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A Study on the Construction of Test Anxiety Intervention Model for Higher Vocational Students Based on the Perspective of Cognitive Behavioral Theory

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Abstract Test anxiety is an important factor affecting the learning effect and psychological health of higher vocational students. This study constructed a test anxiety intervention model based on the combination of cognitive-behavioral theory and neurofeedback technology. Using a 2×2 mixed experimental design, 50 higher vocational students were selected as the research subjects, divided into 25 each of the experimental group and the control group, and a five-week intervention experiment was implemented. The cognitive behavioral changes and EEG activity characteristics of the students before and after the intervention were analyzed through EEG signal acquisition and psychological scale measurement. The study used a portable three-lead EEG acquisition device to collect five types of EEG signals, Delta wave, Theta wave, Alpha wave, Beta wave and Gamma wave, and extracted linear and nonlinear features for difference analysis. The results showed that the experimental group showed significant improvement in cognitive test anxiety, and the group and time-point interactions reached a significant level ($p=0.041$); subject 1 scores improved significantly, with a significant interaction ($p=0.021$); obsessive-compulsive symptoms were effectively alleviated, with a significant interaction ($p=0.011$); and the Beta wave of subjects in the high-test anxiety group was significantly higher than that of subjects in the low-test anxiety group ($p= 0.038$). The study shows that cognitive behavioral therapy combined with neurofeedback technology can effectively reduce the test anxiety level of higher vocational students and improve their academic performance, which provides a scientific basis and practical guidance for test anxiety intervention.

Index Terms Cognitive-behavioral theory, neurofeedback technology, test anxiety, EEG signals, intervention model, higher vocational students

I. Introduction

Test anxiety is a highly worrying negative emotion such as fear, nervousness, irritability, depression, etc., which leads to certain cognitive activity disorders in an individual in a test situation. At the same time, being in this anxiety state for a long time can cause different degrees of damage to cognition, emotion, mental state and even personality, which seriously affects physical and mental health [1]-[4]. Test anxiety deeply constrains students' motivation and academic quality, exacerbates physiological arousal, as well as inefficient learning behaviors, which in turn have a worse impact on students' academic performance, and is a key factor in triggering numerous adverse learning consequences for students [5]-[7]. Due to the dynamic and hidden nature of test anxiety itself, coupled with the complexity and variability of various influencing factors in the context of social development and the coordinates of the times, students' test anxiety and its intervention mode have become a “frequently talked about” research topic [8]-[10].

Higher vocational students due to the difference in basic knowledge, family financial resources, parental expectations, academic pressure and other factors, appear before the examination insomnia, anxiety, physiological discomfort in the examination room, such as test anxiety phenomenon, and the phenomenon seriously affects the next test whether anxiety [11]-[13]. According to statistics, about more than 10% of students in higher vocational colleges and universities have different degrees of anxiety about exams, and some schools even more than 50% [14], [15]. The number of college students who have test anxiety before and after exams and to a greater extent exceeds 20% of the total number of college students [16]. Synthesizing these research data, it is found that test anxiety has now spread in major higher vocational colleges and universities, and the degree of students' test anxiety has affected their physical and mental health and growth, which should be appropriately intervened.

This study designed a test anxiety intervention model based on the combination of cognitive behavioral theory and neurofeedback technology. The study adopts the experimental design method to verify the effectiveness of the model by comparing the intervention effects of the experimental group and the control group. Specifically, the study will select a homogeneous group of higher vocational students, divided into experimental and control groups, and implement a five-week cognitive-behavioral therapy and neurofeedback intervention for the experimental group, while the control group carries out routine mental health education. The effect of the intervention was assessed from multiple dimensions such as test anxiety level, academic performance, and mental health status through pre- and post-test comparisons. At the same time, the EEG signal acquisition technology was used to analyze the characteristics of EEG activities of students with different anxiety levels, which provided objective physiological indicators to support the intervention effect.

II. Cognitive-behavioral and neurofeedback-based models of anxiety intervention

II. A. Theories related to cognitive behavioral therapy

Cognitive behavioral therapy combines cognitive theory and behavioral therapy organically, so that they complement each other and promote each other to form a kind of psychotherapy. The human body's chain of perception of the outside world is shown in Figure 1.

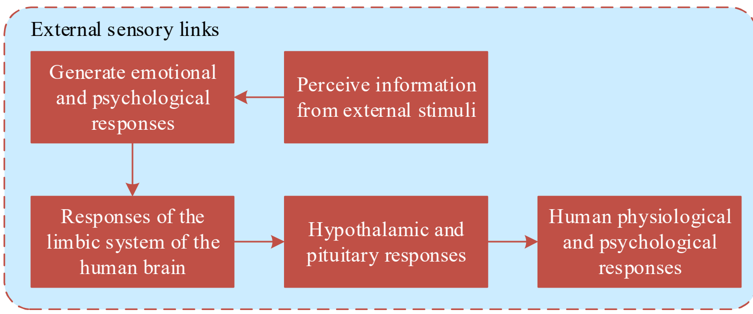

Figure 1: The human body's external awareness link

II. B. Theories related to neurofeedback

Bioinformatic feedback is a self-regulation technique. The neurofeedback loop is shown in Figure 2. Firstly, the physiological information of the human body is collected, and at the same time, it is converted into visual or auditory information and fed back to the individual, and then the brain senses the physiological and psychological state at this time, and consciously self-regulates.

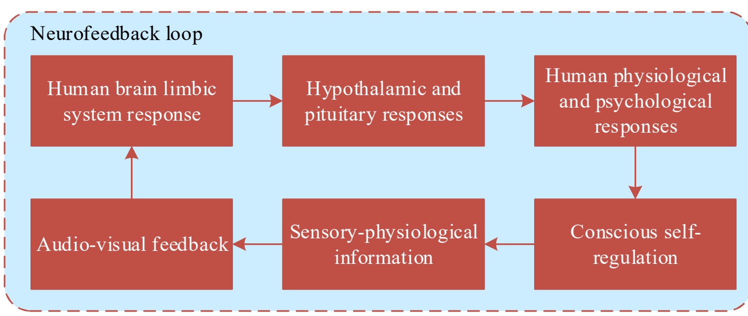

Figure 2: Neural feedback loop

II. C. Anxiety EEG Signal Collection Methods

The human brain is made up of numerous multiple neuron cells. Brain waves can be categorized into five different bands, Delta (δ), Theta (θ), Alpha (α), Beta (β), and Gamma (γ), based on the range of frequency . The human brain is the highest and most complex organizational structure in the nervous system, regulating all activities within the body, and consists of the left and right cerebral hemispheres. According to the mapping of physiological functions, brain regions can be divided into parietal, occipital, temporal, and frontal lobes. The parietal lobe is the sensory center of the human body and is responsible for the processing of perceptual functions such as smell, taste, touch, and pain sensation [17]. The occipital lobe, as the visual center, is located at the back of the brain and is responsible for the processing of vision-related information. The temporal lobe is the auditory center located at the back of the human brain.

II. C. 1) Acquisition methods and equipment

EEG signal acquisition methods are usually categorized as non-invasive and invasive. In this paper, a portable three-lead EEG acquisition device will be used. The device is non-invasive and uses semi-wet electrodes with a small amount of conductive liquid carried on the dry electrode sheet and sealed with a plastic sheet.

II. C. 2) EEG data preprocessing

In this paper, the median filtering method will be used to eliminate the single-direction deviation caused by baseline drift and calibrate the motion trajectory of the EEG signals, which is calculated as shown in (1).

$$Y(i) = Med[X(i-N),\ldots,X(i),\ldots,X(i+N)] \tag{1}$$

where $X(i)$ is the value of the EEG signal samples in the window, N is a positive integer, Med is a median taking operation, and $Y(i)$ is the output value.

II. C. 3) EEG data feature extraction

In this paper, we will extract the linear and nonlinear features of Beta wave, Alpha wave, Gamma wave, Theta wave, and the full waveform for the subsequent differential analysis of EEG features. The detailed description of EEG features is as follows:

A. Linear features

(1) Absolute power (AP): the absolute value of the actual power of EEG signals in each band. Its counting formula is as follows:

$$AP = 10\log P \tag{2}$$

(2) Relative power (AP): the ratio of the absolute power of each sub-band EEG signal to the power of the full band.

(3) Center frequency (CF): the value of the center frequency of each band.

(4) Relative center frequency (RCF): the ratio of the center frequency of each sub-band to the center frequency of the whole band.

(5) Mean Peak Value (MPV): the average of the peak-to-peak values, i.e., the average of the difference between the maximum peak and the minimum peak of the EEG signal over all cycles.

(6) Skewness (SD): the extent to which the EEG signal deviates from a symmetrical distribution. The formula is as follows:

$$SD(x) = E\left[\left(\frac{x_i-\mu}{\sigma}\right)^3\right] \tag{3}$$

where σ is the sample standard deviation of the data, μ is the sample mean, and E is the expectation operation.

(7) Cliffiness: the degree of convergence of EEG signal distribution. Its calculation formula is as follows:

$$Kurt(x) = E\left[\left(\frac{x_i-\mu}{\sigma}\right)^4\right] \tag{4}$$

(8) Ratio of Alpha wave power to Beta wave power (ABR): The formula is as follows:

$$ABR = \frac{P_{alpha}}{P_{beta}} \tag{5}$$

(9) Ratio of Theta wave power to Beta wave power (TBR): it is calculated as follows:

$$TBR = \frac{P_{theta}}{P_{beta}} \tag{6}$$

B. Nonlinear Characterization

(1) Power Spectral Entropy (PSE): is a feature used to study and analyze the time-series signals of EEG data to assess the brain activity [18]. For a signal $X(m)$, the power spectral density $Px(m_i)$ can be calculated by Fourier transform, and then the corresponding power spectral entropy can be obtained. Its calculation formula is as follows:

$$PSE = -\sum_{i=0}^{N-1} Px(m_i)\log_2\left[(Px(m_i)\right] \tag{7}$$

(2) Variance: Used in the time domain analysis of EEG signals to assess the degree of dispersion of EEG signals. The formula is as follows:

$$\sigma^2 = \frac{\sum_{i=1}^{M}(x_i - \mu)^2}{M} \tag{8}$$

(3) Shannon entropy (SE): the amount of information is measured by the amount of information uncertainty. In this paper, Shannon entropy is used to quantify the amount of information in EEG signals. Its calculation formula is as follows:

$$SE = -\sum_{i=1}^{N} P(w_i)\log_2[(P(w_i)] \tag{9}$$

(4) Correlation Dimension (CD): is a characterization index used to quantify the degree of freedom of EEG data. It is used to quantify the complexity of EEG signals when analyzing EEG data, and the value of the correlation dimension is negatively correlated with the complexity of EEG signals. Its calculation formula is as follows:

$$CD = \lim_{x \to 0} \frac{\ln C(x)}{\log x} \tag{10}$$

(5) Kolmogorov entropy (KE): used to measure the amount of information lost per unit of time during system operation. Its calculation formula is as follows:

$$KE = \lim_{M \to 0} \lim_{f \to 0^+} \lim_{N \to \infty} \frac{1}{NM} \sum_{n=0}^{N-1} K_{n+1} - K_n \tag{11}$$

(6) C0 complexity (C0): C0 complexity represents the number of non-regular components, the larger the value of C0 complexity, the more non-regular components, the higher the stochasticity of the EEG signal time series. The formula is as follows:

$$CO = \frac{\sum_{n=0}^{N-1}\left|x(w) - \tilde{x}(w)\right|^2}{\sum_{n=0}^{N-1}\left|x(w)\right|^2} \tag{12}$$

where $x(w)$ denotes the original EEG signal, and $\tilde{x}(n)$ is the inverse calculation of the original EEG signal after the fast Fourier transform.

(7) Sample Entropy (SE): It is a time-domain method used to measure the complexity of the time series of EEG signals, and the sample entropy is extremely sensitive and can respond to the subtle changes of EEG signals. Its calculation formula is as follows:

$$SE(m, x, N) = -\ln\left[D^{m+1}(x) / D^m(x)\right] \tag{13}$$

where $D^m(x)$ denotes the probability that two signal time series have m matching points.

(8) Hjorth parameter (HP): is a method to analyze the EEG signal amplitude changes in the time domain. In this paper, the Activity parameter is chosen to quantify the amplitude of EEG. Its calculation formula is as follows:

$$HP\_Activity = \frac{1}{N}\sum_{n=0}^{N-1}\left|x(n) - \mu\right|^2 \tag{14}$$

III. Research design

III. A. Purpose of the study

Through five weeks of cognitive behavioral therapy and neurofeedback regulation model, to examine the impact of cognitive behavioral therapy and neurofeedback intervention on senior students' test anxiety and other aspects, to verify the effectiveness of this paper's method intervention to alleviate test anxiety.

III. B. Research ideas

This study utilized a mixed experimental design of 2 (time: pre-intervention, post-intervention) x 2 (groups: experimental, control), with group as the between-subjects variable and time as the within-subjects variable. Subjects in the experimental group were given weekly sessions for five weeks. The control group was given a regular mental health education program. The results of the Study 1 measurements were used as a pre-test, and a post-test was administered to both the intervention and control groups one week after the five-week intervention was completed.

III. C. Research methodology

III. C. 1) Subjects

In this study, two classes with comparable number of students, close gender ratio and taught by the same mental health teacher were selected as experimental and control groups. The two groups did not differ significantly on any of the three variables and were homogeneous and suitable for conducting this study. In this study, subjects' implicit self-esteem and trait anxiety were additionally measured, and subjects with an error rate greater than 20% in the implicit self-esteem experiment were excluded as one of the criteria for screening the validity of the questionnaire. Trait anxiety was measured to test the specificity of test anxiety. In the end, 25 subjects in the experimental group and 25 subjects in the control group received the intervention and participated in the pre- and post-tests with valid data.

III. C. 2) Research tools

(1) Rosenberg Self-Esteem Scale
(2) Test Anxiety Questionnaire
(3) Cognitive Behavioral Therapy and Neurofeedback Intervention Scale
(4) Implicit Association Test
(5) Trait Anxiety Scale

Only the Trait Anxiety Scale was chosen for this study. The subscale consists of 20 items, including 10 reverse-scored and 10 positive-scored entries. A 4-point scale was used, with higher scores indicating higher levels of trait anxiety. α The reliability coefficient was 0.835 and validity was good.

III. D. Research procedures

III. D. 1) Determination of experimental and control groups

In order to improve the ecological validity of this study, as well as combining the school curriculum and class schedules, this study was conducted on the basis of the pre-test by using the whole cluster sampling method, with the whole class as the experimental or control group, and utilizing the mental health class to carry out the experimental study.

III. D. 2) Intervention phase

Participants in this intervention program were required to have an informed consent form signed by the student's guardian prior to the start of the program. In this study, the intervention was conducted using the time of the mental health class of the experimental group, while the control group was taught by the psychology class teacher as usual, and the psychology class of both the experimental and control groups was held once a week for 40 minutes. The intervention in the experimental group was conducted during the fourth session on Wednesday mornings, attended by all the students in one of the selected classes, in the classroom where the regular classes were held. After each session, the methodology of this paper was practiced every day before the evening study in that class, for a total of five times per week.

After the last intervention in the experimental group, a post-test was conducted for both groups of subjects within a week, with the same procedure as the pre-test, and the data were organized immediately after the post-test. The method of 2.3 was used to collect EEG data from the students.

IV. Analysis of the results of the experiment

IV. A. Characterization of EEG activity under different tasks in individuals with high and low test anxiety

IV. A. 1) Examination of exam stress situations

The normality test was performed on the subjects' galvanic skin data in the baseline and quiz phases, and it was found that both sets of data did not conform to normal distribution, so the Wilocoxon rank sum test was performed on both sets of data. The rank sum test on the subjects' galvanic skin responses under different tasks is shown in Table 1, and there is a significant difference between the subjects' galvanic skin responses in different task phases (P<0.001), which is manifested in the significantly higher level of galvanic skin responses in the test stress situation, and the above analysis indicates that the setting of the stress test situation is effective.

Table 1: Rank and test of the skin electrical reactions that were tried on different tasks

	Base line(M±SD)	Examination(M±SD)	Z	P
Electrocutaneous reaction	4.23±2.51	5.72±2.59	-3.96	<0.001

IV. A. 2) EEG Characterization of the High and Low Test Anxiety Groups at Baseline

Independent samples t-test was performed on the brain wave data of the baseline stage of the subjects in the high test anxiety group and the subjects in the low test anxiety group, and the results of the independent samples t-test on the brain wave frequencies in the baseline state of the high and low test anxiety groups are shown in Table 2, the mean values of the α wave and θ wave in the high test anxiety group were higher than that of the low test anxiety group, and the mean values of the α/θ wave mean was lower than that of the low test anxiety group, but there was no significant difference between the two groups of subjects (p>0.05). And according to the results of t-test, there is a significant difference (p<0.05) in the θ/β wave and β wave between the two groups of subjects, as shown by the fact that θ/β wave is significantly higher in the high-test anxiety group than in the low-test anxiety group, and β wave is significantly lower in the high-test anxiety group than in the low-test anxiety group.

Table 2: Test results of the independent sample t in the lower brain wave frequency

Brain wave	High test anxiety group M±SD	Low test anxiety group M±SD	t	p	d
θ/β wave	2.16±0.29	1.85±0.35	2.77	0.013	0.73
α/θ wave	0.95±0.19	1.13±0.16	-0.23	0.832	0.08
α wave	7.37±2.45	7.34±1.61	0.25	0.774	0.07
β wave	3.87±0.62	4.54±1.08	-2.39	0.02	0.65
θ wave	8.7±1.21	8.3±1.4	0.55	0.615	0.18

IV. A. 3) EEG Characterization of High and Low Test Anxiety Groups during the Test Phase

Independent samples t-test was conducted on the brainwave data of the test phase between the subjects in the high test anxiety group and the subjects in the low test anxiety group, and the results of the independent samples t-test on the brainwave frequencies in the test state of the high and low test anxiety groups are shown in Table 3, which shows that there is no significant difference between the high and low test anxiety groups in the test phase on the β wave, and in the other brainwave bands of the α/θ wave, α wave, and θ wave on high and low test anxiety groups were also not significant (p>0.05). Significant (p<0.05) differences between the two groups existed only on the θ/β wave, as shown by the fact that the θ/β wave was significantly higher in the high test anxiety group than in the low test anxiety group.

Table 3: Test results of independent sample t of brain wave frequency

Brain wave	High test anxiety group M±SD	Low test anxiety group M±SD	t	p	d
θ/β wave	2.17±0.27	1.96±0.4	2.76	0.038	0.58
α/θ wave	0.83±0.2	0.87±0.15	-0.23	0.808	0.08
α wave	7.42±2.32	7.19±1.64	0.31	0.506	0.24
β wave	3.83±0.6	4.43±0.95	-2.43	0.064	0.58
θ wave	8.57±1.19	8.44±1.44	0.56	0.43	0.24

IV. B. Analysis of application effects

IV. B. 1) Pre- and post-test difference analysis on test anxiety

Pre- and post-test differences between the experimental and control groups on test anxiety were analyzed as shown in Table 4. The group and time-point interaction analyses on test anxiety are shown in Table 5. A 2 (group: experimental group, control group) × 2 (time point: pre-test, post-test) two-factor mixed repeated-test ANOVA was used to test the pre and post-test differences between the experimental and control groups on cognitive test anxiety. The results showed a significant group and time-point interaction on cognitive test anxiety, F(1,35)=4.302, p=0.041, η^2 =0.11. The interaction between the two groups on test anxiety at the group and time-point was not significant, F(1,35)=1.399, p=0.259, η^2 = 0.029.These results suggest that the method of this paper can effectively reduce cognitive test anxiety.

Table 4: The experimental and control group analyzed the analysis of the differences

Scale	Laboratory group		Cross-reference group	
	Pre-test	Post-test	Pre-test	Post-test
Cognitive anxiety	76.25±11.25	71.76±11.89	70.79±8.38	72.35±9.66
Test anxiety	23.54±4.69	21.87±6.07	21.19±3.44	21.22±5.75

Table 5: The group and the time point interaction analysis in the exam anxiety

Variable	Scale	F	df	p
Time*group	Cognitive anxiety	4.302	40	0.041
	Test anxiety	1.399	40	0.259

IV. B. 2) Analysis of pre- and post-test differences in test scores in various subjects

Pre- and post-test differences between the experimental and control groups in terms of test scores in each subject were analyzed as shown in Table 6. The group and time point interactions on final grades in each subject were analyzed as shown in Table 7. A 2 (group: experimental, control) × 2 (time point: pretest, posttest) two-factor mixed repeated-test ANOVA was used to test the pre-post-test differences between the experimental and control groups on final exam scores in each subject. The results showed a significant group and time-point interaction on subject 1 scores, F(1,35)=5.919, p=0.021, η^2 =0.147. Simple effects analyses were conducted, and the results indicated that the difference between the experimental group and the control group in math scores was not significant in the pre-test.

Table 6: The analysis of the differences in the test scores

Disciplines	Laboratory group		Cross-reference group	
	Pre-test	Post-test	Pre-test	Post-test
Disciplines 1	95.966±13.39	100.93±16.94	89.34±11.98	86.4±13.5
Disciplines 2	110.82±8.27	116.36±8.26	106.74±7.71	114.67±6.33
Disciplines 3	95.3±14.07	106.17±14.36	96.59±10.05	105.95±14.64
Disciplines 4	32.18±5.32	38.37±5.89	30.88±5.04	37.67±4.79
Disciplines 5	29.05±5.59	31.09±5.57	26.96±5.79	31.57±5.95
Disciplines 6	58.05±11.51	49.16±8.92	53.51±10.5	48.84±7.59
Final grade	421.366±58.15	442.08±59.94	404.02±51.07	425.1±52.8

Table 7: The group and the time point interaction analysis in the final grades of each section

Variable	Disciplines	F	df	p
Time*group	Disciplines 1	5.919	40	0.021
	Disciplines 2	0.612	40	0.447
	Disciplines 3	0.349	40	0.564
	Disciplines 4	0.082	40	0.886
	Disciplines 5	2.044	40	0.137
	Disciplines 6	2.05	40	0.149
	Final grade	0.011	40	0.916

IV. B. 3) Analysis of pre- and post-test differences in mental health

Comparison of pre- and post-test differences between the experimental and control groups on the dimensions of mental health is shown in Table 8. The group and time-point interaction analyses on the dimensions of mental health are shown in Table 9. A 2 (group: experimental group, control group) × 2 (time point: pre-test, post-test) two-factor mixed repeated-test ANOVA was used to test the pre- and post-test differences between the experimental and control groups on the dimensions of mental health. The results showed a significant group and time-point interaction on obsessive-compulsive symptoms, F(1,35) = 7.465, p = 0.011, η^2 = 0.179. The two groups did not have significant group and time-point interactions on the other nine dimensions of mental health. Meanwhile, the results indicated that the pre- and post-test differences between the two groups on paranoia, hostility, interpersonal sensitivity, depression, maladjustment, emotional imbalance, and psychological imbalance were significant. These results indicate that as time approaches the exam, students have elevated on multiple dimensions of mental health such as paranoia, hostility, interpersonal sensitivity, depression, maladjustment, emotional imbalance, and psychological imbalance. The methodology of this paper is effective in reducing obsessive-compulsive symptoms.

Table 8: The comparison between the different dimensions of mental health

Scale/dimension	Laboratory group		Cross-reference group	
	Pre-test	Post-test	Pre-test	Post-test
Mental health(MSSMHS)	155.46±38.99	166.7±45.02	140.83±43.98	161.81±43.17
Compulsion	17.26±2.85	16.29±3.73	14.55±3.54	18.01±2.66
Paranoia	14.96±3.82	16.08±5.14	13.75±4.65	16.4±3.77
Antagonism	13.56±4.49	14.01±4.75	12.87±6.87	13.27±5.26
Interpersonal sensitivity	15.21±3.43	15.76±4.27	14.28±4.58	17.34±5.2
Depression	14.61±4.37	17.15±5.58	13.83±3.55	15.75±4.42
Anxiety	18.38±6.08	18.75±4.73	16.27±5.64	18.21±5.64
Learning pressure	16.4±3.12	17.2±4.69	15.04±3.96	17.37±3.5
Maladjustment	14.45±3	17.23±3.61	13.16±2.81	14.81±4.62
Mood inequality	17.51±4.62	19.84±3.83	15.43±4.65	17.8±4.13
Psychological inequality	13.12±3.21	14.39±4.69	11.65±3.73	12.85±3.97

Table 9: The group and the time point interaction analysis in the various dimensions

Variable	Scale/dimension	F	df	p
Time point	Mental health(MSSMHS)	11.281	40	0.001
	Compulsion	1.975	40	0.159
	Paranoia	6.489	40	0.007
	Antagonism	4.187	40	0.051
	Interpersonal sensitivity	20.344	40	0
	Depression	9.246	40	0.004
	Anxiety	0.703	40	0.421
	Learning pressure	1.765	40	0.187
	Maladjustment	15.028	40	0.011
	Mood inequality	6.328	40	0.013
	Psychological inequality	5.782	40	0.02
Time*group	Mental health(MSSMHS)	0.893	40	0.322
	Compulsion	7.465	40	0.011
	Paranoia	1.419	40	0.243
	Antagonism	0.225	40	0.633
	Interpersonal sensitivity	0.03	40	0.849
	Depression	0.263	40	0.607
	Anxiety	2.425	40	0.127
	Learning pressure	2.356	40	0.15
	Maladjustment	0.434	40	0.51
	Mood inequality	0.039	40	0.813
	Psychological inequality	0.915	40	0.342

V. Conclusion

This study verified the significant effect of this comprehensive intervention model in alleviating test anxiety of higher vocational students through a five-week cognitive behavioral therapy and neurofeedback intervention experiment.

The results of EEG signal analysis showed that the Beta wave of students in the high test anxiety group was significantly higher than that of the low test anxiety group in the baseline state (p=0.013), and the Alpha wave was significantly lower than that of the low test anxiety group (p=0.02), which indicated that there were obvious neurophysiological differences in high-anxious individuals. Analysis of the intervention effect showed that the experimental group achieved significant improvement in the cognitive test anxiety dimension, and the group and time-point interaction reached statistical significance (F=4.302, p=0.041), indicating that cognitive-behavioral interventions are effective in changing the students' cognitive patterns of anxiety. In terms of academic performance, the experimental group's subject 1 score improved from 95.966 to 100.93, forming a significant difference with the control group (F=5.919, p=0.021), confirming the positive impact of the intervention on learning outcomes. Mental health was significantly improved, and the improvement effect of the obsessive-compulsive symptom dimension was particularly prominent (F=7.465, p=0.011), with the experimental group's obsessive-compulsive symptom score decreasing from 17.26 to 16.29, while the control group's score increased from 14.55 to 18.01. The stressful situation validation experiment confirmed the effectiveness of the exam stressful situation setting, and the subjects' galvanic skin response was significantly higher in the exam state than in the baseline state (p<0.001).

Comprehensive analysis shows that the intervention model constructed by cognitive behavioral therapy combined with neurofeedback technology can work synergistically from three levels of cognitive reconstruction, behavioral regulation and physiological regulation to effectively alleviate the test anxiety of higher vocational students, enhance the learning performance and improve the level of mental health, which provides scientific theoretical guidance and practical support for the work of mental health education in higher vocational colleges and universities.

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