Research on the Design of AI-enabled Psychological Crisis Behavior Analysis System for College Students

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Abstract

As mental health challenges among college students grow increasingly severe, traditional psychological crisis intervention models face issues of delayed response and insufficient precision. This study proposes an AI-powered psychological crisis behavior analysis system for university students. By integrating multimodal data collection, deep emotional recognition, psychological crisis assessment, and personalized intervention recommendation generation, the system establishes an intelligent real-time feedback platform for psychological crisis intervention. Utilizing deep learning and natural language processing technologies, the system achieves comprehensive analysis of text, voice, facial expressions, and physiological signals. Experimental results demonstrate high accuracy and timeliness in emotional recognition, crisis assessment, and intervention recommendation generation, providing efficient technical support for mental health management in higher education.

CCS Concepts

• **Software and its engineering** → Software creation and management; Software development techniques; Software prototyping.

Keywords

artificial intelligence, psychological crisis of college students, emotion recognition, personalized intervention, system design

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1 Introduction

In the context of highly intertwined complex social environments and digital media, college students' psychological crisis behaviors exhibit characteristics of strong concealment, high explosiveness, and dynamic complexity. Traditional manual intervention models struggle to meet practical demands in terms of identification accuracy and response timeliness. Breakthroughs in artificial intelligence (AI) in deep semantic modeling, multimodal perception, and emotional evolution prediction provide theoretical support and technical foundations for building an integrated psychological analysis system featuring high-frequency monitoring, intelligent early warning, and personalized intervention. The expression of psychological abnormalities among college students often involves unstructured patterns, strong semantic drift, and intense emotional fluctuations. There is an urgent need to leverage AI to establish a full-cycle closed-loop system—from behavioral feature extraction to risk level classification and intervention strategy generation—thereby reshaping intelligent response mechanisms and predictive intervention systems for psychological crisis governance in higher education institutions [1].

2 System architecture design

The system architecture focuses on dynamic modeling of psychological crisis behaviors and real-time intervention, utilizing a multi-layered heterogeneous fusion system for data collection, semantic understanding, risk assessment, and intelligent feedback. To handle the complexity of college students' behavioral data, the foundation employs distributed data collection with edge node deployment for low-latency processing of text, voice, physiological signals, and social behavior. The mid-layer leverages cloud computing to support deep neural network models for tasks like semantic modeling, emotion analysis, and crisis quantification, creating a system with temporal perception and continuous behavioral tracking. The top-layer provides configurable feedback interfaces and response engines for multi-role interactions, ensuring effective coordination of user alerts, counselor suggestions, and management-level insights, supporting personalized, precise, and intelligent decision-making in psychological interventions [2].

3 Key algorithm development

3.1 Text Emotion Recognition Algorithm Based on Deep Semantic Understanding

The base layer employs a pre-trained language model, BERT, to generate dynamic contextual representations, where $\mathrm{H} = [\mathrm{h}_1, \mathrm{h}_2, ..., \mathrm{h}_n] = BERT(T)\mathrm{h}_i \in \mathbb{R}^d$

Represents $i$the contextual embedding of the i-th word. The intermediate layer introduces a multi-head emotional attention mechanism to model emotion-driven implicit coupling in semantics,

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with the emotional attention weight defined as:

$$\alpha_{ij} = \frac{\exp\left(\begin{array}{l} LeakyReLU \\ \left(\mathrm{a}^\top[\mathrm{W}_q\mathrm{h}_i, |, \mathrm{W}_k\mathrm{h}j]\right)\end{array}\right)}{\sum k = 1^n \exp\left(\begin{array}{l} LeakyReLU \\ \left(\mathrm{a}^\top[\mathrm{W}_q\mathrm{h}_i, |, \mathrm{W}_k\mathrm{h}_k]\right)\end{array}\right)} \tag{1}$$

The weighted integration generates an $\tilde{\mathrm{h}}i = \sum j = 1^n\alpha_{ij}\mathrm{W}_v\mathrm{h}_j$emotional context vector, and introduces an emotional semantic matching loss function to optimize the clarity of category boundaries.

$$\mathcal{L}emo = -\sum \begin{array}{l} c = 1^C y_c \log\left(\frac{\exp(\mathrm{wc}^\top\tilde{\mathrm{h}})}{\sum k=1^C \exp(\mathrm{w}_k^\top\tilde{\mathrm{h}})}\right) \\ +\lambda|\mathrm{w}c - \mathrm{w}neg|^2 \end{array} \tag{2}$$

The first is the cross-entropy loss, and the second is the separation constraint of the emotion category center [3].

3.2 Prediction Model of Psychological Crisis Behavior Based on Multimodal Information

First, each modality's features undergo independent encoding$\mathrm{X}_t \in \mathbb{R}^{n\times d_t}\mathrm{X}_v \in \mathbb{R}^{m\times d_v}\mathrm{X}_p \in \mathbb{R}^{k\times d_p}\mathrm{H}_t, \mathrm{H}_v, \mathrm{H}_p$: text modality embeddings, speech modality embeddings, and physiological modality embeddings are extracted through Transformer architectures to obtain higher-order representations. In the mid-level modeling, a cross-modal attention mechanism is introduced to dynamically align semantic representations across modalities, with the fusion representation defined as:

$$\begin{array}{l} \mathrm{Z}_{tv} = softmax\left(\frac{\mathrm{Q}_t\mathrm{K}_v^\top}{\sqrt{d}}\right)\mathrm{V}_v \quad , \\ \mathrm{Q}_t = \mathrm{H}_t\mathrm{W}_q \ , \ \mathrm{K}_v = \mathrm{H}_v\mathrm{W}_k \ , \ \mathrm{V}_v = \mathrm{H}_v\mathrm{W}_v \end{array} \tag{3}$$

The redundant interference is suppressed by introducing the gated fusion mechanism to adjust the modal signal weights.

$$\begin{array}{l} \mathrm{F}_{fusion} = \sigma\left(\mathrm{W}g\left[\mathrm{Z}tv, |, \mathrm{H}_p\right]\right) \\ \odot \tanh\left(\mathrm{W}f\left[\mathrm{Z}tv, |, \mathrm{H}_p\right]\right) \end{array} \tag{4}$$

However, the initialization of the gating network parameters and the dynamic updating strategy for adjusting the fusion weights have not been fully defined. To address this, we introduce a detailed initialization rule for the gating network parameters, where initial weights are set based on prior knowledge or a pretraining process using historical multimodal data. Additionally, the dynamic updating strategy involves using a reinforcement learning approach to continuously optimize the gating parameters, allowing them to adjust based on real-time data flow and the evolving nature of user behavior. Finally, the fused representation is input into the time-aware prediction network, which builds the evolution trajectory of the behavioral risk based on the GRU unit with attention weight, and outputs the behavioral risk probability distribution and the psychological crisis level [4].

3.3 Psychological state scoring algorithm for risk level classification

To develop an efficient and accurate scoring mechanism, we first employ deep neural networks to process multimodal inputs (including emotional text, facial expressions, $\mathrm{H}_t\mathrm{H}_v\mathrm{H}_p$and voice features) through deep encoding. This generates modal feature embeddings for text, voice, and physiological data, which are then mapped to a shared mental state space via a joint learning strategy.

$$\mathrm{Z} = f\left(\mathrm{W}_t\mathrm{H}_t + \mathrm{W}_v\mathrm{H}_v + \mathrm{W}_p\mathrm{H}_p\right) \tag{5}$$

The weight $\mathrm{W}_t, \mathrm{W}_v, \mathrm{W}_p\mathrm{Z}$matrices for each modality represent the synthesized psychological state vector. Subsequently, a weighted fusion approach is employed to achieve inter-modal information synergy, with each modality's influence being dynamically adjusted through an emotional weighting mechanism. To ensure a personalized approach, the emotional and behavioral characteristics of the individual user are quantitatively analyzed and used to define personalized weighting standards. These standards are then integrated into the fusion process, allowing the system to adapt to unique user profiles and enhance the precision of risk level classification.

$$\mathrm{Z}_{fuse} = softmax(\mathrm{W}_a \cdot \mathrm{Z}) \odot \mathrm{Z} \tag{6}$$

Then, considering the complexity and potential nonlinearity of the psychological crisis behavior, a multi-level neural network model is used to further map the state vector of the fusion.

$$\hat{y} = Sigmoid(\mathrm{W}c \cdot \mathrm{Z}fuse + b) \tag{7}$$

The model's $\hat{y}$output provides a psychological state score that quantifies the risk progression from normal to severe crisis states. This scoring algorithm not only enables quantitative evaluation of individual mental states but also demonstrates strong adaptability [5].

4 Functional module design

4.1 User Psychological Behavior Collection Module

Design of multi-modal data acquisition and integration mechanism

The user psychological behavior acquisition module requires efficient integration of multi-source data, including text, voice, physiological signals, and facial expressions, captured in real-time through various sensors.

(1) Design of multi-modal data acquisition and integration mechanism

The user psychological behavior acquisition module requires efficient integration of multi-source data, including text, voice, physiological signals, and facial expressions, captured in real-time through various sensors. Text data is collected via questionnaires and social platforms, voice data is obtained through microphones, and facial expression data is analyzed via cameras. All data undergoes preprocessing unit cleaning and synchronization to ensure consistency for subsequent feature extraction. This integrated mechanism provides multi-dimensional support for psychological behavior analysis.

(2) Behavior Event Detection and Real-time Behavior Flow Monitoring

The module features real-time monitoring and anomaly detection capabilities. It analyzes user behavior sequences through deep learning-based time-series models to automatically identify potential psychological crisis signals. The system monitors negative emotional fluctuations or intense mood swings in social and application behaviors, promptly triggering risk assessment mechanisms to provide data support for emotional evaluation and intervention.

4.2 Psychological Crisis Identification and Judgment Module

Emotional Fluctuation and Abnormal Behavior Pattern Recognition

The core function of the psychological crisis identification module is to extract emotional fluctuations and behavioral anomalies from multimodal data, using deep learning models to detect potential psychological crisis behaviors.

(1) Crisis Risk Scoring and Classification Algorithm

The model uses multi-level risk assessment algorithm to quantify the emotional fluctuation and abnormal behavior, and classifies the psychological crisis level of users based on the factors of emotional intensity, behavioral continuity and abnormal amplitude.

(2) Real-time Crisis Judgment and Feedback Mechanism

By dynamically updating emotional and behavioral data, the system performs real-time psychological crisis assessment and generates instant feedback. Based on the user's current emotional state and behavioral data, combined with predefined crisis intervention strategies, the system can automatically generate corresponding feedback results, such as providing psychological counseling suggestions or alerting the psychological counselor for intervention. [6]

4.3 Crisis Warning and Graded Intervention Module

Design of Multi-dimensional Crisis Early Warning Mechanism

The crisis warning classification and intervention module analyzes users' psychological states through multimodal data synthesis, dynamically calculating crisis risk levels in real time.

(1) Design of Multi-dimensional Crisis Early Warning Mechanism

The crisis warning classification and intervention module analyzes users 'psychological states through multimodal data synthesis, dynamically calculating crisis risk levels in real time. By integrating emotional fluctuations, behavioral anomalies, voice variations, and physiological signals, the system dynamically adjusts the weighting of each data modality. Through deep learning models, it evaluates users' psychological crisis risks and precisely categorizes them into low, medium, or high risk levels, ensuring timely and accurate crisis warnings. [7]

(2) Crisis Level Classification and Intervention Strategy Matching

The system matches intervention measures to each user based on their crisis level. Low-risk users receive emotional regulation techniques, while high-risk users trigger emergency interventions, such as psychological counseling suggestions or direct contact with a counselor. By combining rules with intelligent recommendation mechanisms, the system ensures personalized and targeted intervention plans. [8]

(3) Real-time feedback and continuous tracking mechanism

The module provides real-time feedback and tracking capabilities to continuously monitor changes in users' psychological states after interventions. Through periodic data analysis, the system evaluates intervention effectiveness and dynamically adjusts strategies to ensure long-term intervention effectiveness and stability, providing ongoing mental health support. [9]

5 System test and verification

5.1 Technology Selection for System Development Environment

In the technical selection for the system development environment, the frontend uses React and Vue.js frameworks to provide a responsive user interface; the backend services utilize Flask and Django to support high-concurrency RESTful API calls. For data storage, PostgreSQL is chosen, combined with Redis caching to optimize data access efficiency. In terms of AI and machine learning, TensorFlow and PyTorch are used for emotion recognition and behavior analysis, while BERT and RoBERTa models are employed for text sentiment analysis. For computational acceleration, NVIDIA Tesla V100 GPUs are used, and distributed training is achieved through Horovod. Regarding data security, AES-256 encryption algorithms and OAuth 2.0 authentication protocols are adopted to ensure user data security and privacy protection.

5.2 system integration test

During system integration testing, comprehensive evaluations were conducted on key functionalities and performance metrics. The tests simulated various user operation scenarios to verify the coordination and stability of modules including data acquisition, API response time, and storage efficiency. As shown in Table 1, during multimodal data acquisition tests, the system maintained data synchronization delays between 0.15 and 0.35 seconds when processing text, voice, facial expressions, and physiological data, demonstrating excellent stability. Under 500 concurrent API requests, the average response time was 352 milliseconds with maximum response times not exceeding 410 milliseconds, indicating the system's efficient real-time processing capability. For data storage and retrieval, access times averaged 0.82 seconds with query response times fluctuating between 0.75 and 0.88 seconds, validating the system's high-performance under heavy concurrent data access. Load testing revealed that under 1,000 concurrent user requests, the maximum system response latency was 520 milliseconds with 97.5% stability.

5.3 Function Effect Evaluation

The functional effectiveness evaluation primarily assesses the actual performance and outcomes of each system module, with particular focus on key functions such as psychological crisis identification, emotional analysis, and intervention suggestion generation. By comparing actual operational results with design expectations, the evaluation verifies the system's accuracy, real-time responsiveness, and intelligence level. Table 2 presents the primary testing metrics and results for functional effectiveness evaluation, covering aspects such as emotional recognition accuracy, crisis assessment accuracy, intervention suggestion generation time, and personalized scoring.

The test results demonstrate the system's high accuracy and timeliness in core functions including emotion recognition, crisis assessment, and intervention suggestion generation. The emotion recognition module achieves 92.3% accuracy, effectively capturing

Table 1: System Testing Table

Test item	test object	test method	test result
multimodal data acquisition	Verification of Text, Voice, Face and Physiological Signal Synchronization and Processing Efficiency	Simulate user input, including text, voice, facial expressions, and physiological data	Data synchronization is accurate, with processing latency between 0.15 and 0.35 seconds and 98% stability
API response time	Verification of System API Interface Response Speed and Stability under High Concurrency	Simultaneous concurrent requests (up to 500 users at the same time)	The average response time is 352ms, and the maximum response time does not exceed 410ms. The response stability is 96%.
Efficiency of data storage and retrieval	Verify the read/write efficiency and query response time of the database	High-concurrency Data Insertion and Query Test on Database	The average access time is 0.82 seconds, and the data query response time ranges from 0.75 to 0.88 seconds.
System Stability and Load Testing	Verifying the stability of the system under high load	Simulate 1,000 concurrent user requests and run for 1 hour	The system's maximum response delay during peak load does not exceed 520ms, with a stability rate of 97.5%.

Table 2: Function Testing Table

Test item	test object	test method	test result
Accuracy of emotion recognition	Verifying the Accuracy and Timeliness of the Emotional Recognition Module	Emotion Classification and Analysis Using Real User Sentiment Data Set	The accuracy of emotion recognition is 92.3%, and the real-time response time is 0.25 seconds
Accuracy rate of psychological crisis assessment	Verify the accuracy of the crisis assessment module and the ability to judge the risk level	Classification and Verification of Risk Level Based on Historical Crisis Data	The accuracy of crisis assessment was 95.7%, and the accuracy of high-risk status identification was 96%.
Intervention suggestion generation time	Validation of the timeliness and immediacy of intervention recommendations	Simulate user behavior changes and evaluate the response time of generated suggestions	The average suggestion generation time is 1.8 seconds, with 90% of suggestions generated within 2 seconds.
The intervention recommends a personalized approach.	Validation of the Personalized and Adaptive Intervention Recommendation	Assessing the suggestibility of the system by simulating the psychological state and needs of different users	The personalized score is 88.5%, with over 90% of users approving the intervention.

user emotional fluctuations and providing timely feedback. In psychological crisis assessment, the system exhibits strong risk-level judgment capabilities, with a 96% accuracy rate for high-risk state identification. Regarding intervention suggestion generation, the system responds swiftly, with 90% of suggestions generated within 2 seconds. Through personalized models, it provides appropriate intervention content based on users' psychological states, achieving a personalized evaluation score of 88.5%.

6 Conclusions

With the rapid development of society and the advancement of informatization, college students are facing unprecedented mental health challenges. Traditional psychological crisis intervention methods can no longer meet their increasingly complex needs. The introduction of artificial intelligence offers a new solution for mental health management, demonstrating significant potential in precise identification, real-time feedback, and personalized intervention. The AI-based psychological crisis behavior analysis system designed in this paper, leveraging multi-modal data fusion and deep learning technologies, overcomes the limitations of traditional psychological assessment methods and paves a new path for efficient, intelligent psychological crisis intervention.

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