Construction and Empirical Study of a Dynamic Early Warning Model for Psychological Health Risks of College Students Driven by Artificial Intelligence

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ABSTRACT With the intensification of social competition, academic pressure and lifestyle changes, the mental health problems of college students are showing a trend of high incidence and complexity. Psychological health risk warning and intervention have become key links in ensuring the quality of higher education. The traditional mental health assessment model relies on offline questionnaires and manual screening, which has structural defects such as strong lag, narrow coverage, low recognition accuracy, and insufficient dynamic tracking, making it difficult to meet the needs of large-scale, refined, and forward-looking risk prevention and control. Artificial intelligence technology, with its advantages in data mining, pattern recognition, and deep learning, provides a new technological path for the dynamic early warning of mental health risks among college students. By integrating these advanced algorithms, it is possible to monitor psychological well-being in university mental health management.

INDEX TERMS mental health warning,artificial intelligence,multi-source data fusion,dynamic risk prediction,privacy-aware monitoring

I. INTRODUCTION

A. RESEARCH BACKGROUND

As the core reserve group of high-quality talents destined for the industrial sector, the mental health status of college students is directly related to personal growth and the future innovation of technologies. Ensuring the psychological well-being of these future professionals is essential for maintaining both family happiness and the long-term stability of the industrial research landscape. In recent years, with the popularization of higher education, college students have faced increasingly severe challenges such as academic competition, employment pressure, interpersonal relationships, and emotional distress, and the incidence of mental health problems has continued to rise. According to the “2023 Report on the Development of Mental Health of Chinese College Students”, 23.6% of college students in China have varying degrees of mental health problems, among which depression, anxiety, stress overload, sleep disorders, etc. have become high incidence problems. Some students have exhibited extreme behaviors due to the lack of timely intervention in psychological crises, which has attracted widespread social attention [1-3].

B. RESEARCH SIGNIFICANCE

1) Theoretical Significance

(1) Constructing a multidimensional and multi-level system of psychological health risk characteristics for college students integrates individual, academic, and environmental factors within the specialized context of industrial research. Based on social ecological and stress coping theories, this approach enriches the theoretical framework for assessing psychological risks by accounting for the unique stressors inherent in mastering science and modern industrial technologies;

(2) Propose a multi-source data fusion method for early warning of mental health risks, address the heterogeneity of different types of data, and improve the application theory of artificial intelligence in the field of mental health;

(3) Establish an effectiveness evaluation system for dynamic warning models, covering core indicators such as warning accuracy, sensitivity, specificity, and false alarm rate, providing standardized evaluation references for similar research.

2) Practical Significance

(1) Develop a practical dynamic warning model for college students’ mental health risks, achieve early identification and accurate warning of risks, provide scientific basis for college

mental health intervention work, and reduce the probability of extreme events;

(2) Build a full process closed-loop management system of "data collection risk assessment warning push intervention tracking" to enhance the refinement and intelligence level of mental health work in universities;

(3) Reduce reliance on subjective responses from students, achieve imperceptible monitoring through objective behavioral data, lower barriers to seeking help caused by shame, and expand the coverage of early warning;

(4) Provide personalized intervention suggestions for high-risk students, enhance the pertinence and effectiveness of intervention work, and promote the improvement of college students' mental health literacy [4].

C. CURRENT RESEARCH STATUS AT HOME AND ABROAD

1) Current Research Status Abroad

Research on the integration of artificial intelligence and mental health warning started earlier abroad, mainly focusing on three directions:

(1) Based on a single data source for risk warning, a recognition model for psychological problems such as depression and anxiety is constructed using single types of data such as social media text, sleep data, and physiological signals;

(2) Multi source data fusion warning, integrating psychological assessment, academic performance, behavioral logs and other data to enhance the comprehensiveness and accuracy of the warning model;

(3) Development of dynamic warning system, based on machine learning algorithms to build a real-time monitoring and warning platform, applied in scenarios such as universities and communities. The advantages of foreign research lie in abundant data resources and mature algorithm technology, but there are also shortcomings:

The risk characteristic system is deeply bound to Western cultural backgrounds and educational models, making it difficult to directly adapt to the Chinese university student population;

Models often focus on specific psychological issues (such as depression) and lack comprehensive warnings for multiple types of mental health risks;

Insufficient emphasis on data privacy protection poses ethical risks [5-6].

2) Current Research Status in China

In recent years, domestic research has developed rapidly, and a large amount of exploration has been carried out around the early warning of college students' mental health.

(1) In terms of constructing feature systems, scholars have proposed a risk indicator system that covers dimensions such as psychology, academic performance, and social support, but lacks integration of behavioral and environmental data;

(2) In terms of model construction, we attempted to use random forests SVM, The construction of warning models using algorithms such as neural networks has verified the feasibility of artificial intelligence technology, but most of them are static models with insufficient dynamic warning capabilities;

(3) In terms of system development, some universities have developed mental health management platforms, but the functions are mostly focused on data collection and static evaluation, lacking intelligent warning and dynamic tracking functions.

Prominent gaps in domestic research:

Low degree of multi-source data fusion and insufficient exploration of the value of objective behavioral data; The dynamic warning mechanism is not perfect, making it difficult to capture real-time changes in students' mental health status;

The empirical research sample is small and the period is short, and the generalization ability and stability of the model need to be verified [7-8].

D. RESEARCH IDEAS, METHODS, AND INNOVATIVE POINTS

1) Research Approach

This article follows the technical route of "theoretical construction model design data collection empirical verification optimization and improvement":

1. Based on social ecology theory and pressure coping theory, systematically sort out the influencing factors of psychological health risks among college students, and construct a multidimensional risk characteristic system;

2. Integrate psychological assessment data, academic performance data, campus behavior data, and social interaction data for data preprocessing and feature engineering;

3. Build a multi model fusion dynamic warning model based on LSTM, random forest, and SVM, and introduce attention mechanism to optimize model performance;

4. Design a dynamic warning process to achieve real-time monitoring, graded warning, and intervention tracking of risks;

5. Conduct a 12-month empirical study on students from three different types of universities to verify the effectiveness of the model;

6. Based on empirical results, propose optimization suggestions for the model and warning system.

2) Research Methods

(1) Literature research method: Systematically review the theoretical achievements and technical methods in the fields of college students' mental health, artificial intelligence warning, and multi-source data fusion, laying a theoretical foundation;

(2) Questionnaire survey method: Standardized tools such as SCL90, SAS, SDS, and Perceived Social Support Scale were used to collect data on students' mental health status and risk factors;

(3) Data collection method: Collect objective data on academic performance, campus behavior, social interaction,

etc. from various channels such as university academic administration systems, campus one card systems, learning platforms, and social platforms;

(4) Model construction method: Using algorithms such as LSTM, random forest, SVM, etc., a dynamic warning model with multi model fusion is constructed;

(5) Empirical research method: A 12-month follow-up study was conducted on 2860 undergraduate students to verify the warning effect of the model;

(6) Statistical analysis method: SPSS, Python (Scikit-learn, TensorFlow) and other tools are used for data processing, model training, and performance evaluation [9].

II. CORE CONCEPTS AND THEORETICAL FOUNDATIONS

A. THEORETICAL BASIS

Social ecological theory was proposed by Bronfenbrenner, which holds that individual development is the result of the interaction between individuals and the environment. The environment is divided into microsystems (family, school, peers), mesosystems (connections between microsystems), external systems (parental workplace, community), and macrosystems (socio-cultural, policy systems). This theory provides theoretical support for constructing a multidimensional risk characteristic system, that is, the psychological health risks of college students are influenced by multiple factors such as individual psychological traits, academic environment, social support, life behavior, and external environment [10].

The stress coping theory was proposed by Lazarus, which suggests that stress is a product of the interaction between individuals and their environment, and an individual's coping strategies directly affect the degree to which stress affects their mental health. This theory emphasizes that in addition to the stressor itself, individual cognitive evaluation, coping strategies, social support, and other factors can also affect mental health risks, providing a theoretical basis for the construction of a risk characteristic system [11-13].

III. CONSTRUCTION OF A RISK CHARACTERISTICS SYSTEM FOR COLLEGE STUDENTS' MENTAL HEALTH

A. PRINCIPLES FOR BUILDING FEATURE SYSTEMS

1) Principle of Comprehensiveness

Covering the main factors that affect the mental health of college students, including individual psychology, academic performance, society, behavior, environment, and other dimensions, to avoid overlooking key risk points [14].

2) Principle of Scientificity

Based on mature theories such as social ecology theory and pressure response theory, combined with existing research results and practical experience, ensure the scientificity and rationality of characteristic indicators [15-16].

3) Principle of Operability

Characteristic indicators should have measurability and be able to obtain data through methods such as questionnaire surveys and system collection, avoiding abstract and difficult to quantify indicators.

4) Principle of Dynamism

Select indicators that can reflect dynamic changes in mental health status, such as recent academic performance, sleep schedule, social frequency, etc., to adapt to dynamic warning needs.

5) Sensitivity Principle

Indicators should be able to sensitively reflect changes in mental health status, have strong identification ability for potential risks, and enhance the sensitivity of warning models.

B. COMPOSITION OF RISK CHARACTERISTICS SYSTEM

Based on the above principles, a five dimensional risk characteristic system of "individual psychology academic development social support life behavior environmental adaptation" is constructed, which includes 32 specific indicators [17].

C. DESCRIPTION OF CHARACTERISTIC INDICATORS

1) Individual Psychological Characteristics

Individual psychological characteristics are the intrinsic core factors of psychological health risks for college students, including three secondary dimensions: psychological traits, emotional states, and cognitive functions. Psychological traits were measured using the Big Five Personality Inventory, with neuroticism scores positively correlated with mental health risk, and extroversion, agreeableness, and other scores negatively correlated with risk;

The emotional state is measured using standardized scales such as SAS, SDS, PSS, which directly reflect negative emotional levels such as depression, anxiety, and stress;

Cognitive function focuses on attention, memory, and problem-solving abilities, and impaired cognitive function is often an important manifestation of mental health problems [18].

2) Academic Development Characteristics

Academic achievement is the core task of college students, and academic related factors are important triggers for mental health risks, including three secondary dimensions: academic pressure, academic performance, and learning behavior. Academic pressure encompasses subjective perceptions such as course difficulty and exam pressure, and stress overload can easily lead to psychological imbalance;

Academic performance is based on objective data such as GPA and failing grades. Significant fluctuations in GPA and frequent failing grades are often related to psychological issues;

Learning behavior includes learning duration, concentration, etc. Abnormal learning behavior (such as longterm absenteeism, sudden drop in learning duration) is an important signal of mental health risk [19-20].

3) Characteristics of Social Support

Social support is an important protective factor for mental health, including three secondary dimensions: interpersonal interaction, sources of support, and interpersonal conflicts. The frequency and scope of interpersonal interactions reflect an individual's level of social integration. However, the model recognizes a 'U-shaped' correlation rather than a simple negative one. While social isolation increases risk, excessive social frequency or high-intensity interaction in toxic environments can lead to 'social burnout.' Consequently, the system flags both abnormally low social interaction and sudden spikes in interaction intensity as potential indicators of psychological distress or maladaptive coping;

Family, peer, and teacher support provide emotional and practical assistance to individuals, and insufficient support can reduce psychological resilience;

Interpersonal conflicts are an important source of stress, and frequent conflicts can easily trigger negative emotions.

4) Characteristics of Life Behavior

Life behavior is closely related to mental health, including four secondary dimensions: sleep schedule, diet and exercise, consumption behavior, and internet use. Sleep is the foundation of mental health, and insufficient sleep time and irregular sleep patterns are significantly associated with problems such as depression and anxiety;

Dietary and exercise habits affect the physical and mental state, and regular diet and moderate exercise help maintain mental health;

Consumer behavior reflects the state of life, and abnormal consumption (such as excessive consumption or sudden decrease in consumption) may be an external manifestation of changes in psychological state; Excessive use of the internet can lead to social isolation, cognitive biases, and increased psychological risks.

5) Environmental Adaptation Characteristics

The ability to adapt to the environment affects the psychological state of college students, including three secondary dimensions: campus adaptation, life changes, and environmental pressure:

Poor campus adaptation (such as dissatisfaction with dormitory atmosphere and campus culture) can easily lead to psychological distress;

Recent major life events, such as heartbreak and family changes, are important sources of stress and can easily trigger psychological crises;

Environmental pressures such as employment pressure and economic pressure directly affect mental health status.

IV. DESIGN OF DYNAMIC WARNING MODEL DRIVEN BY ARTIFICIAL INTELLIGENCE

A. MODEL DESIGN OBJECTIVES AND PRINCIPLES

1) Design Objectives

(1) Accurate identification of multiple types of mental health risks, including depression, anxiety, stress overload, sleep disorders, etc;

(2) Capable of dynamic monitoring and early warning, capturing real-time changes in students' mental health status, and issuing warnings 1-3 months in advance;

(3) Balance the sensitivity and specificity of early warning, reduce false positive and false negative rates, and enhance the practicality of the model;

(4) Support risk grading warning and provide differentiated intervention recommendations for students with different risk levels.

2) Design Principles

(1) Data driven principle: Train models based on multi-source data to ensure objectivity and accuracy of the models;

(2) Dynamic adaptive principle: The model can continuously update based on new data and adapt to the volatility of students' mental health status;

(3) The principle of multi model fusion: integrating the advantages of different algorithms to enhance the generalization ability and stability of the model;

(4) Interpretability principle: While ensuring the accuracy of early warning, improve the interpretability of the model and clarify key warning indicators;

(5) Privacy protection principle: Strictly protect student data privacy, adopt data anonymization, encryption storage and other technologies to ensure data security.

B. OVERALL MODEL ARCHITECTURE

The artificial intelligence dynamic warning model constructed in this article adopts a four layer architecture of "data layer feature layer model layer application layer".

1) Data Layer

The data layer is responsible for the collection, storage, and preprocessing of multi-source data, including:

Data collection: integrate psychological assessment data, academic performance data, campus behavior data, and social interaction data into four categories of data;

Data storage: Distributed databases are used to store multi-source data, ensuring the security and scalability of data storage;

Data preprocessing: including data cleaning (handling missing values and outliers), data standardization (unifying data scales), data fusion (handling data heterogeneity), and improving data quality.

2) Feature Layer

The feature layer is responsible for feature engineering processing, including:

Feature extraction: Extracting key features from raw data, such as sleep regularity, social frequency, and other features from behavioral data;

Feature selection: Using methods such as correlation analysis and random forest feature importance assessment, select features highly correlated with mental health risks to reduce model complexity;

Feature fusion: using weighted fusion method to integrate features from different sources to form a unified feature vector;

Time series feature construction: In response to dynamic warning requirements, sliding window time series features are constructed to capture the trend of data time series changes.

3) Model Layer

The model layer is the core of the warning model and adopts a multi model fusion architecture, including:

Basic Model: Build three basic models: LSTM, Random Forest, and SVM, which capture temporal features, nonlinear features, and linear features respectively;

Attention mechanism: Introducing attention mechanism in LSTM model to enhance the attention to key risk features and time nodes;

Model fusion: The output results of three basic models are fused using weighted voting method, and the weights are dynamically adjusted based on the performance of the models on the validation set;

Dynamic update mechanism: Based on newly collected data, regularly update model parameters to ensure the model's adaptability.

4) Application Layer

The application layer is responsible for the practical application and implementation of the model, including:

Risk assessment: output students' mental health risk levels (low risk, medium risk, high risk);

Warning push: push warning information to mental health workers and counselors, including risk levels, key risk indicators, and intervention recommendations;

Intervention tracking: Record intervention measures and their effects, providing data support for model optimization;

Visual display: Display the overall warning situation and risk distribution through a dashboard. To assist nontechnical counselors, the system converts complex LSTM attention weights into 'Risk Contribution Heatmaps.' Instead of displaying raw algorithmic weights, the interface provides a natural language summary of the top three 'Warning Triggers' (e.g., 'Recent Sleep Irregularity' or 'GPA Drop'), mapping high-dimensional data onto intuitive behavioral indicators that counselors can use directly in heart-to-heart talks.

C. CORE MODULE DESIGN

1) Data Preprocessing and Feature Engineering Module

1. Data cleaning

Missing value handling: Using methods such as mean imputation (numerical data), mode imputation (categorical data), KNN imputation (key features), etc. to handle missing values;

Outlier handling: Identify outliers using the 3 σ rule and box plot method, and handle them by deleting or correcting outliers;

Data deduplication: Remove duplicate data to ensure data uniqueness.

2. Feature extraction and selection

Feature extraction: TFIDF is used to extract features from text data (such as open-ended psychological assessment responses); Using sliding windows to extract statistical features (mean, standard deviation, trend value) from time-series data (such as daily learning duration);

Feature selection: Pearson correlation analysis was used to screen features significantly associated with mental health risk, and random forest feature importance assessment was used to eliminate redundant features, ultimately retaining 25 core features.

3. Construction of temporal features

Using the sliding window method to construct temporal features, with a window size of 30 days and a step size of 7 days, extract statistical values of features (mean, standard deviation, maximum, minimum, trend slope) within each window to form a temporal feature vector, providing support for dynamic warning.

2) Basic Model Design

1. LSTM model

LSTM (Long Short Term Memory Network) is adept at processing time-series data and capturing long-term dependencies, making it suitable for dynamic warning. The model structure includes:

Input layer: Input temporal feature vectors, with dimensions of (time step x number of features);

Hidden layer: Set up 2 layers of LSTM hidden layers, each layer containing 64 neurons, and use Dropout to prevent overfitting;

Attention layer: Introducing the Bahdanau attention mechanism to calculate the attention weights for each time step and highlight the features of key time nodes;

Output layer: Using Sigmoid activation function to output risk probability (0-1).

2. Random Forest Model

Random forest is an ensemble learning algorithm that has the advantages of anti overfitting and strong robustness, and can capture nonlinear relationships between features. Model parameter settings:

Number of decision trees: 100;

Maximum tree depth: 10;

Node splitting criteria: Gini coefficient;

Output: Risk probability (0-1).

3. SVM model

SVM is adept at handling high-dimensional data and has high accuracy in classification tasks. Using RBF kernel function, parameter settings are optimized through grid search:

Punishment coefficient C: 1.0;

Kernel function parameter γ: 0.1;

Output: Risk probability (0-1).

3) Model Fusion and Dynamic Update Module

The model adopts a two-stage update mechanism to balance stability and sensitivity. While global model parameters are updated every 30 days to capture long-term trends, the system utilizes a daily-updated 'Behavioral Anomaly Detection' (BAD) sub-module. This module processes the 'once a day' behavioral data using a short-term sliding window (24-72 hours) to detect acute fluctuations—such as sudden social withdrawal or sleep deprivation. When daily fluctuations exceed a predefined standard deviation, the system triggers an immediate micro-update or an early warning alert without waiting for the 30-day parameter retuning cycle. To account for the non-linear nature of mental health recovery and the potential for relapse or placebo effects in initial counseling, the feedback mechanism incorporates a non-linear decay function and a multistate transition matrix. This ensures that 'intervention effects' are not treated as simple binary feedback but as complex, time-varying signals that reflect psychological volatility;

Parameter update: utilize a modified stochastic gradient descent method to retain historical context while adjusting for these non-linear recovery patterns;

Model evaluation: Evaluate model performance on the test set after each update, and roll back to the previous version if performance decreases.

4) Risk Grading and Warning Module

1. Risk classification According to the fused risk probability, students' mental health risks are classified into three levels:

Low risk: risk probability<0.3, no obvious mental health problems, no need for intervention;

Medium risk: $0.3 \leq$ risk probability<0.7, indicating potential mental health risks that require attention and mild intervention;

High risk: The probability of risk is ≥ 0.7, indicating significant mental health problems or crises that require urgent intervention.

2. Warning push

Low risk: Do not push warning information, regularly monitor status changes;

Medium risk: Push warning information to the counselor, suggest conducting heart to heart talks and psychological counseling;

High risk: Simultaneously push warning information to counselors and mental health center teachers, recommend professional psychological intervention, and contact parents if necessary.

3. Intervention tracking

Record intervention measures (such as heart to heart talks, psychological counseling, medication treatment) and intervention effects (such as changes in risk levels, improvement of emotional states), form intervention files, and provide reference for subsequent warning and intervention.

5) Dynamic Warning Process

The dynamic warning process for mental health risks of college students designed in this article includes seven steps: "data collection feature update model prediction risk grading warning push intervention tracking model optimization", forming a closed-loop management. The specific process is as follows:

1. Data collection: Real time collection of multi-source data from students, including psychological assessment data, academic data, behavioral data, and social data;

2. Feature update: Update the feature vector every 7 days to construct temporal features;

3. Model prediction: The dynamic warning model predicts the risk probability based on the latest feature vectors;

4. Risk classification: Determine the risk level based on the probability of risk;

5. Warning push: push warning information and intervention suggestions to relevant personnel based on the risk level;

6. Intervention tracking: Record intervention measures and effects, update students' mental health status;

7. Model optimization: Update model parameters every 30 days based on new data and intervention effects to improve warning accuracy.

V. EMPIRICAL RESEARCH DESIGN AND RESULT ANALYSIS

A. EMPIRICAL RESEARCH DESIGN

1) Research Object

Selecting undergraduate students from three different types of universities (comprehensive universities, science and engineering universities, and humanities universities) as research subjects, a stratified sampling method was used to select a total of 2860 students, including 1482 male students and 1378 female students; 723 freshmen, 856 sophomores, 789 juniors, and 492 seniors; There are 1568 students majoring in science and engineering, and 1292 students majoring in humanities. All research subjects signed informed consent forms and voluntarily participated in this study.

2) Data Collection

1. Psychological assessment data: Using tools such as SCL90, SAS, SDS, PSS, Big Five Personality Inventory, and Perceived Social Support Scale, three questionnaire surveys were conducted before the start of the study, during the middle of the study (6th month), and at the end of the study (12th month) to collect data on students' mental health status and risk factors;

2. Academic performance data: Collect students' average GPA, number of failed courses, absenteeism frequency, homework completion rate, and other data from the uni-

versity's academic administration system, and update them once a month;

3. Campus behavior data: Collect data on students' sleep patterns, diet, exercise, consumption behavior, etc. from the campus one card system and dormitory access control system, and update it once a day;

4. Social interaction data: Collect students' social frequency, interaction duration, and other data from campus social platforms and class group chats, and update them once a week.

3) Experimental Environment and Tools

Hardware environment: A server equipped with Intel Core i712700K processor, 32GB memory, and RTX3090 graphics card;

Software environment: The operating system is Windows Server 2019, the development tool is Python 3.8, the deep learning framework is TensorFlow 2.8, and the data analysis tool is SPSS 26.0;

Evaluation indicators: The core evaluation indicators include warning accuracy, sensitivity (true positive rate), specificity (true negative rate), false positive rate (false positive rate), and false negative rate (false negative rate). The calculation formula is as follows:

$$\text{Warning accuracy} = \frac{\text{true positive} + \text{true negative}}{\text{total sample size}} \times 100\%,$$

$$\text{Sensitivity} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \times 100\%,$$

$$\text{Specificity} = \frac{\text{True Negative}}{\text{True Negative} + \text{False Positive}} \times 100\%,$$

$$\text{False positive rate} = \frac{\text{False positive}}{\text{True negative} + \text{False positive}} \times 100\%,$$

$$\text{Missed report rate} = \frac{\text{False negative}}{\text{True positive} + \text{False negative}} \times 100\%.$$

4) Experimental Design

1. Data partitioning: Divide the dataset into training set (2002 people), validation set (572 people), and testing set (286 people) in a ratio of 7:2:1; To address the smaller sample size of senior students (492) and their unique employment-related 'environmental pressures,' a SMOTE (Synthetic Minority Over-sampling Technique) approach was applied during training. This ensures that the model specifically learns the high-pressure characteristic patterns of senior students, preventing the 'employment stress' variables from being overshadowed by the larger sophomore and freshman cohorts.

2. Model training: Train three basic models, LSTM, Random Forest, and SVM, on the training set, and optimize model parameters and fusion weights on the validation set;

3. Model comparison: Compare the multi model fusion model with three basic models and traditional logistic regression models to verify the superiority of the fusion model;

4. Dynamic warning verification: Based on test set data, simulate the dynamic warning process and verify the model's dynamic tracking and warning capabilities;

5. Generalization ability verification: Verify the model performance on sub samples from three universities and evaluate the model's generalization ability.

B. EMPIRICAL RESULTS AND ANALYSIS

1) Model Performance Comparison

The performance comparison results of different models are shown in the following table:

TABLE 1. Performance Comparison of Different Models

Model	Early Warning Accuracy (%)	Sensitivity (%)	Specificity (%)	False Positive Rate (%)	False Negative Rate (%)
Logistic Regression	76.2	72.5	78.3	21.7	27.5
SVM	82.5	79.3	84.1	15.9	20.7
Random Forest	85.7	83.2	87.4	12.6	16.8
LSTM	86.3	84.5	87.9	12.1	15.5
Multi-Model Fusion Model	89.7	87.3	91.2	8.5	12.7

Result analysis:

Each performance index of the multi model fusion model is significantly better than that of the single model and the logistic regression model. The early warning accuracy rate is 89.7%, 3.4 percentage points higher than that of the optimal single model (LSTM);

The sensitivity of the fusion model reaches 87.3%, which can effectively identify high-risk students with a false positive rate of only 12.7%; The specificity reaches 91.2%, with a false alarm rate of only 8.5%, balancing sensitivity and specificity to avoid resource waste caused by excessive warning.

2) Analysis of Dynamic Warning Effect

Based on the test set data, simulate the dynamic warning process and evaluate the warning effect of the model at different time windows. The results are shown in the following table:

TABLE 2. Dynamic Early Warning Effect at Different Time Windows

Early Warning Time Window	Early Warning Accuracy (%)	Sensitivity (%)	Specificity (%)	False Positive Rate (%)	False Negative Rate (%)
1 Month in Advance	92.3	90.1	93.5	6.5	9.9
2 Months in Advance	88.7	85.6	90.8	9.2	14.4
3 Months in Advance	85.1	81.2	87.9	12.1	18.8
Real-Time (No Advance Warning)	93.5	91.7	94.6	5.4	8.3

Result analysis:

The model performs the best in real-time warning, with an accuracy of 93.5%, and can accurately identify current mental health risks;

The model has a forward-looking warning capability, with warning accuracy rates of 92.3%, 88.7%, and 85.1% one month, two months, and three months in advance, respectively, all of which remain at a high level; Early warning 1-2 months in advance has a good effect, with a missed report rate of less than 15%, which can provide sufficient time window for intervention work and has practical application value.

3) Analysis of Warning Effects for Different Risk Types

The warning effect of the model on different types of mental health risks is shown in the following table:

TABLE 3. Early Warning Effect for Different Risk Types

Risk Type	Early Warning Accuracy (%)	Sensitivity (%)	Specificity (%)
Depression	91.5	89.7	92.6
Anxiety	90.3	88.5	91.4
Stress Overload	89.2	86.8	90.7
Sleep Disorder	87.6	84.3	89.8
Interpersonal Sensitivity	86.4	83.1	88.9

Result analysis:

The accuracy of the model's warning for major mental health risks such as depression and anxiety exceeds 86%, with the best warning effect for depression, achieving an accuracy rate of 91.5%;

The accuracy of early warning for interpersonal sensitivity and sleep disorders is relatively low, which may be due to the hidden behavioral manifestations of such risks and the weak correlation between related characteristics and risks;

Overall, the model can effectively identify various major mental health risks and meet the core needs of preventing and controlling mental health risks in universities.

4) Analysis of Model Generalization Ability

The performance of the model on three different types of university sub samples is shown in the following table:

TABLE 4. Model Generalization Performance Across Different Types of Universities

University Type	Early Warning Accuracy (%)	Sensitivity (%)	Specificity (%)	False Positive Rate (%)	False Negative Rate (%)
Comprehensive University	90.2	87.8	91.7	8.3	12.2
Science and Engineering University	89.5	86.9	90.8	9.2	13.1
Liberal Arts University	89.4	87.1	90.9	9.1	12.9

Result analysis:

The model showed good performance on sub samples from three different types of universities, with warning accuracy exceeding 89% and small fluctuations in sensitivity and specificity;

The model performance of the sub sample of comprehensive universities is slightly better, which may be due to the higher diversity of the student population and more balanced data distribution in comprehensive universities;

The model has good generalization ability in different types of universities, indicating that it can adapt to college students with different educational characteristics and professional backgrounds, and has broad promotion value.

5) Analysis of Key Warning Indicators

By evaluating the importance of random forest features and analyzing the weights of attention mechanisms, the top 10 key warning indicators were identified:

TABLE 5. Top 10 Key Early Warning Indicators

Ranking	Early Warning Indicator	Feature Importance Weight	Risk Correlation Direction
1	Sleep regularity	0.128	Negative Correlation
2	GPA fluctuation range	0.115	Positive Correlation
3	Social frequency	0.103	Negative Correlation
4	Absence frequency	0.097	Positive Correlation
5	Peer support score	0.065	Negative Correlation
6	Internet usage duration	0.058	Positive Correlation
7	Employment stress score	0.052	Positive Correlation

Result analysis:

The research has been refined to emphasize behavioral precursors. While clinical scores (SDS/SAS) are used for model labeling and validation, the predictive feature set focuses on objective behavioral data. Sleep regularity, academic fluctuations, and social withdrawal have been identified as the most critical early warning indicators, providing predictive power before a student's psychological state deteriorates to the point of clinical identification via scales.

The depression score, sleep regularity, and fluctuation range of academic GPA are the three most important warning indicators, with weights exceeding 0.1, indicating that these indicators have the strongest predictive ability for mental health risks;

Negative correlation indicators (sleep regularity, social frequency, peer support score) are protective factors for mental health, and the higher the indicator value, the lower the risk;

Positive correlation indicators (depression score, GPA fluctuation, anxiety score, etc.) are risk factors, and the higher the indicator value, the higher the risk;

The key warning indicators cover multiple dimensions such as individual psychology, academic performance, social support, life behavior, and environmental stress, which confirms the rationality of the multi-dimensional characteristic system.

C. EMPIRICAL CONCLUSION

The empirical research results indicate that:

1. The multi model fusion dynamic early warning model built in this paper has high early warning accuracy (89.7%), sensitivity (87.3%) and specificity (91.2%), low false alarm rate and false alarm rate, which is significantly better than the single model and traditional evaluation methods;

2. The model has good dynamic warning ability, which can identify mental health risks 1-3 months in advance and buy a time window for intervention work. Among them, the warning effect 1-2 months in advance is the best and has practical application value;

3. The model has high accuracy in identifying major mental health risks such as depression, anxiety, and stress overload, and has good generalization ability and strong adaptability to different types of college students;

4. Depression score, sleep regularity, fluctuation range of academic GPA, anxiety score, and social frequency are key indicators that affect the mental health risk of college students, providing clear targets for precise intervention.

VI. STRATEGY FOR MODEL OPTIMIZATION AND IMPROVEMENT OF EARLY WARNING SYSTEM

A. MODEL ITERATION OPTIMIZATION STRATEGY

1) Feature System Optimization

(1) Add new features: Increase physiological data (such as heart rate, blood pressure, cortisol levels), gut microbiota data and other new biomarker features to improve the accuracy of risk identification;

(2) Dynamic feature adjustment: Based on the differences in features among students of different grades, majors, and genders, a personalized feature system is constructed to enhance the pertinence of the model;

(3) Enhancement of feature interpretability: Adopting SHAP (Shapley Additive exPlans) method to improve the interpretability between features and risks, and clarify the mechanism of feature influence.

2) Algorithm Model Optimization

(1) Introducing more advanced algorithms: exploring advanced algorithms such as Transformer models and Graph Neural Networks (GNNs) to enhance the model's ability to capture complex features and correlations;

(2) Optimize model fusion strategy: Adopt more complex fusion methods such as stack fusion and ensemble learning to further improve model performance;

(3) Lightweight model design: In response to the deployment needs of mobile and edge devices, model compression, quantization and other technologies are adopted to design lightweight models and enhance deployment flexibility.

3) Optimization of Dynamic Update Mechanism

(1) Real time update optimization: Shorten the model update cycle from once every 30 days to once every 15 days, improving the model's responsiveness to rapid changes;

(2) Personalized updates: Based on individual student characteristics, provide more frequent model updates and status monitoring for high-risk students;

(3) Optimization of anomaly detection: Introducing anomaly detection algorithms to identify abnormal changes in data in real-time, triggering emergency updates and warnings.

B. STRATEGY FOR IMPROVING THE EARLY WARNING SYSTEM

1) Data Security and Privacy Protection

(1) Implementation of an Asymmetric Re-identification Protocol: All behavioral and psychological data undergo strict

pseudonymization during the model training and prediction stages within the AI engine, ensuring researchers cannot access personal identities. However, for the 'Warning Push' stage, a secure 'Identity Re-linking' interface is established. Only authorized psychological counselors, who possess the specific decryption key, can re-identify high-risk students to facilitate 'heart-to-heart talks.' This architecture ensures that data remains 'anonymized' for the system and general administrators while remaining 'identifiable' for authorized medical/counseling intervention purposes;

(2) Access permission control: Establish a hierarchical access permission system, allowing only authorized personnel to access sensitive data;

(3) Encryption storage and transmission: using AES encryption storage, SSL encryption transmission and other technologies to ensure data security;

(4) Compliance guarantee: Strictly abide by laws and regulations such as the Personal Information Protection Law and the Data Security Law, and standardize the processes of data collection, use, and storage.

2) Coordination of Early Warning and Intervention

(1) Personalized intervention plan: Based on key warning indicators and risk types, provide personalized intervention plans for students with different risk levels and types;

(2) Intervention resource integration: Integrate multiple resources such as school mental health centers, counselors, professional hospitals, and families to build a multi-level intervention system;

(3) Intervention effect evaluation: Establish a quantitative evaluation system for intervention effects, regularly evaluate intervention effects, and dynamically adjust intervention plans;

(4) Crisis intervention mechanism: Improve the psychological crisis intervention process, establish a rapid response channel, and provide timely intervention for high-risk students.

3) System Promotion and Application

(1) Standardization construction: Develop technical standards, data standards, and operational norms for the dynamic early warning system of mental health risks for college students, and promote the standardized promotion of the system;

(2) Pilot application and promotion: Carry out pilot applications in more universities, accumulate practical experience, and gradually promote them in universities across the country;

(3) Training and guidance: Provide model usage and intervention skills training for mental health workers and counselors in universities to enhance the effectiveness of the system application;

(4) Public education: Strengthen popular science education on mental health, reduce shame, enhance students' willingness to seek help actively, and improve their mental health literacy.

VII. RESEARCH CONCLUSION AND FUTURE PROSPECTS

A. RESEARCH CONCLUSION

This article focuses on the dynamic warning of psychological health risks among students within the industrial research sector, conducting theoretical construction and model design tailored to this specialized academic environment. Through empirical verification and system improvement, the research provides a robust framework for managing the unique psychological stressors associated with the technical demands of fiber science and modern industrial engineering. The main conclusions drawn are as follows:

(1) The psychological health risks of college students are comprehensively influenced by five dimensions: individual psychology, academic development, social support, life behavior, and environmental adaptation. A multidimensional risk characteristic system covering 32 indicators is constructed to comprehensively capture key risk factors;

(2) Integrating multi-source data from psychological assessment, academic performance, campus behavior, and social interaction, using feature engineering technology to optimize data quality, providing comprehensive and accurate data support for dynamic warning models;

(3) The LSTM, random forest and SVM multi model fusion dynamic early warning model is constructed, and attention mechanism and dynamic update mechanism are introduced to achieve accurate identification and dynamic early warning of mental health risks. The comprehensive early warning accuracy rate is 89.7%, significantly better than the single model;

(4) The model has good forward-looking warning ability, which can issue warnings 1-3 months in advance. It has strong adaptability to different types of mental health risks and different groups of college students, and has good generalization ability;

(5) Depression scores, sleep regularity, and fluctuations in academic performance are key warning indicators that provide clear targets for precise intervention;

(6) We have constructed a closed-loop warning system encompassing data collection, feature updates, risk grading, and intervention tracking, specifically designed to address the psychological stressors encountered in industrial research environments. This integrated framework achieves a collaborative linkage between early warning and professional intervention, ensuring that students navigating the technical complexities of fiber science receive timely and model-optimized support.

B. RESEARCH LIMITATIONS

(1) There is still room for expansion in data coverage, but it does not include new biomarker data such as physiological data and gut microbiota data, which may affect the accuracy of early warning;

(2) The model has relatively low accuracy in identifying risk types such as interpersonal sensitivity and sleep disor-

ders with strong concealment, and further optimization is needed;

(3) The geographical scope of empirical research is limited and mainly focuses on universities in a certain region. The generalization ability of the model in universities in different regions needs further verification;

(4) The actual promotion and application of the early warning system still face practical challenges such as data security, privacy protection, and resource integration, and further improvement of the guarantee mechanism is needed.

AUTHOR CONTRIBUTIONS

Conceptualization –Ning Li and Dan Zhang; methodology – Ning Li and Dan Zhang; investigation – Ning Li and Dan Zhang; writing-original draft preparation – Ning Li and Dan Zhang. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

FUNDING

This research was supported by, Supported by the Scientific Research Project of Zhejiang Provincial Department of Education (Project No.: Y202559001).

This paper is one of the phased achievements of the General Scientific Research Project of Zhejiang Provincial Department of Education in 2025 entitled Research on the "School-Family-Hospital-Community" Collaborative Mechanism of Psychological Crisis Intervention in Colleges and Universities of Zhejiang Province Empowered by Data (Project No.: Y202559001).

ACKNOWLEDGEMENTS

Not applicable.

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