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# Mental Health Status and Influencing Factors of College Students

Liangqun Yang, School of Education Science, Neijiang Normal University, China*

## ABSTRACT

This study aims to address the mental health challenges brought about by the diversified development and rapid changes in society, with special attention to the psychological status of the student population. By using the SCL-90 mental health testing tool, collecting students' mental health data, and applying the fuzzy comprehensive evaluation method to analyze and evaluate students' mental health and its influencing factors in depth, the study aims to provide more effective countermeasures for students' mental health education as well as targeted teaching assistance for teachers. This study combines the BP neural network prediction model, which is committed to improving the accurate prediction of students' mental health status. The results of the study will help to assess the mental health level of students, detect and intervene in psychological crises in a timely manner, provide schools with more comprehensive mental health management and services, and promote the overall healthy growth of students.

## KEYWORDS

College Students, Fuzzy Comprehensive Evaluation Model, Influencing Factors, Mental Health Problems

## INTRODUCTION

In this era of rapid development of knowledge economy, the social demand for high-quality talents is growing, which makes the number of college students in China surge. With the progress of massification of higher education in China, the penetration rate of higher education has increased from 30% in 2012 to 57.8% in 2021, signifing that higher education is moving to a higher level of development (Coghill, 2021).

Both the social development needs and students' self-requirements have elevated students' requirements, which invariably increase the burden on college students. The pressure faced by college students is gradually increasing, and at the same time, the change in environment also puts forward new requirements for college students. College students are generally in the age of 18-23 years old. They enter college from high school, breaking the closed learning state of junior and senior high school and entering a colorful mini-society (Paton et al., 2022). Facing heavy academic pressure, college students often must cope with academic tasks such as exams and assignments and deal with practical work such as internships and part-time jobs, which may cause them to feel anxious, nervous, and stressed. In addition, social pressure is also an essential factor as college students need to adapt to

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new social environments, establish interpersonal relationships, and face expectations and evaluations from classmates, teachers, and family members, and this social pressure may also have an impact on their psychological conditions (Moran et al., 2022).

Meanwhile, employment pressure is also a common challenge faced by college students, who need to cope with issues such as future career planning and employment competition, while the uncertainty and pressure will also burden college students psychologically (Timimi, 2020). All aspects require college students to grow up quickly, which leads to many college students not adapting to college life quickly, and the pressure from all aspects comes, which can easily lead to mental health problems (Patabendige et al., 2020). This situation greatly challenges the state, society, and schools in mental health education (Clark et al., 2021).

In response to this situation, China has strengthened its efforts to provide psychological education to college students. For undergraduate and specialized students, mental health education has become a major part of university psychological education. However, China's current psychological education is still in its infancy. Compared with our country, psychological research in the West started early, developed relatively quickly, and is relatively high.

The SCL-90 scale is the most widely used measurement tool at present. It is designed to be more comprehensive, containing several mutually independent factors which can comprehensively understand the psychological condition of the respondents. The SCL-90 uses a simple and straightforward way, which is easy to be understood by the respondents (Daley et al., 2020). At this stage, most of the measurements of college students' mental health status in China are based on this scale.

In this paper, the SCL-90 scale is combined with the fuzzy comprehensive evaluation method to establish a model for predicting the mental health status of college students, which can more accurately predict the mental health status of students. The innovation of this method is to introduce advanced machine learning technology into the mental health field. By combining the complexity and flexibility of neural network models and the actual needs of the mental health field, this paper attempts to achieve more accurate and personalized mental health prediction. This interdisciplinary integration of research methods is expected to bring new ideas and methods for predictive analysis in the mental health field, and to provide more effective means for the maintenance and promotion of graduate students' mental health. Therefore, exploring the neural network-based predictive analysis of graduate students' mental health status is of great theoretical and practical significance.

## RELATED WORKS AND THEORETICAL BASIS

### Related Works

Bryant et al. (1986) used confirmatory factor analysis with national survey data to explore how educational status affects the criteria men and women use to evaluate their subjective well-being. College may sensitize men to mental health issues and may thereby broaden the realm of psychological criteria that they consider relevant for their self-evaluations (Bryant et al., 1986). Guo et al. (2010) described the health quotient of Chinese undergraduates to discern whether socio-demographic characteristics, academic achievements, and perceived health status significantly affect the health quotient of Chinese college students and to identify the predictable factors of health quotient in undergraduates. Holistic health of college students is essential and implies positive health behaviors and a focus on health promotion (Guo et al., 2010). A dual-factor mental health model includes measures of positive psychological well-being in addition to traditional indicators of psychopathology to comprehensively determine mental health status (Antaramian, 2015). The current study examined the utility of this model in understanding the psychological adjustment and educational functioning of college students. Furthermore, there is strong evidence that perceiving that close peers drink heavily is particularly risk-enhancing for anxious and depressed college students and offers implications for alcohol intervention targeted at these subgroups (Kenney et al., 2018). Rasmussen et al. (2020)

investigated the link between social media use and mental well-being, focusing emotion regulation challenges and perceived stress among group of adult college students in the U.S. The findings indicated that social media is indirectly related to mental health issues in cases where emerging adults experience challenges in managing emotions and perceived stress (Rasmussen et al., 2020).

To understand the mental health status of "college students with left-behind experience" in colleges and universities, its influencing factors are analyzed, provide countermeasures to improve the mental health of "college students with left-behind experience," and provide references for the prevention of mental health problems of left-behind children in the future. Zhang et al. (2020) showed that the left-behind population had a high positive rate of psychological problems, suggesting that left-behind experience is the main factor affecting their mental health. A mixed method involving quantitative survey and qualitative interview was employed to explore the influence of LBE on the mental health of college students (Zhang et al., 2020). 1605 college students from three universities in Shandong province in China were recruited in a mixed-method study to examine the mental health problems of college students who had left-behind experiences (Liu et al., 2021), showing that college students experienced pronounced mental health difficulties because of the COVID-19 pandemic. MacDonald (2023) studied risk and resilience factors associated in 135 college students' psychological distress and PTSD symptoms during the COVID-19 pandemic.

## Theories Related to Mental Health

With the advent of the new century and the popularization of education, the education of undergraduates and college students in China has made significant progress, and the education of college students has developed rapidly. As an essential part of high-level talents, the number of students in colleges and universities is increasing. The bigger it is, the more pressure it faces, which seriously affects the mental health of this group of college students. As highly educated personnel, college students have long been understood as the leaders in society and are considered to have good psychological qualities, but the actual situation backfires. There are many bloody examples on the Internet. Research and analysis of health status is necessary.

In recent years, as people have paidy more and more attention to mental health awareness, there are many kinds of measurement tools for mental health involving various fields, and each has its own merits. According to incomplete statistics, there are more than 85 test methods for personal mental health testing, and the research on them is still developing. This article will analyze the four most used measurement methods (Table 1).

**Table 1. Comparison of test scales**

| Test Scale | Testing Purposes | Test Function | Test Features | Suitable |
|---|---|---|---|---|
| Cartel personality test (16PF) | Diagnose the personality type of the manager or candidate | Predict test takers' job stability | Use factor analysis | various personnel |
| Eysenck Personality Questionnaire (EPQ) | Classification of personality traits through three aspects: extrapolation tendency, neuroticism, and psychoticism | Extraversion Dimensions: Extraversion and Introversion | Has high reliability and validity | Medicine, Justice, Education |
| College Student Personality Questionnaire (UPI) | Screening of college students' mental health | Screening out students with mental health abnormalities | Simple and easy to do, much information | College students over 16 years old |
| symptom self-rating scale (SCL-90) | assess whether a person has a specific psychological symptom | Good discrimination between people with psychological symptoms | You can test yourself, or you can check with others | Junior high school students to adults |

Among the many measurement tools, the most extensive, frequently used, and more selective measurement tool is the SCL-90 Mental Health Symptom Self-Rating Scale, which has good test effect, reliability, and validity. The public recognize them all, so this paper also uses the scale as the main basis for evaluating the mental health status of college students in my country. Our country has established a norm range that conforms to the actual situation, and the existence of the norm value lays the foundation for the research of this paper.

The SCL-90 screening standard is a total score system. The total score reflects the overall level of mental health. If the score exceeds 160, you may feel discomfort in your heart; if it exceeds 200, you feel moderate symptoms; if it exceeds 250 points, there are more serious psychological problems, as shown in Table 2.

Through the survey on the mental health of college students in this paper, the range value of the measured college student group is compared with the national norm range value. The somatic and interpersonal sensitivity factors are lower, but other factors are lower than the national norm. The range value, through comparison, shows that the existing national norm value is different from the mental health status of contemporary college students. With the continuous updating of college students and the continuous development of society, based on SCL-90 scale, it is necessary to make a linear integration of each factor and make a comprehensive evaluation of the psychological status of college students.

## Fuzzy Comprehensive Evaluation Method

### *Fuzzy Phenomenon and Membership Function*

#### *Blur Phenomenon*

In daily life, there are ubiquitous vague phenomena; for example, we cannot judge whether a person is “bald”; unable to judge people’s “fat” and “thin”; the school’s “excellent party members” or “excellent teachers.” People generally encounter vague phenomena that almost run through their entire life, but we do not consider it a specific concept. Fuzzy objects belong to a type that cannot be precisely defined. Therefore, those fuzzy phenomena almost run throughout our life. On the contrary, those phenomena that seem to be very certain or very certain are relative, and the objects are different. The conclusions will be different. Since humans began to make judgments about things, the way of reasoning we have adopted has been vague, and this is all due to the vagueness of vague concepts.

The existence of fuzzy phenomena is everywhere. Almost all language methods used to express or convey knowledge have vague concepts, significantly impacting precise mathematics. In the era of big data and information explosion, the defects of traditional precise mathematics have been

**Table 2. Question numbers corresponding to each SCL-90 factor**

| Factor | Corresponding SCL-90 Question Number |
|---|---|
| Somatization factor (12 items) | 1,412,27,40,42,48,49,52,53,56,58 |
| Anxiety factors (10 items) | 2,17,23,33,39,57,72,78,80,86 |
| Psychosis (10 items) | 7,16,35,62,77,84,85,87,88,90 |
| Interpersonal Sensitivity (9 items) | 6,21,34,36,37,41,61,69,73 |
| Hostile factor (6 items) | 11,24,63,67,74,81 |
| Fear factor (7 items) | 13,25,47,50,70,75,81 |
| Compulsive Factors (10 items) | 3,9,10,28,35,45,46,51,55,65 |
| Depression factor (13 items) | 5,14,15,20,22,26,29,30,31,32,54,71,79 |
| Paranoia factor (6 items) | 8,18,43,68,76,83 |

revealed in many aspects; a massive amount of fuzzy information needs to be processed, so the opposition between accuracy and fuzzy uncertainty is more prominent. The reliability and validity of the traditional mental health measurement tools mentioned above need to be considered with the changes of the times, and the screening method of the general scale is the total score system. The degree of influence varies, and there are already many biases in such screening methods. The individual differences of modern people are getting bigger and bigger, and different screening criteria should be used to measure different groups. This method is more suitable for the current situation in our country. As far as college students are concerned, after 20 years of education experience, they have a relatively high ability to deal with things, so the psychological adjustment ability in some aspects is better. However, at the same time, the group has less contact with society. The conflict between idealized life and the status quo severely impacts the situation, so the inappropriateness of the total points system screening method has become increasingly obvious.

#### Membership and Membership Function

In past precision mathematics, the descriptions were generally related to group membership. For example, students with a score of 85 or more were defined as "excellent," then a score of 70 was not considered excellent. A student with a score of 85 was considered excellent, and a test score of 90 is also excellent; if this phenomenon is described, it is the situation shown in Figure 2.1. In the universe U of the analysis of student performance shown in the figure, if the students with scores higher than 85 are set A, and each point is the score u of each student, then for the universe U, each point u is for the set A. There are only two kinds of relationships, "belongs to" or "does not belong," and this judgment is inevitable. However, for set A, among the students who belong to set A, the degree of excellence of different scores is different. For example, students with 100 points and 85 points have apparent differences in their mastery of knowledge. Therefore, each element is divided into the degree of belonging to a certain characteristic, that is, the degree to which each student's grade u belongs to the characteristic A of "excellent" is described so that the process of describing the phenomenon with the degree of membership is the process of establishing a fuzzy set.

### Fuzzy Comprehensive Evaluation

#### Fuzzy Comprehensive Evaluation Model

Because mental health is a complex decision-making problem, and there are many influencing factors, each factor has different effects on mental health, and the corresponding weights should be different. In terms of health, the distribution of weights is the core issue. The fuzzy comprehensive evaluation method performs synthetic operations on fuzzy matrices, directly acts on each factor on the comment set. Each weight value will be too small, and many important factors are not reflected, so the single-layer fuzzy comprehensive evaluation model is simply used for evaluation, and the results obtained have a particular deviation from the actual value (Qin et al., 2021).

We adopt the fuzzy comprehensive evaluation model to judge many problems in practical applications. The hierarchical factor set's multi-level fuzzy comprehensive evaluation method is adopted if there are many factors. For example, when making a comprehensive evaluation of a university, the evaluation factors are first divided into several categories, such as the school's hardware equipment, faculty strength, and school development. Then, the hardware equipment category is judged, specifically the school library's collection of books. As well as the configuration of equipment in the school classrooms and other factors to comprehensively evaluate, evaluating each category of factors separately and then making an overall evaluation is a multi-level fuzzy comprehensive evaluation method (Zhang et al., 2023). After the hierarchical division, the relationship of each factor is more apparent, and it is large enough to avoid the occurrence of too small factor weights due to weight normalization. In evaluating the mental health of college students, we propose a multi-factor fuzzy comprehensive decision-making model, that is, a multi-level comprehensive fuzzy evaluation model.

## MATERIALS AND METHODS

There are several standard methods for self-learning of samples by networks, decision trees, KNN, statistics, and neural networks. In terms of simplicity of model description, neural networks are the simplest, while decision trees are more complex. Regarding computational difficulty, utilizing both decision trees and KNN is challenging, while neural networks perform well.

J. Holland first proposed the concept of Genetic Algorithm in 1975. After the conclusion, the Genetic Algorithm was researched in the late 1980s. The algorithm draws on the evolutionary laws described in the biological evolution theory and can randomize the global search.

Similar to the neural network algorithm, when the problems faced are different, the individual coding method, fitness function, and various operators of the genetic algorithm are different, but the essence of all genetic algorithms is the same, that is, the population is carried out according to the fitness function (Li et al., 2022). Selection, mutation, and crossover operations generate new populations through operators. The newly generated populations have higher fitness than previous generations and complete the global search for the optimal population.

In the genetic algorithm, the size of the individual's survivability is determined by the individual's fitness. Fitness is the degree of conformity to the goal of the problem, and the individual with the largest fitness value is searched through the iterative process of the algorithm as the optimal solution. The fitness functions mainly include:

(1) If the objective function is a minimum value problem, then:

$$Fit\left(X\right) = \begin{cases} C_{\max - f\left(X\right),\ \ if\ f\left(X\right) < C_{\max}} \\ 0, else \end{cases} \tag{1}$$

(2) If the objective function is a maximum value problem, then:

$$Fit\left(X\right) = \begin{cases} C_{\min + f\left(X\right),\ if\ f\left(X\right) + C_{min} < 0} \\ 0, else \end{cases} \tag{2}$$

Cmin is a given smaller number and Cmax is a given larger number. According to the specific problem, choose the appropriate fitness function.

The selection operator is an operation for screening individual populations, which can effectively reduce the calculation time, improve the global convergence, and avoid the occurrence of missing important genes.

(1) Proportional selection operator

The basic idea of the proportional selection operator is: the higher the fitness of the group, the greater the probability of being selected; that is, the relationship between the probability Pi of the individual i being selected and the fitness Fi is:

$$P_i = F_i \,/\, \sum_{i=l}^{M} F_i \tag{3}$$

(2) Design of crossover operator

The parent chromosomes are recombined and crossed for the same population to generate new chromosomes, which is also an essential process of new organisms in biological evolution.

One-point Crossover determines the location of a crossing point and places new creatures behind this point after spawning.

Two-point Crossover determines the position of the two crossover points and arbitrarily exchanges this part of the gene.

Arithmetic cross is where a weighted average, two-parent chromosomes produces two daughter chromosomes. If the parent is XtA, XtB, the child is:

$$\begin{cases} X_A^{t+1} = \alpha X_B^t + \left(1-\alpha\right) X_A^t \\ X_B^{t+1} = \alpha X_A^t + \left(1-\alpha\right) X_B^t \end{cases} \tag{4}$$

The constant parameter α represents the uniform arithmetic crossover.

(3) Design of mutation operator

Apply the genetic algorithm to the neural network; that is, assign the optimal solution to the connection weights and thresholds of each factor of the established neural network, and then adjust the weight thresholds through the neural network, and the weights thresholds optimized by the GA algorithm can be closer. The value required by the network.

The empirical formula for the number of hidden layers in a neural network (there is no accurate and reasonable algorithm for finding the optimal number of hidden layers) is:

$$h = \frac{1}{2}\left(Y + O\right) + a\left(a = 1,2,\ldots,10\right) \tag{5}$$

The number of neurons: Y, the number of neurons in the output layer: O, a is a constant, and the number is h=8+a according to the empirical formula.

The activation function Ø(x) of the hidden layer of the network:triangular sigmoid, the activation function is one of the necessary components to regulate the activity of neurons.

$$E = \frac{1}{2}\sum_{p=1}^{P}\sum_{k=1}^{L}\left(T_k^p - o_k^p\right)^2 \tag{6}$$

Each neuron in the input layer acts on each neuron in the hidden layer, and the calculation of the input YSRi of the ith neuron in the hidden layer is:

$$YSR_i = \sum_{j=1}^{14}\omega_{ij} Y_j + \theta_i \tag{7}$$

Its output YSRi is calculated as:

$$YSC_i = \phi\left(YSR_i\right) = \phi\left(\sum_{j=1}^{14}\omega_{ij}Y_j + \theta_i\right) \tag{8}$$

The calculation of the input SCSRk of the kth node of the output layer is:

$$SCSR_k = \sum_{i=1}^{14}w_{ki}YSC_i + a_k = \sum_{i=1}^{14}w_{ki}\phi\left(\sum_{j=1}^{14}\omega_{ij}YSR_j + \theta_i\right) + a_k \tag{9}$$

Its output Ok is calculated as:

$$o_k = \Psi\left(SCSR_k\right) = \Psi\left(\sum_{i=1}^{q}\omega_{ki}YSR_i + a_k\right) = \Psi\left(\sum_{i=1}^{q}w_{ki}\phi\left(\sum_{j=1}^{M}\omega_{ij}YSR_j + \theta_i\right) + a_k\right) \tag{10}$$

By calculating the error between the actual output and the ideal output, the output error of each layer of neurons is adjusted from the output layer of the network; that is, the weight threshold of the neuron is adjusted according to the gradient descent method, and the network is made through continuous backpropagation. The actual output obtained can be substantially close to the ideal output.

The quadratic error for sample data p is calculated as Ep:

$$E_p = \frac{1}{2}\sum_{k=1}^{L}\left(T_k - o_k\right)^2 \tag{11}$$

The composite error of the P sample data is calculated as E:

$$E = \frac{1}{2}\sum_{p=1}^{P}\sum_{k=1}^{L}\left(T_k^p - O_k^p\right)^2 \tag{12}$$

Correction function of output layer weights and thresholds:

$$\Delta\omega_{ij} = -\eta\frac{\partial E}{\partial\omega_{ij}} = -\eta\frac{\partial E}{\partial SCSR_k}\frac{\partial YSC_k}{\partial\omega_{ki}} = \eta\frac{\partial E}{\partial o_k}\frac{\partial o_k}{\partial SRSR_k}\frac{\partial SCSR_k}{\partial\omega_{ki}} \tag{13}$$

Correction function of hidden layer weights and thresholds:

$$\Delta\omega_{ij} = -\eta\frac{\partial E}{\partial\omega_{ij}} = -\eta\frac{\partial E}{\partial YSR_i}\frac{\partial YSR_k}{\partial\omega_{ij}} = \eta\frac{\partial E}{\partial y_i}\frac{\partial y_i}{\partial YSR_i}\frac{\partial YSR_i}{\partial\omega_{ij}} \tag{14}$$

Correction function for output:

$$\frac{\partial E}{\partial_{o_k}} = -\sum_{p=1}^{P}\sum_{k=1}^{L}\left(T_k^p - o_k^p\right) \tag{15}$$

$$\frac{\partial SCSR_k}{\partial \omega_{ki}} = y_i \frac{\partial SCSR_k}{\partial a_k} = 1 \frac{\partial YSR_i}{\partial \omega_{ij}} = x_i \frac{\partial YSR_k}{\partial \theta_i} = 1 \tag{16}$$

The correction amount of the weight threshold is:

$$\Delta\omega_{ij} = \eta\sum_{p=1}^{P}\sum_{k=1}^{14}\left(T_k^p - o_k^p\right)\cdot \Psi'\left(SCSR_k\right)\cdot \omega_{ki}\cdot \phi'\left(YSR_i\right)\cdot Y_j \tag{17}$$

$$\Delta\theta_i = \eta\sum_{p=1}^{P}\sum_{k=1}^{14}\left(T_k^p - o_k^p\right)\cdot \Psi'\left(SCSR_k\right)\cdot \omega_{ki}\cdot \phi'\left(YSR_i\right) \tag{18}$$

The self-learning of the samples through the network can map any complex nonlinear relationship. Its simple learning rules and concise algorithm description are more conducive to solving nonlinear problems.

The research on mental health problems is very complex, involving many factors, and there is no correlation between each factor. Solving this nonlinear relationship has become the core problem. Due to the complex relationship between each influencing factor and its psychological state, the method selected in this paper must find a mapping relationship that conforms to the actual situation from the data corresponding to each factor. Also, it must ensure the model's simplicity and comprehensibility. Therefore, this study uses an artificial neural network algorithm. According to the situation, this paper chooses the backpropagation feed-forward method with supervised learning: BP algorithm (Yu & Li, 2014).

## EXPERIMENTAL RESULTS AND ANALYSIS

### Establishment of the Prediction Model

A neural network model based on the BP algorithm is established. Its structure is (14, 14, 1), in which the first layer is 14 input data, the hidden layer is 14 neurons according to the experimental results, and the corresponding prediction result is the third layer. The activation function of the neurons in the second layer is selected as the Triangular Sigmoid, which is also the activation function of the third layer. The meaning of the function is to adjust the activity of the neurons. The algorithm for network training is selected as the trainlm algorithm (Zhao et al., 2010).

When the genetic algorithm optimizes it, the number of iterations is selected as ten generations, the size of the population is determined according to the structure of the neural network (14, 14, 1), and the probability of the crossover and mutation operators are set between [0, 1] respectively. Through the initialization operation of the population, starting with the initial population, according to the objective function, that is, the minimum error of the neural network error function as the goal, a global search is performed to find the connection weights and thresholds that are most suitable for the network. This value is assigned to the neural network. The BP network optimization process is shown in Table 3.

**Table 3. Optimization process**

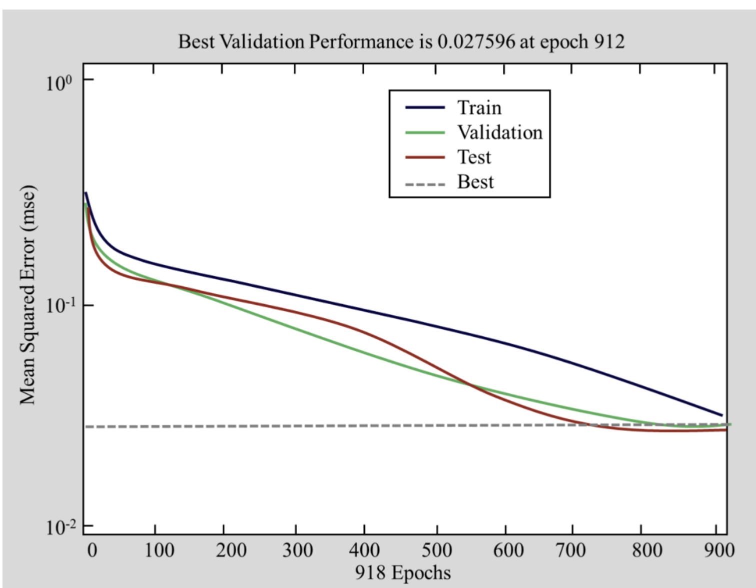
| Specific Procedures | Note |
|---|---|
| Maxgen=10 | Maximum number of iterations |
| Sizepop=238 | Population size |
| Pcross=[0.3] | Crossover probability |
| Pmutation=[0.1] | Probability of variation |
| Fori=1: sizepop | Initialized population |
| individuals=Select(individuals,sizepop) | Selection |
| individuals.chrom=Cross(pcross,lenchrom,individuals.chrom,size pop,bound) | Crossover |
| individuals.chrom=Mutation(pmutation,lenchrom,individuals.chr om,sizepop,i,maxgen,bound) | Mutation |

Use the LM algorithm to self-learn and train the network, and adjust each parameter:

```
net.trainParam.epochs=1000;
The learning step size is 1000;
net.trainParam.lr=0.1;
rate is 0.1;
net.trainParam.goal=0.0000001;
The training target is 0.0000001;
```

The rest of the parameters are default values, by drawing the error change graph, as shown in Figure 1.

**Figure 1. Neural network training process**



The established neural network model is entered for data entry, and the test data is simulated and tested. The network is in the process of self-learning, and the error gradually decreases. The network output is de-normalized, and the comparison between the model results and the ideal output is shown in Figure 2. It can be seen from the simulation tests on several data groups that the error between the prediction results and the actual values is very small. The model's fitting to the input data largely meets the required standards, allowing it to make accurate predictions about the mental health of college students.

According to the established neural network model, the network training results are shown in Figure 3. When the upper limit of the training step is 1000 steps, the neural network completes the data fitting in 6 seconds, and the error rate is 3.04%. Regarding model description, algorithm steps, and specific implementation, the mental health prediction model is concise and easy to understand and operate. It has a strong ability to predict data, which can forecast the mental health of college students in China.

As can be seen from Figure 3, by comparing the errors before and after optimization using the genetic algorithm, it can be found that the optimized neural network prediction model is better than the pre-optimized neural network, and the optimized neural network can achieve the data fitting effect faster.

Figure 4 shows the comparison before and after color matching of bundled histograms to analyze SCL-90 symptom self-rating scale data.

At present, the existing mental health assessment systems all evaluate users in the form of text scales. After the users submit the scales, the system calculates and analyzes the scale data, then

**Figure 2. Simulation test**

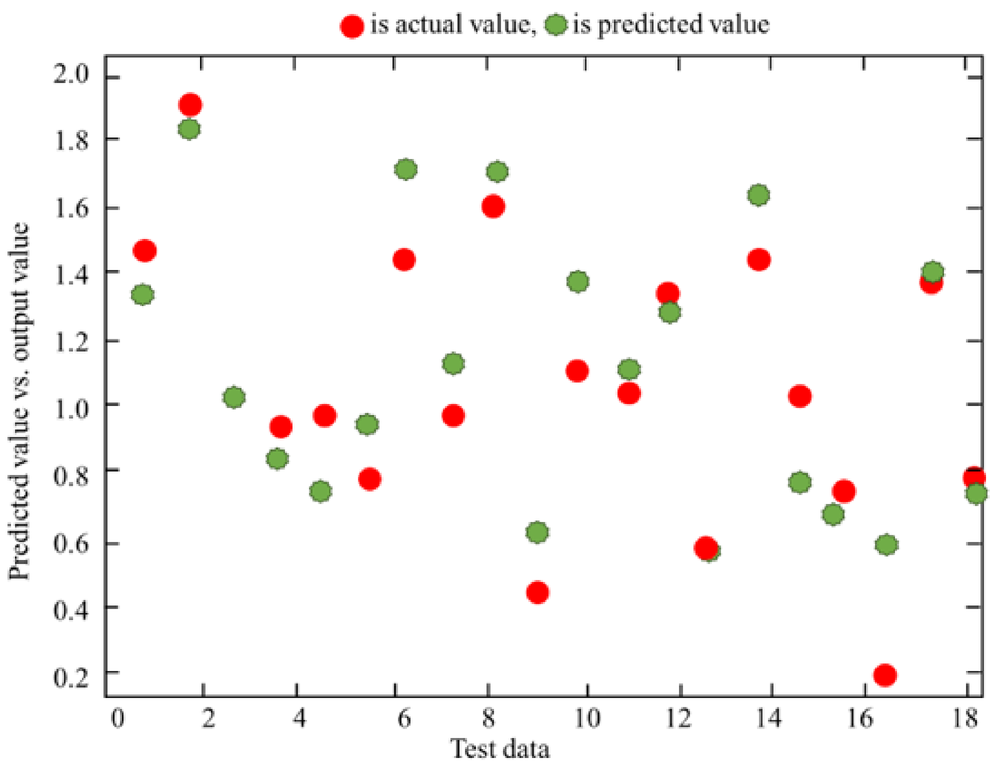


Figure 3. Error comparison before and after optimization

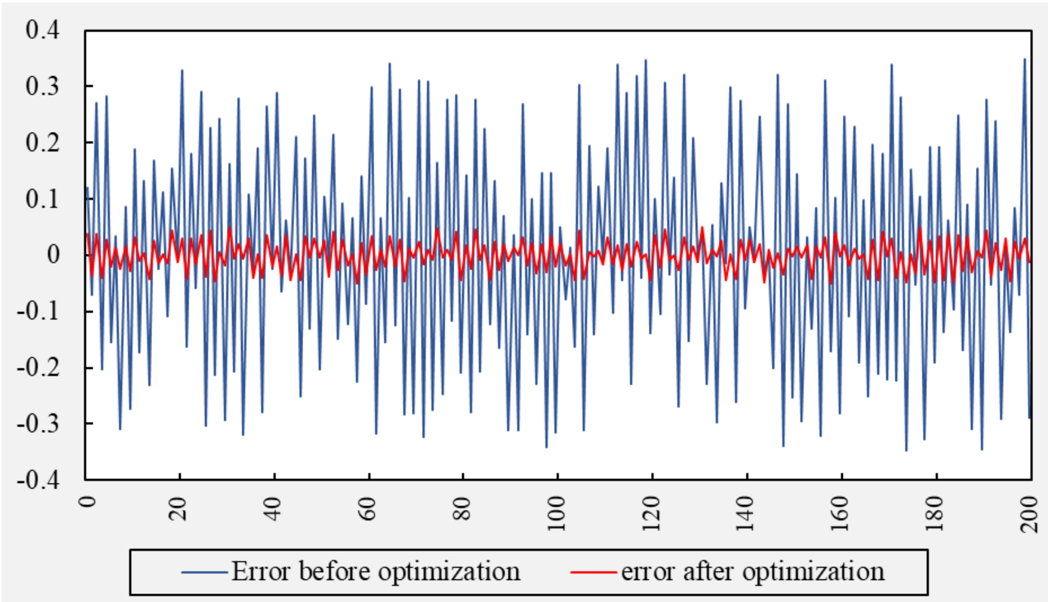
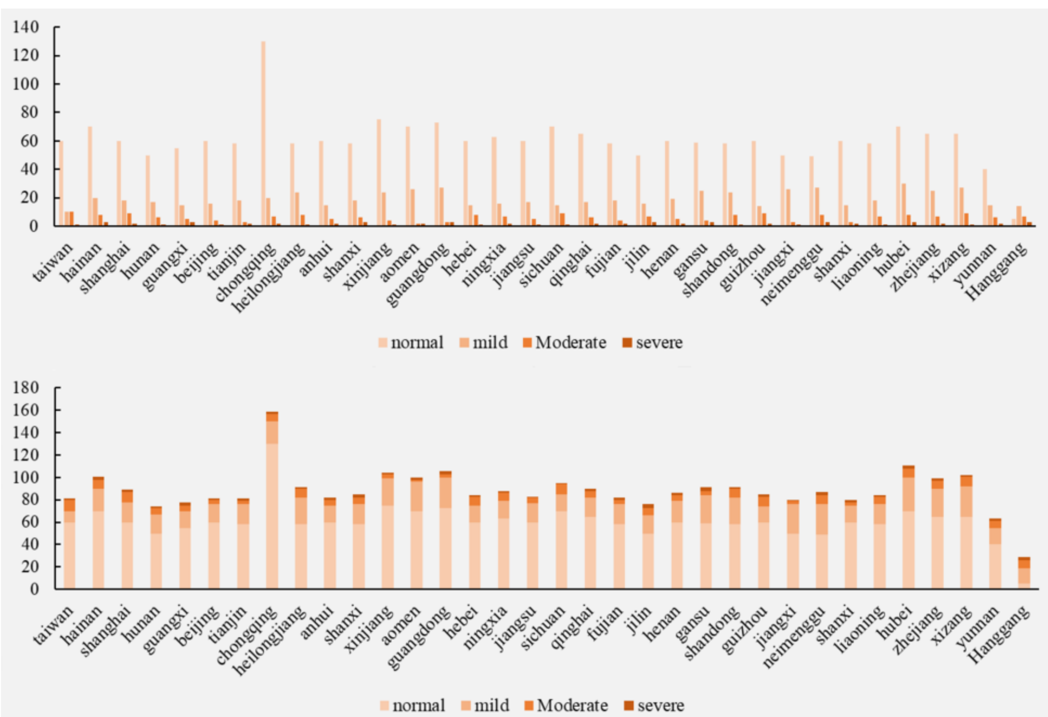



Figure 4. Comparison of the effects before and after the stack chart psychological test



displays the results in the "assessment results" block in Figure 5. However, such a result is not easy to understand directly, and it is unclear what state the user's total evaluation score is in and what the results of each factor are.

The factor line graph in Figure 6 is the factor distribution of each factor, in which the size of each circle represents the factor equalization of the corresponding color factor, and the larger the circle, the larger the factor averaged value of the factor, and the sub-health The more likely the state is. By clicking the circle in the line chart, we can view the specific score of each question under the factor in the bar chart, among which, according to the questionnaire's "none," "very light," "moderate," "heavy," "severe" five questions with a score of 0-4 are not displayed in the bar chart.

Comprehensive statistical analysis is an overall analysis of the data entered by all users. Because the data collected is limited, the system simulated more than 3,000 records from 34 provinces in China between January 1, 2021, and May 10, 2021. This process provided mental health data for people of different genders, ages, and cities and then enabled the data to be analyzed. Figure 7 shows the comprehensive statistical analysis module of the third visualization scheme exploration, the data

**Figure 5. Results of mental health assessment**

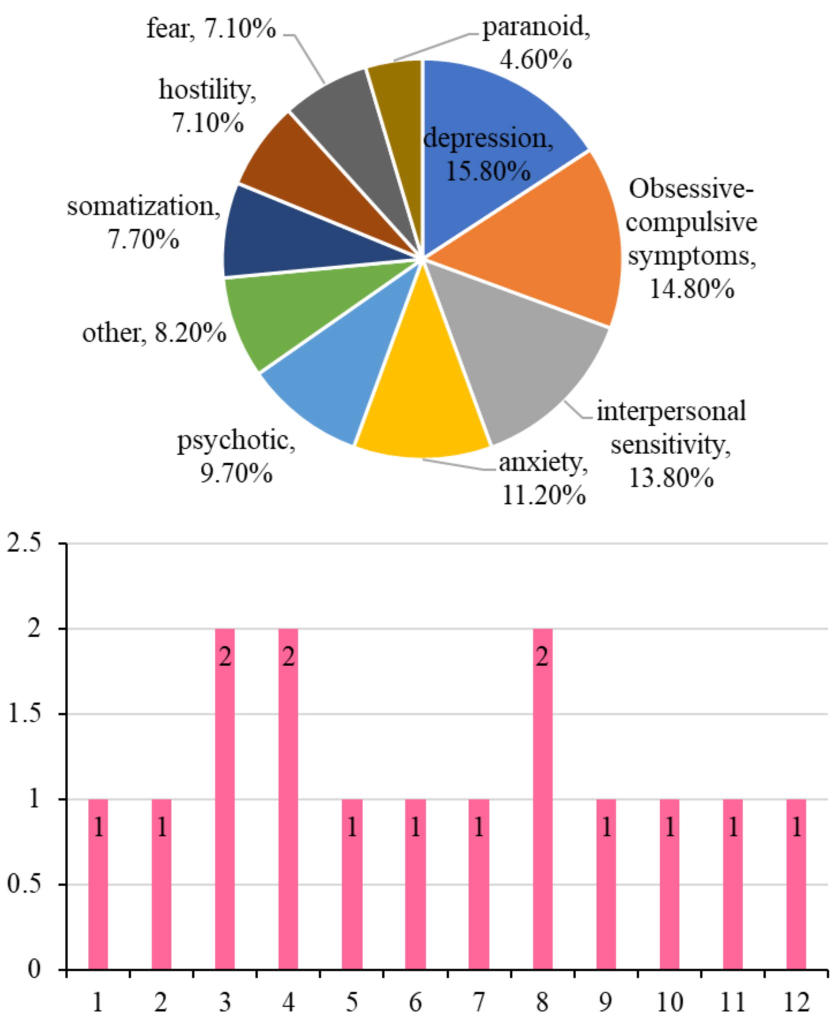


Figure 6. Factor diagram of mental health status

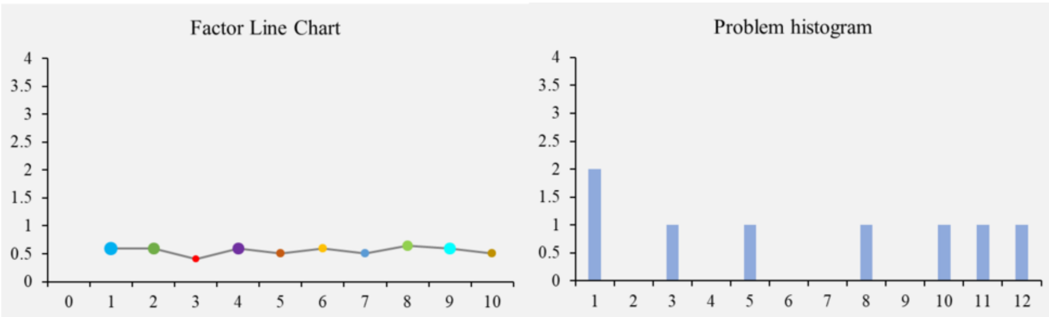
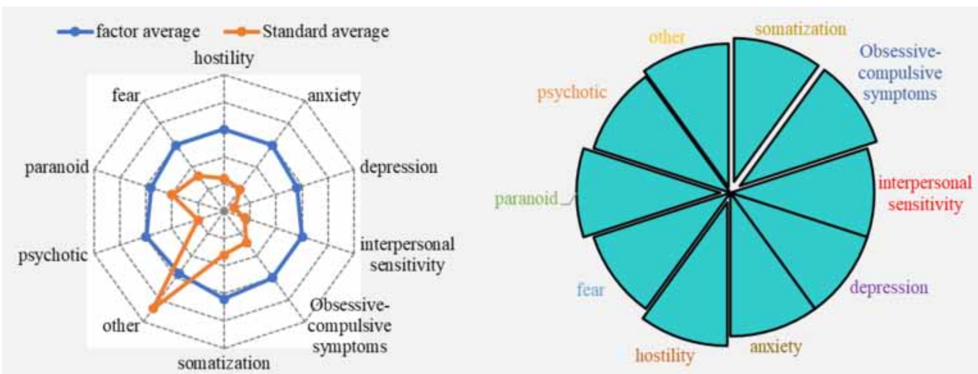



Figure 7. Comprehensive statistical analysis module of mental health




classification module in the figure. When the number of users using the system reaches a specific number, the national or provincial norm of the SCL-90 symptom self-rating scale can be easily obtained by analyzing the data of all users.

The data results show that the prediction model of college students' mental health status established in this paper has very high practical value in real life and application, can more accurately predict students' mental health status, and achieve the expected effect.

## CONCLUSION

In the research on the mental health of college students, we need to improve the measurement tools based on the existing mental health measurement tools. The new measurement tool should be grounded in a specific theoretical construction, and the focus should be college students. It considers the living and learning conditions of college students in China at this stage, integrating these aspects with this demographic's evolving mental health landscape. This approach provides an effective mental health assessment tool for college students.

Under the background of the tense mental health of college students, the fuzzy comprehensive evaluation model is used to judge the mental health of college students. A prediction model of college students' mental health is established, and Matlab was used for simulation to achieve good validity. This paper studies the factors that affect the mental health of college students, and on this basis, proposes a design method of indicators and parameters for evaluating the mental health of college students.

At the same time, the research results show that the mental health prediction model established in this paper can reasonably evaluate mental health situations is feasible.

Neural network-based mental health prediction models have significant advantages over traditional methods. Neural networks can handle complex nonlinear relationships, thus better capturing underlying patterns and interaction effects in mental health prediction. Neural networks perform feature extraction and representation learning through multilayer nonlinear transformations, which can effectively handle high-dimensional data and discover helpful information in the data. Therefore, neural network-based methods provide a powerful and flexible tool for mental health prediction. However, the interpretability of neural network models, the complexity of training, and the demand for computational resources must be considered. Therefore, in specific applications, it is necessary to consider the characteristics of the research problem, the availability of data, and the applicability of the method to select an appropriate method to predict mental health.

## AUTHOR NOTE

The figures and tables used to support the findings of this study are included in the article. The authors declare that they have no conflicts of interest. This work was not supported by any funds. The authors would like to show sincere thanks to those techniques who have contributed to this research.

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