J. COMBIN. MATH. COMBIN. COMPUT. 127b (2025) 485--506

Journal of Combinatorial Mathematics and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Combinatorial Press

Design of a neural network model-based system for predicting students' mental health status and psychological intervention in colleges and universities

Jing Zhao[1,✉], Gangqian Wang[2], Ning Yong[3], Yifan Xue[4]

[1] *School of Accounting, Shaanxi Technical College of Finance and Economics, Xianyang, Shaanxi, 712000, China*
[2] *The Office of Student Affairs, College Student Employment Guidance Center, School of Innovation and Entrepreneurship, Shaanxi Technical College of Finance and Economics, Xianyang, Shaanxi, 712000, China*
[3] *The School of Humanities and Arts, Shaanxi Technical College of Finance and Economics, Xianyang, Shaanxi, 712000, China*
[4] *The Academic Affairs Office, Shaanxi Technical College of Finance and Economics, Xianyang, Shaanxi, 712000, China*

ABSTRACT
At the present stage, the staff of mental health center in colleges and universities have a heavy workload, fatigue work and low work efficiency, and it is urgent to explore new paths to alleviate the severe situation of mental health work in colleges and universities. In this paper, we first start from the students' mental health assessment data and use data mining technology to analyze the students' mental health status. Then, students' behavioral characteristics are digitally represented to construct a prediction model of students' mental health status based on PDNN neural network. Finally, the design method of psychological intervention system in colleges and universities is proposed. In the collected mental health assessment data, the age distribution is skewed toward the younger population, and nearly 55% of these students show a tendency toward psychological abnormality. And the average accuracy and high group recall of the prediction model of students' mental health status established using PDNN neural network were 88.95% and 87.44%, respectively, which verified the feasibility of the modeling method in this paper. Using the psychological intervention system designed based on the method of this paper for the intervention experiments, there is no significant difference between the experimental group using the system and the control group not using the system in the factors before the intervention ($p>0.05$), while after the intervention the experimental group scored significantly lower than the control group in the total mental health score, interpersonal relationship sensitivity, depression and anxiety factor items. This proves the validity of the intervention system design method in this paper, which can be applied in psychological intervention methods in universities.

Keywords: data mining, PDNN neural network model, mental health status prediction, intervention system

✉ Corresponding author.
E-mail address: 18700024444@163.com (J. Zhao).
Received 20 June 2024; Revised 10 September 2024; Accepted 05 January 2025; Published Online 16 April 2025.
DOI: 10.61091/jcmcc127b-028

1. Introduction

With the rapid development of society, adolescent mental health problems have also been widely concerned by all sectors of society, and how to accurately predict adolescent mental health problems and prevent adolescents' physical and mental health from being affected has become the focus of social concern [1-3]. When adolescents experience poor mental health symptoms, they are usually prone to irritability and anger, inability to focus and concentrate, being nervous from time to time, and feeling lonely and worried [4-5]. In the last fifty years, the number of adolescents with mental health symptoms has been increasing, and the related mental health problems will be intensified along with the growth of adolescents until it affects their work and life, and is negatively correlated with social status [6-7]. Therefore, timely detection or prevention of mental health problems is very necessary. The inability of adolescents to accurately judge their own psychological state and the limitations of current medical means have become the main obstacles to the treatment of adolescent mental health problems [8-9]. Compared with traditional means, neural network models can analyze the complicated data in adolescents' lives to automatically judge and predict their psychological status, which has obvious advantages such as high accuracy, high efficiency, high objectivity, and low cost [10-13].

Chinese education departments at all levels attach great importance to the psychological early warning work of higher education students, however, there is a general lack of awareness of the application of informatization technology in practical work, which increases the passivity of the work [14-15]. In addition the mental health level of higher vocational students is affected by many internal and external factors, and there is a complex correlation between the factors, which is a nonlinear problem. In recent years, with the arrival of the big data era and cloud computing, deep learning has a great breakthrough in the practical use of all, it not only has a deeper network structure, is a kind of intelligent machine learning, and through a series of algorithms, so that the computer learns the law from the massive historical data, builds an analytical model, and realizes the whole process of feature extraction to feature classification end-to-end, intelligent identification of the new samples or to future make predictions [16-18].

College students are in their prime, in the period of plucking and gestation, their physiology and psychology tend to mature, and they are open-minded, independent, and brave to compete [19-20]. However, due to the influence of learning environment, interpersonal relationship, love and emotional frustration, employment pressure and other factors, college students' mental health problems are becoming more and more prominent, especially depression, anxiety, psychological disorders and even suicidal tendencies are not uncommon among college students [21-23]. In response to the mental health problems of college students, colleges and universities must take effective countermeasures, through mental health education and intervention, to correct the bad psychology of college students, to avoid the emergence of some radical or extreme behavior, for the fundamental educational task of Lidushi Renren to lay a solid foundation [24-26].

Nowadays, the problem of students' mental health is very serious, and also obtains the key attention of various education experts and scholars, for how to identify and predict students' mental health status has been the focus of research, at present, the main mental health prediction methods used in practice include, based on the data mining technology, based on the machine learning mental health prediction methods. Literature [27] envisioned a psychological management model with k-mean cluster analysis method as the underlying architecture, and introduced data mining technology to analyze students' mental health data information, and confirmed the feasibility of the proposed scheme in predicting students' mental health status through practical tests. Literature [28] conceptualized a mental health prediction system for college students based on the principle of practice sequence and evaluated the performance indexes of the system, such as MSE, f1 score, correct rate, precision and recall, which gained a certain degree of improvement in prediction accuracy compared to both the traditional mental health prediction model based on machine learning and the one based on convolutional neural network technology. Literature [29] examined the mental health status of college students using questionnaires and random sampling methods and conducted a systematic and comprehensive analysis, while using R4.2.3 software to establish a nomogram risk prediction model, which includes predictors such as place of origin, whether the child is an only child, whether there is a major life event, the parents' marital status, regular exercise, close friends, PHQ-9 scores, and was confirmed in numerical tests. And the feasibility of the proposed model was corroborated in numerical tests. Some scholars have also analyzed the optimization method of mental health prediction from the perspective of student mental health data integration. Literature [30] examined the performance of a model trained on joint longitudinal study data to predict mental health symptoms, and based on the results of the study, it was learned that the prediction of mental health of college students using the above method was significantly improved.

To ensure the real-time prediction and supervision of students' mental health status, it is also necessary to pay attention to the effective psychological interventions for students with mental health problems, so scholars mainly through empirical analysis, tracking surveys and other methods to design mental health interventions and verify the effectiveness of these measures. Literature [31] conducted a controlled experiment, revealing that Internet mental health interventions are characterized by low cost and flexibility, and can effectively exert therapeutic effects, but whether it has a long-term effect remains to be further researched. Literature [32] analyzed the feasibility of mental health interventions based on gratitude behavior, combined with randomized controlled experimental design, verified that gratitude thinking behavior helps to alleviate and treat negative emotions such as repression, depression, etc., and also pointed out that gratitude interventions have the need for activity matching and passive control. Literature [33] emphasizes the positive role of digital resource-enabled mental health interventions in the treatment of generalized anxiety based on empirical research tests, and advocates the extension of digital mental health interventions to the general population for the enhancement of mental health and mental well-being. Literature [34] based on a fourteen-day DBT therapy found a significant reduction in negative emotions and a significant increase in positive emotions in the participants, which shows that DBT skill video mental health intervention effectively improved the mental health problems of students in higher education and enumerated the roles of DBT mental interventions, brief and high scalability.

In this paper, on the basis of data mining and big data analysis, we have successfully realized the construction of the prediction model of students' mental health status and proposed the design method of psychological intervention system in colleges and universities. Firstly, students are assessed for their mental health based on the SCL-90 scale and their basic characteristics are mined. On this basis, students' behavioral data were mined and digitally represented, and combined with the improved particle swarm optimization algorithm, a PDNN neural network model was constructed to achieve the prediction of students' mental health status, and the model performance was evaluated through comparative experiments. Finally, the design method of student psychological crisis early warning and intervention system based on PDNN is proposed, and intervention experiments are carried out to confirm the practicality of the constructed system in intervening students' health status.

2. Data analysis of student mental health assessment data based on data mining

In order to realize the dynamic prediction of students' mental health status, this paper firstly uses data mining technology to analyze students' mental health status assessment data, so as to provide data support for the construction of the prediction model.

2.1. Data Mining Methods and Processing Techniques

2.1.1. Data mining techniques. The complete process of discovering value from large amounts of unorganized and incomplete data is called the knowledge discovery (KDD) process, and data mining is one of the most important aspects of it [35].

The whole process of knowledge discovery is shown in Figure 1, which can be divided into three phases: data preparation phase, data mining phase, and result expression and interpretation phase. The data preparation stage can be subdivided into three steps: data screening, preprocessing and conversion.

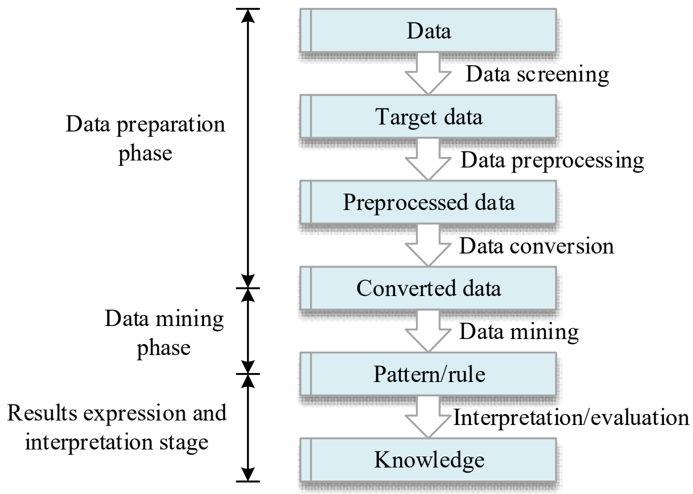


Fig. 1. Process of Knowledge Discovery in Database

Data mining techniques analyze the data stored in the database through the use of machine learning means of in-depth mining to find the existence of valuable correlations hidden in a large amount of data. The main tasks of data mining are:

1) Correlation analysis, i.e., association rule mining. The way to generate association rules is to mine the frequent item set from the data source and then generate strong association rules according to the way to delineate the minimum confidence, which belongs to the category of unsupervised learning methods, and the common algorithms are FP tree frequent set algorithm and Apriori iterative algorithm.

2) Cluster analysis, on the other hand, is a method of mining the hidden structural relationships between the data, by grouping the similar objects in the data into a group, each group is called as a cluster, and the data contained in the same cluster have a high degree of similarity with each other, while there is a certain degree of disparity between the data of the clusters and the clusters. The similarity measure of cluster analysis is realized through the distance formula, the distance is close to be divided into the same cluster, Manhattan distance and Euclidean distance is one of the two most widely used distance calculation methods, and its use of analysis can be based on the division of the five types of division, density, hierarchy, model and grid.

3) Classification prediction, is the first through the existing labeled data characteristics of the dimensions of the mathematical model training, so as to build a model with different classification ability to discriminate, and then its trained model used to judge the unknown data, so as to achieve the purpose of the prediction, the common classification models are SVM model, decision tree model, random forest model and neural networks and so on.

4) Deviation analysis, by analyzing the outlier data that deviates from the standard value, the outlier is also known as abnormal data, such as supervised learning in the same kind of identification of the dataset, but there are some values of abnormally large or small data, these data can not be directly

discarded for processing in mining, you need to analyze the contingency implied by the emergence of its behind the problem, in some of the deviations may contain some of the extremely valuable laws that have been ignored. In some deviations, there may be some extremely valuable laws that have been neglected.

2.1.2. Data-processing techniques. In the process of knowledge discovery, the data processing techniques used in the data preparation stage are collectively referred to as data processing techniques, which mainly include the screening of data in the early stage, the pre-processing of data in the middle stage, and the transformation of data in the late stage, such as transformation or mapping operations. The level of data processing at this stage directly affects the effect of the subsequent data mining model.

1) Data Screening. Although data mining is a method for analyzing massive data, it does not mean that it needs to be applied to all the collected data, because when collecting data in the early stage, there is no specific consideration of the future use of these data, but only to collect more comprehensive data as much as possible. And the value density of these data is very low, which is not conducive to the later data analysis, so when there is a specific research objective, only the data that are useful for the target analysis need to be selected.

2) Data Cleaning. The so-called data cleaning is used to solve the problem of poor data quality due to some accidental factors caused by some useful data after data screening, the main means are the following parts:

(1) Missing value processing: when there is missing data data set in the entire data set accounted for a relatively low, and the data volume of the sample is relatively large, can be processed through the deletion method, that is, directly discard the data items appearing as missing values. Another common processing method is the filling method, which is used in the case where the amount of data itself is not particularly large and there are more samples with missing values, based on the average value of the data near the dimension where the missing value is located to fill it.

(2) outlier processing: also known as outlier processing or error value processing, etc., such as a data item in a dimension of the value is much larger or smaller than the value of the other data items in the sample, then have the dimension of the abnormal value of the data item is called an outlier. When there are outliers in the data, can not be directly discarded for processing, it is necessary to analyze it to determine whether it is reasonable, and then decide on the processing strategy.

(3) De-duplication processing: when the data values between several dimensions are the same or there is a relationship between addition and subtraction operations, it can be assumed that they represent the same data meaning. The elimination of duplicate data dimensions has a certain effect on data slimming and model load reduction, which ensures the uniqueness and representativeness of data dimensions.

(4) Noise data processing: the measured data due to some reasons caused by the random error or variance is the so-called noise, is for the interference of the data, the commonly used means are divided into boxes and regression method. The split-box method by the nearby ordered values into a small group of “boxes”, and then use the mean, median or boundary of the data in the box to smooth these ordered data values, so that these data are locally smooth. The regression method is to use a regression function to fit these noisy data, play the role of smooth data denoising.

3) Data transformation. Data conversion processing can also be called data mapping processing, which generally has three cases. One for the text data encoding conversion, because the computer can not directly deal with text data, so the text needs to be numerical coding. The second is the format

conversion, the data need to be converted to a uniform format type, in order to subsequent analysis and processing. The third is the mathematical processing of numerical data, such as when it is found that the value of a dimension encountered in the form of exponential changes, the formula (1) can be quickly converted into an exponential change in the data to facilitate the observation and analysis of small numerical data:

$$y = \log_m (x + k) \tag{1}$$

Similarly, when the data changes in the form of a power function, it can be processed by opening the root of the n st power, using the formula (2) to convert it to the more easily observed small value data, y is the value after conversion, x is the value before conversion:

$$y = \sqrt[n]{x} \tag{2}$$

4) Data integration. In data analysis and model training, if the simultaneous operation of data in multiple systems is both cumbersome and error-prone, it is necessary to use the data integration method to extract these data and save them in the same environment for processing. The main purpose of data integration is to provide the convenience of data reading and operation for the multi-dimensional characterization of samples in the subsequent data mining process, and to standardize the heterogeneous data sets needed for analysis and save them in the same database system.

2.2. Data analysis and its results

The data used in this paper come from the results of a city student's mental health status assessment, which uses the symptom self-assessment scale SCL-90, and the assessor used the mental health status assessment system to collect a total of 7,846 SCL-90 scale assessment data information, of which 7,840 are valid data. The assessment data mainly included students' basic information after desensitization (including name, age, household type, ethnicity, whether they were only children, etc.), as well as the answers to the 90-item scale and the scores of each dimension.

2.2.1. Analysis of basic user attributes. The information of the assessment data after data preprocessing includes the basic attribute information of the students and the SCL-90 situation of the symptom self-assessment scale. In this paper, the characteristics that do not change over time in the short term are called static characteristics, and the discussed static characteristics of the basic user information data analysis include gender, age, country, type of household registration, and whether or not it is an only child. Characteristics that change over time in the short term are called dynamic characteristics, such as phases of anxiety symptoms, depressive symptoms, obsessive-compulsive symptoms and other psychological abnormalities.

This subsection statistically analyzes the basic user attribute information in the student mental health assessment data, and the distribution of the number of students for each attribute is shown in Table 1.

In the sample of assessors, the ratio of male and female students is about 35:65, with a higher proportion of females compared to males, who may show more delicate emotions. Meanwhile, the results of age distribution showed that most of the students were concentrated between 14 and 25 years old. Specifically, 5,231 students, or about 66.72% of the total, were between the ages of 17 and 22. Therefore, it can be inferred that students at this stage may be in the rebellious stage, with a relatively high incidence of psychological abnormalities. In the distribution of hukou types, the proportion of students with rural hukou was higher, totaling 5836 students, accounting for 74.44% of the total. On the contrary, the number of students with urban household registration is relatively small, with only 2004 students and accounting for only 25.56% of the total. Different backgrounds may have different impacts on students' mental health. In addition, the number of only children in the sample is slightly higher than the number of non-only children, and the numbers of the two groups are closer.

Table 1. Statistical analysis of the number of students with basic attributes

Feature	Categories	Number	Percentage
Gender	Female	5095	64.98%
	Male	2745	35.02%
Age	<14	129	1.65%
	14-16	582	7.42%
	17-18	2104	26.84%
	19-22	3127	39.88%
	23-25	1425	18.18%
	>25	473	6.03%
Type of household registration	Countryside	5836	74.44%
	City	2004	25.56%
Whether they are only children or not	Yes	4108	52.40%
	No	3732	47.60%

Similarly, the ethnic distribution of the assessed population was statistically analyzed. The majority (94.67%) of the assessed population were Han Chinese, totaling 7,422. There were 40 Hui, or 0.51% of the total, while there were 18 Zhuang, or 0.23%. The rest of the data for this category is missing.

Based on the above statistical analysis, it is clear that the age distribution in the collected mental health assessment data is skewed towards the younger population. In addition, nearly 55% of the students showed more or less abnormal psychological tendencies.

2.2.2. Analysis of SCL-90 scale data. The dataset for this paper comes from the Symptom Self-Control Scale SCL-90, which is globally recognized as one of the most prominent mental health assessment scales and is currently the most widely used screening tool for mental disorders and illnesses in outpatient populations.The SCL-90 examines ten dimensions to assess a person's mental health, and the scale consists of 90 items assessing a student's psychological state in a variety of domains, including somatization, obsessive-compulsive symptoms, interpersonal sensitivity, depression, anxiety, hostility, fear, paranoia, and psychoticism.Each item on the SCL-90 scale is rated on a five-point scale ranging from 1 (none) to 5 (severe), indicating the severity of the symptoms experienced. The final results include the total and mean scores for each dimension, as well as the number of positive items and an overall assessment of the number of positive items, which represents the number of items with scores between 2 and 5, indicating the presence of symptoms described in those specific items.

The resultant data from the Symptom Self-Assessment Scale were first analyzed to determine the distribution of scores and degree of each of the measured dimensions in the current student population. Given the multiple measurement dimensions involved, this paper will focus on statistically analyzing a few of the important dimensions and will not describe in detail the statistical analysis of the other dimensions.

The statistical results of the SCL-90 scale assessment factor scores are shown in Figure 2, where the dotted line graph indicates the positive detection rate of each factor and the bar graph indicates the number of positives (score $\geqslant 2$) for each factor.

A total of 1107 students scored more than 160 points on the scale, and their positive detection rate was 14.12%. In addition, the minimum and maximum positive detection rates for each factor were 5.24% and 21.86%, respectively.

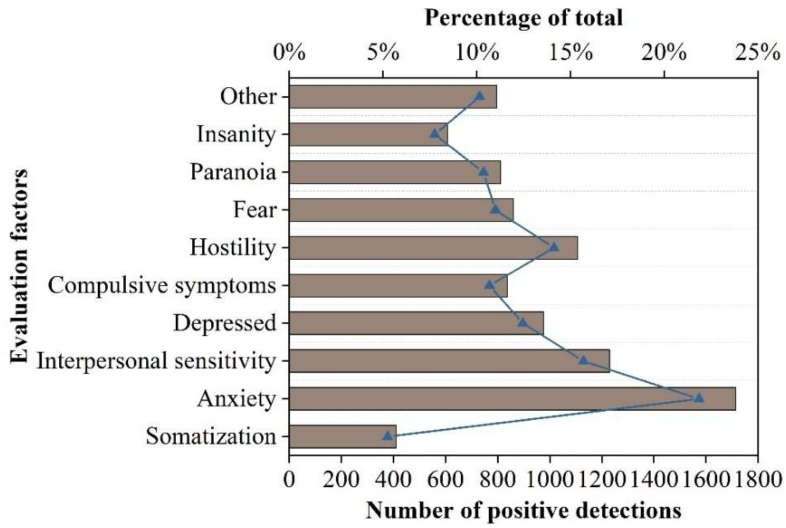


Fig. 2. Measurement factor score statistics of SCL-90 scale

The statistical distribution of the number of anxiety scores is shown in Figure 3.The SCL-90 scale consists of 10 anxiety measurement questions, and the range of anxiety scores is from 10 to 50.The higher the anxiety score, the stronger the anxiety level of the subject. When the anxiety score is more than 30, the subject is more anxious. When the anxiety score is less than 20, the subject's anxiety level is weak. According to the results of this batch of data, the number of people with severe anxiety symptoms can be up to 1,236, and the number of people with severe anxiety symptoms is 478, which means that the number of people suffering from anxiety symptoms is up to 21.86%.

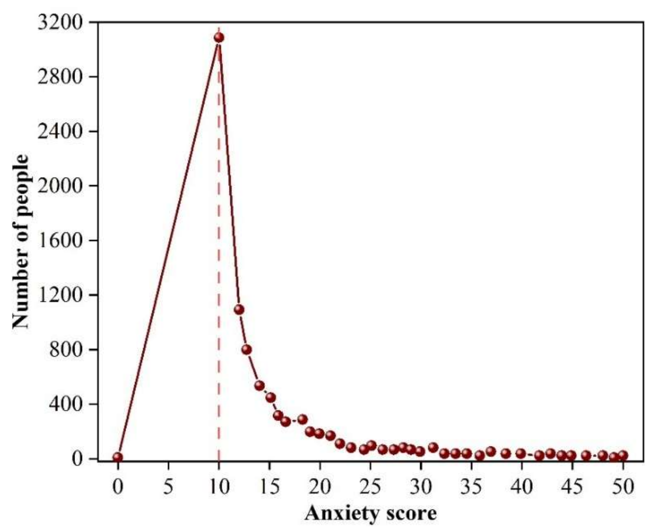


Fig. 3. Statistical distribution of anxiety scores

The statistical distribution of the number of people with depression scores is shown in Figure 4.The range of depression scores in the scale is between 13 and 65.When the depression score exceeds 26, it indicates that the subject is strongly depressed, while exceeding 39 indicates a more severe level of depression. Looking at the distribution of the scores, it can be observed that the percentage of people with high depression scores is relatively high. In fact, those with depression scores over 26 occupied 12.45% of the total number of people. This indicates that the problem of depression is still a serious situation in the mental health of students.

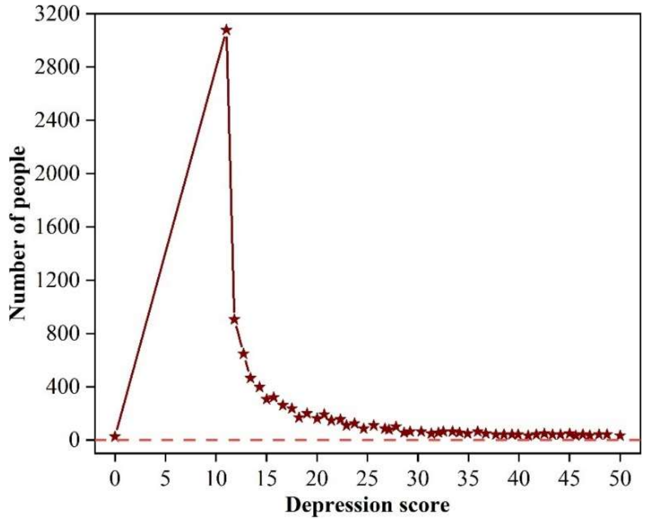


Fig. 4. Statistical distribution of depression scores

The distribution of scores for interpersonal sensitivity as measured by the SCL-90 scale is shown in Figure 5.The SCL-90 scale contains 19 items measuring interpersonal sensitivity, with interpersonal sensitivity scores ranging from 9 to 45.Higher scores indicate greater sensitivity in these relationships, with scores above 8 indicating that the individual is either sensitive or highly sensitive in his or her interactions with others. Figure 5 shows that approximately 15.7% of students exhibit sensitivity in relationships, a sensitivity characterized by introversion and difficulty interacting with others. Over time, this tendency to withdraw leads to the development of a withdrawal mindset, which in turn increases the risk of other psychological disorders such as depression and anxiety.

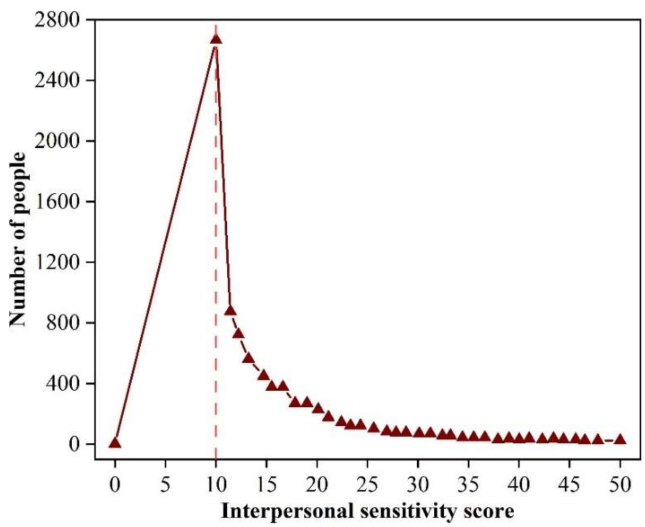


Fig. 5. Interpersonal sensitivity score population statistical distribution

In summary, the majority of students in this age group had varying degrees of mental health disorders. The number of students exhibiting symptoms of anxiety, relationship sensitivity, and depression were 1,714, 1,231, and 976, which accounted for 21.86%, 15.70%, and 12.45% of the total number of mental health anomalies, respectively. Overall, the mental health assessment data collected provided comprehensive information. Among the different symptoms, anxiety seems to be the most prevalent phenomenon among students. Therefore, this study will focus on constructing a predictive model of mental health status for anxiety symptoms.

3. Prediction of students' mental health status based on neural network modeling

Aiming at the background and current situation of mental health screening for college students at this stage, this paper uses the PDNN neural network model to learn to model the behavioral feature data obtained from mining and to predict the mental health status of college students.

3.1. Digital representation of behavioral characteristics

Since only quantitative data operations can be performed in computers, the collected behavioral features need to be mapped to numerical types. In this paper, the collected behavioral features are proposed to be mapped into a behavioral feature vector scheme for data format unification. Firstly, the definition of e.g. expression is given:

$$F=(f_1,f_2,f_3,...,f_n)F^{\alpha}=(f_1^{\alpha},f_2^{\alpha},f_3^{\alpha},...,f_m^{\alpha}) \tag{3}$$

where, set F^{α} represents all behavioral characteristics collected from current college students. Set F^{α} represents the behavioral features contained for a particular student a. n denotes the number of all behavioral features. m represents the number of behavioral features for a particular individual. These behavioral features are mapped into a feature vector:

$$V=(v_1,v_2,v_3,...,v_n) \tag{4}$$

According to the definition of Eq. (4), a particular behavioral feature vector such as $V=\{0,1,0,0,1,0,1,...\}$, 1 means that the feature represented by the location is present in the current student, while 0 means that the feature is not present in the current student.

3.2. Construction of the PDNN model

The performance of the BP neural network depends largely on the interlayer weights of the BP neural network, and if the initialization of the interlayer weights is biased, the network will be prone to local minima and slow convergence and other problems [36]. Therefore, in order to solve the problem of imprecise selection of interlayer weights of the neural network, this paper constructs a PDNN (Particle Difference Neural Network) neural network model based on the improved particle swarm optimization algorithm, so as to dynamically select the interlayer weights of the BP neural network, and then to realize the prediction of the students' mental health state according to the students' behavior. Taking the BPNN (Back Propagation Neural Network) model with two hidden layers and 5 nodes in each layer as an example, the overall structure of the PDNN model is shown in Figure 6. Where w_1,w_2 and w_3 are the weight matrices between the input layer and hidden layer 1, hidden layer 1 and hidden layer 2, hidden layer 2 and output layer, which are dynamically obtained by applying the improved particle swarm optimization algorithm.

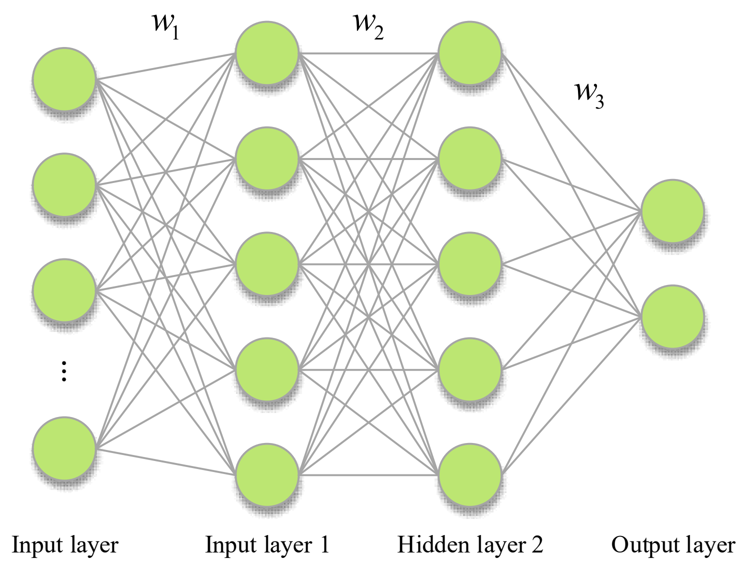


Fig. 6. PDNN model structure

3.2.1. Particle Swarm Optimization Algorithm. Particle Swarm Optimization (PSO) algorithm is based on the fitness information obtained from the environment to find the optimal solution of the problem through particle swarm iteration, and the particles use the local optimal solution and the global optimal solution to adjust the iteration speed and the particle position during the iteration process in order to update the particle swarm [37].

Assuming a group of particles flying at a certain velocity in a d-dimensional search space, the current position of particle i is $X_i = (x_{i1}, x_{i2}, \cdots, x_{id})$ the current velocity is $V_i = (v_{i1}, v_{i2}, \ldots, v_{id})$. The optimal position experienced by particle i is $P_{i\_best} = (P_{i\_best1}, P_{i\_best2}, \ldots, P_{i\_bestd})$, and the optimal position searched by the whole swarm of particles is $G_{levst} = (G_{levst1}, G_{levst2}, \ldots, G_{levstd})$. Therefore, the formula for updating the velocity and position of particle i is:

$$V_i^{t+1} = wV_i^t + c_1 r_1 (P_{i\_best}^t - X_i^t) + c_2 r_2 (G_{best}^t - X_i^t) \tag{5}$$

$$X_i^{t+1} = X_i^t + V_i^{t+1} \tag{6}$$

where w is the inertia weight, V_i is the current particle velocity, c_1 is the cognitive coefficient, c_2 is the social coefficient, r_1 and r_2 are both randomizer beings between [0, 1], and t is the current number of iterations.

3.2.2. Improved particle swarm optimization algorithm:

1) Improvement of inertia weights. In the process of search conducted by particles, larger inertia weights are conducive to the exploration of the whole search space and increase the population diversity, while smaller inertia weights will enhance the local exploitation ability of the population. Therefore, inertia weight is a key factor to balance the local and global search of particle swarm, and the selection of inertia weight has a certain impact on the optimization effect of the algorithm. In this paper, combining the linearly decreasing inertia weights and the nonlinearly decreasing inertia weights method, we propose the dynamic inertia weights, whose formula is:

$$w=\begin{cases} w_{\max}-(w_{\max}-w_{\min})\cos(\frac{T-t+1}{T}(\frac{\pi}{2}))rand\,(0,0.3)\frac{1}{1+e^{-T^2}}, & 0<t\le\frac{T}{6} \\ w_{\max}-(w_{\max}-w_{\min})\cos(\frac{T-t+1}{T}(\frac{\pi}{2}))rand\,(0.3,0.7)\frac{1}{1+e^{-T^2}}, & \frac{T}{6}<t\le\frac{2}{3}T \\ w_{\max}-(w_{\max}-w_{\min})\cos(\frac{T-t+1}{T}(\frac{\pi}{2}))rand\,(0.7,1)\frac{1}{1+e^{-T^2}}, & \frac{2}{3}T<t\le T \end{cases} \tag{7}$$

where $w_{\max}$ is the maximum value of the inertia weights, $w_{\min}$ is the minimum value of the inertia weights, t is the current number of iterations, T is the maximum number of iterations, and rand is the random number generating function.

The linear inertia weights and nonlinear inertia weights are calculated as shown in equations (8) and (9):

$$w=w_{\max}-(w_{\max}-w_{\min})\frac{i}{T} \tag{8}$$

$$w=w_{\max}-(w_{\max}-w_{\min})\left(\frac{i}{T}\right)^2 \tag{9}$$

2) Identification of inferior particles. Inferior particles are the main reason why the whole particle swarm cannot obtain the global optimal solution, identifying the inferior particles and processing the inferior particles to make them jump out of the local optimal solution can effectively optimize the optimal search of the population. Combining the global optimal particle position and the individual historical optimal particle position, the p_{inf} parameter is introduced to recognize the inferior particles, and p_{inf} is defined as:

$$p_{inf}(a,t)=\frac{\sum_{i=t-2}^{t} f(b_a(i-1))-f(b_a(i))}{\sum_{i=t-2}^{t} f(g(i-1))-f(g(i))} \tag{10}$$

where $b_a(i)$ is the historical optimal position of particle a under the i rd iteration, $g(i)$ is the global optimal position of the particle population under the i th iteration, and f is the fitness function. If $p_{inf}<10^{-4}$, it means that the particle is trapped in the local optimal solution and is recognized as an inferior particle. If $p_{inf}>10^4$, it means that the global optimal solution has not been updated for the time being, and if $p_{inf}=NAN$, it means that the whole population has fallen into the local optimal solution. For the above two cases, the particles of the whole population are recognized as inferior particles, and the particles of the whole population are subjected to the mutation process.

3) Mutation of inferior particles. Inspired by the idea of differential evolutionary algorithm, the identified inferior particles are mutated. The mutation formula of the particle is:

$$XV_{i,g}=X_{r1,g}+F(X_{r2,g}-X_{r3,g}) \tag{11}$$

In the particle mutation process, 3 different particles under the current iteration number are randomly selected, and through the mutation formula, new mutated particles are obtained to help the inferior particles jump out of the local optimal solution and continue to find the optimal. Where $X_{n.g}, X_{e2,g}$ and $X_{rs.g}$ are the 3 random particles under the current iteration number and F is the mutation rate.

4) Particle selection. After mutating the inferior particle, calculate the fitness function value of the original particle and the mutated particle, if the fitness function value of the mutated particle is smaller than the fitness function value of the original particle, then put the mutated particle into the next generation particle population. Otherwise, put the original particle into the next generation particle population, and update the individual historical optimal value and optimal position of the particle, and the global optimal value and optimal position of the particle population.

5) Firefly Perturbation Strategy. Inspired by the firefly algorithm, assuming that the global optimal solution is the brightest firefly and the other particles are the darker fireflies, according to the idea of the firefly algorithm, the darker fireflies will move towards the brighter fireflies. Therefore, the whole population of fireflies will move towards the brightest fireflies, so that the particle population gradually converges towards the global optimal solution. The global optimal solution is constantly updated according to the recognition variations of the inferior particles and the selection strategy, which makes the whole particle swarm converge to the final global optimal solution of the optimization problem and accelerates the particle optimization search. The particle swarm position is updated as follows:

$$r_i = \| x_i - x_{best} \| = \sqrt{\sum_{k=1}^{d} (x_{i,k}^t - x_{best,k}^t)^2} \tag{12}$$

$$x_i^{t+1} = x_i^t + e^{-r_i^2}(x_{best}^t - x_i^t) + 0.5(rand(0,1) - 0.5) \tag{13}$$

where $x_{i,k}^t$ is the k th dimensional spatial coordinate value of the i rd particle under t iterations, $x_{bent,k}^t$ is the k th dimensional spatial coordinate value of the globally optimal solution of the particle swarm under t selections, x_{lest}^t is the globally optimal solution of the particle swarm under t iterations, and x_i^t is the position of the particle t under t iterations.

3.2.3. PDNN models. The construction process of the PDNN model is as follows:

1) Determine the topology of the neural network according to the number of features in the dataset and build the neural network model.

2) Initialize the maximum number of iterations of the improved particle swarm optimization algorithm $\max\_iter$, the current number of selected generations $i = 1$, the particle variation rate F, the total number of particles and the particle structure, and set the particle speed range and position range.

3) Initialize the historical optimal position of particles, apply the loss function of BP neural network as the fitness function to initialize the historical optimal value of particles, use the minimum historical optimal value of the particle swarm to initialize the global optimal value of particles, and use the particle position corresponding to the minimum historical optimal value of the particle swarm to initialize the global optimal position of the particle swarm.

4) Identify the inferior particles according to equation (10), and if the conditions of $p_{\inf} > 10^4$, $p_{\inf} < 10^{-4}$ or $p_{inf} = NAN$ are satisfied, then the inferior particles are mutated according to equation (12) to help them get rid of the inferiority and continue to find the optimal.

5) Update the particle velocity and position according to Eq. (5) ~ Eq. (7).

6) Select the original particle and the mutated particle according to the fitness function value.

7) Accelerate the particle swarm to converge to the global optimal solution according to Eq. (12) and Eq. (13).

8) Update the historical optimal value and historical optimal position of the particle, and update the global optimal value and global optimal position of the particle, iteration number $i = i + 1$.

9) If $i \geq max\_iter$, go to step 10). Otherwise, go to step 4).

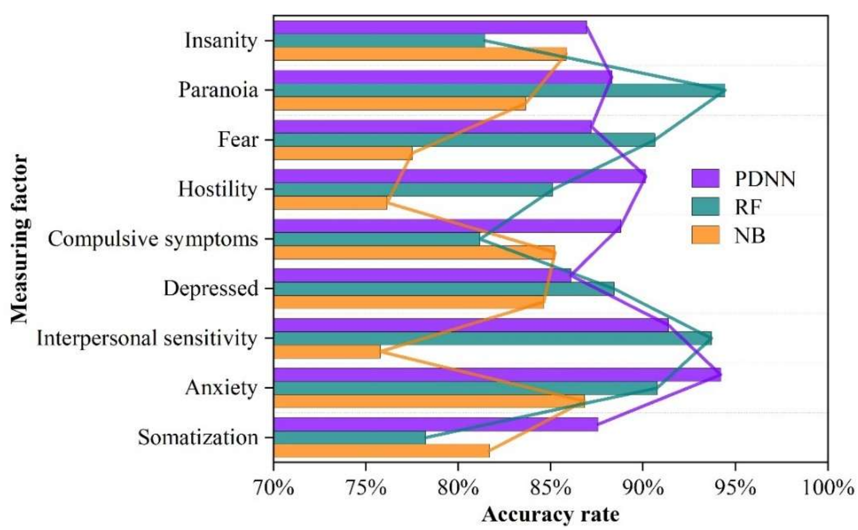
10) Get the global optimal position, encapsulate the weight matrix of the BP neural network, apply the weight to train the BP neural network, and the construction of the PDNN model is completed.

3.3. Evaluation of predictive models of mental health status

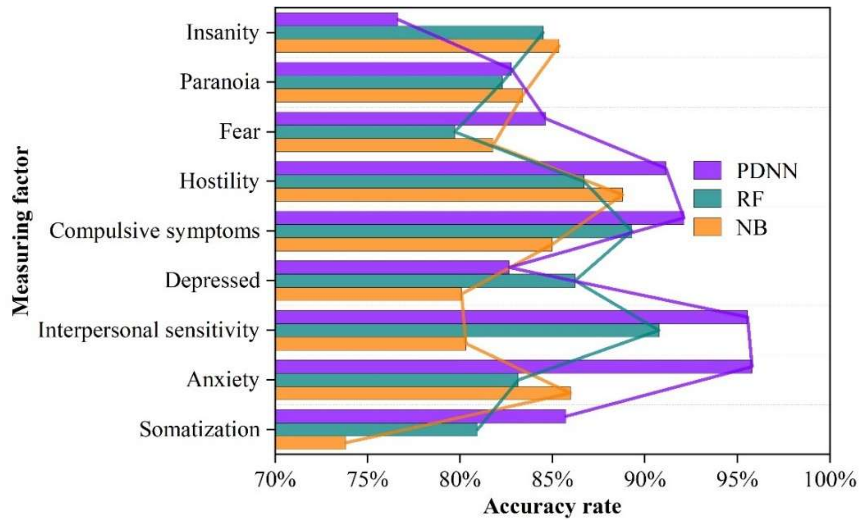
In order to reflect the practicality and accuracy of the model, the PDNN neural network used in this model was compared in detail with two traditional machine learning algorithms, namely, Random Forest (RF) and Plain Bayes (NB), both of which made predictions on 9 factors and performed 5-fold cross-validation. The model comparison results are shown in Fig. 7, where (a)~(b) denote the comparison of model accuracy and high group recall, respectively.

As can be seen from Figure 7, the average accuracy of the prediction model established by the PDNN neural network is 88.95%, while the average accuracy of the prediction model established by random forest and naïve Bayes is 87.10% and 81.92%, respectively, especially the prediction model established by the PDNN neural network under the "anxiety" factor has the highest accuracy of 94.19%, and its high group recall rate is also the highest, reaching 95.79%, reflecting that it can recall "anxiety" well, reflecting that it can recall "anxiety" well Factors under the high-cohort population. In addition, the average value of the high grouping recall of the prediction model built using PDNN neural network is 87.44%, while the average value of the high grouping recall of the prediction model built using random forest and plain Bayes is 84.84% and 82.72%, respectively.

In summary, it can be concluded that in the setting of this experiment, the prediction effect of the model built using PDNN neural network is overall much better than the prediction effect of the model built using Random Forest and Plain Bayes, which fully demonstrates the innovation and practicality of the machine learning algorithm chosen in this paper.



(a) Accuracy rate



(b) High group recall rate

Fig. 7. Model comparison result

4. Design of PDNN-based early warning and intervention system for students' psychological crisis

Based on the prediction model of students' mental health status based on PDNN constructed in the previous paper, this paper analyzes the prediction results of students' mental status by using big data technology, and proposes the design method of students' psychological crisis early warning and intervention system.

4.1. Approach to designing a big data-based psychological intervention system for students

1) Scientific use of network information technology. For the current psychological counseling of college students, it is still mainly in the form of questionnaires to carry out psychological counseling and mental health supervision, so there will be problems such as ineffective supervision and deviation of supervision content.

In order to obtain more accurate results, the first thing to do is to improve the collection of information, only to ensure the accuracy of the information can have an accurate understanding of the students' mental health activities. Based on the big data under the Internet, schools can appropriately improve the quality of the questionnaire.

Secondly, the information collection under big data can be used to individually establish personalized psychological problems for students for the purpose of a win-win resource. At the same time, it can also be through high-quality questionnaires on students can have a more in-depth judgment, to achieve the double control of students, only in this way, can effectively control and monitor the mental health problems of students.

2) Improve the psychological information collection mechanism. The collection of mental health problems is a prerequisite for solving mental health problems, so the collection of effective psychological information is very important. At this stage, the collection of psychological information of college students is mainly psychological questionnaires, in the process of filling out questionnaires, teachers and students need to cooperate with each other, only mutual cooperation between the two can play the role of questionnaires, but also can provide a more professional data for mental health problems.

Secondly, based on the continuous development of network information technology, the Internet platform can be used to collect students' psychological behavior and psychological activities, which can more accurately locate students' psychological crises and help teachers to carry out more effective psychological monitoring.

Again, for schools to ensure the integrity of the data, it is necessary to expand the indicators of psychological early warning, so as to have a more in-depth and comprehensive understanding of the students, the data support will be more convincing.

3) Improve the information analysis method of psychological early warning. The processing of information also plays a more important role in the analysis of mental health problems, so the psychological information should be effectively summarized and analyzed, so as to have a more accurate positioning of mental health. Data processing should also follow certain processing steps and methods, first of all, through the network information platform for a simulation of the student's psychological information, after simulation to give a certain similar model, and then through the student's other mental health information on the student for a deeper degree of positioning, mainly for the analysis of the student's daily activities and academic performance, to achieve the all-round information on the students. The data will then be analyzed and finalized. The analyzed data are then integrated into the PDNN-based psychological state prediction model to realize the early warning and intervention of students' psychological crisis, so that students' mental health problems can be monitored and grasped in real time to promote the overall development of students' physical and mental health.

4) Establishment of Intelligent Early Warning and Intervention Mechanisms. Mental health is a long and complicated problem, its own analysis and treatment process is more cumbersome, the psychological diagnosis and treatment of students not only need to be unified by students and parents, and need to master certain ways and means. Different students have different psychological backgrounds and psychological tolerance, and need to be analyzed in a comprehensive manner in order to give a more comprehensive solution to psychological problems. In terms of treatment of psychological problems, it requires the joint efforts of many parties to realize the intervention and treatment of mental health. The government and relevant mental health organizations need to provide students with certain mental health policy support so that mental health issues can be implemented.

Secondly, for the students themselves, each student's psychological condition and psychological problems are different, so you can build a psychological warning file for each student, for each student to formulate a more complete psychological warning file, not only for the students' psychological problems to give the appropriate answers, and can give the students psychological development of the corresponding preventive measures, in order to realize the students' psychological problems. The dual grasp of the problem. In the early warning at the same time, should also be actively on the psychological problems reported, the relevant mental health analysis institutions need to record the psychological problems in the register, so that in the long term can establish a mental health problems of the resource base, can be real-time analysis of the students' mental health problems, can speed up the efficiency of the mental health problem solving, in order to facilitate the timely detection and guidance of the students' mental health problems. The mental health problems of students can be analyzed in real time, and the efficiency of solving mental health problems can be accelerated, so as to make timely detection and guidance.

5) Dynamic management of information. In terms of college students, their personal subjectivity is strong, so the way they deal with things and the behavior they show when they encounter problems will be very different at different times, so the monitoring of college students' mental health problems should be dynamic detection of information, so that they can analyze and understand the students' mental health problems in real time, and realize the effective control of mental health. Traditional

information processing is too cumbersome, so we should actively use the Internet technology to process mental health data, so as to speed up the processing speed of students' mental health problems, and according to the students' behavior and learning characteristics of the students' mental health problems for effective integration, so as to form a more effective mental health information, in order to be able to grasp the mental health problems in a timely manner.

4.2. Controlled experiments on the effects of system interventions

In order to verify the effectiveness of the proposed design method of the PDNN-based psychological crisis warning and intervention system for students, this paper designs a mental health status intervention experiment. Forty female students were randomly selected as research subjects from 186 people with positive mental health status, and according to the positivity of each factor, the subjects were randomly divided into two groups, i.e., the experimental group (20 people) and the control group (20 people). The experimental group was intervened with mental health status using the intervention system designed according to the methodology of this paper and the control group was kept in its natural state. As the experiment proceeded, 2 subjects in the experimental group withdrew from the experiment due to various circumstances, resulting in 18 subjects in the experimental group.

4.2.1. Differences in pre-intervention mental health levels between the two groups. Before the intervention, an independent samples t-test was conducted on the mental health level between the experimental and control groups. The results of the test for differences in mental health levels between the two groups before intervention are shown in Table 2. It can be seen that no significant difference was found between the experimental group and the control group on the total mental health score and the factor scores on the SCL-90 scale before the intervention (p>0.05).

Table 2. Differences in pre-intervention mental health levels between the two groups

Factors	Control group (N=20)	Experimental group (N=18)	t	p
Somatization	1.91±0.45	1.82±0.50	0.774	0.462
Anxiety	1.98±0.27	2.04±0.32	0.959	0.343
Interpersonal sensitivity	2.41±0.32	2.38±0.61	0.246	0.821
Depressed	2.32±0.34	2.38±0.36	0.753	0.458
Compulsive symptoms	2.73±0.44	2.78±0.49	0.502	0.614
Hostility	1.99±0.46	1.87±0.47	1.426	0.179
Fear	1.92±0.44	1.81±0.48	0.997	0.275
Paranoia	2.03±0.47	1.92±0.45	0.984	0.357
Insanity	2.05±0.33	2.05±0.39	0.041	0.982
Other	1.95±0.52	1.90±0.49	0.295	0.784
Total points	190.37±16.54	189.24±17.03	0.451	0.682

4.2.2. Results of analysis of variance (ANOVA) of mental health level between the two groups. The results of the repeated measures ANOVA for mental health levels between the two groups before and after the intervention are shown in Table 3.

Before and after the intervention, there was a significant interaction between the experimental and control groups on the total mental health score on the SCL-90 scale (F=13.057, p<0.01) and on the factor scores of interpersonal sensitivity (F=4.196, p<0.05), depression (F=24.876, p<0.01), and anxiety (F=10.785, p<0.01).

Table 3. ANOVA results of repeated measures of mental health between the two groups

Factors	Pre-intervention		Post-intervention		F	p
	Control group (N=20)	Experimental group (N=18)	Control group (N=20)	Experimental group (N=18)		
Somatization	1.91±0.45	1.82±0.50	1.72±0.43	1.68±0.48	0.040	0.852
Anxiety	1.98±0.27	2.04±0.32	1.99±0.39	1.68±0.27	10.785	0.000
Interpersonal sensitivity	2.41±0.32	2.38±0.61	2.30±0.51	1.85±0.49	4.196	0.046
Depressed	2.32±0.34	2.38±0.36	2.29±0.38	1.63±0.37	24.876	0.001
Compulsive symptoms	2.73±0.44	2.78±0.49	2.51±0.56	2.42±0.66	0.481	0.504
Hostility	1.99±0.46	1.87±0.47	1.87±0.49	1.39±0.32	2.145	0.161
Fear	1.92±0.44	1.81±0.48	1.84±0.42	1.61±0.35	1.116	0.302
Paranoia	2.03±0.47	1.92±0.45	1.89±0.36	1.72±0.38	0.379	0.538
Insanity	2.05±0.33	2.05±0.39	1.98±0.35	1.82±0.42	1.027	0.322
Other	1.95±0.52	1.90±0.49	2.01±0.43	1.69±0.37	2.798	0.104
Total points	190.37±16.54	189.24±17.03	182.14±21.72	157.14±19.75	13.057	0.002

Post hoc t-tests were conducted on the factor items with interaction effects, and the results of the comparison of within-group differences in mental health levels before and after the intervention were obtained as shown in Table 4. It can be found that before and after the intervention, there were significant differences in the scores of the experimental group on the factor items of total mental health (t=6.264, p<0.01), interpersonal sensitivity (t=2.685, p<0.05), depression (t=8.147, p<0.01) and anxiety (t=4.251, p<0.01) on the SCL-90 scale, while there was no significant difference in the control group.

Table 4. Comparison of intra-group differences before and after intervention

Factors	Experimental group (N=18)		t	p	Control group (N=20)		t	p
	Pre-intervention	Post-intervention			Pre-intervention	Post-intervention		
Interpersonal sensitivity	2.38±0.61	1.85±0.49	2.685	0.016	2.41±0.32	2.30±0.51	0.764	0.462
Depressed	2.38±0.36	1.63±0.37	8.147	0.000	2.32±0.34	2.29±0.38	0.381	0.725
Anxiety	2.04±0.32	1.68±0.27	4.251	0.000	1.98±0.27	1.99±0.39	0.126	0.913
Total points	189.24±17.03	157.14±19.75	6.264	0.000	190.37±16.54	182.14±21.72	1.894	0.081

In addition, the results of the comparison of the differences between the two groups in mental health levels before and after the intervention are shown in Table 5. After the intervention, the experimental group scored significantly lower than the control group on the total mental health score (t=4.425, p<0.01), interpersonal sensitivity (t=3.421, p<0.01), depression (t=5.697, p<0.01), and anxiety (t=2.587, p<0.05) factor items of the SCL-90 scale.

Table 5. Comparison of mental health level between groups before and after intervention

Factors	Pre-intervention		t	p	Post-intervention		t	p
	Experimental group (N=18)	Control group (N=20)			Experimental group (N=18)	Control group (N=20)		
Interpersonal sensitivity	2.38±0.61	2.41±0.32	0.246	0.821	1.85±0.49	2.30±0.51	3.421	0.004
Depressed	2.38±0.36	2.32±0.34	0.753	0.458	1.63±0.37	2.29±0.38	5.697	0.000
Anxiety	2.04±0.32	1.98±0.27	0.959	0.343	1.68±0.27	1.99±0.39	2.587	0.015
Total points	189.24±17.03	190.37±16.54	0.451	0.682	157.14±19.75	182.14±21.72	4.425	0.000

In summary, it can be seen that the psychological intervention system designed based on the methodology of this paper can significantly improve the mental health status of students, which illustrates the effectiveness of the system design methodology of this paper.

5. Conclusion

In this paper, we use big data mining technology to realize the construction of students' mental health state prediction model based on PDNN neural network, and propose the design method of psychological intervention system in colleges and universities.

Nearly 55% of the students in the mental health assessment data collected in this paper showed more or less abnormal psychological tendencies. Among them, the number of students who showed symptoms of anxiety, interpersonal sensitivity, and depression were 1714, 1231, and 976, accounting for 21.86%, 15.70%, and 12.45% of the total number of mental health abnormalities, respectively. Among the different symptoms, anxiety was the most prevalent phenomenon in the student population.

The average accuracy of the prediction model using PDNN is 88.95%, which is higher than the average accuracy of 87.10% and 81.92% of the prediction model using Random Forest and Simple Bayes. The PDNN model achieved the highest accuracy of 94.19% and the highest recall rate of 95.79% for the “anxiety” factor, which indicates that the PDNN model can well recall the highly grouped population under the “anxiety” factor. In addition, the average value of high group recall for the PDNN prediction model is 87.44%, which is also higher than the average value of high group recall for the prediction models built using Random Forest and Plain Bayes, which are 84.84% and 82.72%. This proves the innovation and usefulness of the machine learning algorithm chosen in this paper.

The intervention experiment was conducted based on the psychological intervention system designed by the methodology of this paper, where the experimental group used the psychological intervention system and the control group was kept in its natural state. Before the intervention, no significant differences were found between the experimental and control groups in terms of total mental health scores on the SCL-90 scale and scores on each factor ($p>0.05$). Whereas, before and after the intervention, the interaction between the experimental and control groups was significant ($p<0.05$) on the total mental health score on the SCL-90 scale and on the factor scores of interpersonal sensitivity, depression, and anxiety. Further analysis of these factors showed that after the intervention, the experimental group scored significantly lower than the control group on the total mental health score ($t=4.425$, $p<0.01$), interpersonal sensitivity ($t=3.421$, $p<0.01$), depression ($t=5.697$, $p<0.01$), and anxiety ($t=2.587$, $p<0.05$) factors on the SCL-90 scale. Thus, the practicality of the methodology for designing the school psychological intervention system improved in this paper was verified.

References

[1] Currey, D., & Torous, J. (2023). Digital phenotyping data to predict symptom improvement and mental health app personalization in college students: prospective validation of a predictive model. *Journal of Medical Internet Research*, 25, e39258.

[2] Sahu, B., Kedia, J., Ranjan, V., Mahaptra, B. P., & Dehuri, S. (2023). Mental Health Prediction in Students using Data Mining Techniques. *The Open Bioinformatics Journal*, 16(1).

[3] Liu, X. Q., Guo, Y. X., Zhang, W. J., & Gao, W. J. (2022). Influencing factors, prediction and prevention of depression in college students: a literature review. *World Journal of Psychiatry*, 12(7), 860.

[4] Mutalib, S. (2021). Mental health prediction models using machine learning in higher education institution. *Turkish Journal of Computer and Mathematics Education* (TURCOMAT), 12(5), 1782-1792.

[5] Guo, N. (2024). Mental Health State Prediction Method of College Students Based on Integrated Algorithm. *In Artificial Intelligence, Medical Engineering and Education* (pp. 205-212). IOS Press.

[6] Ebert, D. D., Buntrock, C., Mortier, P., Auerbach, R., Weisel, K. K., Kessler, R. C., ... & Bruffaerts, R. (2019). Prediction of major depressive disorder onset in college students. *Depression and anxiety*, 36(4), 294-304.

[7] Kim, T., Kim, H., Lee, H. Y., Goh, H., Abdigapporov, S., Jeong, M., ... & Hong, H. (2022, April). Prediction for retrospection: Integrating algorithmic stress prediction into personal informatics systems for college students' mental health. *In Proceedings of the* 2022 *CHI Conference on Human Factors in Computing Systems* (pp. 1-20).

[8] Heo, J., Lim, H., Yun, S. B., Ju, S., Park, S., & Lee, R. (2019, March). Descriptive and predictive modeling of student achievement, satisfaction, and mental health for data-driven smart connected campus life service. *In Proceedings of the* 9*th International Conference on Learning Analytics & Knowledge* (pp. 531-538).

[9] Pei, J. (2022). Prediction and analysis of contemporary college students' mental health based on neural network. *Computational Intelligence and Neuroscience*, 2022(1), 7284197.

[10] Liu, L. (2024). Prediction and Intervention of Mental Health Problems in College Students: A Temporal Attention Model Based on Recurrent Neural Network. *In Disruptive Human Resource Management* (pp. 380-387). IOS Press.

[11] Baba, A., & Bunji, K. (2023). Prediction of mental health problem using annual student health survey: machine learning approach. *JMIR Mental Health*, 10, e42420.

[12] Li, J., Wang, L., Pan, L., Hu, Z., Yin, R., & Liu, J. F. (2024). Exercise motivation, physical exercise, and mental health among college students: examining the predictive power of five different types of exercise motivation. *Frontiers in Psychology*, 15, 1356999.

[13] Sahlan, F., Hamidi, F., Misrat, M. Z., Adli, M. H., Wani, S., & Gulzar, Y. (2021). Prediction of mental health among university students. *International Journal on Perceptive and Cognitive Computing*, 7(1), 85-91.

[14] Huang, P. (2022). A mental disorder prediction model with the ability of deep information expression using convolution neural networks technology. *Scientific Programming*, 2022(1), 4664102.

[15] Saha, K., Yousuf, A., Boyd, R., Pennebaker, J. W., & De Choudhury, M. (2021). Mental health consultations on college campuses: Examining the predictive ability of social media. *Available at SSRN* 3774189.

[16] Nanda, A., Tuteja, S., & Gupta, S. (2022). Machine learning based analysis and prediction of college students' mental health during COVID-19 in India. *In Artificial Intelligence, Machine Learning, and Mental Health in Pandemics* (pp. 167-187). Academic Press.

[17] Chen, J. (2024, February). Student Mental Health Risk Prediction Based on Apriori Algorithm in the Context of Big *Data. In 2024 International Conference on Electrical Drives, Power Electronics & Engineering* (EDPEE) (pp. 615-618). IEEE.

[18] Worsley, J., Pennington, A., & Corcoran, R. (2020). What interventions improve college and university students' mental health and wellbeing? A review of review-level evidence. *National Grey Literature Collection*, 1-54.

[19] Morton, D. P., Hinze, J., Craig, B., Herman, W., Kent, L., Beamish, P., ... & Przybylko, G. (2020). A multimodal intervention for improving the mental health and emotional well-being of college students. *American Journal of Lifestyle Medicine*, 14(2), 216-224.

[20] Harrer, M., Adam, S. H., Baumeister, H., Cuijpers, P., Karyotaki, E., Auerbach, R. P., ... & Ebert, D. D. (2019). Internet interventions for mental health in university students: A systematic review and meta - analysis. *International journal of methods in psychiatric research*, 28(2), e1759.

[21] Nguyen-Feng, V. N., Greer, C. S., & Frazier, P. (2017). Using online interventions to deliver college student mental health resources: Evidence from randomized clinical trials. *Psychological services*, 14(4), 481.

[22] Suffoletto, B., Goldstein, T., Gotkiewicz, D., Gotkiewicz, E., George, B., & Brent, D. (2021). Acceptability, engagement, and effects of a mobile digital intervention to support mental health for young adults transitioning to college: pilot randomized controlled trial. *JMIR Formative Research*, 5(10), e32271.

[23] Mailey, E. L., Wójcicki, T. R., Motl, R. W., Hu, L., Strauser, D. R., Collins, K. D., & McAuley, E. (2010). Internet-delivered physical activity intervention for college students with mental health disorders: a randomized pilot trial. *Psychology, health & medicine*, 15(6), 646-659.

[24] Arenas, D. L., Viduani, A. C., Bassols, A. M. S., & Hauck, S. (2021). Peer support intervention as a tool to address college students' mental health amidst the COVID-19 pandemic. *International Journal of Social Psychiatry*, 67(3), 301-302.

[25] Bolinski, F., Boumparis, N., Kleiboer, A., Cuijpers, P., Ebert, D. D., & Riper, H. (2020). The effect of e-mental health interventions on academic performance in university and college students: a meta-analysis of randomized controlled trials. *Internet interventions*, 20, 100321.

[26] Seppälä, E. M., Bradley, C., Moeller, J., Harouni, L., Nandamudi, D., & Brackett, M. A. (2020). Promoting mental health and psychological thriving in university students: a randomized controlled trial of three well-being interventions. *Frontiers in psychiatry*, 11, 534776.

[27] Liu, Y. (2021). Analysis and prediction of college students' mental health based on K-means clustering algorithm. *Applied Mathematics and Nonlinear Sciences*, 7(1), 501-512.

[28] Shan, X. (2024). College Students' Mental Health Prediction Model Based on Time Series Analysis. *Journal of Electrical Systems*, 20(7s), 2952-2963.

[29] Mao, X. L., & Chen, H. M. (2023). Investigation of contemporary college students' mental health status and construction of a risk prediction model. *World Journal of Psychiatry*, 13(8), 573.

[30] Adler, D. A., Wang, F., Mohr, D. C., & Choudhury, T. (2022). Machine learning for passive mental health symptom prediction: Generalization across different longitudinal mobile sensing studies. *Plos one*, 17(4), e0266516.

[31] Becker, T. D., & Torous, J. B. (2019). Recent developments in digital mental health interventions for college and university students. *Current Treatment Options in Psychiatry*, 6, 210-220.

[32] Renshaw, T. L., & Rock, D. K. (2018). Effects of a brief grateful thinking intervention on college students' mental health. *Mental Health & Prevention*, 9, 19-24.

[33] Kanuri, N., Arora, P., Talluru, S., Colaco, B., Dutta, R., Rawat, A., ... & Newman, M. G. (2020). Examining the initial usability, acceptability and feasibility of a digital mental health intervention for college students in India. *International Journal of Psychology*, 55(4), 657-673.

[34] Rizvi, S. L., Finkelstein, J., Wacha-Montes, A., Yeager, A. L., Ruork, A. K., Yin, Q., ... & Kleiman, E. M. (2022). Randomized clinical trial of a brief, scalable intervention for mental health sequelae in college students during the COVID-19 pandemic. *Behaviour research and Therapy*, 149, 104015.

[35] Anna Khalemsky, Roy Gelbard & Yelena Stukalin. (2025). Constructing a Course on Classification Methods for Undergraduate Non-STEM Students: Striving to Reach Knowledge Discovery. Journal of Statistics and Data Science Education(1),68-76.

[36] Chen Zhao, Wei Jin, Yan Shi, Chang An Chen & Yi Ying Zhao. (2024). Utilizing BP neural networks to accurately reconstruct the tritium depth profile in materials for BIXS. Nuclear Science and Techniques(1),15-15.

[37] Borja Benítez Suárez, Román Quevedo Reina, Guillermo M. Álamo & Luis A. Padrón. (2025). PSO-based design and optimization of jacket substructures for offshore wind turbines. Marine Structures 103759-103759.