ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 2 - 2026

The application value of constructing a psychological adaptation enhancement path for college students based on mental health education model in the post epidemic era

Xue Wen[1,*]

[1] School of Education Sciences, Jining Normal University, Ulanqab, Inner Mongolia Autonomous Region, 012000, China

SUMMARY: *Today's society and economy are developing rapidly, and the academic and employment environments faced by college students in them are also changing dramatically, and the psychological pressure is also increasing, so it is urgent to improve their psychological adaptability. In this paper, the EEG signals are transformed into four-dimensional data through the data reconstruction module, and then fed into the multi-scale 3D CNN module to extract the temporal and spatial frequency features of the EEG signals in different scales and dimensions, the spatial attention mechanism module learns the size of the contribution of the different EEG channels to the emotion generation, and assigns a higher weight to the information that has significant emotional information, and then the global temporal features are mined by using the BLSTM module, and the Emotion Classification Module to obtain the final emotion classification results using the fully connected layer and softmax function, and finally complete the emotion recognition model (3DMSCA) construction. The emotion recognition model is integrated into the mental health education of college students to obtain a mental health education model that incorporates emotion recognition technology, and a psychological adaptation enhancement path based on the mental health education model is established, which is explored and analyzed with the help of structural equation modeling. The structural equation models GFI, CFI, NFI, TLI, and RMSEA for college students' psychological adaptation enhancement pathway meet the research requirements, with values of 0.917, 0.924, 0.901, 0.916, and 0.038, which means that the models have a better overall fit, and they can show the interaction mechanism between college students' psychological adaptation enhancement pathway based on the mental health education model. The interaction mechanism of the model has strategic application value for students' mental health education in the post epidemic era.*

KEYWORDS: *3DMSCA; Structural Equation Modeling; Emotion Recognition Model; Mental Health Education; Psychological Adaptation Enhancement Pathway*

1 Introduction

The attack of the new coronavirus has put the country into a state of national war “epidemic”, and the epidemic has not only damaged people's bodies, but also brought great challenges to people's psychology. The new coronavirus pneumonia epidemic has changed people's learning and life style, and many students have psychological adaptation disorder after resumption of schooling, showing different characteristics from those of freshmen's adapting to school [1, 2].

*15848069934@163.com
https://doi.org/10.65102/is2026667 Published: 30 April, 2026

College students are in a special stage of life and diversified social environment, facing individualized pressure and challenges. Firstly, the learning mode has shifted from offline education to online education, and students' lack of self-control can easily lead to lack of concentration, thus affecting the learning effect, and after the epidemic, they have shifted to the mixed mode of online and offline education, which leads to a decline in the learning performance of the under-adapted students, and increases the academic pressure, examination pressure, and the psychological burden [3-6]. Second, the uncertainty and competition in the job market intensified under the epidemic, and the low role of employment guidance increased negative psychological emotions such as employment pressure and anxiety about future confusion among college students [7, 8]. Finally, the epidemic reduces offline social activities, college students' relationship networks are limited, and online communication makes students more dependent on social media, while the complexity of online epidemic information affects students' emotions, and psychological problems such as sleep disorders, loneliness, social fear, and cell phone addiction follow [9-12]. Based on this, college students need to adapt to these changes and psychological problems.

Literature [13] reveals that college students' barriers to adaptation are mainly high academic demands and interpersonal relationships; support networks and academic integration are key facilitators; anxiety and depression are the main symptoms, while skills such as autonomy are central to healthy adaptation. Literature [14] explored the mechanisms of students' psychological adaptation in the context of the epidemic, noting that a sense of belonging to the university mediated between neocoronavirus anxiety and psychological adjustment, and that this mediating pathway was moderated by the degree of social media addiction, with the buffering effect of belonging being more pronounced at low levels of addiction. Literature [15] examined the academic adaptation and engagement of students in higher education who switched from online back to offline learning in a post-epidemic context, and students' academic resilience (including emotional regulation) and engagement significantly influenced the adaptation process, both at high levels. Literature [16] assessed the impact of the epidemic on the psychological adjustment of college students, with students reporting higher levels of psychological distress regardless of their place of residence, while on-campus students showed more significant extrinsic adjustment difficulties, including academic decline and increased alcohol and drug use. Literature [17] questionnaire found that students' psychological adjustment was moderate overall, with factors such as gender and leadership experience leading to significant differences, and that personal factors (especially emotional regulation and coping skills) had the greatest influence on their ecological factors, followed by family, school, and social factors. Literature [18] post-epidemic research indicates that college students' mental health is significantly affected by the negative impact of the epidemic, stress tolerance plays a key regulatory role in this process, and those with high stress tolerance are more significantly affected by the epidemic, highlighting the importance of psychological adaptability and resilience in the intervention. Therefore, in the post-epidemic era, in addition to ensuring the physical health of students, the management of college students should also take intervention measures to improve students' psychological adaptation.

Psychological resilience and psychological adaptation are closely related to each other, and both represent the process of students' coping with stress and psychological difficulties. With the help of different psychological interventions and psychoeducation, psychological adaptation can be promoted directly or indirectly by improving mental toughness. The results of literature [19] show that students demonstrate resilience through mechanisms such as rekindling enthusiasm for learning and adapting to a new normal, transforming challenges into growth, providing empirical evidence for relevant educational policies and interventions. Literature [20] A one-year psychological intervention significantly reduced the detection rate of anxiety, depression and somatization symptoms, and effectively improved the positive and negative coping styles of medical students, suggesting that targeted psychological interventions are effective in promoting psychological adjustment in this group. Literature [21] assessed the feasibility of a brief online positive thinking intervention for students during the epidemic, which significantly reduced stress and anxiety and increased levels of self-compassion, confirming its use as a viable and effective psychological intervention to enhance psychological resilience. The results of literature [22] showed that a counseling intervention combined with outdoor exercise was effective in reducing students' anxiety and depression levels during the epidemic and significantly enhanced psychological resilience, which had a positive effect on promoting students' psychological adaptation. Literature [23] indicated that resilience-enhancing interventions indirectly reduce negative stress responses through the chain-mediated effects of coping styles and positive adaptive responses, suggesting that developing positive coping strategies is a key pathway to enhance students' psychological adaptation. Literature [24] showed that psychoeducational interventions implemented through physical activity resulted in a significant increase in students' psychological resilience scores, suggesting that physical education-based psychoeducational interventions are effective in enhancing students' personal resilience. Literature [25] reported that virtual reality-based psychoeducational interventions significantly increased students' mental toughness scores, and learning engagement, skill application, and self-efficacy were effectively enhanced, suggesting that immersive psychoeducation is an effective way to develop students' mental toughness. Literature [26] studies have pointed out that the psychological problems of students in blended learning models in the post-epidemic era require a combination of mental health interventions, flexible learning environments and inclusive teaching strategies, and attention to culturally targeted measures to promote the stability of students' academic and mental health. It can be seen that mental health education is the main measure of prevention and intervention of students' psychology in universities, and the innovation of education model plays an important role in enhancing the psychological adaptation path of college students, but there is a lack of specific response to the enhancement path of students' psychological adaptation in the post-epidemic era and its application value assessment.

Based on artificial intelligence technology, a multi-scale 3D convolutional attention network and BLSTM based emotion recognition model (3DMSCA) is constructed, which consists of five modules, the data reconstruction module, the multi-scale 3D CNN module, the spatial attention mechanism module SAM, the BLSTM module and the emotion classification module. The data reconstruction module was used to convert the EEG signals into four-dimensional data, which were then fed into the multi-scale 3D CNN module for the temporal, spatial and frequency feature extraction of the EEG signals in different scales and dimensions. The spatial attention mechanism module is then used to assign weights to the extracted features, and the global temporal features are also mined with the help of the BLSTM module, and finally the final emotion classification results are obtained by applying the full connectivity layer and softmax function in the emotion classification module. In the process of mental health education, it is difficult for teachers to accurately identify and analyze students' psychological problems, which directly leads to unsatisfactory educational effects. In this regard, it is proposed to integrate the above-mentioned emotion recognition model into college students' mental health education, and finally design a mental health education model that incorporates emotion recognition technology. The psychological adaptation of students is affected by the interaction between individuals, schools and the social environment, and the mental health education model incorporating emotion recognition technology can reduce the occurrence of students' psychological discomfort. In this regard, the psychological adaptation enhancement pathway based on the mental health education model is proposed from three different dimensions, and the structural equation modeling is used to validate and analyze the pathway.

2 Research on mental health education models

2.1 Emotion Recognition Model

This subsection proposes a multi-scale 3D convolutional attention network and BLSTM based emotion recognition model (3DMSCA), which consists of five modules, a data reconstruction module, a multi-scale 3D CNN module, a spatial attention mechanism module SAM, a BLSTM module, and an emotion classification module. First, the EEG signal is transformed into four-dimensional data by the data reconstruction module, and then this data is input into the multi-scale 3D CNN module to extract the temporal and spatial frequency features of the EEG signal in different scales and dimensions, the spatial attention mechanism module learns the size of the contribution of the different EEG channels to the emotion generation, and assigns a higher weight to the information that is significant to the emotional information, and finally, the global temporal features are mined using the BLSTM module. The final emotion classification result is obtained by applying the fully connected layer and softmax function in the emotion classification module.

2.1.1 Data reconstruction module

When collecting EEG signals, college students are required to wear a multi-channel electrode cap, so the EEG data not only include rich time-frequency domain features, but also include the relative spatial position information between each electrode channel. Firstly, a 2D matrix of 8×9 is formed based on the 3D spatial information mapping of the electrode caps, which simulates the relative positions between electrode channels, and imparts electrode spatial information for emotion recognition. The blue part with electrode distribution is filled with the differential entropy eigenvalue extracted from each electrode, and the gray area without electrode distribution is filled with 0. The electrode distribution of the electrode cap is shown in Figure 1.

0	0	AF3	FP1	FPZ	FP2	AF4	0	0
F7	F5	F3	F1	FZ	F2	F4	F6	F8
FT7	FC5	FC3	FC1	FCZ	FC2	FC4	FC6	FT8
T7	C5	C3	C1	CZ	C2	C4	C6	T8
TP7	CP5	CP3	C1	CZ	C2	C4	C6	FP8
P7	P5	P3	P1	PZ	P2	P4	P6	P8
0	P07	P05	P03	P0Z	P04	P06	P08	0
0	0	CB1	01	0Z	02	CB2	0	0

Figure 1: Electrode cap electrode distribution

For the electrode distribution of 62 channels, the size of the 8×9 2D matrix obtained from the mapping is too small, and the feature values of each electrode are closely surrounded by the values of its neighboring electrodes, and the features are too compact, which leads to the problem of feature loss that may occur during convolution, and affects the performance of the recognition task. Therefore, a bicubic interpolation algorithm is used to scale up the size of the two-dimensional electrode matrix, so that each pixel point of the output image after the size is scaled up or scaled down has a definite value by means of gray scale interpolation processing according to a certain pixel point or pixel points of the input image. Specifically, taking the pixel point (x, y) to be interpolated as an example, the bicubic interpolation algorithm takes a total of 16 field points according to its surrounding 4×4 as the parameter for calculating the pixel value at (x, y). The calculation formula is shown in (1):

$$f(x,y)=\sum_{m=0}^{3}\sum_{n=0}^{3} f(x_m,y_n)R(x-x_m)R(y-y_n) \tag{1}$$

where $f(x,y)$ denotes the data value of the pixel point to be interpolated, and $f(x_m,y_n)$ denotes the data value of the pixel point (x_m,y_n) whose distance from (x,y) is $(x-x_m, y-y_n)$, which is taken as the differential entropy eigenvalue in this paper. $R(x-x_m)$ and $R(y-y_n)$ are then the weight coefficients corresponding to the values of the horizontal and vertical coordinates, which are computed by the BiCubic function to find out, and the formula is shown in (2):

$$W(x)=\begin{cases}(a+2)|x|^3-(a+3)|x|^2+1, & |x|\le 1\\ a|x|^3-5a|x|^2+8a|x|-4a, & 1<|x|<2\\ 0, & \text{otherwise}\end{cases} \tag{2}$$

The constant coefficient a is taken as -0.5, and finally the electrode size of $M\times M$ is generated by the bicubic interpolation algorithm.

The overall construction process of the EEG four-dimensional data is shown in Figure 2. For an EEG signal of length T, for each second, all electrode channels extract the DE features in 5 different frequency bands δ, θ, α, β, γ, and then map these DE features onto a two-dimensional electrode matrix according to the distribution of electrode cap channels. The two-dimensional feature maps of different frequency bands are stacked and the electrode size is enlarged to obtain a three-dimensional EEG feature map with dimensions of $M\times M\times 5$. Finally, the time window of L is used to divide each EEG signal, and four-dimensional input data x_{EEG} of size $M\times M\times 5\times L$ is obtained, which contains features in three different dimensions, namely, time, spatial, and frequency domains.

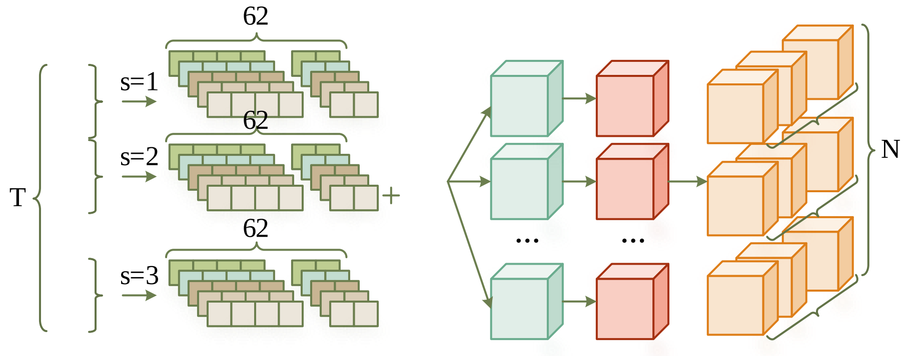


Figure 2: The overall construction process of four-dimensional EEG data

2.1.2 Multi-scale 3D CNN module

CNNs can handle non-linear and non-smooth signals such as EEG very well. When 2D CNNs are applied to extract the features of EEG signals, they can only extract the features in the time or frequency domains purely, whereas the analysis of EEG signals often needs to integrate the features in the time domain, the frequency domain, and the spatial domain, therefore, the 3DCNN possesses a unique advantage. Taking the four-dimensional feature map x_{EEG} as the input of the network, three groups of 3DCNN layers with different sizes of convolution kernels are set up to perform convolution operations on the EEG signal x_{EEG} to learn the emotion-related features of different sizes and levels of x_{EEG}, and the output result obtained from each group of convolution is CNN_{EEG}^{i}. Where the $i-1$th layer features are converted to the ith layer by 3D convolution operation with the convolution formula shown in (3):

$$k_{i,j}^{x,y,z} = \partial\left(\sum_{j=1}^{J_{i-1}}\sum_{h=0}^{H_i-1}\sum_{w=0}^{W_i-1}\sum_{r=0}^{R_i-1} W_{i,j}^{h,w,r} * k_{(i-1),j}^{(x+h)(y+w)(z+r)} + b_{i,j}\right) \tag{3}$$

where * denotes the convolution operation, $J_{(i-1)}$ represents the number of feature maps contained in the ith layer, H_i, W_i, and R_i denote the length, width, and height of the 3D convolution kernel, respectively, $k_{i,j}^{x,y,z}$ denotes the value obtained by convolution of the convolutional layers of the ith layer to the jth feature map at the coordinates of (x,y,z), $W_{i,j}^{h,w,r}$ denotes the weight value of the convolution kernel connecting the jth feature map at the position (h,w,r), h,w,r denotes the indexes in three different dimensions during the convolution process, and $b_{i,j}$ denotes the bias term of the convolution layer of the ith layer at the jth feature map. The ReLU function activation function is chosen, which is characterized by low computational complexity and strong generalization ability. It can be expressed as:

$$\mathrm{Re}LU(k) = \phi(k) = \max(0,k) \tag{4}$$

The 3D pooling layer adopts the MaxPooling pooling method, which is placed in the non-overlapping region of each feature map with a window size of $2\times2\times2$, and takes the maximum value of each window as the output. Suppose $s_{l,m}^{x,y,z}$ is the element of the mth feature map of the lth layer at coordinates (x,y,z), which can be expressed as:

$$s_{l,m}^{x,y,z} = \max\left(Q_{l,m}^{x,y,z}\right) \tag{5}$$

$$Q_{l,m}^{x,y,z} = \left\{ s_{l,m}^{x,y,z} \,\middle|\, x\in\{2x-1,2x\},\ y\in\{2y-1,2y\},\ z\in\{2z-1,2z\} \right\} \tag{6}$$

where the set $Q_{l,m}^{x,y,z}$ contains all the elements in the $2\times2\times2$ window.

2.1.3 Module on spatial attention mechanisms

In this paper, the idea of spatial attention mechanism (SAM) sub-module in CBAM algorithm is borrowed, and Fig. 3 shows the schematic of SAM structure. For the output feature map

$CNN_{EEG}^{i} \in R^{W\times H\times L\times C}$ of each multiscale 3DCNN layer, W, H, L, and C denote the width, height, frequency bands, and the number of channels, respectively, of the output feature map. Firstly, the compression of the channel domain features is carried out, and the feature descriptions $F_{avg} \in R^{W\times H\times L\times 1}$ and $F_{\max} \in R^{W\times H\times L\times 1}$ are obtained by using the average pooling operation and the maximum pooling operation, respectively, and the two are stitched together to obtain new features $F_c \in R^{W\times H\times L\times 2}$. Since the spatial attention mechanism cares more about the size of the contribution of different electrode channels to the emotion recognition task, the redundant frequency band information instead brings a large amount of computation, so in this paper, we add a global adaptive average pooling layer after splicing the feature F_c to compress the multi-band feature into a single band, and get $F_c' = R^{W\times H\times 2}$, and finally the normalized spatial weight information W_s^i is obtained after 2D convolution and sigmoid function, and the operation process can be expressed as follows:

$$F_{\max} = \max\left(CNN_{EEG}^{i}\right) \tag{7}$$

$$F_{avg} = \frac{1}{C}\sum_{c=1}^{C}\left(CNN_{EEG}^{i}\right) \tag{8}$$

$$F_s^i = \delta\left(Conv\left(AAP\left(cat\left(F_{avg}, F_{\max}\right)\right)\right)\right) \tag{9}$$

where δ denotes the Sigmoid activation function, $Conv$ denotes a 2D convolutional layer of size 3×3, and AAP is the global adaptive average pooling layer.

Finally, the spatial weight information W_s^i of size $W\times H$ is multiplied with the corresponding elements of the input feature map CNN_{EEG}^{i} to get the output feature map F_s^i, and the splicing of different scales of F_s^i to form the final feature information F_s which is the input of BLSTM module.

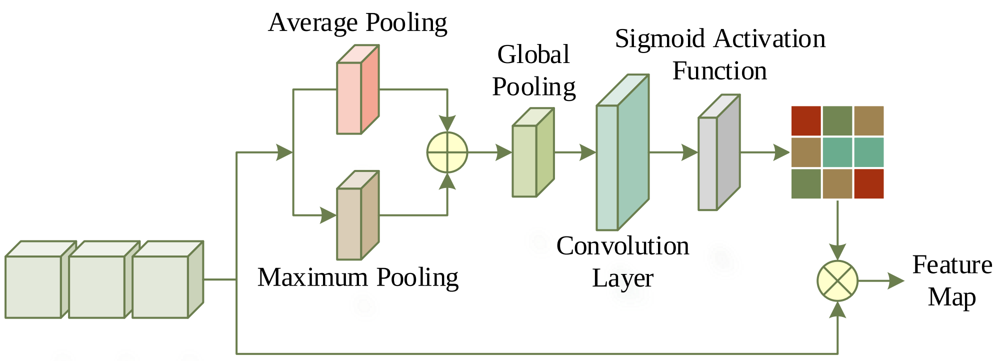


Figure 3: Schematic diagram of SAM structure

2.1.4 BLSTM module

BLSTM consists of two LSTMs superimposed on top and bottom, layer 1 is from the left as the starting input of the sequence, while layer 2 is from the right as the starting input of the sequence, and the final output value is jointly determined by the states of these two LSTMs. Specifically, for the feature vector $F_{s,t}$ at moment t, the BLSTM model computation process can be expressed as follows:

$$\vec{h}_t = \overrightarrow{LSTM}\left(F_{s,t}, \vec{h}_{t-1}\right) \tag{10}$$

$$\overleftarrow{h}_t = \overleftarrow{LSTM}\left(F_{s,t}, \overleftarrow{h}_{t-1}\right) \tag{11}$$

where $\vec{h}_t$ denotes the EEG features learned by the forward LSTM at moment t, and $\overleftarrow{h}_t$ denotes the EEG features learned by the backward LSTM at moment t, and the output vectors obtained by splicing the forward and backward directions are obtained as the output vector of the hidden layer $\vec{h}_t$, which can be expressed as:

$$\overleftarrow{h}_t = \left[\vec{h}_t, \overleftarrow{h}_t\right] \tag{12}$$

The before and after timing features f_t captured by BLSTM at moment t are as follows:

$$f_t = \sigma\left(W_t \overleftarrow{h}_t + b_f\right) \tag{13}$$

where σ denotes the $\tanh$ activation function, W_t is the weight matrix, and b_f is the bias vector.

2.1.5 Sentiment classification module

Finally, the output vector $F_{EEG} \in R^{1\times m}$ of the BLSTM layer is input into the multilayer fully connected layer for dimensionality reduction, and the m-dimensional vector is transformed into an n-dimensional vector using the linear transformation $W \in R^{m\times n}$, to which a bias term $b \in R^n$ is added, and then input into ReLU activation function in the ReLU activation function, the process is shown below:

$$f = \mathrm{Re}LU\left(WF_{EEG} + b\right) \tag{14}$$

The softmax function is excellent in dealing with small samples, nonlinear and high-dimensional pattern recognition problems, so the last layer of the fully connected layer uses the softmax function to get the probability of different emotion categories, and the emotion state with the largest output probability is the final recognition result of the model, and the process is shown in Eq:

$$p_i = \frac{\exp\left(w_i^T x\right)}{\sum_j \exp\left(w_j^T x\right)} \tag{15}$$

where p_i is the probability that sample x belongs to the i th sentiment category.

2.2 Design of mental health education model incorporating emotion recognition technology

It is difficult for teachers to accurately identify and analyze students' psychological problems in the process of mental health education, which directly leads to unsatisfactory educational effects, in this regard, it is proposed to integrate the above mentioned emotion recognition model into the mental health education of college students, and finally design a mental health education model incorporating emotion recognition technology.

(1) Intelligent monitoring and timely feedback of students' emotions

Teachers can use the emotion recognition model to sense students' emotional fluctuations in a timely manner, analyze students' mental health level with the help of the model, carry out targeted mental health guidance activities, and guide students to regulate their mental state independently and learn to express their personal emotions objectively and rationally. Teachers should combine the concept of moral education, real-time monitoring of students' emotions with the help of the emotion recognition model, accurately identifying students' emotional changes, scientifically identifying students' emotional fluctuations such as excitement, depression, anxiety, etc., and providing data support for mental health education.

(2) Customize exclusive resources for psychological construction

Before carrying out mental health education activities, teachers should deeply analyze students' psychological problems, understand students' psychological confusion, combine students' common problems as well as individual problems, scientifically design education programs, and realize targeted and symptomatic medicine. Teachers can use the emotional recognition model to understand the emotional state of students, analyze students' personality preferences and thinking habits, gradually form a wise psychological portrait, provide students with exclusive resources for psychological construction, regulate students' emotions with diversified, customized and personalized resources, give students positive psychological hints, and provide support for students' self-adjustment and self-healing.

(3) Enriching the content of mental health education

Teachers should change the traditional indoctrination and didactic teaching mode, analyze students' psychological problems with the help of emotion recognition technology, and efficiently carry out mental health curriculum activities with targeted use of artificial intelligence tools, so as to enhance students' psychological quality and promote their overall growth and development. Schools should enrich the content of education, improve the curriculum system, and innovate the form of education to realize high-quality teaching and high-quality education. Such as family, social, medical and police linkage of mental health science, prevention and intervention work, a monthly mental health class meeting class, a weekly psychological commissioner club training work, daily broadcasting mental health radio, and monthly organization of the classroom teacher's ability to train in mental education, with rich and diversified mental health education content to promote the healthy growth of students. Again, teachers should skillfully integrate curriculum content from multiple channels, update students' knowledge base in a timely manner, and efficiently carry out mental health education activities with clear themes and diverse forms.

3 Paths of psychological adaptation enhancement based on the mental health education model

3.1 Path construction

Students' psychological adaptation is affected by the interaction between individuals, schools and the social environment, and the mental health education model incorporating emotion recognition technology can be used to reduce the occurrence of students' psychological discomfort and provide rapid and effective assistance to students when they encounter psychological difficulties, and for this reason, a psychological adaptation enhancement path based on the mental health education model is proposed from three different dimensions.

(1) Utilizing self-efficacy

In the face of pressure and difficulties, college students are not completely passive, they are thirsty for help and will actively seek help from outside. With the rapid development of artificial intelligence technology, the mental health education model incorporating emotion recognition technology can provide students with ways to manage stress and deal with difficult situations to enhance personal control, thus realizing the enhancement of students' psychological adaptability.

(2) Building a cultural integration field

Emotional motivation drives behavior, and emotional function is the psychological basis for individual behavior. Therefore, colleges and universities can build a cultural integration field to improve the psychological adaptability of college students on the basis of the mental health education model that incorporates emotion recognition technology.

(3) Advocating multiple evaluation standards

Under the background of increasingly fierce social competition and external achievements as the core evaluation standard, students' learning motivation structure has become imbalanced, which is manifested in the lack of internal motivation and the excessive reinforcement of external motivation. This imbalance not only leads to the increasing prominence of the phenomenon of learning involution, but also restricts the overall development of students and the harmonious progress of society. In order to effectively alleviate this phenomenon, the mental health education model incorporating emotion recognition technology is used to guide students to establish correct values and learning concepts, and actively disseminate and promote the concept of multiple evaluation standards.

3.2 Validation programs

Firstly, freshmen of a comprehensive university in East China were selected as the research object, and structural equation modeling was used to formulate the research program of psychological adaptation enhancement path based on mental health education model, in order to present the application value of the construction of psychological adaptation enhancement path for college students based on mental health education model in the post-epidemic era.

3.2.1 Objects of study

The subjects of this study were freshmen at a comprehensive university in East China, and the final number of valid subjects for the study was 486, of which 242 were male and 244 were female, 208 were from the Arts Department and 278 from the Science Department. Of all the study subjects, 12 did not fill in their age, and the average age of the remaining subjects was 19.22 years old, with an age range of 17-22 years old.

3.2.2 Research methodology

Structural equation modeling, abbreviated as SEM, is a multivariate statistical analysis method that analyzes the relationship between variables and verifies the consistency or otherwise of the theoretical model and sample data. Currently widely used in economics, sociology, tourism and other fields, structural equation modeling can be divided into two parts: measurement model and structural model. Measurement model studies the relationship between a latent variable and its multiple observed variables, and the equation formula of measurement model is as follows:

$$x = \Lambda_x \xi + \delta \tag{16}$$

$$y = \Lambda_y \eta + \varepsilon \tag{17}$$

Equation (16) is an exogenous variable equation, x is an exogenous observed variable and ξ is an exogenous latent variable. Equation (17) is an endogenous variable equation, y is an endogenous observed variable and η is an endogenous latent variable. Λ_x and Λ_y are factor loading matrices indicating the strength of the relationship between the exogenous observed variable x to the exogenous latent variable ξ, and the endogenous observed variable y to the endogenous latent variable η, respectively, and δ and ε are error terms.

Structural modeling studies the relationship between latent variables and latent variables, and the equations of structural modeling are as follows:

$$\eta = \mathrm{B}\eta + \Gamma\xi + \zeta \tag{18}$$

The η on the left side of the equal sign in equation (18) is the endogenous latent variable and the exogenous latent variable on the right side, B is the correlation coefficient matrix reflecting the correlation between the endogenous latent variables, Γ is the matrix of regression coefficients reflecting the effect of the exogenous latent variable ξ on the endogenous latent variable η, and ζ is the residual term reflecting the effect of the endogenous latent variable being explained by the exogenous latent variables, i.e., the unexplained part of the equation.

Structural equation modeling breaks through the traditional treatment of a single factor, and can simultaneously deal with multiple dependent variables and simultaneously estimate multiple factor structures and factor relationships, i.e., it can simultaneously consider the relationship between latent variables and topics as well as between latent variables and latent variables. Structural equations allow for measurement error in both the independent and dependent variables, and since latent variables are often not directly measurable, they can contain errors, and structural equations address just this challenge. The structural equation modeling and analysis steps are divided into the following four main steps:

(1) Model construction

The construction of the model needs to be based on theoretical knowledge, combined with the specific problems under study, including the selection of observed variables and latent variables, the relationship between observed variables and latent variables, and the relationship between latent variables and latent variables.

(2) Model fitting

According to the sample data, the hypothetical model is fitted using relevant software to estimate the parameters of the model.

(3) Model Evaluation

On the one hand, check whether the statistical indicators are significant or within the range of recommended values. For example, check whether there are unacceptable values in the model estimation, i.e., whether the model passes the violation estimation, check the model fitting index (GFI, AGFI, CFI, etc.). On the other hand, check the reasonableness of the parameter-model relationship and whether it conflicts with the assumptions.

(4) Model Revision

On the basis of the model theory, combined with the results of the model statistical indicators, the model is corrected, including the addition, deletion or restructuring of the topic, the addition, deletion or modification of latent variables, the addition, deletion or modification of paths, the addition and deletion of residual covariances, etc., and finally, the modified model is made to pass the non-standardized test, the standardized test, and the test of the fit index.

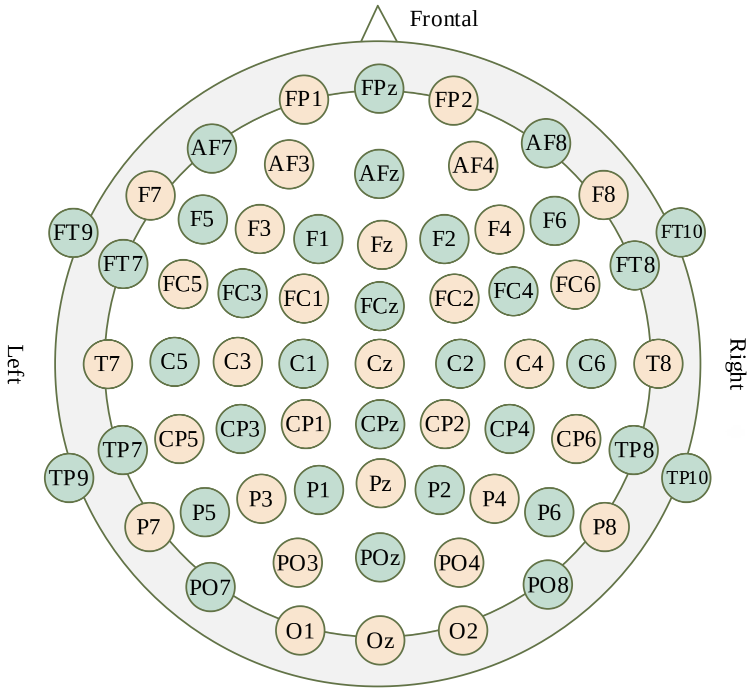
4 In-depth exploratory analysis

4.1 Validation Analysis of Sentiment Recognition Models

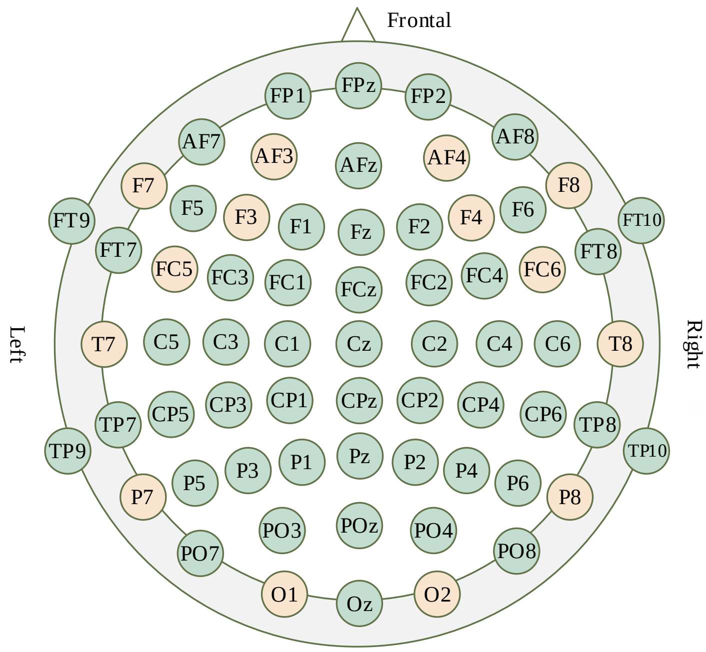
This section conducts a validation analysis of the emotion recognition model based on the EEG signal emotion dataset and performance measurement indicators. The aim is to verify the effectiveness of the emotion recognition model based on the multi-scale 3D convolutional attention network and BLSTM (3DMSCA), ensuring that the psychological health education model integrated with the emotion recognition model is more in line with the actual teaching situation, and thereby providing important technical support for the construction of the psychological adaptation improvement path based on the psychological health education model.

4.1.1 EEG Signal Emotion Dataset

Emotion recognition algorithms and classification models based on EEG signals need to be validated on emotionally labeled EEG signal datasets. In addition to researchers collecting emotion data themselves, there is an international batch of publicly available EEG emotion datasets that can be used. These datasets follow certain experimental paradigms and have been set up with rigorous experimental procedures, providing researchers with a unified standard platform. All the models in this study are also validated on publicly available datasets and the datasets used are DEAP, DREAMER. The dataset electrode locations are shown in Fig. 4, where (a) and (b) are the datasets DEAP, DREAMER, respectively. The DEAP dataset has a total of 1280 samples (32 subjects × 40 experiments) and contains 32 EEG leads with the dimensions of validity, arousal, dominance, liking, and familiarity.The DREAMER dataset has a total of 414 samples (23 subjects × 18 experiments) and contains 14 EEG leads with the dimensions of validity, arousal, and dominance.



(a)Electrode positions in the DEAP dataset



(b)Electrode positions in the DREAMER dataset

Figure 4: Position of the data collector

4.1.2 Model performance metrics

In order to evaluate the generalization ability of the proposed EEG emotion recognition model more comprehensively, the accuracy, precision, recall, and F1 score are used as performance metrics in this study.

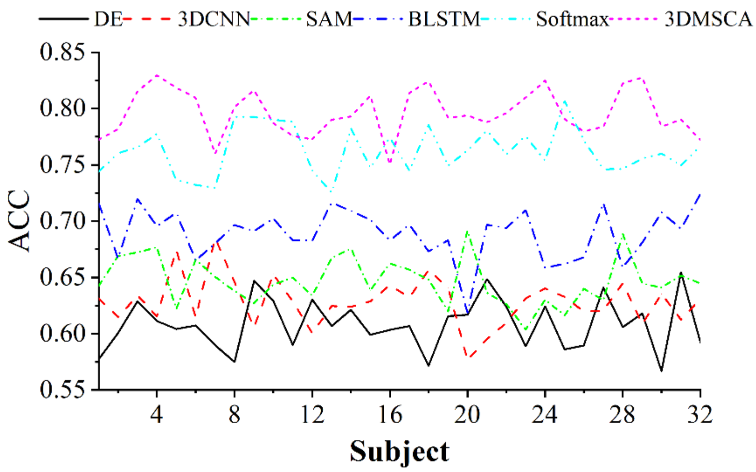
The terms "TP", "TN", "FP" and "FN" are used to denote the true case (TP), true (TP), true counterexample (TN), false positive example (FP), and false negative example (FN), respectively, and each metric is calculated as follows:

$$\begin{aligned}
&Accuracy = (TP + TN)/(TP + TN + FP + FN) \\
&\Pr ecision = TP/(TP + FP) \\
&\text{Re}\, call = TP/(TP + FN) \\
&F1 = 2 \times \text{Re}\, call \times \Pr ecision/(\text{Re}\, call + \Pr ecision)
\end{aligned} \tag{19}$$

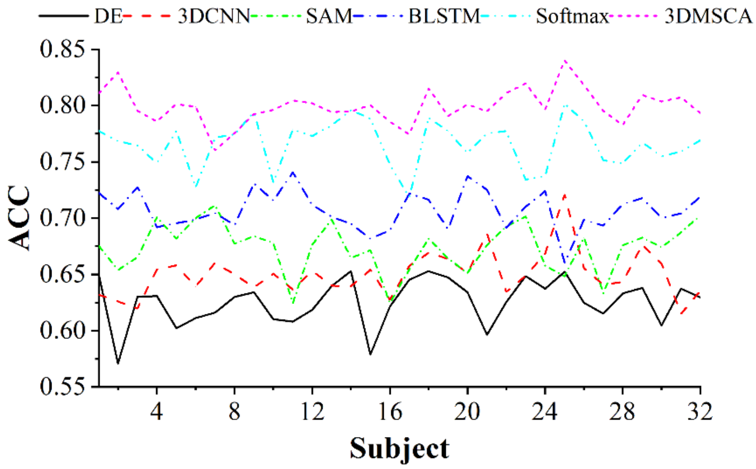
Higher values of these metrics indicate better model performance. In addition, this study used the area under the curve (AUC) of the subjects' job characteristics (ROC) calculated from the classification results.

4.1.3 Ablation experiments

The emotion recognition model (3DMSCA) based on multi-scale 3D convolutional attention network and BLSTM, which includes five modules, data reconstruction module (DE), multi-scale 3DCNN module, spatial attention mechanism module (SAM), BLSTM module, and emotion classification module (Softmax), the results of ablation experiments on the DEAP dataset are shown in Table 1.The results of ablation experiments on the DEAP The accuracy comparison results of different models for a single subject on the dataset are shown in Fig. 5, where (a)~(b) are Valence, Arousal, respectively.Combining the data performance in the figure, it can be seen that 3DMSCA has the best accuracy on Valence, Arousal, with the values of 0.799, 0.798, respectively, and with the addition of the five modules, the 3DMSCA index values show an upward trend, that is, it proves the effectiveness of each module in the emotion recognition model (3DMSCA) based on multi-scale 3D convolutional attention network and BLSTM, and helps the mental health education model incorporating emotion recognition technology to be more in line with the actual teaching situation, and at the same time lays a theoretical basis for the construction of the psychological adaptation enhancement path based on the mental health education model The study also lays a theoretical basis for the construction of a psychological adaptation enhancement path based on mental health education model.



(a)Valence



(b)Arousal

Figure 5: Accuracy comparison on the DEAP dataset

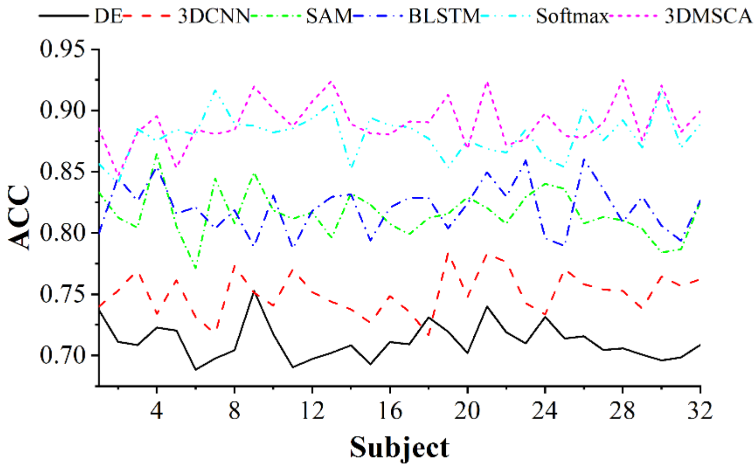
Table 1: Ablation experimental results on the DEAP dataset

Model	Valence					Arousal				
	Acc	Recall	Precision	F1	ROC-AUC	Acc	Recall	Precision	F1	ROC-AUC
DE	0.602	0.632	0.7	0.664	0.609	0.631	0.628	0.615	0.621	0.634
3DCNN	0.625	0.67	0.704	0.687	0.615	0.648	0.666	0.668	0.667	0.644
SAM	0.648	0.679	0.736	0.706	0.665	0.67	0.701	0.672	0.686	0.71
BLSTM	0.693	0.711	0.75	0.730	0.675	0.709	0.75	0.687	0.717	0.727
Softmax	0.764	0.73	0.752	0.741	0.697	0.771	0.773	0.763	0.768	0.736
3DMSCA	0.799	0.799	0.783	0.791	0.785	0.798	0.799	0.785	0.792	0.796

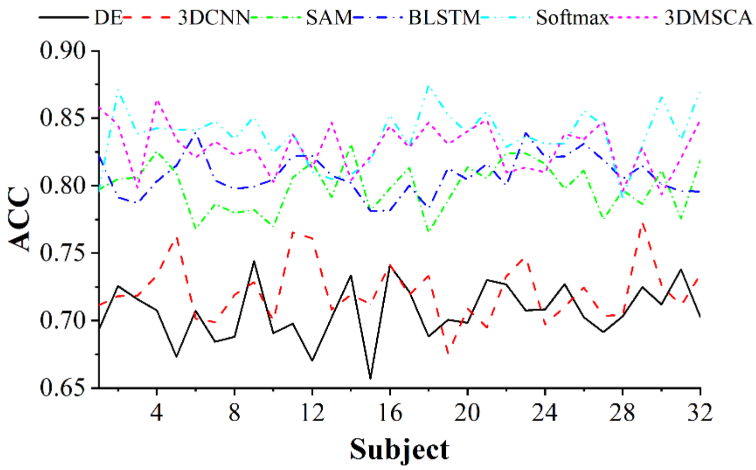
The results of the ablation experiments on the DREAMER dataset are shown in Table 2, and the results of the accuracy comparison of different models for a single subject on the DREAMER dataset are shown in Fig. 6. 3DMSCA has the optimal accuracy on Valence, Arousal, with the values of 0.895 and 0.831, which is a good demonstration of the multiscale 3D convolutional attentional network and BLSTM-based 5 module feasibility in the emotion recognition model (3DMSCA).

Table 2: Ablation experimental results on the DREAMER dataset

Model	Valence					Arousal				
	Acc	Recall	Precision	F1	ROC-AUC	Acc	Recall	Precision	F1	ROC-AUC
DE	0.716	0.715	0.732	0.723	0.713	0.706	0.73	0.728	0.729	0.761
3DCNN	0.75	0.77	0.803	0.786	0.748	0.717	0.786	0.757	0.771	0.799
SAM	0.819	0.814	0.809	0.811	0.792	0.803	0.787	0.798	0.792	0.805
BLSTM	0.825	0.87	0.832	0.851	0.803	0.808	0.792	0.822	0.807	0.818
Softmax	0.882	0.873	0.84	0.856	0.837	0.827	0.794	0.823	0.808	0.857
3DMSCA	0.895	0.877	0.843	0.860	0.857	0.831	0.801	0.899	0.847	0.885



(a)Valence



(b)Arousal

Figure 6: Accuracy comparison on the DREAMER dataset

4.1.4 Benchmark comparison experiments

In order to further validate the effectiveness of the 3DMSCA model proposed in this chapter's study, it is experimentally compared with seven models, namely, DGCNN model, FBCNet model, Tsception model, STNet model, MT-CNN model, SSTD model and STSNet model, which are described as follows:

DGCNN: a multi-channel EEG signal emotion recognition method based on a novel dynamic graph convolutional neural network.

FBCNet: a novel Filter-Bank convolutional neural network that uses multi-view data representation and performs spatial filtering to extract null spectrum discriminative features.

Tsception: an emotion recognition network that captures the temporal dynamics and spatial asymmetry of EEG.

STNet: an EEG-based spatio-temporal emotion recognition network.

MT-CNN: a multi-task convolutional neural network emotion recognition model based on EEG.

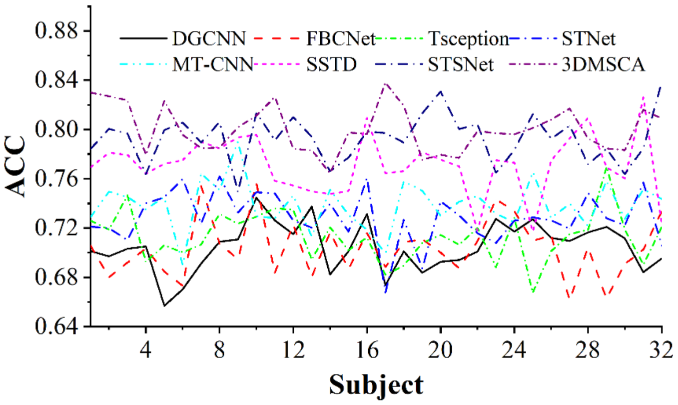
SSTD: An EEG covariance matrix streaming spatio-temporal fusion model based on fusing demographic information with dynamic time windows.

STSNet: deep learning emotion recognition model based on fusion of spatio-temporal spectral features of EEG signals.

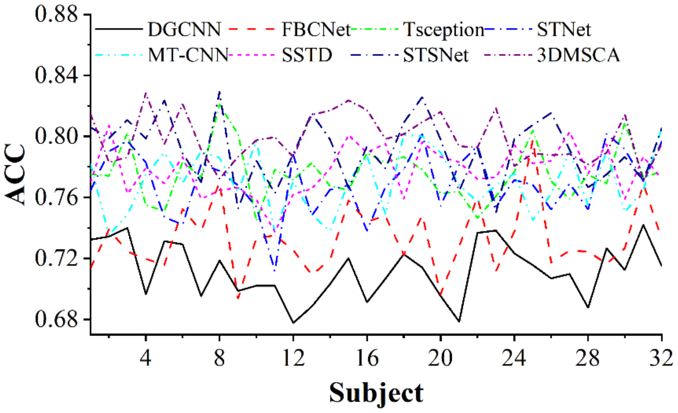
The benchmark comparison results on the DEAP dataset are shown in Table 3, and the accuracy comparison results on the DEAP dataset are shown in Figure 7. Combining the data in the figure and table, it can be seen that the accuracy of the proposed 3DMSCA model is improved by 0.013~0.096 and 0.008~0.083 in the VALENCE and AROUSAL dimensions, respectively, compared with the models DGCNNN, FBCNet, Tsception, STNet, MT-CNN, SSTD, and STSNet.

Table 3: Benchmark comparison results on the DEAP dataset

Model	Valence					Arousal				
	Acc	Recall	Precision	F1	ROC-AUC	Acc	Recall	Precision	F1	ROC-AUC
DGCNN	0.703	0.713	0.714	0.713	0.707	0.715	0.762	0.705	0.732	0.734
FBCNet	0.709	0.717	0.716	0.716	0.709	0.732	0.773	0.714	0.742	0.735
Tsception	0.711	0.733	0.728	0.730	0.713	0.768	0.775	0.739	0.757	0.765
STNet	0.727	0.747	0.73	0.738	0.722	0.771	0.782	0.757	0.769	0.775
MT-CNN	0.74	0.755	0.737	0.746	0.731	0.771	0.787	0.759	0.773	0.777
SSTD	0.776	0.779	0.771	0.775	0.742	0.774	0.795	0.766	0.780	0.795
STSNet	0.786	0.794	0.782	0.788	0.749	0.79	0.798	0.768	0.783	0.795
3DMSCA	0.799	0.799	0.783	0.791	0.785	0.798	0.799	0.785	0.792	0.796



(a)Valence



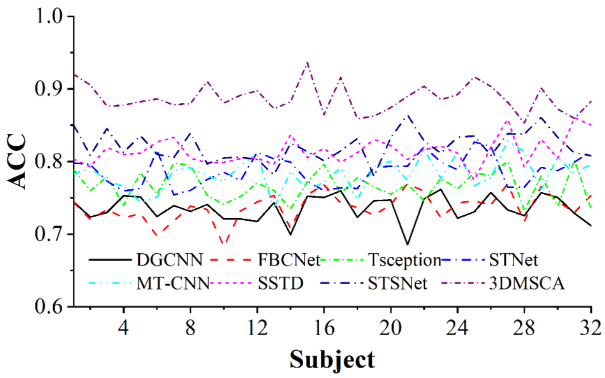
(b)Arousal

Figure 7: Accuracy comparison results on the DEAP dataset

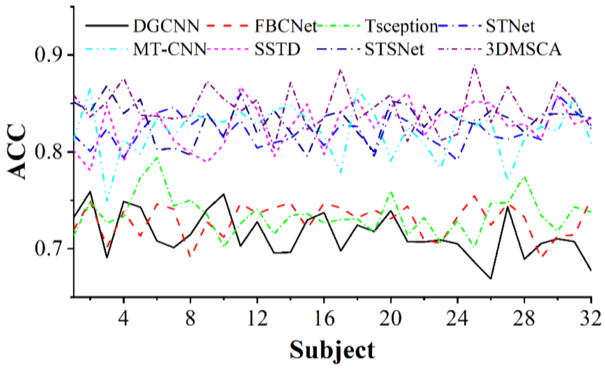
The benchmark comparison results on the DREAMER dataset are shown in Table 4, and the accuracy comparison results on the DREAMER dataset are shown in Figure 8. Combining the data in the figure and table, it can be seen that compared with the models DGCNN, FBCNet, Tsception, STNet, MT-CNN, SSTD, and STSNet, the accuracy of the 3DMSCA model proposed in this paper is improved in the VALUE and AROUSAL dimensions by 0.072~0.16 and 0.016~0.129, respectively. The priority of the emotion recognition model (3DMSCA) based on multi-scale 3D convolutional attention network and BLSTM is fully demonstrated to better serve the current mental health education model in colleges and universities, thus obtaining the mental health education model incorporating the emotion recognition technology, and providing theoretical support for the validation of the mental adaptation enhancement path based on the mental health education model below.

Table 4: Benchmark comparison results on the DREAMER dataset

Model	Valence					Arousal				
	Acc	Recall	Precision	F1	ROC-AUC	Acc	Recall	Precision	F1	ROC-AUC
DGCNN	0.735	0.74	0.713	0.726	0.702	0.718	0.741	0.713	0.727	0.781
FBCNet	0.737	0.75	0.714	0.732	0.756	0.729	0.747	0.725	0.736	0.783
Tsception	0.768	0.752	0.753	0.752	0.763	0.733	0.747	0.773	0.760	0.783
STNet	0.783	0.753	0.759	0.756	0.798	0.822	0.78	0.788	0.784	0.806
MT-CNN	0.784	0.767	0.797	0.782	0.808	0.827	0.784	0.793	0.788	0.809
SSTD	0.814	0.779	0.801	0.790	0.835	0.829	0.801	0.797	0.799	0.819
STSNet	0.823	0.835	0.831	0.833	0.85	0.831	0.808	0.81	0.809	0.844
3DMSCA	0.895	0.877	0.843	0.860	0.857	0.847	0.818	0.899	0.857	0.885



(a)Valence



(b)Arousal

Figure 8: Accuracy comparison results on the DREAMER dataset

4.2 Validation Analysis of Psychological Adaptation Enhancement

Through the above research and analysis, the feasibility of the multi-scale 3D convolutional attention network and BLSTM-based emotion recognition model (3DMSCA) has been proved, which ensures that the mental health education model incorporating the emotion recognition model is more in line with the needs of college students' psychological adaptation, and provides an important technical support for the path of psychological adaptation enhancement based on the mental health education model. Based on this foundation, the verification analysis of the college students' psychological adaptation enhancement path is carried out by combining the above research methods.

4.2.1 Distribution of questionnaires

According to the needs of the study to compile their own "Psychological Adaptation Enhancement Path of College Students", mainly including the basic information questionnaire for college students, self-efficacy scale, cultural intergration field scale, multiple evaluation criteria scale, psychological adaptation scale, a total of 120 questions were created, the scales are all five-point Likert scales, and the questionnaire is mainly divided into four basic self-efficacy, cultural intergration field, multiple evaluation criteria, and psychological adaptation dimensions, and an anonymous survey was conducted. A total of 486 questionnaires were distributed, 372 questionnaires were collected, with a recovery rate of 97.11%. 12 invalid questionnaires were excluded, and the validity rate was 94.65%.

4.2.2 Exploratory factor analysis of structural equations of psychological adaptation

In order to verify the reliability and validity of the data obtained from the questionnaire, the four basic dimensions were tested for reliability. The most commonly used reliability test coefficient - Cronbach's coefficient ($Cronbach'\alpha$ coefficient) was used for the reliability test, and the results of the SPSS reliability test are shown in Table 5. The results show that the overall $Cronbach'\alpha$ of the model is 0.873 (>0.7), indicating that the measurement scale of the model has a high reliability test coefficient, and the questionnaire is more reasonably designed and highly reliable.

Table 5: SPSS reliability test results

Dimension	Measure the number of questions	Cronbach's α
Self-efficacy	30	0.846
A field of cultural integration	30	0.856
Multiple evaluation criteria	30	0.919
Psychological adaptation	30	0.871
Total	120	0.873

Then the validity test was carried out using KMO and Bartlett's spherical test and the results of the SPSS validity analysis are shown in Table 6.The KMO value was 0.859 (>0.8) Bartlett's spherical test p-value was 0.0003, i.e., the questionnaire's statistical test was significant.

Table 6: The results of SPSS validity analysis

Dimension	KMO	Bartlett's spherical P value
Self-efficacy	0.882	0.001
A field of cultural integration	0.837	0.007
Multiple evaluation criteria	0.874	0.005
Psychological adaptation	0.843	0.004
Total	0.859	0.003

4.2.3 Construction of structural equations for the psychological adaptation enhancement pathway

By combing through the previous literature, it was found that by including self-efficacy, cultural intergration field, multiple evaluation criteria, and psychological adaptation into the structural equation model, the structural equation of the psychological adaptation enhancement path is shown in Figure 9. The following paths are made:

(1) Cultural Intergration Field → Multiple Evaluation Criteria.
(2) Self-efficacy → psychological adaptation.
(3) Cultural integration field → self-efficacy → psychological adaptation.
(4) Multiple evaluation criteria → self-efficacy → psychological adaptation.

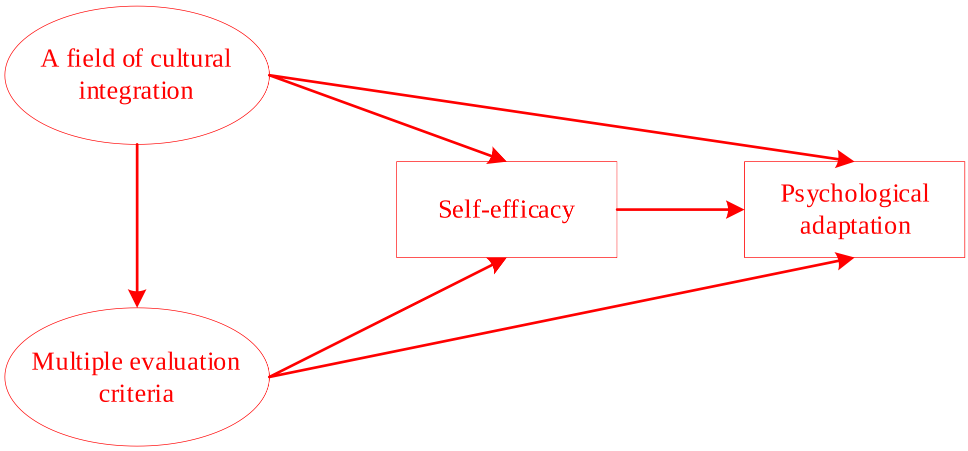


Figure 9: Structural equation of the path for psychological adaptation improvement

4.2.4 Structural Equation Modeling of Psychological Adaptation Lifting Paths

The results of the structural equation goodness-of-fit evaluation are shown in Table 7, and the modified path coefficients of the structural equation model are shown in Table 8. The structural equation model was constructed according to the assumptions, and the evaluation indexes of the model included GFI (Goodness of Fit Index), CFI (Comparative Fit Index), NFI (Normative Fit Index), TLI (Non-Normative Fit Index), (Root Mean Square of the Approximation Error) were all greater than 0.09, and the RMSEA index was less than 0.08, which made the model fit well overall. After multiple revisions and comprehensive considerations, the final structural equation model for the path of enhancing college students' psychological adaptation was obtained. It comprehensively outlines the internal interaction mechanisms among various elements of the psychological adaptation improvement path based on the mental health education model, and has substantive application value for students' mental health in the post-pandemic era. It also interprets the application value of the psychological adaptation of college students based on the mental health education model in the post-pandemic era.

Table 7: Evaluation results of goodness-of-fit of structural equations

Project	CMIN/DF	GFI	CFI	NFI	TLI	RMSEA
Modified model	2.908	0.917	0.924	0.901	0.916	0.038
Judgment method	<3	>0.9	>0.9	>0.9	>0.9	<0.08

Table 8: Path coefficient after modification of the structural equation model

Path	Std.estimate	S.E.	C.R.	P-Value
Cultural integration field → Diverse evaluation criteria.	0.027	0.014	4.954	0.006
Cultural integration field → Self-efficacy	0.028	0.012	3.126	0.007
Multiple evaluation criteria → Self-efficacy	-0.689	0.037	-9.105	0.006
Cultural integration field → Psychological adaptation	0.006	0.006	4.387	0.002
Multiple evaluation criteria - Psychological adaptation	0.028	0.009	3.926	0.002
Self-efficacy → Psychological adaptation	0.006	0.006	1.237	0.001

5 Conclusion

This paper establishes a mental health education model with the help of emotion recognition model in the post epidemic era, proposes a psychological adaptation enhancement path based on the mental health education model, and empirically analyzes the path using structural equation modeling and questionnaires.

(1) Compared with DGCNN, FBCNet, Tsception, STNet, MT-CNN, SSTD and STSNet, the 3DMSCA model has the optimal accuracy in the DREAMER dataset validity and arousal dimensions, with values of 0.895, 0.847, i.e., it indicates that the emotion recognition model based on multiscale 3D convolutional attention network and BLSTM's emotion recognition model (3DMSCA) is prioritized, so that it can be better applied to the mental health education model and provide important technical support for the psychological adaptation enhancement path based on the mental health education model.

(2) GFI, CFI, NFI, TLI are all greater than 0.09, and the RMSEA index is less than 0.08, which indicates that the structural equation model of psychological adaptation enhancement path is better fitted in general, and after correction of the structural equation model, we get the psychological adaptation enhancement path of college students in line with the requirements of the study, and we provide a full overview of the internal interactions between the psychological adaptation enhancement paths of college students based on the mental health education model. It summarizes the interaction mechanism between the psychological adaptation paths of college students based on the mental health education model, which has substantial application value for the psychological health of students in the post epidemic era.

Funding

This study was supported by the Doctoral Innovation Research Fund Project of Jining Normal University (Grant No. jsbsjj2331), "Psychological Adaptation of Special Group College Students in the Post-Pandemic Era" (2023).

References

[1] Zhang, X., Huang, P. F., Li, B. Q., Xu, W. J., Li, W., & Zhou, B. (2021). The influence of interpersonal relationships on school adaptation among Chinese university students

during COVID-19 control period: Multiple mediating roles of social support and resilience. Journal of affective disorders, 285, 97-104.

[2] Crawford, J. (2023). COVID-19 and Higher Education: A Pandemic Response Model from Rapid Adaptation to Consolidation and Restoration. International Education Journal: Comparative Perspectives, 22(1), 7-29.

[3] Fu, L., Li, J., & Chen, Y. (2022). Psychological factors of college students' learning pressure under the online education mode during the epidemic. Frontiers in Psychology, 13, 967578.

[4] Losa-Iglesias, M. E., Calvo-Lobo, C., Jiménez-Fernández, R., Rodríguez-Sanz, D., Corral-Liria, I., Casado-Hernández, I., & Becerro-de-Bengoa-Vallejo, R. (2023). Comparison between virtual and hybrid education for psychological factors and academic stress in freshman nursing students: a case-control study. BMC nursing, 22(1), 300.

[5] Hasan, N., & Bao, Y. (2020). Impact of "e-Learning crack-up" perception on psychological distress among college students during COVID-19 pandemic: A mediating role of "fear of academic year loss". Children and youth services review, 118, 105355.

[6] Song, H. J., Mu, Y. F., Wang, C., Cai, J., Deng, Z. Y., Deng, A. P., ... & Ran, M. S. (2023). Academic performance and mental health among Chinese middle and high school students after the lifting of COVID-19 restrictions. Frontiers in Psychiatry, 14, 1248541.

[7] Levy, I. (2022). Stress, anxiety, and depression in times of COVID-19: Gender, individual quarantine, pandemic duration and employment. Frontiers in Public Health, 10, 999795.

[8] Al-Ansi, A. M. (2021). Students anxiety and recruitment during COVID-19 pandemic: Role of university, specialization and employment expectation. Perspektivy nauki i obrazovania–Perspectives of Science and Education, 49(1), 404-413.

[9] Wang, X., Chen, H., Liu, L., Liu, Y., Zhang, N., Sun, Z., ... & Li, M. (2020). Anxiety and sleep problems of college students during the outbreak of COVID-19. Frontiers in Psychiatry, 11, 588693.

[10] Iqbal, J., Asghar, M. Z., Ashraf, M. A., & Rafiq, M. (2022). Social media networking sites usage and depression among university students during the COVID-19 pandemic: The mediating roles of social anxiety and loneliness. Social Media+ Society, 8(3), 20563051221107633.

[11] Xu, T., Sun, X., Jiang, P., Chen, M., Yue, Y., & Dong, E. (2022). Effects of cell phone dependence on mental health among college students during the pandemic of COVID-19: a cross-sectional survey of a medical university in Shanghai. Frontiers in Psychology, 13, 920899.

[12] Smith, R. A., Brown, M. G., Grady, K. A., Sowl, S., & Schulz, J. M. (2022). Patterns of undergraduate student interpersonal interaction network change during the COVID-19 pandemic. AERA Open, 8, 23328584211073160.

[13] Sahao, F. T., & Kienen, N. (2021). University student adaptation and mental health: A systematic review of literature. Psicologia Escolar e Educacional, 25, e224238.

[14] Arslan, G., Yıldırım, M., & Zangeneh, M. (2022). Coronavirus anxiety and psychological adjustment in college students: Exploring the role of college belongingness and social media addiction. International journal of mental health and addiction, 20(3), 1546-1559.

[15] Sartika, S. H., & Nirbita, B. N. (2023). Academic resilience and students engagement in higher education: study on post-pandemic behaviour. Edu sciences journal, 4(1), 29-34.

[16] Bisconer, S. W., & McGill, M. B. (2023). Undergraduate students and the COVID-19 pandemic: A look-back at first-year constructs of psychological adjustment, implications for clinicians and college administrators. Professional Psychology: Research and Practice, 54(1), 83.

[17] Sheng, J., Ng, D. T. K., Tian, P., & Zheng, Z. (2025). University students' resilience in post-pandemic period: a socio-ecological perspective. Frontiers in Psychology, 16, 1574153.

[18] Magorokosho, N. K., Heraclides, A., Papaleontiou-Louca, E., & Prodromou, M. (2025). Resilience and mental health in university students post-COVID-19 pandemic: insights from the Republic of Cyprus. Frontiers in Public Health, 13, 1638427.

[19] Bolo, M. N. V. (2024). Turning Setbacks into Comebacks: High School Students Academic Resilience in the Post-Pandemic Era. International Journal of Research and Innovation in Social Science, 8(3s), 5661-5685.

[20] Dai, X., & Yu, D. (2023). Analysis of mental health status before and after psychological intervention in response to public health emergencies by medical students: a prospective single-arm clinical trial. Translational Pediatrics, 12(3), 462.

[21] González-García, M., Álvarez, J. C., Pérez, E. Z., Fernandez-Carriba, S., & López, J. G. (2021). Feasibility of a brief online mindfulness and compassion-based intervention to promote mental health among university students during the COVID-19 pandemic. Mindfulness, 12(7), 1685-1695.

[22] Zhang, J., Zhou, Z., & Zhang, W. (2021). INTERVENTION EFFECT OF RESEARCH-BASED PSYCHOLOGICAL COUNSELING ON ADOLESCENTS'MENTAL HEALTH DURING THE COVID-19 EPIDEMIC. Psychiatria Danubina, 33(2), 209-216.

[23] Xu, J., & Yang, X. (2024). The influence of resilience on stress reaction of college students during COVID-19: the mediating role of coping style and positive adaptive response. Current Psychology, 43(13), 12120-12131.

[24] Marheni, E., Purnomo, E., Okilanda, A., Oktavianus, I., Hambali, B., Burstiando, R., ... & Jermaina, N. (2024). Development of mental education through sports to enhance adolescent personal resilience. Journal of Human Sport and Exercise, 19(2), 536-549.

[25] Han, Q. (2025). Design and implementation of VR teaching practice model for higher vocational students' mental health education course oriented towards improving psychological resilience. Journal of Computational Methods in Sciences and Engineering, 14727978251371162.

[26] Firmante, M. C. M. (2025). Hybrid learning and student well-being: a narrative review of

engineering students' post-pandemic experience. Multidiscip. Int. J. Res. Dev, 4, 105-111.