxiety and improving self-efficacy, which is worth publicizing and promoting. Literature [38] demonstrated that music therapy helps to promote the development of college students' mental health, and institutions of higher education can utilize music to treat and resolve college students' psychological barriers, which requires colleges and universities to pay attention to students' psychological guidance in order to promote the development of students' mental health. Literature [39] examined the effect of music therapy on graduate students suffering from depression. It was described that music has a significant effect on the level of depression in graduate students and can be an effective intervention for depression. Literature [40] discussed the effect of music therapy on stress and anxiety in college students. It was noted that females are skewed higher than males in terms of psychological anxiety and that music therapy may be effective in alleviating many psychological problems in students, including depression and post-traumatic stress disorder.

To summarize, music therapy is beneficial to alleviate college students' psychological disorders including depression and anxiety, thus promoting students' mental health and improving their ability to learn and communicate in college life. From many research results, it is easy to see that music therapy has received widespread attention in the treatment of mental health and has achieved good development. However, the evaluation of the effect under the framework of machine learning fails to be reflected in the relevant research in the academic world.

In this paper, the EEG, ECG and eye movement data of college students were collected by portable wearable devices, and the interference signals in the collected EEG signals were denoised by using the independent component analysis method. The ECG signals were decomposed and converted using the EMD algorithm and wavelet transform method, and the eye movement data were smoothed using the weighted moving average method. Subsequently, the processed physiological data were input into the machine learning model, and the physiological and emotional features were extracted through the PPS module and PPE module, respectively, and the fusion of the two was used to output the mental health status values of the subjects from the model, which was used as the objective mental health quantitative results of the students. Meanwhile, the assessment results of SAS and SCL-90 scales were used as the subjective mental health quantitative results. In this study, 52 depressed college students were selected for the intervention experiment, and music therapy was used in the intervention group. By analyzing the objective and subjective quantitative results of college students' mental health before and after the intervention experiment, we explored the effect of music therapy in mental health intervention treatment.

2. Objective machine learning-based measures of mental health

2.1. Physiological data collection

In this study, the physiological signal acquisition devices were selected with due consideration to the application scenarios, and they were all portable wearable devices. The EEG signals were collected by a Neuroscan EEG 64-lead EEG system with a sampling frequency of 1000 Hz, and the data acquisition software was Curry 7. The subjects were asked to wear a disk electrode EEG cap, which was based on the international standard of 10-20 electrode placements, with binaural mastoidal electrodes for reference, and transosseous nerves for detecting the eye movements and facilitating the subsequent de-occlusion of the eye track, and the electrode impedances were stabilized below 10 KΩ during the acquisition process. During the acquisition process, the impedance of each electrode was stabilized below 10KΩ. The EEG signal acquisition device is a combination of SynAmps 2/CURRY 7, which provides powerful recording functions and is capable of multi-conductance impedance measurement, online real-time data processing and spectrum analysis. The ECG signal is collected by the Chero Bluetooth ECG patch with a sampling frequency of 400 Hz, and the subject wears the ECG patch device diagonally above the left chest at a 45-degree angle pointing to the centerline of the sternum.The Chero

Bluetooth ECG patch does not interfere with the subject's normal life and is highly acceptable compared to traditional devices, and it achieves a high detection rate with a long range of 7 days monitoring, and it supports a variety of data transmission modes and real-time viewing. Eye movement data were collected using a Tobii 4c eye-tracker with a sampling frequency of 90 Hz and Tobii software, which was placed horizontally below the stimulation screen, and was not required to be worn by the subject, but only needed to be calibrated in both eyes prior to the experiment. The eye movement data acquisition device consists of a projector, a sensor, and an algorithm. The projector projects an image through the near infrared into the eye, the sensor captures the eye and the effects of the projected image at a high frame rate, and the algorithm searches for specific details of the eye and the reflected image to produce the position of the gaze on the screen.

2.2. Physiological signal noise reduction methods

2.2.1. Electroencephalographic signals.In this study, the traditional denoising process was traded off after referring to a large number of cutting-edge studies, and the final EEG denoising process is as follows.

1) Locate the channel data. The international standard electrode (standard-10-5-cap385) placement method was adopted.

2) Remove useless electrodes. Three useless electrodes, horizontal electrooculographic electrode (HEO), vertical electrooculographic electrode (VEO), and triggering electrode (TRIGGER), were removed.

3) Re-reference. It was statistically found that the signals of bilateral mastoid M1 and M2 electrodes were unstable during acquisition, so the whole-brain averaging electrode method was used for uniform referencing.

4) Filtering. In order to remove the magnetic field interference, the useless frequency band was filtered out using 0.5 Hz high-pass filtering and 40.0 Hz low-pass filtering.

5) Downsampling. In order to improve the calculation speed of subsequent experiments and reduce the risk of experimental failure due to equipment limitations, the data sampling rate was downsampled to 200 Hz and normalized.

6) Independent component analysis (ICA) denoising [41]. ICA, as the core content of EEG signal de-interference, is mainly used to decompose the signal into multiple source signals that are independent of each other, and usually requires manual judgment of the content of the components to decide whether it is a noise component or not, and in this study, we consider the practical application of the problem of choosing automated identification of interference plug-ins.

7) Segmentation. In order to reduce the influence of other characteristic components, according to the mark mark to complete the P300 component latency time period of the title segmentation, and baseline correction uniform zero point to facilitate comparison.

2.2.2. Electrocardiographic signals.The original ECG signal is first modally decomposed using the EMD algorithm [42], the high frequency signal is noise reduced using the wavelet transform method, the median filtering removes the baseline drift for the low frequency signal, and finally the EMD algorithm is used again for reconstruction.

In EMD modal decomposition, the ECG signal $x(t)$ is finally decomposed into a set of Implicit Modal Functions (IMFs) and residual value sums, which are computed as shown in Equation (1):

$$x(t) = \sum_{i=1}^{n} c_i + r_n \tag{1}$$

where C_i represents the IMF and r_n represents the residual. In addition, the EMD modal decomposition process is as follows.

1) Calculate the local maxima and minima of the ECG signal $x(t)$, and calculate the upper and lower envelopes $xu(t)$ and $xl(t)$ by cubic spline interpolation.
2) Calculate the average value of $xu(t)$ and $xl(t)$ to obtain $ml(t)$, as described in Equation (2). Subsequently, the difference between $x(t)$ and $ml(t)$ is calculated to obtain $dl(t)$, and the specific calculation method is shown in Equation (3):

$$ml(t) = (xu(t) + xl(t)) / 2 \tag{2}$$

$$dl(t) = x(t) - ml(t) \tag{3}$$

3) $dl(t)$ as the new signal keep repeating the first two steps until the ECG signal meets the first IMF above: $cl(t)$, the residual value $rl(t)$ is calculated as described in equation (4):

$$rl(t) = x(t) - cl(t) \tag{4}$$

4) $rl(t)$ as a new signal keeps repeating the first 3 steps to get multiple IMFs. after n iterations $m(t)$ becomes a stable signal and stops, signal decomposition is complete.

2.2.3. Eye movement data.Eye movement data smoothing processing using weighted moving average method, in which the single sampling point in the X -axis and Y -axis will be respectively after the combination of the specific calculation process designed as shown in Equation (5):

$$F_t = W_1 A_{t-1} + W_2 A_{t-2} + W_3 A_{t-3} + \ldots + W_n A_{t-n} \tag{5}$$

In the above equation, F_t is the predicted value for the next time sampling point X or Y axis, n is the number of periods for the moving average, A_{t-n} is the actual value for the first n periods, and W_n is the weight of the actual value for the $t-n$th period, where $W_1 + W_2 + W_3 + \ldots + W_n = 1$.

2.3. Mental health detection model based on multimodal fusion

The multimodal objective mental health state detection framework (MMHE) is shown in Figure 1. The framework is divided into two parts: PPS (Predictive Psychological State) and PEF (Predictive Emotional State), which are based on physiological signal features, and PPS (Predictive Psychological State), which assesses the likelihood of mental health abnormality of a subject through the signal features of multimodal physiological signals such as electrocardiography, electroencephalography, and electrocutaneous electricity, and PEF (Predictive Emotional State), which extracts emotional features of multimodal physiological signals and further predicts mental health status through the emotional features. PEF is to extract the emotional features from multimodal physiological signals, and then further predict the mental health status through the emotional features, and finally, the prediction result features obtained from both are fused through TMC evidence fusion to realize the joint detection of the subject's mental health status, and finally, the TMC fusion strategy is utilized to consider the actual assessment credibility of the two parts at the same time in order to arrive at the final results.

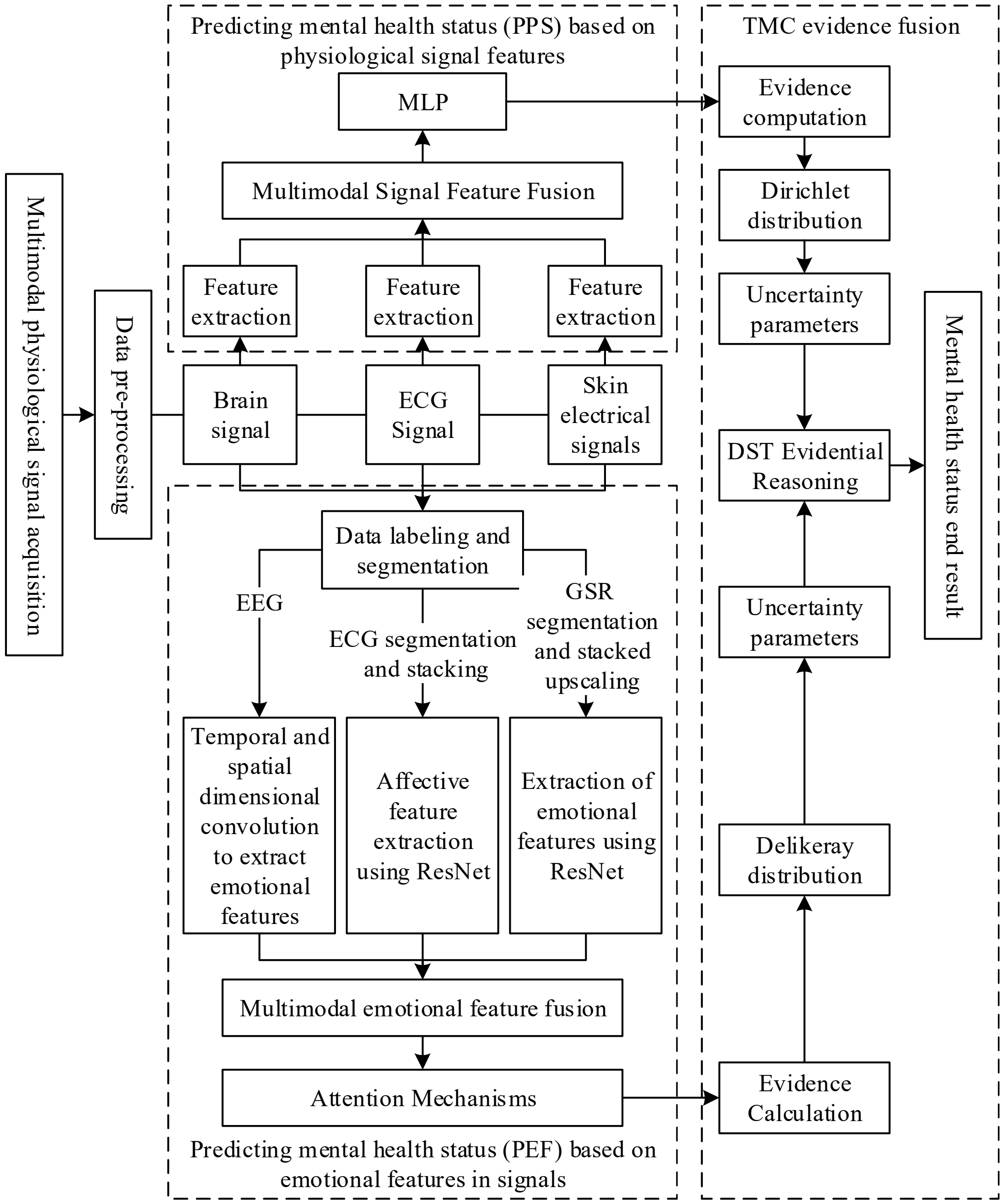


Fig. 1. Multi-modal mental health state detection framework

2.3.1. PPS module.Linear analysis was used in PPS to extract certain linear features in EEG, ECG as well as GSR signals and non-linear features in EEG signals were also used as input features. Finally multilayer perceptron is utilized to predict the risk coefficient of subjects having mental health problems.

The power spectral entropy [43] is calculated from the power spectrum of the signal, which represents the power distribution over different frequency bands. The related calculations are shown in Equation (6) and Equation (7):

$$H_w = -\sum_{i=0}^{N-1} P_x(w_i)\log_2 P_x(w_i) \tag{6}$$

$$P_x(w_i) = P_x'(w_i) \Big/ \sum_{i=0}^{N-1} P_x'(w_i) \tag{7}$$

where $p_x'(w_i)$ is the power spectrum of the signal.

Kolmogorov entropy [44], also known as metric entropy or topological entropy, is a measure of the complexity or randomness of a dynamic system. K The higher the entropy, the faster the nearby trajectories diverge and the more chaotic or complex that signal is considered to be. The relevant calculation is shown in Eq:

$$KE = \lim_{T \to 0} \lim_{\in \to 0^+} \lim_{N \to \infty} \frac{1}{NT} \sum_{n=0}^{N-1} \left(K_{n+1} - K_n \right) \tag{8}$$

Where $K_{n+1} - K_n$ is used to calculate the signal loss when going from N to $N+1$.

Shannon entropy [45] measures the average amount of information required to represent the possible outcomes of a random variable or data source, and the relevant calculation is shown below:

$$K = -\sum_{i=1}^{n} p\left(x_i\right) \log_2 p\left(x_i\right) \tag{9}$$

The correlation dimension quantifies the amount of space occupied by a set of data, which can represent the behavior of a dynamic system over time. The calculation is shown in equation (10):

$$D_2 = \lim_{r \to 0} \ln C(r) / \log r \tag{10}$$

where $C(r)$ is the correlation integral and r is the radial distance around each reference point.

C0 complexity is a measure of the minimum amount of information required to describe a binary sequence or time series to a certain level of accuracy. It is defined as the length of the shortest binary code that can describe the sequence to a certain level of accuracy. Accuracy is controlled by a parameter called error tolerance, which determines the maximum number of errors allowed in the description of a sequence. It is capable of capturing very precise details in a data sequence and it is sensitive to small changes in the sequence. The relevant calculations are shown below:

$$C0 = \sum_{t=1}^{N} \left| s(t) - s'(t) \right| \Big/ \sum_{t=1}^{N} \left| s(t) \right| \tag{11}$$

$$s'(t) = FT - 1(FT(s(t))) \tag{12}$$

Where, $s(t)$ is the original input signal sequence and FT is the Fourier transform.

After manually extracting the signal features of the multimodal signals through the correlation calculation method, all the features are inputted into the multilayer perceptron MLP for classification, and finally a layer of Softmax is connected for the prediction of the results in order to output the coefficients characterizing the presence of mental health status.

2.3.2. PEF Detection Module.Predicting mental health status based on emotional features in PEF starts with extracting emotion-related features from EEG, ECG, and GSR, and in this paper, different machine learning models are used for these three physiological signals to extract the relevant emotional features. The TS-Attention neural network is used to extract features from EEG signal. For ECG and GSR signals, three different scales of sliding windows are used for data cropping and stacking to realize data dimensionality upgrading, and then ResNet is used for emotion classification. After pre-training the emotion classification models for the three physiological signals, EEG, ECG, and GSR, the deep neural network in the models can automatically extract the emotion features. The bottleneck layers of the fully connected layers of these models are individually taken out and spliced together to form a feature fusion matrix, and then the irrelevant features and noise are suppressed by the attention mechanism after the feature matrix, while the relevant features are enhanced.

In order to realize the effect of dynamic fusion, the outputs produced by the two methods PPS and PEF will be virtualized into special modalities for TMC decision fusion, respectively, and the following modalities refer specifically to the PPS virtual modalities as well as the PEF virtual modalities. The method mainly consists of three parts: evidence estimation neural network, Dirichlet distribution, and

DS evidence fusion. The evidence estimation neural network is transformed by replacing the softmax layer of the PPS and PEF classifiers with a non-negative output activation layer, with the aim of obtaining the identification results of different modalities and forming the reliability degree of the related prediction results, followed by the use of Dirichlet distribution for each modal category probability distribution to model the data quality a priori, followed by the use of subjective Logic theory was used to define the uncertainty of each modality, and finally the Dempster-Shafer method was improved to perform a decision level fusion to adapt to changes in the modal quality of the samples, thus adjusting the weights to obtain the reliability of the mental health state outputs. The mental state output values ranged from [-1, 1], where [-1, -0.5), (-0.5, 0.5), and (0.5, 1] belonged to negative, neutral, and positive mental health states, respectively.

3. Subjective mental health assessment tools

3.1. Anxiety Self-Rating Scale

The Self-Assessment Scale for Anxiety (SAS) is a four-point scale consisting of 20 items that assesses the subjective feeling of anxiety and the frequency of symptoms in individuals, including psychological, physical and emotional aspects. Each item is rated on a scale of 1-4, and the total score ranges from 20-80, with higher scores indicating more severe anxiety, and a standardized SAS score of ⩾50 being defined as having anxiety.The SAS scale has been widely used in clinics and research, and is considered to be a simple, valid scale with good reliability and validity.The SAS is suitable for adults with symptoms of anxiety. As the primary scale, it will be measured once a week at the end of the intervention for each of the three groups of subjects.

3.2. POMS Mood State Scale

The POMS Mood State Scale is a psychological assessment tool commonly used to measure mood conditions and is designed to assess an individual's mood state during a specific period of time, making it a simple and valid mood measurement tool.The POMS scale consists of 65 items covering 7 different mood dimensions, namely tension, anger, fatigue, depression, energy, panic, and feelings of self-esteem.A score of 5 indicates none at all, and a score of 0 indicates very much, and the subject college students could express their state of mind with any of the scores from 0-5.

3.3. Symptom Self-Rating Scale

The Symptom Self-Control Scale SCL-90 is a scale commonly used for screening and symptom assessment of psychological disorders. It consists of 90 symptom descriptions covering a wide range of psychological and physical problems such as anxiety, depression, obsessive-compulsive disorder (OCD), and interpersonal relationship difficulties. Subjects check a box in front of each symptom description according to their own situation to indicate the frequency of the symptom, and the total score reflects the degree of distress and severity of illness of the subject for each symptom.The SCL-90 has been used in a wide range of applications including psychological counseling, clinical diagnosis, and epidemiological investigations. As an auxiliary scale, it was assessed once before and once after enrollment in treatment section.

4. Analysis of the effects of music therapy on mental health

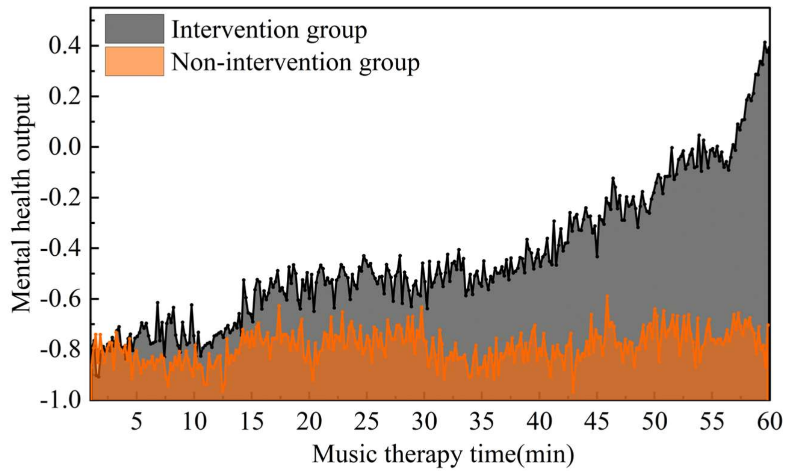
4.1. Experimental design of music therapy intervention

4.1.1. Selection of subjects.Anxiety self-assessment scale was distributed to 200 college students in a college in Changzhou for measurement, and the content of this activity was announced, including the time of this activity and the content of the intervention, etc. Enrollment was carried out in the form of active voluntarism, and 195 valid questionnaires were obtained by combining group and individual testing, including 81 male students and 114 female students. Anxiety self-assessment scale was distributed to the enrolled students, and 52 enrollees were screened in order of total score from highest to lowest. In order to further validate the results of the intervention of music therapy on college students' mental health in the context of cultural education, these 52 students were randomized into two groups, the non-intervention group and the intervention group, with 26 students in each group, and music therapy activities were carried out for the intervention group, while the members of the non-intervention group did not receive any intervention treatment. The 26 members of the intervention group consisted of 11 males and 15 females and the 26 members of the non-intervention group consisted of 13 males and 13 females.

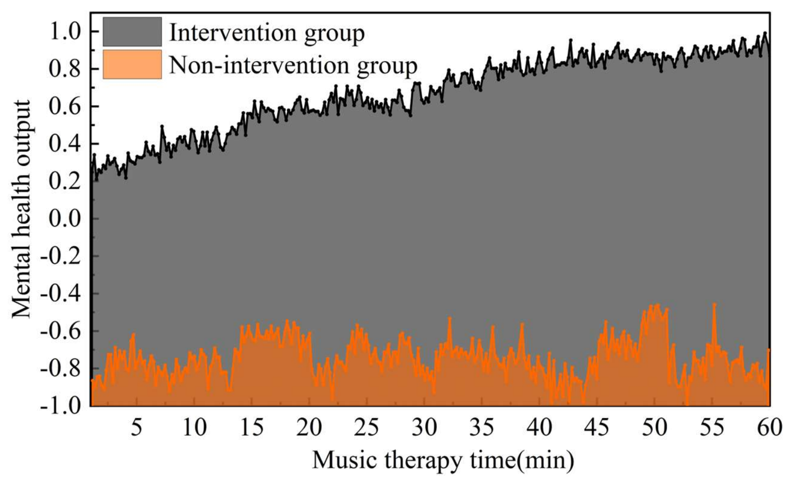
4.1.2. Experimental program.Prior to the music therapy intervention experiment, 52 members of the intervention and non-intervention groups were pretested using the Self-Assessment Scale for Anxiety (SAS), the POMS State of Mind Scale, and the SCL-90 Symptom Self-Assessment Scale, and the pretest data were statistically analyzed to ensure that there was no significant difference between the members of the two groups in terms of the dimensions. Subsequently, an eight-week intervention was conducted using music therapy for the intervention group and no intervention for members of the non-intervention group, and at the end of the eighth activity, a posttest was conducted using the Self-Assessment Scale for Anxiety (SAS), the POMS State of Mind Scale, and the SCL-90 Symptom Self-Assessment Scale for the 52 members of the intervention and non-intervention groups, which was retracted on the spot in order to test the effectiveness of the music therapy activity on the improvement of college students' mental health status. At the same time, physiological data of the subject students were collected during the eight music therapy activities and the machine learning model was utilized to assess the mental health status, and the output of the model was used as an objective quantitative assessment of mental health.

4.2. Analysis of objective changes in mental health status

The objective quantitative outputs of college students' mental health in the two groups detected by the machine learning model in the music therapy intervention experiment are shown in Figure 2, with (a) and (b) representing the results of the analysis at the beginning and end of the experiment, respectively. Students in the intervention group listened to 60-minute-long light music during the experiment, and students in the non-intervention group had no music playing intervention. From the results of the quantitative output of the psychological state of the two groups of students in the first experiment, the output value of the psychological state of the students in the intervention group gradually increased, and the output value of the psychological state of the multimodal fusion model changed from negative to positive, which indicates that the value of the negative emotional state decreases under the intervention of the music therapy, i.e., it means that the mood of the students gradually relaxes, and their tendency to change from the tendency of the negative emotion to the positive emotion or the normal state. The mental state output values of the students in the non-intervention group, on the other hand, did not change significantly and kept fluctuating between -1.0 and 0.6. In the last experiment, the mental state output value at 1 min of the students in the intervention group increased from -0.79 in the initial experiment to 0.25, and the emotional tendency changed from negative to neutral emotions. After conducting 60min of music therapy, the psychological state output value increased to 0.87, which indicated that the frequency and degree of negative emotions appeared decreased with the increase of time, indicating that the music therapy method has a certain effect on the regulation of negative emotions of college students, and verified the improvement effect of music therapy on the mental health state of college students from an objective point of view.



(a) First experiment



(b) The 8th experiment

Fig. 2. Objective psychological state output analysis

4.3. Results of Subjective Assessment of Mental Health of College Students

4.3.1. Test of Homogeneity of Subjects' Mental Health Levels.In order to better measure the intervention and improvement effects of music therapy methods on the mental health status of college students, before conducting music therapy, it is necessary to carry out the t-test of independent samples on the various pre-test indicators of the intervention group and non-intervention group, in order to determine whether there is a more significant difference between the intervention group and the non-intervention group before music therapy. The experimental results of the test of homogeneity of the mental health level of the subject college students are shown in Table 1. There was no significant difference between the intervention group and the non-intervention group in the total scores of the Anxiety Self-Rating Scale, the POMS State of Mind Scale, and the factors of the SCL-90 Symptom Self-Rating Scale, such as the factors of interpersonal sensitivity, depression, anxiety, and hostility ($P>0.05$), and therefore they can be regarded as homogeneous, and they can be analyzed comparatively in terms of the data.

Table 1. The results of the test of mental health of students were tested

Project	Intervention group		Non-intervention group		t	P
	Mean	SD	Mean	SD		

SAS		63.24	18.59	34.52	16.48	1.847	0.892
POMS	Strain	4.84	1.61	4.97	1.22	1	0.429
	Anger	3.9	1.1	4.61	1.46	1.545	0.776
	Fatigue	3.5	1.55	4.59	1.2	1.377	0.468
	Depression	4.43	1.96	4.03	1.87	1.302	0.608
	Energy	3.96	1.61	4.62	1.83	1.222	0.685
	Fluster	4.8	1.54	5	1.08	0.858	0.638
	Sense of self-esteem	4.19	1.99	4.81	1.35	1.553	0.89
	Total score	29.62	6.32	32.63	5.97	1.745	0.387
SCL-90	Somatization	8.64	3.16	7.11	2.11	1.164	0.14
	Obsessive-compulsive disorder	9.11	3.12	8.74	3.31	1.655	0.443
	Interpersonal sensitivity	9.34	3.83	7.11	2.91	0.748	0.226
	Depression	9.07	3.14	9.42	2.35	1.408	0.557
	Anxiety	7.73	3.37	9.12	2.25	1.283	0.251
	Antagonism	8.02	3	8.94	3.88	1.457	0.619
	Horror	9.49	2.69	8.67	2.51	1.982	0.08
	Paranoia	8	2.46	9.05	2.43	1.167	0.183
	Insanity	8.49	2.05	9.92	3.61	0.822	0.898
	Other	7.24	3.36	7.76	2.88	1.577	0.681

4.3.2. Analysis of mental health interventions

1) Analysis of differences in SAS scales. The results of the subjective assessment of the SAS scale in the two groups of college students after the music therapy intervention are shown in Figure 3. Before the music therapy intervention, there was no significant data difference between the intervention group and the non-intervention group, and after the intervention, the difference between the intervention group and the non-intervention group on the SAS scale score in the posttest was significant ($P<0.05$). The mean self-rating scores of college students in the music therapy intervention and non-intervention groups on the SAS scale were 49.67 and 64.46, and this result indicated that music therapy was very effective in alleviating the anxiety level of college students.

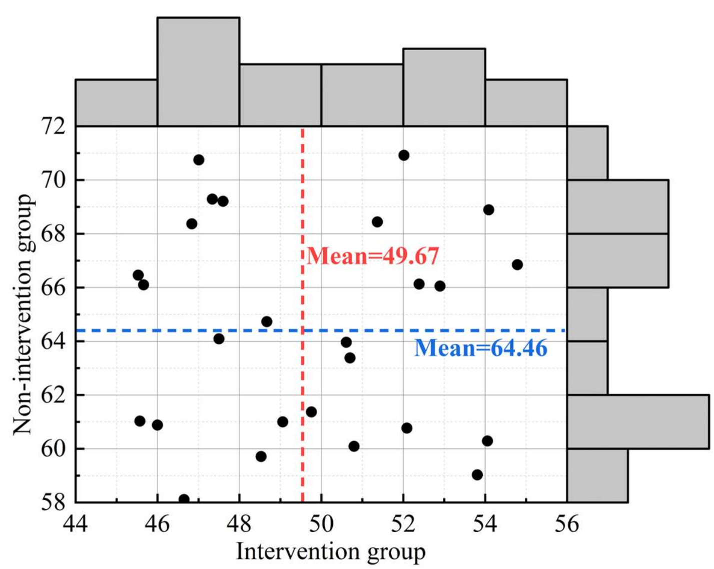


Fig. 3. Comparison analysis of SAS scale evaluation

2) POMS scale assessment results. The results of the subjective assessment of the POMS scale before and after music therapy mental health of the students in the intervention group are shown in Table 2. On the seven dimensions and total scores of the 26 subjects who participated in the treatment, given a significance level of 0.05, since the probability P-value is less than 0.05, it is considered that there is a significant difference between the music intervention experiments on several dimensions of nervousness, fatigue, panic, feeling of inferiority, and the total score of the POMS. In this case, $P<0.01$ on the dimensions of depression and energy, the difference is considered highly significant. However, $P>0.05$ on the dimension of anger indicates that there is no significant difference in the intervention experiment. Overall, the music therapy intervention experiment was useful for most of the dimensions in the POMS State of Mind Scale for college students. During the study, the experimental intervention was conducted through group music relaxation training and mind-body regulation feedback training, in which the improvisational music training method in group music relaxation training fully mobilized the students' enthusiasm for training. In the experimental process, from the initial silence to the relaxed and pleasant conversation between the members all made the subjects relax themselves in a pleasant atmosphere, forget their worries, and alleviate the psychological pressure. The two significant differences in depression and energy indicate that music therapy has a greater therapeutic effect on the mental health level of college students. Comparative analysis of the total results showed significant differences before and after the intervention. The total POMS scores were lower after the intervention, and the sum of the scores of each dimension was relatively lower, indicating a relative increase in the level of mental health of the members.

Table 2. Analysis of the difference between the intervention group's poms

Project	Early stage		Late stage		t	P
	Mean	SD	Mean	SD		
Strain	4.84	1.61	3.14	1.35	2.554	0.016
Anger	3.9	1.1	3.54	1.41	0.863	0.625
Fatigue	3.5	1.55	2.36	1.38	2.986	0.014
Depression	4.43	1.96	2.77	1.11	2.98	0
Energy	3.96	1.61	2.97	1.19	2.823	0.001
Fluster	4.8	1.54	3.24	1.18	2.482	0.006
Sense of self-esteem	4.19	1.99	3.44	1.35	2.706	0.006
Total score	29.62	6.32	21.46	4.52	2.275	0.022

The results of the self-assessment analysis of the POMS scale in the late experimental period of the students in the music therapy intervention and non-intervention groups are shown in Table 3. From the comparative results, there were significant differences between the intervention group and non-intervention group college students in terms of tension, anger, fatigue, depression, energy, panic, and self-esteem on the POMS scale after the 8-week experiment. The total POMS scale score of the intervention group students (21.46) was much lower than that of the non-intervention group students (32.15), indicating that suitable music can provide a relaxing and comfortable environment for college students with mental health crises, thus regulating the imbalance of the psyche and reducing the negative emotions such as tension and anxiety.

Table 3. Results of two groups of students were evaluated in the later POMS scale

Project	Intervention group		Non-intervention group		t	P
	Mean	SD	Mean	SD		
Strain	3.14	1.35	4.58	1.47	2.555	0.039
Anger	3.54	1.41	4.67	1.49	2.833	0.038
Fatigue	2.36	1.38	4.52	1.13	2.297	0.021
Depression	2.77	1.11	4.26	1.48	2.272	0.02
Energy	2.97	1.19	4.51	1.23	2.868	0.02
Fluster	3.24	1.18	4.86	1.19	2.108	0.048
Sense of self-esteem	3.44	1.35	4.75	1.03	2.627	0.047
Total score	21.46	4.52	32.15	5.87	2.281	0.03

3) Differential analysis of SCL-90 symptom self-assessment scale assessment. The results of the difference analysis of the posttest assessment of the SCL-90 Symptom Self-Rating Scale between the intervention group and the non-intervention group of college students are shown in Table 4, and the results of the comparative analysis of the pre-intervention and post-intervention periods of the college students in the intervention group are shown in Table 5. After eight sessions of music therapy intervention, the intervention group students showed very significant differences in the SCL90 scores of interpersonal sensitivity ($5.65 < 9.34$, $P=0.001$), anxiety ($4.00 < 7.73$, $P=0.004$), hostility ($5.15 < 8.02$, $P=0.006$), and terror ($5.39 < 9.49$, $P=0.006$). Symptom factor scores showed highly significant differences ($P<0.01$). It can be seen that this music therapy can effectively alleviate the unhealthy psychological conditions such as anxiety and sensitivity of the college students in the intervention group. In the results of the posttest data of the SCL-90 symptom self-rating scale between the intervention group and the non-intervention group, it was found that the scores of interpersonal factors related to interpersonal communication, such as interpersonal relationship sensitivity ($P=0.001<0.01$), depression ($P=0.006<0.01$), anxiety ($P=0.004<0.01$) in the SCL-90 symptom self-

rating scale assessment of the intervention group were significantly lower than those in the non-intervention group. Exploring the reasons for this, the music involved in this treatment is from the perspective of enhancing the positive emotions of college students as well as promoting the improvement of mental health, helping college students to maintain a positive and healthy state in the music therapy intervention. This enables college students with anxiety or depression to discover the unique charm of the music world in music therapy, and to feel happy and cultivate positive mental emotions through the process of interacting with healthy and positive music melodies. In the process of getting along with themselves, they learn to learn good ways of releasing emotions and managing emotions, and in the process of getting along with others, they can learn to think from others' point of view, and can be understanding and tolerant. Therefore, music therapy not only improves the original negative emotional state of college students, but also relieves the social anxiety symptoms of the members, and helps them to maintain a healthier psychological state in their future study and living environment.

Table 4. Two groups of college students intervened after the results

Project	Intervention group		Non-intervention group		t	P
	Mean	SD	Mean	SD		
Somatization	5.01	2.09	8.20	1.93	0.506	0.028
Obsessive-compulsive disorder	5.45	1.66	9.12	2.24	0.679	0.031
Interpersonal sensitivity	5.65	2.85	7.6	1.76	1.367	0.001
Depression	5.32	2	9.68	2.64	0.998	0.006
Anxiety	4	1.6	8.08	1.64	0.599	0.004
Antagonism	5.15	2.88	9.69	1.61	1.137	0.022
Horror	5.39	1.17	7.05	2.7	0.749	0.018
Paranoia	4.74	2.89	7.47	2.68	0.93	0.041
Insanity	5.84	1.02	8.62	1.37	1.442	0.014
Other	4.44	2.89	7.67	2.41	0.778	0.044

Table 5 Analysis of the intervention group after the intervention group

Project	Early stage		Late stage		t	P
	Mean	SD	Mean	SD		
Somatization	8.64	3.16	5.01	2.09	1.061	0.009
Obsessive-compulsive disorder	9.11	3.12	5.45	1.66	0.855	0.043
Interpersonal sensitivity	9.34	3.83	5.65	2.85	1.044	0.001
Depression	9.07	3.14	5.32	2	0.837	0.016
Anxiety	7.73	3.37	4	1.6	1.095	0.004
Antagonism	8.02	3	5.15	2.88	0.709	0.006
Horror	9.49	2.69	5.39	1.17	0.669	0.006
Paranoia	8	2.46	4.74	2.89	1.114	0.017
Insanity	8.49	2.05	5.84	1.02	1.158	0.017
Other	7.24	3.36	4.44	2.89	1.106	0.027

5. Conclusion

This paper constructs a multimodal objective mental health state detection method based on a machine learning model, predicts and outputs the results of the subjects' mental health state based on

the input physiological signal characteristics, and explores the effect of mental health improvement by combining with the subjective assessment results of the subjects' mental health scale. College students were selected to implement music therapy intervention experiments to analyze the effect of music therapy on mental health level from objective and subjective perspectives, and the results showed that:
1) The model output value of the psychological state of the students in the intervention group increased from -0.79 to 0.25 in 1 min at the beginning and the end of the intervention period, and the emotional tendency gradually changed to a positive direction with the increase of music listening time. There was no significant change in the output value of the psychological state of the students in the non-intervention group.
2) At the end of the intervention experiment, there was a significant difference in the SAS scale scores between the intervention group and the non-intervention group of college students ($P<0.05$), and the mental health status of students in the intervention group was better than that of the non-intervention group. At the same time, there were differences in the assessment results of POMS scale and SCL-90 scale, and the results all indicated that music therapy improved the original negative emotional state of college students, and had a contributing effect on the improvement of their mental health.
3) It is worth paying attention to the fact that the selection and use of music in music therapy is very critical in the whole process, and the next research direction can be considered to explore the impact of different types of music on the mental health of college students, and to maximize the effect of music therapy by selecting the best type of music.

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