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# AI-empowered Three-Dimensional Collaborative Mental Health Model of "Psychology-Culture-Ideology and Politics"—A Case Study of Guangxi Universities

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***Abstract:*** *As the academic and social adaptation pressures permeate even college students, mental health problems are beginning to exhibit a tendency of becoming secretive and sophisticated. The existing model of a single psychological counseling intervention lacks information acquisition, risk identification, and collaboration in education, which does not allow constantly monitoring and thoroughly leading students with their mental condition. In case of this scenario, the current paper creates a three-dimensional model of collaborative education of psychology-culture-ideological and political education with the support of an artificial intelligence technology. This model unites the analysis of student behavior and the collaboration mechanism of educational resources to the solution of the systematic functioning of mental health identification and educational intervention. The study uses machine learning algorithms to classify and identify students' psychological states, employs K-means clustering and decision tree classification to achieve hierarchical identification of psychological risks, and combines collaborative filtering recommendation algorithms to match cultural resources and ideological and political courses. Experimental results show that the overall accuracy of the model in identifying psychological risks reaches 0.931, an improvement of approximately 10.6% compared to traditional methods; the student participation rate in cultural activities increased from 46.3% to 68.7%, and the participation rate in ideological and political courses increased from 71.5% to 84.9%; the comprehensive mental health index rose from 0.67 to 0.82, and the rate of proactive psychological help reached 21.6%.*

***Keywords:*** *College Student Mental Health Education; Collaborative Education Mechanism; Multi-Source Behavioral Data Analysis; Machine Learning Algorithm; Recommendation Algorithm*

## 1. Introduction

As the society is constantly growing and the environment of higher education becomes more diverse, college students experience more pressure in their academic learning, work, and social adjustment. Mental health problems are becoming more secretive, complicated and heterogeneous. It has been revealed that surveys have shown a rise in anxiety, depression and psychological distress among college students affecting their grades, social flexibility and general quality. Mental health education that is currently provided in colleges is mostly based on single-channel counseling or course-based guidance and leads to the acquisition of information in a timely manner, absence of personalized and collaborative treatment, and failure to address multi-level and multi-dimensional development needs of students. In the meantime, cultural identity and ideological and political education can potentially form values and psychological resilience of college students, yet, as per the practice, they are not systematically linked with psychological education, which does not include any mechanisms of collaboration and integration.

To address these issues, the development of artificial intelligence (AI) technology offers new ideas for mental health education. Through multi-source data analysis, intelligent risk identification, and personalized educational resource recommendations, it can achieve accurate identification of psychological states and intelligent matching of intervention strategies, providing technical support for the integration of cultural education and ideological and political guidance. Therefore, this study aims to construct a three-dimensional collaborative education model centered on "psychology-culture-ideological and political education," exploring a systematic, precise, and sustainable development path

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for college students' mental health education driven by AI, and providing theoretical basis and practical reference for mental health management and educational innovation in universities.

## 2. Related Works

In recent years, the mental health problems of college students have received increasing attention, especially the mental health of the first generation of college students and students in the context of the pandemic, leading to a large number of empirical studies and systematic reviews. Rockwell and Kimel systematically reviewed 62 studies on the mental health of first generation college students and found that anxiety, depression, and stress significantly increased when academic activities and social relationships were inconsistent with their dependency norms; However, in general psychological health measurements that do not differentiate between specific contexts, there is no significant difference between first generation and non first generation students, emphasizing the need for psychological health research to be analyzed in conjunction with specific contexts [1]. Roche et al. compared the mental health status of college students in 2016 and 2020 and found that during the pandemic, students' stress, depression, and anxiety significantly increased, with older students being more affected; There was no significant change in compulsive symptoms [2]. Elharake et al.'s research review shows that anxiety, depression, fatigue, and psychological stress have significantly increased in children and college students during the pandemic. Factors such as rural living, low family economic level, and close relationships with medical staff can exacerbate mental health problems [3]. Frazier et al. evaluated the mental health status of American undergraduate students during the COVID-19 pandemic and found that depression and stress symptoms were significantly higher among students in 2020 than in 2017. The main sources of stress include the inability to see friends and academic related stress. During the epidemic, students' perceived control and proactive coping strategies declined, but were associated with better mental health; Avoidance coping increases, leading to a deterioration of mental health status [4]. Salimi et al. explored the impact of the COVID-19 pandemic on the mental health of higher education students, pointing out that the pandemic has exacerbated the psychological pressure on students in terms of virtual learning adaptation, social isolation, and socio-economic uncertainty. They analyzed the additional mental health issues brought about by the epidemic and proposed intervention strategies that mental health practitioners can adopt in practice, including psychological support, adaptive counseling, and coping skills training [5]. Wattick et al. investigated the impact of the COVID-19 pandemic on the mental health and drinking behavior of college students, and evaluated the role of psychological resilience in mitigating negative outcomes. A survey shows that after the epidemic, students' levels of severe depression, anxiety, and high stress have significantly increased [6]. However, existing research still has limitations: most studies focus on single psychological indicators or general measurements, lacking multidimensional analysis combined with specific contexts and exploration of cross factor synergistic mechanisms.

## 3. Methods

### *3.1 Construction of a 3D Collaborative Model for College Students' Mental Health Driven by AI*

With the support of AI technology, the mental health education of college students has shifted from a single psychological intervention to a multidimensional collaborative education model. This study takes the needs of students' psychological development as the core content, and constructs a three-dimensional collaborative model of "psychology culture ideological and political education". It integrates support for mental health, cultivation of cultural values, and guidance of ideological and political education into a unified framework, achieving a synergistic effect of psychological adjustment, cultural identity, and value guidance. With the help of structured integration, a systematic operating mechanism is formed.

In the model, the psychological dimension is responsible for identifying psychological states and providing emotional support. It focuses on students' emotional fluctuations, stress levels, and psychological resilience, providing fundamental information for psychological intervention; The cultural dimension relies on traditional cultural resources and campus cultural environment to enhance students' cultural identity and emotional belonging, promote psychological stability and value internalization; The ideological and political dimension guides students to form positive and stable value orientations through the education of ideal beliefs and the cultivation of social responsibility awareness. These three dimensions reinforce one another: emotional adjustment is based on

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psychological support, spiritual identity is reinforced by cultural nourishment and value direction is given by ideological and political education.

On the basis of the three-dimensional formation, a collaborative direction of psychological recognition cultural adjustment value guidance is further formed: dynamically detecting the psychological state of students to find the possible risks, integrating cultural resources and campus activities to implement emotional adjustment and spiritual support, and eventually realizing the value guidance and responsibility cultivation through ideological and political education, which can help students to attain long-term development of psychological stability and value recognition.

AI technology plays a role in data integration and information linkage within the model. By analyzing students' behavior and psychological information, it dynamically identifies their psychological states and assists in matching cultural resources and educational content, forming feedback and collaborative linkage mechanisms for different educational stages. This enables the "psychological cultural ideological and political" three-dimensional collaborative model to form a continuous educational structure driven by data, providing a systematic support framework for college students' mental health education.

### *3.2 Psychological Health Identification and Data Support Mechanism Based on AI Technology*

#### *3.2.1 Integration and feature extraction of multi-source student behavior data*

In order to achieve unified processing of multi-source data, it is necessary to standardize various types of data so that they can be calculated within the same analysis framework. The common method is to map data of different dimensions to a unified interval through normalization:

$$x_{norm}=\frac{x-x_{min}}{x_{max}-x_{min}} \tag{1}$$

(x) represents the original data value, ($x_{\min}$) and ($x_{\max}$) represent the minimum and maximum values of the feature in the sample, and ($x_{norm}$) is the normalized feature value. Through this method, the influence of dimensional differences between different indicators on model analysis can be eliminated.

For textual data, such as students' online messages, learning feedback, or anonymous psychological platform records, their emotional tendency values can be calculated through emotion analysis methods. The emotional score can usually be expressed as:

$$S_{emotion}=\sum_{i=1}^{n} w_i \cdot e_i \tag{2}$$

($e_i$) represents the emotional intensity value of the (i) th emotional word, ($w_i$) is the weight coefficient of the word in the text, and ($S_{emotion}$) is the overall emotional score of the text. The lower the emotional score, the higher the proportion of negative emotions expressed in the text.

For behavioral data, behavior pattern features are extracted by analyzing the frequency and trend of students' behavior within a certain time window. For example, a learning engagement indicator can be constructed:

$$B_{learn}=\frac{1}{T}\sum_{t=1}^{T} a_t \tag{3}$$

($a_t$) represents the number of learning behaviors of students during the time period (t) (such as course visits, homework submissions, etc.), and (T) represents the statistical period. This indicator can reflect the stability of students' learning participation, and when there is a significant decrease, it may indicate changes in learning motivation or psychological state.

Through the above multidimensional feature extraction, a comprehensive feature vector containing emotional, behavioral, and participation features can be formed:

$$X=(x_1,x_2,x_3,\ldots,x_n) \tag{4}$$

#### *3.2.2 Intelligent Identification and Classification Mechanism for Student Psychological Risks*

This study uses supervised learning methods to establish a psychological risk classification model. Firstly, the student samples are classified into different categories based on their psychological states, such as stable psychological state, mild psychological stress, and high-risk psychological state, and multi-source feature vectors are used as model inputs. The simplistic version of the model is:

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$$y=f(X)=\sigma(w^TX+b) \tag{5}$$

($\mathbf{X}$) denotes the student feature vector, (w) is model weight parameters, (b) is the bias term, and ($\sigma(\cdot)$) is the activation function to be used in mapping the model output results to probability values. The (y) of a model is the likelihood of students being at the risk of psychological problems.

The model parameters during the model training process are constantly optimized with the aim of minimizing the loss function. The loss function that is most frequently used is cross entropy loss:

$$L=-\frac{1}{N}\sum_{i=1}^{N}\left[y_i\log(\hat{y}_i)+(1-y_i)\log(1-\hat{y}_i)\right] \tag{6}$$

(N) is the amount of samples, ($y_i$) is the actual label and ($\hat{y}_i$) is the probability estimated by the model.

Through iterative optimization, the model can gradually improve its ability to identify students' psychological risks.

After obtaining the probability of risk prediction, it is necessary to further establish rules for classifying psychological risk levels in order to provide clear reference for educational interventions. Students' psychological states can usually be classified based on probability thresholds:

$$R=\begin{cases}\text{Low risk}, & 0\le y<\theta_1\\ \text{Medium risk}, & \theta_1\le y<\theta_2\\ \text{High risk}, & y\ge\theta_2\end{cases} \tag{7}$$

(y) is the risk probability predicted by the model, ($\theta_1$) and ($\theta_2$) are the threshold values for risk level classification. Through this rule, students' psychological states can be classified and identified, providing differentiated support for different risk groups.

### *3.3 Design of the Collaborative Education Mechanism of "Psychology Culture Ideology and Politics"*

#### *3.3.1 Personalized psychological intervention and cultural guidance strategies*

At the level of psychological intervention, hierarchical psychological support strategies are constructed based on students' psychological risk levels and differences in psychological characteristics. By quantifying the psychological state of students through multidimensional psychological indicators, it can be described as a psychological feature vector:

$$P=(p_1,p_2,p_3,\dots,p_n) \tag{8}$$

($p_i$) represents the quantitative value of psychological indicators such as emotional stability, stress level, and social adaptation. The comprehensive psychological state index can be obtained through weighted fusion:

$$S_p=\sum_{i=1}^{n} w_i p_i \tag{9}$$

($w_i$) represents the importance weight of each indicator. According to the comprehensive index range, students can be classified into different psychological state categories and matched with corresponding psychological support programs.

In order to achieve more accurate psychological state assessment and student group segmentation, the K-means clustering algorithm can be used to unsupervised group students' psychological characteristics. The objective function is:

$$J=\sum_{i=1}^{k}\sum_{x\in C_i}||x-\mu_i||^2 \tag{10}$$

($C_i$) represents the (i-th) psychological state cluster, and ($\mu_i$) is the center of the cluster. By minimizing the sum of squared distances within the cluster, students with similar psychological characteristics can be grouped together, providing a data foundation for hierarchical psychological intervention.

To improve the accuracy of cultural resource matching, a cultural resource recommendation model based on Collaborative Filtering recommendation algorithm can be constructed. Assuming that the student set is $U=u_1,u_2,\dots,u_n$ and the cultural resource set is ($C=c_1,c_2,\dots,c_m$), the predicted interest scores of student (u) and resource (c) are:

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$$\hat{r}u,c=\bar{r}u+\frac{\sum v\in N(u)sim(u,v)(rv,c-\bar{r}v)}{\sum v\in N(u)|sim(u,v)|} \quad (11)$$

(sim (u, v)) represents the similarity between student (u) and student (v), and (N (u)) is the set of neighbors that are similar to student (u). By calculating interest prediction values, cultural activities or course resources that better meet students' psychological needs and interest preferences can be recommended.

In the process of matching cultural resources with psychological needs, cosine similarity can also be used to evaluate the degree of matching between students' psychological needs and cultural resource characteristics:

$$Sim(P,c_j)=\frac{P\square c_j}{||P||,||c_j||} \quad (12)$$

($\mathbf{c}_j$) represents the feature vector of the (j-th) cultural resource. The higher the similarity, the more suitable the cultural resource is for students' psychological adjustment and value guidance.

#### *3.3.2 Collaborative intervention mechanism for integrating ideological and political education with mental health*

Assuming that the psychological counseling system, ideological and political curriculum system, and cultural activity platform are represented as (M), (I), and (C), respectively, the overall collaborative educational effectiveness can be expressed as:

$$E=\alpha M+\beta I+\gamma C \quad (13)$$

(E) represents the overall collaborative education effect, (α), (β), and (γ) are weight coefficients for different systems. By reasonably allocating the weight ratio of different educational resources, psychological support, value guidance, and cultural experience can form a complementary relationship in the education system.

At the level of information linkage, in order to improve the efficiency of educational resource recommendation and intervention strategy selection, decision tree classification algorithm can be introduced to select student intervention strategies. Assuming the student feature set is (X) and the intervention strategy set is (Y), the decision tree selects the optimal partition feature through information gain:

$$Gain(D,A)=H(D)-\sum_{v=1}^{V}\frac{|D_v|}{|D|}H(D_v) \quad (14)$$

(H(D)) represents the information entropy of the dataset, (A) is the partition attribute, and (D_v) is the subset of attribute (A) with a value of (v). In the day of constant partitioning, classification rules can be produced to make decisions on intervention strategies by constantly choosing features that provide the most information gain.

## 4. Results and Discussion

### *4.1 Data Sources and Sample Composition*

The data based on the experiment is the documentation of the learning behavior, data about the participation in the campus activities, and data about the psychological examination of the students on several universities in Guangxi. The study considered a sample of students of several grades and combined behavioral data of online learning sites and campus management systems in order to make them representative and complete. The samples comprised three categories of data; learning behavior (frequency of course visits, length of time studying online, and assignment completion), campus activities (records of course in clubs, cultural activities, and volunteering services), and psychological assessment (quantitative measures of regular mental health tests).

### *4.2 Training Process of Psychological Risk Identification Model*

Once the construction of feature data completes, machine learning techniques are applied to discover and classify the psychological risk of students. The experiment involved splitting the samples of students into various categories according to their psychological states and the model was fed with multidimensional feature vectors as the input data. Through the constant optimization of the model

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parameters in the training process, the model can be able to detect the difference features between the various psychological states.

In the model training process an optimization technique that is iterative is employed to revise the model weight parameters and the variation between the model prediction results and the actual labels is determined by the loss function. When the loss value decays and is likely to flatten, it means that the model has learnt a fairly stable feature mapping relationship. Cross validation mechanism is added in the training process in order to enhance stability of the model by holding the model in many trainings and validations to ensure that the model is not overfitted.

This paper tests the recognition performance of the model on test data after training. Through the comparison of the consistency between the model predictive results and the real labeling of the psychological state, it is possible to conduct an analysis on the effectiveness of the model on the identification of psychological risks. Meanwhile, by analyzing the importance of different features, it can further observe the extent to which behavioral data, emotional characteristics, and cultural participation indicators play a role in the psychological recognition process.

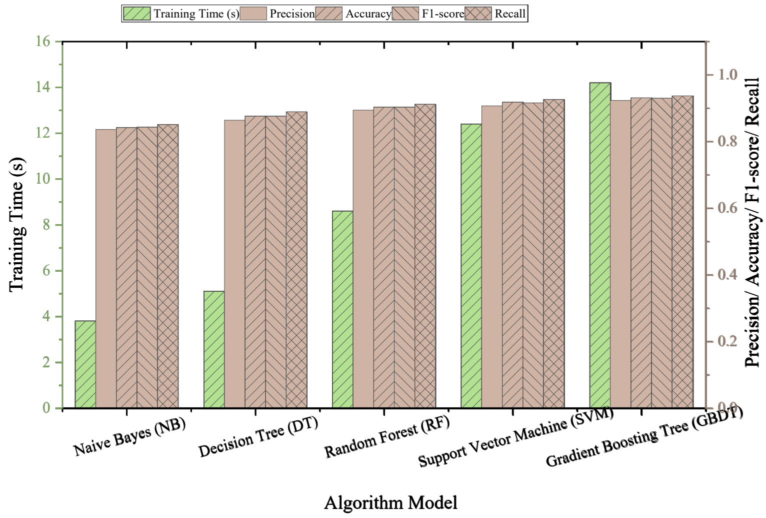


*Figure 1. Performance Comparison of Different Algorithms in Student Psychological Risk Identification*

According to the experimental data analysis in Figure 1, the student psychological risk identification algorithm constructed in this paper shows significant differences in performance among different models. The accuracy of Naive Bayes (NB) algorithm is 0.842, which is relatively basic and difficult to fully capture the multidimensional characteristics of students' psychological states; Decision trees (DT) and random forests (RF) have improved their feature partitioning and integration capabilities, achieving accuracies of 0.876 and 0.903, respectively. The performance of Support Vector Machine (SVM) has been further improved, with an accuracy of 0.918, while the Gradient Boosting Tree (GBDT) model used in this paper has the best overall recognition performance, with an accuracy of 0.931 and F1 score of 0.930, which can efficiently handle the nonlinear relationship between psychological features. Although the training time has increased (14.2 seconds), it is still within an acceptable range for mental health recognition tasks. Overall, the GBDT model performs the best in multi-source behavior data analysis and psychological state classification in this article, providing a stable and reliable algorithm foundation for personalized interventions in collaborative education mechanisms in the future.

*Table 1. Comparison of the Implementation Effectiveness of the "Psychological-Cultural-Ideological and Political" Collaborative Education Mechanism*

| Evaluation Indicator | Before Implementation | After Implementation |
|---|---|---|
| Psychological Risk Identification Accuracy | 0.842 | 0.931 |
| Student Participation Rate in Cultural Activities | 46.30% | 68.70% |
| Participation in Ideological & Political Courses | 71.50% | 84.90% |
| Active Seeking of Psychological Counseling | 12.80% | 21.60% |

According to the experimental data in Table 1, it can be seen that the "psychological cultural ideological and political" collaborative education mechanism has achieved significant results in practical applications. The accuracy of psychological risk identification has increased from 0.842

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before implementation to 0.931, indicating that through multi-source behavioral data analysis and GBDT model classification, the identification of students' psychological states is more accurate, providing a reliable basis for subsequent personalized interventions. The participation rate of students in cultural activities has increased from 46.3% to 68.7%, demonstrating the effectiveness of cultural resources and activity guidance in psychological adjustment, while promoting students' sense of belonging and participation in campus. The participation rate of ideological and political courses has increased from 71.5% to 84.9%, indicating that the collaborative mechanism of value guidance and course content matching can enhance students' sense of identity and willingness to actively learn. In addition, the proactive seeking rate for psychological counseling has increased from 12.8% to 21.6%, reflecting that students are more willing to seek psychological help under the support of collaborative mechanisms, achieving a virtuous cycle of psychological intervention and educational guidance. Overall, this collaborative education mechanism not only enhances the precision of mental health management, but also effectively integrates cultural and ideological education resources, forming a multidimensional interactive educational intervention system.

## 5. Conclusion

This article is based on the construction of a three-dimensional collaborative education model of "psychology culture ideology" using artificial intelligence technology, which successfully achieves multidimensional linkage and precise intervention in college students' mental health education. In the research process, by integrating learning platform behavior data, campus cultural activity records, and psychological assessment information, combined with GBDT classification, K-means clustering, and collaborative filtering recommendation algorithms, high-precision identification and personalized intervention of psychological states were achieved. At the same time, cultural guidance and ideological education were effectively embedded in the mental health education system, forming a collaborative mechanism of psychological support, cultural identity, and value guidance. However, this study still has certain limitations: firstly, the sample sources are mainly concentrated in universities in Guangxi, and regional and cultural differences may affect the applicability of the model for promotion; Secondly, the long-term effects of psychological intervention on cultural and ideological activities have not been longitudinally tracked, and the adaptability of the model to long-term changes in mental health needs to be verified; In addition, some student behavior data may be missing or have recording biases, which may have a certain impact on algorithm training. Future research can explore the applicability of models across universities and cultures by expanding the sample area and quantity, and optimize collaborative mechanisms with long-term tracking data to make the models more generalized and dynamically adaptive.

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