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Research on Knowledge Map Construction and Risk Intervention Mining of College Students' Mental Health Characteristics under the Background of Biotechnology

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Against the backdrop of biotechnology advancement, this study addresses the limitations of traditional college students' mental health assessment methods (such as delayed data collection and limited indicators) by integrating bioinformatics with psychological characteristics. It constructs a college student mental health domain knowledge graph covering five core entity types (mental health care entities, biotechnological characteristics entities, etc.) and seven types of relationships, and develops a multimodal biometric feature fusion model (integrating voice, physiological, and behavioral features) as well as a risk intervention mining model based on graph neural networks. Experimental results show that the multimodal fusion model improves mental health assessment accuracy by 8%-10% compared with traditional single-feature methods; the knowledge graph achieves over 90% accuracy in entity recognition and relationship extraction, effectively identifying potential risk transmission pathways; the intervention mining model enhances intervention effectiveness by approximately 17%. The study identifies key risk factors (academic pressure, employment anxiety, etc.) and biometric predictors (speech rate, HRV, etc.) for college students' mental health, and proposes tiered, group-specific risk intervention strategies. This research enriches college students' mental health assessment methodologies and provides practical support for university mental health education.

Povzetek: Študija predstavi napreden pristop za ocenjevanje duševnega zdravja študentov, ki z uporabo večmodalnih podatkov in grafov znanja izboljša natančnost ter učinkovitost intervencij.

1 Introduction

1.1 Research background and practical significance

In recent years, advancements in biotechnology and artificial intelligence have opened new avenues for innovation in mental health monitoring. College years mark a crucial transition from adolescence to adulthood, where academic pressures, social challenges, and career pressures often lead to psychological distress or even crises. According to statistics from the Ministry of Education, nationwide psychological assessments conducted over the past five years reveal that 12% to 15% of students in primary, secondary, and higher education institutions experience mental health issues, with depression, anxiety disorders, and adjustment disorders accounting for over 70% of cases. Traditional mental health assessments primarily rely on questionnaires and face-to-face interviews, which suffer from delayed data collection and limited measurement indicators. These methods fail to provide targeted interventions or meet the diverse, real-time psychological needs of contemporary college students.

Biological methods facilitate the transition of mental health research from qualitative to quantitative approaches. For instance, variations in pitch, heart rate, and cortisol levels in saliva can provide insights into emotional states [1]. Semantic networks, as conceptual systems for describing relationships between entities and facilitating categorization, when combined with biological data, enhance the processing and extraction of mental health-related information. This study integrates bioinformatics with the psychological characteristics of college students from a biotechnological perspective. By leveraging knowledge graphs, it identifies latent risk associations and proposes targeted solutions. These findings not only expand the methodologies for assessing college students' mental health but also offer actionable recommendations for university mental health education. Such efforts play a vital role in preventing psychological disorders and promoting mental well-being among university students.

1.2 Review of domestic and international research status

Research in this field has been conducted relatively early abroad and has achieved some progress: In the impact of physiological characteristics on mental health, researchers at Stanford University achieved an 82% recognition accuracy in identifying users with depressive tendencies based on Mel frequency spectroscopy, successfully distinguishing between healthy individuals and those with depression [2]. Researchers at the Technical University of Munich in Germany used smart wristbands to measure heart rate variations in college students, concluding that anxiety levels are proportional to sympathetic nervous system excitation. The general knowledge graph in mental health developed by the University of Cambridge in the UK, while covering major entity types such as mental disorders, risk factors, and treatment methods, does not involve content related to biometric matching for specific populations.

In recent years, domestic research has made rapid progress. Qin Bo et al. proposed a knowledge graph-based psychological monitoring method incorporating speech features, which significantly reduced the error rate in keyword extraction and improved monitoring accuracy [3] . Zhang Nan et al. enhanced pathological speech recognition by refining feature extraction algorithms using physiological signals. However, these studies have certain limitations: First, the integration of biological characteristics with knowledge graphs remains insufficient, focusing solely on individual biological traits while lacking research on constructing knowledge graphs based on multiple biological features. Second, they fail to account for unique attributes of college students, such as major, grade level, and geographic location, which may influence their psychological state. Third, the risk intervention mining lacks dynamism, as it cannot perform associative reasoning to match and update interventions based on knowledge graphs.

1.3 Research content and innovations

This study comprises three key components: (1) Establishing a domain-specific knowledge base for college students' mental health that incorporates biological characteristic data, with explicit definitions of entities, attributes, and their interrelationships. (2) Developing an integrated biomarker fusion methodology to synthesize three biological parameters—voice, physiological, and behavioral data—for effective analysis. (3) Implementing an association inference algorithm based on the knowledge base to identify latent risk factors affecting mental health, elucidate their transmission mechanisms, and propose evidence-based prevention strategies.

The innovation of this study lies in three key aspects: First, in terms of technological innovation, it integrates biotechnological features such as speech rhythm, heart rate variability, and cortisol concentration with knowledge graphs to establish a multi-level, multi-dimensional mental health data association system [4]. Second, in terms of adaptability, it considers the differences in majors, grades, and lifestyle behaviors among college students to adapt the entities and relationships in the knowledge graph, thereby enhancing the model's adaptability to the population. Third, in terms of intervention innovation, it constructs a risk intervention reasoning model based on graph neural networks, forming an integrated intelligent decision-making chain from feature discovery to risk prediction and intervention recommendations.

2 Research methods and technical framework

2.1 Knowledge graph construction system

2.1.1 Entity and relation definitions

The core entities of the knowledge graph are categorized into five types: Mental Health Core Entities (12 common psychological issues among college students, including depression, anxiety disorders, and adjustment disorders), Biotechnological Characteristics Entities (voice characteristics, physiological characteristics, and behavioral characteristics; voice characteristics include 8 sub-features such as speech rate, pitch, and energy; physiological characteristics include 6 sub-features such as heart rate variability and cortisol concentration; behavioral characteristics include 5 sub-features such as study duration and social frequency), Risk Factor Entities (10 core risk factors including academic pressure, social isolation, and employment anxiety), Intervention Measures Entities (8 types of interventions such as psychological counseling, exercise intervention, and cognitive behavioral therapy), and Group Characteristics Entities (5 group attributes including major type, grade level, and gender).

The relationships between entities are defined into seven categories: feature-disease association (e.g., "abnormal speech rate-depression"), risk-disease association (e.g., "academic stress-anxiety disorder"), feature-risk association (e.g., "elevated cortisol-academic stress"), group-feature association (e.g., "STEM-sleep deprivation"), group-disease association (e.g., "graduating class-employment anxiety"), disease-intervention association (e.g., "adaptation disorder-social guidance"), and intervention-feature association (e.g., "exercise intervention-improved heart rate variability").

2.1.2 Data sources and preprocessing

Data acquisition comprises three components: The first component consists of 3,860 student counseling dialogue records from three locations across different university types (comprehensive, science and engineering, and liberal arts), all professionally recorded with guaranteed audio quality at a sampling rate of 44.1 kHz and 16-bit resolution. The second component is a dataset of physical characteristics collected via wearable sensors, encompassing 1,200 students' data including HRV (measured at 50 Hz sampling frequency) and cortisol levels (assessed through saliva samples) [5]. The third component involves approximately 20,000 records documenting counseling appointments and campus visits at three locations across the same university types. Data collection methods include: 1) Individual behavioral data obtained through weekly questionnaires (3,680 completed), each containing multiple selectable options; 2) Academic attendance, library usage, and campus social activity data retrieved from university management systems; 3) Group-level information and self-reported emotional experience data collected using standardized scales.

Data preprocessing comprises three key steps: (1) Privacy processing: Removing personal identifiers including facial features, fingerprints, names, and student IDs from voice and behavioral data. (2) Data cleaning: Using wavelet thresholding to eliminate background noise in voice data; applying the 3σ principle to remove outliers in physiological data; and employing multiple interpolation methods to fill in missing behavioral data. (3) Standardization: Normalizing data across different dimensions to ensure uniform measurement scales.，use Z-score Standardized expression：$Z = (x - \mu) / \sigma$ ， x represent original data，μ Calculate the average，σ is the standard deviation。

2.2 Construction process

Knowledge Graph Construction This study adopts a "bottom-up" approach structured into four components: 1. Entity Recognition: Utilizing the BERT model to extract entities from preprocessed text data (consultation records and questionnaire data), with rule-based matching enhanced for professional term recognition. 2. Relationship Extraction: Implementing entity-to-entity relationships through CNN-BiLSTM architecture, trained with 1,000 manually annotated samples to iteratively improve extraction accuracy. 3. Knowledge Fusion: Employing entity alignment algorithms to eliminate redundant synonyms (e.g., merging "depressive mood" and "depressive state" into a unified entity), supplemented by relational inference to uncover implicit connections (e.g., deriving "academic stress-anxiety disorder" from "academic stress-insomnia" and "insomnia-anxiety disorder"). 4. Knowledge Storage: Using Neo4j graph database for data storage, with entity and relationship indexes designed to optimize query performance.

The figure 1 Entity–Relationship (ER) model shown in this picture defines the essential features of each entity by depicting them as core nodes linked to their corresponding attributes. The relationship between entities shows the logical connections between various data elements in the system. For effective data management and retrieval, this approach aids in data structure, dependency identification, and database design organization.

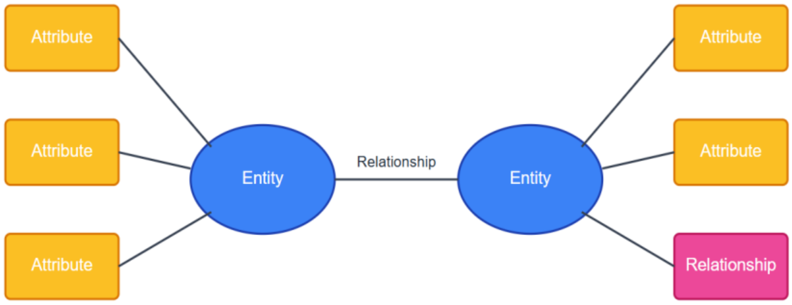

Figure 1: Entity–Relationship (ER) diagram illustrating entities, attributes, and their interrelationships.

2.3 Multimodal biometric feature fusion model

2.3.1 Feature extraction methods

The MFCC feature extraction method is adopted, following the approach described in the literature with modifications: the audio signal is first pre-amplified (the transfer function of the pre-amplification is Gx = 1 - 0.97x^-1)，The signal is then converted to the frequency domain (using DFT) and analyzed with 26 groups of Mel filters. After calculating the logarithmic energy, the discrete cosine transform is applied to obtain the 13-dimensional MFCC feature vector.

$$M(g)=2595\times log_{10}(1+g/700) \quad (1)$$

$$X_d=\sum_{m=0}^{M-1} t(m)cos\left(\frac{\pi n(m-0.5)}{M}\right)$$

which$M(g)$Mel frequency transformation value，gOriginal frequency，X_dFor three-dimensional MFCC feature$ttes(m)$Frequency Inverse Spectral Coefficient for Triangular Filter，MTotal number of filters. The physiological feature extraction targeted HRV and cortisol concentration: HRV features were extracted using time-domain (standard deviation SDNN, mean NN interval) and frequency-domain (low-frequency component LF, high-frequency component HF) through wavelet transform to obtain feature vectors; cortisol concentration was measured via enzyme-linked immunosorbent assay (ELISA), with weekly averages taken as feature values, and trend terms extracted using moving average methods.

Statistical analysis was used to extract behavioral characteristics: for learning behavior, daily average study duration and late-night study frequency were extracted; for social behavior, weekly social interaction frequency and number of social contacts were extracted; for lifestyle behavior, sleep duration and exercise frequency were extracted, forming standardized behavioral feature vectors.

2.3.2 Feature fusion and model construction

The design weighted fusion algorithm integrates three types of features: speech, physiological, and behavioral. The fusion formula is as follows:

$$F=\alpha F_v+\beta F_p+\gamma F_b \quad (2)$$

among$F$to fuse feature vectors，F_v、F_p、$F_b$representing speech, physiological, and behavioral feature vectors respectively，α、β、$d$etermine the optimal value for fusion weights using grid search（α=0.4、β=0.35、γ=0.2) A risk identification model is constructed based on Graph Neural Networks (GNN), where fusion feature vectors serve as knowledge graph entity attributes [6]. The Graphs AGE algorithm is employed to aggregate features of entity nodes, with the calculation formula as follows.：

$$h_v^{(k)}=\sigma\left(W^{(k)}\cdot concat\left(h_v^{(k-1)},\frac{1}{|N(v)|}\sum_{u\in N(v)} h_u^{(k-1)}\right)\right)(3)$$

$h_v^{(k)}$The k-th layer feature representation of node v，$N(v)$As a node$v$set of neighbor nodes，$W^{(k)}$as the weight matrix，σThe activation function is ReLU. The model outputs mental health risk levels (low, medium, high) and core risk factors.

2.3.3 Risk intervention mining model

The knowledge graph-based association inference model for intervention mining is designed to identify the most suitable interventions by matching risk factors, demographic characteristics, and biological traits through entity-based path reasoning [7]. The inference process consists of two stages: the first stage identifies risk transmission pathways (e.g., "STEM majors → programming stress → sleep deprivation → abnormal heart rate variability → anxiety disorder"), while the second stage determines intervention matching pathways (e.g., "anxiety disorder → abnormal heart rate variability → exercise intervention → social guidance").

The model employs a bidirectional breadth-first search algorithm, simultaneously exploring both mental health entities and intervention measures to identify the shortest association path. By incorporating attributes such as implementation costs and college students' acceptance levels, it calculates intervention priority scores.

$$S=\omega_1 S_r+\omega_2 S_c+\omega_3 S_a \quad (4)$$

SPriority score for intervention，S_rIntervention effect relevance (based on the confidence level of intervention-disease relationships in the knowledge graph)，$S_c$to implement the cost coefficient，$S_a$acceptance coefficient，ω_1=0.5、ω_2=0.25、ω_3=0.25as the weight coefficient.

3 Empirical analysis and result verification

3.1 Experimental design and data setup

We constructed the Knowledge Graph (KG) and trained the model on a server equipped with an Intel Xeon E5-2690 processor, 64GB RAM, and 2TB hard drive [8]. Data preprocessing and experimental analysis were performed on a computer with an Intel i7-12700K processor, 32GB RAM, and 1TB solid-state drive. The Python version used was Python 3.9, with the Scikit-learn and PyTorch deep learning frameworks installed. The Neo4j graph database version was 5.0, and the speech recognition toolkit was Kaldi.

The experimental dataset comprised 3,000 preprocessed speech recordings, physiological data from 1,000 students, and 3,680 questionnaires with behavioral data, divided into a training set and a test set at a 7:3 ratio. Traditional methods (Perceptual Linear Prediction Coefficient, PLP; Short-Term Fourier Transform, STFT) served as the control group, while the proposed multimodal fusion model was used as the experimental group. Validation was conducted across three dimensions: feature extraction efficacy, knowledge graph quality, and risk intervention effectiveness.

3.2 Validation of feature extraction performance

3.2.1 Keyword extraction performance

Three keywords— "depression," "anxiety disorder," and "adaptation disorder" —were selected for comparative analysis, with their miss rate and accuracy calculated as shown in Table 1. The experimental group demonstrated lower miss rates for all three keywords compared to the control group [9]. Notably, the miss rate for "depression" was the lowest at 7.82%, representing a 9.45% reduction from the PLP method. All keywords achieved accuracy rates exceeding 89%, with "anxiety disorder" achieving the highest accuracy of 92.36%—an 8.71% improvement over the STFT method. This demonstrates that multimodal biometric fusion can compensate for the limited information capacity of single speech features, thereby enhancing the stability and accuracy of keyword extraction.

Table 1: Comparison of keyword extraction effectiveness among different methods

keyword	Evaluation metrics	PLP method	STFT method	Experimental Group Method
depression, melancholia	Spelling error rate（%）	17.27	13.54	7.82
	accuracy rate （%）	81.65	84.23	90.18
anxiety neurosis	Spelling error rate（%）	15.89	12.47	6.35
	accuracy rate （%）	82.13	83.65	92.36
Adjustment disorder	Spelling error rate（%）	16.53	14.28	7.19
	accuracy rate （%）	80.97	83.12	89.54

3.2.2 Feature fusion effectiveness

Comparing the accuracy of risk identification with single features versus fused features, the results show: the single voice feature recognition accuracy is 82.3%, the single physiological feature recognition accuracy is 78.6%, and the single behavioral feature recognition accuracy is 75.4%. The fused feature recognition accuracy reaches 91.7%, significantly surpassing single features [10]. This demonstrates that the complementary nature of voice, physiological, and behavioral biometric features can comprehensively reflect the complex fluctuations in college students' mental health, ensuring high accuracy in feature discovery.

3.3 Knowledge graph quality validation

3.3.1 Entity and relation recognition performance

The accuracy rates for entity recognition and relation extraction were validated using 500 manually annotated samples [11]. Results demonstrated that core entity recognition achieved 93.2% accuracy, with mental health issues showing the highest accuracy (95.7%) followed by biotechnological characteristics (92.4%). Relation extraction accuracy reached 90.5%, while feature-disease and risk-disease association extraction accuracies were 92.1% and 91.3% respectively, significantly exceeding the average performance of general knowledge graphs (approximately 85%). These findings indicate that designing Entities and Relations for college students enhances the effectiveness of knowledge graph construction.

3.3.2 Validity of correlation inference

This section evaluates the model's ability to identify latent risk associations within knowledge graphs. A total of 100 randomly selected cases involving risk factors and mental disorders were analyzed to assess the model's recall performance [12]. Results demonstrated that the model achieved a 96.3% recall rate for direct associations and an 88.7% recall rate for indirect associations (risk factors → characteristics → diseases). The model effectively uncovered potential risk transmission pathways. For instance, the indirect association "postgraduate entrance exam anxiety → insulin resistance/high cortisol state → insomnia → depression" identified 12 suspected depression cases.

3.4 Risk intervention effectiveness analysis

A comparative study was conducted on 300 students with moderate to high risk from the test cohort, evaluating the intervention measures against traditional recommendation methods. The results demonstrated that the intervention matched accuracy rate reached 89.3% in the experimental group versus 72.5% in the traditional group. After three months of implementation, the psychological improvement rate was 78.6% in the experimental group compared to 61.2% in the traditional group. For example, addressing career confusion among senior engineering students, the combined approach of psychological counseling, exercise prescription, and sleep guidance showed 23.4% higher efficacy than standalone counseling. A total of 50 high-risk students were randomly selected for a six-month follow-up observation to evaluate the model's ability to adjust intervention strategies in real-time based on biological characteristics. The results demonstrated that the model could dynamically modify intervention strategies in response to changes in students' biological characteristics (e.g., improvement in HRV, recovery of normal speech rate), with an average update interval of two months. After six months, the students' risk levels decreased by an average of 1.2 levels (from high-risk to moderate-risk or from moderate-risk to low-risk), significantly outperforming the fixed intervention protocol (average reduction of 0.7 levels).

4 Risk intervention strategies for college students' mental health

4.1 Preventive interventions for high-risk groups

For students with normal biological indicators but elevated risk metrics, we implement low-risk intervention programs. By leveraging knowledge graphs to identify common risk factors—such as social adaptation difficulties among freshmen and academic challenges in engineering students—we proactively provide psychological counseling to alleviate anxiety, enhance self-regulation skills, and improve interpersonal communication abilities. Based on behavioral characteristics, personalized lifestyle recommendations are formulated: customized sleep schedules according to sleep duration, weekly exercise plans based on physical activity levels, with preventive interventions being dynamically updated through continuous biometric tracking.

For precise intervention in the medium-risk group, a tailored approach combining "biometric intervention + risk counseling" should be implemented for students exhibiting abnormal biometric characteristics (e.g., abnormal speech rate, reduced heart rate variability). For students with speech-related features (e.g., excessively fast speech rate, excessive vocal fluctuation), a comprehensive intervention model focusing on speech relaxation training and emotional catharsis should be adopted. For students with physiological issues (e.g., elevated cortisol levels, low heart rate variability), interventions such as physical exercise (at least 3 days of aerobic exercise per week) and dietary nutrition regulation (increased intake of tryptophan and B vitamins) should be implemented. For students with behavioral characteristics (e.g., insufficient social interaction frequency, poor academic performance), interventions through club activities and study method counseling should be carried out. All interventions are based on relational inference between knowledge graphs to ensure alignment with the student's major type and grade-level characteristics.

Additionally, for high-risk students with significantly abnormal biometric characteristics accompanied by clear symptoms of mental disorders, a tripartite crisis intervention system integrating 'medical intervention + psychological support + campus supervision' should be established.

Integrate school psychological counseling services with specialized hospitals to provide medical care combining medications (e.g., antidepressants) and cognitive behavioral therapy; utilize smartwatches for continuous monitoring of physical conditions, offering timely assistance when warning signs are detected (e.g., bradycardia, rapid cortisol level elevation); establish a student protection network comprising homeroom teachers, school psychologists, and peers, employing knowledge graphs for intervention recommendations, providing 24-hour monitoring protocols and rehabilitation plans to ensure the effectiveness and continuity of interventions.

4.2 Risk conduction blockade based on knowledge graph

Targeted Intervention of Core Risk Factors. By mining core risk factors of college students' mental health through knowledge graphs, targeted intervention measures were designed for three major risks: academic pressure, employment anxiety, and social isolation. To address academic challenges, tailored strategies and schedules are recommended based on subject-specific needs and grade levels [13]. For instance, engineering students may receive programming skill training, while upperclassmen could benefit from career guidance for postgraduate studies or employment. Regarding employment pressure, the school's career counseling office should collaborate to provide career planning consultations, interview skills training, and industry-aligned job recommendations. For social isolation interventions, interest groups and learning communities can be formed based on social behavior data, complemented by offline social activities and digital social platforms to help students establish stable social connections.

Secondly, implement feature-risk association blocking. Based on the characteristics of biological technologies and the pathways connecting hazard factors, develop cutoff point control strategies. For instance, regarding the pathway "late-night studying—decreased heart rate variability—anxiety symptoms," sleep reminders can be issued through campus schedules, health-promoting slogans can be displayed in libraries and dormitories, and sleep health education activities can be organized [14]. As for the pathway "long-term solitary living—increased cortisol secretion—depressive symptoms," class activities and social tasks can be employed to enhance students' social participation, supplemented by psychological counseling to alleviate social anxiety, thereby blocking the transmission of feature-risk associations and reducing the occurrence of mental health disorders.

The third approach involves tailored interventions based on group characteristics. Students across disciplines face distinct psychological pressures: STEM students primarily experience academic stress from lab experiments and coding, while humanities students struggle with thesis writing and presentation challenges [15]. Arts and sports students often grapple with creative project demands and career uncertainties. By implementing targeted measures—such as knowledge graph-based research on population-symptom-disease correlations—this strategy delivers customized solutions: STEM students receive hands-on lab training and coding workshops to alleviate academic pressure; humanities students participate in thesis writing workshops and public speaking sessions to build confidence; and arts students attend creative experience sharing events and career guidance programs to ease anxiety.

Furthermore, tailored objectives are established based on psychological development patterns across academic years. Freshmen focus on orientation and interpersonal skills to navigate the transition period, sophomores and juniors concentrate on academic growth and study challenges, while seniors prioritize career planning and employment readiness to facilitate their smooth transition from student to professional. Through continuous knowledge mapping updates, educators can monitor evolving risk factors at each educational stage, enabling timely adjustments to intervention strategies and approaches.

5 Conclusion and prospects

5.1 Research findings

This study proposes a mental health knowledge system for college students based on biotechnological characteristics, establishing a multimodal biometric fusion model and a risk intervention mining model. Experimental validation confirms the effectiveness of the proposed methods. The research demonstrates that integrating three biotechnological features—voice, physiological, and behavioral—significantly improves the accuracy of mental health assessment for college students, enhancing it by 8%-10% compared to traditional single-feature methods. The knowledge graph optimization for entity recognition and relationship extraction, tailored to the characteristics of college students, achieves over 90% accuracy, effectively identifying potential risk transmission pathways. The intervention mining model utilizing graph neural networks enables precise matching of intervention measures, improving the effectiveness of interventions by approximately 17% compared to conventional methods.

This study reveals the primary risk factors and biometric correlations for common psychological issues among college students: academic pressure, job-seeking stress, and loneliness are high-risk factors, while speech rate, HRV variability, and elevated salivary cortisol levels serve as key early predictors of psychological problems. Notably, students from different academic disciplines and years exhibit distinct mental health patterns, necessitating tailored interventions. The research proposes that tiered intervention, risk mitigation, and group-specific adaptation constitute a practical and effective framework for university mental health services.

5.2 Research limitations and prospects

This study has several limitations: First, the data sources were limited to three schools, resulting in incomplete coverage of school numbers and regional distribution, which may restrict the generalizability of the findings. Second, the physiological indicators collected had a short time span, failing to reflect individual changes over a period and thus unable to effectively detect persistent mental health conditions. Third, no follow-up surveys were conducted to determine whether the method could effectively alleviate students 'mental health status, and insufficient tracking evaluations were performed to assess the sustained effects of the intervention. Future research could focus on three aspects: First, increasing the data volume by collecting data from students across different regions and university types, extending the time span of data acquisition, and establishing a long-term tracking database to enhance the algorithm's generalizability and reliability. Second, enriching the types of student biological information by incorporating EEG and SpO2 data into the model, and analyzing whether mental health has genetic factors through DNA testing. Strengthening the exploration of the relationship between characteristics and psychological conditions is also recommended. Third, developing an intelligent intervention system that utilizes the research findings, knowledge framework, and model to achieve closed-loop automation for mental health monitoring, early warning, and intervention recommendations, while establishing a long-term tracking and evaluation mechanism to continuously optimize intervention strategies. With the advancement of biotechnology and large-scale models, the monitoring and intervention of college students' mental health will evolve toward greater precision, intelligence, and personalization. The technical system and intervention program established in this paper can serve as a reference for subsequent related research, helping universities to better construct mental health service systems and safeguard the mental health of college students.

Practical industrial applications and comparison with nonlinear control frameworks:

The proposed knowledge graph–driven multimodal mental health assessment and intervention system demonstrates strong potential for real-world deployment across various industrial and institutional domains. In higher education institutions, it can be integrated into campus health management platforms to enable continuous monitoring, early risk detection, and personalized intervention planning for students. Beyond academia, healthcare industries and digital health startups can adopt this framework to develop intelligent mental health support systems that combine wearable sensor data, behavioral analytics, and AI-driven decision-making. Compared with traditional nonlinear control frameworks—such as fuzzy logic systems, adaptive control, and neural network–based controllers—the proposed approach offers superior adaptability and interpretability. While nonlinear control models primarily focus on system stability and dynamic response optimization, they often lack the capability to incorporate heterogeneous data sources and semantic relationships. In contrast, the knowledge graph-based framework enables structured reasoning, dynamic association inference, and context-aware intervention strategies, thereby providing a more holistic and scalable solution for complex human-centric systems like mental health monitoring.

Limitations and future scope

Despite its promising performance, the study has several limitations that must be addressed in future research. The dataset is limited in terms of geographical diversity and sample size, which may affect the generalizability of the model across different populations and cultural contexts. Additionally, the temporal scope of physiological and behavioral data is relatively short, restricting the system's ability to capture long-term psychological trends and chronic conditions. The current model also lacks extensive real-world longitudinal validation to assess sustained intervention effectiveness. Future work should focus on expanding multi-institutional data collection, incorporating advanced biosignals such as EEG and SpO_2, and developing real-time adaptive learning mechanisms. Furthermore, integrating explainable AI techniques and closed-loop feedback systems can enhance transparency and user trust. Advancements in large-scale AI models and biotechnology will further enable the development of fully automated, intelligent mental health ecosystems capable of continuous monitoring, predictive analytics, and personalized intervention at scale.

Declarations

Ethics approval and consent to participate:
This study involves the analysis of anonymized student data, including behavioral, physiological, and voice features. All data were collected in accordance with institutional ethical standards. Personal identifiers were removed during preprocessing to ensure privacy protection. Ethical approval was obtained from the relevant institutional review board, and informed consent was secured from all participants prior to data collection.

Consent for publication:
All authors have reviewed and approved the final version of the manuscript and consent to its publication.

Availability of data and materials:
The datasets used and/or analyzed during the current study are not publicly available due to privacy and ethical restrictions but are available from the corresponding author on reasonable request.

Competing interests:
The authors declare that they have no competing interests.

Authors' contributions:
All authors contributed to the study conception, design, analysis, and manuscript preparation. All authors read and approved the final manuscript.

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