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Article

Emotion Regulation in Depression of Physical Achievement Based on Machine Learning

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Abstract: Depression is a clinical disease, mainly accompanied by mood or emotional abnormalities, mainly depression, slow thinking, often accompanied by emotional abnormalities, cognitive behavior, psychophysiological and interpersonal changes or disorders. Here, using static and task-state MRI data, we present a comprehensive study of abnormal neural activity in patients with depression through spatiotemporal, static, and dynamic measures, demonstrating its validity as an underlying biological trait. In order to effectively study the role of emotion regulation in depression, a brain dynamic network synthesis method based on support vector machine model and community detection algorithm was established. We selected data on the mental state of 45 patients from a hospital's psychiatric disease control center. They had no history of hearing impairment and normal (or corrected) vision. All procedures are agreed in writing by each participant. The results show that this method can effectively reduce the depression degree of the subjects, and the multi-level features of the integration of task activation and task regulation connection reach 81% (<0.0010, surrogate test) and 83% (<0.0016, surrogate test), respectively. The recovery of its depressive psychological state has a significant impact. Numerous studies have used various forms of emotional stimuli to reveal abnormal behaviors and neural responses in multi-channel emotional processing in patients with depression, providing valuable insights into the mechanism of multi-channel emotion regulation in depression.

Keywords: Depression, Feature selection, Machine learning, Pattern recognition, Generalized linear model

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1. Introduction

Depression is a common mood disorder characterized by significant and persistent depression. The global prevalence of depression is about 4.45%, and the prevalence in China is about 3.02% [1]. There are more than 65 million depression patients in my country. The prevention and treatment of depression has become an important mental health problem [2]. In real life, due to the complex and changeable pattern and duration of depressive episodes, the uncertain number of lifetime occurrences, differences in response to treatment, and unpredictable disease course and prognosis, clinicians are increasingly concerned about the examination, diagnosis and management of depression. are facing enormous challenges [3]. Depression is third cause of disease burden and is expected to become the first in the total disease burden by 2030 [4]. Therefore, it is of great practical significance for clinical practice of depression to explore the abnormal neural response activities and dysfunctional

functional brain network characteristics of patients with depression, and then reveal the pathophysiological mechanisms at the neural level and develop effective diagnostic evaluation methods.

Compared with Healthy Control (HC) group, depressed patients showed more negative emotions and less positive emotions, indicating that their recognition of emotions tends to be negative or sad information [5]. Many studies have proved that depression shows attentional bias to the stimulus of negative emotions, such as self-referential words, facial expressions or voice expressions. Neuroimaging evidence supports that top-down activity of the prefrontal cortex (especially dorsolateral prefrontal cortex) and bottom-up functional activity of the limbic subcortical network (including the amygdala) are the basis for regulating emotional control and are related to the generation of negative emotions. However, the neural mechanisms underlying how emotional regulation determines individual differences remain unclear. This is partly because previous studies have focused on single-channel, and experimental task designs based on single-channel emotional stimuli have not provided a comprehensive neural basis for depression.

The above problems can be overcome by machine learning approaches using whole-brain models, which have been shown to be associated with disease prediction and representation of important brain functional information at the individual level. Therefore, machine learning methods are widely used in neuroimaging data of patients with mental illness, especially depression. A study by [6] showed that the brain's response to facial stimuli of different intensivities of sad emotions could be used to identify depressed patients from healthy controls with an accuracy of 68%. Another study looked at the neural basis of emotional image processing in healthy controls and depressed patients, classifying the two groups based on differences in their brains' responses to emotional cues with 86 percent accuracy [7]. Recent studies have shown that the local activity of brain regions is closely related to the functional connectivity between regions, and considering the interaction between the two can provide supplementary information for understanding the separation and integration mechanism of brain networks. In addition, the combination of multiple functional features can improve the accuracy of clinical disease classification, and the study found that depression classification accuracy increased by 11% by integrating neural activity processes associated with multiple symptoms.

Depression has been described as an ”autoregulatory disorder”, perhaps more accurately described as an ”inability to care for others” [8–10]. This ”capacity to care for others” actually refers to the emotional capacity. As an advanced social cognitive function, emotion refers to the tendency of individuals to share and understand others' emotional states in the process of communicating with others, which plays an important role in social interpersonal communication [11]. Research [12] shows that emotional ability is abnormal in people with subclinical depression, which will promote the occurrence and development of depression, so it is particularly important to improve this abnormal emotional ability. Emotional regulation is closely related to the generation of emotions [13], and emotional regulation strategies is important for the process of emotional regulation in patients with depression [14], but the relationship between emotional regulation strategies and emotions in patients with depression remains unclear.

Brain is a complex neural network system, which contains different regions separated from each other in space but cooperating with each other in function. When performing a specific task, these regions share information with each other in independent activities, thus forming an efficient integrated network [15]. Under the influence of task-specific fMRI stimuli, the brain functional networks within and between brain regions have extensive and close spatial and temporal connections. We mainly study functional brain networks from static and dynamic dimensions, wherein static refers to an average level of the whole time, while dynamic refers to the division of time information into different stages [16]. Specifically, static brain network has two main features:

(1) task-activation representing the internal response of the region (Task-evoked Activation);
(2) A task modulation connection representing the transfer of information between regions (Task-modulated Connectivity).

Dynamic brain networks have three main characteristics;

(1) Flexibility of network activity (Flexibility);
(2) indicates the concentration of network internal relevance (Recruitment);
(3) represents the integration degree of correlation between networks (Integration).

Task activation is defined as the response of neural activity in the region caused by task conditions, which can be measured by the Generalized Linear Model (GLM), as shown in Eq. (1):

$$Y = \beta_1 \times X_{\text{psycho(Condition)}} + \beta_2 \times X_{\text{psycho(Baseline)}} + \varepsilon. \tag{1}$$

Task activation was defined as $[\beta_1 - \beta_2]$to measure the neural activity response of the region affected by experimental conditions. Task modulation connection is defined as the neural Interaction mode between regions stimulated by task, which can be measured by Psychophysiological Interaction (PPI) [17], as shown in Eq. (2):

$$\begin{aligned} Y =& \beta_0 \times X_{\text{psycho}} + \beta_1 \times X_{\text{psycho(Condition)}} + \beta_2 \times X_{\text{psycho(Baseline)}} \\ &+ \beta_3 \times X_{\text{psycho}} \times X_{\text{psycho(Condition)}} + \beta_4 \times X_{\text{psycho}} \times X_{\text{psycho(Baseline)}} + \varepsilon, \end{aligned} \tag{2}$$

where X_{psycho} represents the time series of experimental conditions, and ε represents the residual term. The task-modulated connection was defined as $[\beta_3 - \beta_4]$ to measure the interaction between two regions affected by psychological and physiological variables.

Depression is a typical case of depressive disorder. Depression is a mental disorder with high prevalence and high clinical cure rate. However, due to the lack of awareness of the disease, fewer patients adhere to formal treatment. Therefore, there are also characteristics of low treatment rate and high recurrence rate. It is mainly characterized by significant and lasting depression. Some patients have psychotic symptoms such as delusions and hallucinations, and have depressive stupor, It can be manifested as fixed facial expression, lack of response to stimulation, less speech or even no speech, less movement or even no depression. Generally, it is manifested as depression, decreased interest, lack of energy, etc.

A large amount of evidence shows that depression is an abnormal brain function disease, and its core symptoms are the reduction of positive emotions and the increase of negative emotions, and abnormal activity areas are often distributed in the emotional regulation system [18]. Task fMRI data can reflect the neural activity patterns of specific brain stimuli and reveal the mechanism of mood disorders at the neural level of depression. For example, [19] have revealed that the limbic system and subcortical regions may be related to emotional processing and emotional control. When emotional stimulation is negative, there are abnormal activation and abnormal functional connections in the amygdala, hippocampus, striatum and thalamus in depression. [20] proved that the amygdala is the center of emotion regulation. In the emotion matching task, depression showed enhanced amygdala activation and decreased dorsolateral prefrontal cortex activation. [21] have also found that depression has insufficient activation of local functional activities in different subregions of the prefrontal cortex, and abnormal functional connections appear in the prefrontal cortex and fusiform gyrus, striatum, superior temporal gyrus, orbitofrontal and superior frontal gyrus, suggesting that the prefrontal cortex can provide a compensation mechanism for emotion regulation. Studies have found that depression overactivates the anterior cingulate cortex and has reduced functional connections with the prefrontal lobe, amygdala, striatum and thalamus, proving that the anterior cingulate cortex is a key region of emotion [22]. In addition, studies have shown that the hippocampus, temporal lobe, cerebellum and insula have an impact on emotional control [23]. It is worth noting that [24] explored the emotional regulation system composed of the prefrontal lobe-limbic system-striatum network in patients with depression, and confirmed that the emotional integration ability of the prefrontal lobe as the higher regulation center was impaired, and the regulation mechanism of the limbic network and striatum system was invalid.

In addition to characterizing the temporal correlation of neural activity between brain regions and networks, we can further analyze the dynamic functional integration of the brain at different stages by using the sliding window method. Based on this, [25] proposed the average flexibility in network S, as shown in Eq. (3):

$$F_s = \frac{1}{n_s} \sum_{j \notin s} f_i, \tag{3}$$

where f_i represents the probability that the same node changes its module attributes in a continuous time window. The higher the average flexibility of the network is, the more frequently the modular attributes of all nodes in the network change under different windows.

Further, by calculating the probability that nodes within and between networks are assigned to the same module, we can obtain the average concentration degree within network S (see (4)) and the average integration degree between network S_n and network S_l (see (5)):

$$R_s = \frac{1}{n_s} \sum_{i \in s} \sum_{j \in s} p_{ij}. \tag{4}$$

$$I_{s_n s_l} = \frac{1}{n_{s_n} n_{s_l}} \sum_{i \in s_n} \sum_{j \in s_l} p_{ij}. \tag{5}$$

Among them, p_{ij} said in the network node i and j belong to the same module of probability, the network of the higher average concentration showed that all the nodes within the network under different window was assigned to the same module, the bigger the probability for the higher the average consolidation degree of network said between network nodes are often cross window points within the same module.

This study used cognitive reassessment and expression of inhibition as independent variables, and conducted regression analysis with opinion choice, imagination, attention to emotion regulation ability, and personal pain as dependent variables. The results showed that cognitive reappraisal was a significant predictor of opinion choice, and suppressed expression was a significant predictor of individual pain.

In this paper, we propose a multilevel classification framework to identify patients with depression and their abnormal neural patterns associated with multichannel emotional processing. Firstly, Regions of Interest (ROI) were analyzed on the whole brain level of the two groups by means of generalized linear model and psychophysiological interaction. Then, three functional features at different levels were extracted;

(1) single level feature of task activation;
(2) represents the bi-horizontal characteristics of the task modulation connection;
(3) represents the multi-level characteristics of integration task activation and connection.

The optimal subset of features at each level was obtained by combining mixed feature selection methods of filtering and embedding, and a linear SVM model was used to identify depressed patients from healthy controls. After obtaining the most discriminating features, the Support Vector Regression (SVR) model was further used to evaluate the predictive power of functional features on individual patients. We hypothesized that the individual-based classification method could characterize functional network abnormalities in the multichannel audio-visual affective processing of patients with depression.

2. Data Analysis Method and Process

2.1. Generalized Linear Model

Specifically, we first convolved the Boxcar Function (Hemodynamic Response Function, HRF) at the beginning of the stimulus for each condition to obtain the BOLD level of neural activity signals.

Then, the audiovisual emotional dissonance condition of each run was used as the experimental condition, and the audiovisual emotional congruence condition was used as the control condition (implicit baseline). After model estimation, the experimental condition minus the control condition was the local activation caused by the audio-visual emotional conflict task (audiovisual emotional incongruence vs. audiovisual mood congruence). At the individual level, the local activation caused by each ROI task was fitted, and the regression variables included two task conditions and a residual term. Thus, a GLM model is obtained, as shown in Eq. (6).

$$Y = \beta_1 \times X_{\text{psycho(Incongruent)}} + \beta_2 \times X_{\text{psycho(Congruent)}} + \varepsilon. \tag{6}$$

Task activation was defined as $[\beta_1 - \beta_2]$ to measure local activity in the seed region resulting from the audiovisual emotional dissonance condition minus the audiovisual emotional dissonance condition. The brain was then divided into 246 ROI using a Brainnetome Brain atlas. The individual task activation map at the ROI level was obtained by averaging the signal value of each endovoxel. Finally, each subject could obtain a column vector with a length of 246.

2.2. Psychophysiological Interaction Analysis

We perform Generalized Psycho Physiological Interaction (GPPI) analysis of Physiological and psychological signals in 246 ROI to explore the connections. Specifically, the time series of each ROI was first deconvolution with HRF function, then multiplied point by point with the time series of audiovisual incongruent and audiovisual congruent conditions as regression variables, and then re-convolved with HRF to obtain neural activity signals of PPI effect at BOLD level. Similar to the process of setting the contrast matrix for task activation, the audiovisual emotional dissonance condition of each run was taken as the experimental condition, and the audiovisual emotional congruence condition was taken as the control condition (implicit baseline). After model estimation, the contrast matrices were set as 1 and -1, and the deduction of the two was the modulation connection caused by audio-visual emotional conflict task (audio-visual emotional incongruence vs audiovisual mood congruence). At the individual level, the task-induced modulation connections between each pair of ROI were fitted, and the regression variables included one physiological signal, two psychological conditions, two physiological and psychological interaction terms, and one residual term. Thus, a new GLM model can be obtained, as shown in Eq. (7):

$$\begin{aligned} Y =& \beta_0 \times X_{\text{psycho}} + \beta_1 \times X_{\text{psycho(Incongruent)}} + \beta_2 \times X_{\text{psycho(Congruent)}} \\ &+ \beta_3 \times X_{\text{psycho}} \times X_{\text{psycho(Incongruent)}} + \beta_4 \times X_{\text{psycho}} \times X_{\text{psycho(Congruent)}} + \varepsilon. \end{aligned} \tag{7}$$

The task modulation connection is defined as $[\beta_3 - \beta_4]$, which measures the modulation relationship between two regions under the interaction of physiological and psychological signals. By storing the task modulation connections between each pair of ROIs in a fully connected matrix, each subject finally got a symmetric matrix with a size of 246×246.

2.3. Statistical Test Methods

In order to explore whether the task activation and task modulation connection of patients with depression are abnormal within and between groups, we performed T tests on the two groups respectively. Specific practices are as follows,

Our original hypothesis is $H_0 : \mu = \mu_0$, and our alternative hypothesis is $H_1 : \mu \neq \mu_0$. The statistic is,

$$T = \frac{|\overline{X} - \mu_0|}{\frac{S}{\sqrt{n}}} \sim t(n). \tag{8}$$

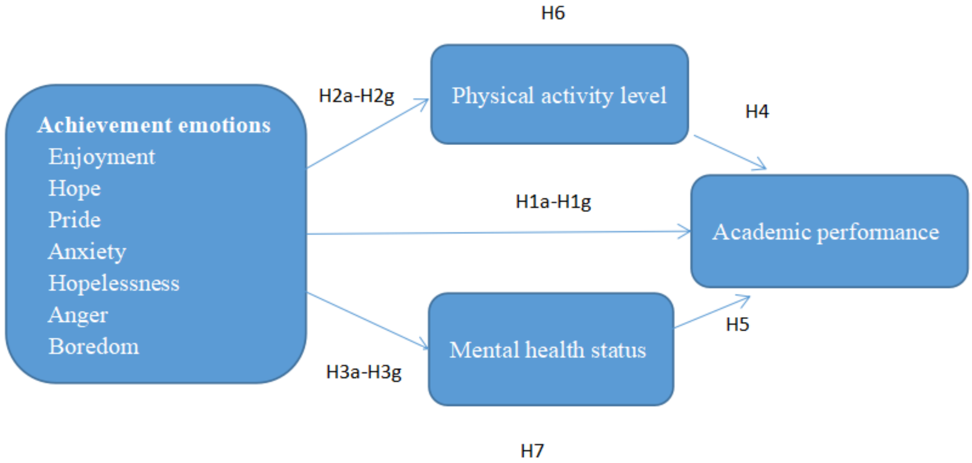


Figure 1. The Proposed Architecture

2.4. Extraction of three Horizontal Features

To identify the neural symptoms characterized by audio and audio emotion processing for depressive patients, we extracted three different levels of features that can be classified. For each subject, the average signal values of all ROI elements are given first, and 246 ROI based active characteristics (primary characteristics) are obtained. Because GPPI analysis removes the upper triangle from the connection matrix as the task modulation attribute (two-layer characteristic), and selects 30135 lower triangles from the matrix to obtain the symmetric connection matrix. To verify whether the multi-level feature combination can improve the classification attributes of single-level and two-level functional features, task activation and task modulation are further integrated, and 30381 items are obtained as task network features (multi-level features).

The research questions aim to investigate the effect of achievement emotions on academic performance, physical activity level, and mental health status among Chinese Physical Education class students in Jiangsu Province. Additionally, the study aims to understand the interplay between physical activity level, mental health status, achievement emotions, and academic performance, as shown in Figure 1. The research can provide insights into the role of emotions in learning and promote the development of strategies and interventions to enhance achievement emotions, physical activity, and mental health outcomes among Chinese Physical Education class students.

In Figure 1 that achievement emotions are independent variables, Physical activity level and mental health status are mediating variables,Academic performance is the dependent variable. The independent variable achievement emotions contain 7 dimensions: Employment, Hope, Pride, Anxiety, Hopelessness, Anger, Boredom. Achievement Emotions Questionnaire (AEQ-G), International Physical Activity Questionnaire (IPAQ), General Health Questionnaire (GHQ-12), academic performance can be measured using academic records such as grades or CGPA.

2.5. Feature Selection Method

Although the amount of measurement in feature space has been greatly reduced, this method is applicable to each feature regardless of the relationship between features. It is worth noting that SVM-RFE considers the interaction of all spatial patterns, but it requires a lot of calculation to select the corresponding characteristics according to the classifier. In addition, the filtering method called minimum redundancy and maximum correlation (MRR) can be independent of the classifier when selecting features with full consideration of feature redundancy and correlation. MRR algorithm is described as follows,

Using mutual information, minimum redundancy $R(S)$ and maximum correlation $D(S, C)$ are defined and relevant criteria $\Phi(D, R)$. Therefore, we propose a hybrid feature selection framework that combines filtering and packaging methods. The two-sample T-test is first used to detect inter-group differences, and the remaining features are further dimensionless based on the SVM-RFE framework of MRMR filters. This method can minimize the redundancy between features and make features converge to the set most relevant to the category.

The mixed feature selection framework adopted in this paper is described as follows,

Randomly divide the data into 10 folds for cross-validation;

Input: training set $\{(x_i, y_i)\}_{i=1}^{N}$, $y_i \in \{+1, -1\}$ consisting of N samples;

1. Initial feature set $S = \{1, 2, ..., N\}$, feature sorting set T= [];
2. Cycle the following process until S = [];
3. The candidate feature set with two-sample T test value $P < 0.01$ in the training set was selected;
4. Train SVM classifier to obtain model weight w;
5. Formula $c_i = w_i^2 + D - \frac{1}{n+1}R, i = 1, 2, ..., N$ is used to calculate the score of the sorting criterion;
6. Find the feature with the lowest ranking score $p = \arg\min\{c_k\}$;
7. Update training set $T = [p, T]$;
8. Other features in S: $S = S - p$.

Output: The selected optimal feature sorting set T.

The feature selection framework is implemented on three levels of features, and for each level of features, we end up with a separate optimal subset of features. In addition, the framework of 10-fold cross-validation (CV10) runs through the entire feature selection process, and all feature selection processes are carried out in the training set to ensure the unbiased prediction.

2.6. SVM Classification Model

Using the LIBSVM toolkit and setting parameters to default values (C=1), we used a linear kernel support vector machine classifier to identify depressed patients from normal subjects. In the classification process, depressed patients were labeled as 1, and normal subjects were labeled as 0. Firstly, the optimal feature subset at different levels is obtained in the training set. The predicted scores of all samples are sorted from high to low, and the lowest score is set as the threshold. Thus, a group (FPR, TPR) can be determined, which is represented in a two-dimensional plane as a truncation point. This process is repeated until all predicted scores are used as threshold values to corresponding cut-off points. The ROC curve representing classification performance can be obtained by connecting all cut-off points in sequence. The AUC value can be obtained by further calculating the area enclosed under the ROC curve. The calculation methods and relationships of the above indicators are described,

$$\mathrm{SE} = \frac{\mathrm{TP}}{\mathrm{TP+FN}} = \mathrm{TPR}. \tag{9}$$

$$\mathrm{SP} = \frac{\mathrm{TN}}{\mathrm{TP+FP}} = 1 - \mathrm{FPR}. \tag{10}$$

3. Experiments

3.1. Research Samples

This study recruited 45 patients with depression from a city mental health center. All the subjects were right handers whose mother tongue was Chinese. They had no history of hearing impairment and normal vision (or corrected vision). All procedures are agreed in writing by each participant.

	Depressive group	Healthy control group	*P* values
Gender (Fe male /male)	29/16	20/23	0.16[a]
Age (years)	31.55±12.13	36.58±16.29	0.19[b]
Years of education (years)	14.32±3.65	12.96±2.79	0.08[b]
Average FD(mm)	0.09±0.07	0.09±0.06	0.75[b]
Handedness (left/right)	0/45	0/43	1[b]
Course of disease (month)	35.93±33.23	-	-
Hamilton depression score	28.37±9.198	-	-
Drug load	2.23±0.822	-	-

Table 1. Data Statistics and Clinical Characteristics of Subjects

IRI-C factor	Study group (n=48)	Control group (n=50)	t values	P values
View see	8.56±4.45	10.87±3.55	-2.607	0.012
Imagination	10.09±4.29	9.11±3.99	1.075	0.287
Empathy concern	11.22±2.93	10.49±2.45	1.223	0.227
Personal pain	12.46±4.67	6.99±4.45	5.445	0.000

Table 2. Comparison of IRI-C Score between Study Group and Control Group (Score, $\overline{x} \pm s$)

The initial sample included 45 clinical patients diagnosed as depression and 43 medical experts, but 5 patients were excluded due to poor quality of MRI data (accuracy rate less than 80%) or incomplete assessment of health status. In addition, four health indicators were deleted due to inaccurate responses to the goals. Finally, 39 cases of depression and 39 cases of health-related complications were included in the analysis. All patients were treated for depression; Five patients received one kind of mood stabilizing drug, eight patients received one kind of psychotic drug, 25 patients received one kind of depression drug, and five patients received various antidepressant drugs. Detailed demographic and clinical data are set out in Table 1. The scores of individual pain factors were higher than those of the control group (P<0.001), as in Table 2.

3.2. Correlation Analysis of Emotion Regulation Strategies and Emotion Regulation Ability

See the team's view, imagination, emotion regulation ability to care for and personal pain factor, respectively, and their age, course and level of education life, depression, cognitive reappraisal and expression suppression, Pearson correlation analysis results show that the fixed number of year of the team's age, course of the disease, affected by education and emotion regulation ability differences had no statistical significance between each factor, as in Table 3.

3.3. Linear Regression Analysis of Emotion Regulation Strategy and Emotion Regulation Ability

In this study, cognitive reappraisal and inhibition of expression were used as independent variables, and opinion selection, imagination, concern about emotional regulation ability, and personal pain were used as dependent variables for regression analysis. The results show that cognitive reappraisal has a significant predictive effect on opinion selection, and inhibition of expression has a significant predictive effect on personal pain, see Table 4.

Project	View see	Imagination	Empathy concern	Personal pain
HAMD	-0.089	0.100	0.055	0.377*
Cognitive reappraisal	0.516**	0.103	0.117	-0.307
Expression inhibition	0.285	0.476*	0.192	0.400**

Table 3. Correlation between HAMD, ERQ and IRI-C Factors (r)

Dependent variable	Predictor variable	Beta	R^2	ADR^2	F values	P values
View see	Cognitive reappraisal	0.516*	0.266	0.245*	13.712**	0.001**
Personal pain	Expression inhibition	0.400*	0.162	0.139	7.227*	0.012*

Table 4. Linear Regression of Emotional Regulation Strategy and Emotional Regulation Ability in the Study Group

Subscale	Case group	Control group	Z	P
E	7(5,9)	12(9,16)	-4.182	0.000
N	22(18,22.30)	6(3,10)	-6.355	0.000
P	5(2,8)	3(2,4)	-2.575	0.012
L	13(9.6,14.5)	13(12,13)	-0.832	0.408

Table 5. Comparison of Scores of Different Factors of Personality Traits

3.4. Comparison of Personality Characteristics between Depression Group and Normal Control Group

Statistical analysis shows that the depression and health control groups have significant differences in Eysenck's endogenous (E), (N) and (P) personality Table 5. Studies have shown that patients with depression are more aggressive and unstable than healthy people, and are prone to excitement, anxiety, depression and impulse.

3.4.1. Comparison of Cognitive Emotion Regulation Strategies between Depression Group and Normal Control Group

There were significant differences in the evaluation of responsibility, meditation, positive reassessment, rational analysis, disaster and condemning others ($p<0.01$). Depression group self-criticism, rumination, disaster and criticism of others compared with the general group. The positive reassessment and rational analysis in the normal group were higher than those in the depression group (Table 6). When it comes to negative or unpleasant experiences, depressed people tend to adopt strategies such as self denial, meditation, catastrophes and condemning others, while healthy people tend to adopt regulation strategies, such as positive reassessment and rational analysis.

3.4.2. Research on the Correlation between Psychological Characteristics of Patients with Depression

Spearman correlation analysis was conducted on various factors of psychological characteristics of the depression group. The results were shown in Table 7. Neuroticism, namely emotional instability, was positively correlated with depression score, and self-blame, meditation and catastrophizing were

Subscale	Case group	Control group	Z	P
Self-blame	15(12,17)	12(9,14)	-4.258	0.000
Accept	14(12,17)	14(13,15)	-1.065	0.288
Meditation	15.5(12,17)	11(10,11)	-5.148	0.000
Actively refocus	11(9.65,12)	12(11,16)	-1.879	0.062
Refocusing on the plan	15.5(12,17)	14(13,15)	-0.605	0.547
Positive re-evaluation	12(11,14)	15(12,17)	-3.193	0..002
Rational analysis	9(6.85,11)	14(13,15)	-5.096	0.000
Catastrophic	13(9,17)	6(5,9)	-5.332	0.000
Blame others	12(11,13)	9(8,10)	-3.277	0.002

Table 6. Comparison of Cognitive Emotion Regulation Strategy Scores

	HAMD	Extrovert	Neuroticism	Spirituality	Covert	Self-blame	Accept	Meditation	Actively refocus	Refocusing on the plan	Positive re-evaluation	Rational analysis	Catastrophic	Blame others
HAMD	-													
Extrovert	0.047	-												
Neuroticism	0.569**	-0.032	-											
Spirituality	-0.219	0.030	-0.183	-										
Covert	0.285	0.065	-0.185	-379*	-									
Self-blame	0.555**	0.159	0.543**	0.008	0.044	-								
Accept	-0.205	0.268	0.273	0.056	-0.032	-0.002	-							
Meditation	0.741–	00048	0.471**	-0.262	0.224	0.378*	-0.027	-						
Actively refocus	0.079	0.188	-0.234	-0.089	0.027	-0.208	-0.023	0.242	-					
Refocusing on the plan	-0.163	0.268	0.058	0.325	-417*	-0.128	0.378*	0.007	0.353	-				
Positive re-evaluation	-0.182	0.350	-0.205	0.122	-0.189	-477**	00222	-0.137	0.535**	0.592**	-			
Rational analysis	0.145	-0.155	0.156	-0.116	0.156	-0.118	-0.304	0.001	-0.202	-0.255	-0.159	-		
Catastrophic	0.409*	-0.234	0.312	-0.092	0.155	0.550**	0.055	0.407*	-0.082	-0.182	-542**	0.262	-	
Blame others	0.055	-0.039	0.023	-0.149	0.252	-0.015	0.067	0.207	-0.119	-0.032	-0.065	0.063	0.517**	-

Table 7. Correlation Analysis of Depressive Patients' Personality Traits, Emotion Regulation Strategies and Depression Score

positively correlated with depression in negative emotion regulation strategies. There is also a certain correlation between personality traits and emotional regulation strategies. For example, neuroticism in personality traits is positively correlated with emotional regulation strategies, while concealment is negatively correlated with psychoticism and refocusing plans. The negative strategies of emotion regulation have mutual influence. For example, self-blame is positively correlated with meditation and catastrophizing. Positive strategies are also correlated with each other. For example, acceptance is positively correlated with repaying the plan, and positive reevaluation is positively correlated with repaying and repaying the plan. Positive and negative strategies are negatively correlated, for example, positive reappraisal is negatively correlated with self-censure and catastrophizing.

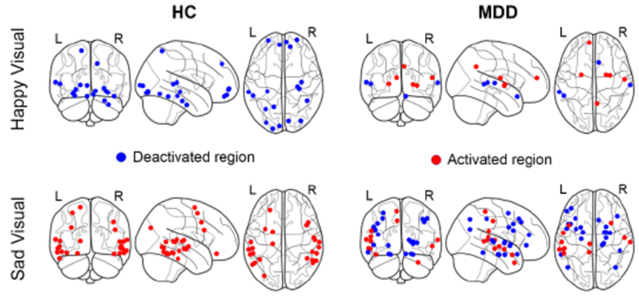
To reveal the spatial distribution patterns of task activation and task modulation connections at the level of healthy controls and depressed patients, we performed a single sample T-test on these two groups respectively, and the results are in Figure 2. Under positive visual mood, healthy controls in the handling of the audio-visual mood consistent conditions for stronger activation and modulation connected task (i.e., audio-visual emotions consistent > audio-visual inconsistent), and the depression patients in the treatment of the audio-visual mood is inconsistent conditions showed a stronger activation and modulation connected task (i.e., audio-visual mood to inconsistencies > audio-visual mood). Notably, the results were reversed under negative visual emotion, with healthy controls showing stronger task activation and task modulation association (i.e., audiovisual dissonance > audiovisual congruence) when dealing with incongruent audiovisual condition. Patients with depression showed stronger task activation and task-modulated connection (i.e., audiovisual congruence > audiovisual incongruence) when dealing with congruent audiovisual condition. These results suggest that there may be different neural responses in task activation and modulated connections between depressed patients and healthy controls. Therefore, we used a relatively weak threshold (P <0.01, uncorrected) to present inter-group differences in task activation and task modulation connection visualization, as shown in Figure 3.

In Figure 2, the color of the region or connection indicates whether the connection increased (red) or decreased (blue) in task activation or task modulation in the audio-visual incongruence condition compared to the audio-visual congruence condition.

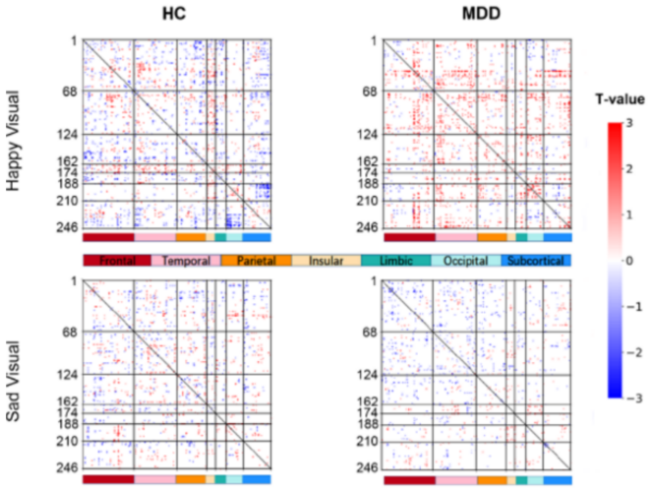
In Figure 3, the color of regions or connections indicates whether task activation or task-modulated connections increased (red) or decreased (blue) in depressed patients compared to healthy controls.

3.4.3. Classification Performance of Multi-Level Features

According to the classification results of three different horizontal features, the multilevel features of integration task activation and task modulation connection reached 81% (P<0.0010, substitution test) and 83% (P<0.0016, substitution test), respectively, under the inconsistent titers of two kinds of audiovisual emotions. In addition, the AUC values of multi-level feature are 0.76 and 0.78, respectively, which are significantly higher than the results obtained by other models based on single-level feature or dual-level feature. The improvement of classification performance indicated that multilevel features had certain advantages in characterizing the neural process of abnormal audio-visual affective

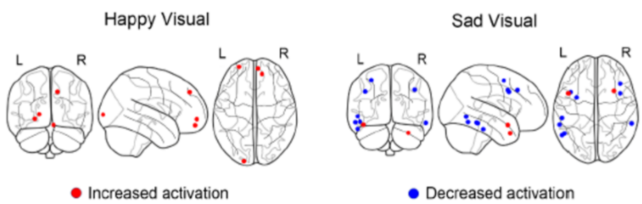


(a) Task-evoked Activation within Groups (Incongruent vs. Congruent)

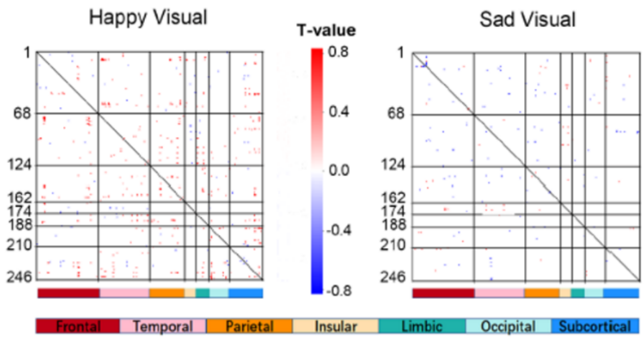


(b) Task-modulated Connectivity within Groups (Incongruent vs. Congruent)

Figure 2. Single Sample T-test at ROI Level (P<0.05, Uncorrected)



(a) Intergroup Task Activation



(b) Inter-group Task Modulation Connections

Figure 3. Two-sample T-test Plot at ROI Level (P<0.01, Uncorrected))

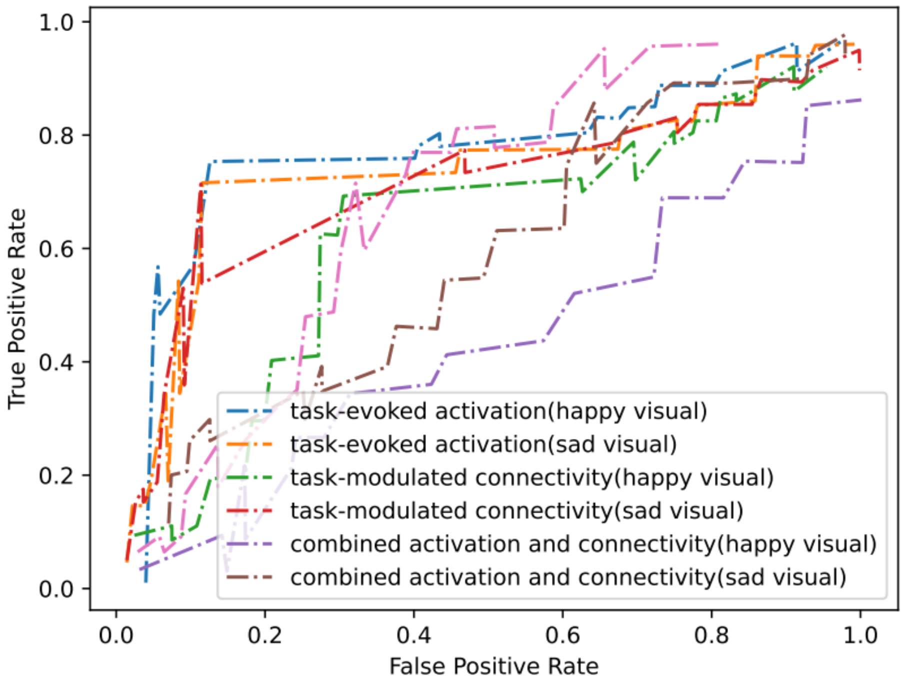


Figure 4. ROC Curves of the three Horizontal Features (Yellow is task activation; Blue is the Task Modulation Connection; Red is Integrated Activation and Connection; Light Color is in the Positive Visual Mood; Dark Colors are in Negative Visual Mood.)

Categorical features	ACC	AUC	SE	SP	*P* values
Task activation (single level)					
Positive visual emotion	0.68	0.63	0.71	0.69	<0.0022
Negative visual emotion	0.72	0.68	0.75	0.72	<0.0013
Task Modulation Connection (double-level)					
Psitive visual emotion	0.73	0.66	0.71	0.74	<0.0027
Ngative visual emotion	0.70	0.64	0.70	0.71	<0.0039
Integrate activation and connectivity (multi-level)					
Psitive visual emotion	0.82	0.77	0.75	0.88	<0.0011
Ngative visual emotion	0.84	0.79	0.77	0.88	<0.0017

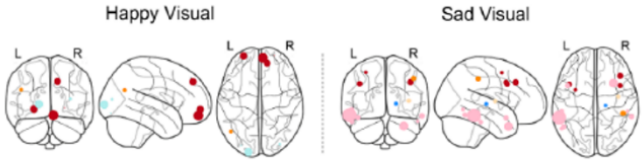
Table 8. Classification Performance of Different Horizontal Features

processing in patients with depression. ROC curves corresponding to the three horizontal features are shown in Figure 4, and corresponding evaluation index values of the classifier are shown in Table 8.

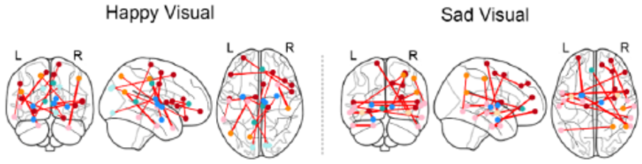
3.4.4. The Most Distinguishing Feature

The return weight of the classification model revealed the contribution of a feature to distinguishing depressed patients from healthy controls, so a feature with a high weight indicated its importance in identifying depression. The most distinguishing features at different levels are shown in Figure 5. We can find that the most important contribution to the area as the prefrontal area. In addition, we examined whether these characteristics differed significantly between the two groups [26, 27].

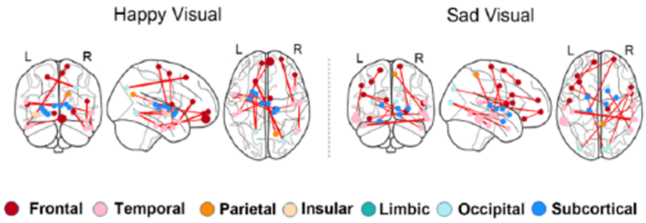
Compared with healthy controls, depressed patients showed increased activation and modulation connections in these networks when they were processing negative auditory emotions under positive visual emotions, but increased when they were processing negative auditory emotions.



(a) Task Activation



(b) Task Modulation Connection



(c) The Integration Activation and Connection

Figure 5. Distribution of the Most Discriminative Force Characteristics (The Thickness of the Line Indicates the Weight Value.)

4. Conclusion

The fact that people with depression pay too much attention to their illness may explain their increased personal distress. Is also faced with when a stranger in trouble problem of their own feelings, and depression will produce more painful emotion regulation ability, because it can imagine if the plight of others what will happen to me, focus on their own feelings, while normal people will generate the appropriate emotion from the perspective of understanding others. In addition, depressed patients will have too much negative emotions brought by excessive attention to themselves in daily life, and this negative emotion is persistent. Research shows that people with depression are unable to quickly and effectively forget negative emotions, which may also contribute to increased personal distress. In this study, among IRI-C depression patients, the selection index of ability factors indicates that depression patients' ability to understand others' views and solve practical problems in interpersonal relationships was weak, and their social functions were disturbed.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declared that they have no conflicts of interest regarding this work.

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