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Optimization of Identification and Intervention Paths for Psychological Problems of College Students in Cultural Education Based on Quantitative Analytical Models

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Abstract The number of middle school students experiencing psychological crises in the field of cultural education is increasing, with psychological issues primarily manifesting as problems related to adaptability and development, specifically characterized by symptoms such as depression, anxiety, and confusion. To address this, the paper proposes an improved iForest algorithm combined with a decision cluster classifier based on agglomerative k-means clustering to develop a psychological issue identification model, and outlines an intervention pathway for addressing student psychological issues. In the results of the graded prediction of students' mental health status, 3.69% of students were found to have Level 1 psychological issues, 11.32% had Level 2 issues, and 15.74% had Level 3 issues. Therefore, it is essential to actively implement student psychological prevention and intervention pathways to maximize the prevention and reduction of psychological crisis incidents among college students.

Index Terms iForest algorithm, k-means, psychological problems, intervention pathways

I. Introduction

With the rapid development of socio-economic and cultural conditions, students' mental health has become increasingly important, especially in the wake of the pandemic. Students are now taking online classes at home, spending more time on their phones, and engaging in less physical activity, all of which have had negative effects on their mental well-being. Additionally, under the influence of exam-oriented education, teachers tend to prioritize academic performance over mental health, failing to provide regular mental health education for students [1]-[4]. As a result, students' mental health has become highly vulnerable. Well-meaning parents or teachers may clash with students by restricting their gaming activities, leading to phenomena such as school refusal and suicidal tendencies [5]-[7]. The identification of mental health issues among middle school students involves conducting surveys and research on the mental health of single-parent students, left-behind children, students with mental health conditions, and orphans. It also includes providing psychological counseling, organizing sunlit sports activities, and fostering the all-round development of students in terms of morality, intelligence, physical fitness, aesthetics, and labor [8], [9].

Typically, the identification of psychological issues relies heavily on psychological questionnaires. However, in questionnaires of varying quality, people tend to present a more positive version of themselves, which often does not accurately reflect their true inner thoughts [10], [11]. Additionally, the quantitative intensity of responses to certain questions varies from person to person. These limitations can result in data that does not adequately characterize participants, with data quality being significantly influenced by participants' subjective perceptions. This issue is particularly severe when the sample size is small [12]. Scholars have found that using such noisy data makes it difficult to accurately identify psychological issues among middle school students. However, various social networks in people's daily lives can most authentically reflect their social status, and many psychological issues are closely related to social status. Therefore, in recent years, the analysis of people's psychological conditions using social information has become increasingly common and has achieved good results [13]-[15].

Thanks to the rapid development of disciplines such as computer science and mathematics, technologies like deep learning, data mining, and big data are also advancing rapidly and increasingly integrating into people's daily lives [16]. The mental health status of today's middle school students is a problem that cannot be ignored, and many experts and scholars have conducted quantitative analysis studies on this issue and proposed relevant countermeasures. Pedrelli, P., et al. [17] examined the prevalence and treatment of mental health issues among students, highlighting the unique developmental stages and environmental factors influencing mental health abnormalities among college students, and summarized the impacts of such issues. Li, J., et al. [18] investigated the prevalence of mental health issues among Chinese adolescents, finding a significant association with poor school interpersonal relationships, underscoring the necessity of improving teacher-student and peer relationships to reduce mental health issues. Chen, M., and Jiang, S. [19] conducted cognitive computing and analysis research, finding that students' mental health status is not optimistic. Most students lead extremely irregular lifestyles, with irregular diets and frequent late-night activities. They discovered a positive correlation between students' lifestyles and mental health, emphasizing the importance of prioritizing mental health education. Hao, L et al. [20] pointed out that school, family, and lifestyle are the primary factors contributing to psychological stress among Chinese middle school students. They proposed alleviating stress through a focus on comprehensive development and healthy lifestyles, and provided recommendations for policymakers, schools, and parents to reduce stress. Kim, E et al. [21] examined the longitudinal changes in mental health issues among Korean middle school students. The study found that as students age, their mental health, self-concept, self-esteem, and self-efficacy decline, while students who engage in regular physical activity experience a smaller decline in mental health. Nguyen, H, and Nguyen, N [22] explored the impact of factors such as school violence, academic issues, and conflicts with teachers on middle school students' psychological problems. The study found that academic issues were the most predictive factor among all factors and suggested that reducing academic stress could help prevent students' psychological problems. These quantitative analyses and studies on students' mental health issues provide clear research directions for studying psychological abnormalities among middle school students.

For the identification of mental health issues, Roy, A., et al. [23] proposed the SAIPH (Suicide Artificial Intelligence Prediction Heuristic) algorithm, which can identify suicidal thoughts by analyzing publicly available Twitter data. The model was validated using field-collected Twitter data, and a significant association was observed between SI (Suicidal Ideation) scores and suicide mortality rates within a specific geographic area over a period of time, with this phenomenon being particularly pronounced among young people. Sharma, M, and Chaturvedi, S [24] developed and validated a mental health screening tool (NIMHANS), demonstrating its reliability and effectiveness in identifying mental health issues in both general and clinical populations. Huang, Y et al. [25] utilized decision tree models and Kendall correlation analysis algorithms to construct a mental health issue identification model aimed at enhancing early detection capabilities for student mental health issues, achieving good accuracy and generalizability. Ahuja, R, and Banga, A [26] calculated students' psychological stress levels during the week before exams and while using the internet. They analyzed how exam stress or recruitment stress affects students' thoughts and used these stress levels to analyze and identify internet usage duration. Zhang, N, et al. [27] employed a gradient boosting classifier as a predictive model to forecast students' subjective well-being, with predictive data collected via survey questionnaires. The above researchers have conducted in-depth analyses of students' mental health from the perspectives of sources, causes, and countermeasures, which is of critical importance for timely identification of abnormal psychological issues among college students. However, in analyzing students' psychological issues, the majority of researchers obtain mental health data through questionnaire surveys and self-assessments, which are then analyzed. However, these research results often exhibit significant subjectivity, leading to data and conclusions that are not sufficiently accurate or reliable.

The article first extracts behavioral characteristics of students at a certain university and analyzes the similarities and differences in behavioral characteristics between students with psychological abnormalities and normal students on campus. It then proposes a data-driven method for identifying student mental health. Using an improved iForest algorithm, abnormal candidate data is screened from student mental health data retrieved from the database. A decision cluster classifier based on agglomerative k-means clustering is employed to extract classification models from trees constructed in a series of top-down nested clusters built on a training dataset composed of abnormal candidate data. High-confidence decision clusters are then extracted from these models to classify unlabeled samples. Comparative experiments are conducted on the NHANES, KNHANES, and BRESS datasets. Additionally, the identification and grading results were analyzed based on the interpretability parameters provided by the model, and the input features were ranked according to their contribution to depression from an algorithmic perspective. Based on this, the paper proposes intervention pathways for student mental health issues from the perspectives of ensuring student safety and conducting personalized teaching. Finally, a random sample of students from a certain school was selected as the research subjects for an intervention experiment to validate the effectiveness of the proposed method.

II. Quantification and analysis of student behavior characteristics

This section uses students from a certain university as the empirical research subjects, focusing primarily on extracting behavioral characteristics from social relationships and academic performance.

II. A. Social Relationships

When students eat in the cafeteria, enter and exit their dormitories, and enter and exit the library, they must use their ID cards to identify themselves, and the data is recorded at that time. The social relationship mining experimental data set is shown in Table 1.

Table 1: Experimental dataset for social relationship mining

Data Type	Data size
Student population	1695
Consumption record	442031
Library ban	66503
Dormitory entrance	106852

Experiments revealed that student friendships were similar based on library access control and consumption data mining, but differed significantly from dormitory access control data, with almost no friendships detected in the latter. Upon investigation, it was found that dormitory access control systems at our school allow multiple people to pass through with a single swipe of a card. If students A and B are friends and enter or exit the dormitory together, only one person needs to swipe the card to gain access. Therefore, dormitory access control data was excluded, and only consumption records and library access control records were used. The visualization of the number of student friends is shown in Figure 1.

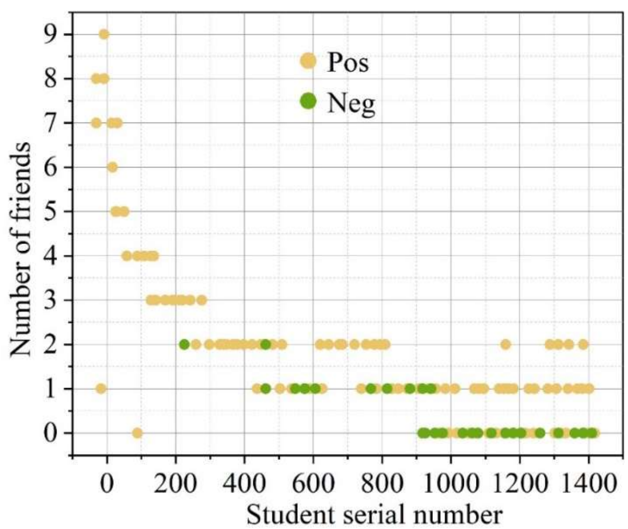
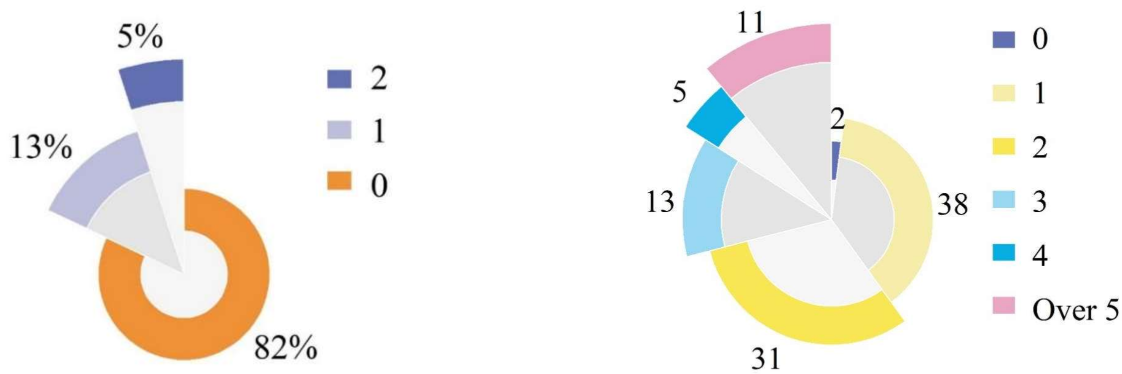


Figure 1: Visualization of the number of student friends

By calculating the number of friends each student has, a mental state of 0 indicates a mentally healthy student, while a state of 1 indicates a student with mental abnormalities. The distribution of the number of friends each student has is shown in Figure 2 (Figure a shows students with mental abnormalities, and Figure b shows mentally healthy students). It can be observed that most students prefer to interact with peers from their own major or grade level, though some isolated cases exist. Additionally, by visualizing the number of friends among mentally healthy and mentally unhealthy students, it was found that most mentally unhealthy students have no friends on campus, while the majority of mentally healthy students have 1–2 friends, and some mentally healthy students have five or more friends. However, it should be noted that among mentally healthy students, a small proportion also have no friends on campus. On campus, some students prefer to go their own way, believing that being alone is more conducive to thinking. However, this may also be due to social difficulties or unwillingness to communicate with others. Although no mental health issues have been identified at present, prolonged isolation may lead to adverse consequences. Therefore, based on the analysis results in this section, we should pay attention to such students and promptly observe and understand the mental state of those without social relationships.



(a) Abnormality (b) Normal

Figure 2: Distribution of student friends

II. B.Student Academic Performance

This section primarily explores whether there are significant differences in academic performance between psychologically normal students and abnormal students based on real data. In this paper, students' academic performance is divided into more granular categories, mainly analyzing students' average grades, failure rates (failing grades are defined as scores below 60), and grade rankings.

II. B. 1) Average Grade Analysis

The comparison of students' academic performance is shown in Table 2. To avoid unnecessary influences caused by sample imbalance, multiple random samples were taken from the normal students' scores to calculate the mean, with the sample size equal to that of the students with psychological abnormalities. It can be seen that the average scores of normal students in each grade are higher than those of students with abnormalities. Moreover, the standard deviation of students with abnormalities is greater. This means that the scores of students with abnormalities are more dispersed, and there are greater differences between individuals.

Table 2: Comparison of students' academic performance

Grade		Freshman		Sophomore year		Junior year	
	Mental condition	Average value	Standard deviation	Average value	Standard deviation	Average value	Standard deviation
2023	Normal	76.51	10.64	79.85	11.71	80.1	11.06
	Abnormality	68.84	19.46	75.79	13.65	72.72	19.45
2024	Normal	75.23	11.43	78.97	11.91	79.8	12.67
	Abnormality	72.01	17.37	73.06	19.66	70.35	20.19

II. B. 2) Analysis of failing grades

This section primarily analyzes whether there are significant differences in the number of failed courses between two categories of students during their academic careers. First, by comparing the differences in the number of failed courses across different grade levels, the comparison of students' academic performance is shown in Table 3. Observation reveals that students with psychological abnormalities have a higher average number of failed courses each year compared to normal students, particularly in the third year of university. The average number of failed courses per student for normal students is 0.52, while for abnormal students, it is 2.95. This means that, on average, each student with psychological abnormalities has nearly three failed required courses. However, the standard deviation of failed courses among abnormal students is also larger. It was observed that some students had as many as 10 failed courses during their third year, which is relatively uncommon among normal students.

Table 3: Comparison of students' failing grades

Mental condition	Freshman		Sophomore year		Junior year		Senior year	
	Mean value	Standard deviation	Mean value	Standard deviation	Mean value	Standard deviation	Mean value	Standard deviation
Normal	0.532	0.29	0.75	0.36	0.52	0.26	0.22	0.15
Abnormality	2.43	2.63	1.55	2.39	2.95	3.75	0.86	1.42

III. Data-driven identification of student psychological issues

After connecting to the MySQL database to obtain student data, the anomaly candidates screened by the improved iForest using a decision cluster classifier based on the k-means clustering algorithm are classified to identify the features possessed by each category of anomalous students. The psychological problem identification process is shown in Figure 3.

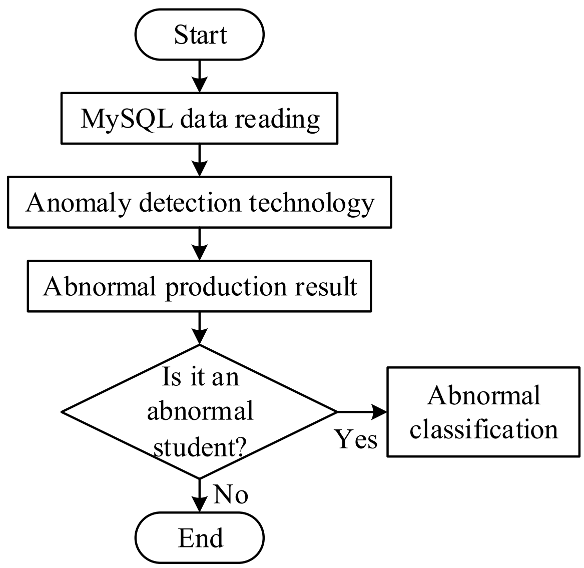


Figure 3: Psychological problem identification process

As shown in Figure 3, after reading student data from the MySQL database, anomaly detection technology is used to filter the data, thereby generating anomaly results and determining whether they are anomalous students. If they are anomalous students, classification is required; if they are not anomalous students, no classification operation is required.

III. A. Data screening based on the improved iFresto algorithm

Since the traditional iForest algorithm has issues with excessive branch construction and inconsistent score partitioning, branch cutting is no longer performed along the coordinate axis based on random dimensions, but rather in all directions using random normal vectors and random intercept points [28]. Equation (1) is the node partitioning formula in a binary tree:

$$(\vec{x}-\vec{p})\cdot\vec{n}\le 0 \tag{1}$$

In the formula, the random normal vector and random intercept are $\vec{n}$ and $\vec{p}$, respectively, and the given data point is x. If x is to be passed to the left branch of the tree, then the inequality must hold. If it is to be passed to the right branch, then the inequality does not hold.

An improved random binary tree, iTree, is assembled to form the entire forest, transforming the original random characteristics into random vectors and random intercepts. Each node has two child nodes or is a leaf node. The iTree construction process is as follows:

(1) $\vec{n}\in R^{|x|}$ is an arbitrarily selected normal vector.

(2) $\vec{p}\in R^{|x|}$ is an arbitrarily selected intercept point within the feature dimension range.

(3) Use filter ($x,(x-\vec{p})\cdot\vec{n}$) to classify each data point, with the left branch representing data less than or equal to 0 in the feature, and the right branch representing data greater than 0.

(4) Recursively construct the left and right branches. If there are multiple data items in the set and the specified tree depth is reached, or if there is only one record, the construction of iTree can be terminated.

Equation (2) defines the normalization factor for the average depth of trees that were not successfully retrieved in the binary tree:

$$(n)=2H(n-1)-\left(\frac{2(n-1)}{n}\right) \tag{2}$$

In the equation, H is Euler's constant.

Equation (3) can be used to obtain the final anomaly score s for a given point x:

$$s(x,n)=2^{\frac{E(h(x))}{c(n)}} \tag{3}$$

The average depth of all trees reaching the point is.

The process for calculating the path length is as follows:

(1) Calculate the depth of the tree traversed by the given record x.

(2) If $e+c(T.size)$ is to be returned, all data should be iterated, and the tree has an external node, where e represents the current path length.

(3) $\vec{n}\in R^{|x|}$ is an arbitrarily selected normal vector.

(4) $\vec{p}\in R^{|x|}$ is an arbitrarily chosen intercept point.

(5) Add 1 to the tree path. If iteration is performed from the left branch, add $(\vec{x},(\vec{x}-\vec{p})\cdot\vec{n})\leq 0$; if iteration is performed from the right branch, add $(\vec{x},(\vec{x}-\vec{p})\cdot\vec{n})>0$.

III. B. Decision cluster classifier based on agglomerative k-means

III. B. 1) Decision Cluster Classifier

Classification models are obtained from different perspectives based on different classification algorithms. The classification model of the decision cluster is constructed using clustering algorithms, and its basic idea is to extract the classification model from a tree constructed from a series of top-down nested clusters built on the training data set. The decision cluster classifier model is shown in Figure 4.

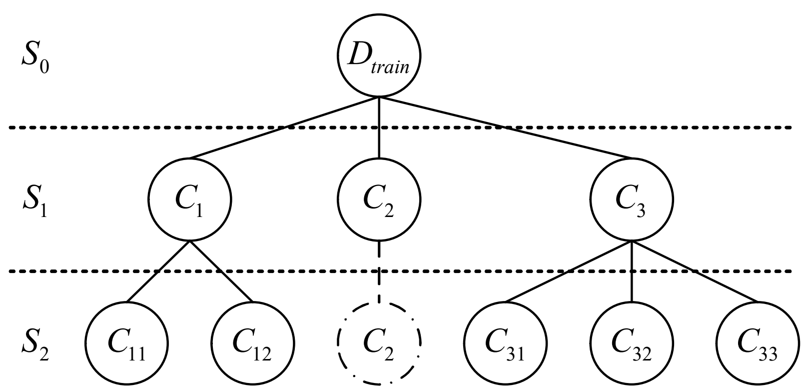


Figure 4: Decision cluster classifier model

Two nested clusters $\{S_1,S_2\}$ on the training dataset constitute the decision cluster classifier. The three clusters and three nodes in the first cluster are obtained by dividing the training data through cluster $S_1=\{C_1,C_2,C_3\}$. The second cluster continues to be divided based on the results of S_1 and obtains $S_2=\{C_{11},C_{12},C_2,C_{31},C_{32},C_{33}\}$. It can be seen that $\{C_{11},C_{12}\}$ and $\{C_{31},C_{32},C_{33}\}$ are further divided by C_1 and C_3, respectively. The decision cluster classifier S_2 is nested within S_1. Thus, the tree constructed through the nested clustering process $\{S_1,S_2,\cdots,S_n\}$ on a series of training datasets constitutes the decision cluster classifier. In this process, the random nodes i and j both satisfy $i>j$, meaning that S_j is completed through the nesting of S_i [29].

To ensure excellent classification quality, most of the training samples in the training dataset are implemented through decision clusters. Therefore, the main category of a cluster is the category identified by a large number of training samples in the cluster. For example, equation (4) describes the main category of cluster C_i:

$$\arg\max_{l \in Y} |\{(x,y) \mid (x,y) \in C_i, y = l\}| \tag{4}$$

In other words, a decision cluster is a cluster with a dominant category.

Many decision clusters containing dominant categories exist in the clustering tree based on training samples. To measure the confidence of a decision cluster, the purity of the dominant category in the decision cluster can be used. The dominant category of decision cluster C_i is l_j, and equation (5) shows the calculation process for its confidence:

$$Purity(C_i) = \frac{|\{(x,y) \mid (x,y) \in C_i, y = l_j\}|}{|C_i|} \tag{5}$$

In the formula, the size of set C_i is represented by $|C_i|$. To classify unlabeled samples, some decision clusters with high confidence can be extracted from the established classifier. Generally, decision clusters at leaf nodes are used to classify new samples. The following describes the process of this algorithm in detail.

III. B. 2) Number of clusters

The nested cluster results are achieved using the k-means clustering algorithm. Since this algorithm uses cluster validation technology to determine the number of clusters, there is a problem of insensitivity to the position of the initial center.

If the n samples in the training data are represented by $D_{train} = \{(x_1, y_1), (x_2, y_2), \cdots, (x_n, y_n)\}$, and each sample is described by a m-dimensional vector $x_i \in R^m$ and a class label y_i, different clusters can be obtained by dividing the training data according to the target function of the k-means clustering based on equation (6):

$$\min_{z,u} P = \sum_{i=1}^{n}\sum_{j=1}^{k} u_{ij} D_{ij} + \lambda \sum_{i=1}^{n}\sum_{j=1}^{k} u_{ij} \log u_{ij} \tag{6}$$

In the formula, the membership relationship between the i st sample and the j nd cluster and the square of the Euclidean distance between them are represented by u_{ij} and $D_{ij} = \| x_i - z_j \|^2$, respectively. The center of the j th cluster is represented by z_j. It should be noted that the target function does not introduce the category of the training sample.

III. B. 3) Termination Conditions

Whether a node is a leaf node must be determined when creating a decision cluster classifier, based on the decision cluster purity of each node. Generally, new samples are classified using the decision clusters of leaf nodes as previously described. The higher the decision cluster purity of a leaf node, the more reliable the classification accuracy. Equation (5) describes the purity calculation process, and the threshold value (denoted as minpurity) is typically 0.92.

Therefore, leaf nodes can be determined based on the purity threshold, with the condition that the purity exceeds this threshold, as expressed in Equation (7).

$$Purity \geq \min purity \tag{7}$$

Each leaf contains only one sample because the decision cluster purity is used as the sole criterion for partitioning, which may lead to overfitting. Therefore, the termination condition can be implemented using the cluster size. If the sample distribution within a cluster is too sparse to reflect its characteristics, it is because there are too many samples within the cluster. If too many clusters are generated, it is because there are too few samples within each cluster, resulting in the inability to achieve the expected classification results.

Equation (8) describes the process of measuring the number of samples within a cluster, where minTrainNum is an empirical value and also the threshold in the equation:

$$th(C) = |C| \tag{8}$$

In the formula, the number of samples in cluster C is described by $|C|$.

The condition for a cluster to be marked as a leaf node is that its size is less than the threshold. Formula (9) is the expression for satisfying this condition:

$$th(C) < \min TrainNum \tag{9}$$

As can be seen from the above, equation (10) is the termination condition for this classification algorithm:

$$th(C) < \min TrainNum \text{ or } Purity \geq \min purity \tag{10}$$

IV. Performance testing of psychological problem identification models

The model proposed in this paper will be tested on three datasets, which are from the National Health and Nutrition Examination Survey (NHANES) in the United States, the Korea National Health and Nutrition Examination Survey (KNHANES) in South Korea, and the Behavioral Risk Factor Surveillance System (BRFSS). These three datasets are officially collected, fully publicly available, and do not contain any personal privacy information. The experiments selected four machine learning methods—logistic regression (LR), factorization machine (FM), random forest (RF), and extreme gradient boosting (XGB)—as well as two deep learning networks—deep neural networks (DNN) and DeepFM—as comparison models. This experiment selected recall rate, F1 score, and AUC as evaluation metrics for model performance. Since the assessment of mental health status involves screening for various mental disorders, this chapter selected depression, the most prevalent condition, as the primary target for identification.

IV. A. Experimental Results

The proposed method and six comparison models were trained and tested on the NHANES, KNHANES, and BRESS datasets. The training, validation, and testing datasets were divided in an 8:1:1 ratio. The model testing results are shown in Table 4. The comparison results show that the proposed method achieved the highest recall, F1 score, and AUC on all datasets, proving the efficiency of the model in identifying psychological problems.

Table 4: Model test results

Model	NHANES			KNHANES			BRESS		
	R	F1	AUC	R	F1	AUC	R	F1	AUC
LR	0.672	0.617	0.854	0.695	0.655	0.905	0.701	0.665	0.822
RF	0.662	0.67	0.843	0.82	0.807	0.95	0.696	0.713	0.834
XGB	0.673	0.664	0.847	0.872	0.881	0.957	0.695	0.671	0.819
FM	0.691	0.661	0.844	0.767	0.739	0.912	0.709	0.695	0.808
DNN	0.701	0.681	0.848	0.835	0.843	0.933	0.687	0.693	0.815
DeepFM	0.709	0.696	0.861	0.907	0.889	0.956	0.699	0.708	0.816
Ours	0.728	0.717	0.888	0.998	0.902	0.967	0.736	0.719	0.846

IV. B. Feature contribution analysis

In the identification of psychological issues, interpretability is equally important as accuracy. The method proposed in this chapter was trained on three datasets: NHANES, KNHANES, and BRESS. Next, the weight parameters in the low-order network will be converted into feature contribution degrees using a formula, and the features will be ranked based on their contribution degrees in each of the three datasets. Due to space constraints, only the top 20 features with the highest contribution degrees in each dataset were selected. The top 20 depression identification variable contribution degree rankings are shown in Table 5. ACE represents adverse childhood experiences in the NHANES dataset. The following conclusions can be drawn from the table: (1) General health status, gender, income level, dietary health status, age, marital status, smoking status, and HIV testing history are among the top 20 contributors in multiple datasets, indicating that these features are important for identifying students' psychological issues. (2) Some factors are indirectly related to mental health issues. For example, in NHANES, understanding nutrition labels reflects concern for dietary health. In BRESS, the frequency of nighttime urination is related to kidney health. Both dietary health and kidney health are related factors for depression.

IV. C. Application

This section applies the proposed psychological issue identification model to the task of grading college students' mental health status. The application data is sourced from the university's counseling center, and the information contained in the data does not include any personal privacy data, being solely for research purposes. The survey data includes students' basic information (gender, place of origin, whether they are an only child, educational background, and college) and the results of the psychological survey questionnaire administered at the time of enrollment. The questionnaire assessed scores across 22 dimensions, including anxiety, low self-esteem, sensitivity, suicidal intent, hallucinations, and delusions. In addition to the above information, the screening data also includes the diagnostic results of mental health professionals for each case. In this section, mental health status is categorized into Level 1 mental health issues, Level 2 mental health issues, Level 3 mental health issues, and no issues. Level 1 mental health issues may include suicidal or self-harming intentions, hallucinations, and delusions. Level 2 mental health issues may include depression, anxiety, and somatization. Level 3 mental health issues may include interpersonal relationship difficulties and adaptation challenges. The results of the classification of college students' mental health status are shown in Table 6. In terms of interpretability, feature contribution analysis using parameters was conducted, and the top five features in terms of contribution in this dataset were: suicidal intent, self-harm behavior, depression, somatization, and sensitivity.

Table 5: The depression recognition variable contribution ranking top20

Sort	NHANES	KNHANES	BRESS
1	ACE: Living with people suffering from depression	Degree of stress	General health condition
2	Attention and memory disorders	Urine occult blood	Age
3	Limited living activities	General health condition	Nighttime wake-up frequency
4	ACE: Has experienced sexual harassment	The number of days one is ill in a month	Gender
5	Age group	Income level	Healthy diet
6	General health condition	Kidney diseases	Sleep disorders
7	Age	Understand the nutrition facts table	Urinary incontinence
8	ACE: Your parents are angry with you	Stress perception	Gastrointestinal diseases
9	Memory loss	Exposure to second-hand smoke	Influenza, pneumonia, ear infection
10	ACE: Has experienced sexual harassment	Sedentary time	Liver diseases
11	Marital status	Fat-energy intake ratio	Changes in health status
12	Gender	Healthy diet	Received a blood transfusion within one year
13	Body Mass Index (BMI)	Weight loss within one year	Have smoked at least 100 cigarettes
14	I am unable to seek medical treatment due to cost issues	Lose weight by taking weight-loss pills	Drink four or more glasses of alcohol every day
15	Employment situation	Relationship with parents	Type of work
16	Injecting drugs or suffering from sexually transmitted diseases	Pain or discomfort	Thyroid diseases
17	Income level	Weight gain within one year	Participate in blood donation within one year
18	Educational level	The daily sodium intake	I hope my weight will decrease/increase/remain the same
19	Have smoked at least 100 cigarettes	How many years has it been since I last had a physical examination	History of HIV. testing
20	History of HIV testing	Arthritis	Marital status

Table 6: Psychological status of college students

Classification of mental health status	Number of Cases	Recall rate
First-level psychological problem	45	0.795
Level two psychological problems	80	0.781
Level three psychological problems	169	0.836
No problem	320	0.899

Next, the trained model was applied to cases of students who had not visited the counseling center to conduct graded predictions, assessing the proportion of students who may have psychological issues, thereby providing a reference basis for the counseling center's early intervention efforts. The results of the graded prediction of college students' mental health status are shown in Figure 5. The figure indicates that among students who have not visited the counseling center, 3.69% have Level 1 mental health issues, 11.32% have Level 2 mental health issues, and 15.74% have Level 3 mental health issues. Using the method described in this paper to classify the mental health status of college students not only provides reference data for assessing the overall mental health status of students but also enables the counseling center to identify students with potential mental health issues earlier, provide timely psychological counseling, and help students recover their mental health as soon as possible.

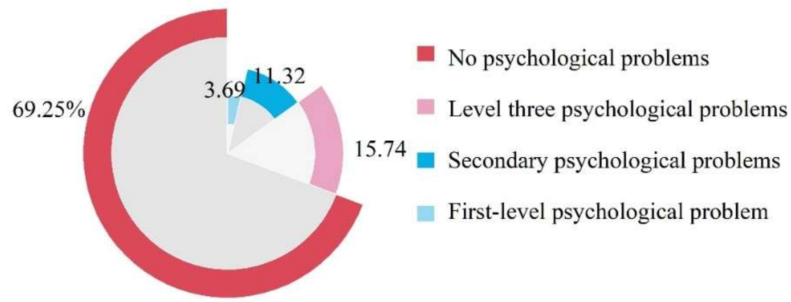


Figure 5: The results of the students' mental health status classification

V. Optimization of intervention pathways for student psychological issues

V. A. Ensuring Student Safety

Addressing a psychological crisis requires immediate action to resolve the most urgent issues, with the primary focus on ensuring the safety of students and maintaining stability in the surrounding environment during an emergency. As a counselor, it is essential to arrive at the scene as quickly as possible. Simultaneously, communication must be established with college administrators, dormitory managers, mental health professionals, the student’s close friends, and peers to coordinate a collective response at the scene. With the collaboration of these three parties and the assistance of student leaders, efforts should be made to stabilize the student’s emotions during the journey to the scene. If a mental health counselor cannot arrive promptly, it is essential to communicate via phone to inform professionals of the student's current condition. Based on the initial assessment by professionals and one's own judgment, further comforting and handling measures should be implemented.

V. B. Long-term tracking of students

When addressing students' issues related to heartbreak, it is important to listen attentively, help students develop a healthy understanding of the situation, and calmly analyze the reasons behind the failure of their relationship. Adjust students' negative emotions and help them establish reasonable beliefs. Encourage students to resolve their emotional distress through appropriate and reasonable means. Finally, further assist students in looking toward the future by continuously improving themselves, participating in various campus activities, and shifting their focus to ensure that heartbreak does not lead to a loss of ambition. Of course, this should be tailored to the specific circumstances. Based on the hospital's diagnosis, if the stress response caused by a temporary, sudden event has not severely impacted the student's ability to function, they may continue their studies with parental accompaniment. Additionally, the role of student leaders should be fully leveraged to demonstrate “great care” through “small dormitories,” providing targeted support and assistance.

V. C. Promoting mental health awareness

In daily work, it is not only ideological and political education classes that are important, but also psychological education classes, which should be integrated into all disciplines at universities. Professional course instructors should collaborate to incorporate mental health education into their teaching. This is achieved through two main approaches. First, collaborating with the school's psychological counseling teachers to further promote the learning of theoretical knowledge. By combining in-class training with the creation of dedicated WeChat official accounts to disseminate relevant psychological content, including scenario-based exercises, establishing psychological theater clubs, and other diverse formats, we expand the methods of psychological education, stimulate students' interest in learning about psychology, and encourage them to confront psychological disorders. Second, organizing a variety of campus activities to broaden learning channels.

V. D. Conduct personalized teaching

V. D. 1) Establish a professional knowledge base based on individual characteristics

Redesign existing knowledge points and establish subject-specific knowledge points based on individual characteristics. To achieve the learning objectives of each knowledge point, set the attributes of each knowledge point according to the characteristics of different students: learning start time, learning end time, learning objectives, knowledge presentation format, case studies, exercises, tests, etc. Let K denote the subject-specific knowledge base constructed based on individual characteristics, and ki denote a knowledge point, where 0 < i ≤ N (N is the number of knowledge points in the knowledge base), then: K = {ki | 0 < i ≤ N}, ki = {kij | 0 < j ≤ M}, kij = {Start[i, j], End[i, j], Target[i, j], Present[i, j], Cases[i, j], Exercise[i, j], Test[i, j], ···}, where kij is the jth parameter set of knowledge point ki. Each knowledge point is integrated to form a knowledge system, constructing a professional knowledge base based on individual characteristics.

V. D. 2) Algorithm Selection

Based on the knowledge system and teaching plan, the optimal strategy for personalized teaching for students with different characteristics is determined using similarity calculations. The similarity calculation formula for selecting knowledge point parameter sets based on different student characteristic sets is as follows.

1) Basic calculation

The basic calculation is shown in Equation (11), where T_{ij} is the similarity between knowledge point parameter set $K(i)$ and student feature set $C(j)$, the denominator $|S(K(i))|$ is the number of student feature sets that match knowledge point parameter set $K(i)$, and the numerator $|S(K(i))\cap S(C(j))|$ is the number of student feature sets that match both knowledge point parameter set $K(i)$ and student feature set $C(j)$.

$$T_{ij}=\frac{|S(K(i))\cap S(C(j))|}{|S(K(i))|} \tag{11}$$

2) Cosine similarity

As shown in Equation (12), cosine similarity can reduce the probability of similarity between certain parameter sets of knowledge points and other parameter sets of knowledge points by lowering the weight of parameter set $K(i)$ of knowledge points, thereby improving the rationality of personalized teaching strategies.

$$T_{ij}=\frac{|S(K(i))\cap S(C(j))|}{\sqrt{|S(K(i)||S(C(j))|}} \tag{12}$$

3) Cosine similarity a

Cosine similarity a As shown in Equation (13), this algorithm better reduces the weight of knowledge point parameter set $K(i)$, and the value of a can be determined based on the actual application results.

$$T_{ij}=\frac{|S(K(i))\cap S(C(j))|}{|S(K(i))|^{a}|S(C(j))|^{1-a}} \tag{13}$$

4) Improved cosine similarity

The improved cosine similarity is shown in Equation (14).

$$T_{ij}=\frac{\sum_{s\in S(K(i))\cap S(C(j))}\frac{1}{lb(1+|S(s)|)}}{|S(K(i))||S(C(j))|} \tag{14}$$

For personalized teaching systems, there are some malicious users who frequently misuse the system. To ensure the reliability of the similarity between the knowledge point parameter set and the student feature set, it is necessary to adjust the contribution of active users to the similarity of the knowledge point parameter set.

5) Improved normalization of cosine similarity

The improved normalization of cosine similarity is shown in Equation (15). To better improve the accuracy of the calculated knowledge point parameter set and enhance the quality of personalized teaching strategies, normalization based on improved cosine similarity can also increase the coverage and diversity of the calculated knowledge point parameter set.

$$T_{ij} = \frac{T_{K(i)C(j)}}{\max_j T_{K(i)C(j)}} \tag{15}$$

After calculating the similarity between the knowledge point parameter set and the student feature set, Equation (16) calculates the student's interest in teaching using parameter set $K(i)$.

$$I_{ij} = \sum_{i \in S(s) \cap S(i,k)} T_{ij} r_{si} \tag{16}$$

Here, $S(s)$ is a set of personalized teaching strategies that can satisfy students' interests, formulated using a set of knowledge point parameters; $S(i,k)$ is a set of k student feature sets that are most similar to the knowledge point parameter set $K(i)$; r_{si} is the interest level of students s when personalized teaching is conducted using the knowledge point parameter set $K(i)$.

For personalized teaching systems, there are some malicious users who frequently misuse the system. To ensure the reliability of the similarity between the knowledge point parameter set and the student feature set, it is necessary to adjust the contribution of active users to the similarity of the knowledge point parameter set.

6) Improved normalization of cosine similarity

To better improve the accuracy of the calculated knowledge point parameter set and enhance the quality of personalized teaching strategies, normalization based on improved cosine similarity can also increase the coverage and diversity of the calculated knowledge point parameter set.

$$T_{ij} = \frac{T_{K(i)C(j)}}{\max_j T_{K(i)C(j)}} \tag{17}$$

After calculating the similarity between the knowledge point parameter set and the student feature set, the interest level of students in teaching using parameter set $K(i)$ is calculated.

$$I_{ij} = \sum_{i \in S(s) \cap S(i,k)} T_{ij} r_{si} \tag{18}$$

Here, $S(s)$ is a set of personalized teaching strategies that can satisfy students' interests, formulated using a set of knowledge point parameters; $S(i,k)$ is a set of k student feature sets that are most similar to the knowledge point parameter set $K(i)$; r_{si} is the interest level of students s when personalized teaching is conducted using the knowledge point parameter set $K(i)$.

V. D. 3) Intervention for psychological problems

Using a personalized teaching system, if the intervention effect for student psl with psychological issues learning knowledge point k_i (the teaching strategy for k_i is determined by parameter set k_{il}) does not meet the requirements, then refine parameter set k_{il} for knowledge point k_i; if the knowledge point cannot be refined, then add parameter set $k_{iM}+1, M=M+1$ for knowledge point k_i, where M is the number of parameter sets for the attributes of knowledge point k_i, and update the knowledge base.

The workflow for intervening in students' psychological problems based on individual characteristics is shown in Figure 6.

VI. Experiment on the impact of psychological intervention on students' mental health

This section of the experiment randomly selected 100 participants from a certain school for measurement. First, the randomly selected 100 participants were administered the Symptom Checklist-90 (SCL-90) and the Subjective Well-Being Questionnaire (SWB). Subsequently, the 40 participants in the experimental group were subjected to an intervention, while the control group received no intervention. The experimental group underwent a 10-session intervention program consisting of specialized lectures, group training, and individual counseling, each session lasting two hours and conducted once a week. The control group, however, received no form of counseling and were unaware of their status as control group members. Finally, the experimental group participants were administered the Symptom Checklist-90 (SCL-90) and the Subjective Well-Being Questionnaire (SWB) again to compare whether their mental health levels and subjective well-being had improved before and after the intervention.

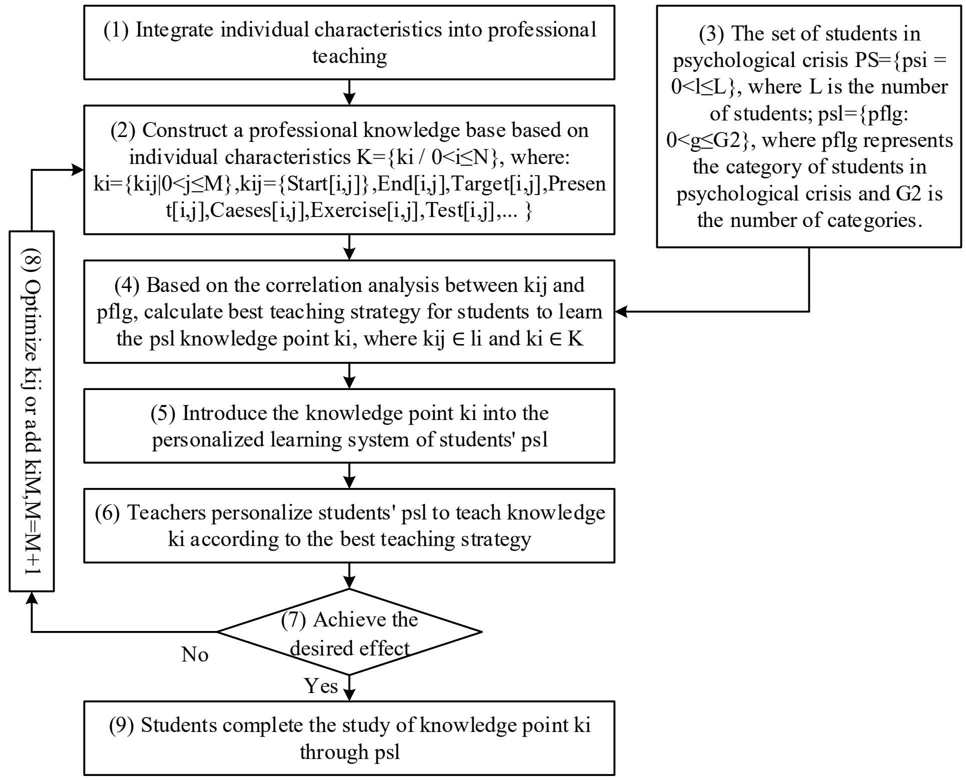


Figure 6: The workflow of student psychological crisis intervention

VI. A. Research Results

VI. A. 1) Statistical results of the experimental group and control group before and after intervention

(1) Statistical results of the experimental group and control group before intervention

The comparison of pre-intervention scores between the experimental group and the control group is shown in Table 7 (* indicates $p < 0.05$, ** indicates $p < 0.01$). As can be seen from the table, prior to the intervention, there were no significant differences between the experimental group and the control group in terms of total scores and scores on the ten factors of the Symptom Self-Rating Scale, indicating that the psychological health levels of the participants in both groups were homogeneous before the intervention.

Table 7: The previous score was compared

Project	Experimental Group	Control group	T value	P
Total score	143.65±31.88	143.42±38.25	-0.46	0.68
Somatization	16.94±6.88	16.66±5.7	0.32	0.73
Obsessive-compulsive disorder	20.27±6.26	19.46±5.01	0.45	0.65
Interpersonal relation	16.75±4	16.53±6.39	0.37	0.69
anxiety	16.04±6.48	15.21±5.02	0.68	0.48
depression	21.08±4.13	21.97±8.16	-0.69	0.53
antagonism	8.64±2.8	8.83±3.23	-0.68	0.50
horror	9.39±2.76	9.77±3.73	-0.37	0.68
paranoia	9.8±3.12	9.31±3.05	0.58	0.57
insanity	14.17±3.05	14.86±4.61	-0.91	0.35
Other factors	10.57±2.56	10.82±3.31	-0.09	0.88

(2) Statistical results of the experimental group before and after intervention

The comparison of pre- and post-intervention scores for the experimental group is shown in Table 8. As can be seen from the table, after two months of intervention, the post-test total score of the Symptom Self-Rating Scale for the experimental group was 17.61 points lower than the pre-test score, and the post-test scores for somatization, interpersonal sensitivity, anxiety, depression, and hostility factors were also lower than the pre-test scores. This indicates that positive psychological intervention has a positive impact on the mental health of college students.

Table 8: The results were compared before and after the active intervention

Project	Before intervention	After the intervention	T value	P
Total score	143.65±31.88	126.04±23.44	2.14*	0.02
Somatization	16.94±6.88	13.69±3.01	2.21*	0.02
Obsessive-compulsive disorder	20.27±6.26	19.45±4.3	0.38	0.67
Interpersonal relation	16.75±4	13.32±4.08	4.27**	0.00
anxiety	16.04±6.48	13.31±3.17	2.31**	0.00
depression	21.08±4.13	16.96±3.84	4.13**	0.00
antagonism	8.64±2.8	6.88±2.38	2.44*	0.03
horror	9.39±2.76	9.47±2.32	-0.20	0.86
paranoia	9.8±3.12	9.26±2.18	0.83	0.54
insanity	14.17±3.05	14.3±2.97	-0.07	0.93
Other factors	10.57±2.56	9.4±2.75	1.93	0.09

VI. A. 2) Statistical results of subjective well-being in the experimental group and control group before and after intervention

(1) Statistical results of subjective well-being between the experimental group and the control group before intervention

The statistical results of subjective well-being in the experimental group and control group before intervention are shown in Table 9. As can be seen from the table, before intervention, there were no significant differences between the experimental group and the control group in terms of questionnaire scores. Specifically, there were no significant differences between the two groups in the three dimensions of life satisfaction, positive emotions, and negative emotional experiences. This indicates that the subjective well-being of participants in both groups was homogeneous before the intervention.

Table 9: Positive intervention before subjective happiness statistics

Project	Experimental Group	Control group	T value	P
Life satisfaction	25.15±5.61	23.33±5.92	1.22	0.19
Positive emotional experience	28.31±5.44	26.1±7.53	1.64	0.12
Negative emotional experience	13.05±5.39	12.72±5.29	0.17	0.89

(2) Statistical results of subjective well-being in the experimental group before and after the intervention

The statistical results of subjective well-being in the experimental group before and after the intervention are shown in Table 10. As can be seen from the table, to further demonstrate the promotional effect of the intervention program on enhancing college students' subjective well-being levels, post-intervention tests were conducted on the experimental group's life satisfaction, positive emotions, and negative emotions. Among the three dimensions of subjective well-being, post-intervention scores for positive emotions were higher than pre-intervention scores, while post-intervention scores for negative emotions were lower than pre-intervention scores. Although there was no significant difference in life satisfaction between pre- and post-intervention, the post-intervention scores were higher than the pre-intervention scores. This indicates that the intervention had a significant impact on improving college students' subjective well-being levels.

Table 10: Subjective happiness statistics after active intervention

Project	Before intervention	After the intervention	T value	P
Life satisfaction	25.15±5.61	25.89±5.33	0.24	0.85
Positive emotional experience	28.31±5.44	31.85±6.81	2.62*	0.02
Negative emotional experience	13.05±5.39	10.54±1.05	-2.00*	0.04

VI. A. 3) Post-test results of the intervention group and follow-up statistical results three months later

The post-intervention results of the experimental group and the follow-up statistics three months later are shown in Table 11. As can be seen from the table, there are no significant differences between the post-intervention data and the follow-up data three months later. This indicates that the intervention not only has a significant effect on college students' mental health and subjective well-being but also that the intervention effects are highly stable. In summary, the research results indicate that positive psychological intervention is effective for mental health and subjective well-being, and its effects are also sustained over time.

Table 11: Active intervention in experimental results and tracking statistics

project	Post-test of the experimental group	Post-test tracking	T value	P
Scl-90				
Total score	126.04±23.44	134.11±42.11	-0.69	0.39
Somatization	13.69±3.01	14.04±6.5	-0.11	0.92
Obsessive-compulsive disorder	19.45±4.3	20.76±5.84	-1.02	0.26
Interpersonal relation	13.32±4.08	12.72±6.33	0.48	0.61
anxiety	13.31±3.17	14.01±5.05	-0.06	0.52
depression	16.96±3.84	21.53±8.44	0.19	0.84
antagonism	6.88±2.38	7.32±0.55	-0.27	0.85
horror	9.47±2.32	9.77±2.4	0.42	0.83
paranoia	9.26±2.18	9.92±3.78	-0.61	0.54
insanity	14.3±2.97	14.75±4.34	0.30	0.80
Other factors	9.4±2.75	9.29±3.26	0.42	0.72
SWB				
Life satisfaction	25.89±5.33	22.65±4.12	1.07	0.28
Positive emotional experience	31.85±6.81	32.11±5.53	0.47	0.60
Negative emotional experience	10.54±1.05	12.41±4.57	-1.86	0.05

VI. B. Analysis of Results

VI. B. 1) The Impact of Positive Psychological Intervention on Interpersonal Sensitivity

As shown by the statistical results, positive psychological interventions exhibit significant differences in scores for the four factors of interpersonal sensitivity, anxiety, depression, and hostility, as well as the total score. However, no significant differences were observed for the factors of somatization, obsessive-compulsive symptoms, phobia, psychoticism, and other items. Individuals with high interpersonal sensitivity primarily exhibit feelings of discomfort and inferiority when interacting with others. Anxiety, feelings of inferiority, and negative expectations in social interactions are typical manifestations of this symptom. Therefore, in a trusting and collaborative group setting, it is important to encourage students to build confidence, overcome communication barriers, develop a positive self-image, open up, and be receptive to others.

VI. B. 2) The Impact of Intervention on Negative Emotions

Factors reflecting negative emotions in the experiment included anxiety, hostility, depression, and fear. The intervention program focused more on increasing positive emotions and reducing negative emotions. As shown in the data, after a period of intervention, as group trust gradually developed and participants fully engaged in each activity under the guidance of the instructor, members of the experimental group gradually established a safe group atmosphere. Through activities related to positive self-awareness and positive interpersonal interactions, they increasingly accepted themselves and effectively regulated their emotions. Consequently, the post-test results for the experimental group showed a significant decrease in scores for anxiety, hostility, and depression factors, indicating that the intervention was effective in alleviating negative emotions.

VI. B. 3) The Impact of Positive Psychological Intervention on Positive Emotional Experiences

The data results indicate that the factor scores for negative emotions decreased, while the factor scores for positive emotional experiences related to subjective well-being significantly increased. In the experimental group, post-test scores for negative emotional experiences decreased compared to pre-test scores, while scores for positive emotional experiences increased. Additionally, the intervention program, which focuses on cultivating positive emotions and feelings to achieve experimental objectives, also organizes individuals with similar characteristics and needs into groups through positive classroom lectures and group counseling training. The positive factors and positive atmosphere within the group easily help experimental group students find a sense of trust, security, and acceptance within the group, thereby fostering hope and the power to improve.

VI. B. 4) The Impact of Positive Psychological Intervention on Subjective Well-Being

The data results show that there was no significant difference in the factor scores for life satisfaction between the pre- and post-tests in the positive psychological intervention experimental group, while there was a significant difference in the factor scores for positive and negative emotions between the pre- and post-tests in the experimental group. The reason for the lack of significant difference in the former is that life satisfaction is a dimension that uses personal evaluation as a reference, representing an individual's overall cognitive assessment of the quality of life over a past period or in the current state based on their own subjective standards.

VII. Conclusion

Mental health issues among college students are becoming increasingly prominent, making mental health crisis intervention for college students particularly important. This paper proposes a data-driven method for identifying mental health issues among students and outlines intervention strategies from the perspectives of ensuring student safety, monitoring emotional dynamics, and implementing personalized teaching. The study concludes that:

Among students who have not visited a counseling center, 3.69% have level 1 psychological problems, 11.32% have level 2 psychological problems, and 15.74% have level 3 psychological problems. This shows that the method described in this paper can be used to classify students' mental health status, thereby helping students recover their mental health at an early stage.

There were significant differences in the scores of the experimental group on the five factors of somatization, interpersonal sensitivity, anxiety, depression, and hostility before and after the positive psychological intervention. The post-test scores of the experimental group were lower than the pre-test scores, while the differences in the other factors were not significant. This indicates that the psychological intervention approach proposed in this paper is helpful in improving students' mental health.

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